Handling Imbalanced Classes: Feature Based Variance Ranking Techniques for Classification

Solomon Henry EBENUWA

A thesis submitted in partial fulfilment
of the requirements of the University
of East London for the degree of
Doctor of Philosophy

Architecture, Computing and Engineering (ACE),
University of East London
September 2019

Supervisors:

Dr Ameer Al-Nemrat
Senior Lecturer in Computer Science
School of Architecture, Computing and Engineering (ACE)
University of East London,
Docklands Campus,
4-6 University Way,
London E16 2RD

Dr Saeed Sharif
Senior Lecturer in Computer Science
School of Architecture, Computing and Engineering (ACE)
University of East London,
Docklands Campus,
4-6 University Way,
London E16 2RD

Abstract

To obtain good predictions in the presence of imbalance classes has posed significant challenges in the data science community. Imbalanced classed data is a term used to describe a situation where there are unequal number of classes or groups in datasets. In most real-life datasets one of the classes are always higher in number than others and is called the majority class, while the smaller classes are called the minority class. During classifications even with very high accuracy, the classified minority groups are usually very small when compared to the total number of minority in the datasets and more often than not, the minority classes are what is being sought. This work is specifically concern with providing techniques to improve classifications performance by eliminating or reducing negative effects of class imbalance. Real-life datasets have been found to contain different types of error in combination with class imbalance. While these errors are easily corrected, but the solutions to class imbalance have remained elusive.

Previously, machine learning (ML) technique has been used to solve the problems of class imbalanced. There are notable shortcomings that have been identified while using this technique. Mostly, it involve fine-tuning and changing parameters of the algorithms and this process is not standardised because of countless numbers of algorithms and parameters. In general, the results obtained from these unstandardised (ML) technique are very inconsistent and cannot be replicated with similar datasets and algorithms

We present a novel technique for dealing with imbalanced classes called variance ranking features selection, that enables machine learning algorithms to classify more of minority classes during classification, hence reducing the negative effects of class imbalance. Our approaches utilised the intrinsic property of the datasets called the variance. As the variance is one of the measures of central tendency of the data items concentration within the datasets vector space. We demonstrated the selections of features at different level of performance threshold thereby providing an opportunity for performance and feature significance to be assessed and correlated at different levels of prediction. In the evaluations we compared our features selections with some of the best known features selections techniques using proximity distance comparison techniques and verify all the results with different datasets, both binary and multi classed with varying degree of class imbalance. In all the experiments, the

results we obtained showed a significant improvement when compared with other previous work in class imbalance.

Dedication

This work is dedicated to those who had to take the brave journey alone. It was cold, lonely and bitter, there was no person nor place to get help. The pains, anxiety and despondence we had to bear, the endless wobbling and falling, the wiping out of my resources and stagnation of every aspects of my existence while waiting for the journey to end. There were days when it seems is not going to end, on hindsight I wondered what kept me going. Some day, perhaps it may be worth all the toiling.

Declaration

I Solomon Henry EBENUWA, Solemnly declare that the work in this thesis are my and that every effort have been made to acknowledge all the academic papers, Journals, book and other material used in accordance to academic best practises by providing appropriate reference. I further state that some part of this thesis have been and will be publish in academic papers, Journals, book and other materials for the purpose of advancing knowledge and information.

Acknowledgements

This research journey would have been impossible if not for the contributions of some notable individuals, I used this juncture to acknowledge their contributions and say a big thank you to them.

First and formost are my able supervisory teams being led by the person of Dr Ameer Nemrat my Director of Studies (DOS) and Dr Saeed Shareef (Supervisor), I would also note the contributions of my first supervisor that started the Journey with me Dr Abdul Tawil, I will remain grateful for all the support, encouragement, endless meetings and corrections that you men provided me with. On many occasions I had wanted to dropout but each time I meet with either of you my interest is reinvigorated and I have a new reason to fight on. You gentlemen provided me an invaluable advise, insight and strength without which this P.hD journey would not have been possible , once again I say "THANK YOU" and "Doff My Hat".

I will not forget the contributions of the following colleagues and friends; notably the person of Dr Kennedy Isibor Ihianle, who specifically introduced me to many skills I had to acquire for a successful Ph.d Journey and insights into Journal publications without which my success today may not have been realistic.

I use this time to recognize the contributions of my senior sister Ms Uche Stella EBENUWA and her daughter Jennifer, there were times when it was only we three that was around each other, there were darkness and hopelessness everywhere how we were able to cope and persevere is still a mystery to me; I really hope that we could one day seat and reminisce.

Finally, I give thanks to God the creator or what ever that is up there watching over me, I believe without any iota of doubt that "Something or Someone" is watching over me! On many occasion I have face an extreme situation that made me think that I am a "lost cause" , the situation was hopeless, but some how I manage to survive, begin again and even prosper. Its just cannot be that is due to my effort because my efforts alone would not have been enough to extricate me from the quagmires that have dug my life ever since, to this I say Thank YOU GOD!.

Let me recognise the contribution of certain people earlier in my life Mr Osadebe, Mr Franklin Eghomien; Oh my God! I remember my time at UNIBEN if not for you two, it would have been worst. I am also acknowledging the contributions of all those I did not mention their names here because of space, particularly the people

I lived in "The Gambia" with notably the ones that has remain good friends up to these days, I say thank you all and may you have the courage to fight for what you desire. For all my former friends that I have fallen apart with, I still say thank you because as at the time we were friends you contributed in making life bearable.
I thank those that will have the patience to read this research work and I say to them, may it give you as much pleasure and excitements as it has given me during the research journey and also remember that a research work is not suppose to be a "finish product" rather an opening to more knowledge questions and that lead to more questions for continuity and advancement of knowledge. For this I extend my thanks to those earlier researcher that their work is in the public domain for affording me the opportunity to read their work and hope that some day this work will also join them in the same public space.
I thank you all , Adieu!!

Contents

List of Figures

List of Tables

Glossary

(FP_{maj}) False Positive Majority xix, 99, 117

(FP_{min}) False Positive Minority xix, 99, 117

(TP_{maj}) True Positive Majority xix, 99, 117

(TP_{min}) True Positive Minority xix, 99, 117

(ADASYN) Adaptive Synthetic Sampling x, xix, 16, 33, 34, 136, 137, 139, 140, 141, 142, 148

(ANN) Artificial Neural Network xix, 26, 28

(ANOVA) Analysis of Variance xix, 55

(API) Application Programming Interface xix, 25, 28

(CRISP) Cross-industry standard process xix, 46

(CSL) Cost-Sensitive Learning xix, 28

(CSV) Comma-separated values xix, 5

(DM) Data mining xix, 37

(DNA) Deoxyribonucleic acid xix, 18

(DNA) deoxyribonucleic acid xix, 8

(DT) Decision Tree xix, 98, 99, 101, 102, 103, 104, 108, 116, 121, 124, 125, 126, 127, 141

(IG) Information Gain ix, xvii, xviii, xix, 13, 58, 71, 72, 74, 75, 78, 79, 82, 83, 84, 88, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 109, 110, 111, 112, 113, 114, 115, 117, 118, 119, 120, 121, 122, 123, 124, 126, 127, 128, 129, 130, 132, 133, 134, 145, 148

(IQR) Interquartile Range xix, 7

(IR) Imbalance Ratio xix, 4, 10, 17, 23, 32, 37, 38, 49, 57, 100, 126, 136

(LR) Logistic Regression xix, 98, 99, 101, 108, 111, 115, 116, 124, 125, 126, 140

(ML) Machine Learning ii, xix, 5, 9, 10, 13, 21, 22, 23, 37, 108, 115, 116, 135, 137, 138, 143, 147, 148

(NN) Neural Network xix

(PC) Pearson Correlation ix, xvii, xviii, xix, 13, 58, 71, 72, 74, 75, 78, 79, 82, 83, 84, 88, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 105, 108, 109, 110, 111, 112, 113, 114, 115, 117, 118, 119, 120, 121, 122, 123, 124, 126, 127, 128, 129, 130, 132, 133, 134, 145, 148

(POC) Prove of Concept xix, 13, 108

(POC) proof of concept xix, 11

(PTA) Peak Threshold Accuracy xix

(PTP) Peak Threshold Performance xiii, xiv, xix, 11, 12, 99, 100, 101, 104, 105, 107, 108, 110, 111, 112, 113, 114, 115, 117, 119, 121, 122, 123, 124, 125, 128, 129, 130, 131, 133, 134, 139, 145

(ROS) Ranked Order Similarity ix, xvii, xix, 11, 13, 14, 71, 78, 79, 82, 83, 84, 85, 86, 88, 90, 91, 92, 93, 94, 95, 96, 97, 101, 116, 145, 146, 147, 148

(SMOTE) Synthetic Minority Over-sampling Technique x, xix, 16, 49, 136, 137, 139, 140, 141, 142, 148

(SMOTE) Synthetic Minority Over-samplingT echnique xix, 33, 37

(SVM) Support Vector Machine xix, 19, 98, 99, 101, 106, 107, 108, 115, 116, 124, 125, 126, 141

(VR) Variance Ranking from the significant of the variances in F-distributions ix, x, xvii, xviii, xix, 11, 12, 13, 14, 15, 16, 48, 50, 58, 59, 61, 64, 67, 70, 71, 72, 74, 78, 79, 82, 83, 84, 88, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 126, 127, 128, 129, 130, 131, 132, 133, 134, 136, 137, 138, 139, 140, 141, 142, 145, 146, 147, 148

Chapter 1

Introduction

Never in the history of humanity has the importance and usage of data has been as it is presently, with the improvement in computer processing power and general mechanism of collecting data have made the availability of any type of data possible. Data could be obtained from practically anything and anywhere due to the robustness of sensors and related technology. Even some activities like leisurely taking a walk or jogging which were not intended to be used for data collections have become very rich sources of data. The Internet which is one of the biggest inventions of our time is just an ocean of data itself.

Collected and stored data could be Structured, Unstructured or Semi-structured [1][2]. A dataset is said to be Structured if it is in any form of an organized format like in databases, flat file, etc, where it could be searched, updated and manipulated with an appreciable level of consistency. Semi-structured data has some level of organizations within the data set but not as much as that of Structured data, while Unstructured does not have any form of organizational formalism within them.

The usage of this data has given rise to a complex field of study aptly called data science which includes but not limited to fields like data mining, machine learning, artificial intelligence. Data science disciplines are ubiquitous and the techniques used for dealing with issues relating to the discipline are equally so. The aims of data science are to extract information and knowledge from data to support decision-making processes. Most real-life datasets have some inherent problems. The nature of input data is a major factor for a dependable result in any data analysis exercise and decision making, therefore input data have to be processed and put into a format that would enable the extractions of knowledge to take place [3][4], processing data before the extraction of knowledge therein has brought the problems associated in dealing with real-life datasets to the fore. In the preceding session, some of the problems would be reviewed.

1.1 Problems with real life data sets

Collected data in Real-life that has not undergone any form of treatment are often referred to as raw or dirty data, it thus means that literally and logically. Its rawness stem from the fact that more often than not, it is not impossible to use such data without some forms of treatments, this is known as data pre-processing. Data pre-processing is an extensive exercise that involves series of activities which depends on the type of problems identified in the raw data, some of the common problems associated with raw data could be categorized into the following; Imbalanced classes, Structuralization, Data Cleaning, Data Transformations etc. Figure 1.1 is a representation of these problems

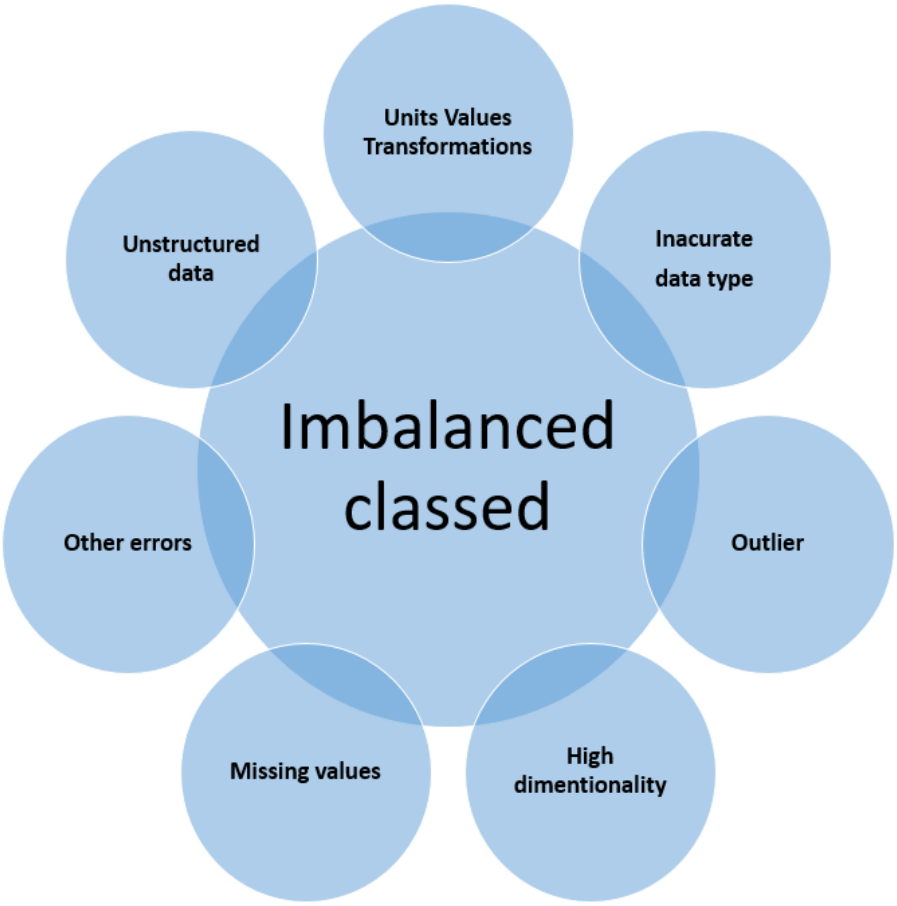


Figure 1.1: Problems of Real-Life data sets

1.1.1 Imbalanced class

This whole work is dedicated to the problems of imbalance classes in real-life data and it would be dealt with exhaustively in consequent sessions, meanwhile Figure 1.1 showed that most real-life data set has classed imbalanced problems in combinations

with other problems, for example in a binary scenario (two-class -yes or no, 1 or 0) and even multi-classed (more than two classes) the data are usually not evenly divided. One group will always be dominant as such the sensitivities of most machine learning algorithms are always predicting more of the dominant group at the expense of the minority groups. The dominant groups with higher number are called majority class, while the smaller group are called minority class. The ratio of the majority class to the minority class is refers to as the imbalanced ratio (IR).
Imbalanced classed is not peculiar to only granular data, but many life scenarios have an imbalanced problem, below are some of the examples, but the list is endless.

- **Oil spillage -** in identifying oil spillage in the ocean, small area of image or water sample with the contamination compared to the large area of water without contamination produces an imbalanced image or data respectively.
- **Tracking migrations of species like birds -** Tracking migrations of species like birds; large areas of topography compared to a very small area dotted with migrating species produces an imbalanced image of topographical identifications.
- **In security image recognition -** In the security image recognition; police tracking a single or few suspects by using a CCTV Camera in a crowd of people produce an imbalanced image recognition scenario.
- **In health or intrusion data -** The minority may be the few patients that have lung cancer compared to a large amount of data of patient without cancer or in intrusion detection data the few times that hackers have successfully breached the network compared to millions of successful login.

Traditional approaches to classifications in the context of imbalanced classed distributions in data sets has serious limitations, these will be introduced and dealt with very well in chapter 2 and later chapters, but Figure 1.1 have left us with compelling evidence of the the pervasiveness of the problem and how easily a data set which exhibit imbalance problems could be mistaken for other problems and vice versa. For example if a predictive modelling produces poor accuracy, this should raise some important questions like, is the poor accuracy due to missing values or other errors or due to uneven classes? What part of the poor performance are due to imbalanced classes and what parts are due to other problems? could the causes easily be identified ? eliminated or minimised?
The effect of class imbalance is a domain constant error inherent in most real life

scenario and manifest in what ever form is used to represent the scenario be it granular or non granular data. Most machine learning (ML) algorithm have proven inadequate [5] in dealing with the imbalanced. In the next sessions some of the errors associated with data sets but are not due to imbalance classes will be reviewed.

1.1.2 Data structuralization

This is the process of giving a structure to a collected data in a data set. The extent to which a dataset is organized is a measure of its level of structuralization, highly organized data set possibly stored in databases, flat files or others that enables manipulation of any sort, integration with other interfaces and software to aid and support exploitation with algorithms and other forms of data processing techniques with a view of extracting information and knowledge from the data are said to be structured [6]. On the other hand, Unstructured data are opposite of this, in that its a collection of data with no identifiable level of organizational formalism, hence Unstructured data cannot be manipulated, queried, integrate or worked on like Structured data.

One of the first activities of a Data Scientist is to improve the level of the structure of the collected data through formalizing the data items structural organizations based on the required and expected usage. Structuring the Unstructured data could be as simple as importing or exporting into a database table by tabulating it with identifiable rows and columns headings, another way may be exporting data into a text or Comma-separated values (CSV) files with identifiable columns and rows. Some could also involve using sophisticated processes and software that could enable any item in the data set to be identified and queried using unique metadata for extractions of a specific data item [7]. Whatever techniques used in structuring unstructured data, the result is that the data set will become more organized and any single data item could be identified and manipulated.

1.1.3 Dirty data

Is a term used in describing the different states of raw data that could impact on its quality, the dirty data must be clean by the process of detecting, correcting or removing inappropriate data item in the data set. To put it in perspective, what makes a data dirty? Dirty data are regarded as having the following common issues as listed below among many others.

- Incomplete data: If any position were a data item should be, have been left blank, nothing is written in the position.

- Duplicate data: mistakenly repeating row in a table more than once.
- Inaccurate data type: the data item input is not correct, for example, if the correct value for age is 36 year, but 360 is written.
- Incorrect data type: this is when wrong data types were used for example if for the age of a person is 36 years, an error was made by inputting the alphabet "wy" in place of 36 due to typographic error.

1.1.4 Cleaning by data transformation

The first part of this transformation is known as unit integration where the unit of measurement of the variables must be equalized [8]. This part of Pre-processing data is usually bespoke and context-dependent because the data transformation is based on local rules and standard compliance [9]. For instance, in a data set that contains a variable of prices of item in Pound Sterling and USA Dollars must be transformed to the same Unit of Currency and scale because one USA Dollar is not equal to One Pound Sterling. Also if in a data set where Date is written in DD/MM/YY and is to be combined with another data set where the date DD/MM/YYYY, the proper transformations must be done before any data mining and machine learning processes should be applied. The Unit integration processes are too numerous to mention but depend on local context and standard, mostly they are typically grouped into what is known as Extractions Transformation and Loading (ETL). Most data mining tools and software have ETL supporting facilities that do this, but the data scientist must know what data item is to be transformed and why.

1.1.5 Identifying outliers and noise

Outliers are values of a data item that are very much different from other values, but noise is wrong values though may appear as real values or may not, in any observation some values may be totally far away from others they are not wrong values these are Outliers, in most cases the observation differs so much from others hence become noticeable immediately [10]. For instance, if observations of adult age contain a value of 400 as age, this would arise suspicious because no living adult is as old as that, this is a noise because is a wrong value. For example, lets consider the average annual income of six middle class adult as $45000, $59000, $66000, $48000, $56000, $60000, $1500000 while most earned a five figure income the last person earned seven figure income, if this is correct such a data is an outlier because is remarkably different from the rest, but noise is just an incorrect data.

There are various ways to detect the presence of outliers in a data set, bar charts and histograms are one of the easiest ways of visually identifying the outliers in data sets. Another way of identifying suspected outlier is to use a statistical analysis known as ***Interquartile Range (IQR)***. To find the (IQR) we have to define the following terms Q_1 which is the first quartile of all the data point from minimum, Q_3 is the third quartile of all the data point from the minimum. These are illustrated in Figure 1.2.

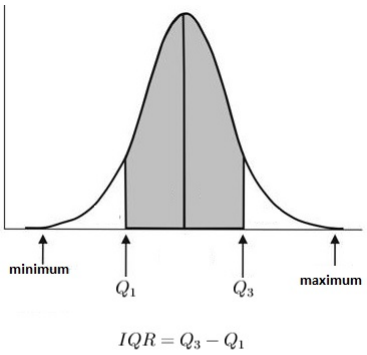


Figure 1.2: Interquartile Range

$$IQR = Q_3 - Q_1 \tag{1.1}$$

To deduce Outliers= Multiply 1.5 and IQR

$$1.5 * IQR$$

Upper Outliers are values greater than $(1.5 * IQR) + Q_3$

Lower Outliers are values lower than $Q_1 - (1.5 * IQR)$

Outliers could also be identified by using Box and Whiskers, Figure 1.3 is example of Box and Whiskers.

Outlier could be shown using Box and Whisker, in general the rule of thumb in identifying the outlier are data points that lie more than 1.5 IQR below the *min* or 1.5 IQR above the *max* are most likely to be Outliers, but the red flag could also lie within Q_1 and Q_3 . Having been able to identify the outliers in your data set, the implications and meaning of the outliers must be ascertained [11]. **Is all Outliers a dirty data?** the answers is "NO", you must infer if the outlier constitute a dirty data that must be corrected or done away with or it may be the "gold" you are mining for.

In a variable of ages of adults, if a value of 500 as the age is identified, is very possible that it is an error and thus a dirty data for obvious reasons that no living person should have such age and it must be appropriately treated like replacing it or out-rightly removing it. But if the data set is for computer network intrusion

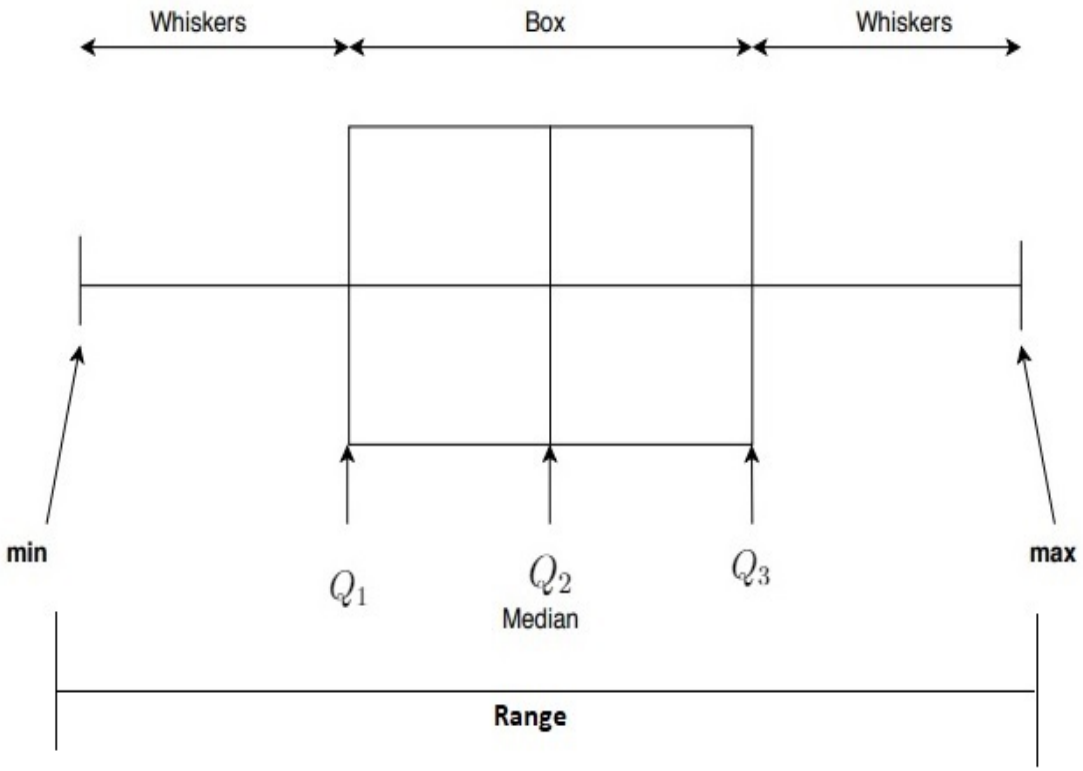


Figure 1.3: Box and Whiskers

detection, the outlier may represent the few times that hackers have breached the network, therefore such outlier may be the "gold" you are mining for hence should be investigated further to ascertain what it stands for. It, therefore, comes down to the domain knowledge of Business Understanding to be able to explain the meaning and the implications of the discovered outliers or data items that are significantly different from others.

1.1.6 High dimensionality

To put it simply dimensionality refers to the number of attributes or features in a data set, if a data set is made of n rows; representing each data item and p columns representing features or attributes, the comparative values of sizes of n to p defines the order of dimensionality of the data set [12], while it has not been conclusively established the values of p that is high dimension due to context domain dependent, but is generally accepted that a data set is regarded as high dimension when $p > n$. In some areas like Bioinformatics, Astronomy, Image Recognition and Finance, data set with thousands of features are not uncommon [13], microarray which are used to measure expression level of gene, Deoxyribonucleic Acid (DNA) information are notoriously known for high dimensionality. The curse of dimensionality is the difficulty associated with extracting the required information from data set due to

the high dimensionality. Techniques for reducing the dimensionality of data set into manageable dimensions is an active areas of research, please see [14] [15] [16].

1.2 Motivation

This research is motivated by the inability of most predictive algorithm in dealing effectively with imbalanced classes in real-life data set. For the fact that imbalanced classed situations in context and concept are pervasive and recognizable in many aspects of our life, therefore providing solutions to this problem will greatly improve all aspects of predictive modeling. In both industries and academia, lots of predictive algorithms are used daily to solve problems or arrive at decisions but the performance of these algorithms varies in accuracy. These variations have been traceable to imbalanced class situational context. To be specific, this research is motivated by the following reasons.

- As depicted in Figure 1.1 imbalanced classed is a default problem that are always present in associations with other (one or more) raw data problems. Consequently, is a systematic error [17] [18] that is inherent in the dataset in combination to other errors that the datasets has. Therefore to say that if it is minimised or eliminated, the general result of all predictive modelling could improve will be an understatement.

- To bring it into situational perspective, this work quest to find the answers to questions like; "why is it that most algorithm could only predict less of the minority classes and in most cases far less than 30% of these minority"? [19], could these limitations in the predictions be attributed to the fault of the algorithms, wrong processes and techniques or because of an underlying characteristic of the data set, furthermore if imbalanced classes can never be eliminated, at what threshold of imbalanced ratio should the result of a classifier begins to loose its dependability, can we quantify these dependability in comparison to the imbalanced ratio?

- It is obvious that much of the general performance of most classifier are limited to their ability to deal with the imbalanced class issues, the data analysis life circle, that are often referred to as Cross Industry Standard Process for Data Mining (CRISP-DM) [20] is a bit silent in this regard for not factoring imbalanced classes to any of its stages, for this we wished to investigate and proffer solutions as to what stage imbalanced will be treated, more precisely we would delve into the applications of this (ML) algorithm and the relationship to

the properties of the data item, we would deduce a quantitative and qualitative generic influences of the algorithms and intrinsic data properties on the (IR) and make recommendation on how to effectively treat imbalanced classes at the appropriate stage in the life circle.

- Imbalanced Ratio(IR) varies significantly, from moderate to severe so are the performance of the (ML) algorithms on the data during classification. But most research have visibly avoided to investigate the relationship of the degree of imbalanced to performance of classifiers. The research will establish the correlations of the variations of imbalanced to the properties of the data item and the performance of the (ML) on various levels of imbalance. This will enable overview of the expected performance to be estimated before a detailed analysis is carried out and also an informed decision on the type (ML), data preprocessing and many other activities that would make sensitivities of existing Machine learning (ML) to be able to target minority in an imbalanced dataset while eliminating the negative influenced of class imbalanced .

Special emphasis will be paid to both binary and multi-classed imbalance with a view of inventing a process that could be applied in both scenario ie binary and multi-classed data. Perhaps since imbalance classes problems cannot be completely eliminated but with the right processes the effects could be reduced to the barest minimum, for this we would produce a system where the threshold of dependable result will be known or estimated .

1.3 Aims

The aims of this research are to provide techniques to eliminate skewness of algorithms towards identifying more of the dominant majority group during the imbalanced classes classification modelling. This will improve the accuracy and general predictive performance in both binary and multi-classed datasets. The ubiquitous nature of real-life datasets is such that a formalized approaches will be invented to find the threshold of imbalanced ratio at which a classifier results becomes less reliable. Finally, the correlation of the degree of overlapping and imbalance will be demonstrated, this will also help in minimising the skewness of algorithm towards capturing more of the dominant majority group(s) instead of the small minority classes that are usually the reasons for the predictive modelling.

1.4 Contributions

In course of achieving the research aims, new processes and procedures will be invented to provide alternatives to already existing techniques in dealing with imbalance data, the solutions we proffer here is a significant contribution, consequently, the work will itemize all major novelty and contribution as follows.

- This research produced a novel technique called Variance Ranking Attribute Selection (VR) to handle imbalanced classes in both binary and multiclass datasets. Though, it has been referred to as Variance Ranking in many instances through out this thesis. The superiority of the (VR) over the existing techniques of dealing with class imbalanced have been demonstrated by producing better results, being able to deal with overlapping classes more effectively and being algorithm independent. For the proof of concept (POC) seven major dataset were used. These are further explained in chapter three session 3.1.1

- A novel method of choosing significant attributes based on Peak Threshold Performance -(PTP), which is defined as the point at which the predictive model accuracy is at his highest, hence two types of (PTP) is identified these are $(PTP)_{Accuracy}$ and $(PTP)_{minority}$. The $(PTP)_{Accuracy}$ is the point in the predictive model were the highest accuracy occurred, while $(PTP)_{minority}$ is the point at which the predictive model has the highest recall of the minority class group. This would also help to identify the threshold of attributes that are required to obtain dependable results based on the context of discourse and at the point where the significant attributes will be selected. These are further explained in chapter five from session 5.0.1 to section 5.0.20.

- An introduction to a new similarity measurement techniques called Ranked Order Similarity-(ROS), as a techniques to quantify the similarities among a sets of items that may contain the same elements but ranked in different order. To accomplished this, a novel distance measure called "proximity distance" that assessed the distances of comparative items were defined. The (ROS) is a novel similarity measure that is applicable in situations where the existing similarity measure is inadequate for example were similarities is by ranked. These are further explained in chapter four session 4.4.

1.4.1 Terms Definitions

Effort have been made for all the invented (coined) words, phrases and nouns used in the thesis to have a specific meaning as will be explained wherever such words are used. When there are more than one words that refers to the same meaning and is unavoidable to used one of the word for example this three words refers to the same meaning; "Variable","Attribute" and "Feature". The three words will be used interchangeably as it has always been used in most academic reports and journals and will comply to academic writing best practises.
One of the main concept is Variance Ranking Attributes selection (VR) and may be referred to as Variance, particularly in some table where there is no enough space. In any other places were any terms or words would appear differently the meaning will be obvious or it will be explained or defined appropriately. Reader's attentions will be drawn to some common coined words that will be used through out this thesis, these are listed below.

- Peak Threshold Performance (PTP); this is the position that at which the highest accuracy and recall of the minority class groups were obtained. They are two types of (PTP), these are , $(PTP)_{Accuracy}$ and $(PTP)_{minority}$.
- Element Percentage Weighting (EPW). This is the sum total percentage quantity of elements in two sets that are going to be compared; see section 4.4.
- Unit Element Percentage Weighting (EPW/n). This is the percentage weighting of a single element in a set; see section 4.4.
- proximity distance; this is the number of steps a Unit element in a set moves to align itself with a similar element in the another set, when both sets are being compared;see section 4.4.

1.5 Research Methodology

The goal of this research is to produce a process that could limit or eliminate the skewness of algorithm toward identifying more of the dominant majority group as against the smaller minority that are often sought when using imbalanced classed datasets. These goal has been fully articulated in the project specification vis-à-vis the aims, and contributions therein. In so doing it will encompass every aspect of relevant discussions that will ensure a wholistic conclusion with adequate proof of validity, reliability of the assertions made in this document.
The techniques and resources used is to ensure that the primary research aims and

its objective are emphasised and not entwined in verbose research discourse [21], hence the general research methodology, the Proof of Concept (POC), results will be precise and straight to the point in order that the experiments could be replicated. The sequence of flow of the research will be in a particular order from inception to finish. Though these order boundaries are not strictly define, but to act as a guide to enable clarity, understanding, and coherency of thought. The sequence is as follows;

- Problem Definition and Specifications and introductions to the real life context of imbalanced data.
- Reviews of state of the art literature in dealing with imbalance data and metrics of evaluating the Binary and Multi-classed data classifications.
- Data acquisition, preparations, and sampling methodology.
- The re-coding of multi-classed into n *Binary*, where n represent the number of classes in the multi-classed datasets.
- Experiment for Variance Ranking Attribute Selection Technique.
- Comparison of Variance Ranking Attribute Selection with two states of the art Attribute Selection using the Pearson Correlation (PC) and Information Gain (IG)
- Comparing the attributes ranked by (PC), (IG) and (VR) using the (ROS).
- Validation experiment of Variance Significant Ranking Attribute Selection using some major (ML) algorithms.
- Comparison by estimating the degree of similarity Variance Ranking Attribute Selection with two sampling technique of dealing with class imbalance.
- Final discussion of results and conclusions.

Software, Hardware, and Algorithms

The list of all the major resources that were used in this research is as follows.

- **Weka data mining software**. That could be downloaded at [22].
- **Python(v3) programming language**. A very robust programming language for scientific computation and data analysis. As at the time of writing this thesis it has version 2 and version 3. The version used here is 3.

- **Microsoft Office (Word, Excel, Paint, etc)**. A popular documentation for PC mac book.
- **Datasets** all downloaded from [23]. This was downloaded from the university of California dataset archive.
- **Hardware, PC and laptop**. The only hardware used is PC,laptop with win10. There was no special capacity, any regular PC or laptop will do.
- **Latex documentation.** Thesis documentation carried out in Latex [24]. Though lots of latex editor online and those that could be installed on the desktops , but I had used specifically the online overleaf that have been cited earlier, I found it more convenient because being online made it accessible anywhere.
- **Algorithms used.** There are two major processes derived in this research, these are (VR) and (ROS). Each of these processes is as a result of other algorithms. The major algorithm that was used to derived the (VR) processes is one of the measure of central tendency called the "Variance", this is further explained in chapter three, session 3.1.1. The (ROS) is derived from the Levenshtein Similarity, this is futher explained in chapter four,session 4.3.1

A clear attempt will be made throughout this work to ensure that the aims, contributions, and processes being carried out are very clear to the reader sometimes through "repetitions of the aims", "similar experimentation that emphasis the same results" and other techniques, this is to ensure that the conclusion will be proven beyond any reasonable doubt and to reinforce the sequence of understanding of the research work.
The work is for Doctor of Philosophy and every aspect of this work must be made to show deep thinking and originality and creation of knowledge. In presenting this documentation, It seek to make sure it complies to be " Clear Precise and Accurate" according to [25].

1.5.1 List of Publication

- Ebenuwa, S.H., Sharif, M.S., Alazab, M. and Al-Nemrat, A., 2019. Variance ranking attributes selection techniques for binary classification problem in imbalance data. IEEE Access, 7, pp.24649-24666.
- Ebenuwa, S.H., Sharif, M.S., Al-Nemrat, A., Al-Bayatti, A.H., Alalwan, N., Alzahrani, A.I. and Alfarraj, O., 2019. Variance Ranking for Multi-Classed

Imbalanced Datasets: A Case Study of One-Versus-All. Symmetry, 11(12), p.1504.

1.5.2 Summary of Thesis Report Layout

Chapter One(Introduction). In the introduction, we made the case for the research topic by introducing the background of the study as being the general problems encountered when working with real-life datasets. The positing of imbalanced classes as being very prevalent in additions to other real-life dataset issues was made here. A detailed explanations of other data sets issues as an addition to imbalanced class was presented. Furthermore, an explanation of similar imbalanced scenario, processes of dealing with raw data. Clear problems definition by explaining the research motivation, aims and contribution to knowledge was firmly rooted in this chapter.

Chapter Two(literature Review). The chapter is an extensive presentation of previous work that has been done in dealing with imbalanced class distribution in data sets, we engage the argument of using data-centric research like data mining and machine learning to provide a solution in real-life scenario, hence the extent and attempt that has been made to provide solutions were explored here in a broader perspective. The metrics of evaluations for classifiers were introduced for both binary and multi-classed data sets, we provided detailed explanation for 2 by 2 confusion matrix for binary classification and One-Versus-All for multi-classed scenario

Chapter Three(Variance Ranking Attribute Selection (VR) Technique) In this chapter we presented the Variance Ranking Attribute Selection technique for handling the imbalanced classed distribution, a detailed explanations of the datasets and data preparations, the theoretical basis of formula derivative used throughout the report and the experiments result were also included in this chapter.

Chapter Four(Comparison of Variance Ranking Attribute Selection (VR) Technique with the Bench Mark) In this chapter a comparison of Variance Ranking Attribute Selection(VR) and other bench mark in attribute selection is provided , also a new similarity measurement techniques "The Ranked Order Similarity measurement-ROS" was used to compare and quantify the similarities between the Variance Ranking Attribute Selection (VR) and two main bench marks which are Pearson Correlation and Information Gain. The novelty of The Ranked

Order Similarity measurement-ROS was invented here.

Chapter Five(Validation) In this chapter predictive modelling experiments were carrieed out using three machine learning algorithm and seven data set (four binary and three multi classed). The accuracy , precision , recall etc were noted. The capturing of the minority class group in the imbalanced situation were proven, hence attesting to the efficacy of the (VR) techniques. More importantly, the comparison of Variance Ranking with (SMOTE) and ADASYN techniques. The chapter provided and consolidated the reasons for the failure of using the algorithm based methods which have been the the conventional means and made a case why the (VR), (SMOTE) and (ADASYN) techniques that rely mostly on the numbers of the class groups is the right approaches to use.

Chapter Six (Summary Discussion and Conclusions) This chapter highlighted the major achievements of the research with a blow by blow summary of how the aims, and contributions were achieved, we also highlighted the shot comings of the existing techniques of handling the imbalanced data set problems. We provided a distinctive yet succinct presentations of all aspects of research that that made it possible to any reader to be familiar with the central knowledge that have been claimed achieved, we made ac case for the relevance of (VR) and the future work.

Chapter 2

Literature Review

2.1 Overview of imbalance data

Class imbalance is a major problem in using real-life data for predictive modelling. A data set is said to be imbalanced when there is unequal number of groups, meaning that one group is more than the others, the larger groups are the majority classes while the smaller groups are called the minority classes, the ratio of the majority class to the minority class is often referred to as the imbalance ratio (IR) in binary classed imbalanced data. In the multi-classed imbalanced, the (IR) will be defined according to the techniques that will be used to express the imbalanced, the Figure 2.1 is a representation of different types of imbalance, for the binary classed, the (IR) is 9:1 or 90%, this is straight forward. But for the multi-classed, the (IR) is 50:30:10:5:3:2, to expressed the (IR) as a percentage will depend on the technique of decomposition of the multi-classed using either "one-versus-one" or "one-versus-all" please see sections 2.3.2.

The problems caused by imbalance classes could affect all known predictive categories; like supervised, unsupervised, and hybrid. In supervised learning, classification could be multi-classed or binary classed, the multi-class is when the target groups are more than two while binary is when the target groups are only two (Yes or No, Positive or Negative), [26] [27].

The effect of class imbalance in binary context is that, the accuracy of the prediction could be as high as 90% yet no minority class group has been captured by the prediction [28]. For example, if a data set has a total of 1000 instances, assuming that 900 are negative while 100 are positive case, if a binary classification predicted all the 1000 cases as negative will still appear to be 90% accurate, whereas none of the 100 minority class group have been captured.

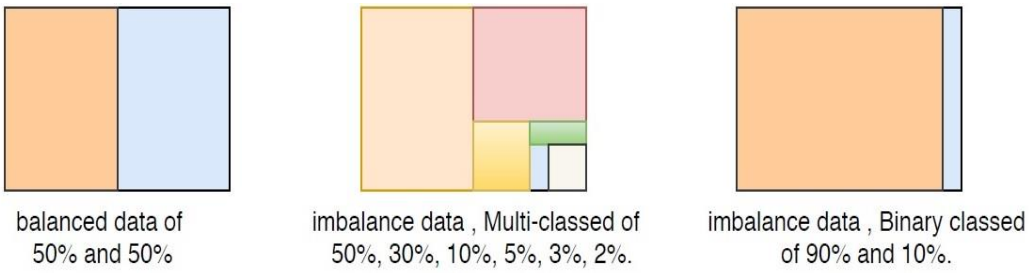


Figure 2.1: Imbalanced and Balance data

The same wrong predictions in binary class is also very noticeable in a multi-classed data as shown in Figure 2.1, consider a data set with classes as follows 50%, 30%, 10%, 5%, 3%, 2% being able to predict the small percentage groups (minority classes) by using the conventional machine learning algorithm and processes is next to impossible because by design and applications these algorithms assumed equal classes, and during implementations the process is usually optimized for accuracy thereby enhancing the capturing of the same majority classes. The irony is that, in most prediction; binary or multi-classed using real-life data, the minority groups are usually the interest or what we are looking to predict. Consider the case of binary classification in intrusion detection dataset. The minority is the few times the network may have been breached, in cancer research dataset, the minority group may be the few patients that have cancer, while in clinical trial of drug interactions, the few adverse interactions are usually the interest groups. In a multi-classed dataset were the prediction of various numbers in group membership is required like the ages of Abalones based on the numbers of rings [29], predicting a protein localization site in the Deoxyribonucleic acid (DNA) [30]. The smaller groups are impossible to capture using the conventional machine learning algorithm and processes.

It is quite obvious that if a technique could be found to eliminate the problems of class imbalance, the performance of most predictive algorithm will improve drastically. At this juncture, let us provide a precise definition of the term predictive modelling. What is predictive modelling? "This a term used to describe processes and techniques that use Statistics and machine learning to predict future events, outcomes or items, while using earlier events, data or observations as inputs during the process."

2.2 Techniques for handling imbalance class distribution

Imbalance classes have been a problem in predictive modelling when using the conventional machine learning algorithm consequently have been a subject of interest in both the academia and industries, different approaches have been proposed to handle this problem with different level of successes. Each of these approaches could be categorized as Machine Learning Algorithm methods, Cost-Sensitive methods, Embedded Approaches, and Sampling-based Methods. In the preceding sections, details of these approaches will be dealt with.

Before delving into these approaches, it is important to have an overview of the general commonality to all of them in context. First and foremost, all the approaches involves the machine learning algorithms at some points in the processes, but the stress on names of the categories is to emphasis the deliberate efforts that have been made to alter, combine or improve the machine learning algorithms for the sole purpose of improving the accuracy of the results or general performance using the standard measurement metrics.

The default predictive modelling techniques is to use machine learning algorithms, data scientist uses algorithms and modifications of parameters to obtain some accurate results, it was not intended to actually solve the problems of imbalance classes because the numbers of classes that made the dataset imbalanced were not considered when using this approaches, but since it sometimes achieved good results particularly when the data are imbalanced it became the norms. The parameter changes like changing the kernel functions in (SVM) and other unstandardized processes became the conventional way of modelling with imbalance data (afterall almost all real-life data set are imbalanced). Other approaches, like the Embedded Approaches and Cost-Sensitive methods, uses the same modification of the algorithm methods. These parameter changes and different "tweaking" of the algorithms are one of the origins of the "trial and error" that has become a well-known process in data mining and machine learning methodology [31][32][33].

The first effort that was made to target imbalance classes in real-life data was carried out by using sampling methods (Over Sampling and Under-Sampling). Though different modifications of these Sampling methods have evolved over time. Section 2.2.6 and chapter 6 are fully dedicated to these techniques, and a detailed discussion will be reserved until then.

2.2.1 Overview of machine learning algorithm

In general, the algorithms used in data science are categorized into supervised and unsupervised learning, as depicted in Figure 2.2. While supervised learning are used when the target output Y is already known, the algorithm have to be trained to learn the function F that is used to map the input X to the output, represented as $Y = F(X)$, hence it shows that any series of input $X = \{x_1, x_2, x_3.....x_n\}$ could be used to predict a series of output $Y = \{y_1, y_2, y_3.....y_n\}$ using a mapping function F [34]. Therefore, all supervised learning has a set of training input that is "learned" by the algorithm to produce a generic mapping function that will be used to map all the input to the various output target. The supervised learning is further classified into two according to the nature of the output target being sort; if the output target is discrete like yes or no, male or female, have the disease or don't have the disease, high or middle or low, there are called classification. The other type of supervised learning is called regression in nature if the output could be a real number like the following continuous values 56.34, 123.03, 0.34.

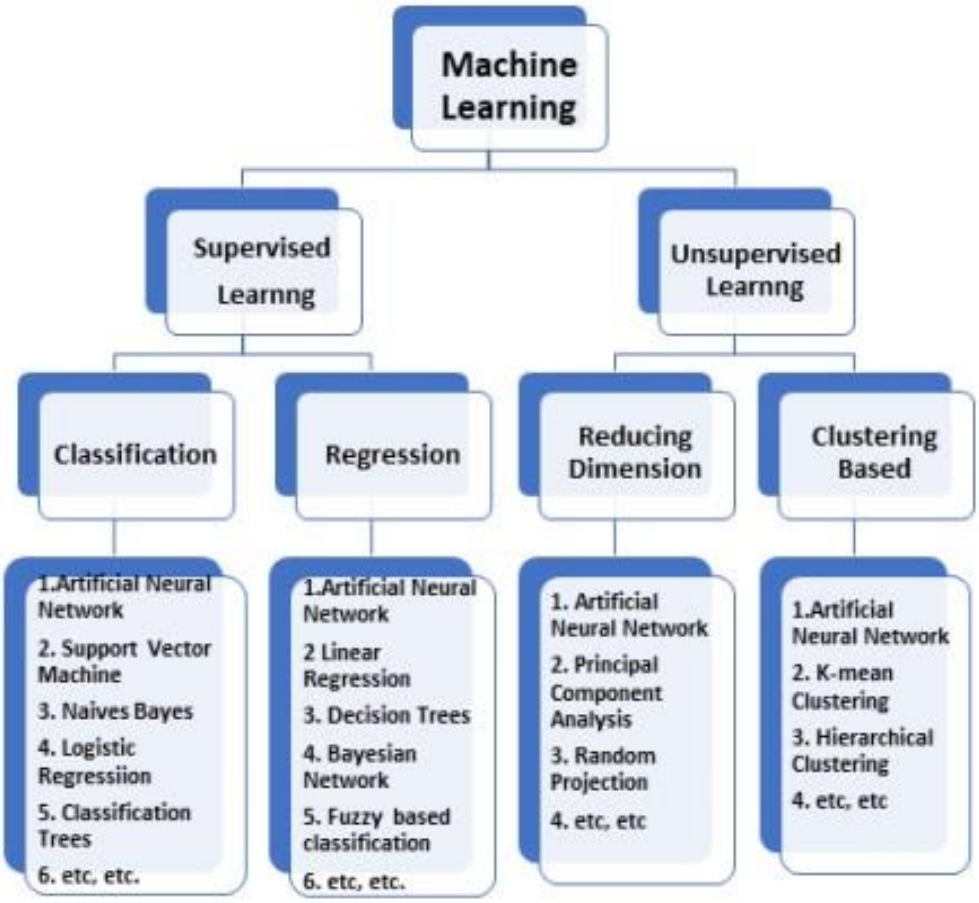


Figure 2.2: Machine learning algorithm

Unsupervised learning are those where there are no known explicit output targets

[35]. It involves the input data being exposed to the machine learning algorithm enabling it to find the previously unknown pattern in the input data. These hidden patterns are usually invisible before being exposed to the algorithm, hence the term mining. Most unsupervised learning algorithms are categorized as being clustering or associations pattern-based. Therefore when the input data interacts with the algorithm, clusters of data that share similar characteristics are noticed. In the same way, if a data item is related to another data item by any associations, a rule-based algorithm would expose the pattern. Semi-supervised learning is a hybrid of supervised and unsupervised learning [34].

2.2.2 Variance Techniques For Handling imbalanced classed data

This is one of the approaches for dealing with imbalanced classed datasets, the variance is always used in combination with other intrinsic properties of the data [36][37]. This research is based on this approach by using the variance to derived the feature that are most significant to eliminate or reduce skewness of the (ML) toward identifying more of the majority class as against the minority class.

The work of [38] provided a pointer as to how variance and feature selection could lead to improved performance in classification. The work demonstrated a techniques known as a Sensitivity Analysis (SA) which is based on Fourier amplitude test. The Fourier test is depended on the variance test of the amplitude function of wave, but the authors were able to applied this to Feedforward Neural Network (FNN) thereby showing that the classes of datasets relatively depended on their variances and this correlations was used to select the significant features. The results obtained showed an improvements in the classifications, but the issues of skewness still remains, particularly in the highly overlapped datasets.

In order to assess the levels of imbalanced quantitatively [39] developend a method called "Bayes Imbalance Impact Index", this techniques uses two metric called "Individual Bayes Imbalance Impact Index-(IBI^3)" and "Bayes Imbalance Impact Index-(BI^3)". The IBI^3 and BI^3 are used to a measure the effects of imbalance on variables as the degree of imbalance increases. The authors also provided a prove to show that if the datasets are normally distributed, the probability density functions and the likelihood of finding a data item in the sample space could be deduced from the mean and variance. Therefore a strong correlation between (IBI^3) and variances of the distribution was established.

Apparently, controlling of the variance to control other variables as evidence of de-

pendencies were used by [40], where it was shown that reducing the variance would optimise a Stochastic processes like the Stochastic Gradient Descent (SGD). Thus as the variance is made smaller the estimated results of the SGD improves. Each part of the Gradient Descent could be regarded as a point in the sample space like each variables. The negative effect of class imbalance are augmented by overlapping of contents classes in the datasets. Such correlation between variances in overlapping classes and imbalance were one of the focus of [41], the work demonstrated the probability density functions in relations to each classes deviation (variance), that the more the classes are overlapped the more the effects of imbalanced.

The model feature selection using tweaking the variances of attributes called "bias variance" have been used by [42], they compared linear model and non linear to make predictions and estimate the errors in the predictions which could be controlled by controlling the variance in both linear and non linear regression models. The variance attributes selection were used to solve the case of high dimensional data by applying Bayesian algorithm by [43] and applying the theory to linear regression models ie Bayesian linear regression. In order to deduce the constant coefficient and reduce the error in the predictions, they initialised the coefficient in median value of 0.5. The selection was done using posterior inclusion probabilities with a threshold $> than$ 0.5.

From these literature is obvious that variance of the datasets in a sample space is synonymous to a density concept, even the units of variance are squared. Therefore, we intend to explore this concept in relation to probability density function and derive the quantitative relationship.

2.2.3 Algorithm Techniques for imbalanced classed data

Over the years, lots of effort have been put into solving the problems associated with imbalanced classes in data sets at mostly at the algorithm level or any modifications of it, owing to the realisations that one of the main reasons for any predictive modelling is to capture the minority class groups, but there continue to be a fixed patterns of inhibiting conditions to the performance, the patterns are that if the minority classes groups are very small the model performs poorly. All the main (ML) algorithms exhibited this pattern, and the analysis of these algorithms designs and implementations did not show where the numbers of the classes in the dataset would be entered. This design by implications assumed balanced classed because there is no quantity that accommodates variations in the number of classes in the algorithm, secondly most algorithms have been optimized for increase in the accuracy of the

identified majority by the design boundary that favours the identifications of the dominant classes [44][45][46] for example in Support Vector Machine, the hyperplane could discover the demarcations line for the majority classes easily, even when a kernel trick is used when the line is not linear. By implications, this led to poor predictive results

All the same, the default and conventional techniques for dealing with the class imbalanced is to interact with the classification algorithm with a view of making it become less sensitive to the class imbalance [19]. Even though these were not standardized, many variations of these algorithm processes could some times achieve good results, but, the issues here is that such results cannot be replicated when using different datasets or when another algorithm is used. Besides, it is not definitive why the improve results were obtained. So why do we get a good results and very poor results some times with the same domain data; like heart data, cancer data, credit score data etc ? If what led to it is not known then our algorithm method solutions is "groping in the dark" and the standardization of this techniques is still a long way due to the pervasiveness of real-life data set and as long as the (IR) which is the main cause of imbalanced is not factored into the design of the algorithms.

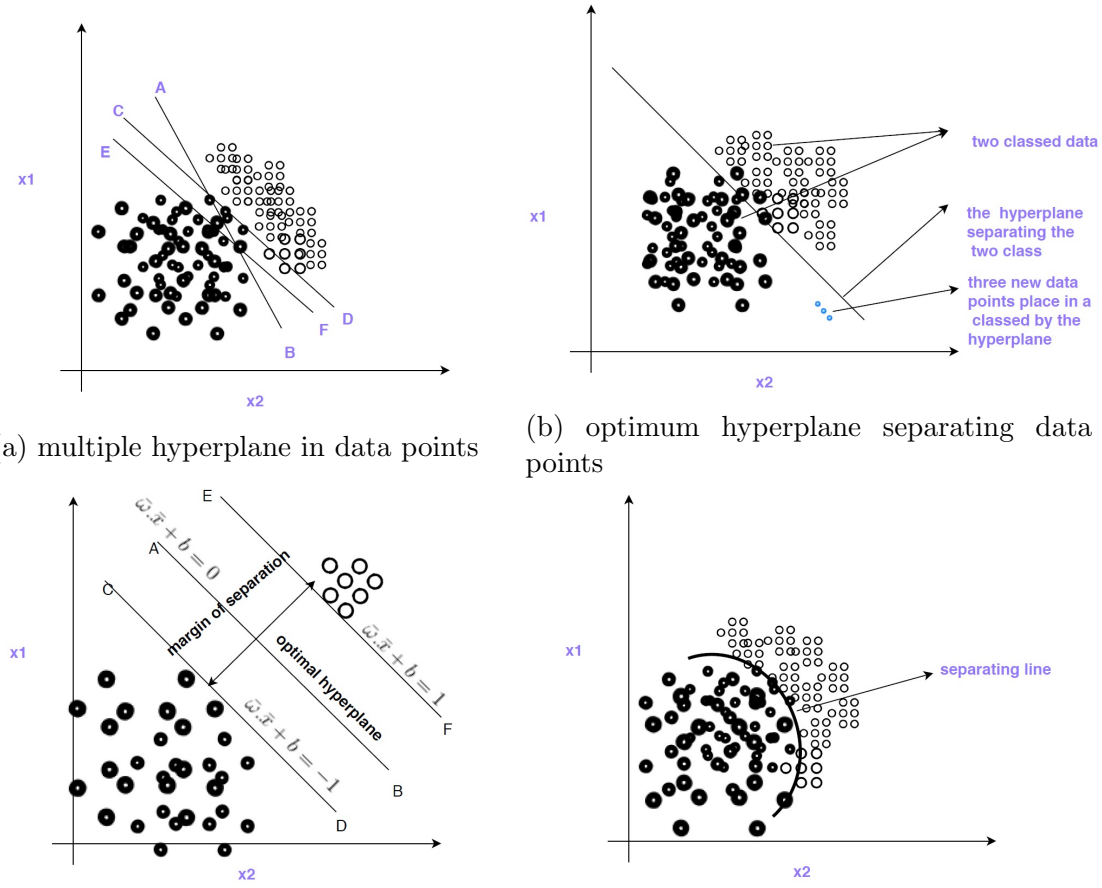
In the next session, the reviews of the classification algorithms and various techniques that have featured prominently in dealing with imbalanced problems with reference to some of the recent modification of such algorithms would be carried out. We have to realise that machine learning (ML) is very fluid and different modifications are being invented by the day as such emphasis will be more on the parent algorithms; after all the modifications and variations have not been fully tested and accepted by the mainstream users as a standard.

Support Vector Machine algorithm and imbalance classed data

Support Vector Machine (SVM) is one of the algorithms that are very prominent among supervised learning because of its applications to both classifications and regressions output. The basic SVM considers all data items as a point in a dimensional space where there is a dividing line that tends to separate the data into different classes, therefore if the input training data is assumed in a two dimensional space [47]. The SVM algorithm is a function that seeks to find the best hyperplane that separates the data points in the dimensional space as in Figure 2.3a. A straight dividing line representing the hyperplane separates the data points into two classes; this enables any new input data to be placed in either of the two classes which the data most likely belong to by the SVM algorithms as in Figure 2.3b. During classifications, the margin of class separation is weakened to allow the hyperplane

to accommodate extraneous data inputs through adjusting the class boundary in what is known as the kernel functions of SVM algorithm [48]. The SVM algorithm is optimised to find the separation hyperplane with the largest margin as depicted in the enhanced diagram of the separation in Figure 2.3c where the separation line is optimal hyperplane represented by the equation $\overline{\omega}.\overline{x} + b = 0$. For the data in the each of the classes are (positive and negative) are represented by the two equations $\overline{\omega}.\overline{x} + b = +1$ and $\overline{\omega}.\overline{x} + b = -1$ respectively.

But most real-life data sets could not be demarcating by straight line and their separations are not distinctively defined due to overlapping of the data points as in Figure 2.3d, therefore the data points may not be linearly separable by straight lines in such situation techniques called Kernel trick"[49][50][51] are used to deduced the separations. There are different Kernel trick such as Polynomial, radial basis function (RBF), Sigmoid and quadratic kernel, and so on. The Kernel trick is just a technique used to map the non-linear separation into a higher dimensional space that it would become possible to be separated.



(a) multiple hyperplane in data points

(b) optimum hyperplane separating data points

(c) large margin of separation

(d) non linear separation

Figure 2.3: Basic SVM imbalanced data points

One of the main SVM modification that is used in the imbalance class situations is called One Class-SVM [52] in this, input data are trained to only recognized one

class aptly called the "normal class" and any other classes that are different from the normal class are detected by the algorithm, a new implementation of such SVM for multi-classed data that combine SVM with a process called "one- versus- one" or one-versus-all were invented by [53]. But as have said earlier, any algorithm dependent processes of solving imbalanced is unreliable because of inconsistencies in results. Besides these modifications are not standardized, and many are continued to be invented by different researchers.

Decision Tree and imbalanced classed data

In the classification algorithms, the decision tree is one of the most popular because of the ease of use and understanding. Descriptively, decision tree has a parent node at the beginning with two splits emanating from the node, each of the two divisions would end in a leave node that will further split again, this goes on until a final leaf node is reached. The final appearance looks like an inverted tree as in Figure 2.4. The basic decision tree algorithm splits a population or sample of the data set into two subgroups based on some of the attributes that have been identified as significant, the continuous splitting developed into a series of rules.
At each splitting node, the algorithm would question the population and deduces the most relevant attributes for the next split, this would add to the rule until the final node. Though, there are various Decision Tree (DT) algorithms modifications like Iterative Dichotomiser 3 (C4.5 and ID3), CHi-squared Automatic Interaction Detector (CHAID), Classification and Regression Tree (CART) and many more [54]. The C4.5, ID3, and J48 are based on the concept of Entropy and Information Gain and are the most recent implementations, and you may see them in the current machine learning software like SPSS, Weka, Rapid Miner, etc. or even in same programming (API) like Python, R, etc. [55][56][57]. Entropy is a test of the homogeneity of data items when they are all the same, i.e. completely homogeneous- the Entropy is zero, but when equally divided - the Entropy is one. The Entropy is given by;

$$Entropy\ H(X) = -\sum p(X)\log p(X) \tag{2.1}$$

and

$$Information\ Gain\ I(X,Y) = H(X) - H(X|Y), \tag{2.2}$$

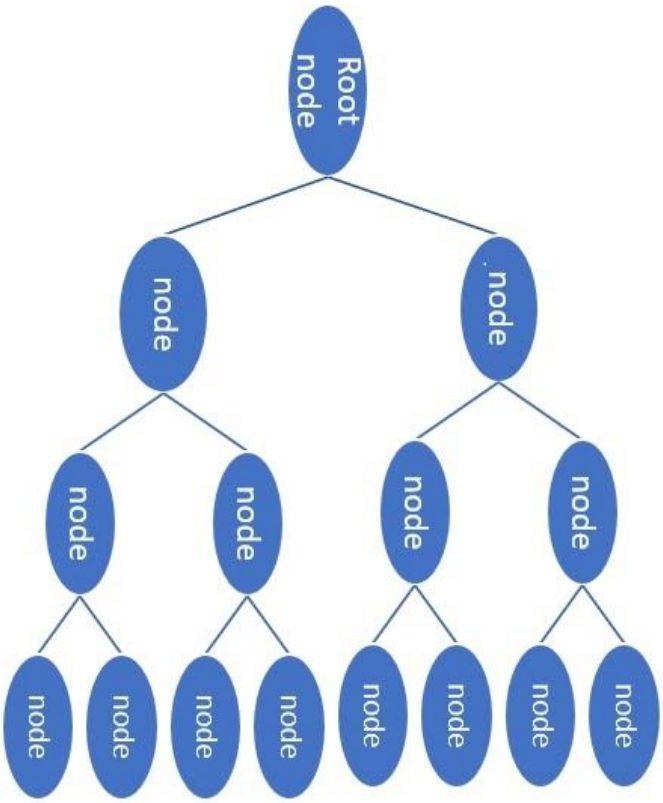


Figure 2.4: Decision Tree

$p(X)$ represent the probability of data item x. The CART algorithm has been used extensively and also popular it uses Gini Index give by

$$Gini(E) = 1 - \sum_{j=1}^{n} (p)^2 \tag{2.3}$$

while p is the probabilities of each class, this is the criteria for node splitting [58]. Compared with most classifiers DT could show good result in dealing with imbalanced classed data for both binary and multi-classed [59] because of its dichotomous nature (could be split into two) and if the node were split at one of the significant attributes, the results could be very accurate beside some new algorithm of decision tree which is not sensitive to the size of classes called Class Confidence Proportion Decision Tree (CCPDT) were developed by [60]. DT has also been used in combination with other classifiers and processes, for example, [61] relied on DT to generate a rule-based for under-sampling the class imbalance.

Neural networks and imbalanced classed data

A neural network or Artificial Neural Network (ANN) is one of the first attempts of designing an algorithm to simulate the working of the human brain; it is designed to replicate the way the biological brains function, its basic structure resembles

the interconnection of neurons working together to solve problems [62][63][64]. The algorithm is made up of three main levels called tiers nodes or layers nodes (input, hidden and output layers), the hidden layer may contain more than one layers see Figure 2.5, it works by receiving data input from the first tier which is like human sensory organ eg, eyes, skin, etc. that is sensitive to sight and touch.

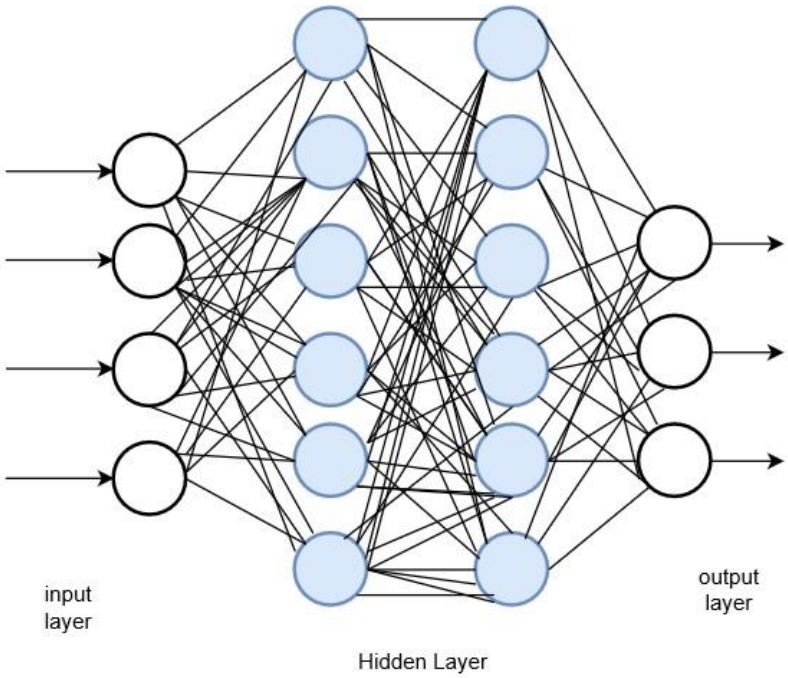


Figure 2.5: Neural Network

Each successive tier will received input from the output of previous tier. The input layer consist of a set of inputs $x_i(i = 1, 2, 3, 4....n)$ each of these input has a weighting $w_i(i = 1, 2, 3, 4....n)$ associated to it and sets of outputs $y_i(i = 1, 2, 3, 4....n)$.

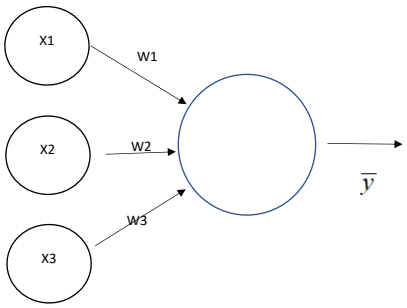


Figure 2.6: Neural Network output

To find the result $\bar{y}$ of a Perceptron is given by. A Perceptron is a representation

of a single output of the neuron showing the inputs and the weightings as in Figure 2.6.

$$\bar{y} = \sum_{i=1}^{n} (x_i w_i) \tag{2.4}$$

ANN has had uncertain past due to its tendency to overfit the training dataset [65], besides its easily affected by outliers and the work of Minsky and Papert in 1969 [66] in the book titled Perceptrons brought about a wane in researcher's interest on neural network. Recently the emergence of Deep learning and the accuracy achieved by computer using deep learning algorithm in image recognition, self-driving cars and winning the world best player in the game of GO have rekindled researcher's interest in (ANN), and these demonstrate its adaptability to learning. In the quest for handling the problems associated to imbalanced classed in data set, Neural network and various modifications of it has had its fair share of outings, [67] presented an approach of using a combination of Synthetic Minority Over-sampling Technique (SMOTE) and Neural Network called Complementary Neural Network (CMTNN) where each weighting w_i of the node-link is optimized by SMOTE algorithm, though an increased in the prediction and general accuracy were observed, but the computational cost became a hindrance. Genetic algorithm (GA) has also been used as the activation function in (ANN) by [68], as GA is based on natural selection when used as the weighting (w_i) to train (ANN) produced an improved recognition of the minority classes in imbalanced data set, inline with using GA and (ANN) [69] proposed a method called multi-objective evolutionary algorithm to optimised the weighting bias toward target classes in a multi-classed scenario. Using a dynamic sampling method (DyS) for each hidden multi layer's perceptrons [70] were able to train (ANN) to target multiple classed in imbalanced data set.

New methods and modifications of (ANN) will continue to emerge, even the Deep Learning that is taking the Data Science community by storm is not yet a matured algorithm concept undermining that some remarkable results have been achieved by it, but the new emergence of different Deep Learning (API) in every version releases of programming language like Python, R, Matlab is an attestation of the fact that Deep Learning is still evolving.

2.2.4 Cost-Sensitive method

The Cost-Sensitive Learning (CSL) approach consider the cost of misclassifications and adjust the result into empirical consequences by allotting a different cost value to the misclassified classes [71]. In a binary classification scenario, the cost of la-

beling positive as negative may be different from the cost of labeling negative as positive. This is true in real-life, considering the two example provided by [72], the cost of misclassifying a cancer patient as not having cancer is more damaging to misclassifying a healthy patient as having cancer, just as the cost of not being able to pick up a terrorist would be more damaging to labelling a none terrorist as terrorist.

This technique could be applied to the result of any classification algorithm (binary or multi-classed). The cost-sensitive approach posits that accuracy is not as important as the implication of the wrongly classified target of interest. The final results are computed with values that leads to minimum cost for wrongly predicted values of least consequence [73] and maximum for values of high consequences. During implementation, the value of the cost is provided and set beforehand [72]. Most time, CSL is used in combination with other classifiers that produce their results in a confusion matrix [74]. It could be applied to both binary and multi-classed classifications, Table 2.1 is a representation of a Cost Matrix using the Confusion Matrix in Table 2.4, given that $c^i c^j$ is the cost of predicting i class while the actual class is j, therefore $c^i c^j$ is false j (Fj).

	Predicted	
	Positive	Negative
Actual positive	c^+, c^+	c^-, c^+
Actual Negative	c^+, c^-	c^-, c^-

Table 2.1: Cost Matrix Representation

The similarities of the two tables are obvious, but the applications is were they differs. If the errors in the classification is c^-, c^+ and c^+, c^-, and no error in correctly classified data given by; c^+, c^+ and c^-, c^- therefore the Cost Matrix in Table 2.1 would reduce to a ratio; c^-, c^+ / c^+, c^-, while the total cost is then dedused as

$$Totalcost = c^-, c^+ * FP + c^+, c^- * FN \tag{2.5}$$

Provided that the classifier's result could be explained using a confusion matrix, CSL could be derived from such classifier. In combining resampling, SVM with CSL [75] showed that a baseline of measuring the acceptable cost could be modified based on context situations. Combined algorithms like ensemble are very popular in using CLS IN handing imbalance classes, [76] provided exploratory study on bagging relationships and classes, [77] proposed a method of using ensemble (AdaBoost), CSL, SVM and query-by-committee (QBC), first the classifier was performed on the subset of the data sample having divided it by the imbalanced proportion, then the QBC is used to produce the training set before the CSL-SVM is used to train

the data. Training with cost-sensitive neural networks and increasing the threshold of the cost such that the output is improved because data item with higher costs become harder to be misclassified as proposed by [78].

K nearest neighbour and imbalanced classed data

This is a classification algorithm used in classifying a new data point within a sample spaced by considering other neighbouring data points [79][80][81], hence the term k-nearest neighbour. In its simplest form, let's consider Figure 2.7a , if a new data point (blue dot) have to be classified as either belonging to the black or the white dot, its nearest neighbours has to be checked. If k is set to 3 (k=3) as in Figure 2.7b, it means the closest 3 data points to the blue dot, in Figure 2.7b, the three nearest neighbour to the blue dots are two white and one black. The majority vote is used to classify the blue dot as belonging to the class of the white dot by measuring the distance between the blue dots and its nearest neighbours, and it is assumed that data points are similar to its neighbors if the distance between them is small.

(a) K nearest Neighbour in sample space

(b) Relevant data

Figure 2.7: Value of K is 3 in the sample space

There are various metrics of measuring the distance of data points in KNN algorithm, the most popular once are listed in Equation 2.6, 2.7 and 2.8 are for continuous variables while the Hamming distance in Equation 2.9 which is almost the same with Manhattan distance but applied when the data is categorical or discrete.

$$Euclidean\ distance = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{2.6}$$

$$Manhattan\ distance = \sum_{i-1}^{n} \parallel x_i - y_i \parallel \tag{2.7}$$

$$Minkowski\ distance = \left[\sum_{i-1}^{n} \parallel x_i - y_i \parallel^q \right]^{\frac{1}{q}} \tag{2.8}$$

$$Hamming\ distance = \sum_{i-1}^{n} \parallel x_i - y_i \parallel \tag{2.9}$$

Various modification of k-nearest neighbour has been used to solve the problems associated with imbalanced classed, for example large weighted- k nearest neighbour (W-KNN) were used by [82], the process is to utilized wider region around the data items distribution to deduced the nearest neighbour, but this has resulted in accommodating some extraneous data like outliers which may add some noise resulting in the whole prediction becoming less accurate with data set that has large variances. All the algorithm techniques for predictive modelling can never be exhausted, the fluidity of the concept is such that on a daily basis, new modifications and modification of first modification are being invented. For example a modification of K nearest neighbour called weighted- K nearest neighbour (W-KNN) that was discussed earlier created by [82], have been modified to used Decision tree boundaries to select its K nearest neighbour, the wider region around the data items now have a different metrics to qualify to vote for a new data as belonging to a particular class, this improve the limited accuracy that was recorded by the (W-KNN), hence some outliers will be voted out.

Recently, a new approach of handling imbalanced data set known as "conditional generative adversarial networks (cGAN)" was introduced by [83], this is based on a concept of continuous competitions by two vectors known as generator and discriminator. While the discriminator tries to learn the actual data set pattern by comparing it to data being generated by the generator as against the feedback between the two vector result, this could lead to adaptation and improvement to the data quality and finally the overall performance algorithm.

2.2.5 Ensemble Methods

Ensemble algorithm is basically a collection of the algorithm that works together to enhance their final predictive capabilities. During classification, each of these algorithms produces output results that acts as an input to the next layer algorithm leading to more refinement until a final layer of the algorithm would produce the final outputs.

The categories of ensemble algorithms are Boosting and Bagging. Boosting algorithm is a family of ensemble invented by [84]. AdaBoost (Adaptive Boosting) classifier is one of the most widely used applications of boosting, and it aimed to

convert weak classifiers into robust classifiers. Given a boosting classifier as;

$$F(x) = \sum_{m-1}^{M} \Theta_m f_{(x)}, \tag{2.10}$$

where $f_{(x)}$ is the function of the weak classifier and Θ_m is the corresponding weighted summation of all of the weak classifiers M. Boosting iterates from $m_1.....M_n$ at each iteration the classifier select one with the lowest weighted error and used that as an input to improve the classification.

The bagging or bootstrap aggregating algorithm as it is popularly called is another family of ensemble invented almost the same time as boosting and were popularised by [85]. It optimises the predictive capabilities of decision tree through using multiples of them in layers and applying the final output result as an input to a bootstrap aggregating to produce the final optimized predictions [86][87]. Though many of the ensemble contains one type of algorithm, while others may be made up of more than one. For instance, Random Forest uses mostly simple collections of the decision tree in layer with each of them adding their result output as the input to the bagging algorithm [88] [89]. The theoretical bases for using bagging and boosting is that each of the weak algorithms could produce strong classifications if combine [90].

Most algorithm that had performed poorly on imbalanced classed data have been shown to be promising when integrated with boosting and bagging. For this, ensemble are mostly applied to optimize the accuracy of other algorithms, notable in this integration is Adaboost with SVM using Gaussian Mixture Modeling Supervector (GSV-ADSVM) by [91]. This work identified the recognition of phoneme in speech using a super-vector generated by Gaussian Mixture Modeling in speech recognition. A comparative work was provided by [92] for common algorithm and imbalanced data the ensemble algorithm produces more stable results. The ensemble has also been used in making selection in streaming life data or processes where selection based on the majority and minority data feed is akin to imbalanced classed situation [93].

2.2.6 Sampling based Methods

This is one of the techniques dedicated to handling imbalanced classed data set, and it is regarded thus because for the first time, the (IR) featured in the derivatives and influenced the overall results of the modelling. The main idea behind sampling-based techniques is to balance the classes, this method of handling imbalance data has become one of the most popular due to the ease of use, the process involves

changing the total number of class data item by either increasing the minority class [94][95] known as oversampling or reducing the majority class known as under-sampling.

Oversampling

The oversampling techniques was made popular by the pioneering work of [94] through a process called Synthetic Minority Over-Sampling Technique (SMOTE). It involves artificially generating data item to increase the minority class in the data set to the level where the imbalance ratio (IR); which is the ratio of the majority to the minority class are approximately equal. The (SMOTE) data is generated by the algorithm in 2.11.

$$x_f = x_i + \Re_{(0,1)}(x_j - x_i) \tag{2.11}$$

If data set of $x_{(i.....j)}$, taking the k-nearest neighbours of sample X as x_j, where x_f is the new generated data item, x_i is an original data item and $\Re_{(0,1)}$ is a random number within (0,1). Though, this (SMOTE) techniques apparently has many advantages, particularly solving the issues of class imbalance. But, it invariably introduced issues like misclassification cost [96], and some researchers have also encountered the problems of overfitting which stem from creating a replica of the same dataset and inheriting intrinsic errors therein, hence the necessity of new approaches to solving the issues of class imbalance like having various modifications of oversampling have been proposed. The Borderline-SMOTE by [97] where data item at the borderline of K-nearest neighbour are over-sampled is one of such example; also there is random oversampling used by [98] that tend to choose the training data by random selection, this method though improved accuracy, but has led to delay in the execution and overfitting when dealing with large data set. A generative oversampling technique was used by [99], the process involves new data being created by learning from the training data. This method made it possible that the created data have the basic characteristics of the existing data thereby maintaining the data integrity, but accuracy improvement is limited since the characteristics of the training data is still maintained.

Adaptive Synthetic Sampling

This is another popular oversampling techniques is known by the acronym (ADASYN), is different from the (SMOTE) due to the way it over sample (generate) the minority data items. While (SMOTE) uses the K-Nearest neighbour of the minority class to

decide which data to produce, the (ADASYN) on the other hand uses the distributions level of difficulties of minority classes ability to learn. This means that the minority data items that have the least ability to learn in the training data will be the one to over-sampled (generated).

Undersampling

An alternative technique called undersampling an opposite of oversampling, which is basically reducing the number of majority classed data items to balance the number of the classes in the dataset. This methods have also gained keen research interest in the academia, [100] presented two methods of under-sampling as random and informative; the random process is by choosing and eliminating data from existing class until the classes are balanced, while the informative under-sampling is by eliminating data observation class from the data set based on pre-selected criterion to achieve balance. A process known as active under-sampling by getting rid of the sample of the data items that are far away from the decision boundary was used by [101]. These sampling methods have a problem with performance with large dataset and could lead to removing important data items. Multiple resampling techniques were employed by [44] as it provides better tuning results with every circle of resampling.

A way of integrating over-sampling technique with cross-validation to improve the general performance was proposed by [102]. Cluster sampling method has also be used by [103] which introduces the process of cluster density and boundary density threshold to determine the cluster and sampling boundary, [104] used a method called A Bi-directional Sampling based on K-Means clustering which performed very well with data that has too much noise and few samples. Each of the sampling techniques has its pros and cons, which are very subjective and depending on the context of application and usage [105].

A techniques that could result in an improved performance might not show the same performance when used in different context. Therefore more modifications and improvements in the existing sampling techniques have continued to be presented and developed by researchers based on some local properties of the dataset. For instance, some under sampling have incorporated the mean of the values of the attributes as the metric for deriving the sampled data [106]. One of the main disadvantages of the over-sampling method is the risk of overfitting due to generating a replica of existing data [107]. For under-sampling; the main disadvantage is the possibility of discarding some data that might present potential useful information particularly during the process of variable selection that is cross dependent on other

variables or when the potential data item is far away from the central means of the attributes data items.

2.2.7 The Attribute/Feature Selection Approaches to imbalanced dataset

Attributes or feature selection are not primarily intended to treat the issues of imbalanced classes. The reasons for supporting feature selection in data-centric research include avoiding overfitting, lengthy training time and resource issues. Imagine obtaining approximately the same level of accuracy by using only 5 selected features instead of a total of 10 features in a data mining process, considering the time and other resources it may take to acquire all 10 that may not be necessary to the prediction. Of course, feature selection improves the accuracy of classifiers and invariably enhances the capture of the minority in a dataset, along with several advantages [108]. Feature selection is categorized into two basic groups, namely, the filter and wrapper techniques; some hybrid techniques that are combinations of these two categories are also available. The filter techniques is algorithm independent, while the wrapper approach is algorithm dependent [109][110]. There are various filter techniques; as shown in Table 2.2, each of them uses different or combinations of statistical functions like distance, correlation, information metric and similarities as a means of ranking the feature relevance in the dataset [111]. Although filter techniques are algorithm independent not all filters can be used for all types of predictive modeling: Some are more suited for different type of modeling like classification, regression and clustering.

Wrapper techniques are algorithm dependent; here a predetermined algorithm used in the modeling is known or the technique recommends which algorithm is most suitable for the selected feature. Hence, a subset of the overall features in the dataset is created, which should comprise the features deemed most important for a specific classifier performance.

Common Filter Techniques for Feature Selection		
Name	**Suitable**	**Basic Metric**
Information Gain	Classification and Regression	Entropy
Pearson Correlation	Classification and Regression	correlation
Gini Ratio/Gini index	Classification and Regression	measure of statistical dispersion
Fisher score	Classification and Regression	distances between data points
Chi-square	Classification and Regression	dependency of two variables
Others	Classification and Regression and others	others

Table 2.2: Common filter feature selection technique

More often than not, not all the features are included in the subset, as some are eliminated. The subsets are combinations of various features based on some black-box search algorithms called "attribute evaluator". Some of the most common wrapper techniques are "CfsSubsetEval," "ClassifierSubsetEval" and "WrapperSubsetEval."

Feature or attributes selection is an active area of research related to solving the issues associated with imbalanced data classes; apart from those listed in Table 2.2 many researchers have recently delved into solving this problem; notably [112] proposed four metrics information gain (IG), chi-square (CHI), correlation coefficient (CC), and odds ratios (OR) the most effective way of selecting the features in a datasets. Although the results of this recommendations were encouraging, but failed when the four metrics did not triangulate or come together. This made the validity of the work conditional based on only three methods triangulating. Another notable work is that of [113] that uses the receiver operating characteristic-(ROC) to imply that the significant features could be obtained using a techniques called "Feature Assessment by Sliding Thresholds" (FAST)", but the ROC is a "what-if" conditional probability simulations scenario, and in reality, such a condition may not arise. The work of [114] uses an adaptations of ensemble (combinations) of multiple classifier based on feature selection, re-sampling, and algorithm learning. In line with using ensemble approaches to feature selections, a method called MIEE

(mutual information-based feature selection for EasyEnsemble) was proposed by [115]. Moreover, a comparison was shown with other ensemble methods, such as asymmetric bagging, which the EasyEnsemble performs better. A technique called K-OFSD, which combines K nearest neighbors and its dependency to rough set theory for selecting features in high-dimensionality datasets was invented by [116]. Feature selection and imbalanced data is an active area of research, and new effort will continue to be made to find solutions to both.

2.2.8 A Case for Hybrid Approach to Imbalanced classed Problems

From the previous sections, it is evident that the imbalance classes in data sets are one of the reasons of poor performance in predictive modelling and extensive research is being conducted in both academia and industries in other to find solutions or to reduce the effects of this bias. Many researchers have used different modifications of (ML) algorithm as shown in sections 2.2, while others have approached the solution by considering different attributes selection techniques as in sections 2.2.7, but the fact remains that the solution has not been found and there is not going to be a single solution due to the "intrinsic properties" of data set. This is the reason why a modelling algorithm that may perform very well on a data set may produce poor results when used on different data set of the same domain and variables, besides the nature of Data mining (DM)and Machine Learning (ML) processes incorporates lots of trial and errors [117].

Therefore, we make a case for using a hybrid approach that could encompass both (ML) algorithm and Feature selections. Another reason for opting for this approach is that in all predictive modelling there is no single algorithm that is a "silver bullet" for all the problems rather a combination of processes and in most cases, trial and error have higher probabilities of success [118][119][120].

Apart from the work of [94] who invented the (SMOTE) processes and some modification of it for example, borderline (SMOTE) by [95][97], no other work that is in public domain have primarily targeted imbalanced classes in their design and implementations. Though, there are huge lot of work that claimed to improve the capturing of the minority groups, but the analysis of most of these works show that the improved results obtained are due to the authors changing algorithm parameters and other variables of the dataset, hence cannot be replicated if the processes were tried on other datasets. Besides the (ML) did not factor the causes of the imbalance which is the imbalance ratio (IR), so how could the problems became solved when

the cause of the problem (the (IR)) is not dealt with?

2.2.9 Researcher's Further Development

This research has been guided by recent papers in this area of interest. These are mostly journal papers, websites and books that are too numerous to mention here, please see the list of references. But the most important literature materials are listed here.

1. A new robust feature selection method using variance-based sensitivity analysis [38].
2. Bayes imbalance impact index: A measure of class imbalanced data set for classification problem [39].
3. Online variance reduction for stochastic optimization [40].
4. Handling imbalanced datasets in machine learning [41].
5. From fixed-x to random-x regression: Bias-variance decomposition, covariance penalties, and prediction error estimation [42].
6. Variance prior forms for high-dimensional Bayesian variable selection [43].

this is not to say that other literature review materials were not useful. But this six listed literature were the guiding this research throughout.

Literature review summary in Chapter 2		
Sections	**Title**	**Summary**
2.2.2	Variance Techniques For Handling imbalanced classeddata	The variance approach of handling classed imbalance problems , this papers used here demontrated that probabaility density distribution has strong correlation with variance of the class which the data point belong to. This is the main techniques that gave rise to Varinace Ranking used in this thesis
2.2.3	Algorithm Techniques for imbalanced classed data	This part of the literature review provided most traditional algorithm that are used for machine learning . It is noteworthy to realised that good result have been produced with imbalanced classed datasets owing to variaus parameter changes in the algorithm being use. But this techniques were not originally intended for imbalanced data. Many of the basic algorithms like Decision Tree, Support Vector Machine and Neural networks and thier modifications were explored.
2.2.4	Cost-Sensitive method	This technique set a cost for the wrongly predicted class, by adjusting each class cost it became possible to control and reset the position of the class boundary
2.2.5	Ensemble Methods	This techniques inolves combination of more than one tree based algorithm to produce better result. Though is among the tradiotional methods, but is its abit different because of the cobinations
2.2.6	Sampling based Methods	This is one of the techniques that is dedicated for imbalanced data. This specifically SMOTE and ADASYN techniques.
2.2.7	The Attribute/Feature Selection Approaches to imbalanced dataset	In this part of litersture review , the techniques of feature selections were addressed.
2.2.8	A Case for Hybrid Approach to Imbalanced classed Problems	In this part emphasis were drawn to intergrations of all multiple approaches that may involved others approaches as the panacea for solving classed imbalanced.

Table 2.3: Literature review summary in Chapter 2

2.3 The Measurement Evaluation for Imbalanced dataset

The general performance for imbalanced classed data set does not follow the usual accuracy measurement, rather the unequal amount of various classes in the data set have to be reflected. Consequently, the metrics of measurement [121][122], have to be specifically direct to empirical values of the numbers of classes captured in the output test data, hence classification performances uses the confusion matrix [123][124] as in Table 2.4; which is a cross-section table that evaluate how accurate the model tends to classify the groups. One major reason for using this metric in measuring classification is the insight into how the algorithm accurately identified the classes and how many classes have been confused and mislabelled, as stated by [125][126]. This would enable the assessment of the accuracy of the model given captured and confused classes. Sections 2.3.1, 2.3.2 and 2.3.3 are the processes measurement evaluation for imbalanced data set for both binary and multi-classed.

2.3.1 Measurement Evaluation for Binary classed data

The binary classification evaluation experiment is represented by a 2 x 2 confusion matrix, as shown in Table 2.4. This is particularly useful for visualising a binary classification against a multi-class classification, where multiple overlappings of classification could confuse the algorithms and make the results; less discriminant; a detailed analysis of the confusion matrix can be found in [127]. The definitions of terms in confusion matrix tables are

- **True positives (TP):** The algorithm predicted yes, and the correct answer is yes; (correctly predicted);
- **True negatives (TN):** The algorithm predicted no, and correct answer is no (correctly predicted);
- **False positives (FP):** The algorithm predicted yes, but the correct answer is no(incorrectly predicted); and
- **False negatives (FN):** The algorithm predicted no, but the correct answer is yes(incorrectly predicted).

	Predicted	
	Positive	Negative
Actual Yes	TP	FN
Actual No	FP	TN

Table 2.4: Confusion Matrix

The true positive rate (TPR) is the same as the sensitivity and recall. It is the proportion of positive values that are correctly predicted:

$$Sensitivity = Recall = \frac{TP}{(TP + FN)}. \tag{2.12}$$

The Precision is the proportion of predicted positives which are actually positive

$$Precision = \frac{TP}{(TP + FP)}. \tag{2.13}$$

Specificity is the proportion of actual negative which are predicted negative

$$FP(rate) = Specificity = \frac{TN}{(TN + FP)}. \tag{2.14}$$

F-measure is the harmonic mean between precision and recall or The harmonic mean between specificity and sensitivity.

$$F_{measure} = 2 * \frac{Precision.Recall}{(Precision + Recall)}. \tag{2.15}$$

$$Accuracy = \frac{tp + tn}{(tp + tn + fp + fn)} = \frac{tp + tn}{n}. \tag{2.16}$$

The formulas show that the F-Measure is another mean of testing the accuracy of binary classification accuracy [128].

2.3.2 Measurement Evaluation for Multi-classed data (One-Versus-all and One -Versus-One)

The measure of classifier performance in imbalanced binary datasets is straightforward and easily understandable, but for multi-class cases, misclassified and overlapping data make it impossible to effectively measure performance. one of the most useful techniques is decomposing the classes into series of n_{total} binary classes where n is the number of classes [129][130].

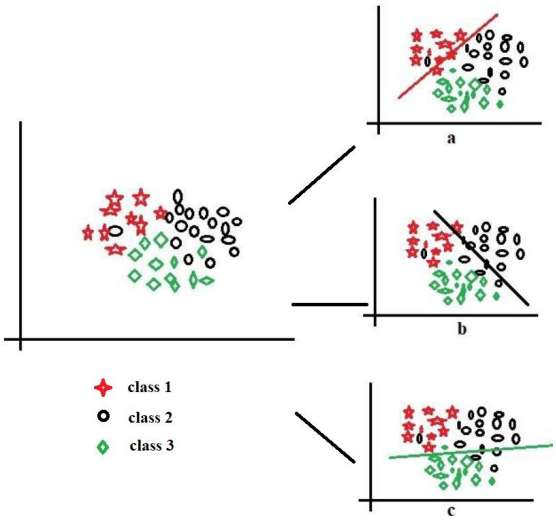


Figure 2.8: Multi-classed to Binary decomposition-One vs All

For clarity, Figure 2.8 shows three-class data represented by red stars, black circle, and green squares for implementing the One-versus-All technique. Let us take the red stars as the positive class (Figure 2.8 a), demarcated by the red line; the other components (black circles and green squares) are the negative class. Sequentially, the black circles (Figure 2.8 b) and green squares (Figure 2.8 c) are taken in turn to be positive while the rest are negative; this is the process of decomposing multiple classes into (n)binary. With this decomposition, the binary performance evaluations in section 2.3.1 could be applied to evaluate the multi-class data. The "One-versus-all" could also be called one-versus-rest" and is one of the most popular and accurate methods for handling multi-class datasets [130][131][132].
Another ways for handling multiple classes is "one-versus-one" techniques; this process takes each pair of classes in the multi-class dataset in turn, until all the classes have been paired with each other

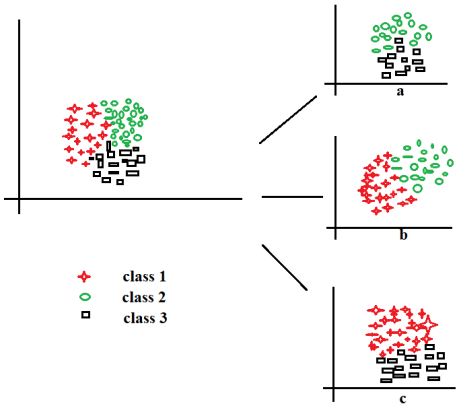


Figure 2.9: Multi-classed to Binary decomposition-One vs One

Figure 2.9 shows the one-versus-One for multi-classed data set were each class

is paired with another until all the classes have been paired, for example in Figure 2.9 a, class 2 and class 3 is paired, class 1 and class 2 are paired in Figure 2.9 b and finally class 1 and class 3 are paired in Figure 2.9 c.

There is extensive literature that has proposed and supported one-versus-all techniques as the most accurate approach in handling multi-class classifications. The work of [133][134][130][132] made strong cases as the only technique that could justifiably claim to have actually handle multiclassed classification in a real sense of it. This is because one versus one makes a pair of binary data without according for the influence of other data items, meaning that other data items that could interact with the modeling have been eliminated or filtered out. In contrast, in one versus all, those classes have not been removed. Furthermore, One-versus-One is computationally expensive. Hence, the one-versus-all approach is implemented in this work. Therefore the metrics of measuring the performance in Equations 2.12, 2.13, 2.14, 2.15 and 2.16 in sections 2.3.1 will then be applicable to multi-classed imbalanced data set because each iteration of classification is binary until all n_{total} binary classification has been completed.

An average performance of the multi-classed n binary classifier may be deduced by the summations of each metric as in

Equations 2.17,2.18,2.19,2.20.

$$Average\ Recall = \frac{\sum_{i=j}^{1} Recall}{n} \tag{2.17}$$

$$Average\ Precision = \frac{\sum_{i=j}^{1} Precision}{n} \tag{2.18}$$

$$Average\ Specificity = \frac{\sum_{i=j}^{1} Specificity}{n} \tag{2.19}$$

$$Average\ F_{measure} = \frac{\sum_{i=j}^{1} Fmeasure}{n} \tag{2.20}$$

There is no any major difference between the metrics for binary classed and that of multi-classed that has been decomposed into "one-versus-all".

2.3.3 The Receiver Operating Characteristics and Area Under the Curve

The graph of Receiver Operating Characteristics (ROC) is used to provides a trade-off value between Sensitivity and Specificity. The y-axis is TP(rate) plotted against

FP(rate) in the x-axis. The graph provides a corresponding score for any change in either value [135][136], using the ROC graph is possible to predict all values of TP(rate) and FP(rate) for any type of classifier both binary and multi-classed. Figure 2.10 is a modified version (included yellow curve) of ROC graph used to quantify the accuracy of a diagnostic test [137]. The scale of the graph is from 0.00 to 1.00 in both axes. The graph has four curves; yellow, green, red and blue. For TP(rate) plotted in the y-axis the highest value is 1.00; therefore, the yellow curve with the highest TP(rate) in y-axis at the position (0.00,1.00) is a perfect classifier (more accurate) followed by green and red accordingly. In Figure 2.11 The blue curve (straight line) is the result of random guess classification. The more the curves get closer to the position (0.00,1.00) the better the classification. The area Under the Curve (AUC) is another important metric, it is used to measure the accuracy of the classification, ie accuracy is proportionally equal to the area under the ROC curve, meaning that the larger this area the more accurate is the classification.

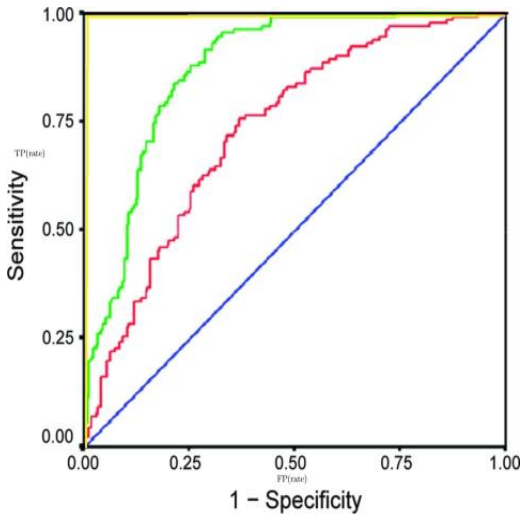


Figure 2.10: ROC Curve

The Figure 2.11 is a representation of an ROC graph with three curves; A, B and C. Curve A is more accurate because it has a larger area, the area of C is used to represent a random guess classification and usually 0.5. The ROC graph for multi-classed (One-Versus-all) as described in section 2.3.2 are the same with binary,

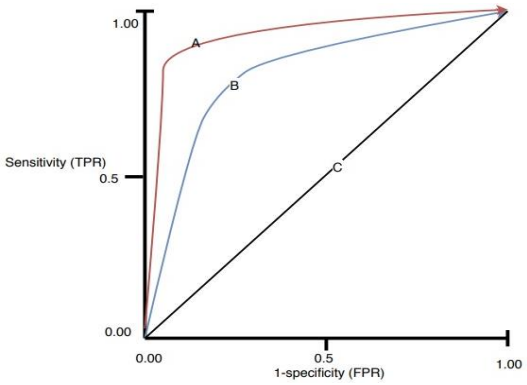


Figure 2.11: The Area Under the ROC Curve

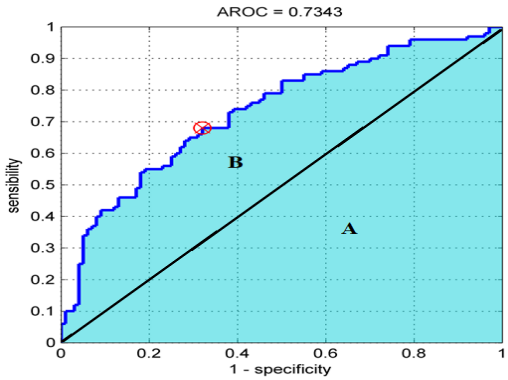


Figure 2.12: Deducing AUC

In Figure 2.11, each of the curve will represent the modelling result of interest and comparison of each algorithm performance would be deduced from the Area Under the Curve, this could be a bit tricky considering that the shape of such area is usually not properly define, Figure 2.12 from [138] is an excellent attempt of calculating the Area Under the Curve (AUC), from the Figure 2.12 the AUC have been divided into A and B. The AUC is then:

$$AUC = A + B = Area\ of\ Shaded\ portions. \tag{2.21}$$

2.3.4 Data acquisition and descriptions:

The datasets used in this research are listed in appendix A.2 and could be downloaded from the machine learning archive [139] and [140], the full descriptions and other details of the datasets have been provided; please see appendix A.2. The data is in the public domain; hence, no extra permission was needed nor sort before using it. All references to the data have been acknowledged. Detailed descriptions like the number of instances, total attributes, missing values, class distributions are all provided.

The datasets have some few similarities, four of the data set are binary classed (two class), these are the Pima India diabetes data, Wisconsin cancer data, Buper liver disease data, and Cod-RNA data. While three of the dataset are multi-classed, these are Iris, Yeast, and Glass data. The Yeast and Glass data set are highly imbalanced, while the Iris data set is three classes and is balanced (50 in each class) thus uniformly classed.

The Glass data has six classes label from 1 to 7 and nine attributes, notice that class 4 is not available in the dataset. The attributes are mostly different chemical elements in various proportions and the refractive index of glass, and these properties made the glass useful for various applications like window glass, cars heard lamp, tableware, window glasses, and so on. The Yeast data set has ten classes and eight attributes, which are the different numerical measurement of nucleus and protein enzymes in various proportions.

2.3.5 General Data preparation and Techniques to Avoid Overfitting.

The purpose of this section is to present some common data preprocessing techniques and the de facto standard procedures that cut across all the experimentation and research design used.

The data sets used in this research has some common issues that were treated in this section. Though during the experimentation in different sections, some specific treatment were also carried out that are aligned to the research design in that section.

The Weka Data Mining and Machine learning software have been used for most analysis, but we have also used Microsoft Excel for initial analysis and data preparation like counting of missing values, descriptive statistics and many more. Also, we had used the Python programming language to present some analysis output screenshot because of the aesthetic look.

As the work involved many data sets (seven); Pima Indians Diabetes data, Wisconsin breast cancer data, BUPA liver disorders data, Cod-RNA Dataset, Glass data, Yeast and Iris data (please see Section 2.3.4). Four of the data sets are binary classed while the other three are multi-classed, as explained in sections 2.3.2, the three multi-classed data set have been converted to *nBinary* using the one-vs-all techniques as explained in section 2.3.2, hence the same data preparation could be applied to all the data sets. Even though the sources information provided for the data sets in A.2 stated that some data has no missing values, but few anomalies

were discovered during exploration (Data understanding) accordance with (CRISP) of Data Mining [141] [142].

Missing data

Some of the data set has problem with missing values which must be dealt with, the Pima India diabetes data, this was treated using the average of the data column items because the Skewness for the missing columns are zero, hence their mean value was used as replacement for the missing data in the body mass index (BMI) and age attributes in the Pima Indians Diabetes data,

The Wisconsin Breast Cancer data are well organized and were treated from source, so there were no problems with the data, while the cod-RNA dataset had very few cases (6) of missing values; thus, it was deleted. Also for the BUPA Liver Disorders data, the aspartate aminotransferase (sgot) and alanine aminotransferase (sgpt) columns were also treated for missing data values. Additionally, none of the data had any problem with outliers. Finally, the inconsistency of representing missing values with zero in the Pima Indians Diabetes data was also addressed in the BMI column.

During machine learning modelling processes one of the most common process error that may occur is ***Overfitting*** and ***Underfitting***, these two errors will be reviewed, and the techniques used in avoiding them explained in these sections. Overfitting is a modelling error that had occurred when the model created performed totally below the result obtained during training when tested on a real independent data [143][144][145]. By independent it means data that the model has not seen before, this is due to the machine learning algorithm memorising the patterns of a dataset. When the algorithm is exposed to the same data it will fit into the data patterns so well that it produces very high accurate result. All this happened during training of the model. But the model is unable to generalise and replicate such high accuracy in a new independent data. This shows that the model learning process is false, although, overfitting has been traceable to be the consequence of noise in the dataset. But other causes such as the over usage of the same data set such that it increases the possibility of the modelling algorithms memorising the pattern of the data items could also contribute to it. The underfitting is opposite of overfitting, the model is unable to fit in the training data such that the accuracy result obtained during training is very low. Perhaps, that is the reason underfitting error is not as popular as overfitting because it cannot be used, after all, why should a model that performed poorly be used?

Cross Validation and Split into Train and Test data are two techniques used to overcome overfitting. Opinions are rife in machine learning and data science communities particularly in the vibrant discussions public forums dedicated to data science like Kaggle [146], Reddit [147], Researchgate [148] e.t.c. as to which technique is the best for solving overfitting. Before going further to explain the details of cross-validation, let me state here that both techniques are confirmed standardised solutions to overfitting. The choices made by any scientist depends on many factors for example; the computational power or does the researcher have enough data to split into training and test data? Even when enough data is available, most researchers still use cross-validation when training the model. This would provide a double assurance that the model will not under-perform during generalisation (a term used to describe models performance with an unseen data), besides most data mining tool/software like weka [22] has incorporated all these techniques, is a matter of just clicking the button.

At present, no evidence has contradicted the fact that the results of a model trained using cross-validations techniques will not be the same during generalisation. Therefore using cross-validation has become the convention as could be seen in many academic journals, thesis, and reports in data sciences. That is not to say that using split into "Train and Test data" is not equally popular, by and large, both techniques are used together.

Cross-Validation is one of the standard technique used to avoid overfitting, and that will be applied in this thesis (10-fold Cross-validation). Figure 2.13 is a diagrammatic representation of the process of K-fold Cross-validation with K = 5, the K represents the number of division (fold) of the dataset [149], in each division 80% is for training the model while the remaining 20% is for the testing, this is repeated to

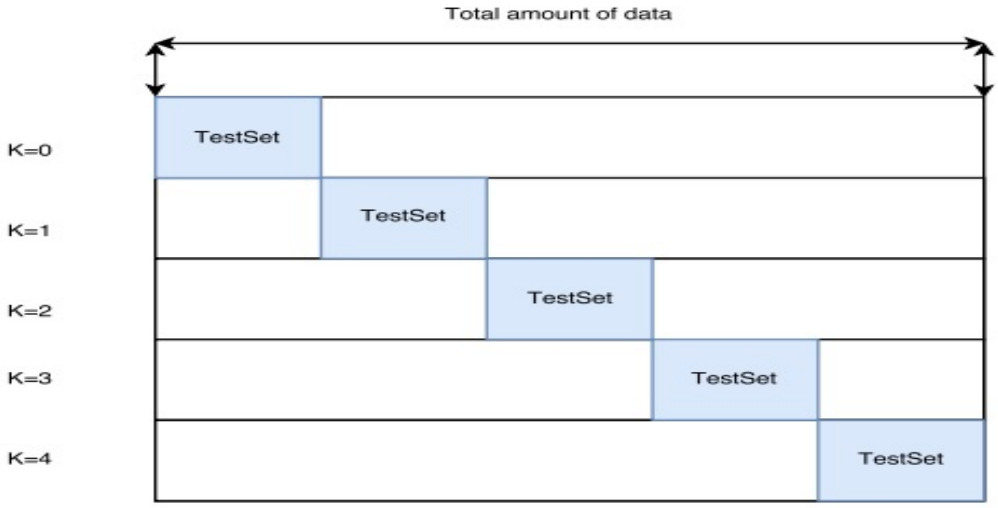


Figure 2.13: K-Fold Cross validation

the number of the fold, the accuracy or performance of the model is obtained by the average performance of each fold. Because the sets of data items being used for the training and test data are repeatedly changed as depicted in Figure 2.13, the machine learning algorithm would not be able memorised the fitting functions hence overfitting problems will not arise. The cross-validation techniques have another advantage of allowing the model to use all the data without dividing the whole data into training and test data particularly when the size of the data set is an issue.
In the next chapter of this research, the theoretical basis of the process that underscores the derivatives of the techniques " Variance Ranking Attribute Selection (VR)" for handling the imbalanced will be deduced, one of the advantages of (VR) is that its algorithm independent, hence machine learning algorithms, that could be applied to both regression and classification problems will be used for validation of our techniques.

Chapter 3

Variance Ranking Attribute Selection Technique

3.1 Proposed Method and Approach

In chapter two, we provided the efforts that have been made so far to handle imbalanced problems and also exposing the inadequacies in many of the existing approaches. Being that many of these approaches did not take the (IR) into consideration nor utilised it in the algorithm. But are mostly based on tweaking and using different modifications of algorithms. Although some good results could be obtained sometimes, but the processes are difficult to replicate. Apart from the sampling techniques were the process involves the (IR) because its either artificially generating or reducing existing data items to equalized the classes as in (SMOTE). Most academic pundits have criticise many of these approaches as not really solving the problems of class imbalance.

Our approach is based on the variance of attributes, the reasons for choosing the variance as against other properties is because its best suited to describe and summarise the positions of multiple data points within a vector space. Secondly, considering the values of the attributes and how there are distributed, attributes that belong to a particular class are usually concentrated together (have density). Therefore, the variance values within a central terms of reference can provide an insight into the relevance of such attribute class cluster and can be used to find the density of the distributions of each cluster which are represented by the classes, hence the variance can be used as a metrics to predict the classes of data item.

In most classification modelling, what we are searching for is just the minority class items in both binary and multi-classed context, recall in chapter 2 that the multi-classed could be decomposed to (n)Binary either using one-versus-one or one-versus-all, but one-versus-all have been selected for this research the reasons for

that, have been explained in chapter 2.

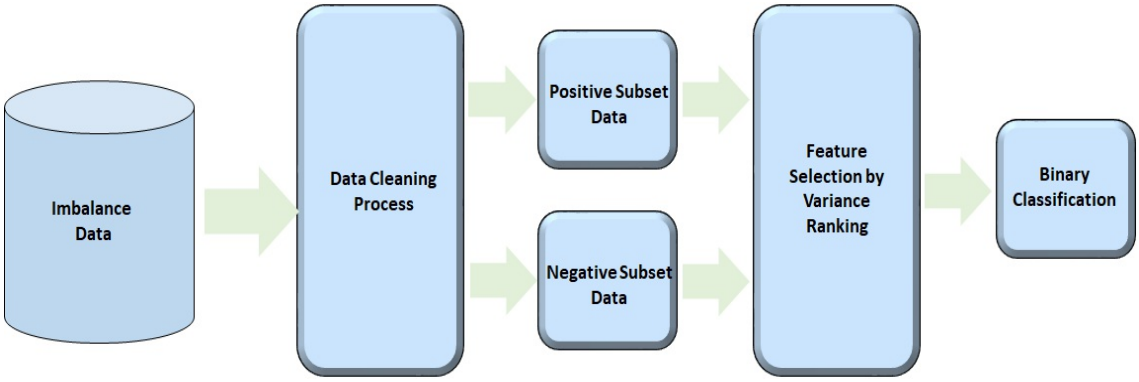


Figure 3.1: An Overview of the Proposed Method

To improve the capturing of minority classes in predictive modelling, new techniques have to be developed because the existing approaches are skewing sensitivities and capturing more of the majority classes which are not needed. To correct this, we propose the processes as illustrated in Figure 3.1.

Though detailed of this process will be dealt with in subsequent sessions, but a general black-box description of the Figure 3.1 will suffice for now. The process is called "Variance Ranking Attribute Selection" (VR) Technique. In the diagram, the process starts with obtaining an imbalanced data (Binary or Multi-classed) then, cleaning the data or any other preprocessing that the data may need. The data is split into two classes (Positive class and negative class) or (class 1 and class 0), the split classes is used to deduce important feature using a Variance Ranking process. Finally, the results are evaluated by binary classifications.

3.1.1 Variance and Variables Properties

A typical datasets has lots of attributes (variables) each measured to different scale, different data types (discrete or continuous). Each variable cluster centroid relative to each may change or remain constant depending on the terms of reference. Some of these variables may be dependent while some may be independent and also the density function will remain constant. The question is, how could all these properties be made to undergo the same statistical treatment? Is there a property of numeric data that equalises them so that they could be subjecting to the same statistical treatment and will not produce any bias. The work of [150][151][152][153] provided a solution of derivative for this equalisation.

The two quantities that are mostly used to measure the distance of data items from their mean position are variance (σ^2) and standard deviation $\sqrt{(\sigma^2)}$.

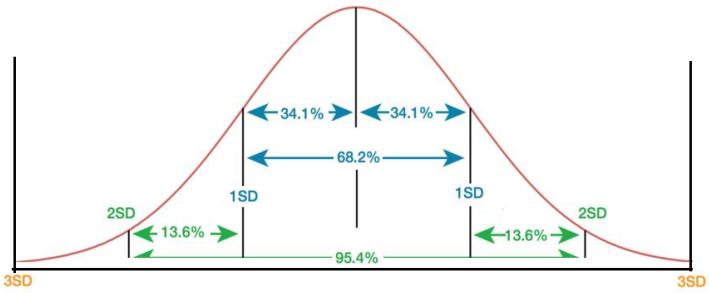


Figure 3.2: Standard Deviation for Single Variable Normal Distribution

Even if, both could be deduced from each other and consequently share many physical characteristic, but there exist some differences in the application of these two quantities. For example, the standard deviation is mostly used for investigating a single variable distribution as shown in Figure 3.2, but if the data set is multivariate then variance are mostly used to describe the general spread of these variables from the conceptual "mean" position [154]. The term conceptual "mean" is used to indicate the fact of the changing values and position of the mean and variances of one class relative to another class. And if the one class is taken in turn relative to the rest as in One-vs-All, the "mean" and "variance" will be different to the next class. But considering the density of all the classes in the sample space, which is called the probability density function will remain constant because the total numbers of the data item and the sample space is not changing, please see [155], though this function is a probability concept and is described as the likelihood that the value of a variable lies within a sample space. The review of Figure 3.3 is a representation of Glass data in the 3D scattered plot, but the values of variances of class relative to the other classes changes depending on the positioning of the class group that is being considered, hence the terms conceptual mean, and variance. But the whole density will remain the same. Note, in this case the density is considered to be probabilistic because the data item in the sample space is not evenly spread and the likely-hood of getting a data item in the sample space depends on the spread or variance. In fact, this density probability concept is an active area of research popularly called "Probability density estimation" [156][157][158].

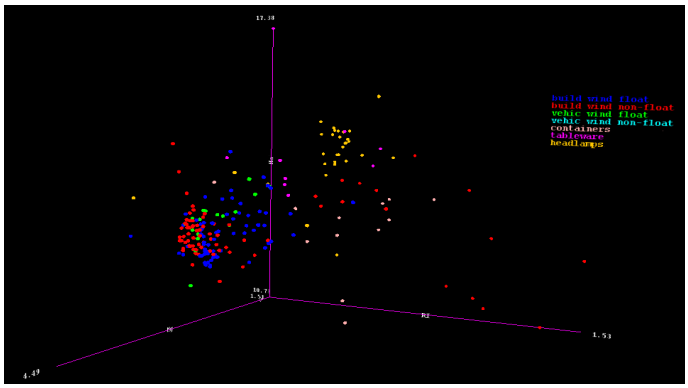


Figure 3.3: 3D Glass data Scatter plot

By definition, variance is how spread the data items of number N from the mean and is given by $\sigma^2 = \frac{\sum(x-\mu)^2}{N}$. If the whole population is considered, however, this equation is slightly different if a sample of the whole population is used and is given by $\sigma^2 = \frac{\sum(x-\mu)^2}{N-1}$ [159][154]. When taking a sample it must be large enough and taken several times and average out to make sure that the sample mean is equal to population mean and the variance of the sample mean is given by ${\sigma_m}^2 = \frac{\sigma^2}{n}$ while ${\sigma_m}^2$ is the variance of the sample and n is equal to the number of times the sample were taken. Therefore the variance of population is equal to $\sigma^2 = \sigma_m^2 * n$ [160].

These data items were collected independently from each other, hence are independent variables. In many numeric data, the variables could either be discrete or continuous. To what extent does the type of variable data item affect the overall distribution from their means ie the variances? The effect of these intrinsic properties of the data item can be deduced accordingly.

For an input dataset with $N = \{n_1.....n_x\}$, where n is a combination of discrete and continuous variables [161][162][163], if the variance of the independent random variable x is given by Var_x which is the expected value of the square of the the deviation, for all the variable x with a mean of μ the variance is;

$$Var_x = E\left\{(x-\mu)^2\right\} \tag{3.1}$$

The constant E represents the density function and $E\ \alpha\ \frac{1}{N}$.
The Equation 3.1 [162] is modified to accommodate both discrete and continuous variables. Hence, when variable x is continuous the variance is

$$Var_x = E\left\{(x-\mu)^2\right\} = \sum_{i=min}^{max} \int_{\min}^{\max} (x-\mu)^2 f(x)\, dx \tag{3.2}$$

Also for discrete variable Equation 3.1 would resolve to;

$$Var_x = E\left\{(x-\mu)^2\right\} = \sum_{i=1}^{n}(x_i-\mu)^2 f(x) \tag{3.3}$$

and the whole population or the sample is considered, the population variance becomes subjective to the probability density function $f(x)$ such that the expectation values and variance of x within the same density is the sum of Equation 3.2 and Equation 3.3 $V_{(total)} = V_{(discrete)} + V_{(continuous)}$. Therefore, for any type of variable (discrete and continuous) their total variances is the sum of individual variance provided there are in the same sample space:

$$V_{total} = \sum_{i=1}^{n}(x_i-\mu)^2 f(x) + \sum_{i=min}^{max}\int_{\min}^{\max}(x-\mu)^2 f(x)\,dx \tag{3.4}$$

each parts of equation 3.4 contains the same quantity apart from the change function dx, therefore it could be simplify to equation 3.5 particularly when the change is minima

$$\sum f(x)dx\,(x-\mu)^2 \tag{3.5}$$

if μ is considered as being the mean and the probability density functions is $f(x)$ and $f(x)dx$

which is constant in the sample space, hence

$$f(x) = f(x)dx = pi \tag{3.6}$$

then for any population or sample variable, $V_{(ar)}$ is also deduced by [164]:

$$V_{(ar)} = \sum_{i=1}^{n} pi.\,(x_i-\mu)^2 \tag{3.7}$$

For all values of pi being the probability density functions, for equation 3.5 and 3.7, the equality is deduced by equating the integral to $f(x)\,dx$ and $\sum_{i=1}^{n} pi$ as in equation 3.6. Due to the premise of the same range of probability density function, the variables transformable vis-a-vis discrete and continuous as provided by [165][163][161].

This link between the discrete and continuous distribution under the condition of the same range and their transformation from one to another were demonstrated by [166][167] therefore equalized the variables; hence, the variances of the discrete and continuous variables are equal if $f(x)\,dx$ and $\sum_{i=1}^{n} pi$ are equal. Our technique

implemented the concept of sample variance by taking n values in the range of $y_1....y_n$ of the population where $n < N$. Estimating the variance of the sample data variables gives the average of the square deviations as in $\sigma_2^y = \frac{1}{n}\sum_{i=1}^{n}(y-\bar{y})^2 = \left(\frac{1}{n}\sum_{i=1}^{n}\right) - \bar{y^2} = \frac{1}{n^2}\sum_{i<j}^{1}(y_i - y_j)^2$.

This computation confirms that the range of the variable values of x is still within that of the mean, as explained earlier. This derivative will hold true in both cases of variance if and only if the distribution of the variable x is completely determined by the probability density function $f(x)$ [168][169], which is shown in Equation 3.5 and 3.7. Having deduced the variance and variables properties, have provided an insight to show that no matter the types of variable whether discrete and or continuous or any other intrinsic properties of the variables, the same statistical operations could be applied to the variables and will not invalidate the experiments.

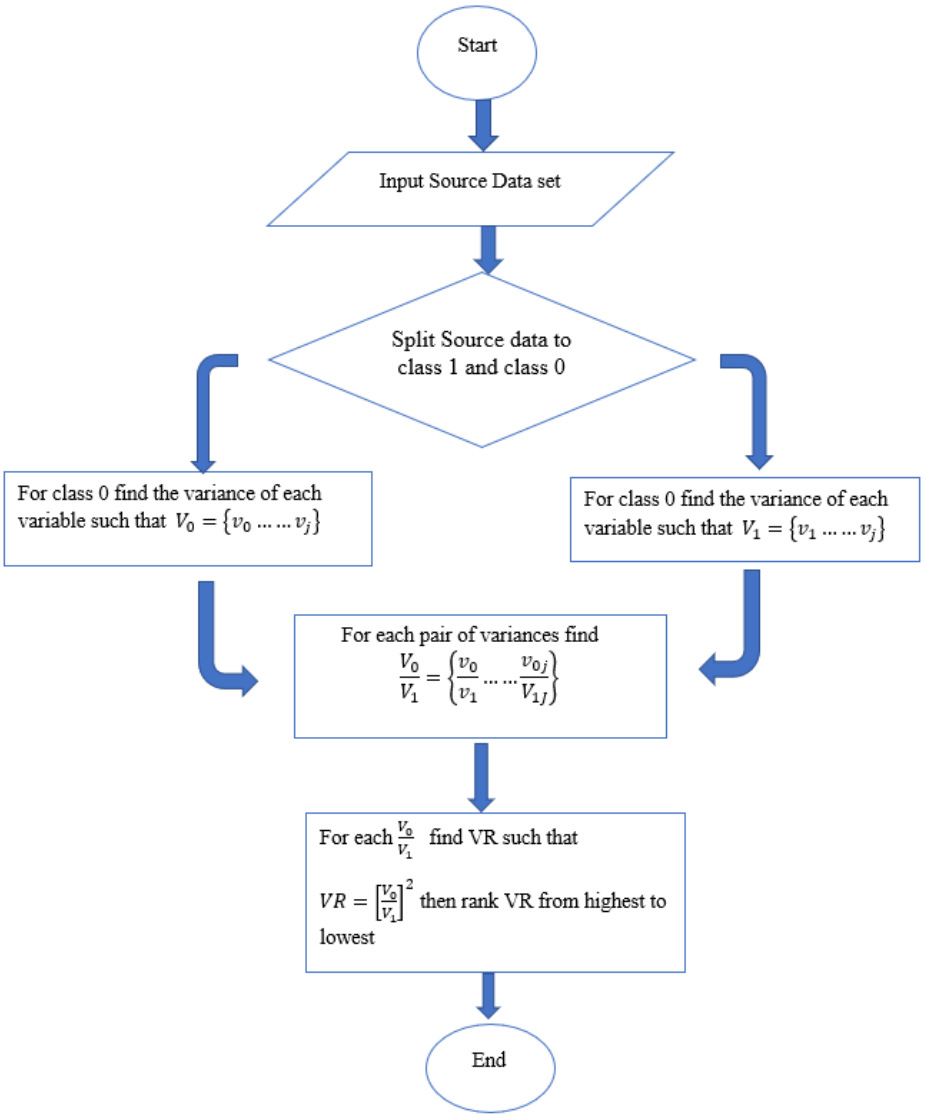


Figure 3.4: Algorithm flow chart for The Variance Ranking Attribute Selection

In carrying out the experiments, this research have explained how the properties of the attributes like the continuous and discrete data, the numerous data types cannot invalidate the technique. Compare equations 3.1 with the derivative in equations 3.7 using a statistical variance comparison that could accommodate the sub-population (binary groups). The work of [170],[171] and [172], that uses comparison of variances to assess the probability density functions of multi-classed data notwithstanding the distributions of the dataset [173][174]. Thus variance comparison could be applied to the same subgroups and this subgroups are represented by the classes, there is a different analysis of variance [175][176][177][178]. No matter the type of subgroup we ended up with, the variances could be compared, for instance, if the subgroups distribution is not a "normal" distribution which are often called nonparametric, they could apply the Kruskal-Wallis one-way analysis of variance by rank test [179] [180][181]. These addresses the nonparametric differences between two groups of variables . This test is used as an alternative to one-way analysis of variance (ANOVA) when a normal distribution in the dataset is not assumed in the probability density functions of $f(x)\,dx$ or $\sum_{i=1}^{n} pi$. The Kruskal-Wallis (ANOVA) by rank is given by

$$H = N - 1\frac{\sum_{i=1}^{g} n_i \left(\bar{r}_i - \bar{r}\right)^2}{\sum_{i=1}^{g}\sum_{j=1}^{n_j} n_j \left(\bar{x}_j - \bar{x}\right)^2} \tag{3.8}$$

where N is the total number of all the groups, n_i and $n_j$is number in groups i and j, and r and x are the each values, while $\bar{r}$ and $\bar{x}$ are their mean. Based on the the comparison we could now represent multivariate ANOVA as in the Equation 3.9

$$Compare\ Ratio = \frac{Variance_{(class1)}}{Variance_{(class2)}} \tag{3.9}$$

The ratio of two variable events can now be a metrics to compare their degree of concentrations in a sample space is equals to the probability density function [182] agreeing with Equation 3.9.

Thus the ratio of the variance of each of the variable in the majority and minority data subsets is inversely proportional to the density functions while the square of the density function is equal to the **F-distribution** [183][184][185] F-distribution could deal with multiple sets of events or variables [186] as represented by different variables in the majority and minority data groups or classes. By definition the

F-distribution (F-test) [184][187] is given by

$$F = \frac{(Larger\ variance)^2}{(smaller\ variance)^2} \tag{3.10}$$

Therefore, for subset (class 1 and 0) with additive variance of independent variable will resolve into please see [188][189];

$$F_{final} = \left\{ \frac{Variance_{(final1)}}{Variance_{(final2)}} \right\}^2 \tag{3.11}$$

therefore the of F_{final} is a ratio concept hence, has no unit, since both units have cancel each other, hence F_{final} is a measure of the density of the variances $Variance_{(final1)}$ to $Variance_{(final2)}$.

For a binary classed data or multi-classed decompose into n binary using One-vs-All, if the sub classes variance is V_i and V_j, then the Equation 3.11 would resolved to Equation 3.12, the squaring eliminates any negative value and also agreed with the F-distribution (F-test), finally the value of (F-test) is F_{final}

$$F_{final} = \left[\frac{V_{0j}}{V_{1j}} \right]^2 \tag{3.12}$$

3.2 The Abstraction and High level Research Design:

The high level research design is explained with the aid of the block algorithm diagram in figure 3.4. From the diagramme, the input data sources are assumed to have been treated for any common error like missing values, incompatible data types etc. The figure in 3.4 showed that each dataset have to be split into two according to their classes. Even the multi-classed will be converted to $nBinary$, where n are equal to the numbers of classes in the dataset. The dataset is split or separated into class 1 and class 0 or class negative and class positive.

If the variances $V_0 = v_{01}, v_{02}, v_{03}.....v_{0j}$ of each of the variables in class 0 and the variances of $V_1 = v_1, v_2, v_3.....v_j$ of each of the variables in class 1 are taken, for each pair of the feature we find the ratio of the $\frac{V_0}{V_1}$.

The value $(\mathbf{V_0/V_1})$ is the division ratio based on the variance significant F-distribution giving by $\left\{\frac{V_0}{V_1}\right\}^2$ to produce the values that could be squared, the squaring of these values are particularly useful in case any of the quantity resolved to negative at any point. The significant feature are selected by ranking the $\left\{\frac{V_0}{V_1}\right\}^2$ from highest to lowest. The highest being the most significant , while the lowest the least signifi-

cant. All these are shown sequentially in the figure 3.4. For each of the datasets in the experiments this high level design would act as a guide for clarity and reference point.

3.3 Experiment Design:

3.3.1 Sampling and Splitting the data set

The dataset used is in Table A.2. The experimentation was conducted on the two classes of data (the majority and minority classes) represented by 0 and 1 for the binary classed and also the multi-classed have been decomposed to $nBinary$ classed using One-versus-all technique as explained in section 2.3.2 hence is also represented by 0 and 1.

Where the number of the whole population is below 2000 like in (Pima India, Wisconsin, Bupa, Iris, Glass, and Yeast), all the data set instances were divided into two classes (0 and 1) to represent the majority and minority classes. But for Cod-RNA with a population of 488565, the data sets were first split into $nBinary$ of 0 and 1. To obtain the ***sample size*** and ensure that the sample collected have the same characteristics as the class population (0 and 1). The process utilised in the work of [190] was used and also the concept of central limit theorem as explained at [191]. This is done by repeatedly randomising the collection of the sample from the population. The sample size selected for each class is based on the ratio of each classes in the population thereby maintaining the imbalance ratio (IR). Furthermore, the integrity of the sample is checked against the subset population by comparing the distribution of the sample to that of the subset population using the Central Limit Theorem concept [191], this is done by checking the n sample skewness given by

$$\frac{\frac{1}{n}\sum_{i=1}^{n}(x_1-\bar{x})^3}{\left[\frac{1}{n-1}\sum_{i=1}^{n}(x_1-\bar{x})^2\right]^{\frac{3}{2}}}$$

(Fisher-Pearson). The skewness is a statistical function used to measure the distribution of a data set, if two data set have the same skewness, therefore, their distributions are the same.

The classes of the two subsets are used to represent the majority and minority classes, the following term definition should be established without any confusion of their meanings.

- **Majority class**, may also be known as negative class or class 0.
- **Minority class**, may also be known as positive class or class 1.

The variance of subset V_0 (Variance of negative class) is $\sum_{i=1}^{g} n_{maj} (x_i - \bar{x})^2$ and V_1 (Variance of positive class) is $\sum_{i=1}^{g} n_{min} (x_j - \bar{x})^2$ of the data set were obtained. The Variance Significant Test (F-distribution), is given by the square of the ratio of V_0 to V_1. The squaring eliminate any negative values, the results were then ranked to achieve the final attribute selection.
The criteria used to validate the results are as follows:

- **Firstly**, we compared the results obtained with two benchmarks of attribute selection (Pearson correlations and information gain) being from the same filter techniques of attributes selection; please see section 2.2.7 for the explanation of the filter technique attributes selection,
- **Secondly**, to select the attributes a series of classification experiments; logistic regression (LR), support vector machine (SVM) and decision trees (DT) were carried out using the ranked attributes for Variance Ranking (VR), Pearson Correlation (PC) and Information Gain (IG),
- **Finally**, a peak threshold graph was developed to demonstrate the selections of the most significant attributes.

In all the experiment, ***Cross-validation*** as expalined in section 2.3.5 have been used to validate the results to ascertain how the model will perform in an independent data sets. K-fold cross-validation is the standard method used for validation of the performance of a model. It is done by dividing the dataset into k subset equal size a more detailed description of the experiment is provided in the next session 3.3.

3.3.2 Experiments for Variance Ranking Attribute Selection

The highlight of this session is to articulate all the experiments to demonstrate Variance Ranking Attributes Selection by following this sequence;

- the raw formula that would initiate the variances of each class and ultimately the Variance Ranking Processes.
- A clear process flow Algorithm in form of a flow chart
- The tabulations of the experiments, Binary and multi classed data set.
- the re-coding of One-vs-All

All the itemised will be presented in this section. When some process has been carried out in other sections or chapters it would be referred and properly signed post. The proposed method of attributes selections is for discrete and continuous numeric data for a binary class and multi-classed (decomposed into n *binary* see section 2.3.2) represented by 1 and 0.

The data preparation have been explained in sections 2.3.5 and 3.3.1 . Each of the data set in Table A.2 was first split into two subsets of class 0 and class 1 and the Variance of each attribute deduced using equation 3.13 and 3.14 respectively. The Variance Significant is deduced using the equation of 3.15. In all the total number of the majority and minority class is maintained through the number of the data items as n_{maj} and n_{minj}. In general the variance of each of the subsections; class target 1 and class target 0, of dataset was computed using the following formula Variance $v = \frac{\sum(x-\bar{x}^2)}{(n-1)}$. If The Variance subsection of class 0 is given by:

$$V_0 = \frac{(x_0 - \bar{x_0}^2)}{(n_{maj} - 1)} \tag{3.13}$$

If then Variance subsection of class 1 is given by:

$$V_1 = \frac{(x_1 - \bar{x_1}^2)}{(n_{min} - 1)} \tag{3.14}$$

The Variance Significant Attribute Selection is then deduced by:

$$VR = \left(\frac{(x_0 - \bar{x_0}^2)}{(n_{maj} - 1)} / \frac{(x_1 - \bar{x_1}^2)}{(n_{min} - 1)} \right)^2 = \left\{ \frac{V_0}{V_1} \right\}^2 \tag{3.15}$$

The total number of data items is inversely proportional to the variance or spread from the mean position, that is $Variance \propto \frac{1}{n_m}$, this relationship shows that the formula is generic, therefore if the ranking is done in either order it would remain consistent. In Tables 3.1, 3.2, 3.3 and 3.4 , the column V_1 and V_0 is the results of the variance of each subsection class (positive=1 and negatives=0) for each attribute.

Binary classed Experiments

The results of the experiment for the binary classed data is in Tables 3.1, 3.2, 3.3 and 3.4. The serial numbers in the tables are not mistakes but show how the attributes were numbered before from the original data sets descriptions in Table A.2 and how the (VR) techniques have ranked them.

Variance Ranking : Attributes selection Using Pima				
sn	Variables	V0	V1	VR
8	age	136.1342	120.3026	1.280514
6	bmass	59.13387	52.75069	1.256656
2	plasglu	683.3623	800.1395	0.729408
4	skinfold	221.7105	312.5722	0.50312
3	diapres	326.2747	461.898	0.49897
1	preg	9.103403	13.99687	0.423005
7	pedi	0.089452	0.138648	0.41625
5	insutest	9774.345	19234.67	0.258229

Table 3.1: Variance Ranking attribute selection using Pima India data

The result of the experiment using the Pima India data in Table 3.1 have a serial number that has identified age followed by Body Mass Index (bmass) and plama glucose as the three most significant. The ranking continued until the last attribute which is insutest.

Variance Ranking Attribute using Bupa				
sn	Variable	V0	V1	VR
4	sgot	127.4371	59.87759	4.529634
3	sgpt	477.2004	248.943	3.674529
6	drinks	8.075069	4.44272	3.303654
5	gammagt	1807.82	1103.902	2.68194
1	mcv	23.08621	14.96964	2.378388
2	alkphos	326.2356	345.6176	0.890986

Table 3.2: Variance Ranking attribute selection using Bupa data

The Bupa data have also been ranked in the order from 4,3, 6, 5, 1 and 2 in Table 3.2. While the Wisconsin and Cod-rna data have been ranked in Table 3.3 and 3.4

Variance Ranking Attributes using Wisconsin data				
sn	**Variable**	**V0**	**V1**	**VR**
1	ClumpT	2.803341	5.899308	0.225813
7	BlandChro	1.167133	5.170401	0.050956
3	Unif CellShape	0.995676	6.564073	0.023009
5	SingEpitCellSize	0.841127	6.010373	0.019585
6	Bare Nuclei	1.348399	9.995747	0.018197
2	UniforCellSize	0.823909	7.395747	0.012411
8	NorMNucl	1.121177	11.22701	0.009973
4	MargAdhesion	0.99367	10.30709	0.009294
9	Mitoses	0.251999	6.54305	0.001483

Table 3.3: Variance Ranking attribute selection using Wisconsin Breast Cancer data

Variance Ranking using Cod-rna Data				
sn	Variables	V0	V1	VR
1	X1	0.9863	0.900203	1.200431
4	X4	1.016567	0.942204	1.164078
2	X2	0.96502	0.909372	1.126132
5	X6	1.025702	0.999488	1.053143
3	X3	0.99855	0.98205	1.033885
6	X5	0.959546	0.994258	0.931394
7	X8	0.942645	0.999864	0.888821
8	X7	0.642895	0.950464	0.457519

Table 3.4: Variance Ranking attribute selection using Cod-rna data

Multi-classed Experiments $(n)Binary$

The above three experiments demonstrated the (VR) technique for binary classed data and is straight forward, but for multi-classed distributed dataset each of the minority classes will be taken in turn as the positive or 1 while the rest will be negative or class 0. This will result in more multiple experimentation equal to the number of target classes. For example, if there are three classes in the dataset, this would result into $(n)Binary$, while $n = 3$. The subsequent sessions would show the experiment with Iris data set that has $n = 3$.

The result for Iris data in Table 3.5 is very obvious, the classes are label originally as Iris Versicolor, Satosa and Virginica. For Iris Versicolor, the Petal width has been identified as the most significant attribute that distinguishes it from the rest, followed by the Petal length, Sepal length and Sepal width. The result for Satosa and Virginica are the most interesting, even if the experiment were performed differently both results are similar thereby showing that both flowers share more similarity to

Iris data using Variance Ranking Attributes				
sn	Variables	V0	V1	VR
1	petal width	0.844924	0.039106	466.8163
2	petal length	4.385794	0.220816	394.4883
3	sepal length	0.893627	0.266433	11.24962
4	sepal width	0.173115	0.098469	3.090777
Versicolor=1, All = 0				

Iris data using Variance Ranking Attributes				
sn	Variables	V0	V1	VR
1	petal length	0.68158	0.030106	512.5353
2	petal width	0.180428	0.011494	246.4201
3	sepal width	0.110723	0.14518	0.581656
4	sepal length	0.439349	0.124249	12.50359
Satosa =1, All = 0				

Iris data using Variance Ranking Attributes				
sn	Variables	V0	V1	VR
1	petal length	2.098339	0.304588	47.45987
2	petal width	0.320682	0.075433	18.07299
3	sepal width	0.22663	0.104004	4.748268
4	sepal length	0.411777	0.404343	1.037108
virginica =1, All = 0				

Table 3.5: Variance Ranking attribute selection using Iris data

each other than Versicolor.

The Glass data set that has $n = 6$ classes for details on this dataset please see Table A.2. The imbalanced classes are from 1 to 7; notice that class 4 is not in this dataset, so the total number of available classes is six, and they are labeled 1, 2, 3, 4, 5, and 7. Using the "one-versus-all" process, as explained in sections 2.8 each of these classes will be taken in turn as class 1 (minority class) and others as class 0 (majority class)

Glass Identification Data. Number of Instances = 214 Number of Attributes: 10 (including an Id#) plus the class attribute. Multi classed (6 classes available in this data set) Missing Values = none		
sn	Abr	Attributes
1	Id	Id number: 1 to 214
2	RI	refractive index
3	Na	Sodium (unit measurement:)
4	Mg	Magnesium
5	Al	Aluminum
6	Si	Silicon
7	K	Potassium
8	Ca	Calcium
9	Ba	Barium
10	Fe	Iron
11	Class	(1 to 7)\\-- 1 building_windows_float_processed -- 2 building_windows_non_float_processed -- 3 vehicle_windows_float_processed -- 4 vehicle_windows_non_float_processed (none in this database) -- 5 containers -- 6 tableware -- 7 headlamps

Table 3.6: Glass data set details showing highly imbalance classes

The Glass data imbalanced contents proportion is shown in Figure 3.5, which represents the chemical elements compositions and the refractive index (RI) which is a physical property of glass that measureS the bending of light as it passes through.

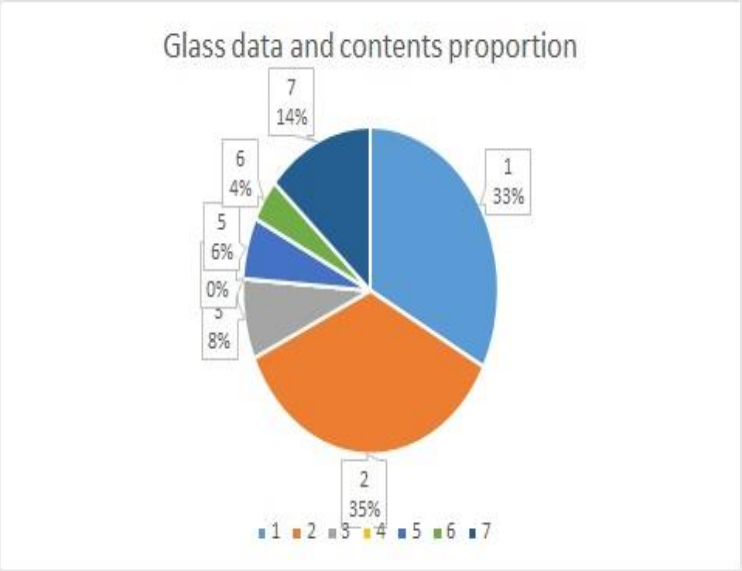


Figure 3.5: Glass data contents proportion

The amount of the chemical compositions of a glass determines its application, type, and classes; for example, class 1 is "Building window float processed", class 2 is the "Building window non-float processed", class 3 is "vehicle window float processed", class 4 (not available in this dataset) is "vehicle window non-float processed", class 5 is "container", class 6 is "tableware," and finally, class 7 is "headlamps." Therefore, the experiment will be conducted with class 1 as the minority while the rest will be class 0 as the majority class. Each of the classes in the minority, as shown in Figure 3.5 will consequently be relabeled as class 1 and class 0. Table 3.7 is the implementation of the one-versus-all approach; it shows the relabeled table with the actual numbers of minority classes as 70, 76, 17, 13, 9 and 29 and the corresponding majority classes are 144, 138, 197, 201, 205 and 185

Original class label	number	minority (one)	majority (all)
1	70	70 class 1	144 class 0
2	76	76 class 1	138 class 0
3	17	17 class 1	197 class 0
4	Unavailable	Unavailable	Unavailable
5	13	13 class 1	201 class 0
6	9	9 class 1	205 class 0
7	29	29 class 1	185 class 0

Table 3.7: Glass data class relabel to One-vs-All

The final result of using the (VR) techniques for the glass dataset is shown in Table 3.10. Again, notice that the serial number as ranked by the experiment is different from that presented in Table 3.6, excluding the ID number. Each of the sub-tables in Table 3.10 is a representation of each class relabelled as class 1 and the rest as class 0; for example, class 2 is relabelled as class 1 and the rest as class 0, (one versus all). This process is continued for all the classes in the dataset; see Table 3.7.

Yeast dataset
Number of Attributes: 9 (8 predictive, 1 Target class)
Number of Instances: 1484
Missing Value: None

sn	Abv	Attributes
1	mcg:	McGeoch's method for signal sequence recognition.
2	gvh:	von Heijne's method for signal sequence recognition.
3	alm:	Score of the ALOM membrane spanning region prediction program.
4	mit:	Score of discriminant analysis of the amino acid content of
5	erl:	Presence of "HDEL" substring (thought to act as a signal for
6	pox:	Peroxisomal targeting signal in the C-terminus.
7	vac:	Score of discriminant analysis of the amino acid content of vacuolar
8	nuc:	Score of discriminant analysis of nuclear localization signals

Target Class:

CYT (cytosolic or cytoskeletal)	463
NUC (nuclear)	429
MIT (mitochondrial)	244
ME3 (membrane protein, no N-terminal signal)	163
ME2 (membrane protein, uncleaved signal)	51
ME1 (membrane protein, cleaved signal)	44
EXC (extracellular)	35
VAC (vacuolar)	30
POX (peroxisomal)	20
ERL (endoplasmic reticulum lumen)	5

Table 3.8: Yeast data set details showing highly imbalance classes

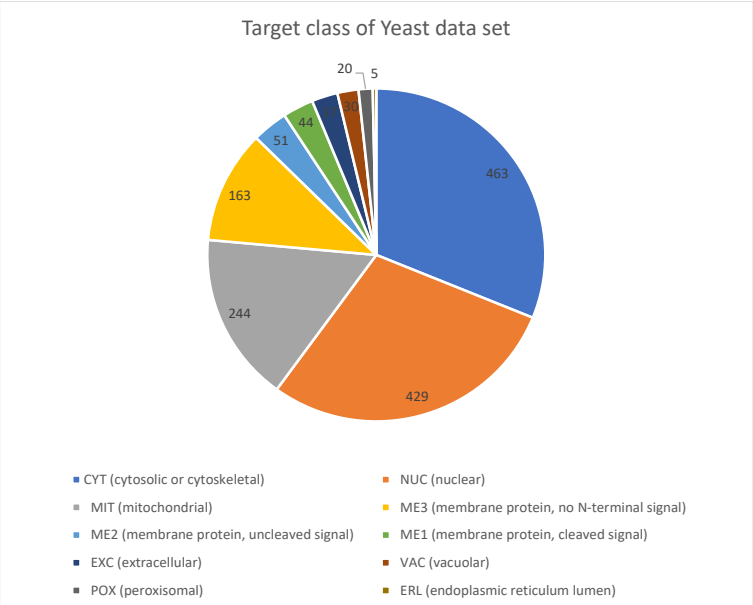


Figure 3.6: Yeast data contents proportion

Original Class label	Number	Minority (one)	Majority (all)
CYT (cytosolic or cytoskeletal)	463	CYT 463 as class 1	1023 as class 0
NUC (nuclear)	429	NUC 429 as class 1	1057 as class 0
MIT (mitochondrial)	244	MIT 244 as class 1	1242 as class 0
ME3 (membrane protein, no N-terminal signal)	163	ME3 163 as class 1	1323 as class 0
ME2 (membrane protein, uncleaved signal)	51	ME2 51 as class 1	1435 as class 0
ME1 (membrane protein, cleaved signal)	44	ME1 44 as class 1	1442 as class 0
EXC (extracellular)	35	EXC 37 as class 1	1449 as class 0
VAC (vacuolar)	30	VAC 30 as class 1	1456 as class 0
POX (peroxisomal)	20	POX 20 as class 1	1466 as class 0
ERL (endoplasmic reticulum lumen)	5	ERL 5 as class 1	1481 as class 0

Table 3.9: Yeast data class relabel to One-vs-All

For the Yeast data, the imbalanced classes could be seen in Table 3.8 and the contents proportions in Figure 3.6. This dataset is one of the most popular ones, and it has been used in various work for imbalanced multi-class data. The data are numeric measurements of different protein in the nucleus and cell materials in Yeast unicellular organisms. The objective of the dataset is using this physical protein descriptor for ascertaining the localization, which in turn, may provide help explaining the growth, health, and other physical and chemical properties of Yeast. The data are made up of 1,484 instances. The re-coding of the dataset to one versus all is shown in Table 3.9. For example, the recoding proceeds as "CYT (463) as class 1, 1023 as class 0"; this continues until the last minority class, which is "ERL(5) as class 1, 1481 as class 0.

sn	Variables	V0	V1	VR
8	Ba	0.345686	0.007029	2418.831
3	Mg	2.521579	0.06103	1707.084
6	K	0.609499	0.046173	174.2486
7	Ca	2.838831	0.330403	73.82303
4	Al	0.277826	0.074615	13.86399
2	Na	0.853034	0.249302	11.70795
5	Si	0.736367	0.324312	5.155397
1	RI	1.12E-05	5.14E-06	4.709949
9	Fe	0.010313	0.007934	1.689589
Class 1= relabelled as class 1, others class 0				

sn	Variables	V0	V1	VR
6	K	0.425354	0.045679	86.71029
4	Al	0.24927	0.101341	6.05026
8	Ba	0.247227	0.131291	3.545884
2	Na	0.666841	0.441108	2.285366
3	Mg	2.08054	1.477833	1.981991
5	Si	0.599921	0.525005	1.305753
9	Fe	0.009494	0.011328	0.702465
1	RI	9.22E-06	1.45E-05	0.407001
7	Ca	2.025366	3.692682	0.300831
Class 2= relabel as class 1, others class 0				

sn	Variables	V0	V1	VR
8	Ba	0.247227	0.001324	34891.9
3	Mg	2.08054	0.026499	6164.313
7	Ca	2.025366	0.144485	196.5007
6	K	0.425354	0.052849	64.77741
2	Na	0.666841	0.256935	6.735968
1	RI	9.22E-06	3.67E-06	6.306561
5	Si	0.599921	0.262426	5.226045
4	Al	0.24927	0.120749	4.261642
9	Fe	0.009494	0.011635	0.665926
Class 3 is relabelled as class 1, others class 0				

sn	Variables	V0	V1	VR
3	Mg	2.08054	0.998292	4.34347
2	Na	0.666841	0.603786	1.219773
1	RI	9.22E-06	1.12E-05	0.679098
8	Ba	0.247227	0.369969	0.44654
4	Al	0.24927	0.481526	0.26798
7	Ca	2.025366	4.768942	0.180369
9	Fe	0.009494	0.024208	0.153822
5	Si	0.599921	1.644342	0.133108
6	K	0.425354	4.574017	0.008648
Class 5 is relabelled as class 1, others class 0				

sn	Variables	V0	V1	VR
3	Mg	2.08054	1.203703	2.98754
7	Ca	2.025366	2.10235	0.928105
1	RI	9.22E-06	9.71E-06	0.902469
4	Al	0.24927	0.327025	0.581003
2	Na	0.666841	1.1751	0.322029
5	Si	0.599921	1.16525	0.265064
6	K	0.425354	0	0
8	Ba	0.247227	0	0
9	Fe	0.009494	0	0
Class 6 is relabelled as class 1, others class 0				

sn	Variables	V0	V1	VR
9	Fe	0.01051	0.000888	140.1712
7	Ca	2.160844	0.947712	5.198688
1	RI	9.41E-06	6.48E-06	2.10864
3	Mg	1.378535	1.249215	1.217759
2	Na	0.505249	0.471088	1.150284
6	K	0.419003	0.446883	0.879119
4	Al	0.17496	0.196006	0.796774
5	Si	0.541864	0.884039	0.375697
8	Ba	0.08243	0.442679	0.034673
Class 7 is relabelled as class 1, others class 0				

Table 3.10: Experiment on Glass data

The first sub-table in table 3.10 is class 1, and the rest classes (class 2,3,5,6 and 7; notice no class 4) are class 0. The (VR) technique ranks the most significant attributes as follows Ba, Mg, K and so forth. The second experiment has class 2 relabeled as class 1 and the other classes (1, 3, 5, 6 and 7) as class 0. They are ranked K, Al, Ba and so on, as the most significant. The next experiment is class 3 relabeled as class 1 while the rest as class 0; they ranked Ba, Mg, Ca, and so on. All six classes are taken in turn.

The general postulate here from the experimental result is that the type of glass depends on the amount of chemical element that the glass contains; this has been captured by the (VR) technique.

Variable	V0	V1	VR
vac	0.003343364	0.00043	60.45474339
nuc	0.011370412	0.00188	36.57941315
mcg	0.018614135	0.00427	19.00334227
mit	0.018828357	0.00443	18.06414534
alm	0.007513117	0.00847	0.78681652
gvh	0.015108362	0.01832	0.680117288
erl	0.001513064	0	0
pox	0.005747052	0	0
ERL as class 1 , others as class 0			

Variable	V0	V1	VR
nuc	0.011506688	0.002702989	18.12225536
mit	0.018930303	0.008878276	4.54629748
vac	0.003347569	0.002432759	1.893481459
mcg	0.018794787	0.019935747	0.888811735
alm	0.007472321	0.008474023	0.777556224
gvh	0.015301079	0.017983448	0.723932642
erl	0.002385616	0	0
pox	0.005844943	0	0
VAC as class 1 , others as class 0			

Variable	V0	V1	VR
nuc	0.011445784	0.001909474	35.93054162
alm	0.007580311	0.002581842	8.62014834
vac	0.00336491	0.001622105	4.303174258
mit	0.018889775	0.012346053	2.340977866
gvh	0.015398875	0.012890526	1.42704174
mcg	0.018872427	0.017735789	1.132281618
pox	0.001280223	0.163845	6.10527E-05
erl	0.002369467	0	0
POX as class 1 , others as class 0			

Variable	V0	V1	VR
nuc	0.011544262	0.0003879	885.7163556
mit	0.019108645	0.00502235	14.47589106
alm	0.007621846	0.00298437	6.522515713
mcg	0.017648872	0.01223143	2.081994308
gvh	0.014292326	0.0115516	1.530811824
vac	0.003257518	0.00491345	0.43954295
erl	0.002393773	0	0
pox	0.005864923	0	0
EXC as class 1 , others as class 0			

Variable	V0	V1	VR
mcg	0.016669872	0.004505074	13.69180369
gvh	0.013590555	0.005371829	6.400737977
alm	0.007151211	0.003563795	4.026556619
nuc	0.011446279	0.007987315	2.053652855
mit	0.018805429	0.01620592	1.346539581
vac	0.003326212	0.003714323	0.801937507
erl	0.002408598	0	0
pox	0.005901233	0	0
ME1 as class 1 , others as class 0			

Variable	V0	V1	VR
nuc	0.011615988	0.002673255	18.88128504
alm	0.007312745	0.00570549	1.642763194
mit	0.018898632	0.015743373	1.441003944
gvh	0.015005273	0.014493961	1.071799768
vac	0.003326793	0.003685961	0.814610814
mcg	0.016815859	0.02571749	0.427544107
erl	0.002248964	0.004901961	0.210487024
pox	0.005929786	0	0
ME2 as class 1 , others as class 0			

Table 3.11: Experiment on Yeast data

Variable	V0	V1	VR
mit	0.020012093	0.00643029	9.685545566
vac	0.003585676	0.00124443	8.302362072
mcg	0.019313072	0.00978074	3.899055003
alm	0.005520929	0.00295305	3.495289833
erl	0.002437891	0.00153374	2.526526767
nuc	0.011722672	0.00825062	2.018739863
gvh	0.015636923	0.01305037	1.435676507
pox	0.006427367	0	0
ME3 as class 1 , others as class 0			

Variable	V0	V1	VR
nuc	0.012644439	0.003246765	15.16691822
mcg	0.020602045	0.009455136	4.747720346
gvh	0.016216741	0.009705112	2.792068368
vac	0.003573308	0.002163009	2.729131551
alm	0.007877112	0.005318195	2.193843196
pox	0.005557072	0.006620077	0.70463786
mit	0.01226686	0.027506254	0.19888588
erl	0.002792965	0	0
MIT3 as class 1 , others as class 0			

Variable	V0	V1	VR
alm	0.008696285	0.003402579	6.532072033
mit	0.020924243	0.012077395	3.001601168
mcg	0.020225563	0.012305911	2.701305387
erl	0.002581904	0.001740082	2.201611278
gvh	0.015601168	0.012087329	1.665917737
vac	0.003186452	0.003680326	0.74962195
nuc	0.006674405	0.01851727	0.129918567
pox	0.008027022	0	0
NUC as class 1 , others as class 0			

Variable	V0	V1	VR
pox	0.008056105	0.00053996	222.6036157
gvh	0.017874002	0.00848525	4.43725396
alm	0.008199094	0.00418635	3.835844787
mcg	0.021930799	0.01154386	3.609163553
mit	0.020553899	0.01326303	2.401610974
nuc	0.01217067	0.00900749	1.825665578
erl	0.002426975	0.0021458	1.279237149
vac	0.002999694	0.00409963	0.535382193
CYT as class 1 , others as class 0			

Table 3.12: Experiment on Yeast data continue

Summary

This chapter presented one of the main assertions of the research, it started with a clear theoretical basis of the nature of numeric data and the techniques for transforming from one data types to another within the conditions of the same range density formalism. Then a demonstration of the framework which lays the background for the heuristic axiomatic inferences that established the relationship between class distribution and the variances of the data items in the domain of discourse vis a vis the sample space were presented. The variance of the data items in the domain space and how this is related to their class distribution was deduced and explained. An introduction of variance comparison testing which culminated into (VR) technique was derived therein. The main research design like the processes of data sampling for experimental validity and reliability were explained in details. A clear process demonstrations for decomposing Multi-classed into Binary classed data were explained in detailed with clear diagrams. The process of avoiding overfitting using the state of the art cross-validation and the justifications as a process of producing more dependable results were also explained.

The results of the experiments carried out in this chapter present a significant contribution to the overall and major insight into some of the discovery and many claims made by this research and also would become an input into later chapters. It is also a whole knowledge in his own right that could lead to future work by any researcher. This work may be seen as pioneering new field because, in most academics and industries, the correlations of the effects of the variances of data points and their classes have not been investigated before. But, this work showed the correlation with a concise inferences and presenting an axiomatic open field for new avenue of knowledge insight and opportunities for further researches. The implication of the knowledge discovered therein is in no doubt and limitless.

Chapter 4

Comparison of Variance Ranking Attribute Selection With Other Attribute Selections

4.1 Introduction

In this chapter, comparison of (VR) technique and two main state of the art features selection techniques (algorithm) will be made, these two are (PC) and (IG) belong to the categories of features selections known as "filter" methods the other(s) are "wrapper" and "hybrid" which are just a combination of filter and wrapper methods. Please refer to section 2.2.7 for the details of these methods and reasons for comparing the (VR) with (PC) and (IG). But just for a hint the (PC) and (IG) are two most popular and state of the art feature selections.

Most feature selection results are heuristics [192][193][194][195], meaning that no two feature selection on the same dataset will produce the same result perfectly, especially in the filter algorithm; instead, each attribute identified are most likely to be ranked slightly differently by different filter feature selection algorithms. To estimate or measure the similarities in these results, the order of ranking of the attributes becomes the metric used to quantify the similarities. Some of the identified attributes may be in the same position in the order of ranking, while others may share similarities by proximity to the attribute's positions. The result of (VR) obtained in sections 3.1 will be paired with the result of (PC) and (IG) on the same data to investigate the extents of their similarities and differences. A novel method of quantifying similarity called "Ranked Order Similarity Index"(ROS) will be dealt with extensively in subsequent sections. The (ROS) is a similarity index quantifier to assess two or more sets that may contain the same object but ranked differently. The necessity of (ROS) came about from the fact that the existing similarity index

measure appeared to be inadequate when quantifying the similarity of sets of the same items that are ranked differently, please see sections 4.3.

4.2 Comparison of Variance Ranking Attribute Selection (VR) Technique with the Benchmarks

Attribute selections, in general, could be categorized as filter or wrapper methods [109][110]. The filter method uses the general characteristics of the data item to determine the features that are more significant without involving any intended learning algorithm, while wrapper method on the order hand tend to determined the features in dataset that would produce the best performance on a predetermined learning algorithm. Putting it succinctly, wrapper method suggest the attributes to use for a given classifier algorithm. This suggestive and predetermining the classifier algorithm made the wrapper method less generic and limited as a means of comparison with our method (VR) technique, which is independent of any learning algorithm. Besides, wrapper methods create a subset of features which are deemed to be most important for a specific classifier's performance. These subsets more often than not does not include all the original features meaning that some features are eliminated in the subsets and each feature relevance to the subsets are not made known. But, filter methods uses ranking processes to produce the order of relevance of each, ie no feature is eliminated from the ranking [109]. The comparison of (VR) attribute selection will be done with similar filter method that is not classifier suggestive. Consequently, we compare our method to the state-of-art filter feature selection methods; the Pearson correlation (PC) and [196][197][198] and information gain (IG)[199][200]. The results are provided in Tables 4.1, 4.2, 4.3 and 4.4 for the data sets used in the experiment.

$$Variance\ Ranking\ (VR) = \left(\frac{(x_0 - \bar{x_0}^2)}{(n_{maj} - 1)} / \frac{(x_1 - \bar{x_1}^2)}{(n_{min} - 1)} \right)^2 = \left\{ \frac{V_0}{V_1} \right\}^2 \tag{4.1}$$

$$Pearson\ Correlation(PC) = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}. \tag{4.2}$$

$$Information\ Gain_{(x,y)}(IG) = Entropy_{(x)} - Entropy_{(x,y)}. \tag{4.3}$$

Ranking of variables based on different feature selection Algorithm			
sn	Varaince Rank	Pearson Correlation	Information Gain
1	age	plasglu	age
2	bmass	bmass	bmass
3	plasglu	preg	plasglu
4	skinfold	age	preg
5	diapress	diapres	insutest
6	preg	skinfold	skinfold
7	pedi	pedi	pedi
8	insutest	insutest	diapres

Table 4.1: Comparison of Variance Ranking with PC and IG variable selection for Pima India diabetes data

Ranking of variables based on different features selection Algorithm			
sn	Variance Ranking	Pearson Correlation	Information Gain
1	sgot	sgot	drinks
2	sgpt	gammagt	gammagt
3	drinks	drinks	sgpt
4	gammagt	mcv	sgot
5	mcv	sgpt	alkphos
6	alkphos	alkphos	mcv

Table 4.2: Comparison of Variance Ranking with PC and IG variable selection for Liver Disorder Bupa data

Ranking of variables based on different features selection Algorithm			
sn	Variance Rank	Pearson Correlation	Information Gain
1	ClumpThickness	UniformityofCellShape	UniformityofCellSize
2	BlandChromatin	UniformityofCellSize	BlandChromatin
3	UniformityofCellShape	BareNuclei	UniformityofCellShape
4	BareNuclei	BlandChromatin	BareNuclei
5	SingleEpithelialCellSize	ClumpThickness	SingleEpithelialCellSize
6	UniformityofCellSize	NormalNucleoli	NormalNucleoli
7	NormalNucleoli	MarginalAdhesion	ClumpThickness
8	MarginalAdhesion	SingleEpithelialCellSize	MarginalAdhesion
9	Mitoses	Mitoses	Mitoses

Table 4.3: Comparison of Variance Ranking with PC and IG variable selection for Wisconsin Breast cancer data

Ranking of variables based on different feature selection Algorithm			
sn	Varaince Ranking	Pearson Correlation	Information Gain
1	X1	X1	X1
2	X4	X2	X2
3	X2	X4	X3
4	X6	X5	X4
5	X3	X8	X5
6	X5	X7	X7
7	X8	X3	X6
8	X7	X6	X8

Table 4.4: Comparison of Variance Ranking with PC and IG variable selection for Cod-rna data

Discussion

In the Table 4.1, 4.2, 4.3 and 4.4 showed the result obtained using the three attribute selections on the four binary classed data set; Pima India diabetes, Bupa Liver Disorder, Wisconsin Breast cancer data, and the Cod-RNA data it ranks the attribute according to their relevance to the target class (1, 0). Though the four results are comparatively similar but have some minor differences, for instance, in Table 4.1, the most significant attribute using the (VR) and (IG) is (age) for Pima India data, while the first in the Pearson correlation is plasma glucose, in row number 2 and 7 of Table 4.1, the three attribute selection techniques picked "bmass" and "pedi" respectively, other similarities row number 8 were the "insutest" is selected for (VR) and (PC) and so on.

For Bupa Liver data in Table 4.2; the most significant using (VR) and (PC) is "agot" while "sgpt" is ranked as the third by the (IG) selection, but in Table 4.2, row number 5 and 6 each of the attribute selection techniques selected "mcv" and "alkphose" respectively as the least significant attribute. For Table 4.3, the Wisconsin Breast cancer data; two of the techniques (VR) and (IG) are in agreement by selecting "Mitoses" and "MarginalAdhesion" as the least significant attribute , while the Pearson Correlation also identified "Mitoses" as the least significant attribute, but picked "SingleEpithelialCellSize" as the second least significant attribute. For Table 4.4 for Cod-RNA data, the (VR) and the (IG) techniques are similar in rows 1, 2, 3 and differs slightly in rows 4 and 5. But clear similarities are very much noticeable all three techniques. By and large, the three selection methods have identified the same sets of attributes but have ranked them slightly in a different order.

In the next sections, the results of the comparison experiments of the three multi-classed (Iris, Glass and Yeast datasets), it is necessary to explain the sequence of the next section. First, the (VR) technique using both Iris and glass data set would

be compared with (IG) and (PC) this will be repeated for each n number of binary classes from the decomposed multi-class data.

Ranking of variable based on different feature selection Algorithms					Ranking of variable based on different feature selection Algorithms					Ranking of variable based on different feature selection Algorithms			
sn	Variance Ranking	Pearson Correlation	Information Gain		sn	Variance Ranking	Pearson Correlation	Information Gain		sn	Variance Ranking	Pearson Correlation	Information Gain
1	petal length	petal width	petal width		1	petal width	petal width	petal length		1	petal length	petal width	petal length
2	petal width	petal length	petal length		2	petal length	petal length	petal width		2	petal width	petal length	petal width
3	sepal width	sepal length	sepal length		3	sepal length	sepal width	sepal length		3	sepal width	sepal length	sepal length
4	sepal length	sepal width	sepal width		4	sepal width	sepal length	sepal width		4	sepal length	sepal width	sepal width
Satose =1, Others =0					Versicolor =1, Others =0					Virginica=1, Others =0			

Table 4.5: Comparison of Variance Ranking with PC and IG variable selection for Iris data

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
Ba	Ba	Ri
Mg	Mg	Na
K	K	Ca
Ca	Al	Al
Al	RI	Si
Na	Na	Mg
Si	Ca	K
RI	Si	Fe
Fe	Fe	Ba
Class 1 = labelled 1, others class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
K	Ba	Ri
Al	Fe	Ca
Ba	K	Na
Na	Mg	Si
Mg	Ri	Al
Si	Al	Mg
Fe	Ca	K
RI	Na	Fe
Ca	Si	Ba
Class 2= relabelled as class 1, others class		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
Ba	Ba	Ri
Mg	Mg	Si
Ca	K	Na
K	Na	Ca
Na	Al	Al
RI	Ca	Mg
Si	Si	K
Al	Ri	Fe
Fe	Fe	Ba
Class 3 is relabelled as class 1, others		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
Mg	Fe	Ca
Na	Mg	Ri
RI	K	Al
Ba	Al	Si
Al	Si	K
Ca	Na	Na
Fe	Ca	Mg
Si	Ri	Fe
K	Ba	Ba
Class 5 is relabelled as class 1, others		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
Mg	Fe	Na
Ca	K	Ca
RI	Ba	Ri
Al	Mg	Si
Na	Al	Mg
Si	Si	Al
K	Na	k
Ba	Ca	Fe
Fe	Ri	Ba
Class 6 is relabelled as class 1, others		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
Fe	Ba	Ri
Ca	Mg	Na
RI	K	Al
Mg	Fe	Ba
Na	Na	Ca
K	Al	Si
Al	Ca	K
Si	Si	Mg
Ba	Ri	Fe
Class 7 is relabelled as class 1, others		

Table 4.6: Comparison of Ranking significant with PC and IG variable selection for Glass data

Discusion

The table 4.5 is a presentation of the result of the Iris comparison using the (VR), (IG) and (PC) techniques. All three feature selection have identified that petal length or petal width as the two most significant and ranked them accordingly. In condition of "Satosa = 1, Others = 0" the (VR) differs to sightly to (IG) and (PC) which are the same. In the condition "Versicolor=1 Others=0" the (VR) and (PC) are similar in identifying the two first attributes in column 1 and 2 while the (VR) and (IG) are similar in columns 3 and 4. In the final condition of "Virginica=1, Others=0", the (VR) and (IG) are similar in the first two rows while (IG) and (PC) in the last two rows.

Table 4.6 is the presentation of the results of the comparison of (VR), (PC) and (IG) feature selection techniques on the highly imbalanced Glass data. Originally, the Glass dataset is made up of six classes labeled class 1,2,3,5,6,7 (notice there is no class 4). Each of the smaller tables in Table 4.6 is a representation of these classes' results. To carry out the "One versus all" experiment explained in the previous sections 2.3.2, and Table 3.7, each class was relabelled in turn as class 1 and others combined as class 0. In the first smaller table, in Table 4.6 (class 1 labeled as 1 and the others as 0), the (VR) and (PC) identifies Ba, Mg, and K in the first rows. The sixth and ninth rows have the same results. The (IG) and (VR) are not far off from each other; the fourth and fifth rows identify Al, while the eighth and ninth rows identify Fe. Although, there are no rows that identifies the same elements the closeness is greater between (VR) and (IG) than it is between (PC) and (IG) for this first experiment, in Table 4.6, (VR) and (IG) are more similar. The quantitative weighting of the similarities in these three feature selection algorithm would be calculated in sections 4.3 using the novel (ROS) technique.

In the second experiment (class 2 relabeled as class 1 and the others as 0), none of the three feature selections ranked any of the elements in the same row, but proximity between rows elements is was highly noticeable for (VR) and (PC) in row one and row three identifying Ba and K, in rows fourth and fifth, Mg is identified, as well as in many other rows. Similar proximities in the elements identified are also noticeable throughout between (VR) and (IG), but the reversal of ranking of identified elements between (PC) and (IG) is also noted.

In the third smaller table in Table 4.6 (class 3 relabeled as class 1 and the others as class 0), rows one, two, seven, and nine are the same in (VR) and (PC) and many other rows have proximity similarities; for example, rows three and four identify K, rows fourth and fifth identifies Na.

In the fourth small table in Table 4.6 (class 5 relabeled as class 1 and the others as class 0), the (VR) does not have any row in common with (PC) and (IG). However, close proximity is noticed in rows one and two for element Mg, rows five and four for element Al, and rows sixth and seventh for elements Ca for (VR) (PC) and (IG) share rows sixth and ninth in common and other rows as proximity.
In the fifth smaller table in Table 4.6 (class 6 relabeled as class 1 and the others as class 0), (VR) and (IG) are more similar; in the second and sixth rows while the other rows are similar by proximity. In the final experiment is (class 7 relabeled as class 1 and the others as class 0), the (VR) and (PC)are more similar because row five and eight, which have Na and Si, respectively. For the Yeast dataset the comparisons are given in Tables 4.7 and 4.8, which are both divided into 10 smaller tables. The tables are labeled according to how the classes have been re-coded using the "one-versus-all" techniques; for example, the following labels are used: "ERL as class 1, others as class 0," "POX as class 1, others as class 0," "EXC as class1, others as class 0," "ME1 as class 1 others as class 0," "ME2 as class 1 others as class 0,"
The table **"ERL as class 1, others as class 0"** in Table 4.7 has lots of similarities between VR, PC, and IG, all the attributes selection identified "pox" in the last row (9) and "mit" in row 4 in addition, VR and PC are similar in row 6 with "gvh" and VR and IG are similar in rows 3 and 5 with "mcg" and "alm". Furthermore, PC and IG are similar in row 1 with "erl" and row 8 with "nuc". Many tables in Table 4.7 and 4.8 have many such similarities between the rankings done by VR, PC and IG. Where the elements were not ranked to be in the same row, there are similar by being rank in proximity rows. In the next sections, the percentage similarities between the results of the ranking done by VR, PC, and IG using the ranked order similarity (ROS) will be carried out.

.

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
vac	erl	erl
nuc	vac	gvh
mcg	alm	mcg
mit	mit	mit
alm	mcg	alm
gvh	gvh	vac
erl	nuc	nuc
pox	pox	pox
ERL as class 1, others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
nuc	pox	pox
alm	nuc	mcg
vac	vac	gvh
mit	mit	mit
gvh	gvh	alm
mcg	mcg	vac
pox	alm	nuc
erl	erl	erl
POX as class 1, others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
nuc	mit	mcg
mit	nuc	gvh
vac	mcg	mit
mcg	vac	alm
alm	gvh	vac
gvh	alm	nuc
erl	pox	pox
pox	erl	erl
VAC as class 1, others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
nuc	nuc	mcg
mit	gvh	gvh
alm	mcg	mit
mcg	mit	vac
gvh	vac	nuc
vac	alm	alm
erl	pox	pox
pox	erl	erl
EXC as class 1, others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
mcg	alm	gvh
gvh	mcg	mcg
alm	gvh	alm
nuc	nuc	mit
mit	vac	vac
vac	mit	nuc
erl	pox	pox
pox	erl	erl
ME1 as class 1, others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
nuc	nuc	mcg
alm	alm	gvh
mit	mcg	alm
gvh	gvh	mit
vac	vac	vac
mcg	mit	nuc
erl	erl	pox
pox	pox	erl
ME2 as class 1, others as class 0		

Table 4.7: Comparison of Variance significant with PC and IG variable selection for Yeast data

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
mit	alm	alm
vac	pox	mcg
mcg	nuc	mit
alm	mcg	nuc
erl	vac	gvh
nuc	mit	vac
gvh	gvh	pox
pox	erl	erl
ME3 as class 1, others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
nuc	nuc	mit
mcg	mit	gvh
gvh	erl	mcg
vac	mcg	nuc
alm	gvh	alm
pox	alm	vac
mit	vac	erl
erl	pox	pox
MIT as class 1, others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
alm	nuc	nuc
mit	pox	mcg
mcg	alm	alm
erl	mcg	gvh
gvh	vac	mit
vac	gvh	vac
nuc	mit	pox
pox	erl	erl
NUC as class 1 , others as class 0		

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
pox	pox	alm
gvh	alm	gvh
alm	gvh	mcg
mcg	mit	mit
mit	mcg	nuc
nuc	vac	vac
erl	nuc	pox
vac	erl	erl
CYT as class 1, others as class 0		

Table 4.8: Comparison of Variance significant with PC and IG variable selection for Yeast data continue

Summary

In this section, the comparison of (VR) and two main filter method attribute selections techniques have been carried out. Lets state here that no two feature selection algorithm ever produces the same results from the same dataset' this have been explained in details in sections 4.1.

An extensive experiment has been conducted in this section using six data sets (see table A.2), four of the data set are Binary (two classes distributed). The other three (Iris, Yeast and Glass) are multi-classed, the Iris data is uniformly distributed (Balanced), the Glass and Yeast data is highly imbalanced. The multi-classed data have been decomposed into n *Binary* using "One versus All" (see section 2.3.2).

The results are all in tables 4.1, 4.2, 4.3 and 4.4 for the binary classed data, for the multi-classed data the results are in tables 4.5 and 4.6. The results in these tables confirm the heuristic nature of the feature selection results meaning that no two feature selection algorithm produces results that are perfectly the same. The filter feature selection algorithm that uses ranking optimisation to present the selected attributes tend to be more prone to this, which could be more or less an advantage depending on context. Imagine if an attribute is ranked as fourth by an algorithm but another algorithm ranked it as third or even fifth both algorithm shares a similarity by the proximity of the results of the ranking, what it means is that in place of this attribute the other may suffice.

Though in some of the results in the tables some reversal of ranking of identified elements between the algorithms; (VR), (PC) and (IG) is also noted, these sequence of consistency sort of add more veracity to the claimed superiority of (VR) technique. The next section 4.3 would investigate by presenting a novelty technique to quantify the similarities between the results of (VR), (PC) and (IG).

4.3 Calculating Similarities of (VR) (PC) and (IG) using Ranked Order Similarity-(ROS)

In both industry and academics, many types of similarity measure have been used to compare the different concept to ascertain the accuracy, resources management and general veracity of new techniques. The Similarity and dissimilarity measure has been used to compare item and results of two or more structures, but quite recently many data-centric types of research like data mining and machine learning have used this process to compare and validate the results [201][202][203] of experiments and predictive modeling. This is done by measuring the similarity index of a new

concept with existing benchmarks knowledge, concept or results. With this in mind we propose a novel similarity measure technique called Rank Order Similarity (ROS). We want to determine how similar the results of each of the three ((VR), (PC) and (IG)) features selection algorithm are similar in Tables 4.1, 4.2, 4.3 and 4.4 and also in 4.5 and 4.6. Should we say that the result((VR), (PC) and (IG)) are 80% or 90% similar? How could their similarities be graded?

Though, there are different approaches to measure similarities, the most common is Euclidean distance, Manhattan Distance, Minkowski distance, Cosine Similarity, and Jaccard similarity index. These are deduced as follows: the Euclidean is just similar to Pythagoras theorem. In general, it is the square root of the sum of all the data points and is given by:

$$Euclidean\ Distance\ (x, y) = \sqrt{\sum_{i=1}^{n} -(x_i - y_i)^2} \tag{4.4}$$

The Manhattan is often called the office block as it resembles the grid direction within an office block. It shares a geometric diagram with Euclidean distance as depicted in the diagram below:

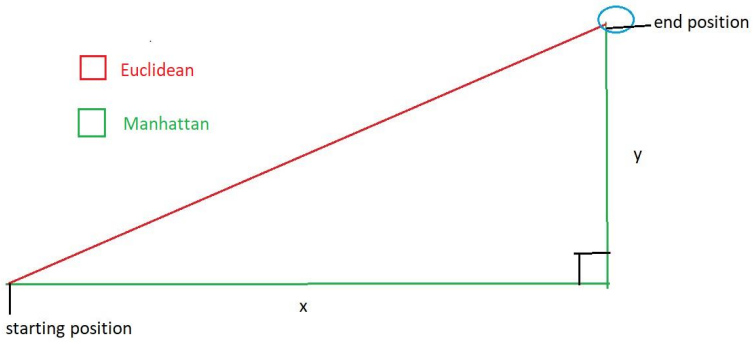


Figure 4.1: Presentation of Euclidean and Manhattan distance

The Cosine similarity is a calculation of angular differences between two point in the domain of interest. It uses the angular differences and the dot product between the two data points as the metric, is given by Equation 4.5 and in Figure 4.2

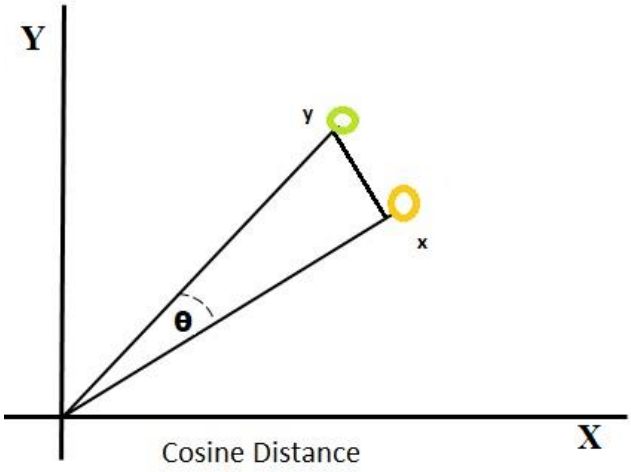


Figure 4.2: Cosine Similarity

$$s_{\text{cosine}}(\boldsymbol{x}, \boldsymbol{y}) = \cos\theta = \frac{\boldsymbol{xy}}{||\boldsymbol{x}|| \cdot ||\boldsymbol{y}||} = \frac{\sum_{i=1}^{n} \boldsymbol{x}_i \boldsymbol{y}_i}{\sqrt{\sum_{i=1}^{n} \boldsymbol{x}_i^2}\sqrt{\sum_{i=1}^{n} \boldsymbol{y}_i^2}} \tag{4.5}$$

In the context of the comparison of (VR), (PC) and (IG) algorithms, the Euclidean, Manhattan, and Cosine similarity index is totally none applicable because the Euclidean and Manhattan is using vector space as the metric parameter while the Cosine is also using the angular metrics, hence none applicable also. The closest similarity grading that is similar to the (ROS) is the Jaccard similarity index that deduces similarity in a Sets of items. The Jaccard similarity is calculated by taking the size of the intersection in a Set divided by the size of the union of the sets, as provided in Equation 4.6. But the Jaccard fell short of its applications in the present context due to not measuring similarities by ranking items, section 4.4

$$J(A, B) = \frac{|A \bigcap B|}{|A \bigcup B|} = \frac{|A \bigcap B|}{|A| + |B| - |A \bigcap B|} \tag{4.6}$$

4.3.1 Levenshtein Similarity

In sections 4.3 it was establish that the Cosine, Jaccard and the corresponding distance metrics like Euclidean and Manhattan could not measure or be applicable to find the similarity of item in Sets that has been ranked. Therefor the (ROS) will be compared with Levenshtein Similarity [204][205][206]. If absolute length of string a and b is given by $\mid a \mid and \mid b \mid$. The similarity between a and b is given by

piecewise function in equation 4.7

$$l_{ev_{a,b}}(i,j) = \begin{cases} max(i,j) & if\ min(i,j) = 0, \\ min \begin{cases} l_{a,b} & (i-1,j)+1 \\ l_{a,b} & (i,j-1)+1 \\ l_{a,b} & (i-1,j-1)+1_{(a_i \neq b_j)} \end{cases} & otherwise. \end{cases} \tag{4.7}$$

Where $1_{(a_i \neq b_j)}$ is a conditional function that resolved to 0 when $a_i = b_j$ and 1 if $a_i \neq b_j$ [206][207]. The $l_{ev_{a,b}}(i,j)$ is the length between first i characters of a and the first j character of b, also i and j is equal to 1-base index value. To convert one string to the other only three operations are allowed these are "insert", "replace", "delete". The Levenshtein follows the same techniques as (ROS), by using a distance metric and ranking the similarity between two string between, hence have the same terms of reference.

1st Step
0 written here
because "s"
are the same.

		s	a	t	u	r	d	a	y
	0	1	2	3	4	5	6	7	8
s	1	0	1	2	3	4			
u	2								
n	3								
d	4								
a	5								
y	6								

Table 4.9: Levenshtein Process

Mostly it has been used to measure the similarity between two strings in by implementing the distance in form of dynamic programming[208][209]. Usually presented in form of a matrix. For example lets compare the word "Saturday" and "Sunday" using Levenshtein techniques.The step are demonstrated in table 4.9. The two string are laid out and the position of each letter number starting from zero as shown in the, the simple rules to complete the rest is that if the two letters are similar, the diagonal value is written. For example, the two letter "s" are similar therefore value 0 will be written between the two value. 1 at the intersections of the "s". The next steps is to always take values in the semi-circle like the green, orange, blue and yellow semi-circle. The green has values of 0,1 and 2. The least of them is 0.Therefore $0+1=1$, the value of 1 is written for the green. For the orange the values are 1,2 and 3. The least is 1. Therefore $1+1=2$. The value of 2 is written for the orange.

This will continues until all the matrix are filled. The edit distance is 3 which is the value furthest to zero. The completed table is 4.10.

		s	a	t	u	r	d	a	y
	0	1	2	3	4	5	6	7	8
s	1	0	1	2	3	4	5	6	7
u	2	1	1	2	2	3	4	5	6
n	3	2	2	2	3	3	4	5	6
d	4	3	3	3	3	4	3	4	5
a	5	4	3	4	4	4	4	3	4
y	6	5	4	4	5	5	5	4	3

Table 4.10: Comparing two string using Levenshtein Similarity techniques

To get the Levenshtein distance could be a lengthy process but the grid table as explained in table 4.9 and finally in 4.10 is to ensure accuracy. In most applications like search engines Levenshtein distance is converted to ratio or percentages[210][211] by normalising as in equation 4.8

$$Edit\ Ratio\ (a,b) = 1 - \frac{Edit\ Distance(a,b)}{\mid a \mid + \mid b \mid} \tag{4.8}$$

Therefore, if $Edit\ Distance(a,b)$ between the two string "saturday" and "sunday" is 4 gotten from converting "sunday" to "saturday" by inserting a, t and r and deleting n and if $\mid a \mid$ and $\mid b \mid$ are 6 and 8 respectively. The

$Edit\ Ratio\ (a,b) = 1 - \frac{4}{|6|+|8|} = 0.71$ or 71%

4.4 Motivation and Deriving Rank Order Similarity-(ROS)

In the preceding sections 4.3, some expositions of the inadequacies of existing similarity measures in context of a ranking based algorithm [212][213]. Therefore, it is imperative that a new similarity measure that accommodates the ranking of items in a set [88][214]. For instance, how could the similarity of two or more sets that contains the same objects but arranged or ranked differently be measured? If three Sets $\alpha = \{a,b,c,d,e,f\}$, $\beta = \{a,b,c,f,e,d\}$ and $\gamma = \{f,b,c,d,e,a\}$ contain the same elements but arranged or ranked in different order as in Table 4.11. Based on the order of ranking, what are the percentage similarities between them?.

sn	α		β		ϒ
1	a		a		f
2	b		b		b
3	c		c		c
4	d		f		d
5	e		e		a
6	f		d		e

Table 4.11: Three Sets arranged and ranked in different order

Let us determine the similarities between α and β. The total elements in α and β is 12 ie N=12. Since we wish to find the percentage similarities, this thesis use Equation 4.9 to define a quantity which is called *Element Percentage Weighting* = EPW given by:

$$EPW = \sum \frac{100}{N} \tag{4.9}$$

Therefore, $100/N = 8.33$; thus, each element of the set has a percentage weighting of 8.33%; two elements in a row would have a total percentage weighting of the sum of their weightings. For example, in row 1 in Figure 4.3, the total percentage weighting of an element a in Set α and element a in Set β is $8.33 + 8.33 = 16.66$. Additionally, each set has a total number of n. When an element moves downward or upward in a column to be in the same row with its similar element, it loses a percentage weighting equal to $EPW - (2 * \frac{EPW_j}{n}) * S_t$, while S_t is called the *similarity proximity distance*, and is equal to the number of steps moved to the new row starting from the elements initial row. The value 2 used above is because there are two elements f and f. The quantity $(\frac{EPW_j}{n})$ is called the unit *Element Percentage Weighting*. The sum of all the $(\frac{EPW_j}{n})$ is equal to the EPW for the two set. This means that it takes a pair to earn an EPW hence if no pair, no similarity or values to be summed:

$$ROS = \sum_{1-j}^{n} 2 * EPW - \left(2 * \frac{EPW}{n} * S_t\right) \tag{4.10}$$

ROS calculation for α and β				
sn	α	β	St	2*EWP-(2*EWP/n) * St
1	a	a	0	16.66
2	b	b	0	16.66
3	c	c	0	16.66
4	d	f	3	8.332
5	e	e	0	16.66
6	f	d	3	8.332
EPW = 100/12 = 8.33 EPW/n = 8.33/6 = 1.388				
ROS =	$ROS = \sum 2 * EPW - \left(2 * \frac{EPW}{n} * S_t\right)$			83.304

Figure 4.3: Ranked Order Similarity-ROS Percentage Weighting Calculation for α and β

In rows 4 and 6 for sets α and β, the element d and f are not in the same row with their similar item. To calculate their weighting using Equation 4.9 is given by 8.33-$\sum$ *Loss percentage weighting*, If *Loss percentage weighting* = $EPW/n = 8.33/6 = 1.388$. Elements d and f have moved up and down three steps (including their row). Therefore $S_t = 3$, the total Loss percentage weighting for each is $3 * 1.388 = 4.164$, and the final weighting for each is $8.33 - 4.164 = 4.166$. Therefore in row 4, $f+ f= 4.166 + 4.166 = 8.33$. Additionally, in row 6, $d+ d= 4.166 + 4.166 = 8.33$. The similarity between sets α and β is 83.3%, please see equation 4.10 and Figure 4.3 represents the process of calculating the ranked order similarity-(ROS) in a tabular descriptions of the processes.

The steps below is the calculation between VR and PC using ROS for the sub-table of **"ERL as class 1, others as class 0."**

If the EPW between VR and PC is given by $EPW = \sum \frac{100}{N} = \frac{100}{16} = 6.25$,

the unit *Element % Weighting* is given by

$\frac{EPW_j}{n} = \frac{6.25}{8} = 0.781$.

The calculation of the similarity between VR and PC for the the sub-table of **"ERL as class 1, others as class 0"** shows that both are 67.198% similar, please see Table 4.12 for the steps to calculate ROS. In the next sections, the similarities between the (VR), (PC) and (IG) for Glass and Yeast dataset are calculated using the ROS technique.

Ranking of variable based on different feature selection Algorithms		
Variance Ranking	Pearson Correlation	Information Gain
vac	erl	erl
nuc	vac	gvh
mcg	alm	mcg
mit	mit	mit
alm	mcg	alm
gvh	gvh	vac
erl	nuc	nuc
pox	pox	pox
ERL as class 1, others as class 0		

Table 4.12: ROS Calculation between VR and PC for Sub-table "ERL as class 1, others as class 0" in table 4.7

2* EPW-(2*(EPW/n) *St	Proximity distance (St) Using column of VR	Variance Ranking	Pearson Correlation
2*6.25- (2*0.781*2) =9.376	2 (vac moved 2 to align with vac)	vac	erl
2*6.25- (2*0.781*6) =3.128	6 (nuc moved 6 to align with nuc)	nuc	vac
2*6.25- (2*0.781*3) =7.814	3 (mcg moved 3 to align with mcg)	mcg	alm
2*6.25- (2*0.781*0) =12.5	0 (mit moved 0 to align with mit)	mit	mit
2*6.25- (2*0.781*3) =7.814	3 (alm moved 3 to align with alm)	alm	mcg
2*6.25- (2*0.781*0) =12.5	0 (gvh moved 0 to align with gvh)	gvh	gvh
2*6.25- (2*0.781*7) =1.566	7 (erl moved 7 to align with erl)	erl	nuc
2*6.25- (2*0.781*0) =12.5	0 (pox moved 0 to align with pox)	pox	pox
Total = 67.198%			

Table 4.13: ROS Calculation between VR and PC for Sub-table "ERL as class 1, others as class 0" in table 4.7

4.4.1 Comparison of Rank Order Similarity with Levenshtein Similarity

Datasets	Rank Oder Similarity (ROS) and Levenshtein Similarity (LEV)	Similarity Value (%)
pima	VR-ROS	78
	VR-LEV	77
Wisconsin	VR-ROS	68
	VR-LEV	56
Bupa	VR-ROS	75
	VR-LEV	75
Califonia and Basket	ROS	7.4
	LEV	40

Table 4.14: Comparison of Rank Order Similarity with Levenshtein Similarity

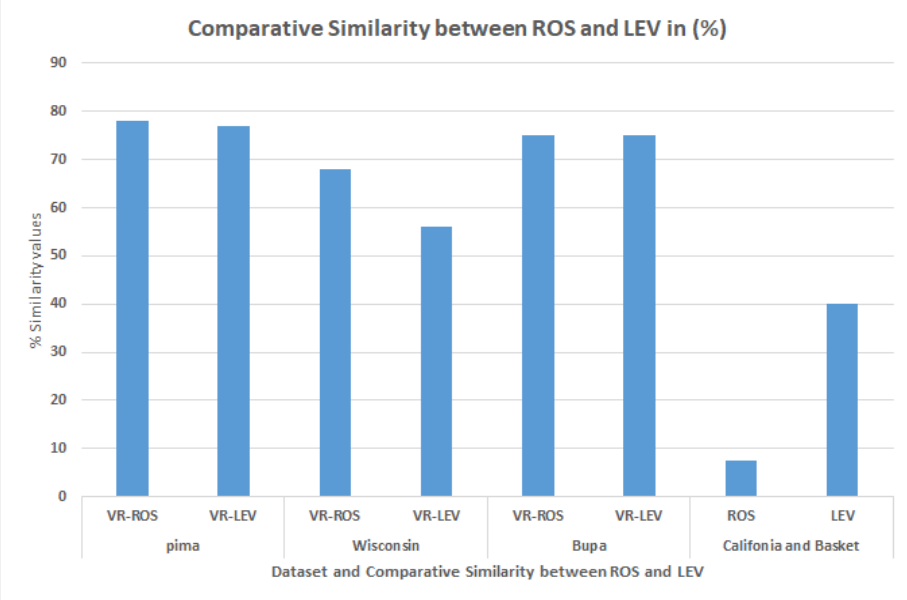


Figure 4.4: Comparative Similarity between ROS and LEV

The table 4.14 and the associated graph in figure 4.4 is to present the superiority of ROS over Levenshtein similarity. There are lots of similarity between both algorithm (Levenshtein and (ROS)). The (ROS) were actually derived from the Levenshtein, but instead of using the Edit distance as in the Levenshtein , the (ROS) uses the proximity distance between item or letter in the objects being compared. Just like many algorithm Levenshtein could be accurate in many instances but could also fail woefully in some. For example in both the table table 4.14 and figure 4.4, the Levenshtein calculated the similarity between Califonia and Basket string is

40% , that is rather very odd and totally wrong. But the (ROS) calculated it as being 7.4%. This is because both have a common character "a" and the answer of 7.4% is more reasonable and accurate. The problem of Levenshtein is that is incapable of calculating dissimilarity because is base on numbers of steps to convert one string to another, even if the two string are not similar in anyway (dissimilarity), the Levenshtein will still go ahead and convert, therefore is incapable of providing zero similarity. Most search engines that uses Levenshtein can easily be identified by putting item that are not similar, it will still return some results even if those results are totally wrong. This may be regarded as good or bad depending on the user perspective.

This is one of the reasons (ROS) is better as shown in the figure 4.4. Apart from the comparison of Califonia and Basket done above with the prove of the failure of Levenshtein and superiority of (ROS). The rest charts also showed the comparison of (ROS) and Levenshtein using the following datasets Pima, Wisconsin and Bupa. In all the (ROS) showed a better results. The (ROS) is just a modification of Levenshtein by using proximity distance instead of edit distance. In the next session; session 4.5. The (ROS) will be used to compare the (VR) and two known attributes selections the (PC) and (IG).

4.5 The Results of Comparing (VR),(PC) and (IG) using (ROS) technique

From sections 4.14 the (ROS) is a better similarity comparative metrics than Levenshtein and the rest like Jaccard, cosine etc are not applicable in ths context. Therefore the (ROS) will be used to compare the results of (VR),(PC) and (IG). This is to ascertain how class the (VR) is to the two well established bench marks.

Pima India diabetes			
	Variance	Pearson Correlation	Information Gain
Variance	100	78.13	78.13
Pearson Correlation	78.13	100	73.44
Information Gain	78.13	73.44	100
Bupa Liver Disorder data			
	Variance	Pearson Correlation	Information Gain
Variance	100	75	56
Pearson Correlation	75	100	58.35
Information Gain	56	58.35	100
Wisconsin Breast cancer			
	Variance	Pearson Correlation	Information Gain
Variance	100	68	82
Pearson Correlation	68	100	78
Information Gain	82	78	100
Cod-rna data			
	Variance	Pearson Correlation	Information Gain
Variance	100	59.4	60.9
Pearson Correlation	59.4	100	70.3
Information Gain	60.9	70.3	100

Table 4.15: Comparison of (VR), (PC) and (IG) using the (ROS) technique for Pima, Bupa, Wisconsin and Cor-rna data

Discussion

As no two feature selection algorithm could produce precisely the same result, particularly the ranking algorithms. Therefore, (ROS) has been used to measure the similarities between the results of this feature selection, for example in Table 4.1 the result of (PC) and (VR) on Pima diabetes data, what is the percentage similarity of the two results?

All the results obtained using (VR), (PC) and (IG)) for the four binary data set in Tables 4.1, 4.2, 4.3 and 4.4 have been compared using (ROS) and the comparison is in table Table 4.15.

The Pima india diabetes data results for (VR), (PC) and (IG) is in table 4.1 and the (ROS) comparison resuls is in Table 4.15. The result indicated that (VR) technique has 78.13% similarity to both (PC) and (IG) , while (PC) and (IG) are 73.44% similar to each other. For the Bupa Liver Disorder data in Table 4.2, the (VR) is 75% similar to (PC), while it is 56% similar to (IG), also (PC) is 58.35% similar to (IG). In Wisconsin Breast cancer data in table 4.3, the (VR) is 68% similar to (PC) and 82% to (IG), while (PC) and (IG) are 78% similar. Finally in Cod-rna data in table 4.4, the (VR) is 60.9% similar to (IG) and 59.4% similar to (PC), the (IG) and (PC) are 70.3% similar.

Iris data: Satosa as class1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	50	50
Pearson Correlation	50	100	100
Information Gain	50	100	100
Iris data: Versicolour as class1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	75	75
Pearson Correlation	75	100	50
Information Gain	75	50	100
Iris data: Virginica as class1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	50	75
Pearson Correlation	50	100	75
Information Gain	75	75	100

Table 4.16: Comparison of (VR), (PC) and (IG) using the (ROS) technique for Iris data

Glass data: class 1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	85.2	49.4
Pearson Correlation	85.2	100	55.6
Information Gain	49.4	55.6	100
Glass data: class 2 relabelled as class 1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	58	47
Pearson Correlation	58	100	34.6
Information Gain	47	34.6	100
Glass data: class 3 relabelled as class 1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	81.5	49.4
Pearson Correlation	81.5	100	50.6
Information Gain	49.4	50.6	100

Table 4.17: Comparison of (VR), (PC) and (IG) using the (ROS) technique for Glass data

Glass data: class 5 relabelled as class 1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	49.4	49.4
Pearson Correlation	49.4	100	56.8
Information Gain	49.4	56.8	100
Glass data: class 6 relabelled as class 1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	45.7	75.3
Pearson Correlation	45.7	100	39.5
Information Gain	75.3	39.5	100
Glass data: class 7 relabelled as class 1, Others class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	56.8	49.38
Pearson Correlation	56.8	100	44.44
Information Gain	49.38	44.44	100

Table 4.18: Comparison of (VR), (PC) and (IG) using the (ROS) technique for Glass data

The comparison of the (VR), (PC) and (IG) feature selection results using the multiclassed data is in Tables 4.16 for the uniformly distributed Iris data. The attributes are only four in number (Petal length, Petal width, Sepal length and Sepal width). TableS 4.17 and 4.18 are for the highly imbalanced Glass datasets.
In Table 4.16 for the Iris dataset, the table divided into three parts each for different type of Iris flower; which are Satosa, Versicolour Virginica. When Iris Satosa is taken as class 1 and the rest is taken as class 0, the (VR) technique is 50% similar to both (PC) and (IG), while the both (PC) and (IG) are 100% similar to each other. But when Versicolour is taken as class 1 and the other is taken as class 0 (VR) is similar to (PC) by 75% and 50% with (IG) and (PC) and (IG) are similar to each other by 50%. Finally, when Virginica is taken as class 1 and the rest as class 0 , the similarity is reversal the (VR) is 75% to (IG) but 50% to (PC), also (IG) and (PC) are 75% similar.
For the highly imbalanced Glass dataset, the similarity measure using the (ROS) technique shown in Tables 4.17 and 4.18; the two tables are divided into six parts (three and three), for different classes of glass, recall that the Glass dataset has six classes, originally labelled as classes 1, 2, 3, 5, 6 and 7 (no class 4); see Table 3.6 and Figure 3.5. Each class is relabeled in turn as class 1, while others are 0, using the "one versus all" technique to convert multi classed into n binary classes as explained in earlier sections

In Table 4.17, when class 1 labeled as class 1 and all others as class 0, the (VR) is 85.2% similar to (PC) and 49.4% similar to (IG), with a 55.6% similarity between (IG) and (PC). When class 2 is relabelled as class 1, while all others are class 0, the (VR) is 58% similar to (PC) and 47% similar to (IG). There is 34.6% similarity between (IG) and (PC). When class 3 is relabelled as class 1 and all others as class 0, (VR) and (PC) are 81.5% similar and 49.4% similar to (IG) with 50.6% between (IG) and (PC).

In Table 4.18, when class 5 is relabeled as class 1 and others as class 0, the (VR) is 49.3% similar to both (IG) and (PC), while the latter two are 56.8% similar to each other. When class 6 is relabeled as class 1 and the others as class 0, the similarity between (VR) and (PC) is 45.7% while VR is 75.3% similar to (IG). Furthermore,(IG) and (PC) are 39.5% similar. Finally, when class 7 is relabelled as class 1 and all the others as class 0, (IG) and (PC) are 44.44% similar, while (VR) exhibits 56.8% and 49.38% similarity to (PC) and (IG), respectively.

ERL as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	67.2	62.5
Pearson Correlation	67.2	100	75
Information Gain	62.5	75	100
POX as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	76.5	53.13
Pearson Correlation	76.5	100	67.2
Information Gain	53.13	67.2	100
VAC as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	75	59.4
Pearson Correlation	75	100	68.75
Information Gain	59.4	68.75	100
EXC as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	70.31	59.4
Pearson Correlation	70.31	100	81.25
Information Gain	59.4	81.25	100
ME1 as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	88.3	76.6
Pearson Correlation	88.3	100	81.25
Information Gain	76.6	81.25	100

Table 4.19: Comparison of (VR), (PC) and (IG) using the (ROS) technique for Yeast data

ME2 as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	87.5	64
Pearson Correlation	87.5	100	67
Information Gain	64	67	100
ME3 as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	51.6	59.4
Pearson Correlation	51.6	100	68.8
Information Gain	59.4	68.8	100
MIT as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	57.8	64
Pearson Correlation	57.8	100	67
Information Gain	64	67	100
NUC as class 1 , others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	47	61
Pearson Correlation	47	100	73.44
Information Gain	61	73.44	100
CYT as class 1, others as class 0			
	Variance	Pearson Correlation	Information Gain
Variance	100	76.6	67.2
Pearson Correlation	76.6	100	73.4
Information Gain	67.2	73.4	100

Table 4.20: Comparison of (VR), (PC) and (IG) using the (ROS) technique for Yeast data continue

The Yeast comparison in Table 4.19 and tables 4.20 using the (ROS) also provided the similarities of (VR), (PC) and (IG); lets us take the work example in Table 4.12 and 4.13 as a case study on how the similarity is arrived at. The similarity between the (VR), (PC) is approximately 67.2% . while the similarity between (PC) and (IG) is 75% and that between (IG) and (VR) is 62.5%. If the sub-table "pox as class 1 and others as class 0 " is considered, the similarity between (VR) and (PC) is 76.5%, and 53.13% with (IG), but it is 67.2% between (PC) and (IG). For further similarity in all Yeast data "one versus all" sub-tables between (VR), (PC), and (IG), please see Tables 4.19 and 4.20

Summary and Conclusion

This chapter has presented very important aspect to evaluate the (VR) technique in handling imbalanced distributed data by comparing the result of using the (VR) technique with that of two State-of-the-art ((IG) and (PC)) feature selections on the same data set. Owing to the fact that no two feature selection methods ever produce the same results.

The feature selection method is categorised into Filter, Wrapper and Hybrid approach, the (VR) belong to the Filter approach which tends to rank the bases of the feature on the degree of their significance in predicting the target class. Therefore

the issue here is to find the degree of similarity of the result of the two State-of-the-art ((IG) and (PC)) on the same data set and also the same degree of similarity will be used to compare with the (VR) technique. All the known similarity index are not applicable to ranking items, hence a new similarity algorithm the (ROS) was invented to accommodate similarity when items are ranked. From the analysis of the results of similarities in the four tables (4.15, 4.16, 4.17 and 4.17) at any point in time the similarity between (VR) and either of the technique is higher than the similarity between the two (IG) and (PC).

Chapter 5

Validation

In this chapter, all the validation of (VR) technique will be carried out. To put in specific terms, an assessment of the superiority of (VR) over (PC) and (IG) for selecting the most significant attributes in a datasets that could make the machine learning algorithm capture more of the minority classes during predictive modeling processes will be verified.

The sequence of the section, is as follows; First using the result of the ranked attributes obtained in earlier sections by (VR) and those ranked (IG) and (PC) will be used on the following predictive algorithms: Decision Tree (DT), Support Vector Machine (SVM), and Logistic Regression (LR) for the experiments.

One of the banes of predictive modelling is knowing the algorithm to choose from the list of over fourteen major algorithms, besides how will parameters be changed; by parameters here, it means the optimisation functions of the chosen algorithm for example if you are using Support Vector Machine (SVM) on a particular data set what kernel function would produce better results? If Decision tree algorithm is being used, how will the confidence factors be set, that will in turn affects the pruning and performance of the algorithm on the training and test data? The altering and tweaking of parameters and other variables during data mining and machine learning processes are just too much to itemize and did not make modelling processes and exact science, hence trial and error are often associated with the processes. Choosing the right algorithm is a huge topic that depends on lots of factors, you only have to take a look at the research gate forum at [148] to realise how popular this topic is.

Therefore different results could be obtained on the same dataset because of different algorithm parameters tweaking and other variables that could be modified. But the results should be within a certain heuristic range that is acceptable.

The reason for selecting these three algorithms for validating the (VR) is the

intention to use more broader family of algorithms that are representatives of other major aalgorithms. For instance, the family of tree-based algorithms is represented by (DT), while the family of regression classifiers is represented by (LR), and finally, the hyperplane and vector-based algorithms are represented by (SVM). Apart from this, many researchers, academics, and data scientists who have ventured into the area of selecting the right algorithm, such as in [215]and [216], have produce some guidelines for selecting the right algorithms. Therefore, if the (VR) techniques works on these three algorithm, it will work on other algorithms.
Hence making the (VR) as not algorithm dependent. The performance of (VR) on any dataset would depend on the intrinsic properties of the data, comparing these results will establish the efficacy of (VR) techniques. During this validation each of the confusion matrix and all associated metrics of measurement like the True positive for majority (TP_{maj}), True positive for Minority (TP_{min}), False positive for Majority and Minority (FP_{maj}) and (FP_{min}) and others will be made available, please refer to sections 2.3.1 and 2.3.2 for various metric of measuring the binary and multiclass data. Also, the technique of Peak Threshold Performance for selecting the most significant features will be demonstrated and shown in this chapter. The investigation into Imbalanced and Overlapped, extreme imbalanced and their effects in predictive modeling will be carried out in this chapter and next.

Tabular Descriptions and Results Presentations

For this validation, experiments were conducted using Weka data mining software and Python programming language, two major tables and graphs will be created; the tables will have majority and minority classes as headings. The contents of the tables are as follows:

- Algorithm: This comprises the attribute selection algorithm techniques, which are (VR), (PC), and (IG);
- (%)Accuracy: This is the accuracy of the model; it is the measure of the $(PTP)_{Accuracy}$ and is the same for both tables. It is obtained from the confusion matrix (see section 2.3.1), and it is recorded in the tables as $\frac{accuracy\ value}{100}$
- Precision: This is the precision of the majority or minority class, which will be different for the two tables. It is obtained from the confusion matrix (see section 2.3.1), and it is recorded in the tables as $\frac{Precision\ value}{100}$
- Recall: This is the recall value of the majority or minority class; the values are different for both tables. The Recall for the minority table will be used to

indicate the position of $(PTP)_{minority}$. Recall is obtained from the confusion matrix (see section 2.3.1), and its is recorded in the tables as $\frac{Recall\ value}{100}$

- F-measure: This is the F-measure value of the majority or minority class; the values are different for both tables, and they are obtained from the confusion matrix (see section 2.3.1); it is recorded in tables as $\frac{F-measure\ value}{100}$
- ROC: This represents the area under the ROC curve for both the majority and minority table is recorded in the tables as $\frac{ROC\ Area\ value}{100}$ and they are the same for the majority and minority table.
- Graphs: There are two main graphs in this sections; their titles are "Accuracy versus Number of Attributes for VR" and "Recall versus Number of Attributes for VR". Both graphs are plotted from the minority table. The graph "Accuracy versus Number of Attributes for VR" will indicate the $(PTP)_{Accuracy}$ and is labelled in the graph as "PTP for Accuracy". The graph "Recall versus Number of Attributes for VR" will indicate the $(PTP)_{minority}$ and is labelled in the graph as "PTP for Accuracy."

5.0.1 Validation of (VR) Technique for Binary Imbalance Dataset

The (VR) technique have stood out as one of the few techniques that have specifically targeted the imbalanced classed distributions in data sets and could be applied to other imbalanced scenarios as provided in sections 1.1, The main reasons for this claim is that the (VR) technique have factored the numbers of the majority class and minority class group, ie the process is subject to the (IR) unlike many other techniques.

The binary classed data set that will be used for this validations will be selected from the list of the four data set that we had used in chapters 2 and three; these are Wisconsin Breast cancer, Pima India diabetes, Bupa Liver disease, and Cod-RNA data sets, for details of these data sets please see Table A.2.

The (VR) technique have been demonstrated in Tables 3.1, 3.2, 3.3 and 3.4, the algorithm process flow chart is Figure 3.4, the results obtained have been compared with that of the two most popular filter attributes selection techniques; the (IG) and (PC), the results of the comparison is in chapter 4 Tables 4.1, 4.2, 4.3 and 4.4. from these tables the following postulations are apparent;

- No two filter feature selection algorithms could produce results that are 100% the same.

- The results of filter feature selection on the same data set using the same algorithm may differs slightly by *proximity distance*.(please see section 4.4 for the meaning of term *proximity distance* used in developing the concept of (ROS)).

Experiments Process.

The three classification algorithms; (DT), (SVM) and (LR) is used on the four binary data sets starting with all the features and eliminating the features in accordance to the ranking obtained by (VR),(IG) and (PC). The eliminations were done statistical quartiles (dividing into four groups); that is if the total number of features were 8, the elimination will be first 2, followed by another two (A total of four), then another 2 (total of six), this would continue until the Peak Threshold Performance (PTP) is reached, at that point any other elimination will lead to the reversal of accuracy. Note that the (PTP) is the highest accuracy at which the most significant feature will be selected, the (PTP) are of two forms; these are;

- $(PTP)_{Accuracy}$ This is the point with the highest accuracy of the predictions, but that may or may not show the best results for the minority class groups, recall that one of the problems of imbalanced class is that a prediction may show high accuracy while not capturing properly the minority in the data sets
- $(PTP)_{minority}$ This is the point at which the highest number of the minority class group were captured, recall that this may not be at the points of the highest accuracy, after all, prediction could appear to have high accuracy while not capturing any or very low numbers of minority groups.

Notice that in this experiments we did try to start with the least numbers of attributes and start adding others in 2(s) until all the attributes have bee added, a reversal of the 5.0.1, it produces the same result.

5.0.2 Decision Tree Experiments for Pima diabetes Data

The comparison table of Pima diabetes data attributes in Table 5.1 as ranked by variance significant the (VR), (PC) and (PC) will be used with the Decision Tree for the experiments.

59

Ranking of variables based on different feature selection Algorithm			
sn	Varaince Rank	Pearson Correlation	Information Gain
1	age	plasglu	age
2	bmass	bmass	bmass
3	plasglu	preg	plasglu
4	skinfold	age	preg
5	diapress	diapres	insutest
6	preg	skinfold	skinfold
7	pedi	pedi	pedi
8	insutest	insutest	diapres

Table 5.1: Comparison of (VR), (PC) and (PC) Attributes selection for Pima India diabetes data

Minority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.685	0.538	0.679	0.601	0.696	182
	4	0.741	0.646	0.571	0.606	0.741	153
	6	0.757	0.663	0.616	0.638	0.75	165
	8	0.738	0.632	0.597	0.614	0.751	160
PC	2	0.745	0.67	0.53	0.592	0.707	142
	4	0.749	0.652	0.601	0.625	0.753	161
	6	0.757	0.663	0.616	0.638	0.75	165
	8	0.738	0.632	0.597	0.614	0.751	160
IG	2	0.685	0.538	0.679	0.601	0.696	182
	4	0.749	0.652	0.601	0.625	0.753	161
	6	0.742	0.63	0.634	0.632	0.773	170
	8	0.738	0.632	0.597	0.614	0.751	160

Table 5.2: Results of majority class for Pima data set for DT by (VR) feature selection

The interface of two of the Experiments for Decision Tree algorithm for two feature is in figure A.1 and eight features are in figure A.2 using Weka data mining software. Tables 5.2 and 5.3 are the results of the same experiments using (DT) on the Pima diabetes data, the tables were separated for majority and minority class for clarity. The main interest is table 5.3 because it shows the minority captured by the predictions, the highest is 182 when the attributes are two, while the accuracy at that point is the lowest at 68.5%. The (VR) technique and (IG) performed better than the (PC).

Minority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.685	0.538	0.679	0.601	0.696	182
	4	0.741	0.646	0.571	0.606	0.741	153
	6	0.757	0.663	0.616	0.638	0.75	165
	8	0.738	0.632	0.597	0.614	0.751	160
PC	2	0.745	0.67	0.53	0.592	0.707	142
	4	0.749	0.652	0.601	0.625	0.753	161
	6	0.757	0.663	0.616	0.638	0.75	165
	8	0.738	0.632	0.597	0.614	0.751	160
IG	2	0.685	0.538	0.679	0.601	0.696	182
	4	0.749	0.652	0.601	0.625	0.753	161
	6	0.742	0.63	0.634	0.632	0.773	170
	8	0.738	0.632	0.597	0.614	0.751	160

Table 5.3: Results of minority class for Pima data set for DT by (VR) feature selection

The highest minority that the (PC) was able to capture is 165 at a percentage of 75.7% by using six attributes, (VR) also got that same percentage of 75.7% also using the same six attributes. The (DT) experiment is a classical example that shows that high accuracy does not lead to high capture of minority in the predictions.

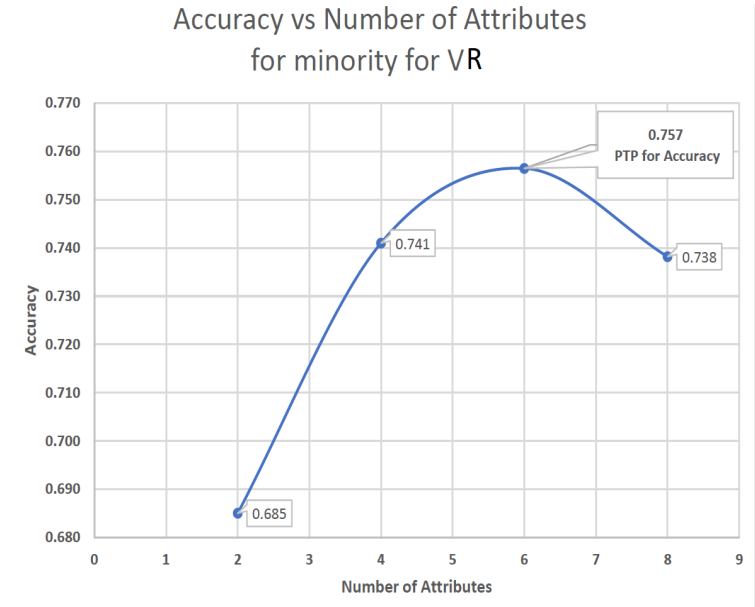


Figure 5.1: Accuracy vs Number of Attributes for Pima data using Decision Tree

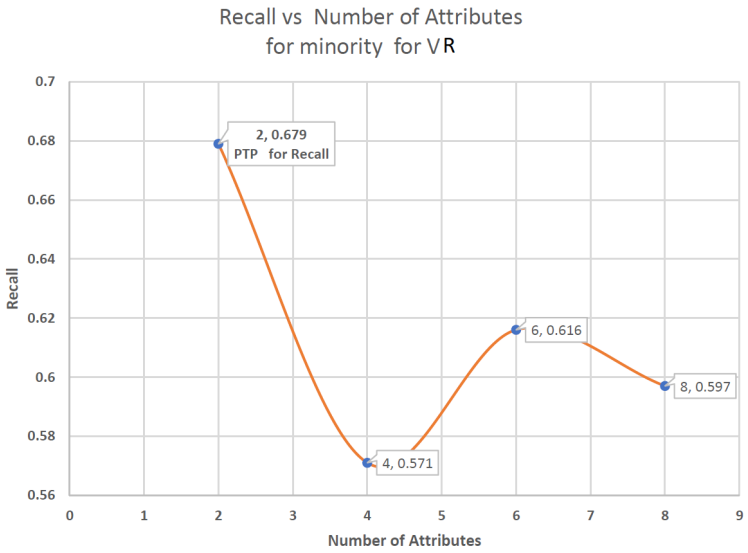


Figure 5.2: Recall vs Number of Attributes for Pima data using Decision Tree

The Figure 5.1 is the $(PTP)_{Accuracy}$ and 5.2 is the $(PTP)_{minority}$, both demonstrations how the the most significant attributes is selected. At the position of $(PTP)_{minority}$ shown in the graph in Figure 5.2 at that point has the highest recall of 0.678 with two attributes and the total number of the minority captured is 182 which is also the highest in all the (DT) experiments.

5.0.3 Logistic Regression Experiments for Pima diabetes data

The experiments of using the Logistic Regression algorithm on the Pima diabetes data is provided in the next sessions.

Majority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.681	0.709	0.864	0.779	0.732	432
	4	0.771	0.795	0.874	0.832	0.824	437
	6	0.766	0.788	0.876	0.83	0.816	438
	8	0.772	0.79	0.88	0.834	0.832	440
PC	2	0.764	0.779	0.89	0.831	0.81	445
	4	0.767	0.789	0.876	0.83	0.823	438
	6	0.771	0.795	0.874	0.832	0.824	437
	8	0.772	0.79	0.88	0.834	0.832	440
IG	2	0.681	0.709	0.864	0.779	0.732	432
	4	0.767	0.789	0.876	0.83	0.823	438
	6	0.762	0.785	0.874	0.827	0.821	437
	8	0.772	0.79	0.88	0.834	0.832	440

Table 5.4: Results of majority class for Pima data set for LR by (VR) feature selection

The Logistic Regression experiments results is in Tables 5.4 for majority class and 5.5 for the minority class, emphasis is on the general accuracy representaed by $(PTP)_{Accuracy}$ and number of minority capture represented by $(PTP)_{minority}$

Minority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.681	0.572	0.34	0.426	0.732	91
	4	0.771	0.711	0.578	0.638	0.824	155
	6	0.766	0.708	0.56	0.625	0.816	150
	8	0.772	0.718	0.571	0.636	0.832	153
PC	2	0.764	0.721	0.53	0.611	0.81	145
	4	0.767	0.709	0.563	0.628	0.823	151
	6	0.771	0.711	0.578	0.638	0.824	155
	8	0.772	0.718	0.571	0.636	0.832	153
IG	2	0.681	0.572	0.34	0.426	0.732	91
	4	0.767	0.709	0.563	0.628	0.823	151
	6	0.762	0.701	0.552	0.618	0.821	148
	8	0.772	0.718	0.571	0.636	0.832	153

Table 5.5: Results of minority class for Pima data set for LR by (VR) feature selection

The Table 5.5 showed the $(PTP)_{minority}$ of (VR) techniques has the value of Recall of 0.578 and highest number of capture minority of 155. At that point the number of attributes used to achieve this are four. The next best attributes selection that achieve the same results is the (PC), but uses six attributes to achieve the result. Figures 5.3 and 5.4 showed that the highest accuracy $(PTP)_{Accuracy}$ point occurred with all the eight attributes, while the highest Recall $(PTP)_{minority}$ point is with four attributes.

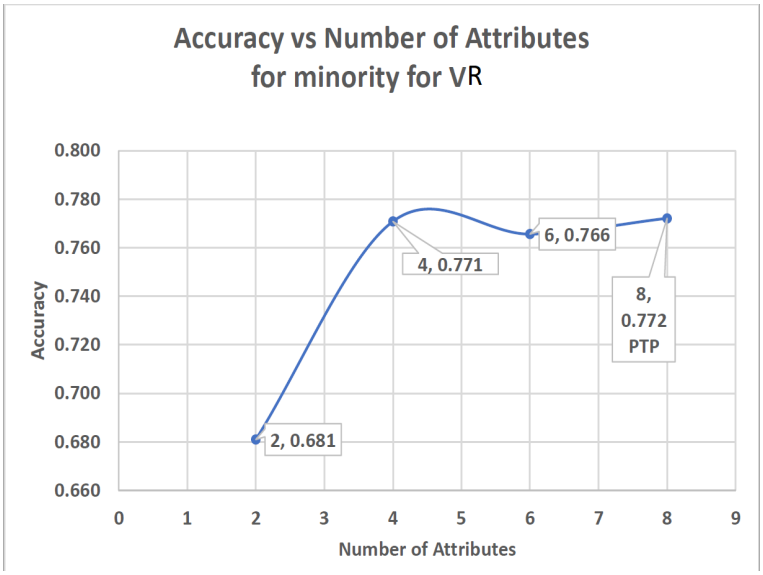


Figure 5.3: Accuracy vs Number of Attributes for Pima data using Logistic Regression

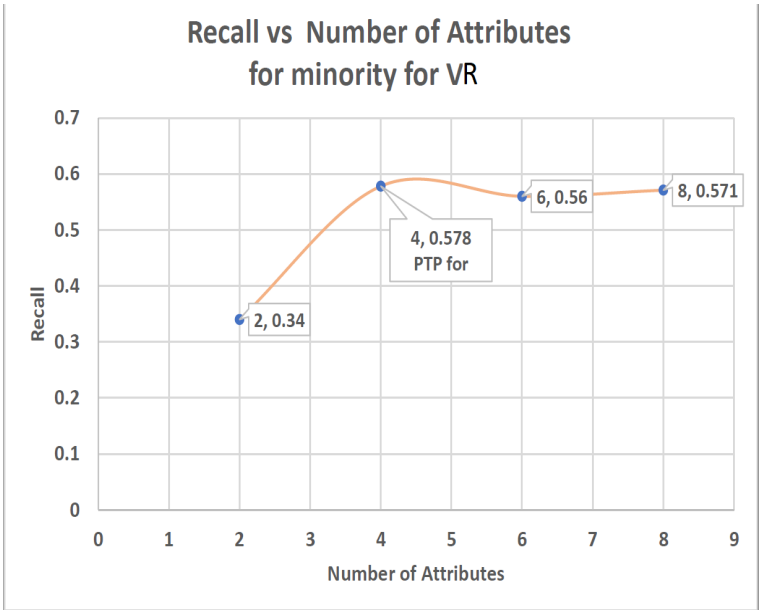


Figure 5.4: Recall vs Number of Attributes for Pima data using Logistic Regression

5.0.4 Support Vector Machine Experiments for Pima diabetes data

The Support Vector Machine experiments is in Tables 5.6 and 5.7, the same numbers of features were used just like in the Decision Tree and Logistic Regression.

Majority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.643	0.651	0.976	0.781	0.499	488
	4	0.767	0.784	0.886	0.832	0.715	443
	6	0.763	0.78	0.886	0.83	0.71	443
	8	0.773	0.785	0.898	0.838	0.72	449
PC	2	0.759	0.764	0.912	0.831	0.693	456
	4	0.771	0.784	0.894	0.836	0.718	447
	6	0.767	0.784	0.886	0.832	0.715	443
	8	0.773	0.785	0.898	0.838	0.72	449
IG	2	0.643	0.651	0.976	0.781	0.499	488
	4	0.760	0.778	0.884	0.828	0.707	442
	6	0.759	0.777	0.884	0.827	0.705	442
	8	0.773	0.785	0.898	0.838	0.72	449

Table 5.6: Results of majority class for Pima data set for SVM by (VR) feature selection

The results of the experiments has lots of interesting insight. For one, (SVM) algorithm rely very much on demarcating data class groups in a hyperplane such that the algorithm needs minimum number of features in a particular data set to

function properly, this fact of (SVM) was captured in the work of [217], hence the algorithm could be extremely accurate of inaccurate. This extreme tendency is noticeable Tables 5.6 and 5.7

Minority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.643	0.333	0.022	0.042	0.499	6
	4	0.767	0.719	0.545	0.62	0.715	146
	6	0.763	0.715	0.534	0.611	0.71	143
	8	0.773	0.74	0.541	0.625	0.72	145
PC	2	0.759	0.743	0.474	0.579	0.693	127
	4	0.771	0.732	0.541	0.622	0.718	145
	6	0.767	0.719	0.545	0.62	0.715	146
	8	0.773	0.74	0.541	0.625	0.72	145
IG	2	0.643	0.333	0.022	0.042	0.499	6
	4	0.760	0.71	0.53	0.607	0.707	142
	6	0.759	0.709	0.526	0.604	0.705	141
	8	0.773	0.74	0.541	0.625	0.72	145

Table 5.7: Results of minority class for Pima data set for SVM by (VR) feature selection

The best accuracy of 77.3% which is the $(PTP)_{Accuracy}$ point shown in Figure 5.5 were achieved using all the eight features and best recall of 0.545 for the minority $(PTP)_{minority}$ shown in 5.6 point captured 146 minority class data.

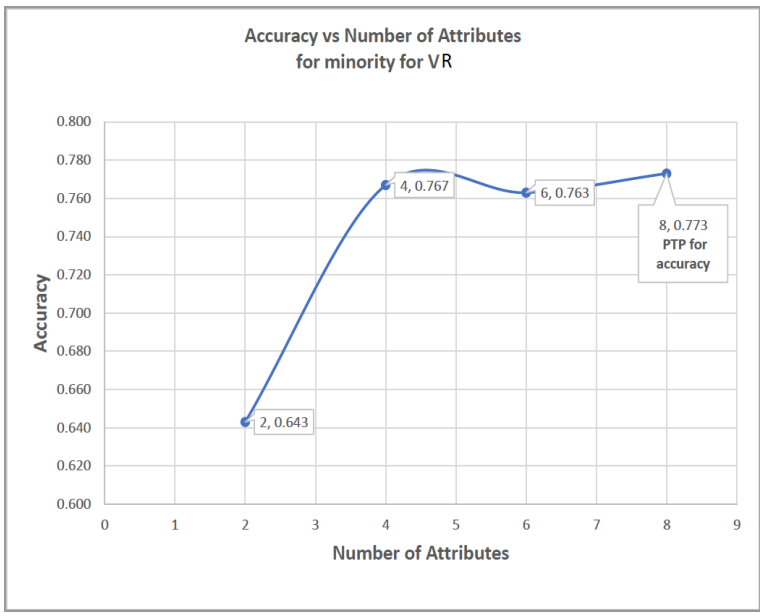


Figure 5.5: Accuracy vs Number of Attributes for Pima data using Support Vector Machine

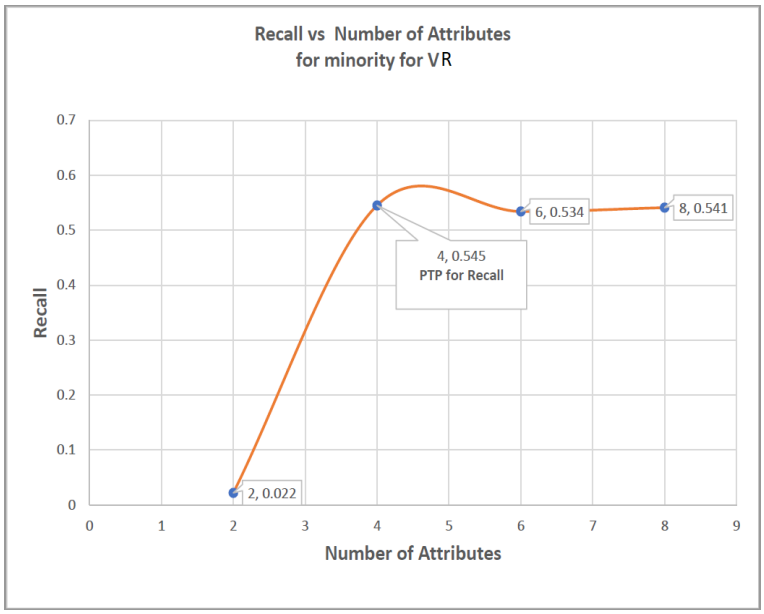


Figure 5.6: Recall vs Number of Attributes for Pima data using Support Vector Machine

Summary and Conclusion

In the section, the first of the series of validation of the Prove of Concept (POC) as regard to the (VR) technique have been carried out. A popular binary dataset; Pima diabetes data were used and three (ML) algorithms specially chosen because of their being the foundation or being related to many other algorithms. In general, the experimental results are in line with the expectations, for instance, the best experiments that captured more of the minority ie $(PTP)_{minority}$ is the (DT) with a recall of 67.9% of the minority, and two of the most significant attributes as identified by the (VR) were used. (DT) is known to perform very well in binary context by splitting its node into two, but the power of the (VR) is knowing the two most significant feature to split through.

The (LR) is the next best performing experiment and the $(PTP)_{minority}$ point is at four feature, the Recall is 57.8% while the same Recall was achieved by (PC) but with six attributes.

The (SVM) has the least performance but the same pattern is also noticed. The (VR) has the best $(PTP)_{minority}$ at the point of four features but reduced drastically to a Recall of 2.2%.

5.0.5 Decision Tree Experiments for Wisconsin Breast cancer data

The Wisconsin Breast cancer data set has 699 instances, binary classed representing Benign (458) and malignant (241), nine features (attributes) and target class, please refer to Appendix A.2 for more details. The attributes selections by the ranking are in Table 5.8, all the attributes selection have been ranked differently by each of the algorithms, but some very close similarities still exist among the rankings. The order of ranking and deducing the level of the similarities based on the rankings have been dealt with extensively in section 4.3

Ranking of variables based on different features selection Algorithm			
sn	**Variance Rank**	**Pearson Correlation**	**Information Gain**
1	ClumpThickness	UniformityofCellShape	UniformityofCellSize
2	BlandChromatin	UniformityofCellSize	BlandChromatin
3	UniformityofCellShape	BareNuclei	UniformityofCellShape
4	BareNuclei	BlandChromatin	BareNuclei
5	SingleEpithelialCellSize	ClumpThickness	SingleEpithelialCellSize
6	UniformityofCellSize	NormalNucleoli	NormalNucleoli
7	NormalNucleoli	MarginalAdhesion	ClumpThickness
8	MarginalAdhesion	SingleEpithelialCellSize	MarginalAdhesion
9	Mitoses	Mitoses	Mitoses

Table 5.8: Comparison of Variance significant with PC and IG variable selection for Wisconsin Breast cancer data

Majority class							
Algorithm	**numer of Attributes**	**Accuracy**	**Precision**	**Recall**	**F-measure**	**ROC**	**total Captured**
VR	2	0.901	0.931	0.912	0.922	0.945	405
	4	0.956	0.966	0.964	0.965	0.977	430
	6	0.930	0.947	0.945	0.946	0.967	430
	9	0.927	0.947	0.941	0.944	0.96	431
PC	2	0.894	0.905	0.933	0.919	0.912	420
	4	0.908	0.926	0.934	0.930	0.936	425
	6	0.914	0.926	0.942	0.934	0.945	423
	9	0.927	0.947	0.941	0.944	0.96	431
IG	2	0.926	0.937	0.949	0.943	0.954	428
	4	0.940	0.957	0.953	0.955	0.975	446
	6	0.924	0.936	0.947	0.942	0.955	427
	9	0.927	0.947	0.941	0.944	0.96	431

Table 5.9: Results of majority class for Wisconsin data set for DT by (VR), (PC) and (IG) feature selection

The Tables 5.9 and 5.10 is the result of Decision Tree for the Wisconsin data, the superiority of the (VR) to target the minority class group is shown in both tables and the associated graphs for the accuracy and recall of the minority class groups are in the Figure 5.7 and 5.8. This particular experiments is note worthy in that it is one of such cases where the accuracy of the predictions and the recall occurred

at the same number of attributes that mean the $(PTP)_{Accuracy}$ and $(PTP)_{minority}$ are at the same point when the first four attributes where used,

Minority class							
Algorithm	numer of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.901	0.852	0.882	0.867	0.945	225
	4	0.956	0.937	0.941	0.939	0.977	238
	6	0.930	0.898	0.902	0.900	0.967	220
	9	0.927	0.889	0.900	0.895	0.96	217
PC	2	0.894	0.872	0.823	0.847	0.912	205
	4	0.908	0.875	0.861	0.868	0.936	210
	6	0.914	0.893	0.864	0.878	0.945	216
	9	0.927	0.889	0.900	0.895	0.96	217
IG	2	0.926	0.905	0.883	0.894	0.954	219
	4	0.940	0.906	0.913	0.909	0.975	211
	6	0.924	0.901	0.883	0.892	0.955	219
	9	0.927	0.889	0.900	0.895	0.96	217

Table 5.10: Results of minority class for Wisconsin data set for DT by (VR), (PC) and (IG) feature selection

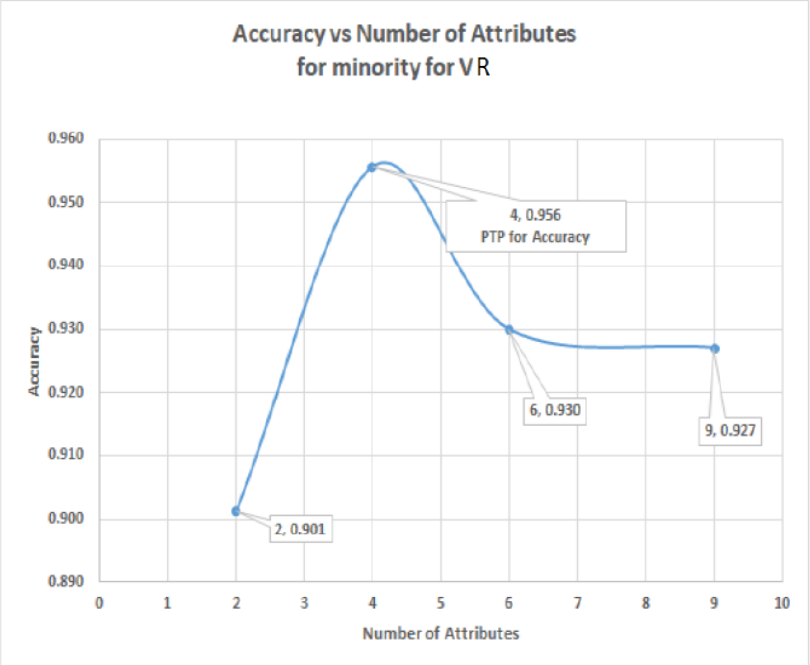


Figure 5.7: Graph of DT Accuracy vs Numbers of Attributes for Wisconsin data showing $(PTP)_{Accuracy}$

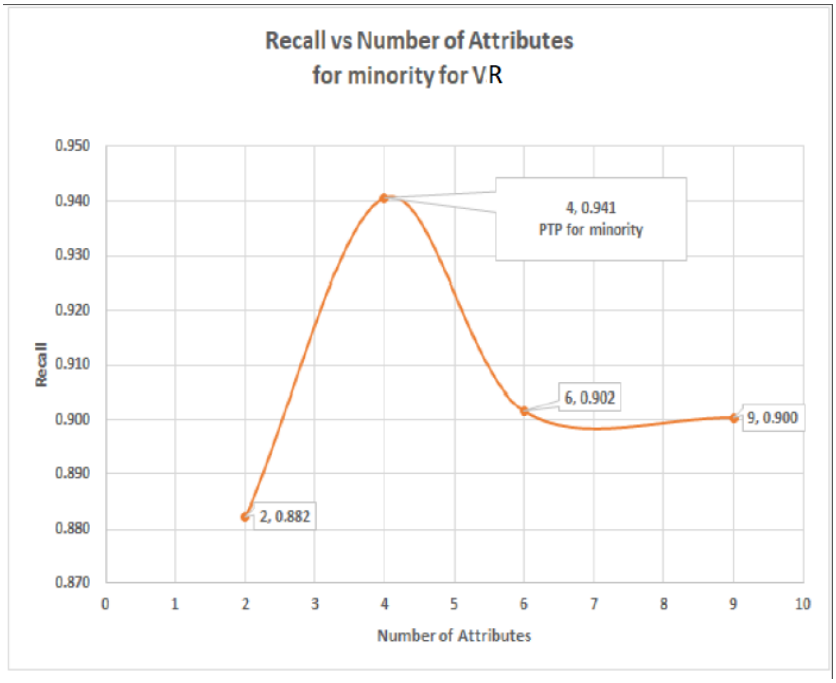


Figure 5.8: Graph of DT Recall vs Numbers of Attributes for Wisconsin data showing $(PTP)_{Recall}$

In general the (VR) technique performed better as always when compared with the (PC) and (IG), the best in (PC) occurred when the whole nine attributes were used, while the best by (IG) with a value of 219 as the total minority captured occurred at the point where the first two attributes were used. Though the capturing of the minority group meaning the the highest value of $(PTP)_{minority}$ is by the (VR) technique, but its note worthy to appreciate that (IG) technique also achieved a good level of high score $(PTP)_{minority}$ by using only two attributes.

5.0.6 Logistic Regression Experiments for Wisconsin Breast cancer data

The (LR) also demonstrated the same case were there is differences between the accuracy and minority captured, meaning that the $(PTP)_{Accuracy}$ and $(PTP)_{minority}$ points are different. The results in Tables 5.11 and 5.12 also confirms the superiority of the (VR) as against the other two the (PC) and (IG).

Majority class							
Algorithm	numer of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.928	0.927	0.961	0.944	0.94	420
	4	0.943	0.981	0.929	0.955	0.944	420
	6	0.963	0.972	0.972	0.972	0.966	445
	9	0.941	0.946	0.965	0.956	0.931	442
PC	2	0.937	0.943	0.963	0.953	0.936	446
	4	0.941	0.933	0.978	0.955	0.943	435
	6	0.931	0.952	0.943	0.947	0.941	432
	9	0.941	0.946	0.965	0.956	0.931	442
IG	2	0.910	0.894	0.976	0.933	0.915	440
	4	0.911	0.937	0.929	0.933	0.925	430
	6	0.940	0.945	0.965	0.955	0.93	445
	9	0.941	0.946	0.965	0.956	0.931	442

Table 5.11: Results of majority class for Wisconsin data set for LR by (VR), (PC) and (IG) feature selection

Minority class							
Algorithm	numer of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.928	0.931	0.874	0.902	0.94	229
	4	0.943	0.882	0.968	0.923	0.944	239
	6	0.963	0.946	0.946	0.946	0.966	228
	9	0.941	0.931	0.896	0.913	0.931	216
PC	2	0.937	0.925	0.886	0.905	0.936	209
	4	0.941	0.957	0.878	0.916	0.943	223
	6	0.931	0.894	0.909	0.901	0.941	219
	9	0.941	0.931	0.896	0.913	0.931	216
IG	2	0.910	0.947	0.790	0.862	0.915	196
	4	0.911	0.863	0.877	0.870	0.925	207
	6	0.940	0.930	0.891	0.910	0.93	212
	9	0.941	0.931	0.896	0.913	0.931	216

Table 5.12: Results of minority class for Wisconsin data set for LR by (VR), (PC) and (IG) feature selection

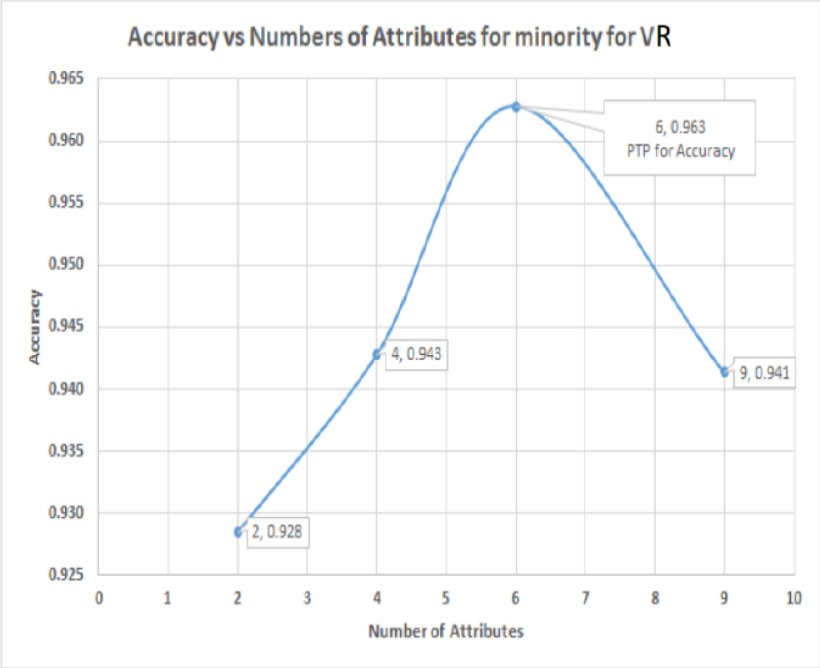


Figure 5.9: Graph of LR Accuracy vs Numbers of Attributes for Wisconsin data showing $(PTP)_{Accuracy}$ at the position 6 attributes

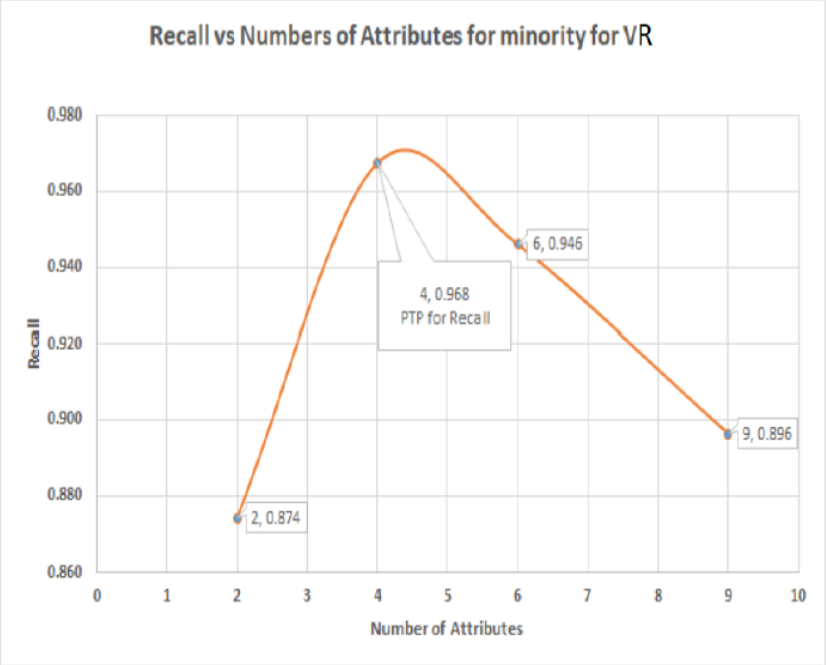


Figure 5.10: Graph of LR Recall vs Numbers of Attributes for Wisconsin data showing $(PTP)_{minority}$ at the position of 4 attributes

The recall is highest for all aspects of the (VR) technique. In this experiment the highest recall did not occur at the point of highest accuracy, meaning the $(PTP)_{Accuracy}$ point is different from $(PTP)_{minority}$ but the increase in the recall rate is more than 10% for the best performing of the (PC) and (IG) techniques.

5.0.7 Support Vector Machine Experiments for Wisconsin Breast cancer data

The Wisconsin breast cancer also demonstrated the (VR) abilities to target the minority class group effectively, Tables 5.13 and 5.14 is the majority and minority tables for the confusion matrix, the graphs of the relationships between the accuracy and the recall is in Figure 5.11 and 5.12.

Majority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.948	0.955	0.967	0.961	0.94	443
	4	0.967	0.976	0.974	0.975	0.964	446
	6	0.959	0.969	0.967	0.968	0.96	443
	9	0.954	0.965	0.965	0.965	0.950	442
PC	2	0.950	0.963	0.961	0.962	0.95	448
	4	0.963	0.974	0.970	0.972	0.940	447
	6	0.96	0.97	0.97	0.97	0.96	443
	9	0.954	0.965	0.965	0.965	0.95	442
IG	2	0.950	0.963	0.961	0.962	0.95	448
	4	0.966	0.976	0.972	0.974	0.95	446
	6	0.959	0.969	0.967	0.968	0.96	443
	9	0.954	0.965	0.965	0.965	0.95	442

Table 5.13: Results of majority class for Wisconsin data set for SVM by (VR), (PC) and (IG) feature selection

Table 5.14 is the main focus and interest here, from the analysis the (VR) have out performed the (PC) and (IG), with a highest minority Recall of 95.4% closely followed by (IG) with also 95.4% but when the total number of the minority group Recall is check is 230 and 229 respectively.

Minority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.948	0.936	0.913	0.924	0.94	220
	4	0.967	0.950	0.954	0.952	0.964	230
	6	0.959	0.938	0.942	0.940	0.96	227
	9	0.954	0.934	0.934	0.934	0.950	225
PC	2	0.950	0.923	0.927	0.925	0.95	216
	4	0.963	0.942	0.950	0.946	0.940	226
	6	0.96	0.94	0.94	0.94	0.96	227
	9	0.954	0.934	0.934	0.934	0.95	225
IG	2	0.950	0.923	0.927	0.925	0.95	216
	4	0.966	0.946	0.954	0.950	0.95	229
	6	0.959	0.938	0.942	0.940	0.96	227
	9	0.954	0.934	0.934	0.934	0.95	225

Table 5.14: Results of minority class for Wisconsin data set for SVM by (VR), (PC) and (IG) feature selection

The graph of the Accuracy against total number of attributes and Recall against total number of Attributes also showed that the $(PTP)_{Accuracy}$ and $(PTP)_{minority}$ occurred on the same number of attributes (4). The (VR) and (IG) has lots of similarities in their results, for instance, both of their results are the same in for 9 and 6 attributes and both also show the highers Recall in the 4 attributes which is the $(PTP)_{minority}$ but the actual value Recall is 230 and 229 respectively. The Weka interface for the results is in Appendix A.12 and A.13

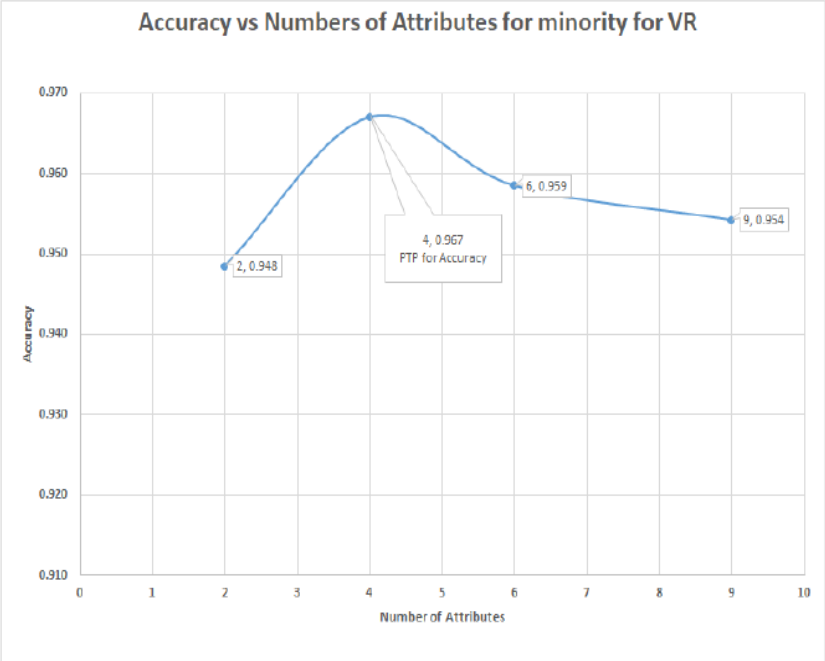


Figure 5.11: Graph of SVM Accuracy vs Numbers of Attributes for Wisconsin data showing $(PTP)_{Accuracy}$ at the position of 4 attributes

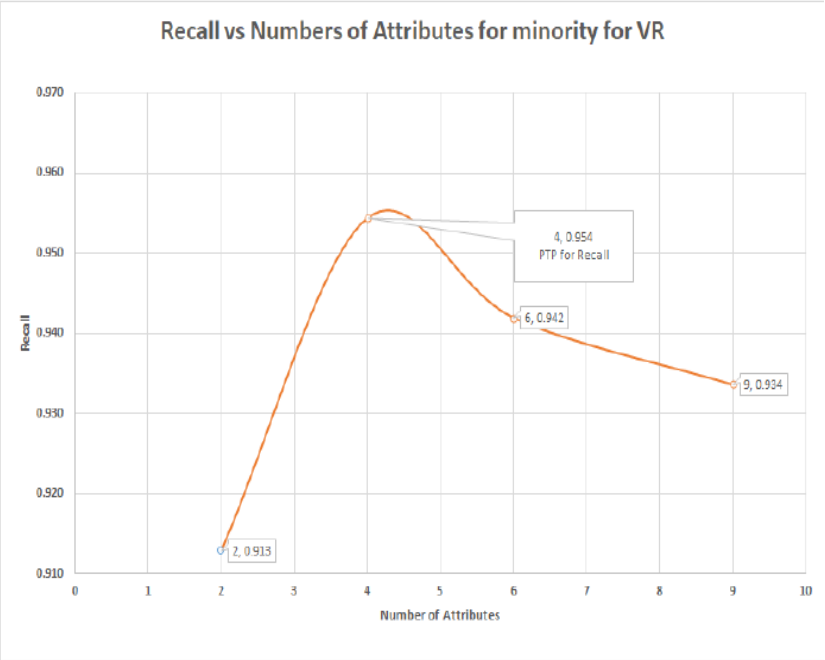


Figure 5.12: Graph of SVM Recall vs Numbers of Attributes for Wisconsin data showing $(PTP)_{minority}$ at the position of 4 attributes

Summary and Conclusion

The Wisconsin data validation experiments also supported the superiority of (VR) over (PC) and (IG) feature selection. In all the experiments (VR) has shown more capture of the minority class group as against the attributes suggested by (PC) and (IG), these experiments have been carried out using the selected (ML) algorithms. In the Wisconsin Experiments using the DT in table Tables 5.10, the (VR) uses four attributes for a Recall of 94.1% the highest that was attained (PC) and (IG) is a Recall of 90% using nine attributes, thus the (VR) is superior in term of higher Recall and using less attributes, though the $(PTP)_{Accuracy}$ and $(PTP)_{minority}$ occured at the same value of four attributes.

The (LR) and (SVM) in Tables 5.14 and 5.12 and the graphs in Figures 5.9 and 5.10 for LR and 5.11 and 5.12 for SVM. Also shows similar higher performance of (VR) over (PC) and (IG) by the Recall of 96.8% and 95.4% respectively.

5.0.8 Validation of (VR) technique for Multiclassed Imbalance Data set

This sections would validate the (VR) technique for the Multi-Class data set using the One-versus-All that has been explained and supported with proof of concept in earlier chapter 2 section 2.3.2.

The multiclass data set used for this validation are Glass and Yeast data set (highly

imbalanced) please see Tables A.2 for details of the data sets, all data preparations, re-coding from multi-class to One-versus-All were done and explained in sections 3.3.2. In this section, the results in Table 4.6 for the Glass data and Tables 4.7 and 4.8 for the Yeast data will be used. Notice that the Glass data Table able (4.6) and Yeast data TableS (4.7 and 4.8) are six and ten Tables in total, for clarity and to avoid repetitions some sections of the tables have been selected for the validation, these section is provided in Tables 5.15 and 5.16 below. The criteria for the selection is to make sure class item groups are highly (extreme) imbalanced and Overlapped and the two tables could be identified and located by the reader

Ranking of variable based on different feature selection Algorithms			Ranking of variable based on different feature selection Algorithms			Ranking of variable based on different feature selection Algorithms		
Variance Significant	Pearson Correlation	Information Gain	Variance Significant	Pearson Correlation	Information Gain	Variance Significant	Pearson Correlation	Information Gain
Ba	Ba	Ri	K	Ba	Ri	Ba	Ba	Ri
Mg	Mg	Na	Al	Fe	Ca	Mg	Mg	Si
K	K	Ca	Ba	K	Na	Ca	K	Na
Ca	Al	Al	Na	Mg	Si	K	Na	Ca
Al	RI	Si	Mg	Ri	Al	Na	Al	Al
Na	Na	Mg	Si	Al	Mg	RI	Ca	Mg
Si	Ca	K	Fe	Ca	K	Si	Si	K
RI	Si	Fe	RI	Na	Fe	Al	Ri	Fe
Fe	Fe	Ba	Ca	Si	Ba	Fe	Fe	Ba
Class 1 = labelled 1, others class 0			Class 2= relabelled as class 1, others class			Class 3 is relabelled as class 1, others		

Table 5.15: A section of 4.6 table for Glass data

Ranking of variable based on different feature selection Algorithms			Ranking of variable based on different feature selection Algorithms			Ranking of variable based on different feature selection Algorithms		
Variance Significant	Pearson Correlation	Information Gain	Variance Significant	Pearson Correlation	Information Gain	Variance Significant	Pearson Correlation	Information Gain
vac	erl	erl	nuc	pox	pox	nuc	mit	mcg
nuc	vac	gvh	alm	nuc	mcg	mit	nuc	gvh
mcg	alm	mcg	vac	vac	gvh	vac	mcg	mit
mit	mit	mit	mit	mit	mit	mcg	vac	alm
alm	mcg	alm	gvh	gvh	alm	alm	gvh	vac
gvh	gvh	vac	mcg	mcg	vac	gvh	alm	nuc
erl	nuc	nuc	pox	alm	nuc	erl	pox	pox
pox	pox	pox	erl	erl	erl	pox	erl	erl
ERL as class 1, others as class 0			POX as class 1, others as class 0			VAC as class 1, others as class 0		

Table 5.16: A section of 4.7 table for Yeast data

The Glass data is made up of six target classes and the Yeast data is ten target classes each of these target classes have been recorded as class 1 while the rest as class all in accordance with One-vs-All(Please see sections 3.3.2 tables 3.7 and 3.9) for the re-cording. The characteristics of the tables 5.15 and 5.16 shows some levels of similarities that has been deduced, calculated and adequately discussed in section 4.3 using the (ROS) techniques.

The sequence of the validation experiments for (VR) will go as follows;

- Run the selected (ML), experiments which may be (DT),(SVM),(LR) on all

the attributes in the tables 5.15 and 5.16. Then eliminate the least significant attributes as suggested by (VR), (PC) and (IG) by the rate of statistical quantile for example if attributes total is 8 you eliminate the first 2, follow by another 2 finally another 2 But if attributes is a total of 9 you eliminate the first 3 , then follow by another 2 finally another 2

- On each of the elimination experiment carried out Obtained the Confusion matrix and record the following; (TP_{maj}), True positive for Minority (TP_{min}), (FP_{maj}) and (FP_{min}),Accuracy and Recall for both the majority and minority
- Provide a graphical and visualisation of the Recall metrics from the experiments and conclusion based on the analysis and Recall therein.

During the course of the attributes elimination, the Accuracy and Recall for the minority will peak at the point we defined as the Peak Threshold Performance (PTP) when this is reached the significant attributes will be selected after which there would be reversal for both the $(PTP)_{Accuracy}$ and $(PTP)_{minority}$.
Multi-classed imbalanced has some peculiar behaviour that could also affect the abilities to capture the minority class, its called "classed Overlapped", though this will be dealt with in detail in chapter 6, we may encounter such phenomena in this chapter, therefore is proper to mention it now. Class overlapped is a situation where the intrinsic properties of the data item of two or more classes are the same, because of this the data items will occupy the same data point in a sample space such that is difficult for any algorithm to differentiate which the classes the data item belong to.

5.0.9 Validation Experiments using the Glass data set results

For this validations experiments, two Tables in 5.15 will be used, representing a section of much larger Table 4.6. The Glass dataset is highly imbalanced and multi-classed, each class represent a type of glass, such as tableware, car headlight, or window glass. are originally labelled as class 1, class 2, and so on up to class 7. However class 4 is not available, so a total of six classes is present in the original datasets. The re-coding of multiple classes into "one versus all" was done and explained in earlier sections. However, to review, the re-coding involves labeling class 1 as class 1 and the other classes as class 0, then using it for the experiments after that round of experimentation. Then, class 2 is re-coded as class 1 and the others as class 0, and this setup is used for the experiments. Next, class 3 is re-coded

as class 1 and others as class 0. This is continued until the experiment is complete. The tabulation of the results and graphs is presented below. Our interest here is in the minority table results that were used for the graphs.

5.0.10 Logistic Regression Experiments for Glass data using One vs All (class 1 as 1 and the others as class 0) see table

Majority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.640	0.796	0.625	0.700	0.710	90
	4	0.654	0.917	0.535	0.675	0.740	77
	6	0.659	0.899	0.556	0.687	0.777	80
	9	0.654	0.872	0.569	0.689	0.736	82
PC	2	0.617	0.701	0.750	0.725	0.644	108
	4	0.664	0.761	0.729	0.745	0.676	105
	6	0.650	0.790	0.653	0.715	0.714	94
	9	0.654	0.872	0.569	0.689	0.736	82
IG	2	0.678	0.739	0.806	0.771	0.643	116
	4	0.668	0.823	0.646	0.724	0.723	93
	6	0.668	0.848	0.618	0.715	0.749	89
	9	0.654	0.872	0.569	0.689	0.736	82

Table 5.17: Results of majority class for Glass data set for LR by (VR), (PC) and (IG) feature selection for class 1 as 1 and the others other as class 0

Minority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.617	0.400	0.343	0.369	0.644	24
	4	0.654	0.485	0.900	0.630	0.740	63
	6	0.659	0.488	0.871	0.626	0.777	61
	9	0.654	0.483	0.829	0.611	0.736	58
PC	2	0.617	0.400	0.343	0.369	0.644	24
	4	0.664	0.487	0.529	0.507	0.676	37
	6	0.650	0.474	0.643	0.545	0.714	45
	9	0.654	0.483	0.829	0.611	0.736	58
IG	2	0.678	0.509	0.414	0.457	0.643	29
	4	0.668	0.495	0.714	0.585	0.723	50
	6	0.668	0.495	0.771	0.603	0.749	54
	9	0.654	0.483	0.829	0.611	0.736	58

Table 5.18: Results of minority class for Glass data set for LR by (VR), (PC) and (IG) feature selection for class 1 as 1 and the others as class 0

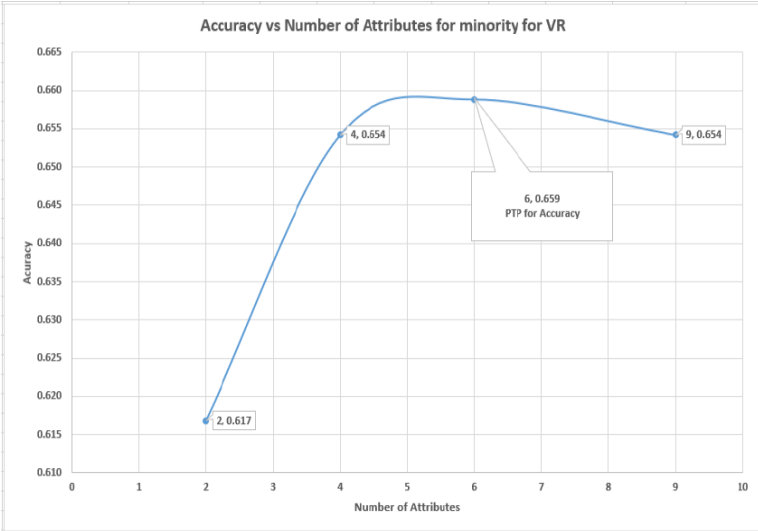


Figure 5.13: Graph of LR Accuracy vs Numbers of Attributes for Glass data Minority class: Class 1 as 1 and the others as class 0, the $(PTP)_{Accuracy}$ position.

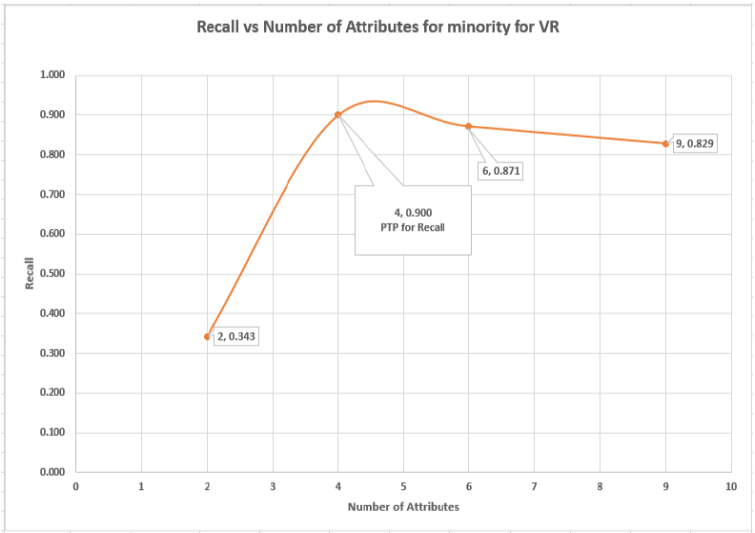


Figure 5.14: Graph of LR Recall vs Numbers of Attributes for Glass data Minority class: Class 1 as 1 and the others as class 0, the $(PTP)_{minority}$ in different position.

In this section, which is the 5.0.10 Logistic Regression experiments, where class 1 (70) is labelled as class 1 and other classes as class 0 (144). the interface for the Weka reading for all the 9 attributes is in Appendix A.4 and ROC in Appendix A.5. The (VR) outperformed the (PC) and (IG) with a value of 90% of recall of the minority, representing a total of 63 from 70 of the number of the minority data items. The graph of accuracy and recall for the minority is in Figure 5.13 and 5.14, and it shows the positions of accuracy and recall and the number of the attributes that were used to achieve them.

5.0.11 Decision Tree Experiments for Glass data using One vs All (class 1 as 1 and the others as class 0) see table 5.15

Majority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.603	0.671	0.806	0.732	0.670	116
	4	0.696	0.824	0.745	0.783	0.610	117
	6	0.743	0.738	0.958	0.834	0.640	138
	9	0.67	0.67	1.00	0.80	0.49	144
PC	2	0.603	0.671	0.806	0.732	0.670	116
	4	0.720	0.720	0.920	0.808	0.620	126
	6	0.743	0.738	0.958	0.834	0.640	138
	9	0.673	0.673	1.000	0.804	0.490	144
IG	2	0.743	0.738	0.958	0.834	0.640	138
	4	0.743	0.738	0.958	0.834	0.640	138
	6	0.743	0.738	0.958	0.834	0.640	138
	9	0.673	0.673	1.000	0.804	0.490	144

Table 5.19: Results of majority class for Glass data set for DT by (VR), (PC) and (IG) feature selection for class 1 as 1 and the others as class 0

Minority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.603	0.317	0.186	0.234	0.670	13
	4	0.696	0.444	0.561	0.496	0.610	32
	6	0.743	0.778	0.300	0.433	0.640	21
	9	0.673	0.000	0.000	0.000	0.490	0
PC	2	0.603	0.317	0.186	0.234	0.670	13
	4	0.720	0.718	0.364	0.483	0.620	28
	6	0.743	0.778	0.300	0.433	0.640	21
	9	0.673	0.000	0.000	0.000	0.490	0
IG	2	0.743	0.778	0.300	0.433	0.640	21
	4	0.743	0.778	0.300	0.433	0.640	21
	6	0.743	0.778	0.300	0.433	0.640	21
	9	0.673	0.000	0.000	0.000	0.490	0

Table 5.20: Results of minority class for Glass data set for DT by (VR), (PC) and (IG) feature selection for class 1 as 1 and the others as class 0

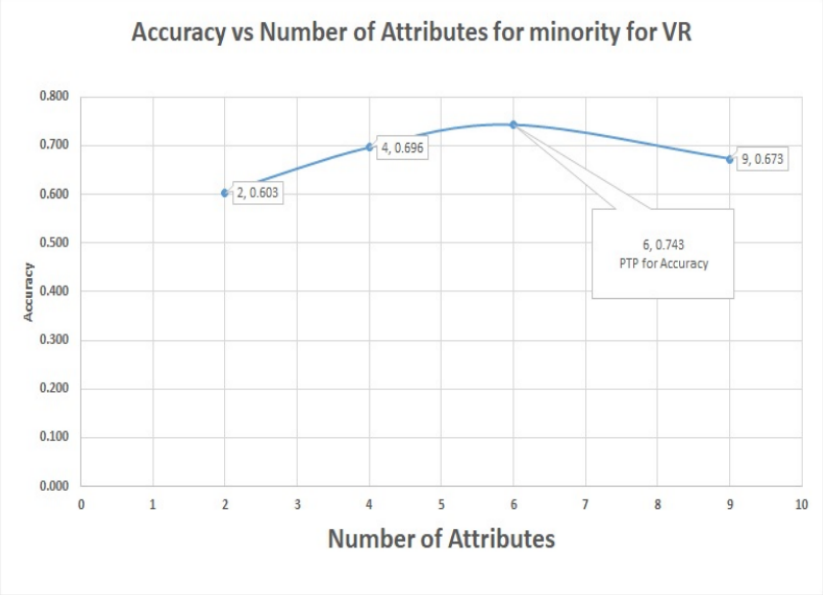


Figure 5.15: Graph of DT Accuracy vs Numbers of Attributes for Glass data Minority class: Class 1 as 1 and the others as class 0 $(PTP)_{Accuracy}$ in the 6 attribute position

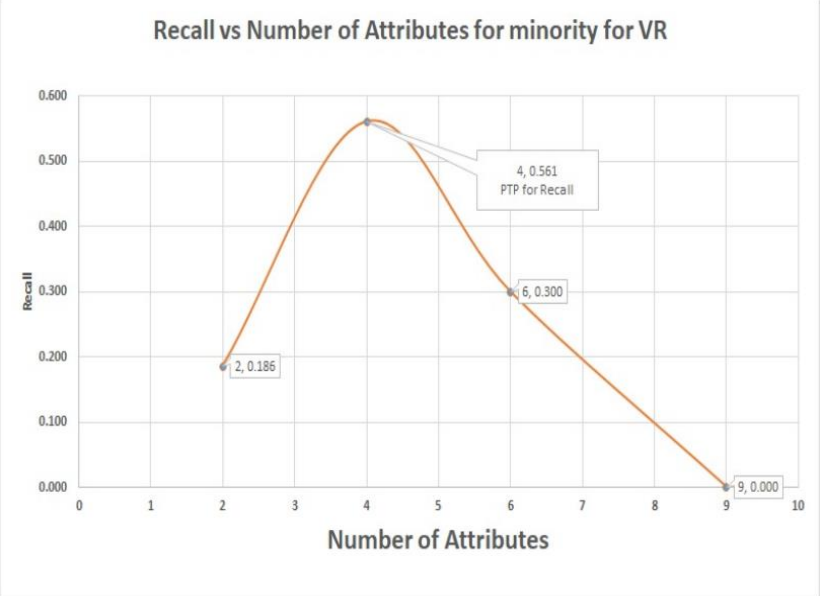


Figure 5.16: Graph of DT Recall vs Numbers of Attributes for Glass data Minority class: Class 1 as 1 and the others as class 0 $(PTP)_{minority}$ in the 4 attribute position

The above Tables 5.19 and 5.20 show the (DT) results for the Glass data in the one versus all approach for class 1 re-coded as class I and the others as class 0. some of the Weka out put interface for the 21, 13 and 0 number of minority capture which is common in is tables 5.20, please see appendix A.6, A.7 and A.8 The minority table 5.20 is our interest here; notice that the (VR) techniques captured more minority class groups than (PC) and (IG) did, with a recall of 56% at an accuracy of 69.6%, this result is a classic case of low accuracy but high recall. The graphs for the

accuracy and recall versus numbers of attributes is in Figure 5.15 and 5.16 which shows the $(PTP)_{Accuracy}$ and $(PTP)_{minority}$ at the position of the most significant attributes to be selected for the highest accuracy or highest recall of the minority class.

5.0.12 Support Vector Machine for Glass data using One vs All (class 1 as 1 others as class 0) see table 5.15

Majority class							
Algorithm	number of Attributes	Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.692	0.691	0.979	0.810	0.540	141
	4	0.743	0.738	0.958	0.834	0.630	138
	6	0.706	0.755	0.833	0.792	0.640	120
	9	0.71	0.71	0.98	0.82	0.56	141
PC	2	0.682	0.771	0.828	0.799	0.580	135
	4	0.771	0.775	0.946	0.852	0.680	141
	6	0.794	0.766	1.000	0.867	0.643	144
	9	0.715	0.709	0.979	0.822	0.560	141
IG	2	0.687	0.760	0.842	0.799	0.560	133
	4	0.766	0.822	0.883	0.851	0.580	143
	6	0.668	0.730	0.806	0.766	0.643	116
	9	0.715	0.709	0.979	0.822	0.560	141

Table 5.21: Results of majority class for Glass data set for SVM by (VR), (PC) and (IG) feature selection for class 1 as 1 other as class 0

Minority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.692	0.700	0.100	0.175	0.540	7
	4	0.743	0.778	0.300	0.433	0.630	21
	6	0.706	0.564	0.443	0.496	0.640	31
	9	0.715	0.800	0.171	0.282	0.560	12
PC	2	0.682	0.282	0.216	0.244	0.580	11
	4	0.771	0.750	0.369	0.495	0.680	24
	6	0.794	1.000	0.371	0.542	0.643	26
	9	0.715	0.800	0.171	0.282	0.560	12
IG	2	0.687	0.359	0.250	0.295	0.560	14
	4	0.766	0.525	0.404	0.457	0.580	21
	6	0.668	0.491	0.386	0.432	0.643	27
	9	0.715	0.800	0.171	0.282	0.560	12

Table 5.22: Results of minority class for Glass data set for SVM by (VR), (PC) and (IG) feature selection for class 1 as 1 other as class 0

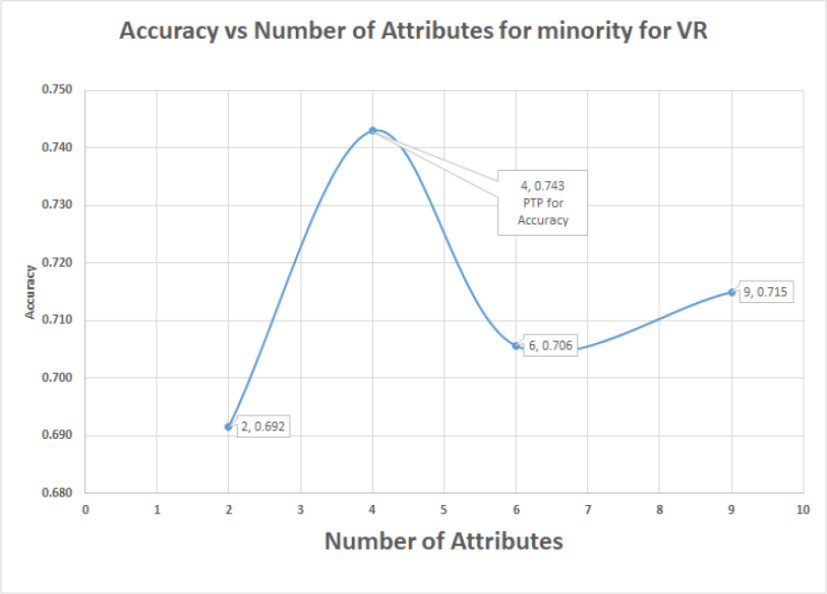


Figure 5.17: Graph of SVM Accuracy vs Numbers of Attributes for Glass data Minority class: Class 1 as 1 and the others as class 0, $(PTP)_{Accuracy}$ in the position of 4 attributes

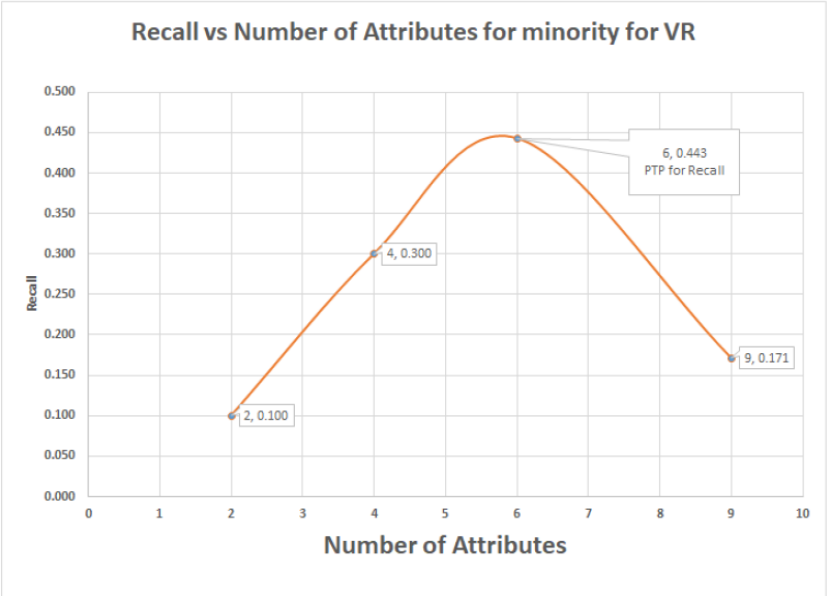


Figure 5.18: Graph of SVM Recall vs Numbers of Attributes for Glass data Minority class: Class 1 as 1 and the others as class 0, $(PTP)_{minority}$ in the position of 4 attributes

The SVM uses six attributes to attain the highest recall of 44.30% for the (VR), while the highest levels for the (PC) and (IG) are recall rate of 37.1% and 38.6%, respectively. The SVM result was the only situation where the highest accuracy was attained with the lowest number of attributes (four), while the highest recall had six attributes. These are shown in Table5.22 and Figures 5.17 and 5.18.

5.0.13 Conclusion

During the Glass dataset validation experiments, the sub-table "class 1 as 1 and the others as class 0" was employed, the three algorithms that were used were the (DT), (LR) and (SVM). In all the experiments (VR) captured more of the minority class data than PC and IG attribute selection did. These attributes were identified using the $(PTP)_{Accuracy}$ and $(PTP)_{minority}$ positions in the various graphs. The PC and IG are benchmark attribute selection techniques known in the data science community, but VR has been shown in many instances to produce equivalent or better results.

5.0.14 Logistic Regression Experiments for Glass Data Using One Versus All (Class 3 as Class 1 and the Others as Class 0)see table 5.15

Majority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.836	0.962	0.862	0.909	0.600	175
	4	0.818	0.927	0.864	0.894	0.610	165
	6	0.818	0.918	0.876	0.897	0.590	169
	9	0.841	0.922	0.904	0.913	0.560	178
PC	2	0.804	0.934	0.850	0.890	0.680	170
	4	0.836	0.946	0.876	0.910	0.660	176
	6	0.860	0.967	0.880	0.921	0.630	176
	9	0.841	0.922	0.904	0.913	0.560	178
IG	2	0.724	0.811	0.870	0.839	0.510	154
	4	0.799	0.923	0.853	0.887	0.640	168
	6	0.799	0.924	0.854	0.888	0.630	170
	9	0.841	0.922	0.904	0.913	0.560	178

Table 5.23: Results of majority class for Glass data set for LR by (VR), (PC) and (IG) feature selection for class 3 as class 1 other as class 0

Minority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.836	0.125	0.364	0.186	0.600	4
	4	0.818	0.278	0.435	0.339	0.610	10
	6	0.818	0.200	0.286	0.235	0.590	6
	9	0.841	0.095	0.118	0.105	0.560	2
PC	2	0.804	0.063	0.143	0.087	0.680	2
	4	0.836	0.107	0.231	0.146	0.660	3
	6	0.860	0.250	0.571	0.348	0.630	8
	9	0.841	0.095	0.118	0.105	0.560	2
IG	2	0.724	0.042	0.027	0.033	0.510	1
	4	0.799	0.094	0.176	0.122	0.640	3
	6	0.799	0.033	0.067	0.044	0.630	1
	9	0.841	0.095	0.118	0.105	0.560	2

Table 5.24: Results of minority class for Glass data set for LR by (VR), (PC) and (IG) feature selection for class 3 as class 1 other as class 0

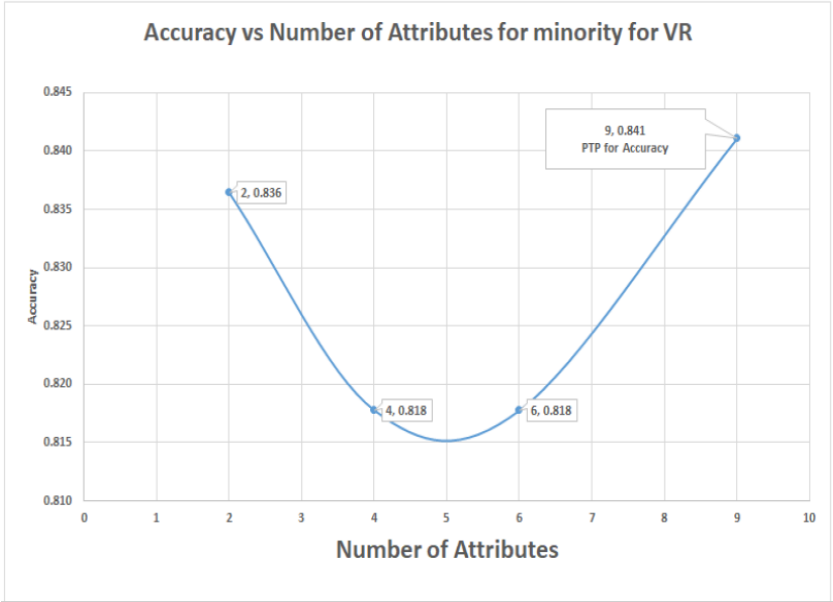


Figure 5.19: Graph of LR Accuracy vs Numbers of Attributes for Glass data Minority class: Class 3 as Class 1 and the others as class 0 $(PTP)_{Accuracy}$ at the position of 9 attributes

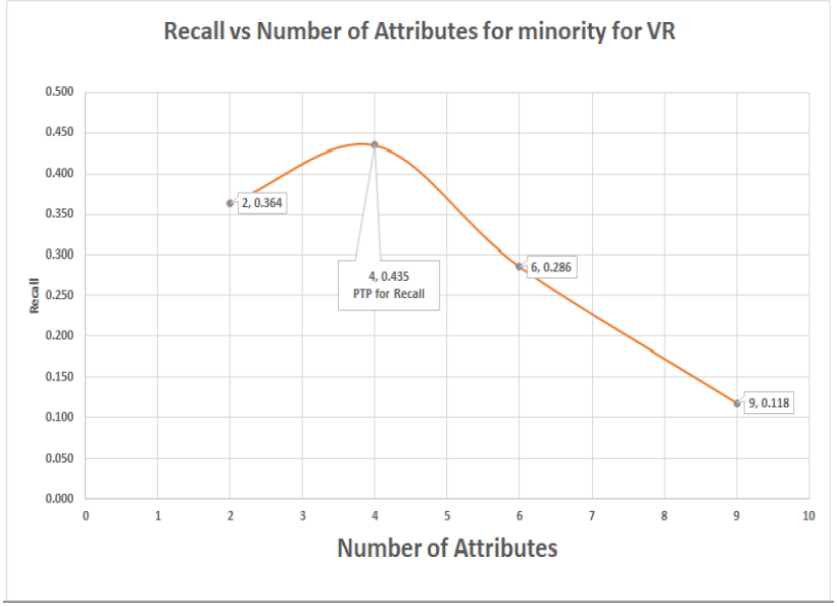


Figure 5.20: Graph of LR Recall vs Numbers of Attributes for Glass data Minority class: Class 3 as Class 1 and the others as class 0, $(PTP)_{minority}$ at the position of 4 attributes

The Weka interface for the capture of 2 minority is in Appendix A.9 and 0 minority is in Appendix A.10. The (LR) algorithm worked best for this dataset and produced the only meaningful result. The other selected algorithms; (DT) and (SVM) were unable to capture any minority class even if the accuracy is above 80%, Although this may appear to be a failure, a closer analysis shows that what affects the state-of-the-art attribute selection like PC and IG also affects the invented VR. This

supports the claim that VR belongs to the same league with the state of the art PC and IG and in many instances have shown that it is performed better. All results are in Tables 5.23 and 5.24, the graphs are in Figures 5.19 and 5.20.

5.0.15 Validation Experiments using the Yeast data set results

The components of the Yeast data make it one of the imbalanced datasets with the most classes in the data science community; see appendix A.11 for Yeast data class distribution and Table 3.9 for the representation of the class re-coding as "one versus all." There are 10 classes with varying degree of imbalanced Ratio (IR) between each class as class 1 and the rest classes (all) as class 0. The next sections present the experiments for (LR), (DT) and (SVM) for the attributes selected by (VR), (PC) and (IG).

5.0.16 Decision Tree Experiments for Yeast Data Using One Versus All (Class ERL(5) as 1 and the others as class 0 (1479)) see Table 5.15

The Tables 5.25 and 5.26 relate to the (DT) experiment for class ERL(5) as class 1 and the others as class 0 (1479), the (IR) is 5:1479 or approximately 1: 296. This means that for every 1 data item of class 1 (ERL), there are 296 data items of class 0 (others). This is an extreme case of imbalance, and Figure 5.21 shows how scanty class ERL(5) is as class 1 is in the midst of the others as class 0 (1479). Thus, even if any predictive modeling accuracy is as high as above 99%, it may not even capture any minority data. The next session showed the table of majority and minority capture recalls in different algorithms. This a case of extremely imbalanced and extremely overlapped, see the 3D scattered plot in figure 5.21

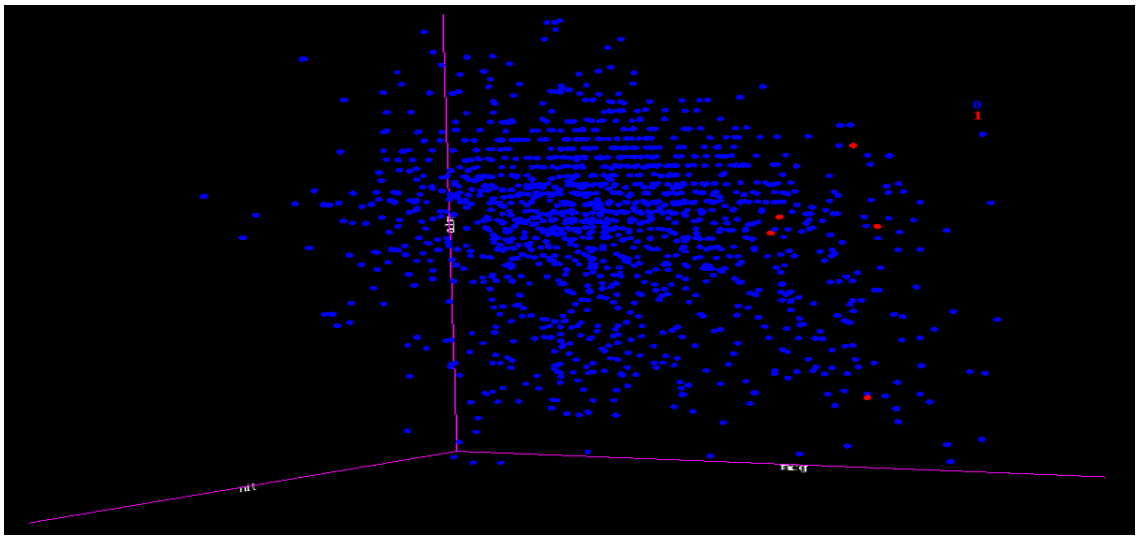


Figure 5.21: Extreme case of Ibalance of class ERL(5) as 1 others as class 0 (1479)

This extreme case of imbalanced is such that no single data points that the minority class occupies will not have one or more of the majority class occupy the same point, hence it becomes almost impossible for any algorithm to pick the minority. This is one of the reasons why imbalanced class problems exist.
The Weka interface of (DT) of 0 (zero) capture of minority and the ROC of 0.25 is in Appendix A.14 and A.15. for the capture of 1 minority the Weka interface of (DT) analysis and ROC of 0.697 is in Appendix A.16 and A.17.

Majority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.996	0.997	0.999	0.998	0.480	1478
	4	0.997	0.998	0.999	0.998	0.770	1477
	6	0.996	0.997	0.999	0.998	0.697	1477
	8	0.997	0.997	1.000	0.998	0.250	1479
PC	2	0.997	0.997	0.999	0.998	0.890	1478
	4	0.996	0.997	0.999	0.998	0.697	1477
	6	0.996	0.997	0.999	0.998	0.697	1477
	8	0.997	0.997	1.000	0.998	0.250	1479
IG	2	0.996	0.997	0.999	0.998	0.480	1478
	4	0.997	0.997	0.999	0.998	0.890	1478
	6	0.996	0.997	0.999	0.998	0.697	1477
	8	0.997	0.997	1.000	0.998	0.250	1479

Table 5.25: Results of majority class for Yeast data set for DT by (VR), (PC) and (IG) feature selection for class ERL(5)as Class 1, Others(1479) as class0

Minority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.996	0.000	0.000	0.000	0.480	0
	4	0.997	0.500	0.400	0.444	0.770	2
	6	0.996	0.333	0.200	0.250	0.697	1
	8	0.997	0.000	0.000	0.000	0.250	0
PC	2	0.997	0.500	0.200	0.286	0.890	1
	4	0.996	0.333	0.200	0.250	0.697	1
	6	0.996	0.333	0.200	0.250	0.697	1
	8	0.997	0.000	0.000	0.000	0.250	0
IG	2	0.996	0.000	0.000	0.000	0.480	0
	4	0.997	0.500	0.200	0.286	0.890	1
	6	0.996	0.333	0.200	0.250	0.697	1
	8	0.997	0.000	0.000	0.000	0.250	0

Table 5.26: Results of minority class for Yeast data set for DT by (VR), (PC) and (IG) feature selection for class ERL(5)as Class 1, Others(1479) as class 0

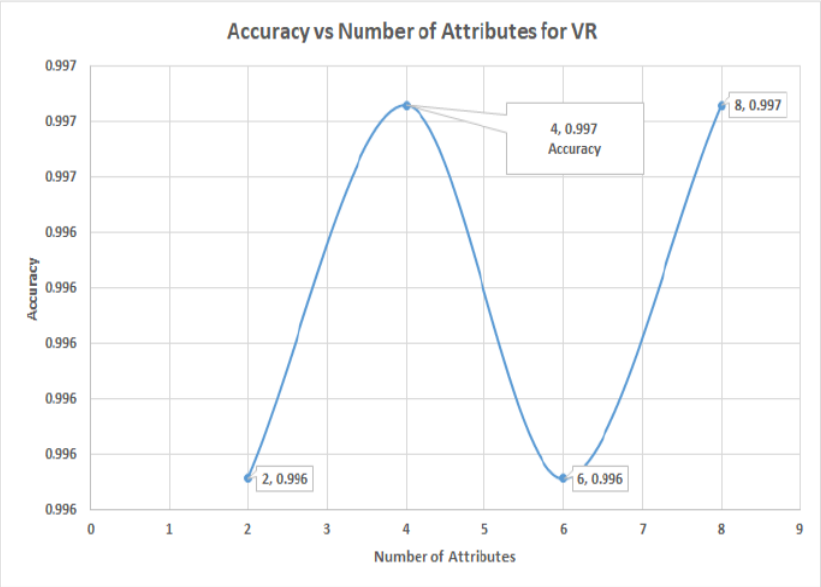


Figure 5.22: Graph of Accuracy vs Numbers of Attributes for Yeast class ERL(5) as class 1 and the others as class0(1479) for DT minority showing $(PTP)_{Accuracy}$ in both 8 and 4 attributes position

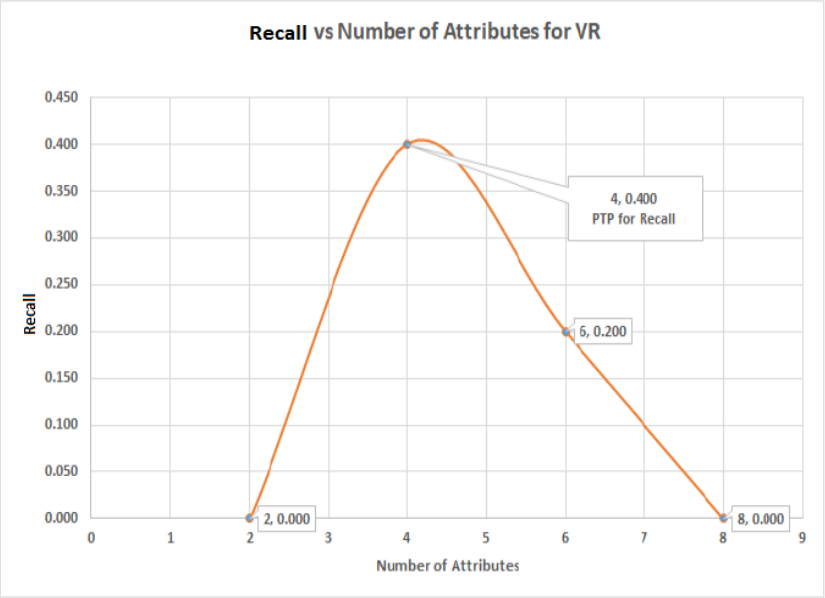


Figure 5.23: Graph of Recall vs Numbers of Attributes for Yeast class ERL(5) as 1 and the others as class0(1479) for DT minority showing $(PTP)_{minority}$ in the position of 4 attributes

5.0.17 Logistic Regression Experiments for Yeast data using One vs All (class ERL(5) as 1 others as class 0 (1479)) see Table 5.15

The results are in Tables 5.27 and 5.28, the graph is in Figure 5.24 and 5.25. The logistic experiment performed better than the Decision tree in 5.0.19.

Majority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.997	0.997	1.000	0.998	0.420	1479
	4	0.995	1.000	0.995	0.997	0.992	1471
	6	0.993	0.997	0.995	0.996	0.680	1472
	8	0.994	0.997	0.997	0.997	0.761	1475
PC	2	0.998	0.998	1.000	0.999	0.810	1479
	4	0.995	0.999	0.997	0.998	0.880	1474
	6	0.990	0.997	0.993	0.995	0.992	1468
	8	0.994	0.997	0.997	0.997	0.761	1475
IG	2	0.997	0.997	1.000	0.998	0.810	1479
	4	0.998	0.999	0.999	0.999	0.810	1477
	6	0.990	0.997	0.993	0.995	0.992	1468
	8	0.994	0.997	0.997	0.997	0.761	1475

Table 5.27: Results of majority class for Yeast data set for LR by (VR), (PC) and (IG) feature selection for class ERL(5)as Class 1, Others(1479) as class0

Minority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.997	0.000	0.000	0.000	0.420	0
	4	0.995	0.385	1.000	0.556	0.992	5
	6	0.993	0.125	0.200	0.154	0.680	1
	8	0.994	0.000	0.000	0.000	0.761	0
PC	2	0.998	1.000	0.400	0.571	0.810	2
	4	0.995	0.375	0.600	0.462	0.880	3
	6	0.990	0.083	0.200	0.118	0.992	1
	8	0.994	0.000	0.000	0.000	0.761	0
IG	2	0.997	0.000	0.000	0.000	0.810	0
	4	0.998	0.667	0.800	0.727	0.810	4
	6	0.990	0.083	0.200	0.118	0.992	1
	8	0.994	0.000	0.000	0.000	0.761	0

Table 5.28: Results of minority class for Yeast data set for LR by (VR), (PC) and (IG) feature selection for class ERL(5)as Class 1, and the others(1479) as class0

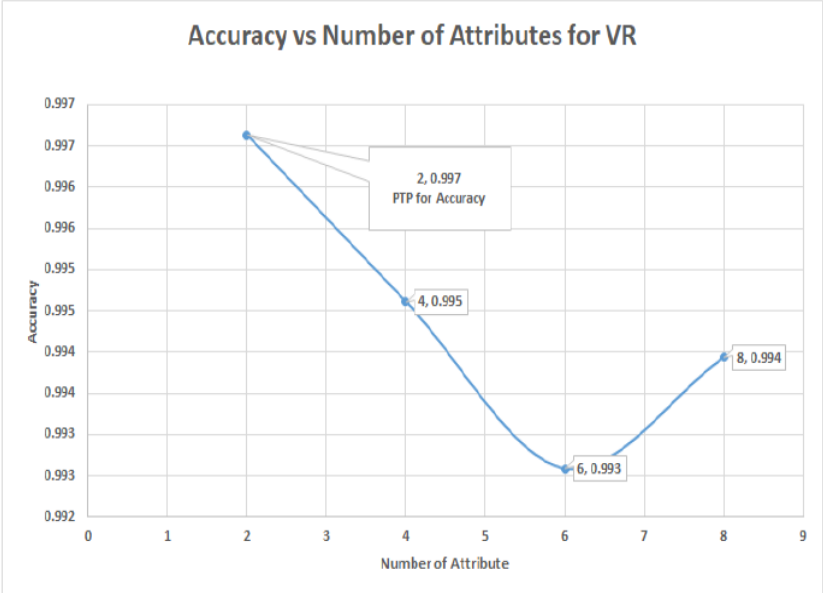


Figure 5.24: Graph of Accuracy vs Numbers of Attributes for Yeast class ERL(5) as class 1 and the others as class 0 (1479) for LR minority showing $(PTP)_{Accuracy}$ in the position of 2 attributes

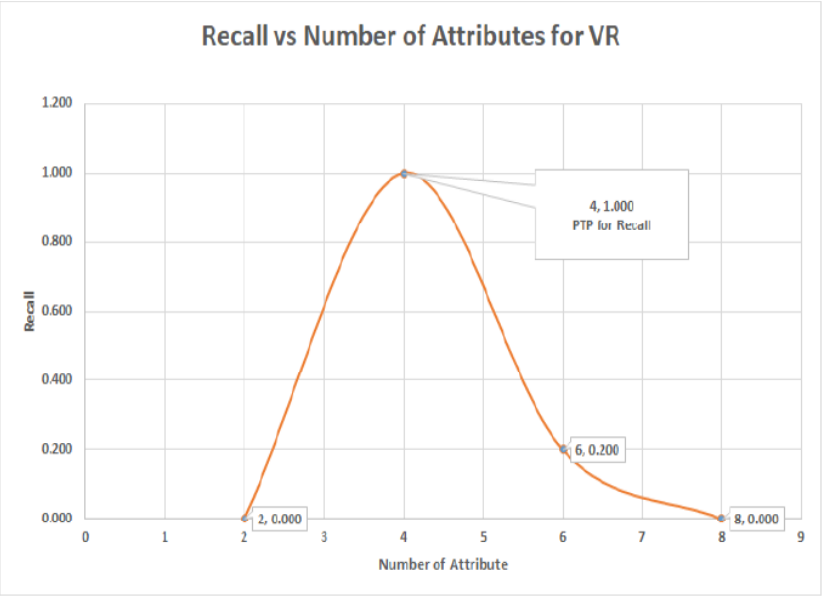


Figure 5.25: Graph of Recall vs Numbers of Attributes for Yeast class ERL(5) as class 1 and the others as class0(1479) for LR minority showing $(PTP)_{minority}$ in the position of 4 attributes

This results is one of the best that demonstrates the performance by (VR) over most other techniques; for being able to pick all the minority classes in an extremely imbalanced situation, the analysis interface of the experiments is in Appendix A.18

5.0.18 Decision Tree and Support Vector Machine Experiments for Yeast data using One vs All (class VAC (30) as class 1 others as class 0 (1454)) see table 5.15

This two algorithm experiments was combined because their results were similar and they were unable to capture any minority in a case of extreme imbalance and extremely overlapping. Figure 5.26 is the 3D representation of the classes; notice the small numbers of the minority classes and how they are overlapped with the majority. This is regarded as the extreme case of imbalance.

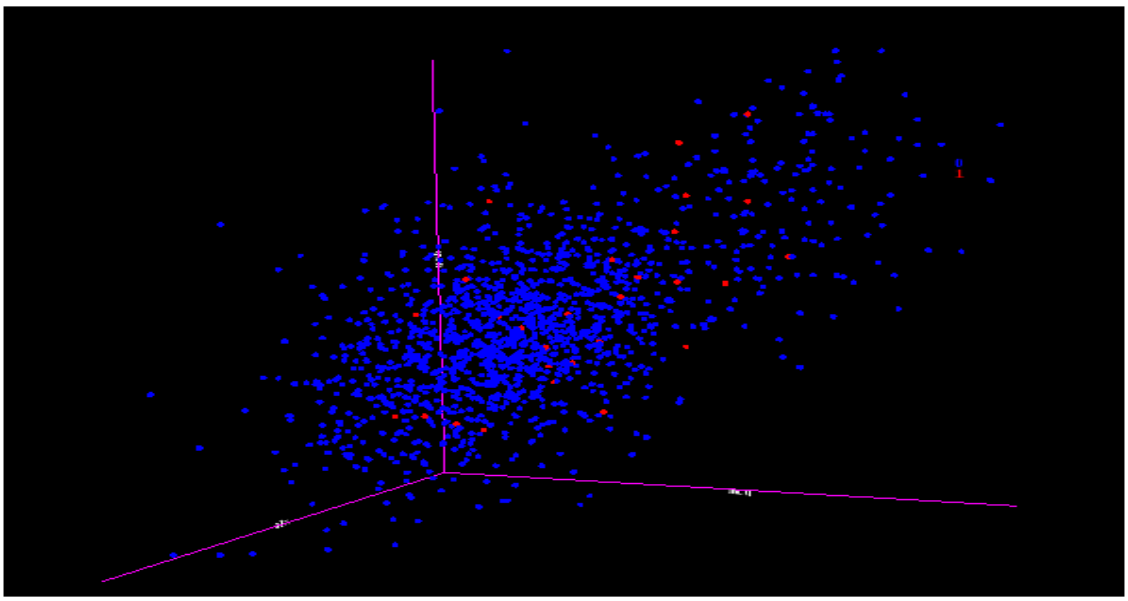


Figure 5.26: Extreme case of Imbalance class VAC(30) as 1 others as class0 (1454).docx

The Decision Tree and Support Vector machine algorithm is unable to capture any minority even using any attributes selections including our (VR). The Weka software analysis interface for the results and ROC Area values is in the Appendix A.19, A.21 and A.20 This shows that the effects of an extreme case of imbalance could also the effects the VR, PC, and IG. The point of this is that what ever affects the benchmark attributes selections also affects our VR; hence, we make the case that the VR is equal to the established attribute selections in terms of performance, and in many instances, it is better than the benchmark attribute selections.

5.0.19 Logistic Regression Experiments for Yeast data using One vs All (class VAC (30) as class 1 others as class 0 (1454)) see table 5.15

Majority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.920	0.980	0.937	0.958	0.660	1363
	4	0.887	0.981	0.902	0.940	0.660	1312
	6	0.887	0.981	0.902	0.940	0.660	1312
	8	0.975	0.980	0.994	0.987	0.660	1446
PC	2	0.920	0.980	0.937	0.958	0.660	1363
	4	0.887	0.981	0.902	0.940	0.660	1312
	6	0.887	0.981	0.902	0.940	0.660	1312
	8	0.975	0.980	0.994	0.987	0.660	1446
IG	2	0.969	0.980	0.988	0.984	0.690	1437
	4	0.913	0.981	0.929	0.954	0.690	1351
	6	0.887	0.981	0.902	0.940	0.660	1312
	8	0.975	0.980	0.994	0.987	0.660	1446

Table 5.29: Results of majority class for Yeast data set for LR by (VR), (PC) and (IG) feature selection for class VAC(30)as Class 1, Others(1454) as class 0

Minority class							
Algorithm	number of Attributes	(%) Accuracy	Precision	Recall	F-measure	ROC	total Captured
VR	2	0.920	0.022	0.067	0.033	0.660	2
	4	0.887	0.034	0.167	0.056	0.660	5
	6	0.887	0.034	0.167	0.056	0.660	5
	8	0.975	0.111	0.033	0.051	0.660	1
PC	2	0.920	0.022	0.067	0.033	0.660	2
	4	0.887	0.034	0.167	0.056	0.660	5
	6	0.887	0.034	0.167	0.056	0.660	5
	8	0.975	0.111	0.033	0.051	0.660	1
IG	2	0.969	0.056	0.033	0.042	0.690	1
	4	0.913	0.037	0.133	0.058	0.690	4
	6	0.887	0.034	0.167	0.056	0.660	5
	8	0.975	0.111	0.033	0.051	0.660	1

Table 5.30: Results of minority class for Yeast data set for LR by (VR), (PC) and (IG) feature selection for class VAC(30)as Class 1, Others(1454) as class 0

The results of the LR in Table 5.30 may initially appear odd because both (VR) and (PC) have the same results (same number of minority values captured). However, on close inspections of their comparison tables in 4.7 for the Yeast dataset with "class VAC as class 1 and the others as class 0," it can be observed that both attribute rankings of (VR) and (PC) are the same; as such; they should produce the same result.

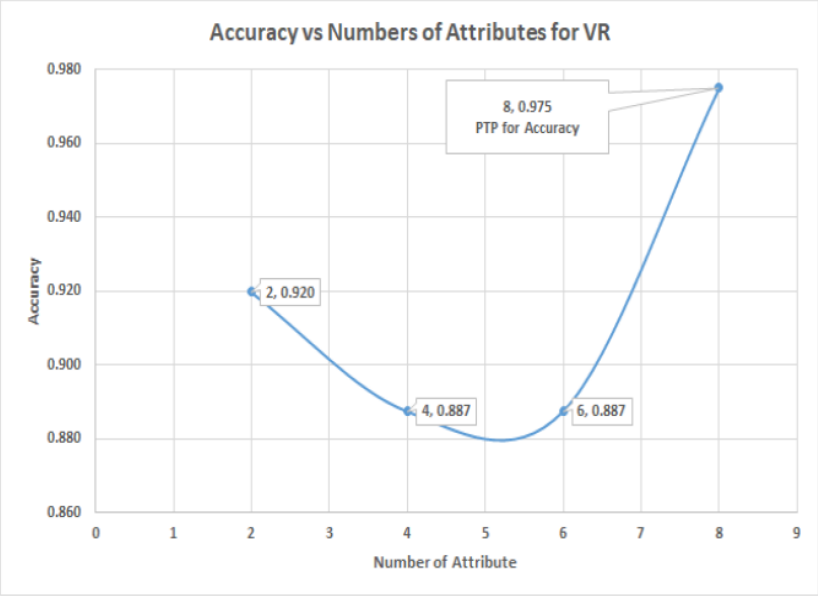


Figure 5.27: Graph of the Accuracy vs Numbers of Attributes for Yeast class VAC(30) as 1 others as class0(1454) for LR minority showing $(PTP)_{Accuracy}$ at the position of 8 attributes

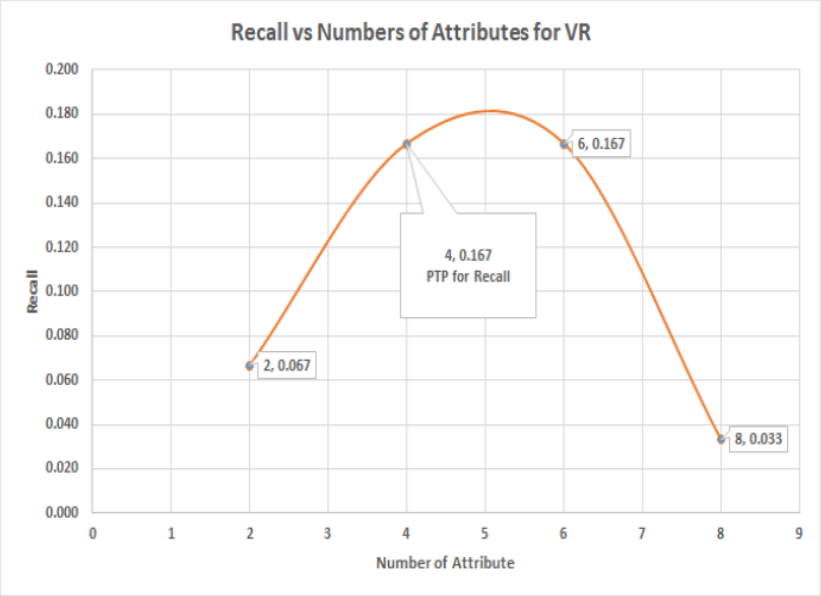


Figure 5.28: Graph of the Recall vs Numbers of Attributes for Yeast class VAC(30) as 1 others as class0(1454) for LR minority showing $(PTP)_{minority}$ at the position of 4 attributes

5.0.20 Conclusion

In this section, extensive experimentation was carried out to validate the VR technique by using multi-class datasets. We have explained and provided evidence of $(PTP)_{Accuracy}$ and $(PTP)_{minority}$ by using various graphs of accuracy and recall versus numbers of attributes in so doing we provided a method of recognizing the most significant attributes.

The experimentation and evidence provided in this section have shown that (VR) technique is usually superior and sometimes comparable to the benchmark attribute selections. The experiments also showed that (VR) techniques have more capability to capture the minority groups in an imbalanced data and the performance is equal or better when compared to either (PC) and (IG). Another advantages of the (VR) is that the same level of performance could be achieved with fewer attributes hence using less resource.

5.1 Comparison of Variance Ranking with the Work of Others On Imbalanced classed Data

5.1.1 Introduction

The research into imbalance classes and various ways to target minority class in both binary and multi-classed context have been one of the major challenges in

data science and its allied disciplines, and it will continue to remain so inasmuch as whatever knowledge we sought to support decision making processes will remain hidden in the midst of other distracting variables. For instance:

- If we sought to categorise different species of insects in a habitat.
- if we wish to identify a particular species of plant in the midst of other plants (multi classed imbalanced).
- The search for a particular protein strand that has the same dimension to more than ten other proteins (multi class imbalanced).

The list or situational occurrences of imbalanced classes are endless. Needless to say, that data scientist is faced with imbalanced data class issues much more than any other data analysis problems even if it may not be apparent. The questions then are " Why have they not been able to solve the problem up till now?" Though some efforts have been made over the years to solve this problem, but the success that has been achieved is abysmal in comparison to the enormity of the problems and the research interest it has garnered over the years. So what is the problems? During this research, we have come to conclusions that enough effort has been put into the research of imbalance classes but the poor results are due to the approaches that have been used, many researchers have approached the issues from the perspectives of the algorithm. By the way, there is no shot of machine learning algorithm and many of these have stood the test of time, from the last count, there are about fourteen major (ML) algorithm and counting [218], not to talk of different modifications of each, for example, Neural Network have been extended or rather modify to be Deep Learning and many others, also there are different modifications of decision tree, for example, ID3 (Iterative Dichotomiser 3), Classification and Regression Trees (CART), and C4.5. Hence enough (ML) algorithm are available and more will continue to come into the scene, please see [219].
From the analysis of all the major (ML) algorithm and their application in the context of imbalanced data issue, most algorithms are not designed to capture the minority group rather there are optimises to always capture the dominant majority group classes. That is why, most modelling excises always fall shot in performance as regard to the minority classes because by approaching the problems of imbalanced data from the algorithm perspectives without taking into consideration the reasons for the imbalanced.

5.1.2 New approaches to Imbalanced Data And Introduction To Sampling

In all the research work available to improve predictive performance. The only one, that correctly dealt with class imbalanced is the sampling techniques. There are two categories of sampling (Oversampling and Undersampling). Oversampling is to increase the data items while Undersampling is to reduce them. We are concentrating on the Oversampling (please see chapter 2 for the reasons). Prominent amongst the oversampling, which of course is the first to be invented is (SMOTE) which stands for Synthetic Minority Over-sampling Technique. This was invented by [94], followed a few years later by (ADASYN) which stands for Adaptive Synthetic Sampling and invented by [220]. Over the years different modifications of oversampling techniques like the BorderlineSMOTE, SMOTETomek, etc have continued to be invented, Please see [221] [222].

First and foremost, what is the reason for the imbalance? This due to the unequal numbers of the classes and is called the imbalanced ratio (IR), therefore any technique, formula or algorithm that did not factor the causes of the imbalance i.e.(IR) will always produces unreliable and inconsistent results when trying to replicate the experiments using different or even the same data.

Apart from the sampling techniques like the (SMOTE) and (ADASYN), Variance Ranking (VR) is the only techniques that have factored the (IR) in dealing with the imbalanced class problems. A detailed explanation of the (SMOTE) and (ADASYN) technique have been provided in section 2.2.6. just to summarised it, is artificially generating data items for the minority classes in other to make all the class groups equal, making the (IR) become 1:1, meaning that equal numbers of both the majority and minority classes. In the preceding sections the (VR) would be compared with (SMOTE) and (ADASYN) the reasons is that sampling techniques (Oversampling) is the only techniques that have applied the (IR) in their implementations for that, both techniques fell withing the same "Terms of Reference" with (VR) this provides the basis of the comparison between the three.

5.1.3 Similarities and Differences between (VR), (SMOTE) and (ADASYN)

One of the first similarities within these techniques is that all three processes involved the numbers of minority class groups, for example in (SMOTE) and (ADASYN), the numbers are increased (Oversampled) to equalised with the number of the majority class groups this, in turn, will interfere with the (IR).

Another basic similarity is that the three techniques are grouped as preprocessing activities, that is (VR), (SMOTE), and (ADASYN) are carried out on the datasets before any active (ML) algorithm is used or before modelling is carried out. There are also similarities in the area of sampling which is subjective to the amount of original dataset in the population. If the data set is in hundreds or a few thousand, the researcher may wish to use all the dataset instance but if the dataset instances is in the tens of thousands an appropriate sampling mechanism should be employed to make sure the active sample used in the experimentation is a true representation of the populations.

Impact of Class Overlapped to Performance of Modelling

There are also some differences between (VR) and the two oversampling; (SMOTE) and (ADASYN). First, during the process of (VR) the number of minority class groups or instances does not change, rather each of the class groups are separated into their various classes eg class 0 for negative and class 1 for positive class, before the sampling is done (please see section 3.3.2 for detailed explanations of (VR) and Figure 3.4 for its algorithm in form of flow chart). The choice of oversampling to use depends very much on the intrinsic properties of the classes of the data items. For example, how well separated or the values variances of each classes groups. The Figures 5.29 and 5.30 is a 3D scatter plot of Glass (Multi classed imbalanced) and Pima (Binary classed imbalanced).

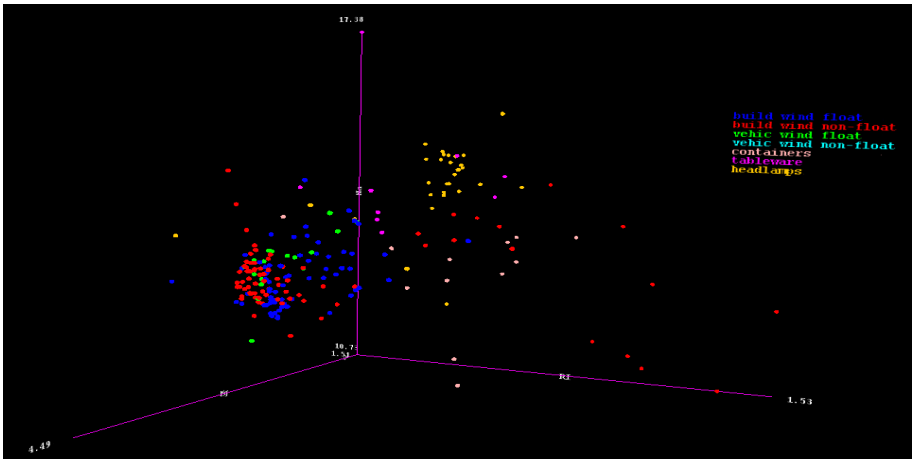


Figure 5.29: 3D Glass data Scatter plot

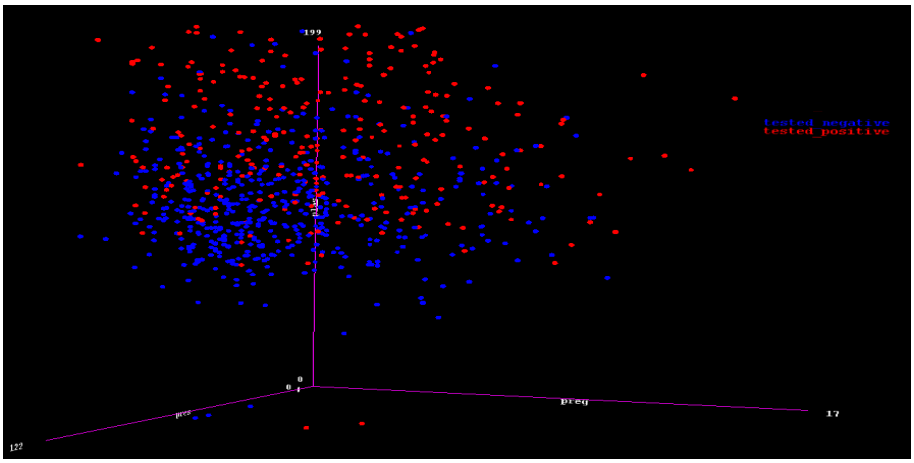


Figure 5.30: 3D Pima data Scatter plot

It could be observed that the values of the variances of each classes (both multi and Binary classed data set) are not separated, but very much overlapped, compare this two to Figure 5.31 of 3D scattered plot of Iris data set. notice the distinctive concentrations of each classes, hence there are not as overlapped as the other two (Figures 5.29 and 5.30).

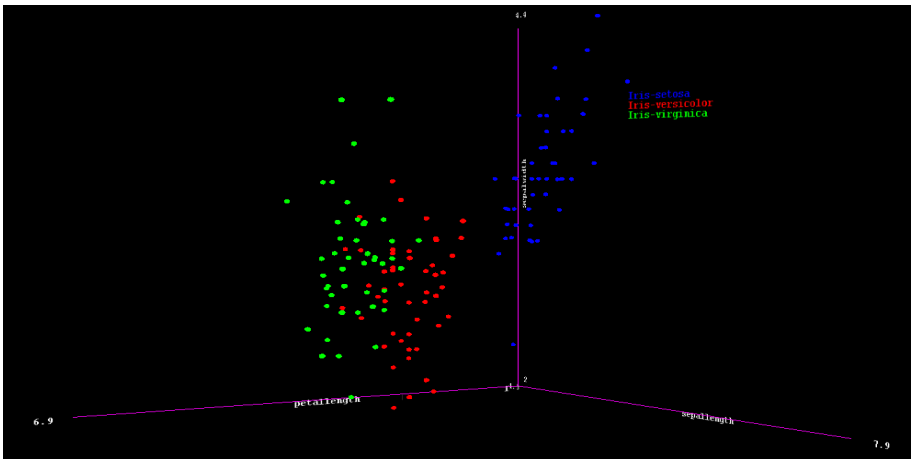


Figure 5.31: 3D Iris data Scatter plot

Therefore due to this overlap of the classes, the sampling techniques may perform very poorly but when the classes are separated as in Figure 5.31, sampling technique will perform very well. This is one of the disadvantages of sampling techniques in general and the advantage of (VR) over oversampling. Classes overlapped is one of the hindrances to achieving good result in predictive modelling, overlapped classes have most unit values of their attributes the same as such the (ML)algorithm will not be able to differentiate class group members, therefore, more data point will be confused and group into the wrong classes leading to high False Positive(s) and False Negative(s). (VR) has an added advantages of not being affected by this overlap and "One versus All" used in this work have also augmented the separations of the

classes adding to distinctiveness of the class separation and better performance

5.1.4 Performance comparisons Between (VR), (SMOTE) and (ADASYN) on Common data sets

In this section, a comparatives performance between these three ((VR), (SMOTE), and (ADASYN)) imbalanced data classification techniques would be investigated. before that is done, lets review "The terms of reference" under which this comparison will be carried out and to establish the "comparator" in this case the results obtained from the (VR). Therefore the terms of reference are as follows:

- which of these three techniques would capture the highest number of minority class or have the highest "Recall" at a specific number of attributes (The point of $(PTP)_{minority}$)
- of this three tecniques which shows the highest "Accuracy" and at which specific number of attributes (the points of $(PTP)_{Accuracy}$)

As the focus is specifically on the recall of the minority class group, the comparison will be focusing on that, this is to underscore the emphasis on the minority class and the primary aim of any techniques to handle imbalanced data is to reduce the bias toward the majority and provide an even playing field for the modelling algorithm to equally target all the classes

5.1.5 Experiment Set up

In this comparative experiment. We shall try to replicate the (SMOTE) and (ADASYN) experiment as much as possible and compare their performance with that of (VR), the idea is to ascertain the one that will produce the best performance in terms of the "Accuracy" and the "Recall" of the minority class groups. Three of the data set (Pima diabetes, Ionosphere, and Wisconsin cancer data) that was used in the initial experiment by [94] to the invent (SMOTE) in 2002 and also used by [220] to invent (ADASYN) in 2008, are still available in public domain and I have also used two of them extensively in this research. All data preparations, sampling, and processes have been discussed in details in chapter 2.
The Table 5.31 is the experiments conducted for the comparisons, The relevant metric is the $(PTP)_{Accuracy}$ represented by the Accuracy, the $(PTP)_{minority}$ represented by the Recall and the F-measure.

Data Set	Techniques	Accuracy	Recall	F-measure
Pima	SMOTE-LR	0.691	0.535	0.507
	ADASYN-LR	0.717	0.619	0.563
	VR-LR	0.771	0.578	0.638
Wiscosin	SMOTE-LR	0.927	0.864	0.892
	ADASYN-LR	0.941	0.896	0.913
	VR-LR	0.943	0.968	0.923
Ionosphere	SMOTE-LR	0.849	0.735	0.785
	ADASYN-LR	0.863	0.736	0.793
	VR-LR	0.906	0.777	0.860

Data Set	Techniques	Accuracy	Recall	F-measure
Pima	SMOTE-DT	0.732	0.601	0.610
	ADASYN-DT	0.733	0.600	0.612
	VR-DT	0.685	0.679	0.601
Wiscosin	SMOTE-DT	0.924	0.899	0.889
	ADASYN-DT	0.923	0.900	0.888
	VR-DT	0.956	0.941	0.939
Ionosphere	SMOTE-DT	0.880	0.762	0.821
	ADASYN-DT	0.872	0.740	0.812
	VR-DT	0.926	0.849	0.892

Data Set	Techniques	Accuracy	Recall	F-measure
Pima	SMOTE-SVM	0.732	0.581	0.594
	ADASYN-SVM	0.733	0.600	0.612
	VR-SVM	0.742	0.612	0.616
Wiscosin	SMOTE-SVM	0.931	0.890	0.897
	ADASYN-SVM	0.937	0.901	0.908
	VR-SVM	0.967	0.954	0.952
Ionosphere	SMOTE-SVM	0.880	0.762	0.821
	ADASYN-SVM	0.895	0.825	0.843
	VR-SVM	0.926	0.838	0.893

Table 5.31: Evaluation Metric And Performance Comparison VR, SMOTE and ADASYN

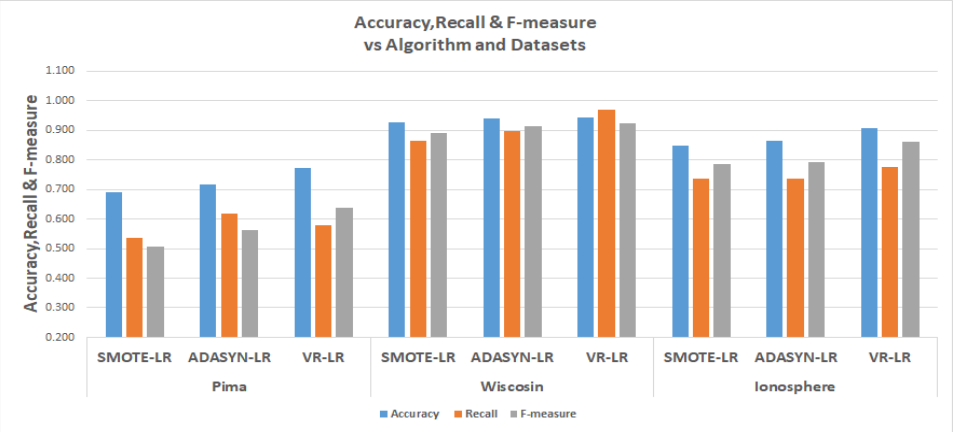


Figure 5.32: Graph Evaluation Metric And Performance Comparison LR

Detailed graphs of the tables are also presented in Figures 5.32, 5.33 and 5.34. In the Table, the results of (SMOTE) and (ADASYN) have been compared to the results of (VR). The in (LR) experiments for the Pima data the (ADASYN) performed better in terms of the recall, but in term of the accuracy with 77.1% the (VR) performed better, for the Wisconsin and Ionosphere data the (VR) performed better in terms of both recall and accuracy. The Wisconsin has a value of 94.3% and 96.8% for the accuracy and recall. For the Ionosphere, the (VR) also outperformed the (SMOTE) and (ADASYN) with of accuracy of 90.6% and 77.7% for recall. For clarity, the graph in figure 5.32 is the (LR) experiments.

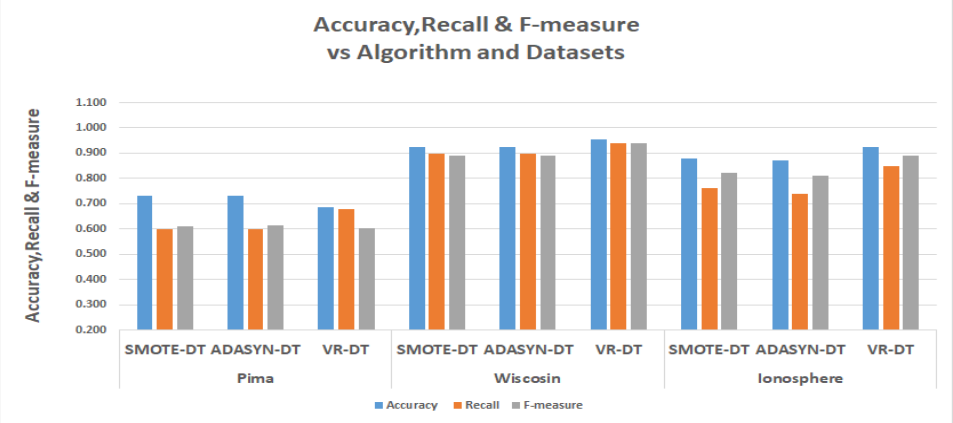


Figure 5.33: Graph Evaluation Metric And Performance Comparison DT

The (DT) experiments in the second table of Tables 5.31, the (VR) performed better than (SMOTE) and (ADASYN) in recalls. In the Pima data the (VR) has a recall of 67.9% as against 60% and 60.1% for (SMOTE) and (ADASYN), in Wisconsin (VR) has a recall of 94.1% while (SMOTE) and (ADASYN) has 90% and 89.9% respectively. In the Ionosphere data (VR) has a recall of 84.9%, while (SMOTE) and (ADASYN) has recalls of 74% and 76.2%.

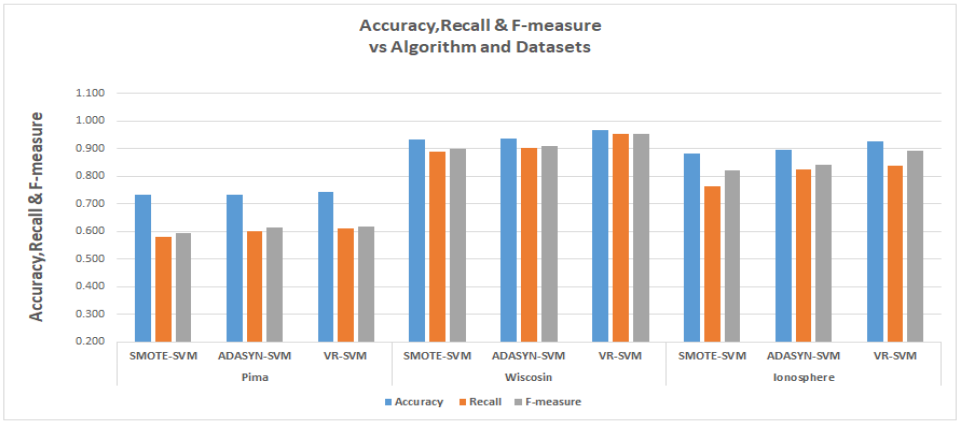


Figure 5.34: Graph Evaluation Metric And Performance Comparison SVM

Finaly, in the (SVM) experiments the (VR) also has a better recall for Pima data with 74.2% while (SMOTE) and (ADASYN) has recalls of 58.1% and 60%. In Wisconsin data, (VR) has recall of 95.1% and (SMOTE) has 89% while (ADASYN) has 90.1%. The Ionosphere data has 83.8% for (VR) while (SMOTE) and (ADASYN) has recall of 76.2% and 82.5% respectively.

5.1.6 Conclusion

The (VR) techniques for dealing with imbalanced class problems have shown better performance in the nine experiments carried out to compare it with (SMOTE) and

(ADASYN) techniques that are dedicated for dealing with imbalanced classed data. Just like the (SMOTE) and (ADASYN), it's also algorithm independent. In the field of predictive modelling, the techniques to use depends on lots of factors like computational power, scattered plot distributions of variable and even the intrinsic properties of the data items, but (VR) have come to stay as a superior alternative which has been demonstrated here.

Chapter 6

Summary Discussion and Conclusions

This work has established the fact that imbalance data problems pervade all sections of real-life predictive modelling no matter the scenario or the nature of the data (granular or non-granular), therefore devising the ways of dealing with this problems will drastically improve the results of any predictive modelling.
This research is motivated by the apparent gap in knowledge as regards to the unreliable way that the existing techniques of dealing with imbalanced classed data since the existing technique results are very subjective to lots of factors thereby bringing the validity and reliability of the results obtained to question
The main aim of this research is to invent a new techniques (if not better one) to handle imbalanced classed data that would be "foolproof" and not subjective to machine learning algorithm being used and or any other intrinsic properties of the dataset and host of other factors that has been the bane of the existing techniques.

6.1 Summary Critique of Existing Algorithm and Sampling Approaches

Though some good result have been achieved using different (ML) algorithm and the sampling techniques, but the critiques of these techniques is around the context of the validity and reliability of the modelling results, the reasons that led to this criticism are summarised as follows:

6.1.1 Critique of Existing Algorithm Techniques.

- Most machine learning algorithm did not factor the imbalanced ratio in their design as such were not made to be sensitive to small class groups (minority) in the dataset.
- Most algorithm has optimisation functions that tend to recognise the majority class groups, for example in Support Vector Machine algorithm has more than four Kernel functions, while K- Nearest Neighbour could use Euclidean or Manhattan distance, etc.
- Using algorithm involved changing the different parameter to achieve a desirable result, such parameter is not fixed but is different for different algorithms, even when using the same algorithm the parameter could change depending on the intrinsic properties of the data sets being used.
- It is difficult to replicate the results obtained using the algorithm methods, hence the reliability and validity of the results are in question.

6.1.2 Critique of Existing Sampling Techniques.

Though in this work we have emphasis more on oversampling technique for the simple fact that is more popular and undersampling is discouraged because of the chances of removing important data items. In general sampling techniques critiques could be summarised as follows:

- Very sensitive to overlapping classes, please see Figures 5.29, 5.30 and 5.31
- Oversampling produces a replica of the existing data items thereby increasing the confused classes (False positives and false negatives) that will further reduce the general accuracy of the model
- Sampling also has all the disadvantages of the algorithm techniques as mentioned above.

6.1.3 Summary of the Contributions of this Thesis

The contents of this research have provided completely new approaches to solving the imbalanced classed problem that is algorithm independent, not affected by class attributes overlapped and uses One-versus-All to augment the process. All major contributions listed in the specifications have been achieved and evidenced with a series of examples, for clarity, a summary review of the aims and objectives and the

Contributions are below.
The aim and objective of the research are to develop new techniques to solve the problems of imbalanced classes in both binary and multi-classed data set. All aspects of this research are channel towards achieving these aims and objectives that led to a series of processes, procedure, and experimentation. And also many contributions to knowledge.

- ***Review of Variance Ranking Technique.*** A novel attributes selection called the (VR). The superiority of the techniques of over existing methods were also vetted with adequate proof of Concept of how (VR) is algorithm independent and not affected by overlapping classes. All these were developed and explained chapter three session 3.1.1 .

- ***Review of Peak Threshold Performance.*** We demonstrated and introduced the concept of Peak Threshold Performance to establish the points to select the significant attributes at which the modelling performance could have high Accuracy and high Recall for the minority class group. These two conceptual points were defined as $(PTP)_{Accuracy}$ and $(PTP)_{minority}$. And also We introduced and provide ways to identify the point and the number of attributes required to get dependable performance in any machine learning or data mining activity. These are further explained in chapter five from session 5.0.1 to section 5.0.20.

- ***Review of Ranked Order Similarity .*** In comparing (VR) and other established state of the art attributes selections that are categorised as filter method, notably the (PC) and (IG) a new similarity measure was invented called Ranked Order Similarity (ROS). Please see chapter four session 4.4. for a complete explanations.

These are just the summary of the contributions of this thesis that has made this work stand out. We believed beyond any doubt that this work has answered lots of questions and in so doing has also raised some too, any person(s) that took the pain to read it will have lots of insight for future work and scholarship.

6.2 Recommendations

The work has been exhaustive and many techniques invented were directly or indirectly intended to minimise the negative effects of class imbalance, but along the line many new and existing processes and procedures has been applied in a way that

has not been done before, that provided a novelty in his own right. On this note the following recommendations is being made to further help in the implementations of the novelty processes that were carried out in this research.

- This processes of (VR) is highly recommended for numeric data type where the measurement of central tendency is possible.
- It is recommended that an exploratory activities should be carried in each dataset to investigate the extent of overlapping of the classes before a detailed implementation of the (VR) is carried out, this would give the researcher an idea of the sample size that is needed.
- Just like most data centric research, the more sample the better results. No matter the distribution of the data in the sample space, central limit theorem may be used to estimate the population mean, deviation both before and after the datasets are separated into their respective classes. This would enable the research to estimate the differences between the classes data descriptive statistics.
- Comparative feature selections should be run to compare (VR) and other feature selection. This would provide higher level of confidence to the ranking of the (VR) results.
- The (ROS) is recommended to quantify the similarity between two or more items when other similarity index is not applicable.
- The (ROS) has also been found to be very accurate in word recognition. In a situation where word recognition for query recall or when an Anagram is needed.

6.3 Limitations

In formulating these research specifications and carrying it out, efforts have been made to ensure that the solutions proffered are as encompassing and far-reaching as much as possible to enable most imbalanced classed problems to be solved.
But there are some limitations, these have been explained below.

- The (VR) technique can only be applied to numeric data. we should remember that is based on the measurement of one of the central tendency (variance). Provided the central tendency like mean, median, mode standard deviation of the attributes in the data set have a meaning in terms of being used to explain

and provide a "summary statistics" of the data set, then this techniques could be applied, but if the central tendency of the data could not be measure eg categorical data this technique is not applicable.

- If some interval data could be re-corded into numeric data, for example first position is 1, second position is 2 and third position is 3. In such situation the mean, standard deviation and probability distribution could be obtained, Then it is possible to apply the (VR). But not all interval scale could be re-coded into numeric data and as such the measurement of the central tendency is not possible, therefore (VR) will not be possible.

- Though many classed imbalanced problems have been solved here. That is not to say that this thesis is the panacea to all imbalanced classed problems. Far from it, the ubiquitous nature of real-life data is such that there will never be a single solution to any modelling problems imbalanced or not, rather collections of procedures and processes will continue to be invented to tackle each peculiarity of imbalanced problems, hence they may be issues relating to imbalanced that may emerge in future that we may not have seen before because data science is relatively new and evolving by the day.

- The Ranked Order Similarity (ROS) is also limited to textual similarity just like levenshtein similarity. It could identify and retreived a text if there is similarity between a search input and a "bag of words". It does not use angles between words like cosine similarity.

6.4 Future Work

The future work will be extending the technique to categorical data by implementing a weighting strategy to enable a "summary statistics" on such data type. Finding a techniques to calculate the descriptive statistics of categorical data is an active area of research for quite some time; one has to check the research data banks like google scholar to realise the enormity of the research interest, the new direction is, therefore, to utilise some of the research concepts to implements (VR) on categorical data.

Classification algorithms are dichotomised, meaning the algorithm classifies a data point to belong to this class or that class, therefore is very possible to integrate (VR) techniques into many (ML) algorithm for more augmented dichotomy which may improve the distinctions between the classes and improve the general performance

of the algorithm, the future research implications are in the direction of integration of (VR) and most (ML) algorithm

6.4.1 Final Summary

In this thesis, we have ended up with the solution that addresses problems of classed imbalanced in classification modelling. Thus has addressed a significant problems associated with predictive modelling when using real-life dataset. It has proven that classed imbalanced problems is more prevalent than any other errors associated with data and shows that imbalance problems are always in addition to any other problems that the dataset may have. A techniques called Variance Ranking Attributes Selection (VR) has been produced and demonstrated. A methods of choosing the most significant attributes that would enable higher recall of the minority class groups through a process of Peak performance Threshold has also been demonstrated. A process of similarity index called the Ranked Order Similarity (ROS) has also been developed to compare the result of (VR) and that of (PC) and (IG).

The question now remaining is this "At what stage during predictive modelling processes" does (VR) fit into? To answer this let us find a parallel with the techniques we have compared (VR) with and find where all those techniques fit into. We have compare (VR) with (PC) and (IG) attributes selection in chapter 4 because it is an attributes selection technique, we have also compared it with (SMOTE) and (ADASYN). All these four comparisons are at the stage of Preprocessing, therefor without any doubt, (VR) should be carried out at the data Preprocessing stage.

Intriguing, revolutionary, etc, these are some of the words that have been used to describe this thesis by the few people that have read it. I believe that the basis of a Ph.D. is to think "out of the box" with new radical ideas, not "Business as usual". Knowledge grows when we experiment with new things and ideas and it will continue to evolve. There were times when the best brain mankind could boast of were those that believe the Earth was flat, we may laugh at them now, but alas! they were the people that first raise the questions by asking what is the shape of the Earth?

When the (SMOTE) techniques were invented it may also have been described as intriguing and revolutionary then, but here I am trying to find solutions to some of its shortcomings. Therefore this work is not intended to diminish their contributions at all rather give maximum accolade to these deep thinking scholars. Maybe in some years to come a new work may emerge onto the scene and provide some correction

to this work, but before then, I say have an exciting time as you read this thesis and God Bless!!.

The End.

Appendix A

Appendix

Yeast dataset Number of Attributes: 9 (8 predictive, 1 Target class) Number of Instances: 1484 Missing Value: None		
sn	Abv	Attributes
1	mcg:	McGeoch's method for signal sequence recognition.
2	gvh:	von Heijne's method for signal sequence recognition.
3	alm:	Score of the ALOM membrane spanning region prediction program.
4	mit:	Score of discriminant analysis of the amino acid content of
5	erl:	Presence of "HDEL" substring (thought to act as a signal for
6	pox:	Peroxisomal targeting signal in the C-terminus.
7	vac:	Score of discriminant analysis of the amino acid content of vacuolar
8	nuc:	Score of discriminant analysis of nuclear localization signals
Target Class:		
CYT (cytosolic or cytoskeletal)		463
NUC (nuclear)		429
MIT (mitochondrial)		244
ME3 (membrane protein, no N-terminal signal)		163
ME2 (membrane protein, uncleaved signal)		51
ME1 (membrane protein, cleaved signal)		44
EXC (extracellular)		35
VAC (vacuolar)		30
POX (peroxisomal)		20
ERL (endoplasmic reticulum lumen)		5

Table A.1: Data used in the experiment continue

Pima Indians Diabetes data

Number of Instances: 768

Attributes: 8 plus one class

Negative: 500 (65.10%) =0

Positive: 268 (34.90%) = 1

Missing Attribute Values: Yes

#	Abrv	Attribute
1	preg	Number of times pregnant
2	plas	Plasma glucose concentration a 2hours in an oral glucose tolerance test
3	diapres	Diastolic blood pressure (mm Hg)
4	skin	Triceps skin fold thickness (mm)
5	insutest	2-Hour serum insulin (mu U/ml)
6	mass	Body mass index (weight in kg/ (height in m) ^2)
7	pedi	Diabetes pedigree function
8	age	Age (years)
9	class	Class variable (0 or 1)

Wisconsin breast cancer

(as of 15 July 1992) Number of Instances: 699

Benign: 458 (65.5%) =2

Malignant: 241 (34.5%)=4

Missing values: none

#	Attribute
1	Sample code number
2	Clump Thickness
3	Uniformity of Cell Size
4	Uniformity of Cell Shape
5	Marginal Adhesion
6	Single Epithelial Cell Size
7	Bare Nuclei
8	Bland Chromatin
9	Normal Nucleoli
10	Mitoses
11	Class: (2 for benign=0, 4 for malignant=1)

BUPA liver disorders

Number of instances: 345

Number of attributes: 6 and one class, 7 overall

Class2:200(57.97%)=2

Class1:145(42.20%)=1

Missing values: none

#	Abv	Attribute
1	mcv	mean corpuscular volume
2	alkphos	alkaline phosphotase
3	sgpt	alamine aminotransferase
4	sgot	aspartate aminotransferase
5	gammagt	gamma-glutamyl transpeptidase
6	drinks	number of half-pint equivalents of alcoholic beverages drunk per day
7	Class	selector field used to split data into two sets Class split (1 or 2)

Cod-rna

Number of Instances: 488565

Number of Attributes = 8 and 1 class, 9 overall

Class negative as 0 =325,710 (67%)

Class positive as 1=162,855 (33%)

Missing Values: None

#	Abv	Attribute
1	X1	Ribonucleic acid identified (numeric)
2	X2	Ribonucleic acid identified (numeric)
3	X3	Ribonucleic acid identified (numeric)
4	X4	————-As above——
5	X5	————-As above——
6	X6	————-As above——
7	X7	————-As above——
8	X8	————-As above——

Glass Identification Data

(including an Id#) plus the class attribute. Multi classed (6 classes available in

sn	Abr	Attributes
	Id	Id number: 1 to 214
1	RI	refractive index
2	Na	Sodium (unit measurement:)
3	Mg	Magnesium
4	Al	Aluminum
5	Si	Silicon
6	K	Potassium
7	Ca	Calcium
8	Ba	Barium
9	Fe	Iron
10	Class	(1 to 7)\\-- 1 building_windows_float_processed -- 2 building_windows_non_float_processed -- 3 vehicle_windows_float_processed -- 4 vehicle_windows_non_float_processed (none in this database) -- 5 containers -- 6 tableware -- 7 headlamps

Iris data

Number of Instances: 150 (50 in each of three classes)

Number of Attributes: 4 numeric

Missing Attribute Values: None

Class Distribution: 33.3% for each of 3 classes.

#	Attribute
1	sepal length in cm
2	sepal width in cm
3	petal length in cm
4	petal width in cm
5	class:
	-- Iris Setosa
	-- Iris Versicolour
	-- Iris Virginica

Table A.2: Data used in the experiment continue

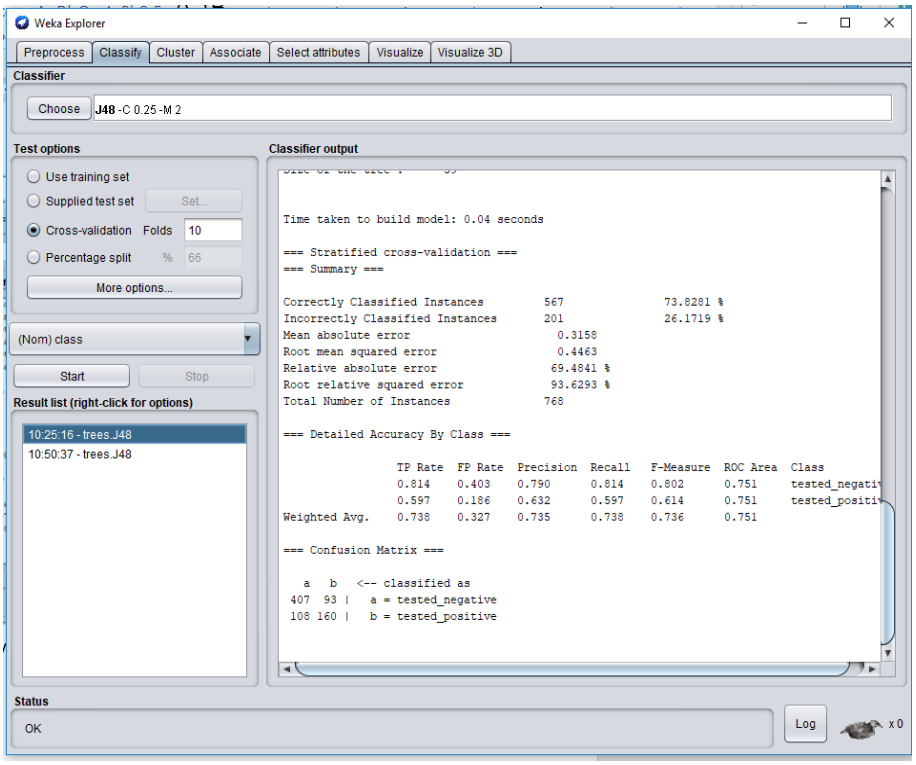


Figure A.1: Weka Interface experiment for all features in Pima data using Decision Tree

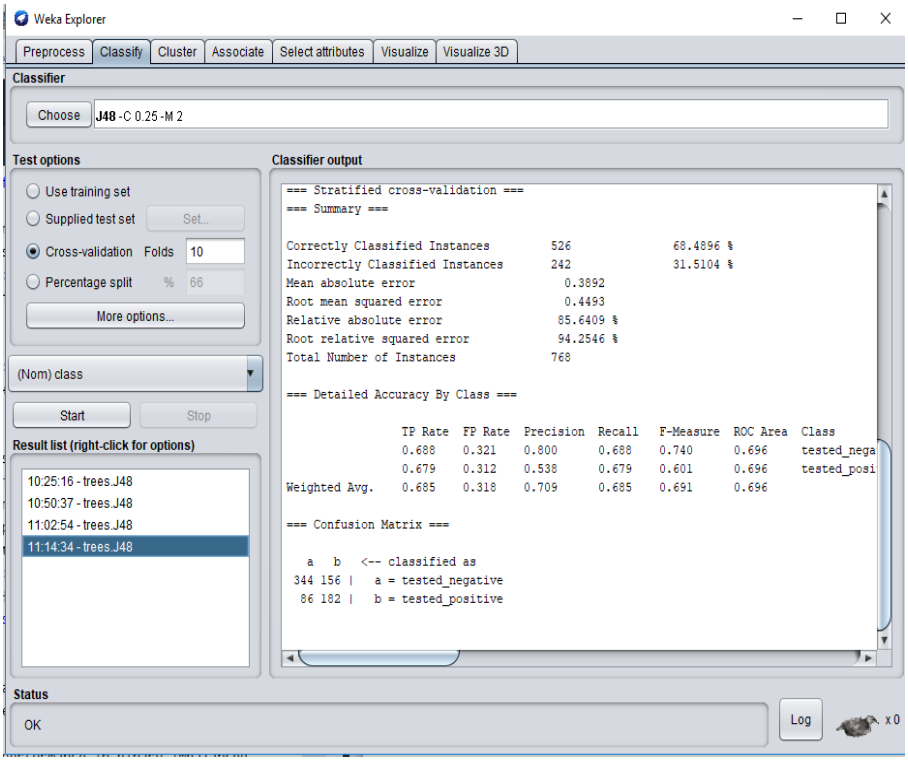


Figure A.2: Weka Interface experiment for only two features in Pima data using Decision Tree

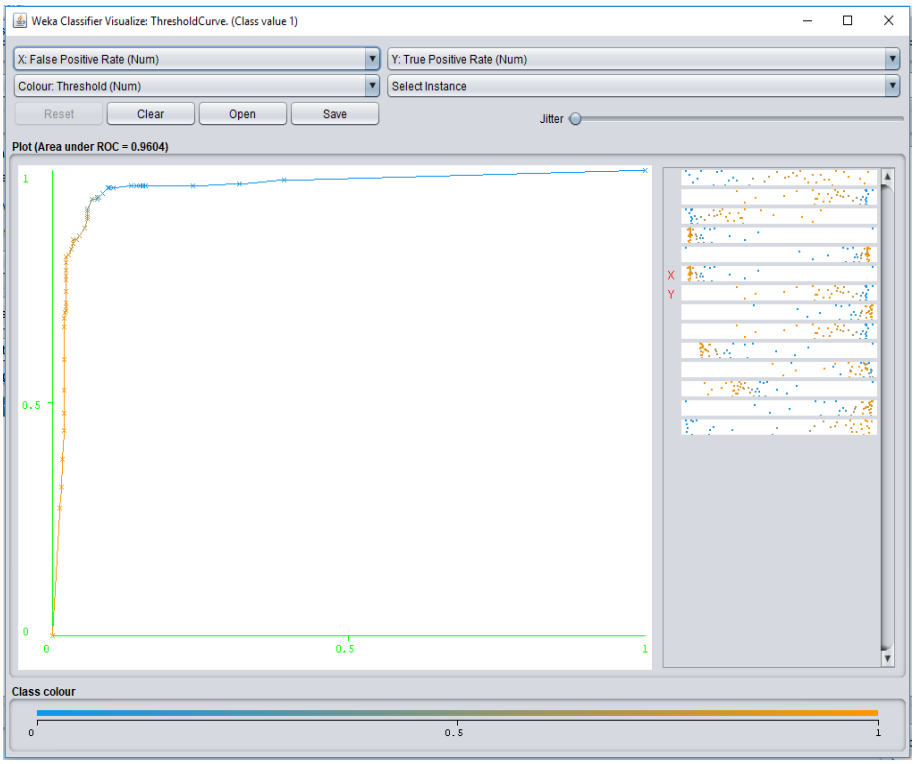


Figure A.3: Weka ROC for DT Wisconsin

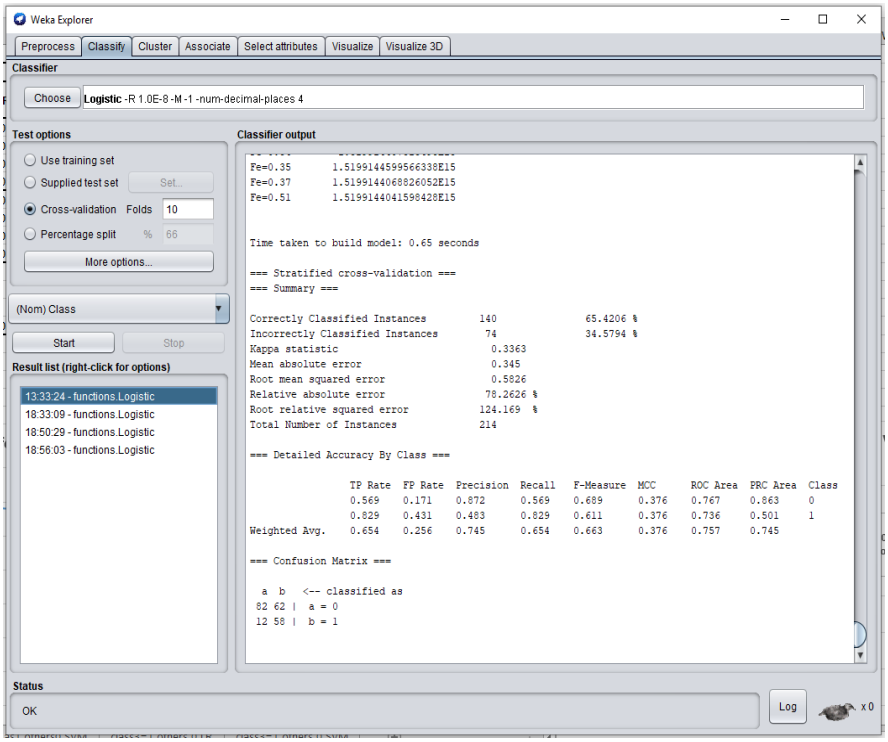


Figure A.4: weka Glass class1 as1 other0 LR, for minority captured

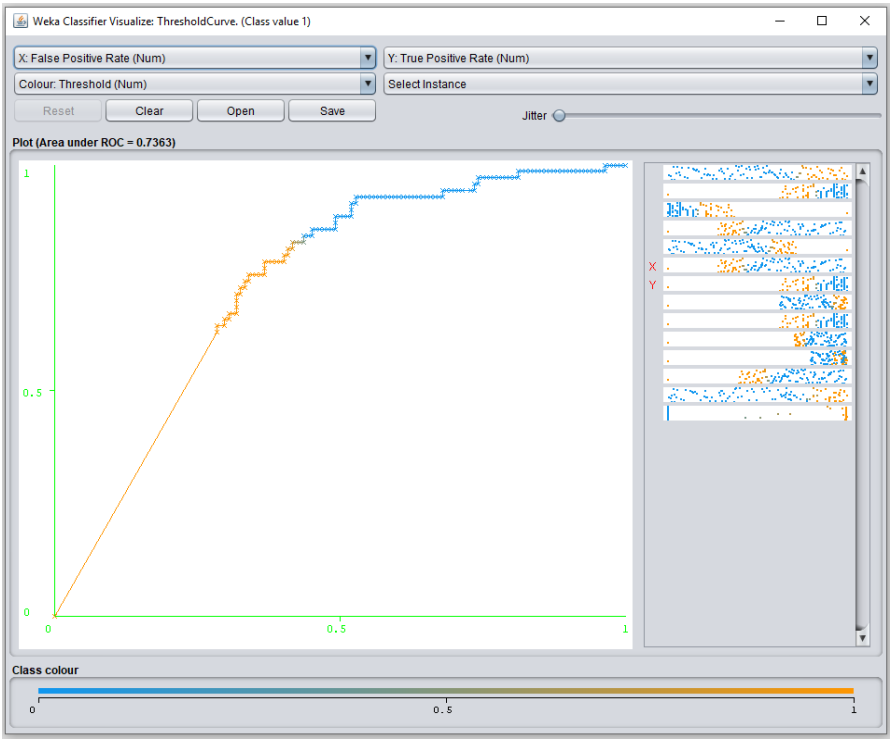


Figure A.5: weka Glass class1 as1 other0 LR, for minority captured the ROC

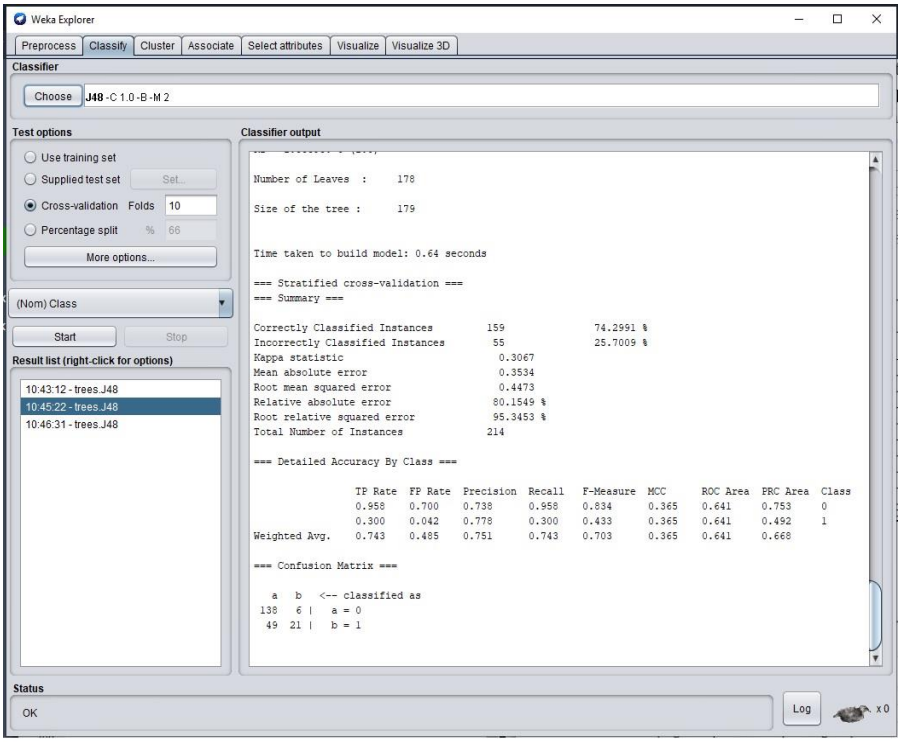


Figure A.6: weka Glass class1 as1 other 0 DT-21 minority captured

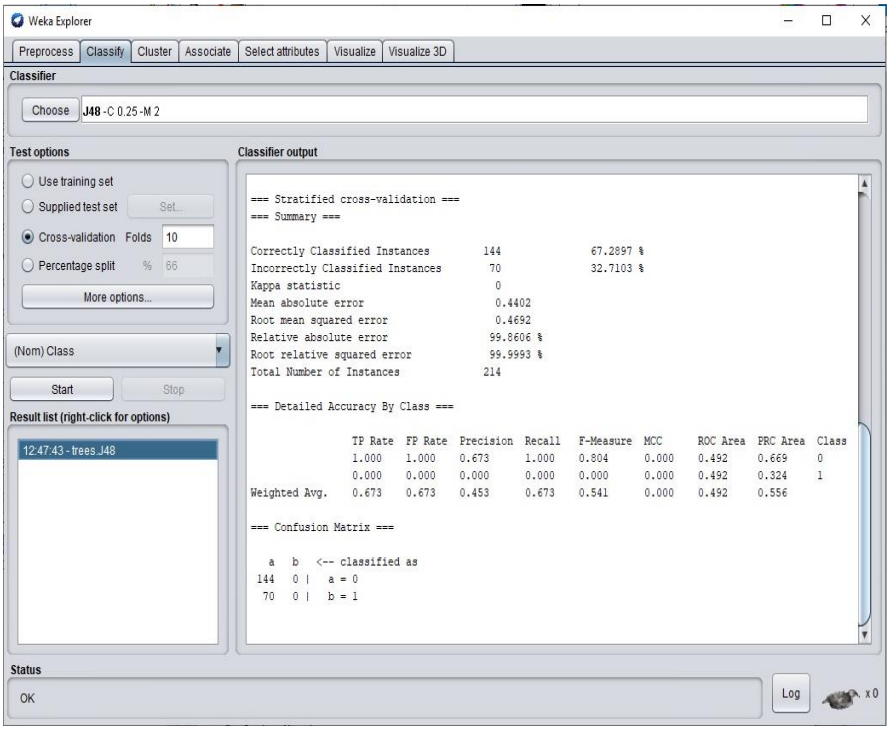


Figure A.7: weka Glass class1 as 1 other 0 DT, 0 minority captured

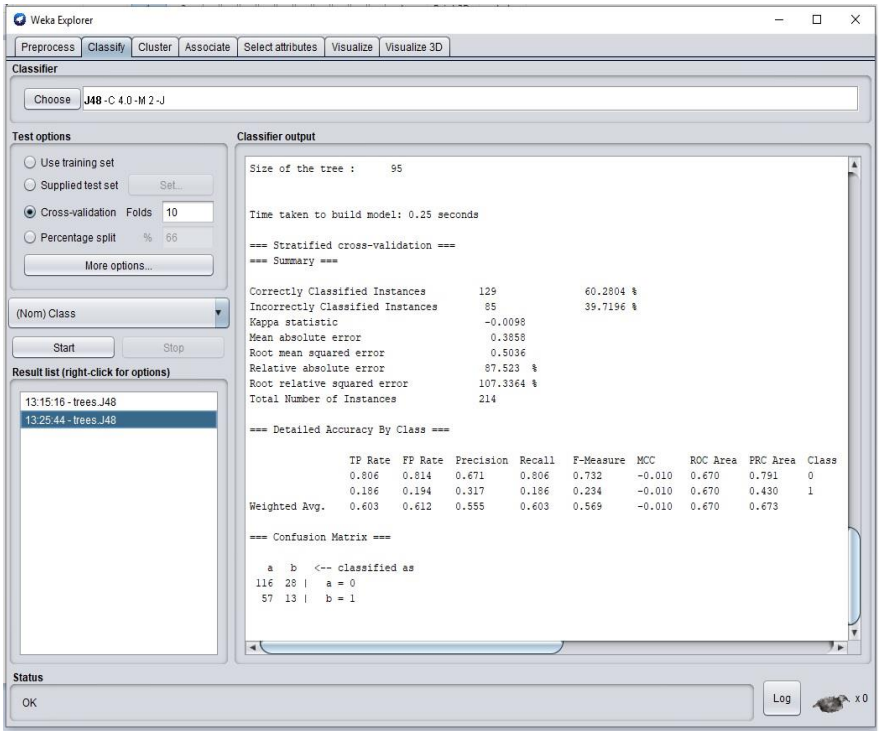


Figure A.8: weka Glass class1 as1 other 0, DT 13 minority captured

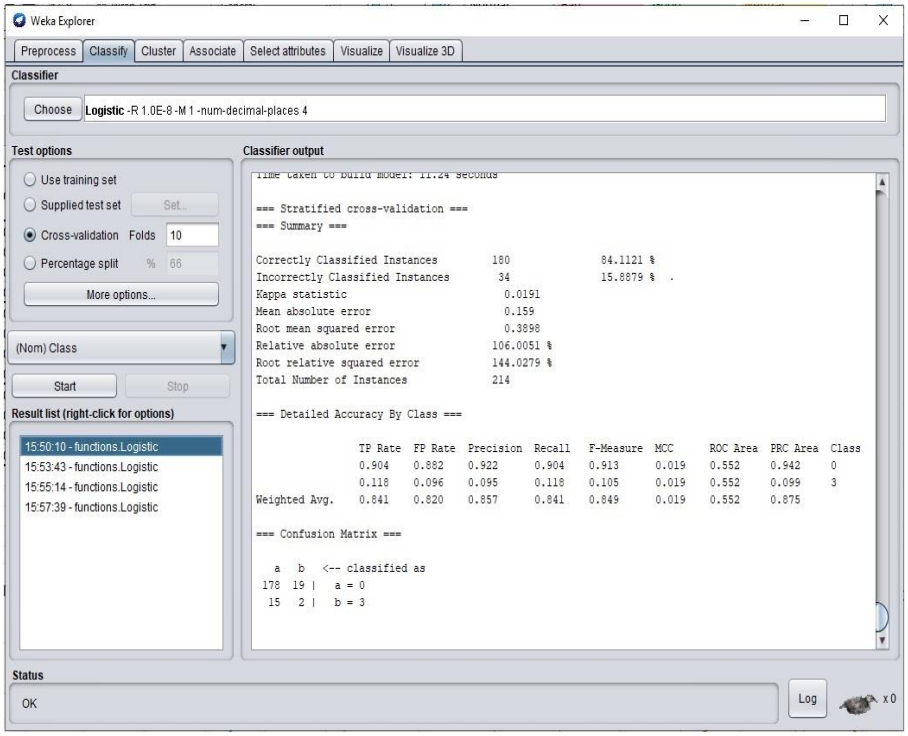


Figure A.9: weka Glass class3 as1 other0 LR, 2 minority captured

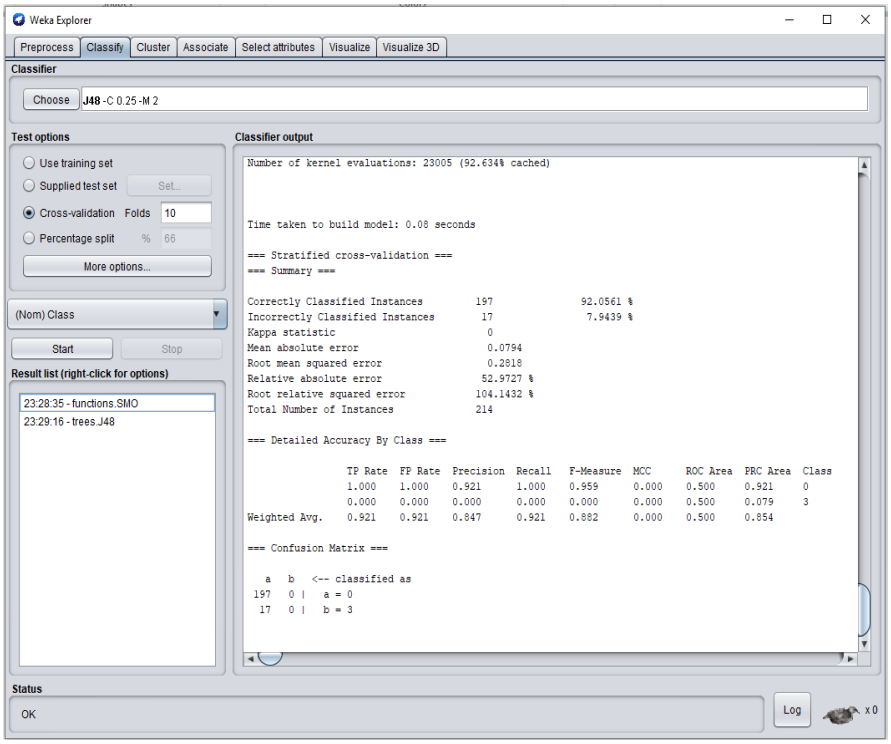


Figure A.10: weka Glass class3 as1 other0 DT SVM, no minority captured

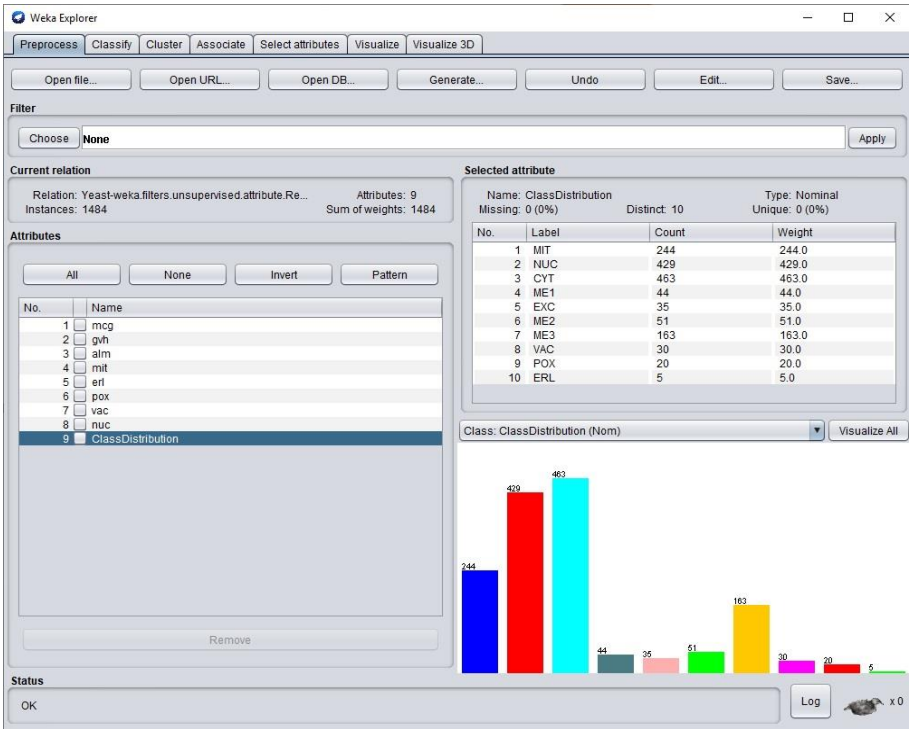


Figure A.11: Class Distribution Of Yeast Data

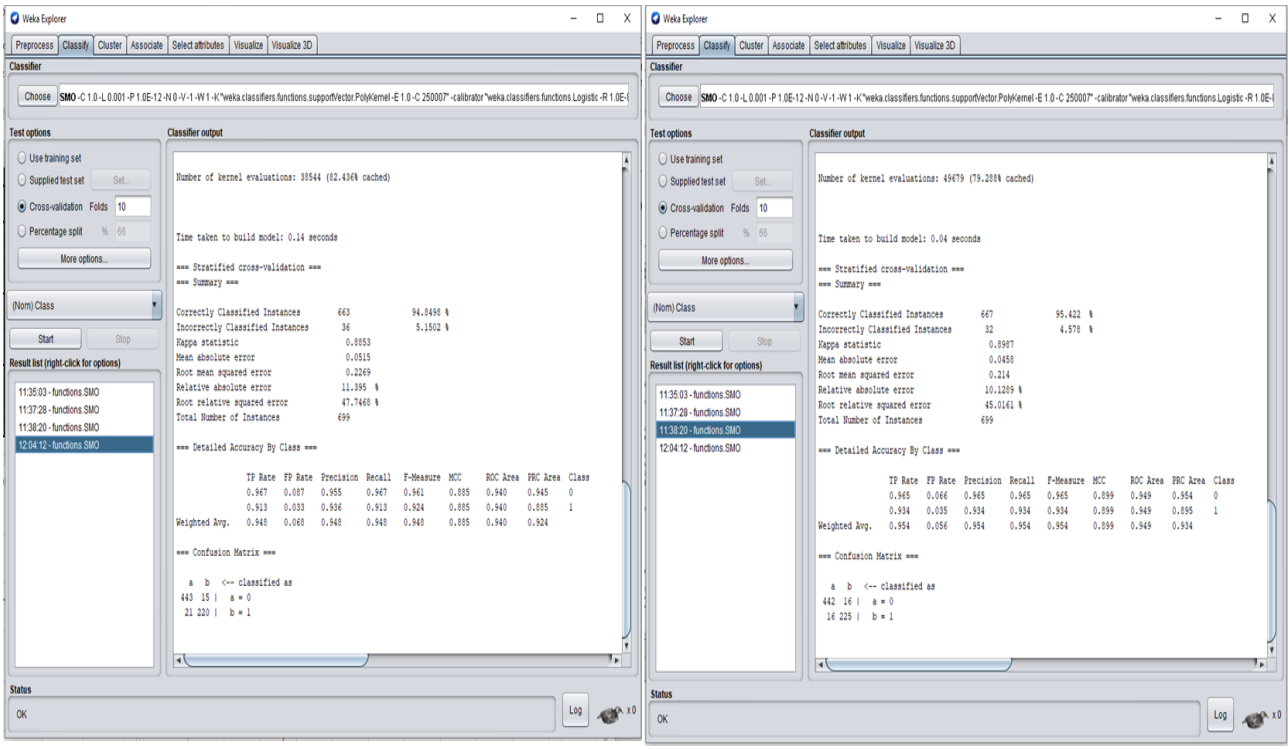


Figure A.12: weka Interface SVM for Wisconsin

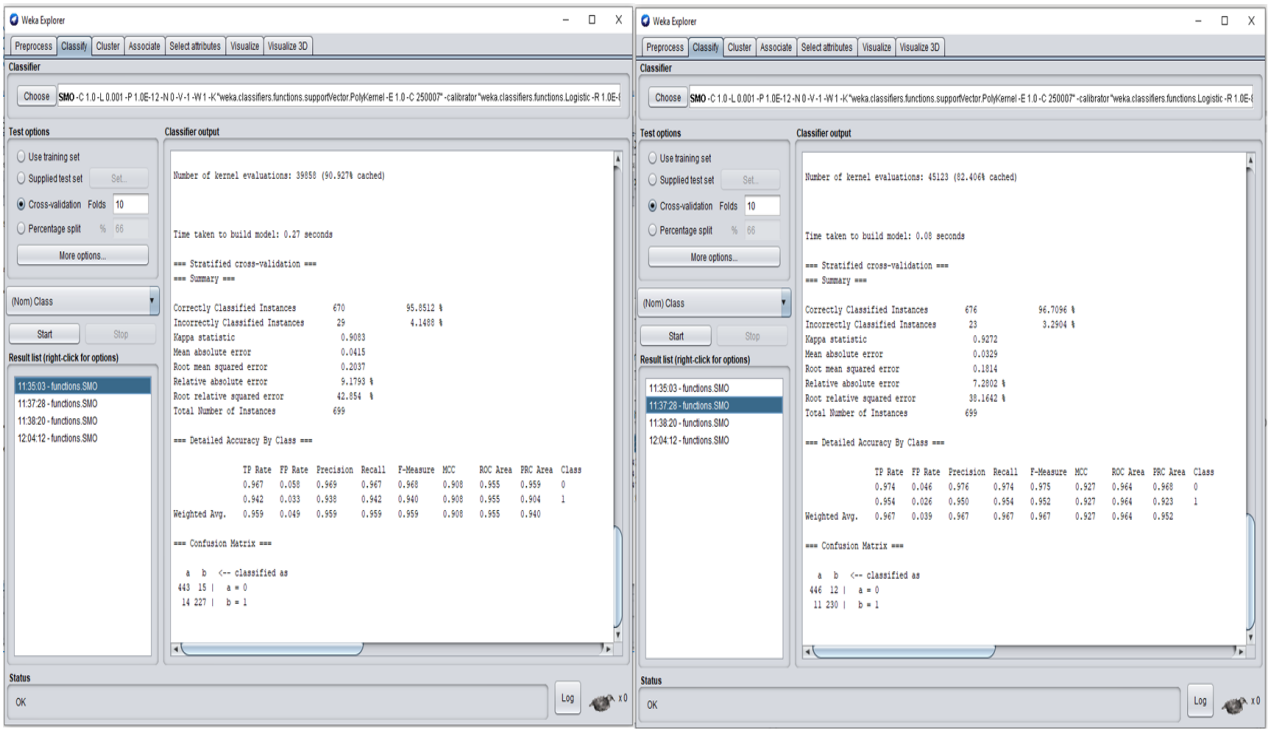


Figure A.13: weka Interface SVM for Wisconsin-2

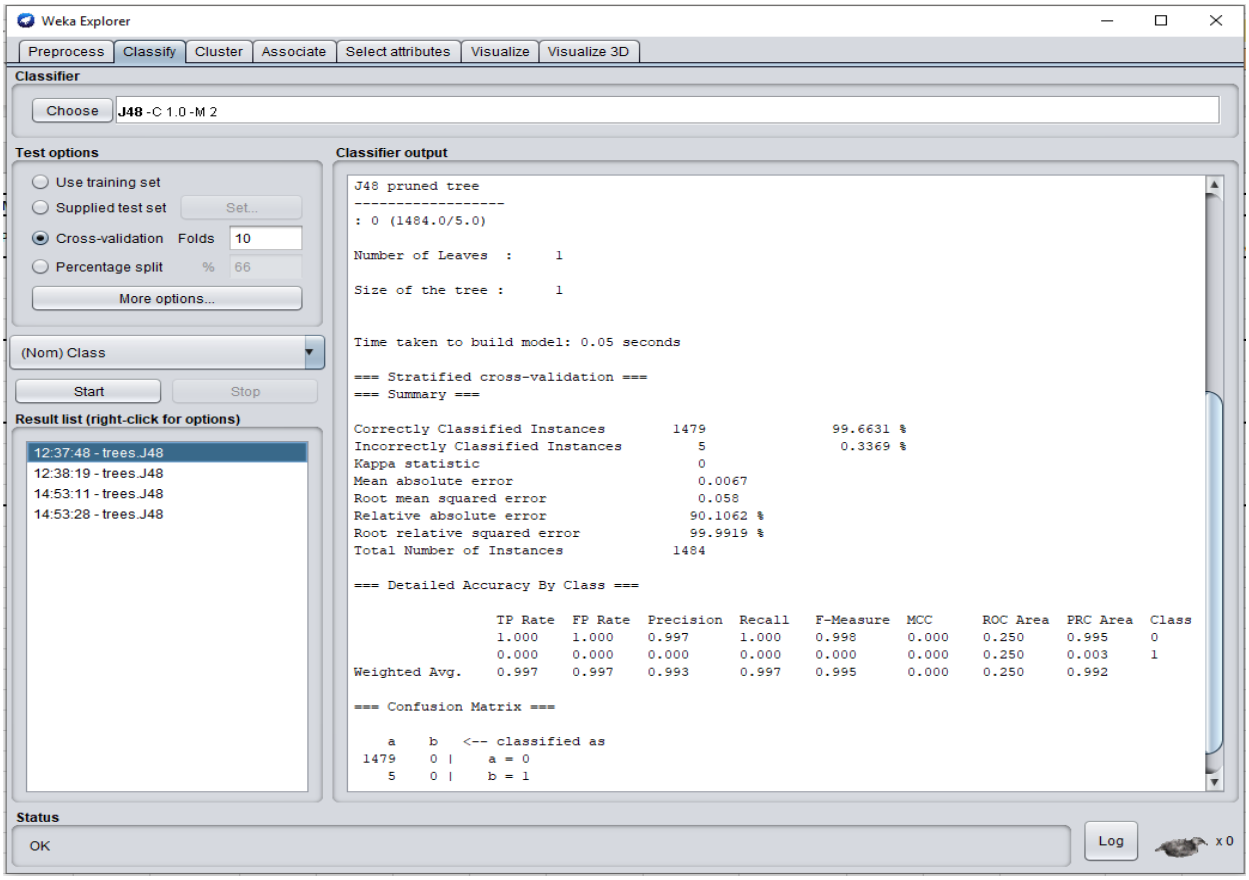


Figure A.14: wekaYeastclassERL(5)as1othersasclass0(1479) for DT

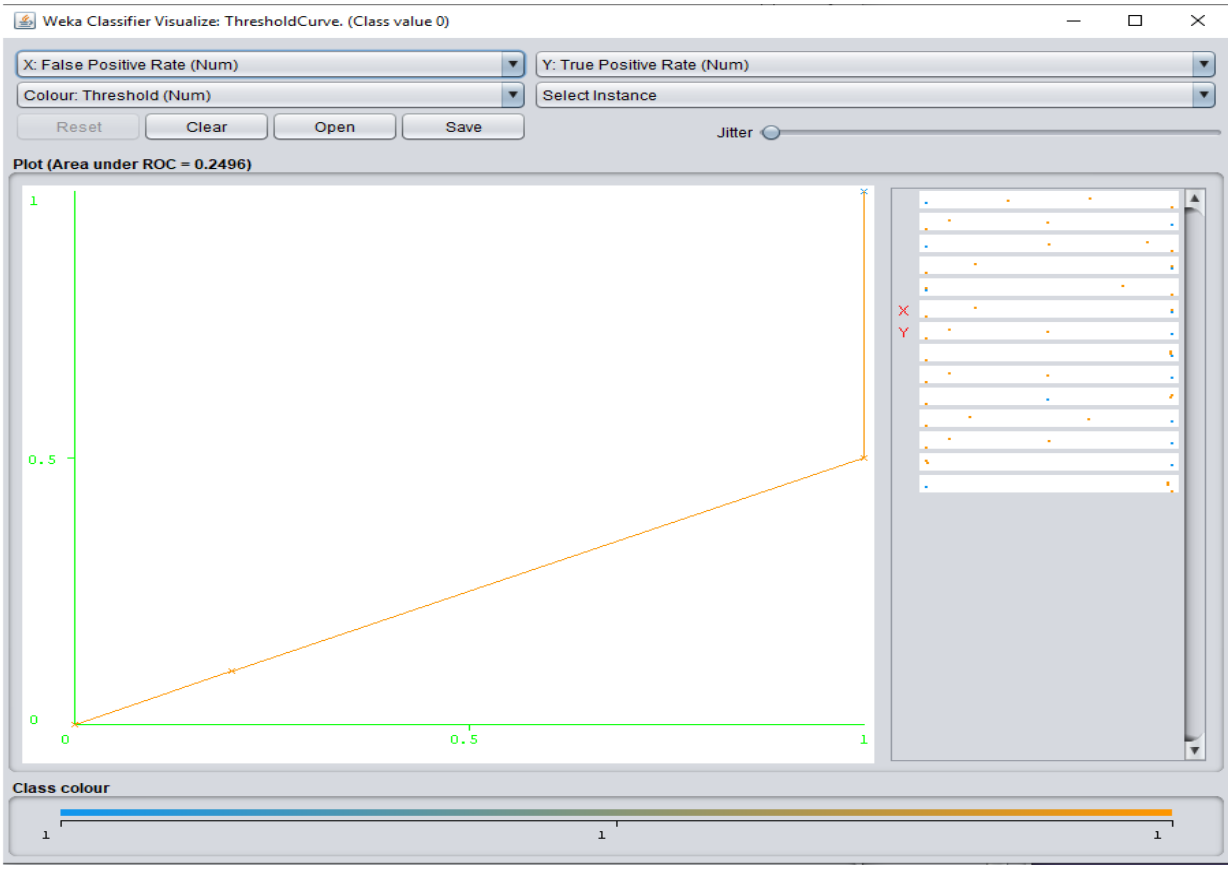


Figure A.15: wekaYeastclassERL(5)as1othersasclass0(1479) the ROC for DT

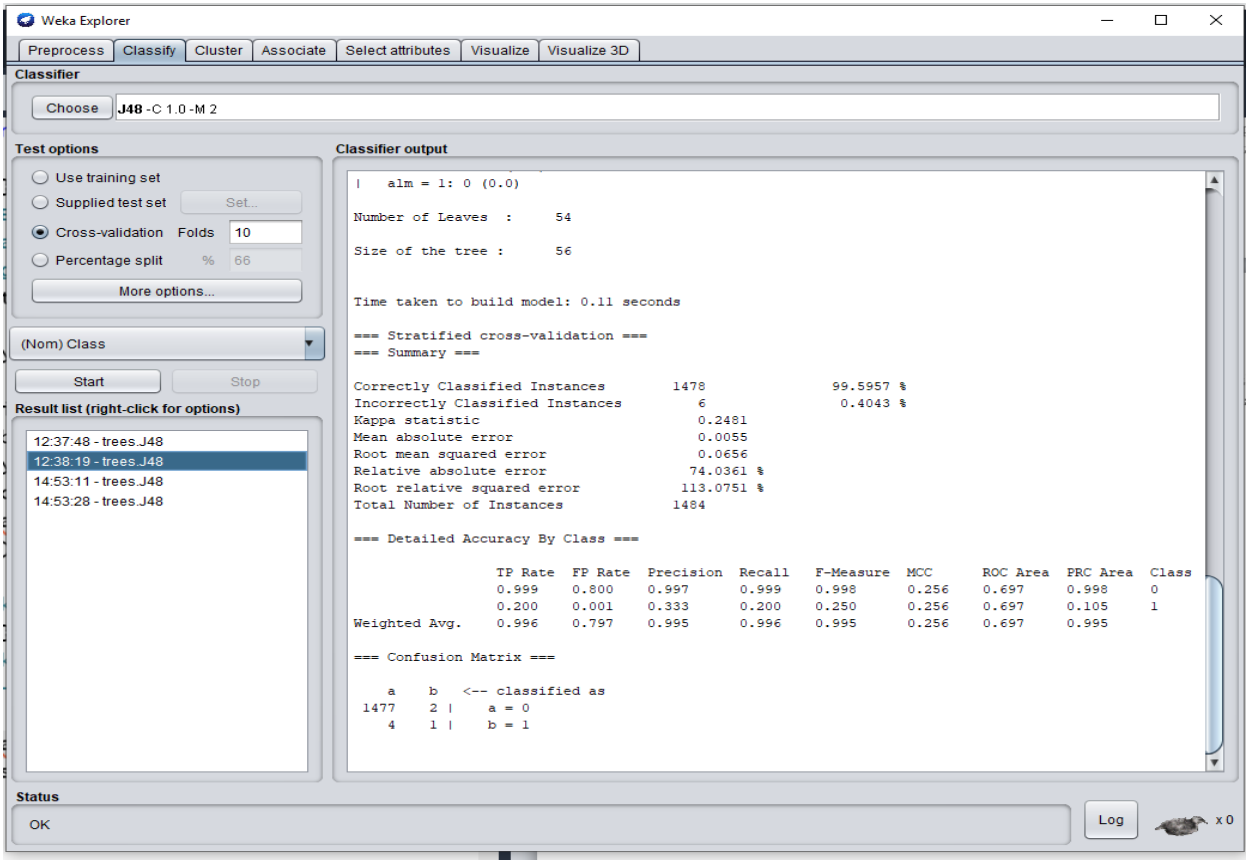


Figure A.16: wekaYeastclassERL(5)as1othersasclass0(1479) for DT capture 1 Minority

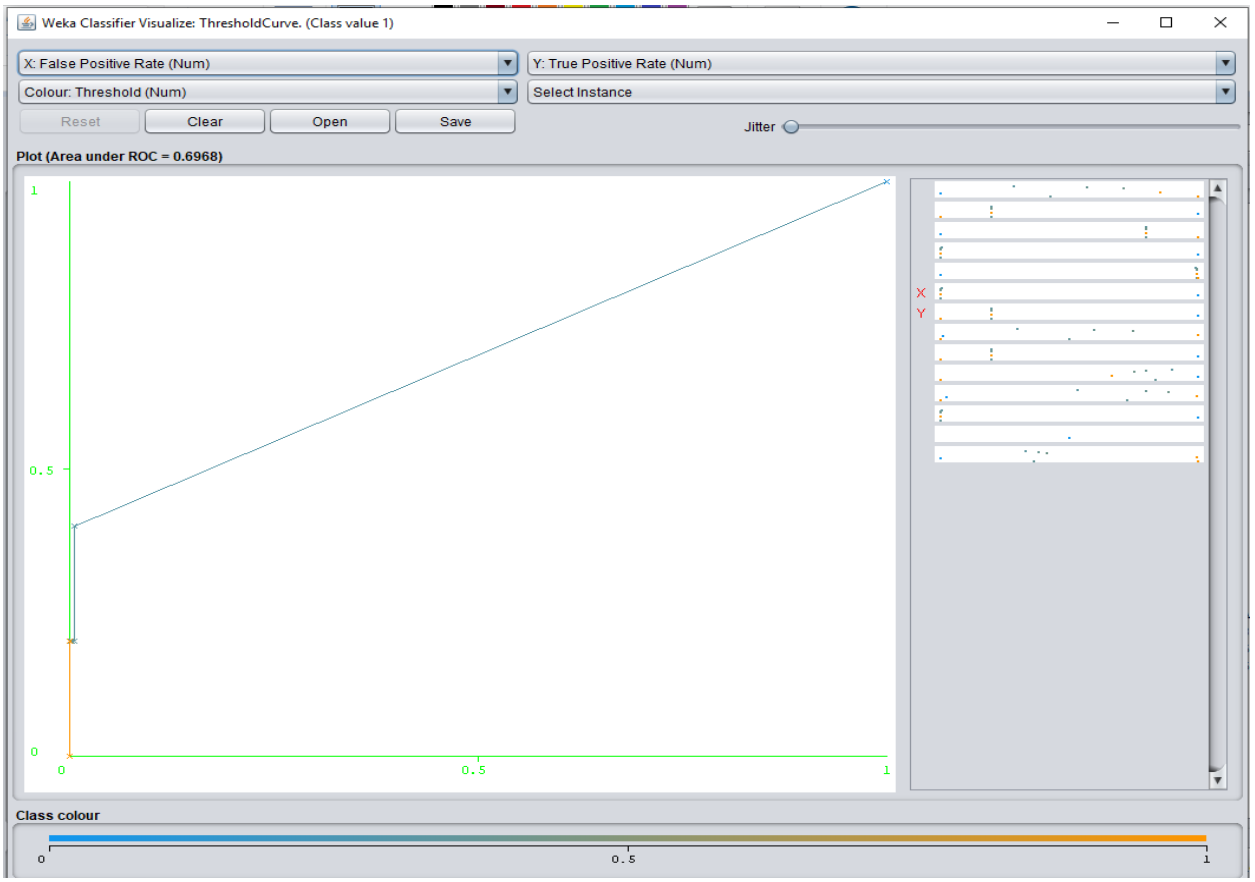


Figure A.17: wekaYeastclassERL(5)as1othersasclass0(1479) the ROC Capture 1 for DT

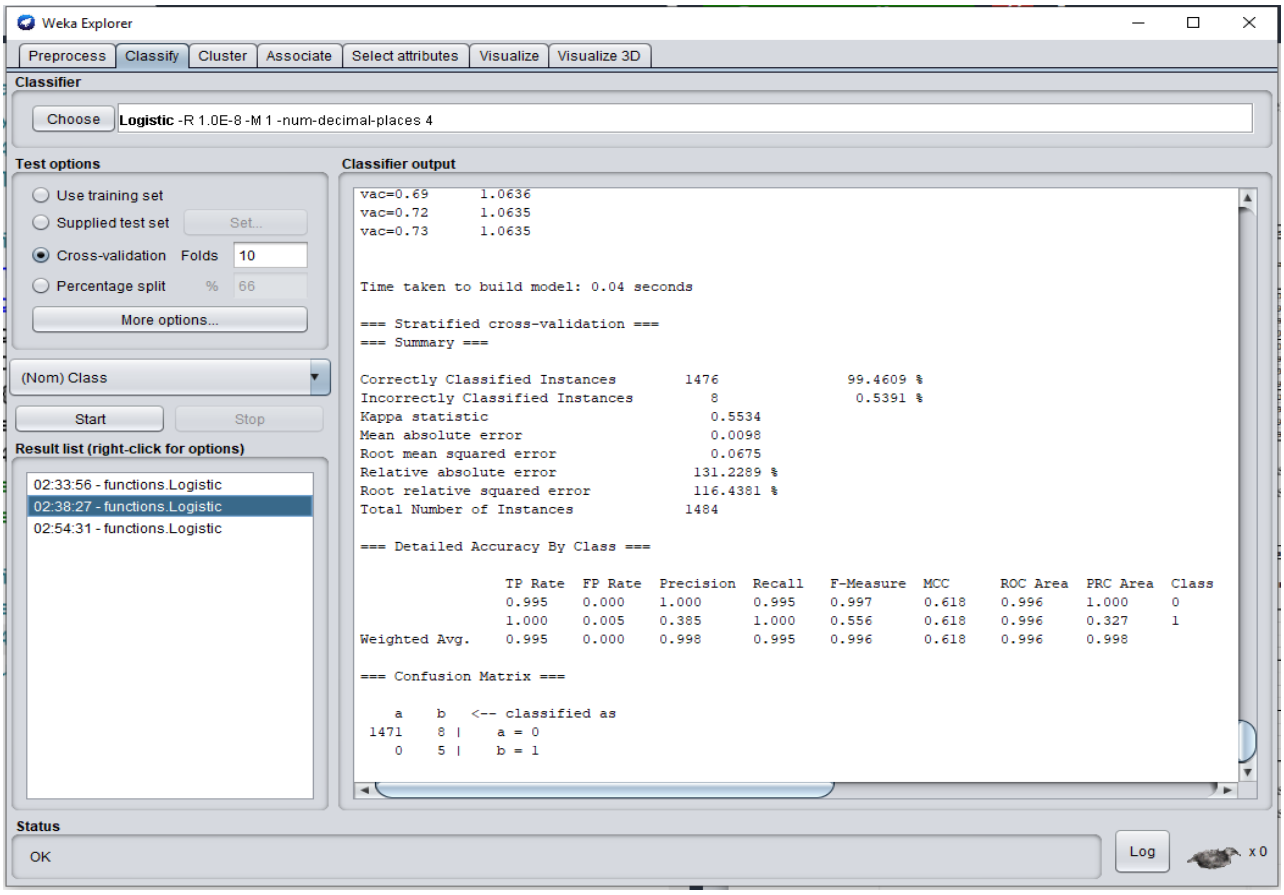


Figure A.18: weka Interface for Yeast class ERL(5)as 1 others as class0(1479) for LR Capture all 5 minority

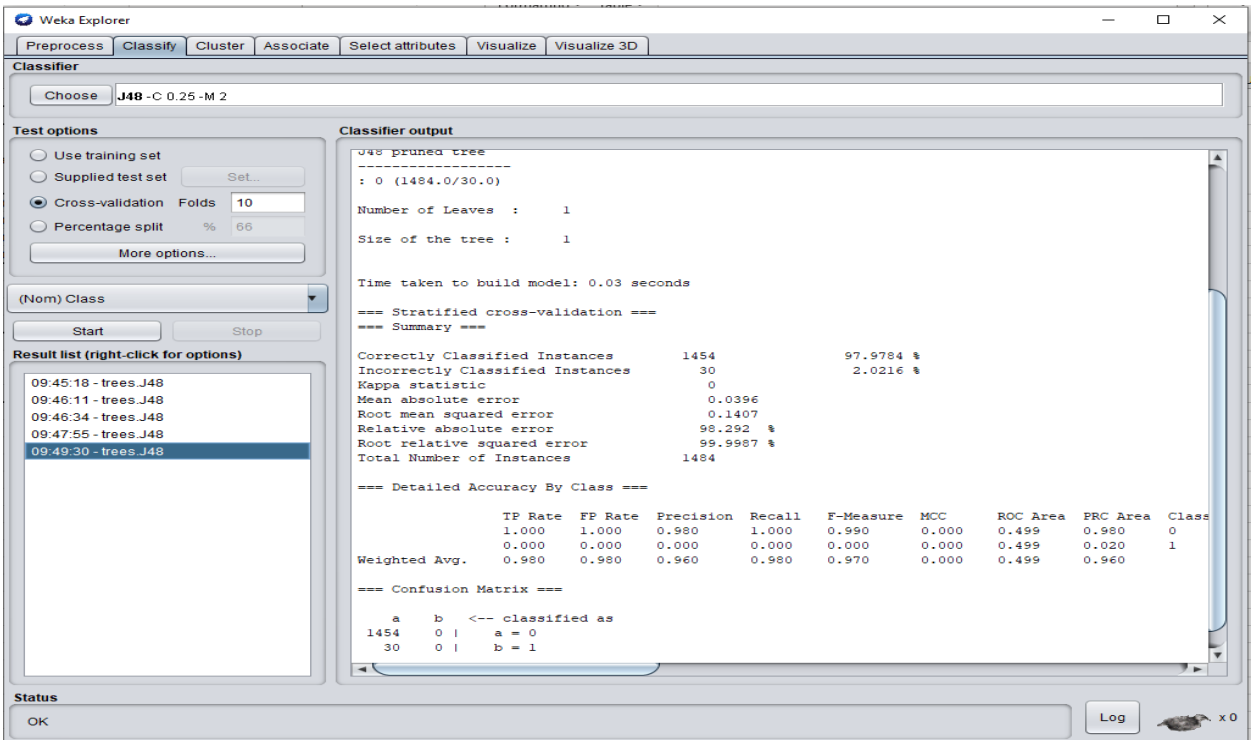


Figure A.19: weka Interface for Yeast class VAC(30)as 1 others as class0(1454) for DT Capture 0 minority

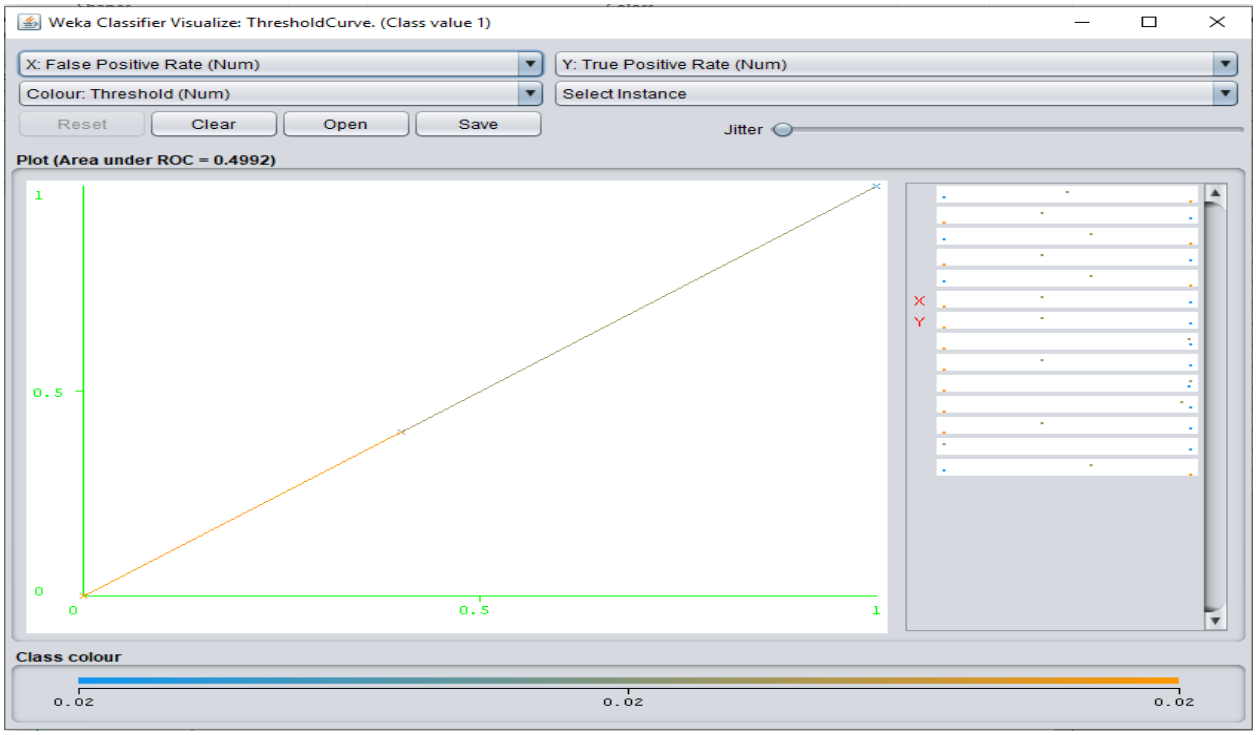


Figure A.20: weka Interface for Yeast class VAC(30)as 1 others as class0(1454) for ROC of DT Capture 0 minority

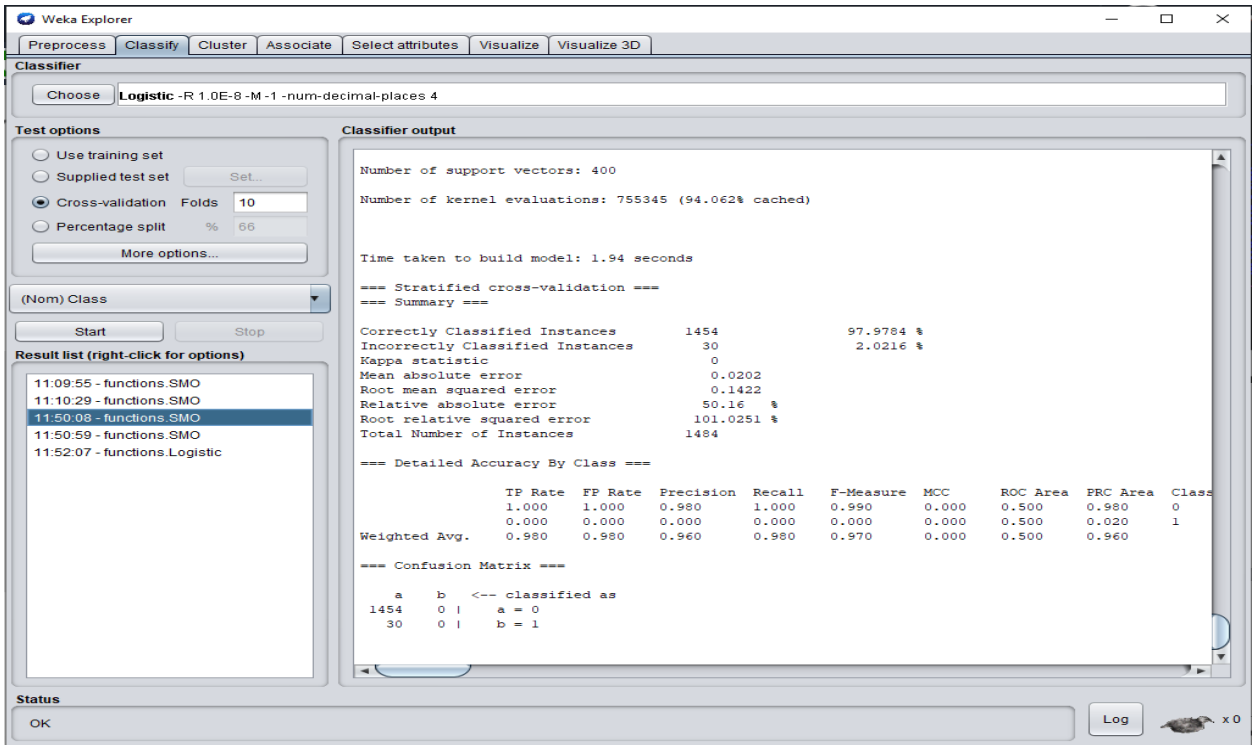


Figure A.21: weka Interface for Yeast class VAC(30)as 1 others as class0(1454) for SVM Capture 0 minority

Bibliography

[1] Fay Chang, Jeffrey Dean, Sanjay Ghemawat, Wilson C Hsieh, Deborah A Wallach, Mike Burrows, Tushar Chandra, Andrew Fikes, and Robert E Gruber. Bigtable: A distributed storage system for structured data. *ACM Transactions on Computer Systems (TOCS)*, 26(2):4, 2008.

[2] Brandon Doran. Structured vs. unstructured data, Nov 2017.

[3] Ian H Witten, Eibe Frank, Mark A Hall, and Christopher J Pal. *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, 2016.

[4] Anna L Buczak and Erhan Guven. A survey of data mining and machine learning methods for cyber security intrusion detection. *IEEE Communications Surveys & Tutorials*, 18(2):1153–1176, 2016.

[5] X Rong Li and Zhanlue Zhao. Relative error measures for evaluation of estimation algorithms. In *Information Fusion, 2005 8th International Conference on*, volume 1, pages 8–pp. IEEE, 2005.

[6] Henning Baars and Hans-George Kemper. Management support with structured and unstructured data—an integrated business intelligence framework. *Information Systems Management*, 25(2):132–148, 2008.

[7] Justin Langseth, Nithi Vivatrat, and Gene Sohn. Analysis and transformation tools for structured and unstructured data, January 11 2007. US Patent App. 11/172,957.

[8] Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, and Ian H Witten. The weka data mining software: an update. *ACM SIGKDD explorations newsletter*, 11(1):10–18, 2009.

[9] Ralph Kimball and Joe Caserta. *The Data WarehouseÂ ETL Toolkit: Practical Techniques for Extracting, Cleaning, Conforming, and Delivering Data*. John Wiley & Sons, 2011.

[10] Simon Hawkins, Hongxing He, Graham Williams, and Rohan Baxter. Outlier detection using replicator neural networks. In *International Conference on Data Warehousing and Knowledge Discovery*, pages 170–180. Springer, 2002.

[11] Antonio Loureiro, Luis Torgo, and Carlos Soares. Outlier detection using clustering methods: a data cleaning application. In *Proceedings of KDNet Symposium on Knowledge-based Systems for the Public Sector. Bonn, Germany*, 2004.

[12] Marius Muja and David G Lowe. Scalable nearest neighbor algorithms for high dimensional data. *IEEE transactions on pattern analysis and machine intelligence*, 36(11):2227–2240, 2014.

[13] Claudio Reggiani, Yann-Aël Le Borgne, and Gianluca Bontempi. Feature selection in high-dimensional dataset using mapreduce. *arXiv preprint arXiv:1709.02327*, 2017.

[14] PULKIT SHARMA. The ultimate guide to 12 dimensionality reduction techniques. https://www.analyticsvidhya.com/blog/2018/08/dimensionality-reduction-techniques-python/, 27 August 2018. (Accessed on 31/07/2019).

[15] Melanie Hilario and Alexandros Kalousis. Approaches to dimensionality reduction in proteomic biomarker studies. *Briefings in bioinformatics*, 9(2):102–118, 2008.

[16] Btissam Zerhari, Ayoub Ait Lahcen, and Salma Mouline. Big data clustering: Algorithms and challenges. In *Proc. of Int. Conf. on Big Data, Cloud and Applications (BDCA'15)*, 2015.

[17] Klaus Krippendorff. Estimating the reliability, systematic error and random error of interval data. *Educational and Psychological Measurement*, 30(1):61–70, 1970.

[18] Greg Atkinson and Alan M Nevill. Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports medicine*, 26(4):217–238, 1998.

[19] Rukshan Batuwita and Vasile Palade. Class imbalance learning methods for support vector machines. 2013.

[20] Rüdiger Wirth and Jochen Hipp. Crisp-dm: Towards a standard process model for data mining. In *Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining*, pages 29–39. Citeseer, 2000.

[21] Rachel Philpott. Entwined approaches: integrating design, art and science in design research-by-practice. https://dspace.lboro.ac.uk/2134/12964, 10 Dec 2012. (Accessed on 04/06/2019).

[22] weka. Weka 3: Machine learning software in java. https://www.cs.waikato.ac.nz/ml/weka/, 25 June 2019. (Accessed on 25/06/2019).

[23] All data set used. All data set used. https://archive.ics.uci.edu/ml/index.php, 12 July 2015. (Accessed on 15/08/2018).

[24] latex documentation. Overleaf, online latex editor. https://www.overleaf.com/, 12 July 2015. (Accessed on 15/08/2018).

[25] Monash University RESEARCH and LEARNING ONLINE. Writing clearly, concisely and precisely. https://www.monash.edu/rlo/research-writing-assignments/writing/clear-communication/writing-clearly-concisely-and-precisely, 12 July 2017. (Accessed on 16/08/2018).

[26] Shuo Wang and Xin Yao. Multiclass imbalance problems: Analysis and potential solutions. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 42(4):1119–1130, 2012.

[27] T Ryan Hoens, Qi Qian, Nitesh V Chawla, and Zhi-Hua Zhou. Building decision trees for the multi-class imbalance problem. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 122–134. Springer, 2012.

[28] Xu-Ying Liu, Jianxin Wu, and Zhi-Hua Zhou. Exploratory undersampling for class-imbalance learning. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 39(2):539–550, 2009.

[29] University of California data set. Machine learning repository. https://archive.ics.uci.edu/ml/datasets/Abalone, June 2017. (Accessed on 24/06/2018).

[30] University of California data set. Machine learning repository. https://archive.ics.uci.edu/ml/datasets/Yeast, June 2017. (Accessed on 24/06/2018).

[31] Guorui Feng, Guang-Bin Huang, Qingping Lin, and Robert Gay. Error minimized extreme learning machine with growth of hidden nodes and incremental learning. *IEEE Transactions on Neural Networks*, 20(8):1352–1357, 2009.

[32] Hai-Jun Rong, Yew-Soon Ong, Ah-Hwee Tan, and Zexuan Zhu. A fast pruned-extreme learning machine for classification problem. *Neurocomputing*, 72(1-3):359–366, 2008.

[33] Donald Michie, David J Spiegelhalter, CC Taylor, et al. Machine learning. *Neural and Statistical Classification*, 13, 1994.

[34] Olivier Chapelle, Bernhard Scholkopf, and Alexander Zien. Semi-supervised learning (chapelle, o. et al., eds.; 2006)[book reviews]. *IEEE Transactions on Neural Networks*, 20(3):542–542, 2009.

[35] Trevor Hastie, Robert Tibshirani, and Jerome Friedman. Unsupervised learning. In *The elements of statistical learning*, pages 485–585. Springer, 2009.

[36] Anurag Jha, Anand Chandrasekaran, Chiho Kim, and Rampi Ramprasad. Impact of dataset uncertainties on machine learning model predictions: the example of polymer glass transition temperatures. *Modelling and Simulation in Materials Science and Engineering*, 27(2):024002, 2019.

[37] Anton Tsitsulin, Marina Munkhoeva, Davide Mottin, Panagiotis Karras, Alex Bronstein, Ivan Oseledets, and Emmanuel Müller. The shape of data: Intrinsic distance for data distributions. In *Iclr 2020: Proceedings of the International Conference on Learning Representations*, 2020.

[38] Saman Sadeghyan. A new robust feature selection method using variance-based sensitivity analysis. *arXiv preprint arXiv:1804.05092*, pages 3–6, 2018.

[39] Yang Lu, Yiu-ming Cheung, and Yuan Yan Tang. Bayes imbalance impact index: A measure of class imbalanced data set for classification problem. *IEEE transactions on neural networks and learning systems*, 2019.

[40] Zalán Borsos, Andreas Krause, and Kfir Y Levy. Online variance reduction for stochastic optimization. *arXiv preprint arXiv:1802.04715*, pages 13–15, 2018.

[41] Baptiste Rocca. Handling imbalanced datasets in machine learning. https://towardsdatascience.com/handling-imbalanced-datasets-in-machine-learning-7a0e84220f28, 27 Jan 2019. (Accessed on 13/04/2020).

[42] Saharon Rosset and Ryan J Tibshirani. From fixed-x to random-x regression: Bias-variance decompositions, covariance penalties, and prediction error estimation. *Journal of the American Statistical Association*, pages 1–14, 2018.

[43] Gemma E Moran, Veronika Ročková, Edward I George, et al. Variance prior forms for high-dimensional bayesian variable selection. *Bayesian Analysis*, pages 1091–1119, 2018.

[44] Andrew Estabrooks, Taeho Jo, and Nathalie Japkowicz. A multiple resampling method for learning from imbalanced data sets. *Computational intelligence*, 20(1):18–36, 2004.

[45] Yanmin Sun, Andrew KC Wong, and Mohamed S Kamel. Classification of imbalanced data: A review. *International Journal of Pattern Recognition and Artificial Intelligence*, 23(04):687–719, 2009.

[46] YANMIN SUN, ANDREW K. C. WONG, and MOHAMED S. KAMEL. Classification of imbalanced data: A review. *International Journal of Pattern Recognition and Artificial Intelligence*, 23(4):687–719, 2009.

[47] Florian Steinke, Bernhard Schölkopf, and Volker Blanz. Support vector machines for 3d shape processing. In *Computer Graphics Forum*, volume 24, pages 285–294. Wiley Online Library, 2005.

[48] DF Team. Kernel functions-introduction to svm kernel examples. https://data-flair.training/blogs/svm-kernel-functions/, 12 Aug 2017. (Accessed on 24/07/2018).

[49] Bernhard Schölkopf. The kernel trick for distances. In *Advances in neural information processing systems*, pages 301–307, 2001.

[50] Martin Hofmann. Support vector machines—kernels and the kernel trick. *Notes*, 26, 2006.

[51] Sebastian Mika, Gunnar Ratsch, Jason Weston, Bernhard Scholkopf, and Klaus-Robert Mullers. Fisher discriminant analysis with kernels. In *Neural networks for signal processing IX, 1999. Proceedings of the 1999 IEEE signal processing society workshop.*, pages 41–48. Ieee, 1999.

[52] Jose Martens Gary Ericson Roope Astala Jeannine Takaki, Berth-Anne Harvey. One-class support vector machine. https://docs.microsoft.com/en-us/azure/machine-learning/studio-module-reference/one-class-support-vector-machine, Jan 2018. (Accessed on 01/24/2018).

[53] Hanaa Sameeh A Aziz Othman et al. *A New Hierarchical Support Vector Machine based Model for Classification of Imbalanced Multi-class Data*. PhD thesis, Sudan University of Science and Technology, 2017.

[54] Bhumika Gupta, Aditya Rawat, Akshay Jain, Arpit Arora, and Naresh Dhami. Analysis of various decision tree algorithms for classification in data mining. *International Journal of Computer Applications*, 163(8), 2017.

[55] Lior Rokach and Oded Maimon. Top-down induction of decision trees classifiers-a survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 35(4):476–487, 2005.

[56] Peter Waiganjo Wagacha. Induction of decision trees. *Foundations of Learning and Adaptive Systems*, 2003.

[57] J. Ross Quinlan. Induction of decision trees. *Machine learning*, 1(1):81–106, 1986.

[58] B Chandra and P Paul Varghese. Fuzzifying gini index based decision trees. *Expert Systems with Applications*, 36(4):8549–8559, 2009.

[59] Nitesh V Chawla. C4. 5 and imbalanced data sets: investigating the effect of sampling method, probabilistic estimate, and decision tree structure. In *Proceedings of the ICML*, volume 3, page 66, 2003.

[60] Wei Liu, Sanjay Chawla, David A Cieslak, and Nitesh V Chawla. A robust decision tree algorithm for imbalanced data sets. In *Proceedings of the 2010 SIAM International Conference on Data Mining*, pages 766–777. SIAM, 2010.

[61] Salvador García, Alberto Fernández, and Francisco Herrera. Enhancing the effectiveness and interpretability of decision tree and rule induction classifiers with evolutionary training set selection over imbalanced problems. *Applied Soft Computing*, 9(4):1304–1314, 2009.

[62] Sulafa Hag Elsafi. Artificial neural networks (anns) for flood forecasting at dongola station in the river nile, sudan. *Alexandria Engineering Journal*, 53(3):655–662, 2014.

[63] Martin T Hagan, Howard B Demuth, Mark H Beale, and Orlando De Jesús. *Neural network design*, volume 20. Pws Pub. Boston, 1996.

[64] B Yegnanarayana. *Artificial neural networks*. PHI Learning Pvt. Ltd., 2009.

[65] MathWorks. Improve neural network generalization and avoid overfitting. https://uk.mathworks.com/help/nnet/ug/improve-neural-network-generalization-and-avoid-overfitting.html, November 18 2017. (Accessed on 03/09/2018).

[66] Andrey Kurenkov. A 'brief' history of neural nets and deep learning. http://www.andreykurenkov.com/writing/ai/a-brief-history-of-neural-nets-and-deep-learning/, November 18 24, 2015. (Accessed on 01/09/2018).

[67] Piyasak Jeatrakul, Kok Wai Wong, and Chun Che Fung. Classification of imbalanced data by combining the complementary neural network and smote algorithm. In *International Conference on Neural Information Processing*, pages 152–159. Springer, 2010.

[68] Apurva Sonak, Ruhi Patankar, and Nitin Pise. A new approach for handling imbalanced dataset using ann and genetic algorithm. In *Communication and Signal Processing (ICCSP), 2016 International Conference on*, pages 1987–1990. IEEE, 2016.

[69] Alex Shenfield and Shahin Rostami. Multi-objective evolution of artificial neural networks in multi-class medical diagnosis problems with class imbalance. In *Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), 2017 IEEE Conference on*, pages 1–8. IEEE, 2017.

[70] Minlong Lin, Ke Tang, and Xin Yao. Dynamic sampling approach to training neural networks for multiclass imbalance classification. *IEEE Transactions on Neural Networks and Learning Systems*, 24(4):647–660, 2013.

[71] Yanmin Sun, Mohamed S Kamel, Andrew KC Wong, and Yang Wang. Cost-sensitive boosting for classification of imbalanced data. *Pattern Recognition*, 40(12):3358–3378, 2007.

[72] Charles X. Ling and Victor S. Sheng. *Cost-Sensitive Learning*, pages 231–235. Springer US, Boston, MA, 2010.

[73] Charles Elkan. The foundations of cost-sensitive learning. In *International joint conference on artificial intelligence*, volume 17, pages 973–978. Lawrence Erlbaum Associates Ltd, 2001.

[74] Takaya Saito and Marc Rehmsmeier. Basic evaluation measures from the confusion matrix. https://classeval.wordpress.com/introduction/basic-evaluation-measures/, May 2015. (Accessed on 14/07/2018).

[75] Nguyen Thai-Nghe, Zeno Gantner, and Lars Schmidt-Thieme. Cost-sensitive learning methods for imbalanced data. In *Neural Networks (IJCNN), The 2010 International Joint Conference on*, pages 1–8. IEEE, 2010.

[76] Mateusz Lango and Jerzy Stefanowski. Multi-class and feature selection extensions of roughly balanced bagging for imbalanced data. *Journal of Intelligent Information Systems*, 50(1):97–127, 2018.

[77] Yong Zhang and Dapeng Wang. A cost-sensitive ensemble method for class-imbalanced datasets. In *Abstract and applied analysis*, volume 2013. Hindawi, 2013.

[78] Zhi-Hua Zhou and Xu-Ying Liu. Training cost-sensitive neural networks with methods addressing the class imbalance problem. *IEEE Transactions on Knowledge and Data Engineering*, 18(1):63–77, 2006.

[79] Dr Saed Sayad. K nearest neighbors - classification. https://www.saedsayad.com/k_nearest_neighbors.htm, November 18 24, 2015. (Accessed on 01/09/2018).

[80] Srishti Sawla. K-nearest neighbors. https://medium.com/@srishtisawla/k-nearest-neighbors-f77f6ee6b7f5, Jun 8 2015. (Accessed on 01/06/2018).

[81] Adi Bronshtein. A quick introduction to k-nearest neighbors algorithm. https://medium.com/@adi.bronshtein/a-quick-introduction-to-k-nearest-neighbors-algorithm-62214cea29c7, April, 11 2017. (Accessed on 01/09/2018).

[82] Harshit Dubey and Vikram Pudi. Class based weighted k-nearest neighbor over imbalance dataset. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 305–316. Springer, 2013.

[83] Georgios Douzas and Fernando Bacao. Effective data generation for imbalanced learning using conditional generative adversarial networks. *Expert Systems with applications*, 91:464–471, 2018.

[84] Yoav Freund, Robert Schapire, and Naoki Abe. A short introduction to boosting. *Journal-Japanese Society For Artificial Intelligence*, 14(771-780):1612, 1999.

[85] Leo Breiman. Stacked regressions. *Machine learning*, 24(1):49–64, 1996.

[86] Andy Liaw, Matthew Wiener, et al. Classification and regression by randomforest. *R news*, 2(3):18–22, 2002.

[87] Jisoo Ham, Yangchi Chen, Melba M Crawford, and Joydeep Ghosh. Investigation of the random forest framework for classification of hyperspectral data. *IEEE Transactions on Geoscience and Remote Sensing*, 43(3):492–501, 2005.

[88] Saimadhu Polamuri. How the random forest algorithm works in machine learning. https://dataaspirant.com/2017/05/22/random-forest-algorithm-machine-learing/, May 2017. (Accessed on 14/07/2018).

[89] Leo Breiman and Adele Cutler. Random forests. https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm, May 2014. (Accessed on 14/07/2018).

[90] Chi Zhang. Adaboost and support vector machines for unbalanced data sets.

[91] Rimah Amami, Dorra Ben Ayed, and Noureddine Ellouze. Adaboost with svm using gmm supervector for imbalanced phoneme data. In *Human System Interaction (HSI), 2013 The 6th International Conference on*, pages 328–333. IEEE, 2013.

[92] Hezlin Aryani Abd Rahman, Yap Bee Wah, Haibo He, and Awang Bulgiba. Comparisons of adaboost, knn, svm and logistic regression in classification of imbalanced dataset. In *International Conference on Soft Computing in Data Science*, pages 54–64. Springer, 2015.

[93] Albert Bifet, Geoff Holmes, Bernhard Pfahringer, Richard Kirkby, and Ricard Gavaldà. New ensemble methods for evolving data streams. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 139–148. ACM, 2009.

[94] Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357, 2002.

[95] J Brownlee. 8 tactics to combat imbalanced classes in your machine learning dataset. *Machine Learning Mastery*, 2015.

[96] Gary M Weiss, Kate McCarthy, and Bibi Zabar. Cost-sensitive learning vs. sampling: Which is best for handling unbalanced classes with unequal error costs? *DMIN*, 7:35–41, 2007.

[97] Hui Han, Wen-Yuan Wang, and Bing-Huan Mao. Borderline-smote: a new over-sampling method in imbalanced data sets learning. In *International Conference on Intelligent Computing*, pages 878–887. Springer, 2005.

[98] Chris Drummond, Robert C Holte, et al. C4. 5, class imbalance, and cost sensitivity: why under-sampling beats over-sampling. In *Workshop on learning from imbalanced datasets II*, volume 11. Citeseer Washington DC, 2003.

[99] Alexander Liu, Joydeep Ghosh, and Cheryl E Martin. Generative oversampling for mining imbalanced datasets. In *DMIN*, pages 66–72, 2007.

[100] Analytics Vidhya Content Team. Practical guide to deal with imbalanced classification problems. https://www.analyticsvidhya.com/blog/2016/03/practical-guide-deal-imbalanced-classification-problems, March 2016. (Accessed on 19 03 2017).

[101] Zeping Yang and Daqi Gao. An active under-sampling approach for imbalanced data classification. In *Computational Intelligence and Design (ISCID), 2012 Fifth International Symposium on*, volume 2, pages 270–273. IEEE, 2012.

[102] Analytics Vidhya Content Team. Dealing with imbalanced data: undersampling, oversampling and proper cross-validation. https://www.marcoaltini.com/blog/dealing-with-imbalanced-data-undersampling-oversampling-and-proper-cross- Aug 2015. (Accessed on 10/07/2018).

[103] Peng Li, Tian-ge Liang, and Kai-hui Zhang. Imbalanced data set csvm classification method based on cluster boundary sampling. *Mathematical Problems in Engineering*, 2016, 2016.

[104] Jia Song, Xianglin Huang, Sijun Qin, and Qing Song. A bi-directional sampling based on k-means method for imbalance text classification. In *Computer and Information Science (ICIS), 2016 IEEE/ACIS 15th International Conference on*, pages 1–5. IEEE, 2016.

[105] Krystyna Napierala and Jerzy Stefanowski. Types of minority class examples and their influence on learning classifiers from imbalanced data. *Journal of Intelligent Information Systems*, 46(3):563–597, 2016.

[106] David J Dittman, Taghi M Khoshgoftaar, Randall Wald, and Amri Napolitano. Comparison of data sampling approaches for imbalanced bioinformatics data. In *FLAIRS Conference*, 2014.

[107] Vaishali Ganganwar. An overview of classification algorithms for imbalanced datasets. *International Journal of Emerging Technology and Advanced Engineering*, 2(4):42–47, 2012.

[108] J Brownlee. 8 tactics to combat imbalanced classes in your machine learning dataset. https://machinelearningmastery.com/tactics-to-combat-imbalanced-classes-in-your-machine-learning-dataset/, Aug 18 2015. (Accessed on 04/28/2018).

[109] S Sasikala, S Appavu alias Balamurugan, and S Geetha. Multi filtration feature selection (mffs) to improve discriminatory ability in clinical data set. *Applied Computing and Informatics*, 12(2):117–127, 2016.

[110] Isabelle Guyon and André Elisseeff. An introduction to variable and feature selection. *Journal of machine learning research*, 3(Mar):1157–1182, 2003.

[111] Alan Jović, Karla Brkić, and Nikola Bogunović. A review of feature selection methods with applications. In *2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, pages 1200–1205. IEEE, 2015.

[112] Zhaohui Zheng, Xiaoyun Wu, and Rohini Srihari. Feature selection for text categorization on imbalanced data. *ACM Sigkdd Explorations Newsletter*, 6(1):80–89, 2004.

[113] Xue-wen Chen and Michael Wasikowski. Fast: a roc-based feature selection metric for small samples and imbalanced data classification problems. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 124–132. ACM, 2008.

[114] Li Yijing, Guo Haixiang, Liu Xiao, Li Yanan, and Li Jinling. Adapted ensemble classification algorithm based on multiple classifier system and feature selection for classifying multi-class imbalanced data. *Knowledge-Based Systems*, 94:88–104, 2016.

[115] Tian-Yu Liu. Easyensemble and feature selection for imbalance data sets. In *2009 International Joint Conference on Bioinformatics, Systems Biology and Intelligent Computing*, pages 517–520. IEEE, 2009.

[116] Peng Zhou, Xuegang Hu, Peipei Li, and Xindong Wu. Online feature selection for high-dimensional class-imbalanced data. *Knowledge-Based Systems*, 136:187–199, 2017.

[117] Meta S. Brown. 10 common data mining mistakes (that you won't make). https://www.dummies.com/programming/big-data/data-science/10-common-data-mining-mistakes-that-you-wont-make/, 10 Dec 2018. (Accessed on 02/06/2019).

[118] Seth DeLand. Building a machine learning model through trial and error. https://www.kdnuggets.com/2018/09/mathworks-building-machine-learning-model-through-trial-error.html, 2017. (Accessed on 02/21/2019).

[119] Kunihiro Nishimura and Michitaka Hirose. The study of past working history visualization for supporting trial and error approach in data mining. In *Symposium on Human Interface and the Management of Information*, pages 327–334. Springer, 2007.

[120] Chidanand Apte, Bing Liu, Edwin PD Pednault, and Padhraic Smyth. Business applications of data mining. *Communications of the ACM*, 45(8):49–53, 2002.

[121] Mark Dredze, Koby Crammer, and Fernando Pereira. Confidence-weighted linear classification. In *Proceedings of the 25th international conference on Machine learning*, pages 264–271. ACM, 2008.

[122] Pierre Baldi, Søren Brunak, Yves Chauvin, Claus AF Andersen, and Henrik Nielsen. Assessing the accuracy of prediction algorithms for classification: an overview. *Bioinformatics*, 16(5):412–424, 2000.

[123] Howard Hamilton. Confusion matrix. http://www2.cs.uregina.ca/~dbd/cs831/notes/confusion_matrix/confusion_matrix.html, July 9 2018. (Accessed on 24/07/2018).

[124] Jason Brownlee. What is a confusion matrix in machine learning. https://machinelearningmastery.com/confusion-matrix-machine-learning/, November 18 2016. (Accessed on 24/07/2018).

[125] Victoria López, Alberto Fernández, and Francisco Herrera. On the importance of the validation technique for classification with imbalanced datasets: Addressing covariate shift when data is skewed. *Information Sciences*, 257:1–13, 2014.

[126] Juan M Cespedes-Sanchez, Raúl Ayuso-Montero, Antoni Marí-Roig, Carlos Arranz-Obispo, and José López-López. The importance of a good evaluation in order to prevent oral nerve injuries: a review. *Acta Odontologica Scandinavica*, 72(3):161–167, 2014.

[127] David Martin Powers. Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation. 2011.

[128] Tom Fawcett. An introduction to roc analysis. *Pattern recognition letters*, 27(8):861–874, 2006.

[129] Wiesław Chmielnicki and Katarzyna Stapor. Using the one–versus–rest strategy with samples balancing to improve pairwise coupling classification. *International Journal of Applied Mathematics and Computer Science*, 26(1):191–201, 2016.

[130] Ryan Rifkin and Aldebaro Klautau. In defense of one-vs-all classification. *Journal of machine learning research*, 5(Jan):101–141, 2004.

[131] Mikel Galar, Alberto Fernández, Edurne Barrenechea, Humberto Bustince, and Francisco Herrera. An overview of ensemble methods for binary classifiers in multi-class problems: Experimental study on one-vs-one and one-vs-all schemes. *Pattern Recognition*, 44(8):1761–1776, 2011.

[132] Jin-Hyuk Hong, Jun-Ki Min, Ung-Keun Cho, and Sung-Bae Cho. Fingerprint classification using one-vs-all support vector machines dynamically ordered with naı¨ ve bayes classifiers. *Pattern Recognition*, 41(2):662–671, 2008.

[133] Xiaopeng Zhang, Hongkai Xiong, Wengang Zhou, and Qi Tian. Fused one-vs-all mid-level features for fine-grained visual categorization. In *Proceedings of the 22nd ACM international conference on Multimedia*, pages 287–296. ACM, 2014.

[134] Yashima Ahuja and Sumit Kumar Yadav. Multiclass classification and support vector machine. *Global Journal of Computer Science and Technology Interdisciplinary*, 12(11):14–20, 2012.

[135] Bob Horton. Calculating auc: the area under a roc curve. https://www.r-bloggers.com/calculating-auc-the-area-under-a-roc-curve/, November 22 2016. (Accessed on 24/07/2018).

[136] Kevin Markham. Roc curves and area under the curve explained (video). https://www.dataschool.io/roc-curves-and-auc-explained/, November 2014. (Accessed on 24/07/2018).

[137] Kristian Linnet, Patrick MM Bossuyt, Karel GM Moons, and Johannes BR Reitsma. Quantifying the accuracy of a diagnostic test or marker. *Clinical chemistry*, pages clinchem–2012, 2012.

[138] Víctor Martínez-Cagigal. Roc curve. https://www.mathworks.com/matlabcentral/fileexchange/52442-roc-curve, 13 Dec 2018. (Accessed on 27/05/2019).

[139] National Diabetes Data Group (US), National Institute of Diabetes, Digestive, and Kidney Diseases (US). *Diabetes in America*. Number 95. National Institutes of Health, National Institute of Diabetes and Digestive and Kidney Diseases, 1995.

[140] Rong-En Fan and Chih-Jen Lin. Libsvm data: Classification, regression, and multi-label. https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/, May 5 2017. (Accessed on 10/06/2018).

[141] Pete Chapman, Julian Clinton, Randy Kerber, Thomas Khabaza, Thomas Reinartz, Colin Shearer, and Rudiger Wirth. Crisp-dm 1.0 step-by-step data mining guide. 2000.

[142] SB Kotsiantis, D Kanellopoulos, and PE Pintelas. Data preprocessing for supervised leaning. *International Journal of Computer Science*, 1(2):111–117, 2006.

[143] Will Kenton. Overfitting. https://www.investopedia.com/terms/o/overfitting.asp, Jan 2019. (Accessed on 12/03/2019).

[144] Keith T. Butler. Example of overfitting and underfitting in machine learning. https://keeeto.github.io/blog/bias_variance/, March 08 2018. (Accessed on 12/03/2019).

[145] Eric Cai. overfitting and underfitting. https://chemicalstatistician.wordpress.com/2014/03/19/

machine-learning-lesson-of-the-day-overfitting-and-underfitting/, March 19 2014. (Accessed on 12/03/2019).

[146] kaggle discussion. kaggle,discussion. https://www.kaggle.com/discussion, 25 June 2019. (Accessed on 25/06/2019).

[147] reddit discussion. reddit,discussion. https://www.reddit.com/r/MLQuestions/comments/7e9zft/kfold_cross_validation_vs_train_test_split/, 25 June 2019. (Accessed on 25/06/2019).

[148] researchgate discussion. researchgate,discussion. https://www.researchgate.net/post/Why_is_the_cross_validation_a_better_choice_for_the_testing, 25 June 2019. (Accessed on 25/06/2019).

[149] The Social Science Research Institute The Pennsylvania State University. Cross-validation tutoria. https://quantdev.ssri.psu.edu/tutorials/cross-validation-tutorial, 2019. (Accessed on 12/03/2019).

[150] Star Trek. Independent random variables. https://stattrek.com/random-variable/independence.aspx, 07 Feb 2015. (Accessed on 02/08/2019).

[151] Tugkan Batu, Eldar Fischer, Lance Fortnow, Ravi Kumar, Ronitt Rubinfeld, and Patrick White. Testing random variables for independence and identity. In *Proceedings 42nd IEEE Symposium on Foundations of Computer Science*, pages 442–451. IEEE, 2001.

[152] Valentin Vladimirovich Petrov. *Sums of independent random variables*, volume 82. Springer Science & Business Media, 2012.

[153] Abram M Kagan and Gábor J Székely. An analytic generalization of independence and identical distributiveness. *Statistics & Probability Letters*, 110:244–248, 2016.

[154] Tim Venn. Probability, mathematical statistics, stochastic processes. http://www.randomservices.org/random/sample/Variance.html, 07 March 2014. (Accessed on 02/08/2019).

[155] Department of Statistics Online Programs. Probability density functions. https://newonlinecourses.science.psu.edu/stat414/node/287/, 12 Aug 2018. (Accessed on 03/08/2018).

[156] Luca Scrucca, Michael Fop, T Brendan Murphy, and Adrian E Raftery. mclust 5: clustering, classification and density estimation using gaussian finite mixture models. *The R journal*, 8(1):289, 2016.

[157] Markus Michael Rau, Stella Seitz, Fabrice Brimioulle, Eibe Frank, Oliver Friedrich, Daniel Gruen, and Ben Hoyle. Accurate photometric redshift probability density estimation–method comparison and application. *Monthly Notices of the Royal Astronomical Society*, 452(4):3710–3725, 2015.

[158] David W Scott. *Multivariate density estimation: theory, practice, and visualization*. John Wiley & Sons, 2015.

[159] Stephanie Glen. Sample variance. https://www.statisticshowto.datasciencecentral.com/probability-and-statistics/descriptive-statistics/sample-variance/, 15 March 2017. (Accessed on 02/08/2019).

[160] David M. Lane. Sampling distribution of the mean. http://onlinestatbook.com/2/sampling_distributions/samp_dist_mean.html, 12 July 2015. (Accessed on 15/08/2018).

[161] Prof. D. Joyce. Expectation and variance for continuous random variables. https://mathcs.clarku.edu/~djoyce/ma217/contexp.pdf, Fall Fall 2014. (Accessed on 05/13/2018).

[162] The Wyzant Team. Variance and standard deviation of a random variable. https://www.wyzant.com/resources/lessons/math/statistics_and_probability/expected_value/variance, May 2016. (Accessed on 05/13/2018).

[163] Jeremy Orloff and Jonathan Bloom. Expectation, variance and standard deviation for continuous random variables. https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/readings/MIT18_05S14_Reading6a.pdf, Spring 2014. (Accessed on 05/15/2018).

[164] yale university. Mean and variance of random variables. http://www.stat.yale.edu/Courses/1997-98/101/rvmnvar.htm, 2017. (Accessed on 10/06/2018).

[165] PROBABILITY DISTRIBUTIONS. Probability distributions. https://www.le.ac.uk/users/dsgp1/COURSES/LEISTATS/STATSLIDE4.pdf, 06th Jun 2014. (Accessed on 24/Nov/2018).

[166] Kyle Siegrist. Transformations of random variables. http://www.randomservices.org/random/dist/Transformations.html, July 24 2014. (Accessed on 30/03/2019).

[167] Sven Erlander. On the relationship between the discrete and continuous models for combined distribution and assignment. *Transportation Research Part B: Methodological*, 22(5):371–382, 1988.

[168] Maths Lecture Note. Mixed distributions. http://math.bme.hu/~nandori/Virtual_lab/stat/dist/Mixed.pdf, 2014. (Accessed on 05/09/2018).

[169] Hossein Pishro-Nik. Introduction to probability, statistics and random processes. http://math.bme.hu/~nandori/Virtual_lab/stat/dist/Mixed.pdf, 2016. (Accessed on 02/03/2018).

[170] Scott Bruce, Zeda Li, Alex Hsiang Chieh, and Subhadeep Mukhopadhyay. Nonparametric distributed learning architecture for big data: Algorithm and applications. *IEEE Transactions on Big Data*, 2018.

[171] Francis Sahngun Nahm. Nonparametric statistical tests for the continuous data: the basic concept and the practical use. *Korean journal of anesthesiology*, 69(1):8–14, 2016.

[172] Suxin Guo, Sheng Zhong, and Aidong Zhang. Privacy-preserving kruskal–wallis test. *Computer methods and programs in biomedicine*, 112(1):135–145, 2013.

[173] Salvador García, Daniel Molina, Manuel Lozano, and Francisco Herrera. A study on the use of non-parametric tests for analyzing the evolutionary algorithms' behaviour: a case study on the cec'2005 special session on real parameter optimization. *Journal of Heuristics*, 15(6):617, 2009.

[174] Nancy L Leech and Anthony J Onwuegbuzie. A call for greater use of nonparametric statistics. 2002.

[175] Analytics Vidhya Content Team. A simple introduction to anova (with applications in excel). https://www.analyticsvidhya.com/blog/2018/01/anova-analysis-of-variance/, Aug 2015. (Accessed on 10/07/2018).

[176] SPSSTUTORIALS Team. Spss tutorials. https://www.spss-tutorials.com/anova/, 12 Aug 2015. (Accessed on 03/08/2018).

[177] Delphine S Courvoisier and Olivier Renaud. Robust analysis of the central tendency, simple and multiple regression and anova: A step by step tutorial. *International Journal of Psychological Research*, 3(1):78–87, 2010.

[178] Brian J Reich, Curtis B Storlie, and Howard D Bondell. Variable selection in bayesian smoothing spline anova models: Application to deterministic computer codes. *Technometrics*, 51(2):110–120, 2009.

[179] Francis Musyimi. Kruskal wallis h test: Definition, examples assumptions. http://www.statisticshowto.com/kruskal-wallis/, May 5 2017. (Accessed on 23/05/2018).

[180] William H Kruskal and W Allen Wallis. Use of ranks in one-criterion variance analysis. *Journal of the American statistical Association*, 47(260):583–621, 1952.

[181] Richard Lowry. Concepts and applications of inferential statistics-the kruskal-wallis test. http://vassarstats.net/textbook/ch14a.html, 1999-2018. (Accessed on 20/05/2018).

[182] Bertrand Delgutte. Random variables and probability density functions-biomedical signal and image processing. http://web.mit.edu/~gari/teaching/6.555/lectures/ch_pdf_sw.pdf, Spring Spring 2007. (Accessed on 27/05/2018).

[183] wikipedia. F-distribution. https://en.wikipedia.org/wiki/F-test. (Accessed on 12/25/2018).

[184] Introduction to Statistics. The f distribution and the f-ratio. https://courses.lumenlearning.com/introstats1/chapter/the-f-distribution-and-the-f-ratio/. (Accessed on 12/25/2018).

[185] Stat Trek Teach yourself statistics. F distribution. https://stattrek.com/probability-distributions/f-distribution.aspx. (Accessed on 12/25/2018).

[186] John Clark. F-distribution explained. https://magoosh.com/statistics/f-distribution-explained/. (Accessed on 04/28/2018).

[187] Douglas G Altman and J Martin Bland. Parametric v non-parametric methods for data analysis. *Bmj*, 338:a3167, 2009.

[188] properties of variance. properties of variance. https://courses.cs.washington.edu/courses/cse312/13wi/slides/var+zoo.pdf. (Accessed on 12/25/2018).

[189] Isao Ishida and Robert F Engle. Modeling variance of variance: The square-root, the affine and the cev garch models. *Working Papers of Department of Finances, Nueva York*, 2002.

[190] Glenn D Israel. Determining sample size. 1992.

[191] Wayne W. LaMorte. Central limit theorem. http://sphweb.bumc.bu.edu/otlt/MPH-Modules/BS/BS704_Probability/BS704_Probability12.html, July 24 2016. (Accessed on 21/03/2019).

[192] Lori A Dalton et al. Heuristic algorithms for feature selection under bayesian models with block-diagonal covariance structure. *BMC bioinformatics*, 19(3):70, 2018.

[193] Stjepan Oreski and Goran Oreski. Genetic algorithm-based heuristic for feature selection in credit risk assessment. *Expert systems with applications*, 41(4):2052–2064, 2014.

[194] Miron B Kursa, Witold R Rudnicki, et al. Feature selection with the boruta package. *J Stat Softw*, 36(11):1–13, 2010.

[195] Mark A Hall and Lloyd A Smith. Practical feature subset selection for machine learning. 1998.

[196] Mark A Hall. Correlation-based feature selection of discrete and numeric class machine learning. 2000.

[197] Michal Kosinski, David Stillwell, and Thore Graepel. Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, page 201218772, 2013.

[198] Genevieve Patterson, Chen Xu, Hang Su, and James Hays. The sun attribute database: Beyond categories for deeper scene understanding. *International Journal of Computer Vision*, 108(1-2):59–81, 2014.

[199] Nazrul Hoque, DK Bhattacharyya, and Jugal K Kalita. Mifs-nd: a mutual information-based feature selection method. *Expert Systems with Applications*, 41(14):6371–6385, 2014.

[200] Wei Dai and Wei Ji. A mapreduce implementation of c4. 5 decision tree algorithm. *International journal of database theory and application*, 7(1):49–60, 2014.

[201] Raymond T Ng and Jiawei Han. E cient and e ective clustering methods for spatial data mining. In *Proceedings of VLDB*, pages 144–155, 1994.

[202] Jiawei Han, Jian Pei, and Micheline Kamber. *Data mining: concepts and techniques*. Elsevier, 2011.

[203] Pavel Berkhin. A survey of clustering data mining techniques. In *Grouping multidimensional data*, pages 25–71. Springer, 2006.

[204] Andre Hasudungan Lubis, Ali Ikhwan, and Phak Len Eh Kan. Combination of levenshtein distance and rabin-karp to improve the accuracy of document equivalence level. *International Journal of Engineering & Technology*, 7(2.27):17–21, 2018.

[205] Min-Min Shao and Dong-Mei Qian. The application of levenshtein algorithm in the examination of the question bank similarity. In *2016 International Conference on Robots & Intelligent System (ICRIS)*, pages 422–424. IEEE, 2016.

[206] Athanasios Kiourtis, Argyro Mavrogiorgou, Sokratis Nifakos, and Dimosthenis Kyriazis. A string similarity evaluation for healthcare ontologies alignment to hl7 fhir resources. In *Intelligent Computing-Proceedings of the Computing Conference*, pages 956–970. Springer, 2019.

[207] Khin Moe Myint Aung. *Comparison of Levenshtein Distance Algorithm and Needleman-Wunsch Distance Algorithm for String Matching*. PhD thesis, University of Computer Studies, Yangon, 2019.

[208] Rein Luus. *Iterative dynamic programming*. CRC Press, 2019.

[209] Sergey Anatolievich Gorobets, Neil Richard Darragh, and Liam Michael Parker. Dynamic programming adjustments based on memory wear, health, and endurance, March 5 2019. US Patent 10,223,029.

[210] Sandip Sarkar, Dipankar Das, Partha Pakray, and Alexander Gelbukh. Junitmz at semeval-2016 task 1: Identifying semantic similarity using levenshtein ratio. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 702–705, 2016.

[211] Chen Hao, Tao Chuanqi, and Jerry Gao. A quality evaluation approach to search engines of shopping platforms. In *2017 IEEE Third International Conference on Big Data Computing Service and Applications (BigDataService)*, pages 299–304. IEEE, 2017.

[212] Tie-Yan Liu et al. Learning to rank for information retrieval. *Foundations and Trends® in Information Retrieval*, 3(3):225–331, 2009.

[213] Yizhou Sun, Yintao Yu, and Jiawei Han. Ranking-based clustering of heterogeneous information networks with star network schema. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 797–806. ACM, 2009.

[214] Sung-Hyuk Cha. Comprehensive survey on distance/similarity measures between probability density functions. *City*, 1(2):1, 2007.

[215] Microsoft Azure. Machine learning algorithm cheat sheet for azure machine learning studio. https://docs.microsoft.com/en-us/azure/machine-learning/studio/algorithm-cheat-sheet, 7 July 2019. (Accessed on 10/07/2019).

[216] Zaid Alissa Almaliki. Do you know how to choose the right machine learning algorithm among 7 different types? https://towardsdatascience.com/do-you-know-how-to-choose-the-right-machine-learning-algorithm-among-7-di 19 March 2019. (Accessed on 10/07/2019).

[217] Minh Hoai Nguyen and Fernando De la Torre. Optimal feature selection for support vector machines. *Pattern recognition*, 43(3):584–591, 2010.

[218] NewTechDojo. List of machine learning algorithms. https://www.newtechdojo.com/list-machine-learning-algorithms/, 6 March 2018. (Accessed on 19/07/2019).

[219] SUNIL RAY. List of common machine learning algorithms. https://www.analyticsvidhya.com/blog/2017/09/common-machine-learning-algorithms/, 9 Septemeber 2019. (Accessed on 25/06/2019).

[220] Haibo He, Yang Bai, Edwardo A Garcia, and Shutao Li. Adasyn: Adaptive synthetic sampling approach for imbalanced learning. In *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, pages 1322–1328. IEEE, 2008.

[221] Rohit Walimbe. Handling imbalanced dataset in supervised learning using family of smote algorithm. https://www.datasciencecentral.com/profiles/blogs/handling-imbalanced-data-sets-in-supervised-learning-using-family, 24 April 2017. (Accessed on 15/07/2019).

[222] D. Oliveira C. Aridas G. Lemaitre, F. Nogueira. Comparison of the different over-sampling algorithms. https://imbalanced-learn.readthedocs.io/en/stable/auto_examples/over-sampling/plot_comparison_over_sampling.html#comparison-of-the-different-over-sampling-algorithms, 24 April 2017. (Accessed on 15/07/2019).

End of Document.