CHAPTER 8

FINDINGS AND DISCUSSIONS

8.1. INTRODUCTION

This chapter presents the simulated experimented results of this research. This gives the way to high light research reflects, differs from and extends current knowledge of the area credit card fraudulent detection. This chapter demonstrates exactly the interpretation of the findings and the outlining of the research. Results provided by the performance analysis explain the findings.

The performance measures used to evaluate the proposed SHMM-FIC, MSHMM, AHMM and OMSHMM against the HMM are

✓ Precision value
✓ Recall value
✓ F-Measure value

The performance improvement of the fraud detection is computed based on the precision, recall and the F-Measure value

Data Set Description

The data set used in this research work for predicting the fraudulent behaviour in the credit card transaction system are germen data set which consists of the spending profile of germen users. This data set consists of various fields which is used to indicate the user spending behaviour in different transaction. Those fields are Body, Body name, Card holder, Card description, Transaction date, Posting date, Merchant
name, Merchant city, Foreign currency, Foreign currency amount, Home currency, Transaction amount, cycle reference.

Confusion matrix

A confusion matrix is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. This matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The following table shows the confusion matrix for a two class classifier. The entries in the confusion matrix have the following meaning in the context of our study:

- $a$ is the number of correct predictions that an instance is negative,
- $b$ is the number of incorrect predictions that an instance is positive,
- $c$ is the number of incorrect of predictions that an instance negative
- $d$ is the number of correct predictions that an instance is positive.

![Fig 8.1 Confusion Matrix](image-url)
Several standard terms have been defined for the 2 class matrix:

**The accuracy (AC)** is the proportion of the total number of predictions that were correct. It is determined using the equation:

\[ AC = \frac{a+d}{a+b+c+d} \]  
\[ (7.1.1) \]

**The recall or true positive rate (TP)** is the proportion of positive cases that were correctly identified, as calculated using the equation:

\[ TP = \frac{d}{c+d} \]  
\[ (7.1.2) \]

**The false positive rate (FP)** is the proportion of negatives cases that were incorrectly classified as positive, as calculated using the equation:

\[ FP = \frac{b}{a+b} \]  
\[ (7.1.3) \]

**The true negative rate (TN)** is defined as the proportion of negatives cases that were classified correctly, as calculated using the equation:

\[ TN = \frac{a}{a+b} \]  
\[ (7.1.4) \]

**The false negative rate (FN)** is the proportion of positives cases that were incorrectly classified as negative, as calculated using the equation:
Finally, precision (P) is the proportion of the predicted positive cases that were correct, as calculated using the equation:

\[ P = \frac{d}{b+d} \]  

(7.1.6)

The confusion matrix is shown in below screen shot.

![Confusion matrix](image)

**Fig.8.1.1 Confusion matrix**

The following are the performance graphs that show the effectiveness of our implemented system:

### 8.1.1 Accuracy

The following is an accuracy graph that shows Optimized HMM is having highest accuracy over all other system whereas HMM is having least accuracy level.
Fig. 8.1.2 Accuracy graph

8.1.2 Precision

The following is a precision graph that shows Optimized HMM is having highest precision over all other system whereas HMM is having least precision level.

Fig. 8.1.3 Precision graph
8.1.3 Recall

The following is a recall graph that shows optimized HMM is having highest recall over all other system whereas HMM is having least recall level.

![Recall graph](image)

**Fig.8.1.4 Recall graph**

8.1.4 F-Measure

F-scores are how HQ determines your accuracy based on what was added and what was missed. The formula for the traditional F-score is:

\[
F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]

The following is a F-Measure graph that shows optimized HMM is having highest F-measure over all other system whereas HMM is having least F-measure.
Figure 8.1.5. F-Measure

ROC Curve

A receiver operating characteristic (ROC) curve, is a graphical plot which illustrates the performance of a binary classifier system as its discrimination threshold is varied. It is created by plotting the fraction of true positives out of the positives (TPR = true positive rate) vs. the fraction of false positives out of the negatives (FPR = false positive rate), at various threshold settings. TPR is also known as sensitivity (also called recall in some fields), and FPR is one minus the specificity or true negative rate. In general, if both of the probability distributions for detection and false alarm are known, the ROC curve can be generated by plotting the Cumulative Distribution Function (area under the probability distribution from $-\infty$ to $+\infty$) of the detection probability in the y-axis versus the Cumulative Distribution Function of the false alarm probability in x-axis. ROC analysis provides tools to select possibly optimal models and to discard suboptimal ones independently from (and prior to
specifying) the cost context or the class distribution. ROC analysis is related in a direct and natural way to cost/benefit analysis of diagnostic decision making.

The ROC curve was first developed by electrical engineers and radar engineers during World War II for detecting enemy objects in battlefields and was soon introduced to psychology to account for perceptual detection of stimuli. ROC analysis since then has been used in medicine, radiology, biometrics, and other areas for many decades and is increasingly used in machine learning and data mining research. The ROC is also known as a relative operating characteristic curve, because it is a comparison of two operating characteristics (TPR and FPR) as the criterion changes.

A classification model (classifier or diagnosis) is a mapping of instances between certain classes/groups. The classifier or diagnosis result can be a real value (continuous output), in which case the classifier boundary between classes must be determined by a threshold value (for instance, to determine whether a person has hypertension based on a blood pressure measure). Or it can be a discrete class label, indicating one of the classes.

Let us consider a two-class prediction problem (binary classification), in which the outcomes are labelled either as positive (p) or negative (n). There are four possible outcomes from a binary classifier. If the outcome from a prediction is p and the actual value is also p, then it is called a true positive (TP); however if the actual value is n then it is said to be a false positive (FP). Conversely, a true negative (TN) has occurred when both the prediction outcome and the actual value are n, and false negative (FN) is when the prediction outcome is n while the actual value is p.
To get an appropriate example in a real-world problem, consider a diagnostic test that seeks to determine whether a person has a certain disease. A false positive in this case occurs when the person tests positive, but actually does not have the disease. A false negative, on the other hand, occurs when the person tests negative, suggesting they are healthy, when they actually do have the disease.

Let us define an experiment from $P$ positive instances and $N$ negative instances. The four outcomes can be formulated in a $2 \times 2$ contingency table or confusion matrix, as follows:

![Contingency Table](image)

The following is the ROC Curve of our implemented system which shows Advanced HMM is having higher ROC Curve than the other methods.

![ROC Curve](image)

Fig.8.1.5 ROC Curve