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PCA versus LDA as Dimension Reduction for Individuality of Handwriting in Writer Verification

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***Abstract*—Principal Component Analysis and Linear Discriminant Analysis are the most popular approach used in statistical data analysis. Both of these approaches are usually implemented as traditional linear technique for Dimension reduction approach. Dimension reduction is useful approach in data analysis application. The concept of dimension reduction will help the process of identifying the most important features in handwritten data which also called as individuality of the handwriting. Where, this individuality will help the verification process in order to verify the handwritten document. The purposed of this paper is to perform both techniques above in writer verification process in order to acquire the individuality of the handwriting. Classification process will be use to evaluate the effectiveness of both approach performance in form of classification accuracy.**

Keywords-Principal Component Analysis; Dimension Reduction; Linear Discriminant Analysis; individuality of Handwriting; Writer Verification

I. INTRODUCTION

Dimension reduction (DR) is important in many domains, since it facilities classification, visualization and compression of high-dimensional data, by decreasing the curse of dimensionality and other undesired properties of high-dimensional spaces [1]. Curse of the dimensionality refer to various phenomena that arise when analyzing and organizing data in high-dimensional data. In the absence of simplifying assumptions, the sample size needed to estimate a function of several variables to a given degree of accuracy grows exponentially with the number of variables. This situation will not be occurred in low-dimensional data. Ideally, DR is the process of transforming high-dimensional data into a meaningful representation of reduced dimensionality or low-dimensional data.

Dimension reduction can be divided in two categories which are linear technique and nonlinear technique. Linear techniques assume that the data lie on or near a linear subspace of the high-dimensional space. Nonlinear techniques for dimensionality reduction do not rely on the linearity assumption as a result of which more complex embeddings of the data in the high-dimensional space can be identified [2]. However, This study only focus on linear techniques because of the data involved is not very complex where only eight features column will be examined and also not a nonlinear data [2]. There are two commonly used methods in linear DR which are Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Both methods can performed DR in order to reduce the dimension of data eventhough the way of their performance is different. On the other hand, the goal of DR can be achieved either using PCA or LDA depends on the data that used in the experiments.

In the data analysis, not all the features can yield important information that represents unique individualities of the writer, because maybe there is a lot of data redundancy which is not very useable in the analysis. In these issues, dimension reduction is useful to in order to improve that quality of the data used in analysis of data [3]. The objective of this paper is to implement PCA and LDA in writer verification, in order to acquire the most signification feature which can represent the individuality of the handwriting. That means, the selected features is unique and belong only to the writer. So that this features will easier and shorted the verification process. Writer Verification task is determined whether two samples of handwriting is written by the same writer or not [4] [5]. The Comparison will be conducted by examining the classification accuracy and number of features data has been effectively reduced using both methods above.

This paper is organized as follows in section 2 the detail explanation of Linear Dimension Reduction Technique is provided. In section 3, the comparison of PCA and LDA will be Elaborate in detail in order to give brief overview of both methods. In section 4 the description about Writer Verification and the way of acquiring their individuality will be showed. Section 5 will describe about the Experiment setup of the process. The result explanation will be in Section 6 Finally, conclusion will be in section 6.

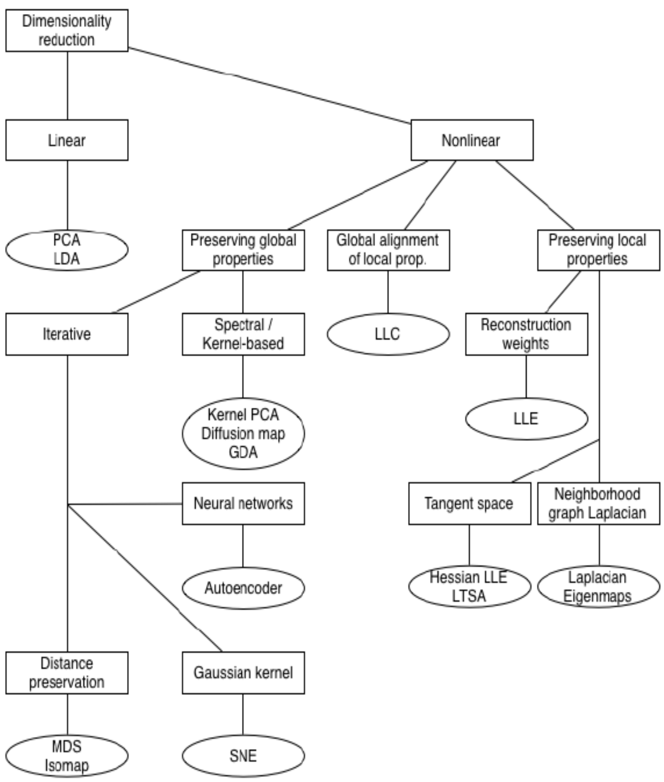


Figure 1. Taxonomy of Dimension Reduction Techniques

II. DIMENSION REDUCTION METHODS

This Section will discuss about two methods of DR in detail. Principal Component Analysis and Linear Discriminant Analysis is traditional Linear DR methods which has been proposed to be used in experiment in order to observe which methods a more capable in achieving the goal of this study.

A. Principal Component Analysis (PCA)

Principal Component Analysis is a statistical tool used to analyst data set. The main idea of PCA is to reduce the dimensionality of the data consisting of large number of interrelated variables, while retaining as much as possible of the variation present in the data set [6]. The reduction dimensions of the data that performed by PCA will not influent the originality of the data, so that the process will produce more accurate result and also will show their similarity and differences. That means, once the pattern of the data is found this technique will reduce the dimension without losing many features components from the original data like stated in [7]. Ideally of PCA are composed by several concept of statistic which is variance, covariance, eigenvector and eigenvalue to undergo the analysis task on any sample of data that uncorrelated to each other. Therefore, PCA will reduce the dimensionality of the data set by transforming the original data to a new set of variables called Principal Component (PCs) [6].

PCA computes principal components which are obtain as linear combinations of the original variables in order to achieve three goal of PCA. Which are extract the most important information from the data set, compress the size of data by keeping only important information and third goal is simplify the description of data and analyze the structure of an observation. In this study, PCA was proposed to acquire the most significant feature from handwritten data to represent the individuality of handwriting. This individuality of handwriting will be use by writer verification process in order to verify the author of the handwritten document.

Typically in this work, the objective of PCA is to transform the data into another set of feature f', for example x_i transformed into x'_i in k dimensions shows:

$$x'_i = W x_i \tag{1}$$

The transformation of PCA is by reducing the space that captures most of the variance in the data. The whole idea of PCA is rest on the covariance matrix of the data as:

$$C = \frac{1}{n-1} X X^T \tag{2}$$

C, Captures the variance in the individual features and the off-diagonal terms quantify the covariance between the corresponding pairs of features. C, can produce C_{PCA}, when the data is transformed by Y = PX where the rows of P are the eigenvector of XX^T, then

$$C_{PCA} = \frac{1}{n-1} Y Y^T \tag{3}$$

$$C_{PCA} = \frac{1}{n-1} (PX)(PX)^T \tag{4}$$

C_{PCA}, is the quantifier of variance of the data in the direction of the corresponding principal component. So that, this technique will reduce the dimensionality by discarding the lesser principal component while the accepted one is the most significant feature.

In Figure 2 below was showed the detail flow process of PCA. The most important process in PCA is calculation process where this calculation will influences the transformation process. Especially eigenvector and eigenvalue calculation because it was used in order to perform the reduction of data dimension.

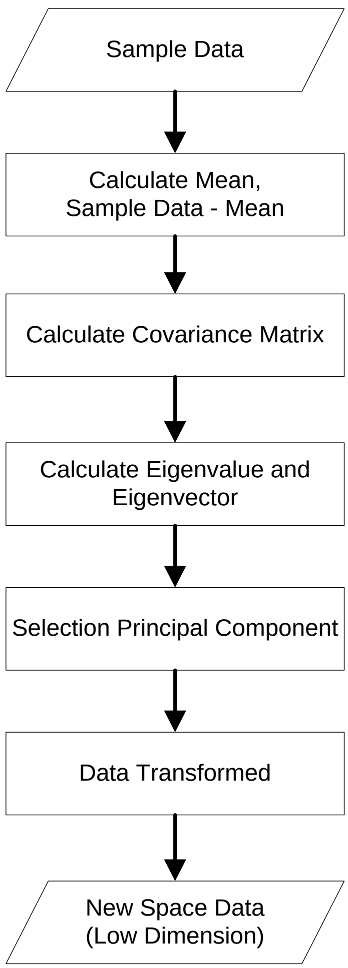


Figure 2. Flowchart of PCA

B. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is a classical linear technique dimension reduction and it is designed to optimal cluster different classes of objects under a projection to a low dimensional subspace [7]. The main idea of LDA is involved the measurement of between-class scatter and within-class scatter in order to quantify the quality of the cluster in the sample data. This method will maximize the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability [10]. Moreover, optimal transformation in LDA can be computed by applying an eigendecomposition also call as a scatter matrix [26][27]. On the other hand this eigendecomposition is important in statistics because it is used to find the maximum or minimum of function involving the data matrices.

Basically, LDA process doesn't change the location when transformed the data, but only to provide more class separability and draw the decision region between the given classes. This process will help to better understand the distribution of the features data [10]. From this situation this method can detect the significant features from the classes, and then will transform it to a new space data which consist of most significant feature that can represent the individuality of handwriting. The within-class (S_w) and between-class (S_b) measurements are compute using equation below:

$$S_w = \sum_j P_j \times (cov_j) \tag{1}$$

$$S_b = \sum_j (\mu_j - \mu_3) \times (\mu_j - \mu_3)^T \tag{1}$$

P_j Is a probabilities of the classes, cov_j is covariance matrices. S_b is the between-class which can be though as the covariance of data set whose members are the mean vector of each class in the handwritten data that need to be transformed in order to find the significant feature.

Beside of that transformation involved in LDA can be classified into two different approaches. Firstly, class-dependent transformation involves maximizing the ratio of between class variance to within class variance so that adequate class separability is obtained as well as this approach also using only two optimizing criteria for transforming the data. Secondly, class-independent transformation which involves maximizing the ratio of overall variance to within class variance but this approach used only one optimizing criterion to transform the data and each class is considered as a separate class against all other classes [10].

In figure 3 below was showed the flow process of LDA, where LDA is always concerned in calculation of the scatter matrix of the data. There are two types of scatter matrix which is within-class scatter and between-class scatter. In LDA calculation of scatter matrix is represent the calculation of eigenvector and eigenvalue. Therefore, the result from this calculation has been used in order to transform the original data into a lower dimension of data.

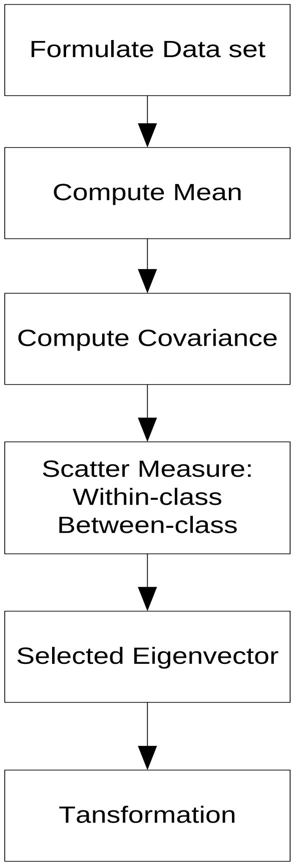


Figure 3. Flowchart of LDA

III. COMPARISON OF PCA AND LDA

Both methods can achieve goal of dimension reduction which extracts a small number of features by removing irrelevant, redundant, and noisy information in data [28]. However, the way of both methods in achieving it is different between each other. Where, PCA will compute vector that has the largest variance and not required to utilize the class information such as within-class scatter and between-class scatter. In contrast, LDA will compute a vector which best discriminates between the classes and this method concerned about the within-class scatter and between-class scatter. In addition PCA give class representations which are in orthogonal linear space, however LDA generates class discriminatory information in a linear separable space which is not necessarily orthogonal [32]. Therefore, PCA tries to simplify the input data by extracting the features while LDA tries to distinguish the input data by dimension reduction process.

There are several other differences between PCA and LDA that has been highlighted other research. Firstly, both methods are from different group of DR based on the learning process. PCA is unsupervised methods of DR and LDA is supervised methods of DR. Where supervised methods need a training set with the class label information to learn the lower dimensional representation according some criteria and make some prediction on testing data. On the other hand, unsupervised methods project the original data to a lower dimensional space without utilizing the label information [31].

The other differences is related to number of sample that used, when the number of samples per class is small or training data non-uniformly sample the underlying distribution PCA might outperform LDA [33][34]. In addition, LDA cannot process small sample data effectively because a singular scatter matrix problem occurs when the number of feature dimension is large compared to the number of training examples. A final difference is PCA change the shape and location of the original data sets while transforming the data into a new data space with lower dimension. In contrast, LDA doesn't change the location but only tries to provide more class separability and draw a decision region between the given classes.

TABLE I. SUMMARY OF DIFFERENCESS

PCA	LDA
Unsupervised Technique	Supervised Technique
Experimental more to features analysis	Experimental more to data analysis
Can perform with small sample data.	Cannot perform with small sample of data.
Change the shape and location.	Doesn't change the location.

IV. INDIVIDUALITY OF HANDWRITING IN WRITER VERIFICATION

In theory, Writer Identification and Writer Verification belong to the group of behavioral methods in biometrics. The biometric analysis of handwriting requires a broad knowledge at multiple levels of observation. The major issue in this field is the way to acquire the most significant feature that can represent the individuality of handwriting data. This is because writer individuality rest on the hypothesis that each individual has consistent handwriting that is distinct from the handwriting of another individual [4]. Both methods will come to a conclusion of identifying the unknown writer, but the difference is according to the task of their performance.

Writer Identification task concerns about the retrieval of handwritten samples from a database using the handwritten sample under study as a graphical query and provide a subset of relevant writer's documents [5][13]. While, Writer Verification task is determined whether two samples of handwriting is written by the same writer or not [4][12]. Most of the recent research focuses on signature verification especially in field of on-line writer verification, where the verification process is used to perform the matching of two sample signature from one writer. To solve the problem of forged handwriting, dynamic information such as velocity, acceleration, and force exerted on the pen are utilized [11].

In this research, the verification process is chosen to be performed in text verification, because this task consists in matching the unknown writer with each of those in the selected subset. However, sometimes verification task can be adapted to each known reference writer based on the individual description of their handwriting [9]. The individuality of handwriting will be use in order to verifying the writer of the document, by using the technique has been proposed this individuality will be represented by the most significant feature which is very important in detecting the unique handwritten information of the writer.

Figure 4. Basic Design of Verification Process.

V. EXPERIMENTAL

In this experiment, there are two components which is the most important which is Data Set and Verification framework. This section will explain the data collection process and illustrate the flow of verification operation.

A. Handwriting Data

This section describes the process involved in collecting and preparing the dataset used in this study. Where the dataset used is taken from IAM Handwriting Database [14]. It has been developed by Computer Vision and Artificial Intelligence Group (FKI) at Institute of Computer Science and Applied Mathematics in Universität Bern, Switzerland. This database contains images of handwritten English text that can be used as training and testing sample data in handwriting recognition, writer identification and writer verification experiments.

There are 657 writer's contributed their handwriting sample available in forms of image to be used, however only five writers with 3619 instance of images are chosen for the experiment. 9 documents of handwriting samples is taken from each writer and more than 50 word randomly divided into training and testing dataset based on percentage shown in figure below. The selection and processing of the data is suitable with the concept of Writer Verification process.

Firstly, the form of handwriting text will be extracted by using United Moment Invariance (UMI). After extraction process has been done, eight features from one word of handwriting data are generated by UMI, where the feature is a representation an important feature of original handwriting data like shown in the table below. UMI is a useful approach in describing the shape of image in form of scaling, translating, rotation, and reflection that affect the shape of feature because of they are invariance [15]. In addition, as each writer has a different style of writing, this suggests that they may also have different shape of features.

TABLE II. EXAMPLE OF DATA

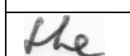
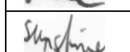
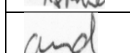
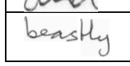
Word	F1	F2	F3	F4	F 5	F 6	F 7	F8
	0.75	0.38	0.44	0.19	0.67	4.62	0.50	4.59
	0.71	0.37	0.49	0.23	0.73	4.66	0.63	4.13
	0.72	0.40	0.53	0.28	0.75	4.41	0.69	3.79
	0.82	0.49	0.57	0.31	0.71	3.86	0.63	3.58

TABLE I shows the example of data after UMI process, and this data will be examined for the next process. In this experiment, we choose five samples of handwriting data where each sample are divided as training and testing data that consist a few numbers of writers to be processed.

B. Experimantal Framework

We design our work following the traditional of pattern recognition task for writer verification process is consisting of preprocessing, feature extraction, and verification process. This process begins, with preprocessing task, which is to process the data before extracting the real word features. UMI is applied in feature extraction part where all the handwriting text is changed to the word features representation. In this study, we develop this experiment by using Waikato Environment for Knowledge Analysis (WEKA) 3.7.5 for classification process [18]. Feature reduction process will be conducted by MATLAB, where PCA and LDA are implemented for dimension reduction will be developed by using this software before the classification process. The proposed framework is shown below:

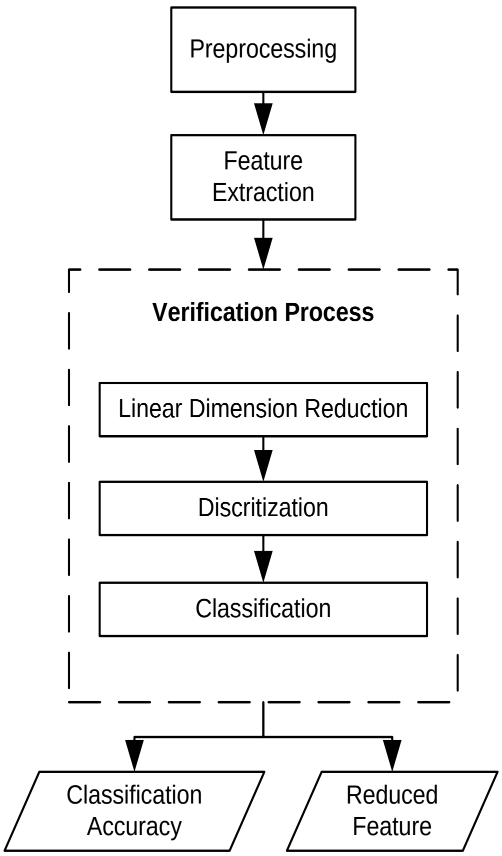


Figure 5. Design Framework of Verification Process.

According to the framework above, the most important part that must be focus is Verification Process which contains three major parts:

1) Dimension Reduction Approaches: This Approach will be applied by implimented PCA and LDA to reduce the feature to a new space with low-dimensional data. The new feature will represent the individuality of handwriting which to be use in verification process.

2) Discritization: Discretization process will be a additional part process the data becomes more clean and easy to determine the unique feature of the writer's data before we proceed to feature selection and classification task. This is because discretization is important in order to obtain the detachment of writer's individuality and prodece better data representation [16][19]. The method used for discretization is Equal Width Binning (EWB). The main goal of EWB is minimize the number of intervals without significant loss of class-attribute mutual dependence [17]. On the other hand, EWB is a simlest methods to discretize a continuous value attribute into a discrete value in order to enhance the data representation and improve the classification process. The advantages of using discrete value instead of continous value is bring smaller demands on system storage, discrete features are closer to a knowledge level representation, these type of values are easier to understand, use and explain, finally discrete can make learning more accurate and faster [20]. In Figure 6 below was showed the flow process of EWB. There are several term which is very important and usually used in EWB process such as Sorting, evaluation, spiltting or merging and stoping. In addition, each term was explained in the diagram below.

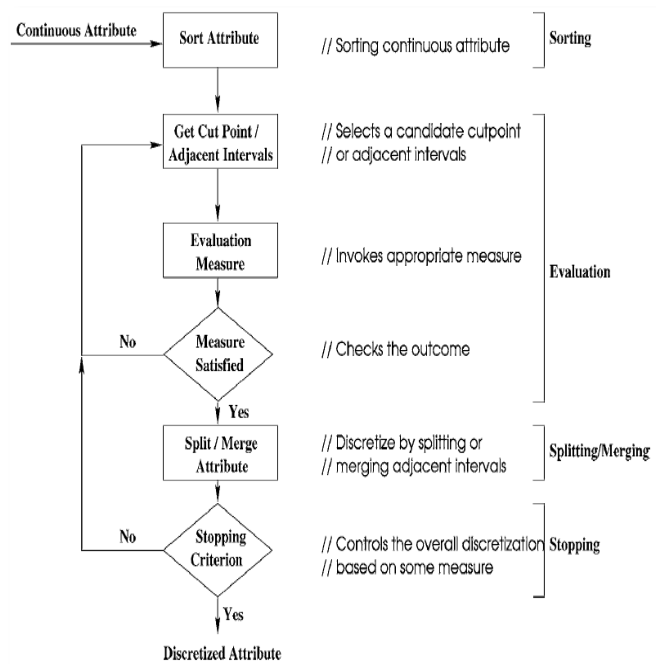


Figure 6. Design Framework of EWB

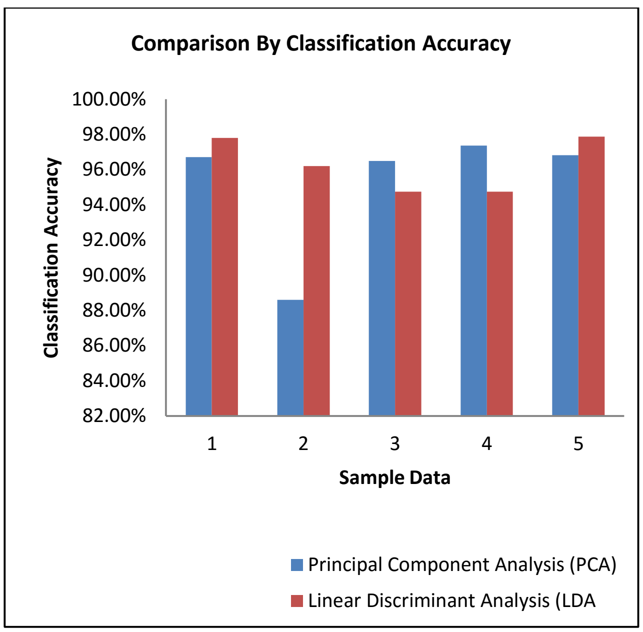
3) Classification: Classification activities have a responsibility to verify the writer of the sample data by producing the classification accuracy. By that value we can prove that which method will produce the higher classification accuracy and reduced most features, besides of measuring the performances. The classifier for this classification is using K-Nearest Neighbor (KNN), this classifier will classifying objects based on closest training examples in the future space. KNN impliment Euclidean Distance in order to classify the features, and groud them in one class if they has a similirities also call as nearest. The perpurse of this classifier was to classify the same class of the same writer.

VI. RESULT AND DISCUSSION

Two categories values are used to measure the performance of the chosen techniques also will be final result of this study. First is classification accuracy and second is the number of features that has been reduced by PCA and LDA. In general, the best methods will produce higher percentage classification accuracy and low dimension of features are selected. Below is the result that has been produced after the experiment:

TABLE III. RESULT OF THE EXPERIMENT

Verification Process		Sample Data 1	Sample Data 2	Sample Data 3	Sample Data 4	Sample Data 5	AVERAGE
Principal Component Analysis (PCA)	Classification Accuracy	96.7033%	88.6076%	96.4912%	97.3684%	96.8085%	95.1958%
	reduced Feature	5	3	5	6	6	5
Linear Discriminant Analysis (LDA	Classification Accuracy	97.8022%	96.2025%	94.7368%	94.7368%	97.8723%	96.2701%
	reduced Feature	6	0	6	4	6	4.4



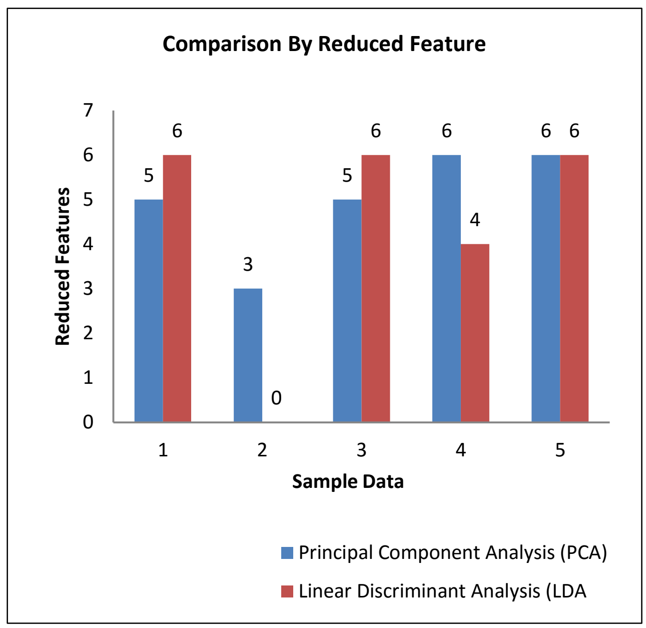


Figure 7. Comparison Graph of Experimantal Result By Classification Accuracy and Reduced Features.

A. Result Discussion

There are two types of comparison are conducted by observing the experimental result. Firstly, the comparison is carried out by observed the classification accuracy also called as verification accuracy. According to the result, both PCA and LDA performances have presented increment in verification accuracy more that 95 %. It means, the verification process is accurately verify the author that produced by both methods. Thus, this value of accuracy can prove that DR is useful in improving the quality of data analysis [3]. Therefore, DR is worth to be explored and adopted as a new task in traditional WV framework.

Second comparison is determined the number of feature dimension that has been reduced by both techniques. The results have shown that all sample data have been successful reduced its dimension by using PCA. On the other hand, the performance of LDA in reducing this sample data is not effective although the verification process can be successfully executed. There is one sample data that cannot be reduced by the LDA because of the size or quantity of the sample data to be examined. Furthermore, LDA will maximize the ratio of between-class variance to within-class variance in the data set in order to guaranteeing maximal separability. Usually the type of reduction like LDA is used in large number size of sample data to easier the reduction process when the data is complex [10]. Contrarily, PCA is more in reducing the data dimension that consist a large number of interrelated variables.

Based on the Comparison Graph above, PCA is effective in both type of comparison and fulfill the requirement of this study. Where this method can effectively reduced the dimension of the data henceforth increased the verification accuracy. Meanwhile, LDA can increase the verification accuracy nevertheless less effective in reduction process using this data. This is because depend on the characteristic of sample data that involved in the experiment especially the content of the data.

VII. CONCLUSION

As a conclusion, the experimental result has proved that both PCA and LDA can be applied in dimension reduction approach successfully, both techniques can reduce the dimension by transforming the original data into a new space data that consist of the most significant feature. Where, this feature will represent the individuality and useful in verification process especially in processing data activities. However, there are several situations that can influence the performances of PCA and LDA. Where PCA will less perform when the data used was correlated between each other. While LDA was not perform when the number of sample data is small. Dimension reduction is more concern in eliminating the redundant data, so that this characteristic can improve the performance of the process. Redundancy will increase the relation among the feature and will cause the feature strongly depend on each other. Reducing the dimension will improve the verification process in term of selecting the feature, this because after the unimportant feature are remove classification process became easier to class the writer according to the writer.

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