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Knowledge Extraction from Survey Data using Neural Networks

Imran Ahmed Khan

KNOWLEDGE EXTRACTION FROM SURVEY DATA USING NEURAL NETWORKS

by

IMRAN AHMED KHAN

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Arun Kulkarni, Ph.D., Committee Chair

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IMRAN AHMED KHAN

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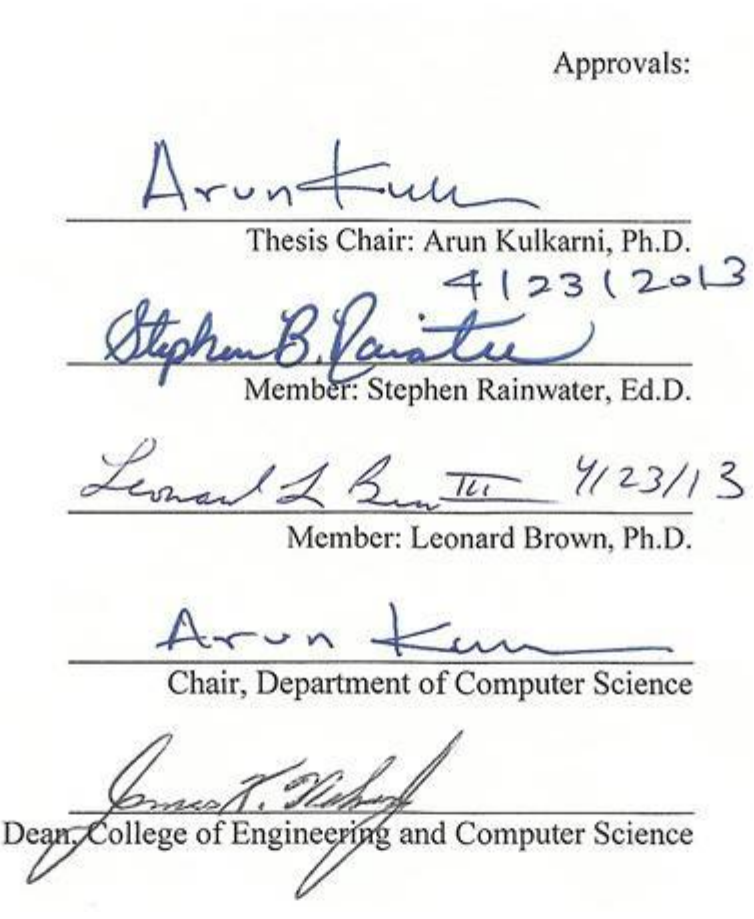

Approvals:

Arun Kul

Thesis Chair: Arun Kulkarni, Ph.D.

4/23/2013

Stephen B. Rainwater

Member: Stephen Rainwater, Ed.D.

Leonard L. Br III 4/23/13

Member: Leonard Brown, Ph.D.

Arun Kum

Chair, Department of Computer Science

Dean, College of Engineering and Computer Science

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Abstract

KNOWLEDGE EXTRACTION FROM SURVEY DATA USING NEURAL NETWORKS

IMRAN AHMED KHAN

Thesis Chair: Arun Kulkarni, Ph. D.

The University of Texas at Tyler
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Surveys are an important tool for researchers. Survey attributes are typically discrete data measured on a Likert scale. Collected responses from the survey contain an enormous amount of data. It is increasingly important to develop powerful means for clustering such data and knowledge extraction that could help in decision-making. The process of clustering becomes complex if the number of survey attributes is large. Another major issue in Likert-Scale data is the uniqueness of tuples. A large number of unique tuples may result in a large number of patterns and that may increase the complexity of the knowledge extraction process. Also, the outcome from the knowledge extraction process may not be satisfactory. The main focus of this research is to propose a method to solve the clustering problem of Likert-scale survey data and to propose an efficient knowledge extraction methodology that can work even if the number of unique patterns is large. The proposed method uses an unsupervised neural network for clustering, and an extended version of the conjunctive rule extraction algorithm has been proposed to extract knowledge in the form of rules. In order to verify the effectiveness of the proposed method, it is applied to two sets of Likert scale survey data, and results show that the proposed method produces rule sets that are comprehensive and concise without affecting the accuracy of the classifier.

Chapter 1

Introduction

A survey is conducted to collect data from individuals to find out their behaviors, needs and opinions towards a specific area of interest. Survey responses are then transformed into usable information in order to improve or enhance that area. It is also referred to as a research tool. It consists of a series of questions that a respondent has to answer in a specific format. The respondent has to select among the options given to each question. Survey data attributes can come in the forms of binary-valued (or binary-encoded), continuous data or discrete data measured on a Likert scale. All three forms of data attributes are used according to the survey requirements. Discrete data can be used as a measure on a Likert scale to provide some distinct advantages over the other two types of data attributes. A Likert scale gives more options to respondents as compared to a binary valued survey. A Likert scale also helps respondents choose an answer. For instance, some respondents may be too impatient to make fine judgments and to give their responses on a continuous scale. The options provided in a typical five-level Likert item are Strongly Disagree, Disagree, neither Agree nor Disagree, Agree and Strongly Agree. The collected data might be contaminated if the difficult or time consuming judgmental task is beyond the respondent's ability or tolerance. The use of a Likert scale has been proposed to alleviate these difficulties.

Extracting knowledge from survey data is a very important step in the decision-making process. Based on this knowledge, decisions are taken to improve the area for which the survey was conducted. Collected data may not be useful if proper analysis is not conducted. There are statistical methods available to perform analysis on survey data. A few of them are discussed in the next chapter. These methods can perform basic to advanced response analysis. Some of the methods are also effective to perform clustering of the survey data. Clustering is a process that groups data into classes or categories based on the features or attributes of the data. The partitioning of data is performed by a clustering algorithm without any explicit knowledge about the groups. Clustering is useful where groups are unknown or previously unknown groups need to be found [1]. Some clustering algorithms are discussed in the next chapter. Statistical methods can cluster data, but in-depth knowledge cannot be extracted using these methods.

Clustering of Likert-scale survey data depends on the type of data and the number of attributes. The process of clustering becomes more complex when the number of Likert scale options and attributes in the survey is large. In the case of a survey, these attributes or features are the questions. Another major issue in Likert-Scale data is the uniqueness of the tuples. Clustering algorithms group data based on the patterns of the attributes. A large number of unique tuples may result in a large number of patterns. Due to a large number of patterns, the knowledge extraction process from these classifiers becomes complex, and often the outcome of knowledge extraction process may not be satisfactory. The extracted information is usually expressed in the form of if-then-else rules. These rules describe the extent to which a test pattern belongs or does not belong to one of the classes in terms of antecedent and consequent. The main focus of this research was to apply an unsupervised neural network to cluster Likert-scale survey data and to propose an efficient knowledge extraction methodology that can work even if the number of patterns is large.

There are many classifiers available such as an Artificial Neural Network (ANN) [2, 3, 4, 5], C4.5 [6] and ID3 [7] etc. An ANN is a powerful technique to solve many real world problems. They have the ability to learn from observation in order to improve their performance and to adapt themselves to changes in the environment. The basic architecture of an ANN consists of three types of neuron layers: input, hidden, and output. An ANN is further divided into two categories: supervised and unsupervised. In unsupervised learning, no class label information exists, and the system forms groups on the basis of input patterns. An unsupervised neural network adjusts itself with new input patterns. These input patterns are presented to the network and it is supposed to detect the similarity in the input patterns. There are several unsupervised neural networks, but the project has applied the Kohonen neural network due to its simple architecture [8]. The Kohonen neural network is one of the simplest unsupervised networks that consist of two layers. The first layer is the input layer, and the second layer is the Kohonen Layer. Each unit in the input layer has a feed-forward connection to each neuron in the Kohonen layer.

The method proposed in this research consists of three steps. The first step is preprocessing. In the preprocessing step, data cleaning techniques are applied on survey responses and convert those responses into a network readable format. The second step is to apply the Kohonen neural network to group data tuples into different clusters. The third step is to extract knowledge from the neural network in the form of rules and optimize them to obtain a comprehensive and concise set of rules.

The proposed method was applied to two Likert scale surveys. The first survey was about the reading strategies of students. The name of the survey was “Metacognitive Awareness of Reading Strategies Inventory (MARSI)” [9]. It has 30 questions, and each question has five options. The second data set is a teacher evaluation survey. The teacher evaluation survey form consisted of eight questions; each question had five options. It was used to evaluate a teacher’s performance and helped in decision making.

1.1 Organization of the Thesis

The chapters in this thesis are organized as follows. Chapter 2 reviewed the statistical methods for analysis of Likert scale data. An artificial neural network is discussed along with clustering algorithms. Various rule extraction techniques are also explained in the chapter. Chapter 3 describes the proposed methodology and clustering using unsupervised neural networks. It also explains the proposed rule extraction algorithm. Chapter 4 mainly illustrates the results. The error matrix and other performance measures are discussed for each example. It also compares the results of the proposed method with results of C4.5 classifier. Chapter 5 provides a conclusion and a discussion of future work.

Chapter 2

Background

Survey responses contain an enormous amount of data, consisting of binary-valued or binary-encoded data, continuous data, or discrete data measured on a Likert scale. Extracting knowledge from survey data is a very important step in a decision-making process. Analyzing results of a survey depend on the type of data and the number of attributes. The process of data analysis becomes more complex when the number of questions and attributes in the survey is large.

Statistical analysis of survey results is limited. It only describes the percentage for each response. For example, a typical question on a binary survey would be “Do you own a Smartphone?” and provided response options are “Yes” and “No”. An Analysis of this type of survey would result in some kind of percentage of responses as described in Table 1 [10].

Table 1. Survey Results Analysis I

Value	**Percentage**
Yes	87%
No	13%

It is also common to analyze survey results by separating respondents into groups or categories based on the gender or any other attribute. In this way, an analysis report may generate results in a more detailed format. Taking the same example as above, it is possible to generate results in more detail by categorizing responses based on the kind of Smartphone they have [10].

Table 2. Survey Results Analysis II

Smartphone Kind	Percentage of users
iPhone	62%
Android	22%
RIM (blackberry)	30%
Palm	1%
Windows	1%
Other	2%

The above analysis can be helpful in a binary valued survey, but in the case of a Likert scale survey, it will be a problem to organize results into a coherent and meaningful set of findings. As in a Likert scale survey, the response of a person can vary between given options. Generally, five options are provided for selection. Some examples of those options are shown in Table 3.

Table 3. Examples of Likert Scale Response Categories

Scale	1	2	3	4	5
	Never	Seldom	Sometimes	Often	Always
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
	Most important	Important	Neutral	Unimportant	Not Important at all

Analysis of Likert scale survey data is a much more complex task as compared to a binary valued survey due to the number of options for each question. Analyzing the Likert scale survey data in the same way as a binary valued survey might show incorrect analysis results. One mistake commonly made in analyzing this type of survey is the improper analysis of individual questions on an attitudinal scale. Another important aspect in analyzing this type of survey is to understand the difference between Likert-Type and Likert Scales [11]. Analysis procedures are different for both Likert-Type and Likert Scale surveys. Basic concepts about Likert survey are reviewed below.

2.1 Likert-Type Items

The difference between Likert-type items and Likert scales is described in [12]. Likert-type items are identified as a single question that uses some aspect of the original Likert response alternatives. While multiple questions may be used in a research instrument, there is no attempt by the researcher to combine the responses from the items into a composite scale. Five samples of Likert-Type questions are shown in Table 4. These questions have no center or neutral point, so they cannot be combined into a single scalar value. A respondent has to choose whether they agree or disagree with the question [12].

Table 4. Five Likert-Type Questions with Four Options

	Strongly Disagree	**Disagree**	**Agree**	**Strongly Agree**
1. I feel good about my work on the job.	SD	D	A	SA
2. I am satisfied with job benefits	SD	D	A	SA
3. My office environment is friendly	SD	D	A	SA
4. I feel like I make a useful contribution at work	SD	D	A	SA
5. I can start working on a project with little or no help	SD	D	A	SA

2.2 Likert-Scale

A Likert scale is composed of a series of four or more Likert-type items that are combined into a single composite score/variable during the data analysis process [11]. These Likert-type items may vary from one survey to another. An example of five Likert-scale questions is shown in Table 5. The MARSI survey used the following Likert-type items.

Option 1: I have never heard of this strategy before.

Option 2: I have heard of this strategy, but I don’t know what it means.

Option 3: I have heard of this strategy, and I think I know what it means.

Option 4: I know this strategy, and I can explain how and when to use it.

Option 5: I know this strategy quite well, and I often use it when I read.

Table 5. Five Likert-Scale Questions with Five Options

	Option 1	**Option 2**	**Option 3**	**Option 4**	**Option 5**
1. Having a purpose in mind when I read	1	2	3	4	5
2. Taking written notes while reading	1	2	3	4	5
3. Using what I already know to help me understand what I’m reading	1	2	3	4	5
4. Previewing the text to see what it’s about before reading it	1	2	3	4	5
5. Reading aloud to help me understand what I’m reading	1	2	3	4	5

2.3 Data Analysis Procedures

Analyzing procedures for Likert Type data and Likert Scale data are different as shown in Table 6. Four levels of measurements must be discussed in order to understand the data analysis procedure. These four levels of measurements are also referred as a “Steven's Scale of Measurement” [13].

A Nominal scale can be based on natural or artificial categories with no numerical representation associated with it. Examples of nominal scale data include gender, name of a book etc.

An ordinal scale refers to an order or rank such as ranking of students in a class, achievement etc. With an ordinal scale, order or rank can be described, but the interval between the two ranks or order cannot be measured.

An Interval scale shows the order of things and also reflects an equal interval between points on the scale. Interval scales do not have an absolute zero. Measurement of temperature in degrees Fahrenheit or Centigrade is an example of an interval scale.

A Ratio scale uses numbers to indicate order and reflects an equal interval between points on the scale. A ratio scale has an absolute zero. Examples of ratio measures include age and years of experience.

2.3.1 Analyzing Likert-Type Data

In Likert-type data, the interval between numeric values cannot be measured. A number assigned to Likert-type items has a logical or ordered relationship to each other. The scale permits the measurement of a degree of difference but not the specific amount of difference. Due to these characteristics, Likert-type items fall into the ordinal measurement scale. Procedures to analyze ordinal measurement scale items include median for central tendency, frequencies for variability, and Kendal tau B or C procedure for associations [11].

2.3.2 Analyzing Likert Scale Data

Likert scale data have ordered and equal intervals. Numbers assigned to a Likert Scale have an ordered relationship to each other. It also reflects an equal interval between the points on the scale. Due to these characteristics, Likert Scale items fall into the interval measurement scale. Procedures to analyze interval scale items include: arithmetic mean, standard deviation and Pearson’s *r* procedure [11].

Table 6. Data Analysis Procedures for Likert-Type and Likert Scale Data

	Likert-Type Data	**Likert Scale Data**
Central Tendency	Median or mode	Mean
Variability	Frequencies	Standard deviation
Associations	Kendall tau B or C	Pearson's *r*
Other Statistics	Chi-square	ANOVA, t-test, regression

2.3.2.1 Measure of Central Tendency using the Mean Method

Central tendency is a single value that attempts to describe a set of data by identifying the central position within that set of data. The clusters formed by measuring central tendency are based on the domain and the requirements of the survey. In this method, "mean" has been measured for each section of the survey in order to interpret respondents' answers to it. This approach is demonstrated by using the MARSI survey. This survey has 30 questions and each question has five-level Likert items. The MARSI survey consists of three sections: 'Global Reading Strategies', 'Problem Solving Strategies' and 'Support Reading Strategies'. Each answer is interpreted on a 1 to 5 scale. The mean method is applied to the MARSI survey in the following manner:

First, determine the number of questions in each section. This number will be used to determine the mean for each section. It is recommended to calculate the mean for each section separately [9]. Adding them together may result in an incorrect analysis. The number of questions in each section of the MARSI survey is shown in Table 7.

Second, add responses *r* of each question in a section, and divide it by the total number of questions in that section. In this case, for section 'Global Reading Strategies', the responses of those 13 questions will be added and then divided by 13. This is shown in Table 7.

Table 7. Categories in MARSI

Categories	Questions	Mean
Global Reading Strategies	13	$\frac{\sum_i r_i}{13}$
Problem Solving Strategies	8	$\frac{\sum_i r_i}{8}$
Support Reading Strategies	9	$\frac{\sum_i r_i}{9}$

Third, add the means of all questions, and divide it by the total number of sections in the survey. In this case, the total number of sections is 3. So, the mean of the three sections will be added and then divided by 3. This will result in a single value.

Forth, the result of step 3 can be interpreted according to the requirements. In the case of MARSI, if the value is 3.5 or higher, it will be considered as “High Level of Awareness”. If the value is 2.5 to 3.4, then it will be interpreted as “Medium Level of Awareness”. If the value is 2.4 or lower, then it will be interpreted as “Low Level of Awareness”. This interpretation is strictly based on the domain and the requirements of the survey.

Fifth, repeat steps 1 to 4 for each survey tuple.

This method has been applied to the MARSI Survey and, for illustration purposes, fifteen samples are plotted on a graph as shown in Figure 1. By using a graph, it can be seen how measures of central tendency can act as an effective tool in clustering of the data. The graph below shows the grouping of students, where three different circles indicate three different clusters. Each cluster has 5 samples. The bottom group shows “Low Level of Awareness”. The middle Group shows “Medium Level of Awareness” group. The top group shows “High Level of Awareness”.

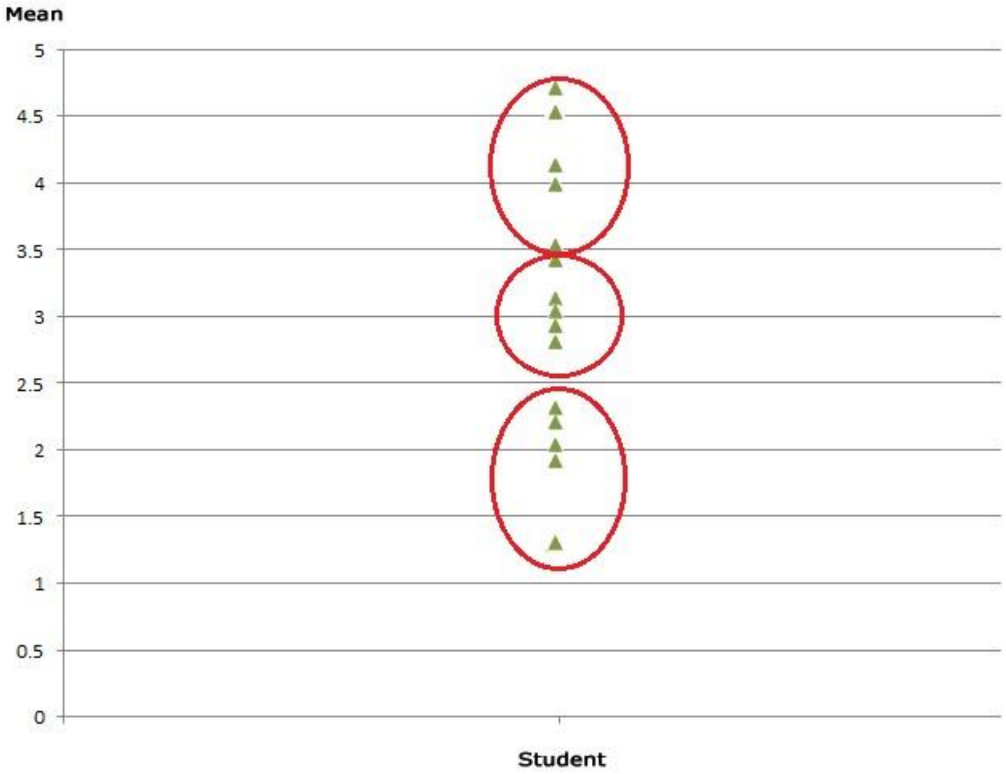

Figure 1. Grouping of Data using Mean Method

This method is effective for grouping, but users cannot extract patterns and trends through which a sample falls into a group. This research has addressed this issue by using an Artificial Neural Network (ANN). An ANN can be used for clustering data into different groups. The ANN uses a rule generation technique to extract patterns and trends in order to justify any decision reached.

2.4 Artificial Neural Networks

An Artificial Neural Network (ANN), usually called a neural network (NN), is a mathematical or computational model that is inspired by biological neural networks. ANN classifiers offer greater robustness, accuracy and fault tolerance. Neural networks are capable of learning and decision making. They are widely used for classification, clustering and prediction such as stocks estimation, remote sensing and pattern recognition. Studies comparing neural network classifiers and conventional classifiers are available [14]. An artificial neural network with three layers is shown in Figure 2. The first layer has input neurons which send data via connection links to the second layer of neurons, and then via more connection links to the third layer of output neurons. The number of neurons in the input layer is usually based on the number of features in a data set. The second layer is also called the hidden layer. More complex systems will have multiple hidden layers of neurons.

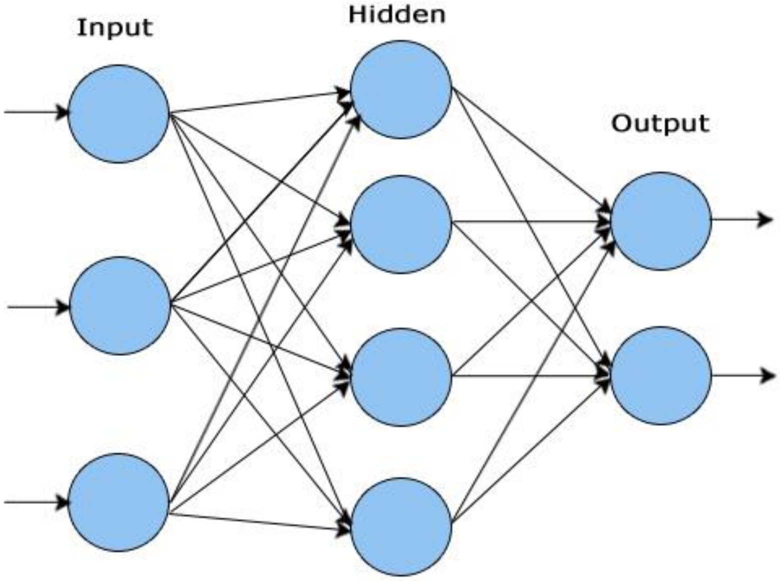

Figure 2. Three Layer Artificial Neural Network

A network with only two layers can be applied to linearly separable problems. Linearly separable problems are those where data samples can be separated by a single line as shown in Figure 3. Data samples in Figure 3 are separated based on features x and y. Networks with one or more hidden layers can be used to classify non-linearly separable data. The links between neurons store parameters called "weights". The entire learning of a neural network is stored inside these weights.

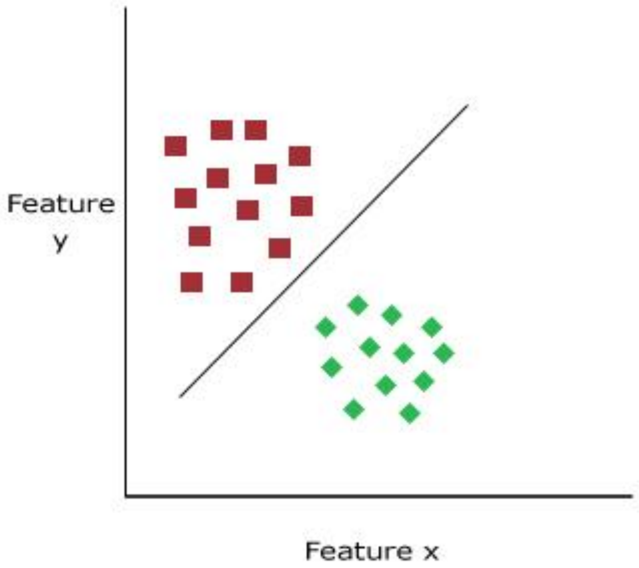

Figure 3. Linearly Separable Data Samples

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Neural network classifiers can be used for a wide variety of problems. There are several pattern recognition techniques used, but they are mainly categorized into two main categories, supervised and unsupervised methods. In the case of supervised methods, a certain number of training samples are available for each class. The neural network uses these samples for training. In an unsupervised method, no training samples are available. An illustration of clustering using the unsupervised method is shown in Figure 4. Many well-defined algorithms are already established for clustering using neural network models. Competitive learning and Kohonen's self-organizing maps are examples of unsupervised learning methods. In this research, Kohonen's learning algorithm has been used to cluster Likert-scale survey data.

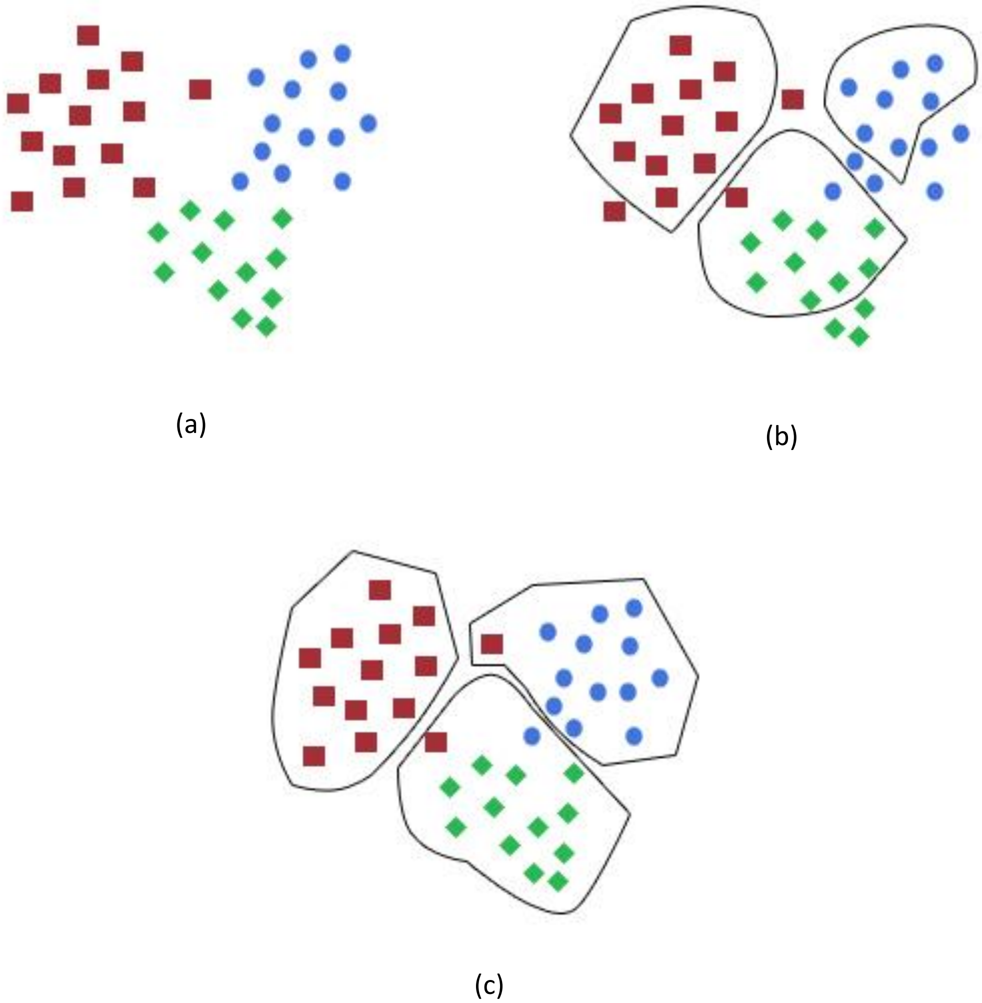


Figure 4. An Illustration of Clustering using Unsupervised Learning (a) Shows the distribution of different samples in the data space. (b) Partitioning of data samples into three clusters.(c) After several iterations, data samples that are similar to one another formed a cluster.

2.4.1 Kohonen Learning

Kohonen Learning is an unsupervised learning technique that searches for patterns in a given dataset and suggests grouping of the data samples without providing the correct output. A Kohonen neural network is comparatively simple in architecture as compared to a feed-forward back propagation neural network. It consists of two layers. There is no hidden layer in a Kohonen network. The first layer is the input layer. The second layer is the Kohonen layer or output layer.

The architecture for a Kohonen network is shown in Figure 5. Each unit in the input layer has a feed-forward connection to each unit in the Kohonen layer. Units in the Kohonen layer compete when an input vector is presented to the layer. Each unit computes the matching score of its weight vector with the input vector. The unit with the highest matching score is declared the winner. Only the winning unit is permitted to learn [15]. The learning algorithm is described below.

First, initialize the elements of the weight matrix **W** to small random values. Element w_{ij} of matrix **W** represents the connection strength for the connection between unit *j* of layer L_1 and unit *i* of layer L_2. These random weights must be normalized before training starts. The weights can be normalized by multiplying the actual weight with a normalization factor. The normalization factor is the reciprocal of the square root of the vector length:

$$NF = \frac{1}{\sqrt{VL}} \qquad (1)$$

where VL is the vector length. Vector length can be calculated using Equation (2).

$$VL_i = \sum_j (w_{ij})^2 \qquad (2)$$

where *i* represents the output class, and j represents the input unit.

For step 2, present the input vector **x**= (x_1, x_2... x_n)^T; the input to the network must be between the values -1 and 1. A normalization factor should be calculated using input values as shown in Equation (1). In this step, the input values will remain unchanged, but the normalization factor will be applied when the output is being calculated in the next step.

For step 3, calculate the value for each output neuron by calculating the dot product of the input vector and weight between the input neurons and output neurons.

$$o_i = \sum_j (w_{ij} \, . \, x_j) \tag{3}$$

This output must now be normalized by multiplying it by the normalization factor that was determined in step 2.

$$o_i = o_i \, . NF \tag{4}$$

Now, this normalized output must be mapped to a bipolar number. A bipolar number is an alternate way of representing binary numbers. In the bipolar system, binary zero maps to -1, and binary 1 remains at 1. As the input was mapped to a bipolar number, similarly the output must be mapped to a bipolar number. It can be accomplished by using Equation (5).

$$o_i = \frac{o_i + 1}{2} \tag{5}$$

For step 4, after calculating the output value for each output neuron, a winner must be chosen. The output unit having the largest output value will be chosen as the winner.

For step 5, the weights of the winning neuron are updated. The weights of a link between an output neuron and an input neuron can be updated by using two methods: the additive method and the subtractive method.

The additive method uses Equation (6).

$$w_{ij}(k+1) = \frac{w_{ij}(k) + \propto x_j}{| \, w_{ij}(k) + \propto x_j |} \tag{6}$$

The subtractive method uses Equations (7) and (8),

$$e = x_j - w_{ij}(k) \qquad (7)$$

$$w_{ij}(k+1) = w_{ij}(k) + \propto e \qquad (8)$$

where **x** is the training vector, k indicates the iteration number, and α is the learning rate. The typical value of the learning rate ranges from 0.1 to 0.9. This research has used the subtractive method.

For step 6, repeat steps 2 to 5 for all input samples.

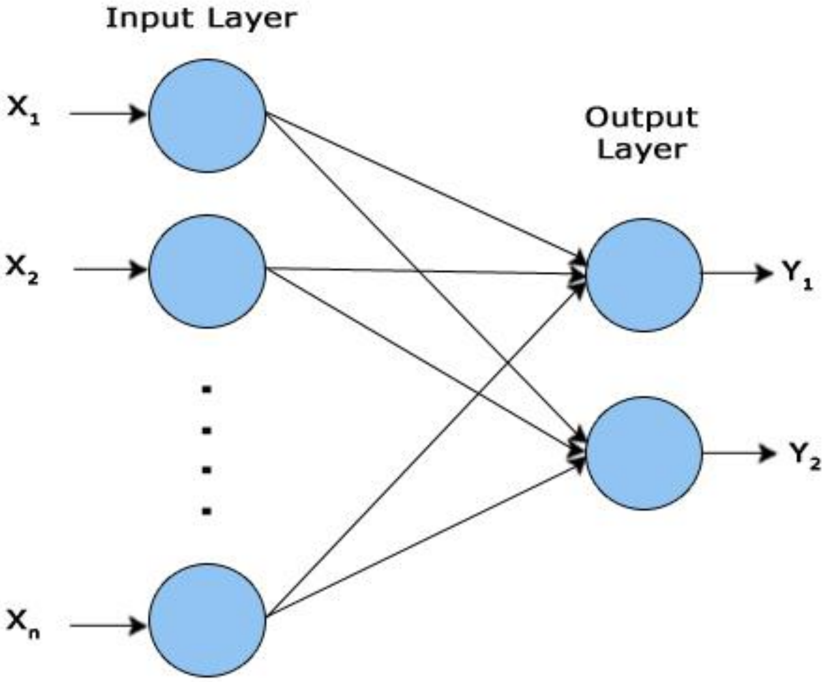


Figure 5. Two Layer Network with Kohonen Learning

2.4.2 Competitive Learning

Malsburg [16] and Rumelhart and Ziper [17] have developed models with competitive learning. It is called a competitive algorithm because units within each layer compete with one another to respond to the pattern given as input. The more strongly any particular unit responds to an incoming pattern, the more it inhibits other units within the layer. Similar to Kohonen, competitive learning uses normalized weights **w** and inputs **x**. The output value of each neuron is calculated by Equation (9),

$$o_i = \sum_j w_{ij} . x_j \qquad (9)$$

where *i* is the output layer neuron, and *j* represents the input unit. The output unit with the largest output value will be chosen as the winner. The weights of all links are updated using Equation (10),

$$\Delta w_{ij} = \propto \left(\frac{C}{n} - \ w_{ij}\right) \qquad (10)$$

where *C* represents the activation value of input neurons. If the input value is greater than the normalization factor, then the input neuron will be considered as active. For active input neurons, the value of C will be 1; otherwise, it will be 0. The variable *n* represents the total number of active lines and. α represents the learning rate. A typical value of the learning rate ranges from 0.1 to 0.9.

2.5 ANN Performance Measure

There are various performance measures that can be evaluated in order to determine the accuracy and performance of a classifier. These measures are used for assessing the prediction accuracy of a classifier. This research has used the following performance measures to assess the ANN model.

2.5.1 Error Matrix

An error matrix is also called the Confusion Matrix (CM). It is a useful tool for analyzing a classifier. It is a square array of numbers arranged in rows and columns. Each column represents the predicted class. However, each row represents the actual class. If CM represents an error matrix, then CM_{ij} indicates the number of tuples of class *i* that were classified in class j. In the same manner, CM_{ii} and CM_{jj} indicate the correctly classified tuples of class *i* and j respectively. To illustrate the comparison of an ANN classifier with other classifiers, an error matrix has been evaluated.

2.5.2 Overall Accuracy

The overall accuracy is computed by dividing the total number of correctly classified samples in all classes by the total number of samples,

$$\eta_o = \sum_{i=1}^{r} \frac{x_{ii}}{N} \qquad (11)$$

where η_o represents overall accuracy, *r* is the number of rows in the matrix, x_{ii} is the number of classified samples in row *i* and column *i* , and *N* is the total number of samples.

2.5.3 User's Accuracy

User's Accuracy indicates the probability that a sample classified in a class actually belongs to that class. It is computed by dividing the total number of correctly classified samples in a class with the total number of samples in that class (i.e., row total in error matrix),

$$\eta_{ui} = \frac{x_{ii}}{x_{i+}} \qquad (12)$$

where η_{ui} is the user's accuracy of class *i*, x_{ii} is the number of samples in row *i* and column *i*, and x_{i+} is the total of row *i* in the error matrix.

2.5.4 Producer's Accuracy

Producer's Accuracy indicates the probability of a reference sample being correctly classified. It is computed by dividing the total number of correctly classified samples in a category with the total number of samples classified in that category by the classifier (i.e., column total in error matrix).

$$\eta_{pi} = \frac{x_{ii}}{x_{+i}} \qquad (13)$$

where η_{pi} is the producer's accuracy of class i, x_{ii} is the number of samples in row *i* and column i, and x_{+i} is the marginal total of column *i* in the error matrix.

2.6 Rule Extraction Techniques

The trained knowledge-based network is used for rule generation in if-then form in order to justify any decision reached. These rules describe the extent to which a test pattern belongs or does not belong to one of the classes in terms of antecedent and consequent clauses. There are numerous methods to extract rules from an ANN. A few of them are described in the following sections.

2.6.1 Rule Extraction from ANN having a Large Number of Features

Sometimes data that are used for classification contain a large number of attributes and features. Having a large feature space may result in a large number of rules with a large number of antecedents per rule. To overcome this issue, "Rule Extraction Artificial Neural Network Algorithm (REANN)" has been proposed [18]. This algorithm proposed that pruning of the neural network will help in extracting more comprehensible and compact rules from the network. Pruning is the process in which features are removed redundantly on the basis of relevance. It simplifies the network and the process of rule extraction. After pruning of the network, the Rule

Extraction (REx) algorithm is applied. REx is composed of three major functions: rule extraction, rule clustering and rule pruning. The pruning function eliminates redundant rules by replacing a specific rule with a more general one, and then removes noisy rules. The efficiency of this method is better in terms of accuracy, number of rules and number of conditions in a rule, but the REANN algorithm is only effective for data having a large number of features.

2.6.2 Rule Extraction from Binary Data

A dataset may often consist of binary data. For example, consider data collected from a survey consisting of binary-valued attributes. Surveys with binary valued attributes are usually less time-consuming. They also facilitate respondents to choose the answer from the given Boolean options. To extract knowledge from a binary-valued survey data, a hybrid method has been proposed [19]. This method has two components, an ANN and a decision tree classifier. The network is trained and pruned using the technique utilized in REx algorithm. Then the decision tree extracts rules from the trained network. This method is also proposed to use the M-of-N construct [20] to describe the rules instead of "if-then-else" form. The M-of-N construct is mostly suited for data with binary-valued attributes. The M-of-N construct expresses rules in a more comprehensive way. It also reduces the number of rules. The proposed method is generally effective, but it has some limitations as well. Survey data usually contain a large amount of attributes and data that affect the training process of the neural network in terms of performance. It also results in a large number of rules with many M-of-N constructs. This method is only applicable to binary-valued survey data. The method also requires preprocessing of data when some of the responses are not binary-valued.

2.6.3 Rule Extraction from Discrete Data

Sometimes a data set contains only discrete-valued attributes. To extract rules from such type of data, the Greedy Rule Generation (GRG) algorithm has been proposed [21]. This algorithm searches for the best rule in terms of the number of samples it classifies, size of subspaces it covers and the number of attributes in the rule. The algorithm consists of three steps. First, it creates a rule set by adding one rule at a time for every input subspace defined by all the combination of the input attribute values. In the second step, the merging process is applied. Rules that classify sample data into the same category are merged into one classification rule. In the third step, rules that cover the maximum number of samples, highest number of irrelevant attributes and the largest subspace of the input are selected as the best rules. This algorithm can be incorporated with other rule extraction techniques as well. The GRG algorithm produces rule sets that are accurate and concise. The method is limited to discrete data only and cannot be extended for continuous data. Also, the performance of this method may decrease with a large number of attributes.

The GRG algorithm emphasizes on better accuracy, but rules extracted from the network using this method might not meet the fidelity requirement. Fidelity is a criterion for assessing the rule extraction method; it reflects how well the rules mimic the network. In order to maintain the fidelity of the rules without affecting the accuracy, the LORE (LOcal Rule Extraction) method has been proposed [22]. The LORE method also overcomes the limitation GRG enforces on the number of attributes. This method can be applied to any number of features. It has mainly four steps. In the first step, partial rules are extracted from each sample. A partial rule contains a subset of features that are sufficient to classify the sample. In the second step, the merging process is applied. The merging process of the LORE algorithm is different from the GRG algorithm. The LORE algorithm uses a Reduced Ordered Decision Diagram (RODD) for merging rules. The RODD is similar to a decision tree, but in the RODD, ordering is defined on features, and every path in the diagram must traverse the nodes in exactly this order. In the third step, generalization is performed to reduce the size of the decision diagram. The LORE algorithm produces a set of rules that are accurate and concise. This method is generally effective, but it has some limitations as well. The LORE method uses the RODD for merging operations. The RODD is highly dependent on feature ordering. Bad feature ordering may result in large decision diagrams, and this increases the computational complexity.

2.6.4 Rule Extraction from Continuous and Discrete Data

Sometimes data sets may contain both continuous and discrete-valued attributes. For example, surveys contain both continuous and discrete-valued attributes. To extract knowledge from such type of data, a new algorithm “TREPAN” has been proposed [23]. There are some similarities between the TREPAN and conventional decision tree algorithms such as CART [24] and C4.5. TREPAN and these other algorithms learn directly from the training set. The difference is that TREPAN interacts with the trained neural network along with the training set in order to extract the decision tree. The TREPAN method is scalable and has the capability to analyze binary data as well. The TREPAN method does not enforce any limitation on the number of attributes; it can be applied to datasets having a large feature space.

Another algorithm “CRED” (a continuous/discrete Rule extraction via a decision tree induction) [25] has been proposed to extract knowledge from data having both continuous and discrete-valued attributes. The difference between this method and TREPAN is the process to build the decision tree. The CRED builds a decision tree based on the activation patterns of hidden-output units and input-hidden units. However, TREPAN builds a decision tree based on activation patterns of input and output units. The proposed method is not limited to just binary data as described in previous sections. It has the capability to process binary, continuous and discrete-valued attributes. The CRED algorithm also uses a hybrid approach. The network is trained and pruned using the technique utilized in the REx algorithm. Decision trees are then extracted from this trained network. Rules are then extracted by merging these trees. The CRED method is effective and gives better accuracy than C4.5 algorithm. A disadvantage is that the CRED is not effective for networks with no hidden layer.

2.6.5 Rule Extraction by Inducing Decision Tree from Trained Neural Network

A decision tree built from the neural network can be used to extract rules. One method is to extract a decision tree using the activation patterns of the input and output units using training data and the given neural network [23]. Another method uses activation patterns of hidden-output units and input-hidden units to build the decision tree [25]. Both of these methods are suitable for discrete and continuous variables. Commonly used decision tree methods are ID3 and C4.5. C4.5 is a descendant of the ID3 algorithm. ID3 selects an attribute based on a property called information gain. The one with the highest information gain is selected as an attribute. Gain measure describes how well a given attribute separates the training sample into a targeted class. Information gain can be calculated using Equation (15). Entropy must be calculated first in order to measure the gain of an attribute. Entropy can be calculated using Equation (14). Entropy measures the amount of information in an attribute. The range of entropy is “0” (perfectly classified) to “1” (totally random),

$$H(S) = -\sum_{x \in X} p(x)\, log_2 p(x) \qquad (14)$$

where :

S is the set of samples.

X is the set of classes in S

$H(S)$ is the entropy of set S

$p(x)$ is the proportion of S belonging to class x.

$$IG(A) = H(S) - \sum_{t \in T} p(t)\, H(t) \qquad (15)$$

where:

$IG(A)$ is the information gain on set S split on attribute A

$H(S)$ is Entropy of set S

T is the subsets created from splitting set S by attribute A such that $S = \bigcup_{t \in T} t$

$p(t)$ is the proportion of the number of element in t to the number of elements in set S

$H(t)$ is Entropy of subset t

2.6.6 Rule Extraction from Two-Layered Networks

Algorithms discussed above can only be applied to multi-layer networks where one or more hidden layer(s) were used. The Kohonen neural network used in this research consists of only two layers: the input and output layer. The Conjunctive Rule Extraction algorithm (CREA) [26] has been introduced to extract rules from this kind of network. The CREA can also be applied to multi-layered neural networks. This algorithm uses two different oracles that answer queries about the knowledge being learned. The conjunctive rule extraction algorithm is outlined in Table 8. The EXAMPLES returns the data tuples, It can be generated randomly or can return the data tuples from the training set. In this research, EXAMPLES simply returned the training set. The SUBSET oracle ascertains that the subset of the original rule agrees with the network or not. An algorithm of method SUBSET is outlined in Table 9. CREA first forms a conjunctive rule by including all the features of the sample provided by the EXAMPLES oracle. This original rule is then generalized by dropping one feature at a time and generating a subset of the original rule. The SUBSET oracle returns true if this subset still agrees with the trained network. Otherwise, it will re-add the dropped feature to the rule.

Table 8. Conjunctive Rule Extraction Algorithm (CREA)

```
/* initialize rules for each class */
for each class c
$R_c$ := 0
repeat
        e := EXAMPLES ()
        c := Classify(e)
        if e not covered by $R_c$ then
                r := conjunctive rule formed from e
                $r_{orig}$ := r
                for each antecedent $r_i$ of r
                        r' := r but with $r_i$ dropped
                        if SUBSET(c,r') = true then r:=r'
                $R_c$ := $R_c$ V $r$
until stopping criterion met
```

Table 9. Subset Oracle

```
/* Test Subset whether it agrees with network or not */
fun SUBSET (c, $r_{sub}$)
$c_{new}$ := Classify( $r_{sub}$)
if $c_{new} =$ c
        return true
else
        return false
```

2.7 Review of Prior Research

There are various ways to extract knowledge from data. A number of previously published papers on knowledge extraction using an ANN used either supervised or unsupervised neural networks. Extraction of if-then rules from an ANN is the essential part of knowledge discovery. Many articles that deal with the application of these knowledge extraction algorithms have been published; a few of them are presented in the following paragraphs.

Kulkarni & McCaslin [27] proposed a method using artificial neural networks to extract knowledge from multispectral satellite images obtained from a Landsat Thematic Mapper sensor. A scene of the Mississippi River bottomland area was used in this study. Fuzzy neural network models have been used to classify pixels in a multispectral image into three classes, water, land and forest and to generate if-then rules. Jiang et al. [28] applied neural networks to medical imaging problems. They analyzed, processed and characterized medical images using neural networks. Panda et al. [29] described an application of artificial neural networks to estimate lake water quality using satellite imagery. They proposed an indirect method of determining the concentrations of chlorophyll-a and suspended matter, two optically active parameters of lake water quality. This application has a potential to make the process of determining water quality cost-effective, quick and feasible. Chan & Jian [30] developed a knowledge discovery system to identify significant factors for air pollution levels using neural networks. Chen et al. [31] applied the neural network system to predict fraud litigation for assisting accountants in developing audit strategy. The results show that neural networks provide promising accuracy in predicting. They proposed that an artificial intelligence technique is effective in identifying a fraud-lawsuit presence, and hence, it could be a supportive tool for practitioners.

Chapter 3

Methodology

The previous chapters have discussed how statistical methods can be used to analyze Likert scale data. Clustering of data into different groups can be done effectively through these statistical methods, but these methods do not describe “why” a data sample belongs to a particular group. In this research, a method has been proposed that will resolve this issue by using the Kohonen neural network for clustering. A Kohonen neural network learns by observation and forms clusters of similar data samples. By using a Kohonen neural network, knowledge can be extracted in the form of rules that explain the reason why the network made the decision to group a data sample into a particular cluster.

The method proposed in this thesis to extract knowledge from Likert scale survey data and group them into different clusters consists of three steps. The first step is preprocessing. In the preprocessing step, data cleaning techniques are applied on survey responses before converting them into a network readable format. The second step is to apply the Kohonen neural network to group data tuples into different clusters. The third step is to extract knowledge from a trained neural network in the form of rules and optimize those rules to obtain a comprehensive and concise set of rules. The optimization of rules includes removing redundant rules, replacing specific rules with more general rules and merging of rules. The overall process is shown in Figure 6.

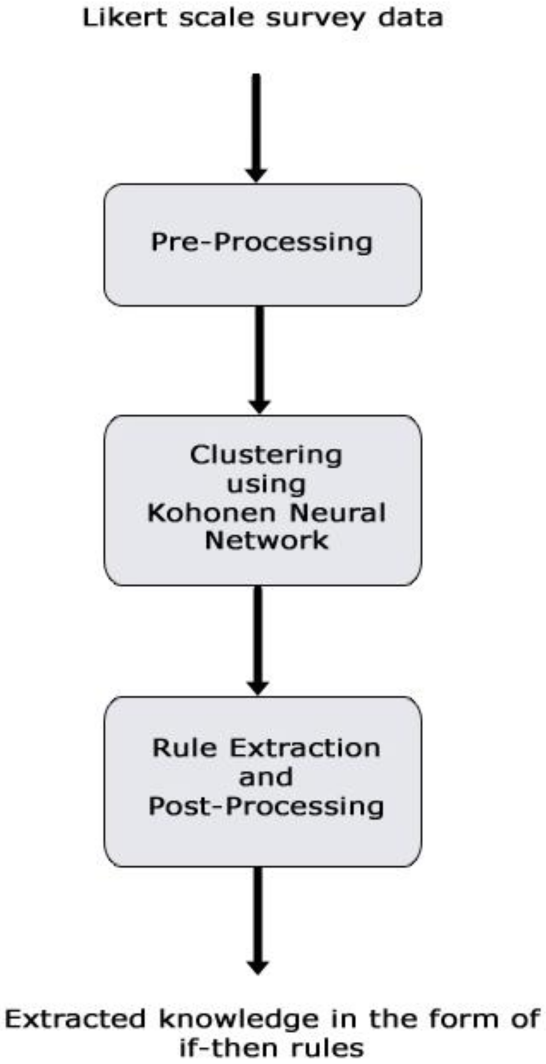

Likert scale survey data
Pre-Processing
Clustering using Kohonen Neural Network
Rule Extraction and Post-Processing
Extracted knowledge in the form of if-then rules

Figure 6. Overall Process to Extract Knowledge from a Likert Scale Data Survey

3.1 Knowledge Extraction Process

Responses of surveys are provided in the XLS format (Microsoft Excel). The data is then processed through different steps in order to obtain meaningful results. An application has been built in C#.NET to implement these steps. The proposed method consists of the following steps, preprocessing, clustering, and rule extraction.

3.1.1 Preprocessing – Data Cleaning and Transformation

The responses of the survey were provided in XLS format (Microsoft Excel). These responses were then transformed to the format readable by the neural network. The overall process is shown in Figure 7.

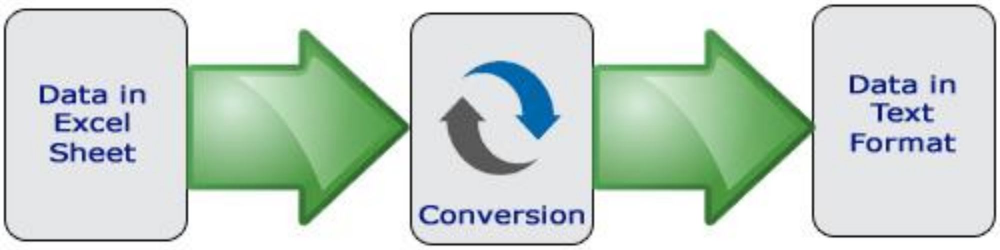


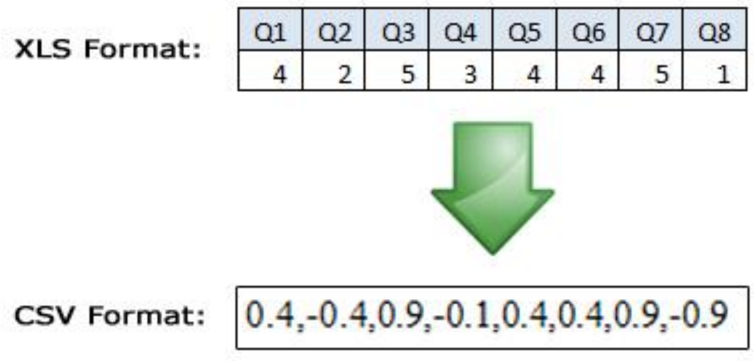
Figure 7: Data Cleaning and Transformation

In the first step, invalid responses must be removed. Invalid responses include questions that are unanswered or answered outside of the given scale. Secondly, personal details must be removed from the data set. Sometime surveys require respondents to enter their personal information such as their ID, name, age, gender and ethnicity etc. These inputs were ignored during conversion as they are not used for analysis. Normalization process is then applied to these data tuples. A Kohonen neural network requires that the input be normalized to the range of -1 and 1. The mapping shown in Table 10 was used.

Table 10. Normalization of Responses

Option	Option Value	Normalized Value
Option 1	1	-0.9
Option 2	2	-0.4
Option 3	3	-0.1
Option 4	4	0.4
Option 5	5	0.9

The results of the survey were provided in XLS format. The current implementation of the neural network allows only comma separated values. To make neural network data readable, the data must be converted into a CSV (comma separated values) file format. Conversion of a single tuple from the XLS format to the CSV format is illustrated using Figure 8.



XLS Format:

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
4	2	5	3	4	4	5	1

CSV Format: 0.4,-0.4,0.9,-0.1,0.4,0.4,0.9,-0.9

Figure 8. Conversion from XLS Format to CSV Format.

3.1.2 Clustering of Data using the Kohonen Neural Network

For clustering, a Kohonen neural network was used. It is an unsupervised learning technique that searches for patterns in a given dataset and suggests grouping of input data samples. The Kohonen neural network is comparatively simple in architecture as compared to a back propagation neural network. It consists of two layers: the input layer and output layer. Due to its simplicity, the network can be trained rapidly. It is also easier to extract rules from such networks. The algorithm of Kohonen neural networks was discussed in detail in Chapter 2. A Kohonen neural network with 30 neurons in the input layer and 3 neurons in the output layer is shown in Figure 9.

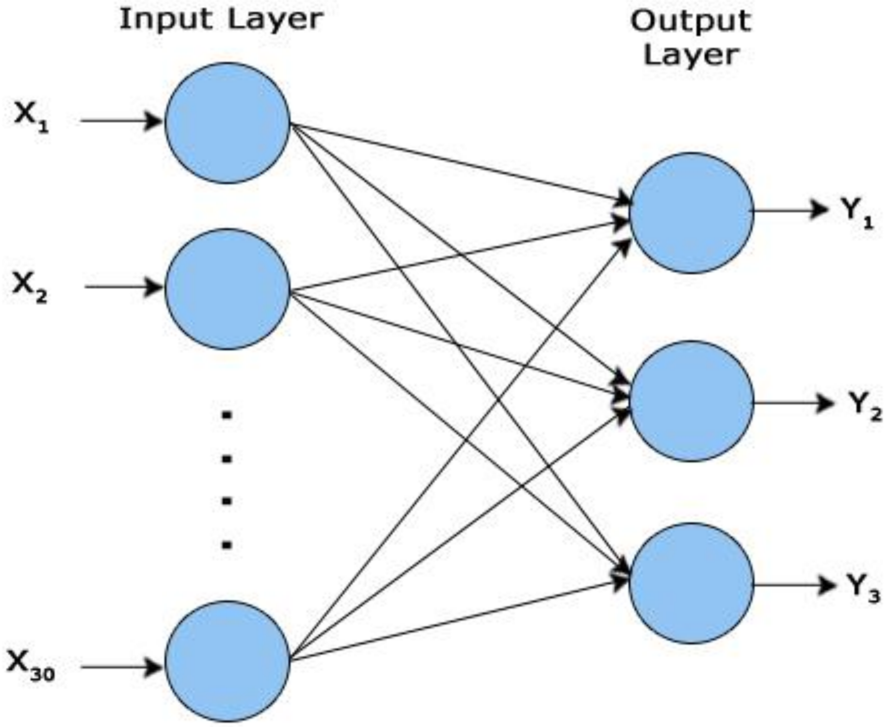


Figure 9. Two Layered Kohonen Neural Network

3.1.3 Rules Extraction Process

Rule extraction algorithms are used for interpreting neural networks and mining the relationship between input and output variables in the data. These rules are usually in the form of “if-then-else” statements. They can also be referred to as extracted knowledge from the neural network. The rule extraction process used in this research consists of two steps: rule extraction and rule pruning. Figure 10 illustrates the process to extract and reduce the number of rules. To prioritize the rules beforehand, class-based ordering has been used as the rule ordering scheme. In class-based ordering, classes were sorted in decreasing order of prevalence [1]. The class that was more frequent came first; next prevalent class came second, and so on.

I. Rule Extraction:

The extended version of the Conjunctive Rule Extraction Algorithm (CREA) has been proposed to extract rules. This algorithm is discussed in the next section.

II. Rule Pruning:

Rule pruning includes removing redundant rules, replacing specific rules with more general rules, and merging of rules.

Determining the default rule is another important aspect of the rule extraction process. The default rule is evaluated when no other rule covers the sample. For different data sets, a different default rule has been selected based on the number of samples classified in a class. The class having the majority of samples classified has been selected as a default class.

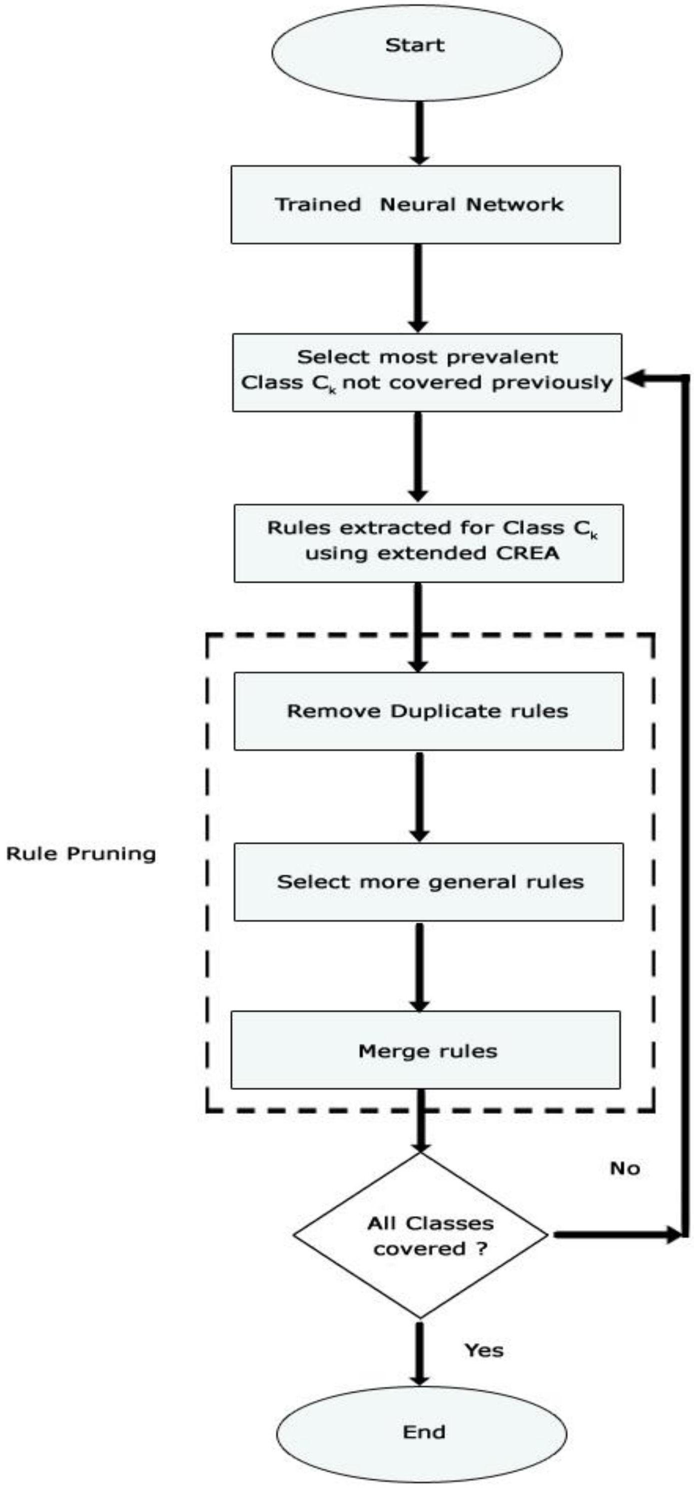

Start
Trained Neural Network
Select most prevalent Class C_k not covered previously
Rules extracted for Class C_k using extended CREA
Remove Duplicate rules
Rule Pruning
Select more general rules
Merge rules
No
All Classes covered ?
Yes
End

Figure 10. Flow Chart of Rule Extraction Process

3.1.3.1 Rules Extraction

Our approach extends the Conjunctive Rule Extraction Algorithm (CREA) discussed in Chapter 2. This algorithm produces rules in an “if-then” format. The problem with Likert scale data is its uniqueness and large number of attributes. If only CREA is applied, then it will result in a large number of rules. It will treat each response separately and, due to the uniqueness in the data tuples, a very small number of rules may be repeated. To overcome this problem, a heuristic approach has been used in conjunction with the CREA algorithm. Instead of treating each response separately, the proposed method calculates the count of each option in a rule generated by the CREA method. The proposed algorithm for extracting rules from trained neural networks is outlined in Table 11. Algorithm of the COUNT_METHOD is outlined in Table 12.

Table 11. Extended Version of Conjunctive Rule Extraction Algorithm

```
/* initialize rules for each class */
for each class c
$R_c$ := 0
repeat
    e := Examples()
    c := Classify(e)
    if e not covered by $R_c$ then
        r := conjunctive rule formed from e
        $r_{orig}$ := r
        for each antecedent $r_i$ of r
            r' := r but with $r_i$ dropped
            if Subset(c,r') = true then r:=r'
        /* Apply count method */
        $r_{count}$ := COUNT_METHOD(r, $r_{orig}$)
        $R_c$ := $R_c$ V $r_{count}$
until stopping criterion met
```

Table 12. Algorithm for Count Method

```
fun COUNT_METHOD(r, $r_{orig}$)
$R_{new}$ := null
for all $O_i$ ∈ List of possible responses
        for all condition $C_i$ ∈ r
                if value-part($C_i$) = $O_i$ then
                        $O_i$ = $O_i$ + 1
                end if
        end for
end for
for all $OG_i$ ∈ List of possible responses
        for all condition $C_i$ ∈ $r_{orig}$
                if value-part($C_i$) = $OG_i$ then
                        $OG_i$ = $OG_i$ + 1
                end if
        end for
end for
for all $O_i$ ∈ List of possible responses
        if $O_i$ > 0 then
                if $OG_i$> $O_i$ then
                        $R_{new}$ := $R_{new}$ ∨ OptionName($O_i$) '>=' $O_i$
                else
                        $R_{new}$ := $R_{new}$ ∨ OptionName($O_i$) '=' $O_i$
                end if
        end if
end for
return $R_{new}$
```

The COUNT_METHOD counts the number of occurrences of each option in a rule generated by the CREA method and forms a new rule. This is accomplished by calculating the number of occurrences of each option in the rule and compares it with the original rule. An original rule consists of all the attributes and their values in a given sample. COUNT_METHOD is effective in this case because survey attributes are of the same type and share the same set of values. Applying this method to a data set with different types of attributes may result in incorrect analysis results. The Extended-CREA can be illustrated with the following example (Table 13).

Table 13. Illustration of Extended-CREA

Assumptions:

1. There are a total five questions in the survey.
2. Five options are given with each question. i.e. OPT1, OPT2, OPT3, OPT4 and OPT5.
3. Responses of a single respondent are

   For Question 1: selected → OPT4
   For Question 2: selected → OPT2
   For Question 3: selected → OPT5
   For Question 4: selected → OPT2
   For Question 5: selected → OPT3

4. Kohonen neural network grouped this tuple in cluster X.

In the first step, the Extended-CREA will form a conjunctive rule that will consist of all the attributes (Equation 16).

If Q1=OPT4 and Q2=OPT2 and Q3=OPT5 and Q4=OPT2 and Q5=OPT3 Then Class X (16)

This original rule is then generalized by dropping one feature at a time and generating a subset of the original rule. This will help to observe if responses to that feature are redundant. In this case, "Question 1" will be dropped in the first iteration (Table 14).

Table 14. Redundant Feature

Question 2 → OPT2
Question 3 → OPT5
Question 4 → OPT2
Question 5 → OPT3

If this subset is classified as cluster X, then the dropped feature will be removed from the original rule and considered as redundant information. If this subset is not classified as cluster X, then this feature will remain part of the original rule. This process will be repeated for each antecedent. Suppose after all iterations, the rule shown in Equation (17) is extracted.

If Q2=OPT2 and Q4=OPT2 Then Class X (17)

By looking at this rule, it can be stated that the features Q1, Q3 and Q5 contain redundant information, and the sample can be grouped in cluster X by using features Q2 and Q4. COUNT_METHOD, being a heuristic approach, is finally applied to this extracted rule, which transforms this rule as:

If C_OPT2 = 2 Then Class X (18)

where C_OPT2 represents the count of OPT2 in the extracted rule. This rule can be expressed in human readable form (Table 15).

Table 15. Rules in Human Readable Form

If OPT2 is selected twice by the respondent Then Class X OR If in two out of five questions respondent selected OPT2 Then Class X

3.1.3.2 Rules Pruning

The rules pruning process consists of three steps: remove redundant rules, replace specific rules with more general ones, and merge rules. The merging of rules consists of two steps: create a tree for rules that has common conditions, and traverse that tree to extract merged rules. Algorithm to create a tree is outlined in Table 16 and algorithm to traverse the tree to extract merged rules is outlined in Table 17.

Table 16. Algorithm to Create a Tree for Rules that has Common Conditions

1. Repeat the following steps for each class.
2. Pull all rules R_c for the current class.
3. Go through each rule in R_c and count the number of occurrences of each condition in a rule.
4. Pick the highest occurred condition C_i and create a root R_{node} node of C_i . Remove C_i from all rules. Add C_i in vector $C_n[i]$. [$Curr_{node} = R_{node}$]
5. Pull the set of rules R_{sub} from R_c that fulfill condition(s) in $C_n[i]$. Find the next highest occurring condition C_i in R_{sub}. If all conditions occurred once, then go to step 8.
6. Create node L_{node} of C_i from $Curr_{node}$. Remove C_i from R_{sub} . Add C_i in vector $C_n[i]$. [$Curr_{node} = L_{node}$]
7. Repeat step 5 and 6 until there is no condition in R_{sub} that occurred more than once.
8. Create nodes of all conditions in R_{sub} from $Curr_{node}$. Remove all these conditions from R_{sub}. Remove the last C_i from vector $C_n[i]$. Repeat steps 5 to 8 until $C_n[i]$ is empty.
9. Remove rules from R_c that are already used.
10. Repeat steps 2 to 9 for the rest of the rules until R_c become empty.

Table 17. Algorithm to Traverse the Tree to Extract Merged Rules

1. Bottom-up, breadth-first traversing has been used.
2. Enqueue $Curr_{node}$ in Queue Q. Get the parent node P_{node} of $Curr_{node}$.
3. Enqueue nodes to Q until $P_{node} \neq Curr_{node}.P_{node}$.
4. Dequeue all nodes from Q and combine those by using “OR”. Remove these nodes from P_{node}.
5. Create node of this combined condition from P_{node}.
6. Repeat steps 2 to 5 until all parent node nodes have only one child. This child must not be a parent of any node.
7. Traverse again in bottom-up, breadth-first order.
8. Merge child to its parent. If this child is not a parent of any child and there is no other sibling of this child, combine parent and child by using “AND”. Add this combine node to $Curr_{node}.P_{node}.P_{node}$. Remove $Curr_{node}$ and P_{node}.
9. Repeat step 2 through 8 until tree-depth reduces to 1.
10. Extract the rule for each child node by combining it with R_{node} using “AND”.

The merging process can be illustrated using the following example:

Suppose the following rules are extracted for class X using Extended-CREA. To make this example simple, the consequent clause is not included as all the rules belong to the same class (Table 18).

Table 18. Extracted Rules

Rule 1: C_OPT3=5 C_OPT4=5 C_OPT5=8
Rule 2: C_OPT3=3 C_OPT4=4 C_OPT5=8
Rule 3: C_OPT4=7 C_OPT5=8
Rule 4: C_OPT2=5 C_OPT3=7 C_OPT4=4 C_OPT5=8
Rule 5: C_OPT3=6 C_OPT4=4 C_OPT5=8
Rule 6: C_OPT2=3 C_OPT3=6 C_OPT4=5 C_OPT5=8

The following tree is generated for these six rules using the above algorithm:

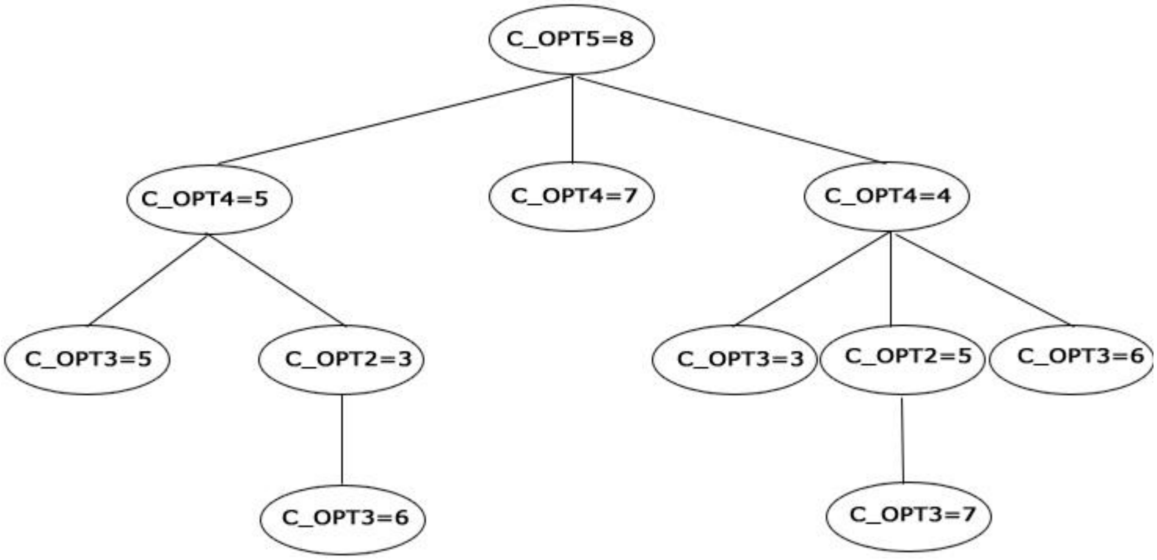


Figure 11. Tree of Generated Rules

This tree will be traversed to obtain following merged rules (Table 19):

Table 19. Merged Rules

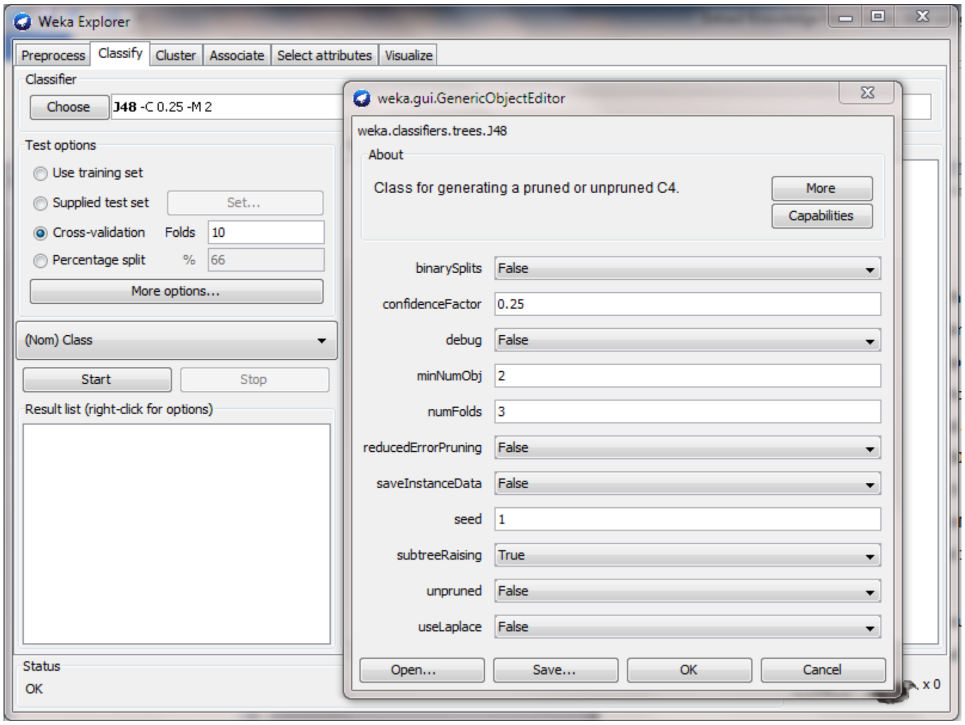
Rule 1: C_OPT5=8 AND C_OPT4=7
Rule 2: C_OPT5=8 AND (C_OPT4=5 AND ((C_OPT2=3 AND C_OPT3=6) OR C_OPT3=5))
Rule 3: C_OPT5=8 AND (C_OPT4=4 AND ((C_OPT2=5 AND C_OPT3=7) OR C_OPT3=6 OR C_OPT3=3))

In this way, six rules are merged to form three rules.

Chapter 4

Results and Discussion

As an illustration, this research has applied the proposed method to two different survey data sets. The first survey is about reading strategies for students, and the second survey is regarding teacher evaluation. To compare the efficiency of this proposed method, C4.5 has been applied to the same datasets. The outcome of C4.5 is then compared to the results of the proposed method. The C4.5 was applied using the open source software package Weka [32]. It is a collection of machine learning algorithms for data mining implemented in Java. The C4.5 classifier was tested with a confidence factor of 0.25. The number of minimum instances per node (minNumObj) was held at 2, and cross validation folds for the testing set (crossValidationFolds) was held at 10 as shown in Figure 12. The confidence factor is used for pruning cross validation. It splits the data set into a training set and a validation set. The algorithm trains using the new training set. Prediction on the validation set is used to determine which model to use. [6].



J48 -C 0.25 -M 2

○ Use training set
○ Supplied test set Set...
● Cross-validation Folds 10
○ Percentage split % 66

(Nom) Class

Status
OK

weka.classifiers.trees.J48

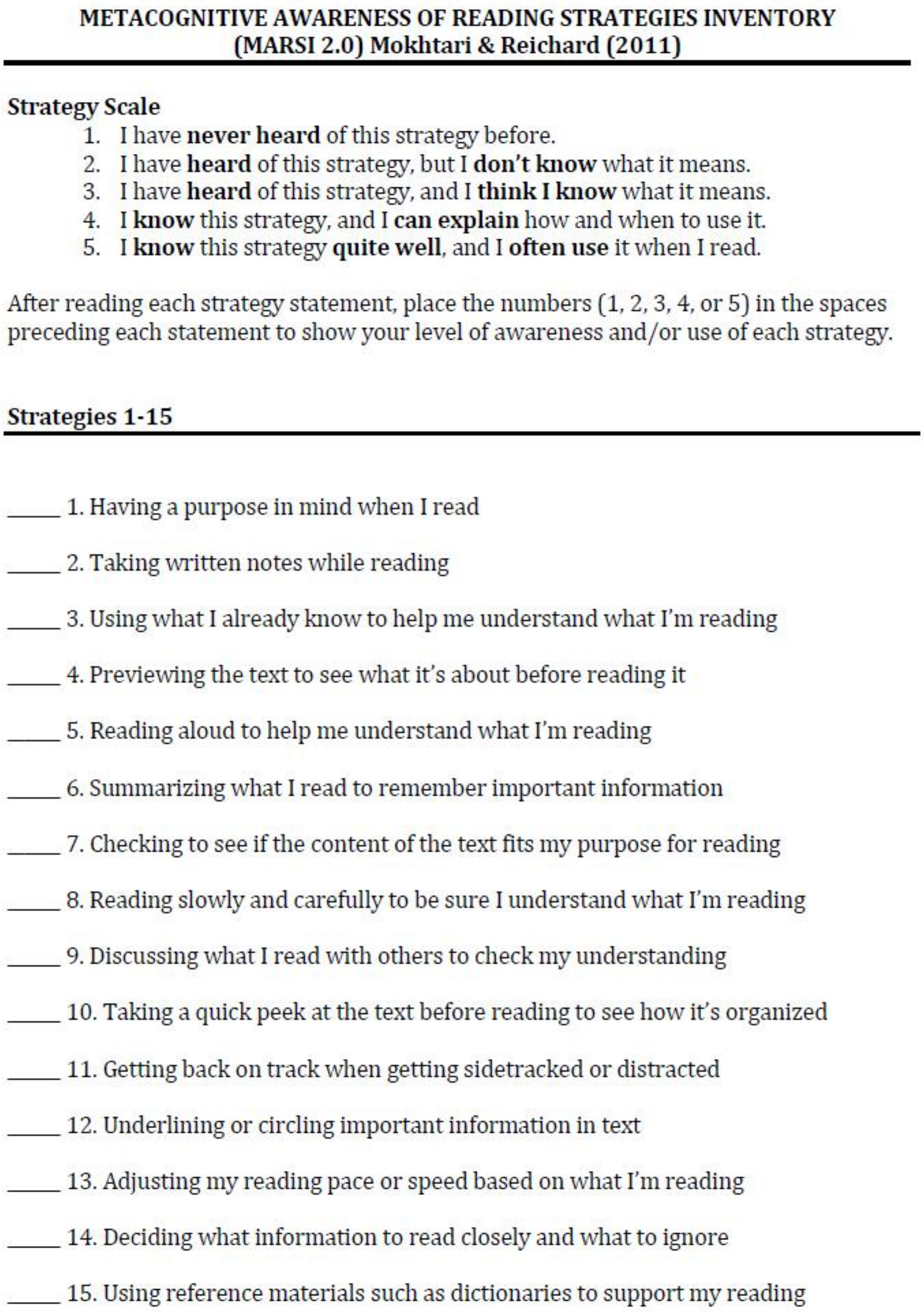
Class for generating a pruned or unpruned C4.

binarySplits False
confidenceFactor 0.25
debug False
minNumObj 2
numFolds 3
reducedErrorPruning False
saveInstanceData False
seed 1
subtreeRaising True
unpruned False
useLaplace False

Figure 12. Screen Shot of Weka. Displaying the Properties Initialized for C4.5 Algorithm

4.1. MARSI Survey

MARSI stands for “Metacognitive Awareness of Reading Strategies Inventory” [9]. It was developed to assess a student’s reading awareness. It has 30 questions, and each question has five-level Likert options. These 30 questions described 30 strategies or actions readers use when reading book chapters, articles etc. This survey is divided into three sections: Global Reading Strategies, Problem Solving Strategies and Support Reading Strategies. The ‘Global Reading Strategies’ section contains 13 questions, the ‘Problem Solving Strategies’ section contains 8 questions and the ‘Support Reading Strategies’ section contains 9 questions (Figure 13).



METACOGNITIVE AWARENESS OF READING STRATEGIES INVENTORY (MARSI 2.0) Mokhtari & Reichard (2011)

Strategy Scale

1. I have **never heard** of this strategy before.
2. I have **heard** of this strategy, but I **don't know** what it means.
3. I have **heard** of this strategy, and I **think I know** what it means.
4. I **know** this strategy, and I **can explain** how and when to use it.
5. I **know** this strategy **quite well**, and I **often use** it when I read.

After reading each strategy statement, place the numbers (1, 2, 3, 4, or 5) in the spaces preceding each statement to show your level of awareness and/or use of each strategy.

Strategies 1-15

_____ 1. Having a purpose in mind when I read

_____ 2. Taking written notes while reading

_____ 3. Using what I already know to help me understand what I'm reading

_____ 4. Previewing the text to see what it's about before reading it

_____ 5. Reading aloud to help me understand what I'm reading

_____ 6. Summarizing what I read to remember important information

_____ 7. Checking to see if the content of the text fits my purpose for reading

_____ 8. Reading slowly and carefully to be sure I understand what I'm reading

_____ 9. Discussing what I read with others to check my understanding

_____ 10. Taking a quick peek at the text before reading to see how it's organized

_____ 11. Getting back on track when getting sidetracked or distracted

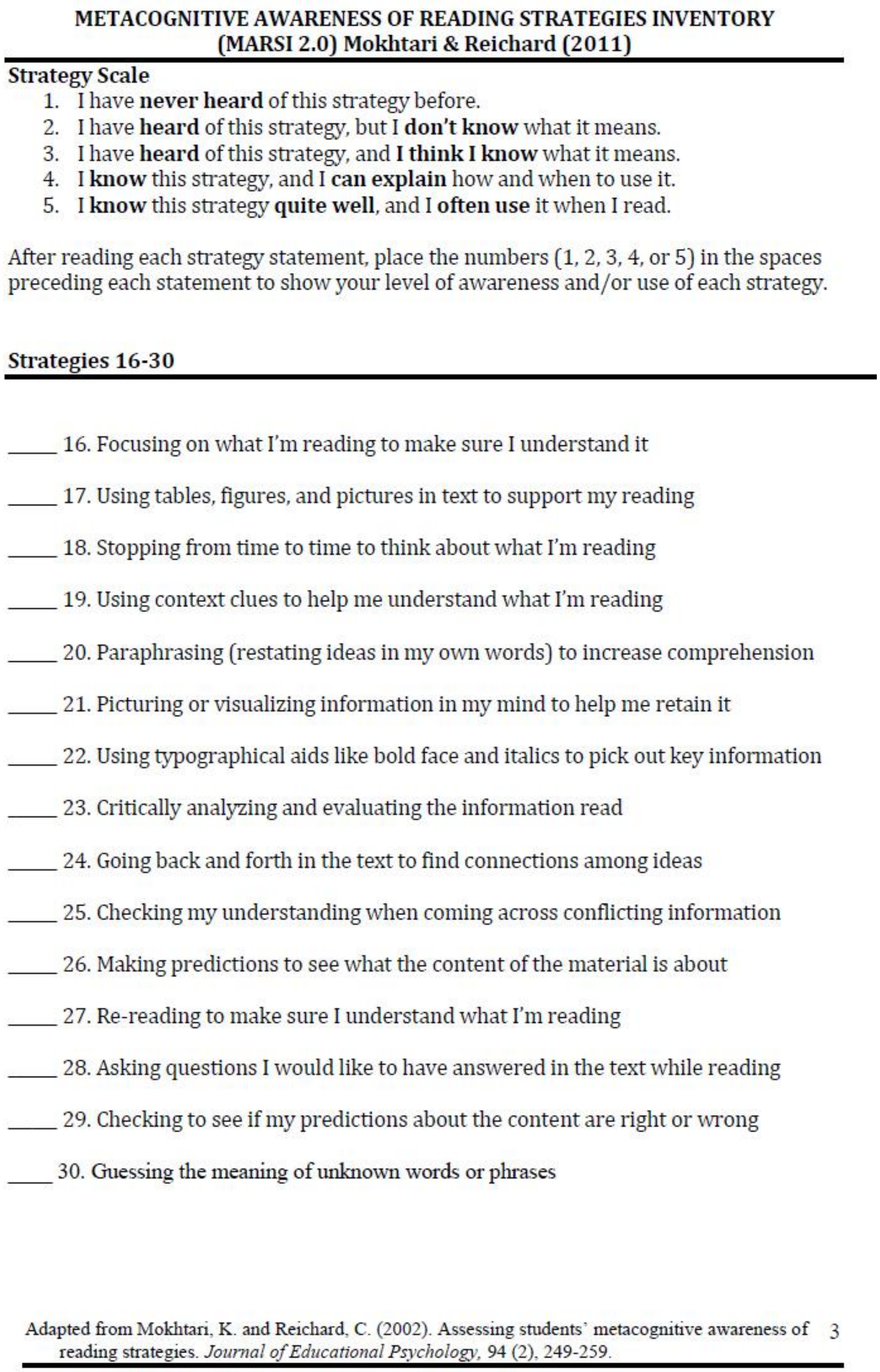
_____ 12. Underlining or circling important information in text

_____ 13. Adjusting my reading pace or speed based on what I'm reading

_____ 14. Deciding what information to read closely and what to ignore

_____ 15. Using reference materials such as dictionaries to support my reading

Figure 13. MARSI Survey (Continued)



METACOGNITIVE AWARENESS OF READING STRATEGIES INVENTORY
(MARSI 2.0) Mokhtari & Reichard (2011)

Strategy Scale

1. I have **never heard** of this strategy before.
2. I have **heard** of this strategy, but I **don't know** what it means.
3. I have **heard** of this strategy, and **I think I know** what it means.
4. I **know** this strategy, and I **can explain** how and when to use it.
5. I **know** this strategy **quite well**, and I **often use** it when I read.

After reading each strategy statement, place the numbers (1, 2, 3, 4, or 5) in the spaces preceding each statement to show your level of awareness and/or use of each strategy.

Strategies 16-30

_____ 16. Focusing on what I'm reading to make sure I understand it

_____ 17. Using tables, figures, and pictures in text to support my reading

_____ 18. Stopping from time to time to think about what I'm reading

_____ 19. Using context clues to help me understand what I'm reading

_____ 20. Paraphrasing (restating ideas in my own words) to increase comprehension

_____ 21. Picturing or visualizing information in my mind to help me retain it

_____ 22. Using typographical aids like bold face and italics to pick out key information

_____ 23. Critically analyzing and evaluating the information read

_____ 24. Going back and forth in the text to find connections among ideas

_____ 25. Checking my understanding when coming across conflicting information

_____ 26. Making predictions to see what the content of the material is about

_____ 27. Re-reading to make sure I understand what I'm reading

_____ 28. Asking questions I would like to have answered in the text while reading

_____ 29. Checking to see if my predictions about the content are right or wrong

____ 30. Guessing the meaning of unknown words or phrases

Adapted from Mokhtari, K. and Reichard, C. (2002). Assessing students' metacognitive awareness of reading strategies. *Journal of Educational Psychology*, 94 (2), 249-259. 3

Figure 13. MARSI Survey

This survey was conducted in December, 2011. The respondents were 6, 7 and 8th graders. A total of 877 students participated in this survey. Most of the students were from ages 11 to 14. 344 students from 6th grade, 263 students from 7th grade, and 270 students from 8th grade participated in the survey. The proposed method has been applied to MARSI survey data in the following manner.

4.1.1 Preprocessing – Data Cleaning and Transformation

The responses of MARSI survey were provided in XLS format (Microsoft Excel). In this step, responses were normalized to the range of 1 to -1. Normalization of the responses is given in Table 20. After data cleaning, 860 records were selected for analysis. After normalization and data cleaning, this file was converted to the CSV format.

Table 20. Normalization of Responses

Survey Option	Short Form	Option Value	Normalized Value
I have never heard of this strategy before.	OPT1	1	-0.9
I have heard of this strategy, but I don’t know what it means.	OPT2	2	-0.4
I have heard of this strategy, and I think I know what it means.	OPT3	3	-0.1
I know this strategy, and I can explain how and when to use it.	OPT4	4	0.4
I know this strategy quite well, and I often use it when I read.	OPT5	5	0.9

4.1.2 Clustering of Data using the Kohonen Neural Network

A total of 860 samples were chosen for clustering. The “Mean” method was used initially for clustering the MARSI survey data. It grouped the data into three clusters: “High Level of Awareness”, “Medium Level of Awareness” and “Low Level of Awareness”. As the “Mean” method was used for clustering the MARSI survey data, its results were taken as the desired output for the C4.5 algorithm. A Kohonen neural network (KNN) does not require the class label information as it learns by observation. It grouped similar objects to form a cluster. In this example, clustering results of the Kohonen neural network were compared with the "Mean" method and C4.5 algorithm to measure the performance accuracy of the neural network.

The "Mean" method classified 607 samples in class 1, 235 samples in class 2 and 22 samples in class 3. The Kohonen neural network clustered 584 samples in class 1, 16 samples in class 2, and 80 samples in class 3. A comparison of results by different classifiers is shown in Table 21.

Table 21. Comparison of Results by Different Classifiers

Method	**Class 1** **High Level of Awareness**	**Class 2** **Medium Level of Awareness**	**Class 3** **Low Level of Awareness**
Mean Method	607	231	22
KNN	584	196	80
C 4.5	627	220	13

The Error matrix of the KNN classifier and C4.5 are shown in Table 22 and Table 23 respectively. "High Level of Awareness", "Medium Level of Awareness" and "Low Level of Awareness" represents clusters. Columns represent the predicted class while the rows represent the actual class. The recognition column represents the user's accuracy.

Table 22. Confusion Matrix/Error Matrix of KNN Classifier

	High Level of Awareness	**Medium Level of Awareness**	**Low Level of Awareness**	**Total**	**Recognition**
High Level of Awareness	556	7	44	607	91.5%
Medium Level of Awareness	28	167	36	231	72.3%
Low Level of Awareness	0	22	0	22	0%
Total	584	196	80	860	84.06%

KNN classified 91% samples correctly in class “High Level of Awareness”, 72.3% of samples in class “Medium Level of Awareness” and none were classified correctly in class “Low Level of Awareness”. The reason class 3 had poor accuracy might be the small number of data samples in class 3.

Table 23. Confusion Matrix/Error Matrix of C4.5 Classifier

	High Level of Awareness	**Medium Level of Awareness**	**Low Level of Awareness**	**Total**	**Recognition**
High Level of Awareness	528	78	1	607	86.9%
Medium Level of Awareness	97	129	5	231	55.8%
Low Level of Awareness	2	13	7	22	31.8%
Total	627	220	13	860	77.21%

A comparison of overall accuracy of different classifiers on the MARSI survey data is shown in Table 24. A graphical representation of overall accuracy is shown in Figure 14.

Table 24. Performance Measure of KNN and C4.5 Classifiers

Method	**Correctly Classified Samples**	**Incorrectly Classified Samples**	**Performance Accuracy**
KNN	723	137	84.06%
C 4.5	664	196	77.21%

From Table 24, it can be observed that an unsupervised neural network has a higher accuracy in grouping this type of data set as compared to C4.5. From this example, it can be concluded that the unsupervised network successfully classified the dataset with a large number of attributes.

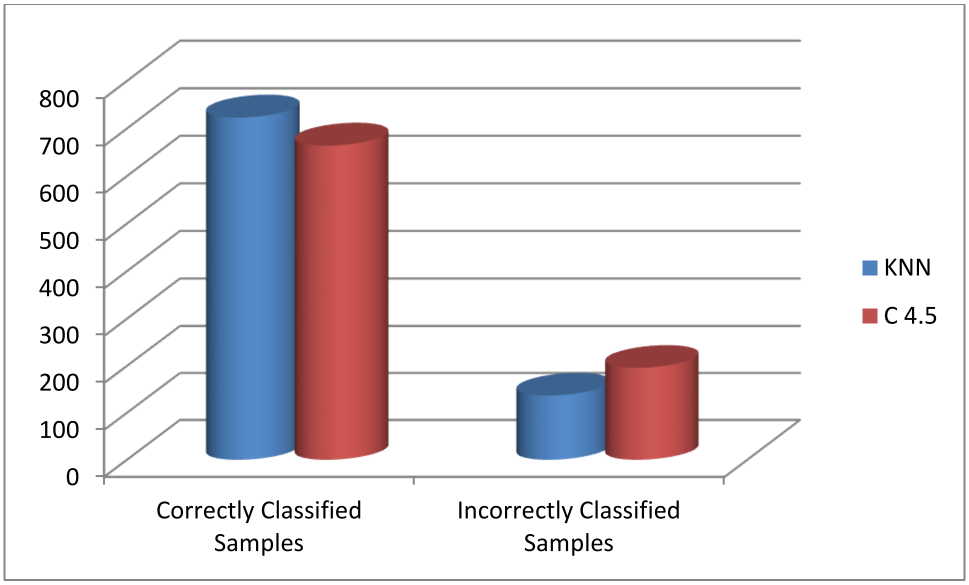


Figure 14. Performance Measure of KNN and C4.5 Classifiers

4.1.3. Rule Extraction Process

The proposed rule extraction method was applied to the neural network to extract concise and accurate rules. For comparison purpose, rules were also extracted from C4.5 algorithm using the WEKA software package.

4.1.3.1 Rules Extracted using Extended-CREA

The following rules were extracted from the network using the Extended-CREA. Due to a large number of rules, only ten rules are shown below. All the rules are enlisted in Appendix-A. The numbers in the parentheses represent the number of samples classified by that rule. These rules were sorted in decreasing order of number of classified samples.

Rule 1: If C_OPT5 >= 7 And C_OPT4 >= 9 Then High Level Awareness (326.0)

Rule 2: If C_OPT3 >= 1 And (C_OPT4 >= 4 And C_OPT5 >= 9) Then High Level Awareness (121.0)

Rule 3: If C_OPT5 >= 14 Then High Level Awareness (53.0)

Rule 4: If C_OPT2 >= 3 And (C_OPT5 >= 5 And ((C_OPT3 >= 2 And C_OPT4 >= 11) OR (C_OPT3 >= 7 And C_OPT4 >= 6))) Then High Level Awareness (46.0)

Rule 5: If C_OPT3 >= 8 And (C_OPT4 >= 10 And C_OPT5 >= 3) Then High Level Awareness (32.0)

Rule 6: If C_OPT3 >= 4 And (C_OPT1 >= 5 And (C_OPT2 >= 4 And C_OPT4 >= 3)) Then Medium Level Awareness (26.0)

Rule 7: If C_OPT3 >= 1 And (C_OPT4 >= 14 And C_OPT5 >= 3) Then High Level Awareness (14.0)

Rule 8: If C_OPT5 >= 7 And (C_OPT2 >= 3 And ((C_OPT3 = 11 And C_OPT4 >= 4) OR (C_OPT3 >= 5 And C_OPT4 = 7))) Then High Level Awareness (13.0)

Rule 9: If C_OPT2 = 1 And (C_OPT3 >= 9 And ((C_OPT4 >= 6 And C_OPT5 >= 5) OR (C_OPT1 >= 1 And (C_OPT4 >= 10 And C_OPT5 >= 3)))) Then High Level Awareness (13.0)

Rule 10: If C_OPT4 >= 4 And (C_OPT1 >= 9 And (C_OPT2 >= 2 And C_OPT3 >= 2)) Then Medium Level Awareness (12.0)

where C_OPT represents the count of option. For illustration, rule 1 can be expressed in human readable form as:

If "Option 5" is selected for at least 7 questions, and "Option 4" is selected for at least 9 questions, Then Class "High Level Awareness"

4.1.3.2 Rules Extracted using C4.5

For comparison, the following rules were extracted using the C4.5 algorithm. Due to a large number of rules, only ten rules are shown below. The complete decision tree and rules are shown in Appendix-A. The numbers in the parentheses represent the number of samples classified by that rule. These rules were sorted in decreasing order of number of classified samples.

Rule 1: If Q18 = OPT5 And Q16 = OPT5 Then High Level Awareness (201.0)

Rule 2: If Q18 = OPT4 And Q29 = OPT5 Then High Level Awareness (129.0)

Rule 3: If Q18 = OPT4 And Q29 = OPT4 Then High Level Awareness (116.0)

Rule 4: If Q18 = OPT2 Then Medium Level Awareness (70.0)

Rule 5: If Q18 = OPT5 And Q16 = OPT4 Then High Level Awareness (44.0)

Rule 6: If Q18 = OPT3 And Q25 = OPT2 Then Medium Level Awareness (28.0)

Rule 7: If Q18 = OPT3 And Q25 = OPT5 Then High Level Awareness (26.0)

Rule 8: If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT5 Then High Level Awareness (17.0)

Rule 9: If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT3 Then Medium Level Awareness (15.0)

Rule 10: If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT5 Then High Level Awareness (15.0)

where Q represents the question and OPT represent the option. For illustration, rule 1 can be expressed in human readable form as: If “Option 5” is selected for Question 18 and 16 Then Class “High Level Awareness”.

A total of 73 rules were extracted, but out of those rules, 17 can be ignored as they did not classify any data sample. So, the total number of rules extracted using the C4.5 method was 56. Rules extracted from CREA, Extended-CREA and C4.5 were then applied to the original data set to measure the accuracy of the rules. A comparison of different rule extraction techniques is shown in Table 25.

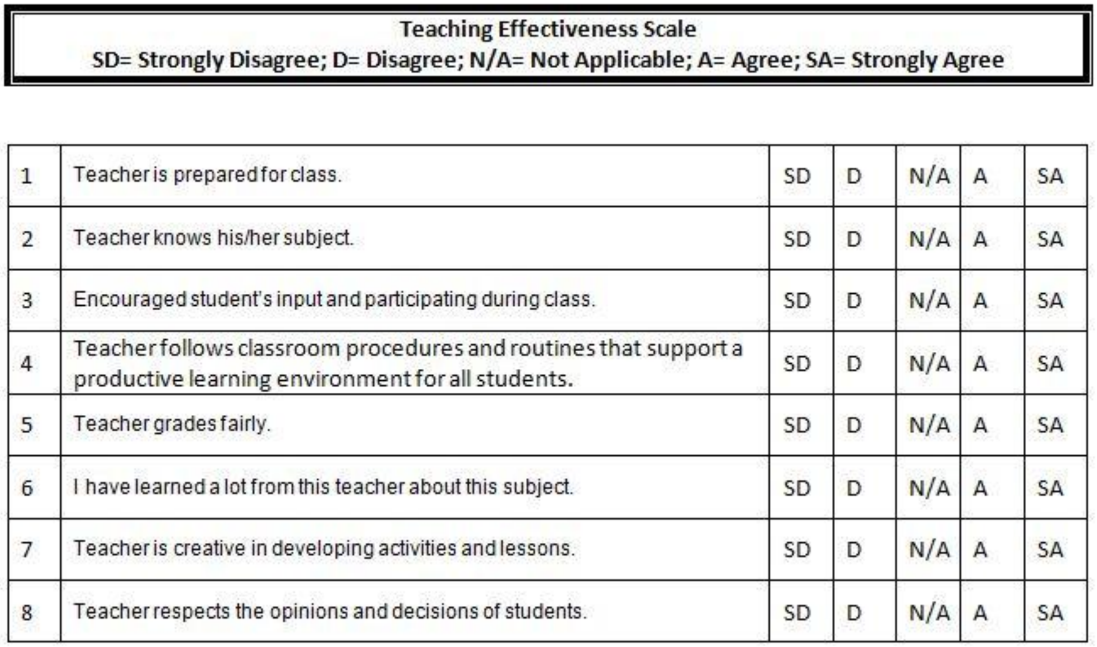
Table 25. Comparison of Different Rule Extraction Techniques

Rule Extraction Technique	**Number Of Rules**				**Performance Accuracy**
	High Level of Awareness	**Medium Level of Awareness**	**Low Level of Awareness**	**Total**	
CREA	576	195	80	851	84.06%
Extended-CREA	29	40	7	76	84.06%
C4.5	22	32	2	56	77.21%

From Table 25, it can be observed that the proposed method has a better performance in terms of the number of rules as compared to the original CREA. CREA extracted a large number of rules as compared to any other methodology. The total number of rules extracted from CREA is almost equal to the number of samples. For instance, for class 1 (High Level of Awareness), out of 584 samples classified, CREA extracted 576 rules. The reason for this large number of extracted rules is the unique patterns in the samples. There were 576 unique patterns in samples provided for class 1. The performance accuracy of CREA and Extended-CREA is the same as the actual network accuracy. The performance accuracy of C4.5 is same as the actual decision tree accuracy. The count of rules extracted from Extended-CREA and C4.5 is comparable, but due to the accuracy, the proposed method has little advantage over C4.5.

4.2. Teacher Evaluation Survey

The teacher evaluation survey contained 8 questions; each question had five options as shown in Figure 15. For the sake of confidentiality, the actual survey is not shown here. Questions were also altered to retain the confidentiality. The classifiers’ performance will not be affected at all due to this change because the classifier only searches for patterns in the responses, and the nature of the question is unimportant for the classifier. It is used to evaluate a teacher’s performance and help in decision making for the future. Different educational institutes use this type of survey to evaluate a teacher’s strengths and limitations. The class label information was not provided with this survey data set but two numbers of classes were known. The first group was those students who were satisfied with the teaching strategies and methods, i.e. satisfied students. The second group was those students who were dissatisfied with the teacher, i.e. dissatisfied students. A total of 265 students participated in this survey.



Teaching Effectiveness Scale
SD= Strongly Disagree; D= Disagree; N/A= Not Applicable; A= Agree; SA= Strongly Agree

1	Teacher is prepared for class.	SD	D	N/A	A	SA
2	Teacher knows his/her subject.	SD	D	N/A	A	SA
3	Encouraged student’s input and participating during class.	SD	D	N/A	A	SA
4	Teacher follows classroom procedures and routines that support a productive learning environment for all students.	SD	D	N/A	A	SA
5	Teacher grades fairly.	SD	D	N/A	A	SA
6	I have learned a lot from this teacher about this subject.	SD	D	N/A	A	SA
7	Teacher is creative in developing activities and lessons.	SD	D	N/A	A	SA
8	Teacher respects the opinions and decisions of students.	SD	D	N/A	A	SA

Figure 15. Teacher Evaluation Survey

The proposed method was applied to this survey data in the following manner.

4.2.1 Preprocessing – Data Cleaning and Transformation

The responses of the teacher evaluation survey were provided in XLS format (Microsoft Excel). In this step, responses were normalized to the range of 1 to -1. Normalization of the responses is given in Table 26. There were no invalid responses in this data, so all records were used. After normalization, this file was converted to the CSV format.

Table 26. Normalization of Responses

Survey Option	Short Form	Option Value	Normalized Value
Strongly Disagree	OPT1	1	-0.9
Disagree	OPT2	2	-0.4
Not Applicable	OPT3	3	-0.1
Agree	OPT4	4	0.4
Strongly Agree	OPT5	5	0.9

4.2.2 Clustering of Data using the Kohonen Neural Network

A total of 265 samples were taken for clustering. The Kohonen neural network (KNN) clustered 177 tuples in class 1 and 88 tuples in class 2. Results of KNN are used as the expected output for the C4.5 algorithm. Table 27 shows in detail the results of the KNN and C4.5 classifiers.

Table 27. Results of KNN and C4.5 Classifiers

Method	Class 1 Satisfied Students	Class 2 Dissatisfied Students
ANN	177	88
C 4.5	204	61

The error matrix of the KNN classifier is not displayed in this example as no class label information was provided. The error matrix of C4.5 is shown in Table 28. ”Satisfied Students” and “Dissatisfied Students” represent the two classes. Columns represent the predicted class while the rows represent the actual class. The recognition column represents the user’s accuracy.

Table 28. Confusion Matrix/Error Matrix of C4.5 Classifier

	Satisfied Students	Dissatisfied Students	Total	Recognition
Satisfied Students	172	5	177	97.17%
Dissatisfied Students	10	78	88	88.63%
Total	182	83	265	94.33%

4.2.3 Rules Extraction Process

The proposed rule extraction method was applied to the neural network to extract concise and accurate rules. For comparison purposes, rules were also extracted from the C4.5 algorithm using the WEKA software package.

4.2.3.1 Rules Extracted using Extended-CREA

The following rules were extracted from the network using the extended-CREA. The numbers in the parentheses represent the number of samples classified by that rule. These rules were sorted in decreasing order of the number of classified samples.

Rule 1: If C_OPT5>=2 Then Satisfied (56.0)

Rule 2: If OPT1>=1 And OPT2>=2 Then Dissatisfied (50.0)

Rule 3: If C_OPT4>=2 And C_OPT5>=1 Then Satisfied (42.0)

Rule 4: If C_OPT4>=1 And (C_OPT3>=1 And ((C_OPT5=1 And (C_OPT2>=1 OR C_OPT2=1)) OR C_OPT5>=1)) Then Satisfied (25.0)

Rule 5: If C_OPT4>=4 Then Satisfied (21.0)

Rule 6: If C_OPT4>=1 And (C_OPT3=2 And C_OPT5>=1) Then Satisfied (19.0)

Rule 7: If C_OPT4>=2 And (C_OPT2=1 And C_OPT3>=2) Then Satisfied (10.0)

Rule 8: If C_OPT4>=1 And (C_OPT3>=2 And (C_OPT5>=1 OR C_OPT5=1)) Then Satisfied (7.0)

Rule 9: If OPT1>=1 And (OPT2=1 And OPT3>=1) Then Dissatisfied (6.0)

Rule 10: If OPT3>=3 And OPT2>=1 Then Dissatisfied (6.0)

Rule 11: If C_OPT4=2 And C_OPT3>=3 Then Satisfied (5.0)

Rule 12: If C_OPT3>=2 And C_OPT4=3 Then Satisfied (5.0)

Rule 13: If C_OPT1>=2 Then Dissatisfied (5.0)

Rule 14: If C_OPT2>=3 Then Dissatisfied (4.0)

Rule 15: If C_OPT3>=5 Then Dissatisfied (4.0)

where C_OPT represents the count of the option. For illustration, rule 1 can be expressed in human readable form as: If "Option 5" is selected for at least 2 questions, Then Class "Satisfied".

4.2.3.2 Rules Extracted using C4.5

For comparison, the following C4.5 tree was extracted using the WEKA software package. A graphical representation of the tree is shown in Figure 16. The numbers in the parentheses represent the number of samples in that leaf (x) or number of samples and the number of false positives for that leaf (x/y).

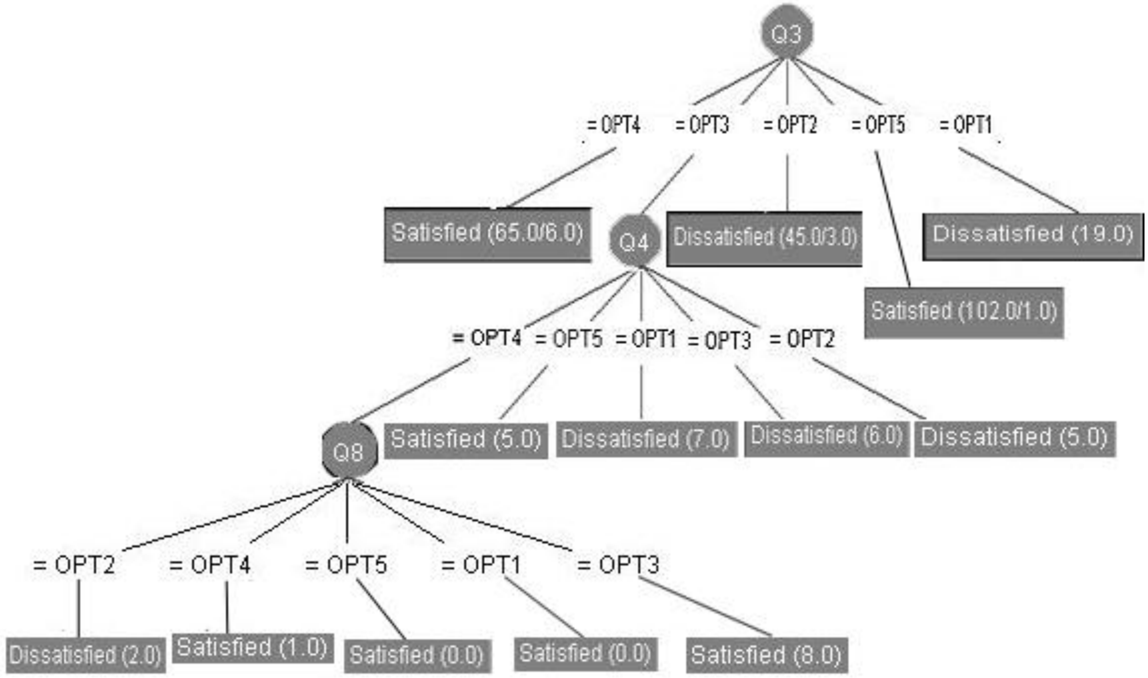


Figure 16. C4.5 Decision Tree of Teacher Evaluation Survey Data

The following rules were extracted from this decision tree. The numbers in the parentheses represent the number of samples classified by that rule. These rules are sorted in decreasing order of the number of classified samples.

Rule 1: If Q3 = OPT5 Then Satisfied (102.0)

Rule 2: If Q3 = OPT4 Then Satisfied (65.0)

Rule 3: If Q3 = OPT2 Then Dissatisfied (45.0)

Rule 4: If Q3 = OPT1Then Dissatisfied (19.0)

Rule 5: If Q3 = OPT3 And Q4 = OPT4 And Q8=OPT3 Then Satisfied (8.0)

Rule 6: If Q3 = OPT3 And Q4 = OPT1 Then Dissatisfied (7.0)

Rule 7: If Q3 = OPT3 And Q4 = OPT3 Then Dissatisfied (6.0)

Rule 8: If Q3 = OPT3 And Q4 = OPT5 Then Satisfied (5.0)

Rule 9: If Q3 = OPT3 And Q4 = OPT2 Then Dissatisfied (5.0)

Rule 10: If Q3 = OPT3 And Q4 = OPT4 And Q8=OPT2 Then Dissatisfied (2.0)

Rule 11: If Q3 = OPT3 And Q4 = OPT4 And Q8=OPT4 Then Satisfied (1.0)

Rule 12: If Q3 = OPT3 And Q4 = OPT4 And Q8=OPT5 Then Satisfied (0.0)

Rule 13: If Q3 = OPT3 And Q4 = OPT4 And Q8=OPT1 Then Satisfied (0.0)

where Q represents the question, and OPT represents the option. For illustration, rule 1 can be expressed in human readable form as: If “Option 5” is selected for Question 3, Then Class “Satisfied”.

The last two rules can be ignored as they did not classify any data sample correctly. The rules extracted from CREA, Extended-CREA and C4.5 were then applied to the original data set to measure the accuracy of the rules. A comparison of the different rule extraction techniques is shown in Table 29.

Table 29. Comparison of Different Rule Extraction Techniques

Rule Extraction Technique	Number Of Rules			Performance Accuracy
	Satisfied Students	Dissatisfied Students	Total	
CREA	34	45	79	100%
Extended-CREA	9	6	15	100%
C 4.5	5	6	11	94.33%

The number of rules extracted for this example is small as compared to the previous example. This is due to the smaller size of the dataset with fewer unique data patterns. From the values in Table 29, the proposed method extracted a fewer number of rules as compared to CREA. The performance accuracy of CREA and extended-CREA is measured by applying these rules on the original data set and then compare the results with the actual network results. CREA extracted a larger number of rules as compared to any other algorithm, but in this example the number of rules extracted from CREA was not equal to the number of samples. This is due to fewer unique patterns in the dataset. The number of rules extracted using extended-CREA and C4.5 were almost the same. The performance accuracy of the proposed method is also comparable with C4.5.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

An unsupervised neural network was applied to two different Likert-scale surveys. From the accuracy measurement shown in Table 24, it can be concluded that the unsupervised neural network offers a higher or comparable accuracy than conventional classifiers such as C4.5. This research proposed an extended-CREA for generating clustering rules from data sets with discrete attributes. The effectiveness of the proposed algorithm was tested by applying it to two different surveys having discrete data measured on a Likert scale. The first survey had a large number of attributes with a large number of unique patterns. The second survey had fewer attributes with fewer unique patterns. By looking at the results shown in Table 25 and Table 29, it can be stated that the proposed method extracts more comprehensive and compact rules as compared to the original CREA without affecting accuracy. Also, the outcome of the proposed rule extraction algorithm had better or comparable results to C4.5.

While the proposed method can be expected to perform well in general, it suffers from some limitations as well. First, the unsupervised neural network training is slow when the data set is large in terms of the numbers of samples and/or attributes [33]. This problem can be solved by using a supervised learning technique or by reducing the features using techniques such as correlation coefficient. Another limitation of this method is its scalability. This method is only limited to Likert-scale data. It can be applied to other data sets but it requires preprocessing of the data. Another limitation of the proposed method is that it assumes that all the attributes in the given data set are discrete data measured on a Likert scale.

5.2 Future Work

Future work should focus on minimizing the limitations discussed in the previous section. The most important aspect is the scalability of the proposed algorithm. Future work should focus on developing a better algorithm that should be scalable to non-discrete attributes as well. For future development, the proposed method could be used as a base line. The viability of this method should be tested on a wide variety of Likert-scale data. The data cleaning process, to handle missing values and noise data, used in this research could be replaced by the regression method. The regression method is a technique that helps to predict missing values and smoothing of data. The effectiveness of the rule extraction process proposed in the research can be increased by integrating the Greedy rule generation (GRG) algorithm [20].

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Appendix A: Rules Extracted for MARSI Survey

The following rules were extracted from the network using the extended-CREA. The numbers in the parentheses represent the number of samples classified by that rule. These rules were sorted in decreasing order of number of classified samples.

If C_OPT5 >= 7 AND C_OPT4 >= 9 Then High Level Awareness (326.0)

If C_OPT3 >= 1 AND (C_OPT4 >= 4 AND C_OPT5 >= 9) Then High Level Awareness (121.0)

If C_OPT5 >= 14 Then High Level Awareness (53.0)

If C_OPT2 >= 3 AND (C_OPT5 >= 5 AND ((C_OPT3 >= 2 AND C_OPT4 >= 11) OR (C_OPT3 >= 7 AND C_OPT4 >= 6))) Then High Level Awareness (46.0)

If C_OPT3 >= 8 AND (C_OPT4 >= 10 AND C_OPT5 >= 3) Then High Level Awareness (32.0)

If C_OPT3 >= 4 AND (C_OPT1 >= 5 AND (C_OPT2 >= 4 AND C_OPT4 >= 3)) Then Medium Level Awareness (26.0)

If C_OPT3 >= 1 AND (C_OPT4 >= 14 AND C_OPT5 >= 3) Then High Level Awareness (14.0)

If C_OPT5 >= 7 AND (C_OPT2 >= 3 AND ((C_OPT3 = 11 AND C_OPT4 >= 4) OR (C_OPT3 >= 5 AND C_OPT4 = 7))) Then High Level Awareness (13.0)

If C_OPT2 = 1 AND (C_OPT3 >= 9 AND ((C_OPT4 >= 6 AND C_OPT5 >= 5) OR (C_OPT1 >= 1 AND (C_OPT4 >= 10 AND C_OPT5 >= 3)))) Then High Level Awareness (13.0)

If C_OPT4 >= 4 AND (C_OPT1 >= 9 AND (C_OPT2 >= 2 AND C_OPT3 >= 2)) Then Medium Level Awareness (12.0)

If C_OPT2 >= 4 AND (C_OPT3 >= 6 AND (C_OPT4 = 5 AND C_OPT5 >= 6)) Then High Level Awareness (12.0)

If C_OPT3 >= 10 AND (C_OPT4 >= 8 AND C_OPT5 >= 3) Then High Level Awareness (11.0)

If C_OPT5 >= 7 AND (C_OPT2 >= 5 AND (C_OPT3 >= 3 AND C_OPT4 = 7)) Then High Level Awareness (9.0)

Appendix A (Continued)

If C_OPT4 >= 4 AND (C_OPT3 >= 7 AND ((C_OPT1 = 1 AND C_OPT2 = 10) OR (C_OPT1 >= 3 AND C_OPT2 = 6) OR (C_OPT1 = 4 AND C_OPT2 = 4))) Then Medium Level Awareness (9.0)

If C_OPT1 = 3 AND (C_OPT4 >= 3 AND ((C_OPT2 >= 7 AND C_OPT3 >= 6) OR (C_OPT2 = 8 AND C_OPT3 >= 4))) Then Medium Level Awareness (9.0)

If C_OPT1 >= 9 AND C_OPT2 >= 3 Then Medium Level Awareness (8.0)

If C_OPT3 >= 4 AND (C_OPT1 >= 8 AND (C_OPT2 >= 1 AND C_OPT4 >= 2)) Then Medium Level Awareness (8.0)

If C_OPT2 >= 9 AND (C_OPT3 >= 7 AND C_OPT4 >= 5) Then Medium Level Awareness (8.0)

If C_OPT2 = 6 AND C_OPT1 >= 7 Then Medium Level Awareness (8.0)

If C_OPT4 >= 4 AND (C_OPT1 = 2 AND (C_OPT2 >= 7 AND C_OPT3 >= 5)) Then Medium Level Awareness (7.0)

If C_OPT5 >= 7 AND (C_OPT2 >= 1 AND (C_OPT3 >= 8 AND C_OPT4 = 6)) Then High Level Awareness (5.0)

If C_OPT4 >= 4 AND (C_OPT2 = 5 AND C_OPT3 >= 14) Then Medium Level Awareness (5.0)

If C_OPT2 = 6 AND C_OPT3 >= 14 Then Medium Level Awareness (5.0)

If C_OPT3 >= 4 AND C_OPT2 >= 14 Then Medium Level Awareness (5.0)

If C_OPT2 >= 9 AND (C_OPT1 >= 3 AND C_OPT3 >= 3) Then Medium Level Awareness (5.0)

If C_OPT1 >= 12 Then Medium Level Awareness (5.0)

If C_OPT2 >= 8 AND C_OPT3 >= 11 Then Medium Level Awareness (5.0)

If C_OPT3 >= 4 AND (C_OPT1 = 7 AND C_OPT4 >= 6) Then Medium Level Awareness (4.0)

If C_OPT1 >= 9 AND C_OPT3 >= 5 Then Medium Level Awareness (4.0)

If C_OPT4 = 8 AND (C_OPT2 >= 5 AND (C_OPT3 >= 4 AND C_OPT5 >= 6)) Then High Level Awareness (4.0)

If C_OPT2 >= 4 AND (C_OPT3 >= 5 AND (C_OPT4 = 2 AND C_OPT5 >= 9)) Then High Level Awareness (3.0)

If C_OPT5 = 6 AND C_OPT4 >= 13 Then High Level Awareness (3.0)

If C_OPT2 >= 6 AND C_OPT3 = 6 AND C_OPT4 >= 5 AND C_OPT5 = 7 Then High Level Awareness (3.0)

If C_OPT3 >= 10 AND (C_OPT1 = 1 AND (C_OPT2 >= 7 AND C_OPT4 >= 3)) Then Medium Level Awareness (3.0)

If C_OPT4 >= 1 AND (C_OPT2 = 7 AND C_OPT3 >= 12) Then Medium Level Awareness (3.0)

If C_OPT4 >= 1 AND (C_OPT1 = 7 AND (C_OPT2 >= 3 AND C_OPT3 >= 3)) Then Medium Level Awareness (3.0)

If C_OPT2 = 1 AND (C_OPT3 >= 10 AND (C_OPT4 >= 11 AND C_OPT5 = 2)) Then High Level Awareness (2.0)

If C_OPT3 >= 10 AND (C_OPT2 = 3 AND (C_OPT4 >= 9 AND C_OPT5 = 2)) Then High Level Awareness (2.0)

If C_OPT5 = 1 AND C_OPT4 >= 17 Then High Level Awareness (2.0)

If C_OPT5 = 1 AND (C_OPT2 >= 2 AND (C_OPT3 >= 11 AND C_OPT4 >= 12)) Then High Level Awareness (2.0)

If C_OPT3 >= 15 AND C_OPT4 >= 6 AND C_OPT5 = 3 Then High Level Awareness (2.0)

If C_OPT3 >= 6 AND C_OPT4 >= 16 Then High Level Awareness (2.0)

If C_OPT3 >= 2 AND C_OPT4 >= 18 Then High Level Awareness (2.0)

Appendix A (Continued)

If C_OPT4 >= 4 AND (C_OPT2 = 2 AND ((C_OPT1 = 6 AND C_OPT3 >= 6) OR C_OPT3 >= 17)) Then Medium Level Awareness (2.0)

If C_OPT2 = 6 AND (C_OPT1 = 2 AND (C_OPT3 >= 8 AND C_OPT4 >= 6)) Then Medium Level Awareness (2.0)

If C_OPT1 = 6 AND (C_OPT2 >= 2 AND (C_OPT3 = 5 AND C_OPT4 >= 5)) Then Medium Level Awareness (2.0)

If C_OPT3 >= 10 AND (C_OPT1 = 5 AND C_OPT2 >= 1) Then Medium Level Awareness (2.0)

If C_OPT2 = 1 AND (C_OPT3 >= 18 AND C_OPT4 >= 8) Then High Level Awareness (1.0)

If C_OPT3 >= 8 AND (C_OPT2 = 8 AND (C_OPT4 = 9 AND C_OPT5 = 4)) Then High Level Awareness (1.0)

If C_OPT3 >= 8 AND (C_OPT2 = 2 AND (C_OPT4 = 2 AND C_OPT5 >= 10)) Then High Level Awareness (1.0)

If C_OPT4 = 8 AND (C_OPT2 = 2 AND (C_OPT3 >= 14 AND C_OPT5 = 2)) Then High Level Awareness (1.0)

If C_OPT5 = 6 AND C_OPT3 >= 20 Then High Level Awareness (1.0)

If C_OPT2 = 9 AND C_OPT3 >= 5 AND C_OPT4 >= 8 AND C_OPT5 = 4 Then High Level Awareness (1.0)

If C_OPT1 = 3 AND (C_OPT2 >= 11 AND (C_OPT3 = 1 AND C_OPT4 >= 2)) Then Medium Level Awareness (1.0)

If C_OPT2 = 6 AND (C_OPT1 = 1 AND (C_OPT3 >= 11 AND C_OPT4 >= 7)) Then Medium Level Awareness (1.0)

If C_OPT1 = 4 AND (C_OPT2 = 8 AND (C_OPT3 >= 3 AND C_OPT4 >= 2)) Then Medium Level Awareness (1.0)

If C_OPT1 = 4 AND (C_OPT2 = 7 AND ((C_OPT3 >= 5 AND (C_OPT4 >= 5 OR C_OPT4 = 6)) OR C_OPT3 = 4)) Then Medium Level Awareness (1.0)

If C_OPT1 >= 9 AND (C_OPT3 >= 2 AND C_OPT4 = 1) Then Medium Level Awareness (1.0)

If C_OPT2 >= 9 AND (C_OPT3 >= 11 AND C_OPT4 = 1) Then Medium Level Awareness (1.0)

If C_OPT3 >= 10 AND C_OPT1 >= 6 Then Medium Level Awareness (1.0)

If C_OPT4 >= 1 AND (C_OPT1 = 1 AND C_OPT2 >= 15) Then Medium Level Awareness (1.0)

If C_OPT2 = 2 AND C_OPT3 >= 22 Then Medium Level Awareness (1.0)

If C_OPT2 = 2 AND (C_OPT1 >= 8 AND C_OPT4 >= 9) Then Medium Level Awareness (1.0)

If C_OPT2 >= 4 AND (C_OPT1 = 2 AND (C_OPT3 >= 8 AND C_OPT4 >= 7)) Then Medium Level Awareness (1.0)

If C_OPT2 >= 4 AND (C_OPT1 >= 4 AND (C_OPT3 = 6 AND C_OPT4 = 6)) Then Medium Level Awareness (1.0)

If C_OPT1 >= 5 AND C_OPT2 >= 3 AND C_OPT3 >= 7 AND C_OPT4 >= 6 Then Medium Level Awareness (1.0)

If C_OPT1 >= 1 AND C_OPT2 >= 12 AND C_OPT3 >= 5 Then Medium Level Awareness (1.0)

If C_OPT3 >= 23 AND C_OPT4 = 3 Then Medium Level Awareness (1.0)

If C_OPT1 >= 10 AND C_OPT3 >= 2 AND C_OPT4 = 2 Then Medium Level Awareness (1.0)

If C_OPT2 = 1 AND (C_OPT4 >= 9 AND ((C_OPT3 >= 10 AND C_OPT5 >= 2) OR (C_OPT1 = 2 AND C_OPT3 >= 12))) Then High Level Awareness (1.0)

If C_OPT1 >= 2 AND (C_OPT2 = 5 AND (C_OPT3 >= 6 AND (C_OPT4 >= 8 AND C_OPT5 = 1))) Then High Level Awareness (1.0)

If C_OPT5 >= 4 AND (C_OPT1 >= 1 AND (C_OPT2 >= 2 AND (C_OPT3 >= 4 AND C_OPT4 >= 4))) Then High Level Awareness (1.0)

If C_OPT1 = 1 AND (C_OPT4 >= 10 AND (C_OPT5 = 1 AND ((C_OPT2 = 1 AND C_OPT3 >= 13) OR (C_OPT2 >= 3 AND C_OPT3 >= 9)))) Then High Level Awareness (1.0)

If C_OPT5 >= 4 AND (C_OPT1 >= 3 AND ((C_OPT2 >= 4 AND (C_OPT3 >= 5 AND C_OPT4 >= 2)) OR (C_OPT3 = 2 AND C_OPT4 >= 8) OR (C_OPT2 = 3 AND (C_OPT3 >= 2 AND C_OPT4 >= 5)))) Then High Level Awareness (1.0)

If C_OPT2 = 4 AND C_OPT3 >= 13 AND C_OPT4 >= 9 Then High Level Awareness (1.0)

If C_OPT1 = 2 AND C_OPT2 >= 1 AND C_OPT3 >= 9 AND C_OPT4 >= 7 Then High Level Awareness (1.0)

The following C4.5 tree has been extracted using the WEKA software package. The graphical representation of the tree is not displayed here due to the large size of the tree. The numbers in the parentheses represent the number of samples in that leaf (x) or the number of samples and the number of false positive for that leaf (x/y).

```
Q18 = OPT1
|  Q25 = OPT5
|  |  Q20 = OPT1: Medium Level Awareness (5.0)
|  |  Q20 = OPT5: High Level Awareness (4.0/1.0)
|  |  Q20 = OPT2: Medium Level Awareness (0.0)
|  |  Q20 = OPT3: Medium Level Awareness (0.0)
|  |  Q20 = OPT4: Medium Level Awareness (1.0)
|  Q25 = OPT4: High Level Awareness (7.0/2.0)
|  Q25 = OPT3
|  |  Q4 = OPT1: Medium Level Awareness (0.0)
|  |  Q4 = OPT4: Medium Level Awareness (0.0)
|   |   Q4 = OPT3: Medium Level Awareness (3.0)
|   |   Q4 = OPT5: Medium Level Awareness (4.0/1.0)
|   |   Q4 = OPT2: High Level Awareness (2.0)
|   Q25 = OPT2: Medium Level Awareness (6.0)
|   Q25 = OPT1
|   |   Q29 = OPT5: Low Level Awareness (0.0)
|   |   Q29 = OPT3: Low Level Awareness (3.0)
|   |   Q29 = OPT4: Medium Level Awareness (3.0)
|   |   Q29 = OPT1: Low Level Awareness (3.0)
|   |   Q29 = OPT2: Medium Level Awareness (1.0)
Q18 = OPT2: Medium Level Awareness (70.0/20.0)
Q18 = OPT4
|   Q29 = OPT5: High Level Awareness (129.0/8.0)
|   Q29 = OPT3
|   |   Q30 = OPT1: Medium Level Awareness (3.0)
|   |   Q30 = OPT5: High Level Awareness (11.0)
|   |   Q30 = OPT3
|   |   |   Q28 = OPT1: Medium Level Awareness (0.0)
|   |   |   Q28 = OPT4: High Level Awareness (2.0)
|   |   |   Q28 = OPT3: Medium Level Awareness (3.0)
|   |   |   Q28 = OPT5: Medium Level Awareness (0.0)
|   |   |   Q28 = OPT2: Medium Level Awareness (2.0)
|   |   Q30 = OPT4
```

Appendix A (Continued)

```
|   |   |   Q16 = OPT1: High Level Awareness (0.0)
|   |   |   Q16 = OPT4: Medium Level Awareness (3.0)
|   |   |   Q16 = OPT5: High Level Awareness (4.0)
|   |   |   Q16 = OPT3: High Level Awareness (0.0)
|   |   |   Q16 = OPT2: High Level Awareness (0.0)
|   |   Q30 = OPT2: Medium Level Awareness (7.0/3.0)
|   Q29 = OPT4: High Level Awareness (116.0/10.0)
|   Q29 = OPT1
|   |   Q8 = OPT1: Medium Level Awareness (0.0)
|   |   Q8 = OPT2: Medium Level Awareness (0.0)
|   |   Q8 = OPT5: High Level Awareness (2.0)
|   |   Q8 = OPT3: Medium Level Awareness (0.0)
|   |   Q8 = OPT4: Medium Level Awareness (2.0)
|   Q29 = OPT2: Medium Level Awareness (14.0/4.0)
Q18 = OPT3
|   Q25 = OPT5: High Level Awareness (26.0/4.0)
|   Q25 = OPT4
|   |   Q30 = OPT1: Medium Level Awareness (1.0)
|   |   Q30 = OPT5: High Level Awareness (15.0)
|   |   Q30 = OPT3: Medium Level Awareness (13.0/3.0)
|   |   Q30 = OPT4
|   |   |   Q19 = OPT5: High Level Awareness (2.0)
|   |   |   Q19 = OPT4: High Level Awareness (10.0/1.0)
```

Appendix A (Continued)

```
|   |   |   Q19 = OPT1: High Level Awareness (0.0)
|   |   |   Q19 = OPT3: Medium Level Awareness (6.0/2.0)
|   |   |   Q19 = OPT2: Medium Level Awareness (3.0/1.0)
|   |   Q30 = OPT2: Medium Level Awareness (3.0/1.0)
|   Q25 = OPT3
|   |   Q16 = OPT1: Medium Level Awareness (2.0)
|   |   Q16 = OPT4
|   |   |   Q19 = OPT5: Medium Level Awareness (2.0/1.0)
|   |   |   Q19 = OPT4
|   |   |   |   Q12 = OPT1: Medium Level Awareness (2.0)
|   |   |   |   Q12 = OPT4: High Level Awareness (2.0)
|   |   |   |   Q12 = OPT3: High Level Awareness (5.0)
|   |   |   |   Q12 = OPT5: High Level Awareness (0.0)
|   |   |   |   Q12 = OPT2: High Level Awareness (0.0)
|   |   |   Q19 = OPT1: Medium Level Awareness (0.0)
|   |   |   Q19 = OPT3: Medium Level Awareness (7.0)
|   |   |   Q19 = OPT2: Medium Level Awareness (2.0)
|   |   Q16 = OPT5: High Level Awareness (17.0/3.0)
|   |   Q16 = OPT3: Medium Level Awareness (15.0/3.0)
|   |   Q16 = OPT2: Medium Level Awareness (4.0)
|   Q25 = OPT2: Medium Level Awareness (28.0/8.0)
|   Q25 = OPT1: Medium Level Awareness (14.0/4.0)
Q18 = OPT5
```

Appendix A (Continued)

```
|  Q16 = OPT1: Medium Level Awareness (6.0)

|  Q16 = OPT4: High Level Awareness (44.0/7.0)

|  Q16 = OPT5: High Level Awareness (201.0/10.0)

|  Q16 = OPT3

|  |  Q28 = OPT1: Medium Level Awareness (1.0)

|  |  Q28 = OPT4: High Level Awareness (2.0)

|  |  Q28 = OPT3: High Level Awareness (6.0/1.0)

|  |  Q28 = OPT5: High Level Awareness (5.0/1.0)

|  |  Q28 = OPT2: Medium Level Awareness (3.0)

|  Q16 = OPT2: High Level Awareness (3.0)
```

The following rules are extracted from this decision tree. The numbers in the bracket represent the number of samples classified by that rule. These rules are sorted in decreasing order of number of classified samples.

If Q18 = OPT5 And Q16 = OPT5 Then High Level Awareness (201.0)

If Q18 = OPT4 And Q29 = OPT5 Then High Level Awareness (129.0)

If Q18 = OPT4 And Q29 = OPT4 Then High Level Awareness (116.0)

If Q18 = OPT2 Then Medium Level Awareness (70.0)

If Q18 = OPT5 And Q16 = OPT4 Then High Level Awareness (44.0)

If Q18 = OPT3 And Q25 = OPT2 Then Medium Level Awareness (28.0)

If Q18 = OPT3 And Q25 = OPT5 Then High Level Awareness (26.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT5 Then High Level Awareness (17.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT3 Then Medium Level Awareness (15.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT5 Then High Level Awareness (15.0)

If Q18 = OPT4 And Q29 = OPT2 Then Medium Level Awareness (14.0)

If Q18 = OPT3 And Q25 = OPT1 Then Medium Level Awareness (14.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT3 Then Medium Level Awareness (13.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT5 Then High Level Awareness (11.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT4 And Q19 = OPT4 Then High Level Awareness (10.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT2 Then Medium Level Awareness (7.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT3 Then Medium Level Awareness (7.0)

If Q18 = OPT1 And Q25 = OPT4 Then High Level Awareness (7.0)

If Q18 = OPT1 And Q25 = OPT2 Then Medium Level Awareness (6.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT4 And Q19 = OPT3 Then Medium Level Awareness (6.0)

If Q18 = OPT5 And Q16 = OPT1 Then Medium Level Awareness (6.0)

If Q18 = OPT5 And Q16 = OPT3 And Q28 = OPT3 Then High Level Awareness (6.0)

If Q18 = OPT5 And Q16 = OPT3 And Q28 = OPT5 Then High Level Awareness (5.0)

If Q18 = OPT1 And Q25 = OPT5 And Q20 = OPT1 Then Medium Level Awareness (5.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT4 And Q12 = OPT3 Then High Level Awareness (5.0)

If Q18 = OPT1 And Q25 = OPT5 And Q20 = OPT5 Then High Level Awareness (4.0)

If Q18 = OPT1 And Q25 = OPT3 And Q4 = OPT5 Then Medium Level Awareness (4.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT4 And Q16 = OPT5 Then High Level Awareness (4.0)

Appendix A (Continued)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT2 Then Medium Level Awareness (4.0)

If Q18 = OPT1 And Q25 = OPT3 And Q4 = OPT3 Then Medium Level Awareness (3.0)

If Q18 = OPT1 And Q25 = OPT1 And Q29 = OPT3 Then Low Level Awareness (3.0)

If Q18 = OPT1 And Q25 = OPT1 And Q29 = OPT4 Then Medium Level Awareness (3.0)

If Q18 = OPT1 And Q25 = OPT1 And Q29 = OPT1 Then Low Level Awareness (3.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT1 Then Medium Level Awareness (3.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT3 And Q28 = OPT3 Then Medium Level Awareness (3.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT4 And Q16 = OPT4 Then Medium Level Awareness (3.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT4 And Q19 = OPT2 Then Medium Level Awareness (3.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT2 Then Medium Level Awareness (3.0)

If Q18 = OPT5 And Q16 = OPT3 And Q28 = OPT2 Then Medium Level Awareness (3.0)

If Q18 = OPT5 And Q16 = OPT2 Then High Level Awareness (3.0)

If Q18 = OPT1 And Q25 = OPT3 And Q4 = OPT2 Then High Level Awareness (2.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT3 And Q28 = OPT4 Then High Level Awareness (2.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT3 And Q28 = OPT2 Then Medium Level Awareness (2.0)

If Q18 = OPT4 And Q29 = OPT1 And Q8 = OPT5 Then High Level Awareness (2.0)

If Q18 = OPT4 And Q29 = OPT1 And Q8 = OPT4 Then Medium Level Awareness (2.0)

Appendix A (Continued)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT4 And Q19 = OPT5 Then High Level Awareness (2.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT1 Then Medium Level Awareness (2.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT5 Then Medium Level Awareness (2.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT4 And Q12 = OPT1 Then Medium Level Awareness (2.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT4 And Q12 = OPT4 Then High Level Awareness (2.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT2 Then Medium Level Awareness (2.0)

If Q18 = OPT5 And Q16 = OPT3 And Q28 = OPT4 Then High Level Awareness (2.0)

If Q18 = OPT1 And Q25 = OPT5 And Q20 = OPT4 Then Medium Level Awareness (1.0)

If Q18 = OPT1 And Q25 = OPT1 And Q29 = OPT2 Then Medium Level Awareness (1.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT1 Then Medium Level Awareness (1.0)

If Q18 = OPT5 And Q16 = OPT3 And Q28 = OPT1 Then Medium Level Awareness (1.0)

If Q18 = OPT1 And Q25 = OPT5 And Q20 = OPT2 Then Medium Level Awareness (0.0)

If Q18 = OPT1 And Q25 = OPT5 And Q20 = OPT3 Then Medium Level Awareness (0.0)

If Q18 = OPT1 And Q25 = OPT3 And Q4 = OPT1 Then Medium Level Awareness (0.0)

If Q18 = OPT1 And Q25 = OPT3 And Q4 = OPT4 Then Medium Level Awareness (0.0)

If Q18 = OPT1 And Q25 = OPT1 And Q29 = OPT5 Then Low Level Awareness (0.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT3 And Q28 = OPT1 Then Medium Level Awareness (0.0)

Appendix A (Continued)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT3 And Q28 = OPT5 Then Medium Level Awareness (0.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT4 And Q16 = OPT1 Then High Level Awareness (0.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT4 And Q16 = OPT3 Then High Level Awareness (0.0)

If Q18 = OPT4 And Q29 = OPT3 And Q30 = OPT4 And Q16 = OPT2 Then High Level Awareness (0.0)

If Q18 = OPT4 And Q29 = OPT1 And Q8 = OPT1 Then Medium Level Awareness (0.0)

If Q18 = OPT4 And Q29 = OPT1 And Q8 = OPT2 Then Medium Level Awareness (0.0)

If Q18 = OPT4 And Q29 = OPT1 And Q8 = OPT3 Then Medium Level Awareness (0.0)

If Q18 = OPT3 And Q25 = OPT4 And Q30 = OPT4 And Q19 = OPT1 Then High Level Awareness (0.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT4 And Q12 = OPT5 Then High Level Awareness (0.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT4 And Q12 = OPT2 Then High Level Awareness (0.0)

If Q18 = OPT3 And Q25 = OPT3 And Q16 = OPT4 And Q19 = OPT1 Then Medium Level Awareness (0.0)