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# FINANCIAL TIME SERIES PREDICTION USING MACHINE LEARNING ALGORITHMS

by

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## LIST OF PUBLICATIONS

- Tiong, L.C.O., Ngo D.C.L. & Lee, Y. (2012), "Stock Price Prediction Model using Candlestick Pattern Feature." in *International Conference of Interactive Digital Media* (pp. 394-401), Langkawi. [Published]

- Tiong, L.C.O., Ngo D.C.L. & Lee, Y. (2013), "Forex Trading Prediction using Linear Regression Line, Artificial Neural Network and Dynamic Time Warping Algorithms." in *Proceedings of the 4th International Conference on Computing and Informatics* (pp. 71 – 77), Kuching Sarawak. [Published]

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## ABSTRACT

Financial time series prediction is a challenging task due to the fluctuation of trading or economic exchange that is difficult to predict. Researchers from different fields have been attracted to perform several techniques for identifying reliability of the financial time series prediction. Finding of research papers, the financial trend patterns repeat itself in the history. Thus, this research motivates and aims to investigate the repeat behaviour and pattern of trends from the historical financial time series data, and utilise the strength of machine learning techniques to develop a promising financial time series predictor engine. In this research, two frameworks are proposed for financial time series prediction. In the first proposed framework, candlestick pattern is utilised as technical analysis method to identify the financial trends. Thereafter, Artificial Neural Network (ANN) and Support Vector Machine (SVM) algorithms are implemented separately to train with the trend patterns for predicting the movement direction of financial trends. In the second proposed framework, Linear Regression Line (LRL) is utilised to identify the trend patterns from historical financial time series, which is supported by ANN and SVM for classification process separately. Subsequently, Dynamic Time Warping (DTW) algorithm is utilised through brute force to predict the trend movement. The experimental results showed that the second proposed model is consistent with the hypothesis, which provides better accuracy of prediction. Therefore, the findings of this research help in improving the accuracy of prediction model.

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| | |
|---|---|
| **AI** | Artificial Intelligence |
| **ANN** | Artificial Neural Network |
| **AUD** | Australian Dollar |
| **CBR** | Case – Based Reasoning |
| **DTW** | Dynamic Time Warping |
| **EMA** | Exponential Moving Average |
| **ES** | Expert System |
| **EUR** | European Union Dollar |
| **FL** | Fuzzy Logic |
| **Forex** | Foreign Exchange Market |
| **HMM** | Hidden Markov Model |
| **ID3** | Iterative Dichotomiser 3 |
| **LRL** | Linear Regression Line |
| **LS** | Lower Shadow of Candlestick Chart |
| **MACD** | Moving Average Convergence-Divergence |
| **MAE** | Mean Absolute Error |
| **MAP** | Maximum a Posteriori |
| **MLP** | Multi-Layer Perceptron |
| **OHLC** | Open, High, Low, Close |
| **RB** | Real Body of Candlestick Chart |
| **RBF** | Radial Basic Function |
| **RMSE** | Root Mean Square Error |
| **RTC** | Regression Trend Channel |
| **SMO** | Sequential Minimal Optimisation |
| **SOM** | Self – Organising Map |
| **SVM** | Support Vector Machine |
| **US** | Upper Shadow of Candlestick Chart |
| **USD** | United State of America Dollar |

## 1.0 INTRODUCTION

This chapter describes the basic concepts of financial time series, issues related to prediction accuracy and the limitations of technical analysis methods. In addition, researchers from the fields of finance and computer science have implemented different types of techniques such as technical analysis methods and Artificial Intelligence (AI) to analyse the financial trends for predictions. The pros and cons of the techniques are discussed in this chapter. Furthermore, motivation and objective of developing a prediction model using machine learning algorithms are also presented.

### 1.1 Overview of Financial Market

Generally, financial market is defined as a marketplace where the process of economic exchange or trade is carried out between buyers and sellers, such as Foreign Exchange (Forex), stock exchange markets and others. The process involves the transfer of funds and financial assets between two or more parties (Ching, 2009). Within the financial field, financial markets are commonly referred to as markets, which are used for finance operations, expansion and economic growth (Vinci & Darskuviene, 2010).

The financial market plays an important role in promoting economic growth. The collection and analysis of financial time series data, as well as investment opportunities are provided to investors, brokers, corporations and other financial institutions. The collection of information assists them in directing funds for the most effective returns

(Jalloh, 2009). The structure of financial market allows buyers and sellers to determine the price and value of financial claims or the desired rate of return on different types of financial assets. Furthermore, the financial market offers liquidity for investors through the ability to convert financial assets into liquid funds.

## 1.2 Concept of Financial Time Series

In financial market, financial time series data is defined as a sequence of repeated observation variables, such as stock price, currency exchange rates, bonds return and commodities price which measures at uniform time intervals. Financial time series data can be described as:

$$T = \{x_1, x_2, x_3, \dots, x_n\} \tag{1.1}$$

$T$ is defined as a dataset of time series, $x_1$ until $x_n$ are defined as a sequential of different variables in different time stamp intervals. The entire variable values of $T$ are treated randomly as they are dependent on the trading and investment.

The basic variables of financial time series data include time stamp, open price, high price, low price, close price and the number of volumes bought. Those variables are described as:

$$x_i = \{o_i, h_i, l_i, c_i, v_i\} \tag{1.2}$$

where $i$ is defined as time stamp, $x_i$ is defined as a single data record in financial time series, $o_i$ is defined as opening price of the current time stamp, $h_i$ is defined as highest price of the current time stamp, $l_i$ is defined as lowest price of current time stamp, $c_i$ is defined as closing price of the current time stamp, and $v_i$ is defined as the volume.

Figure 1.1 shows an example of Forex trading that involves the currency exchange rates between *EUR* – *USD* on 2$^{nd}$ January of 2011 from 17:00 to 23:59. As can be seen, the financial time series data is a sequence of non-stationary values at regular intervals over different time stamp.

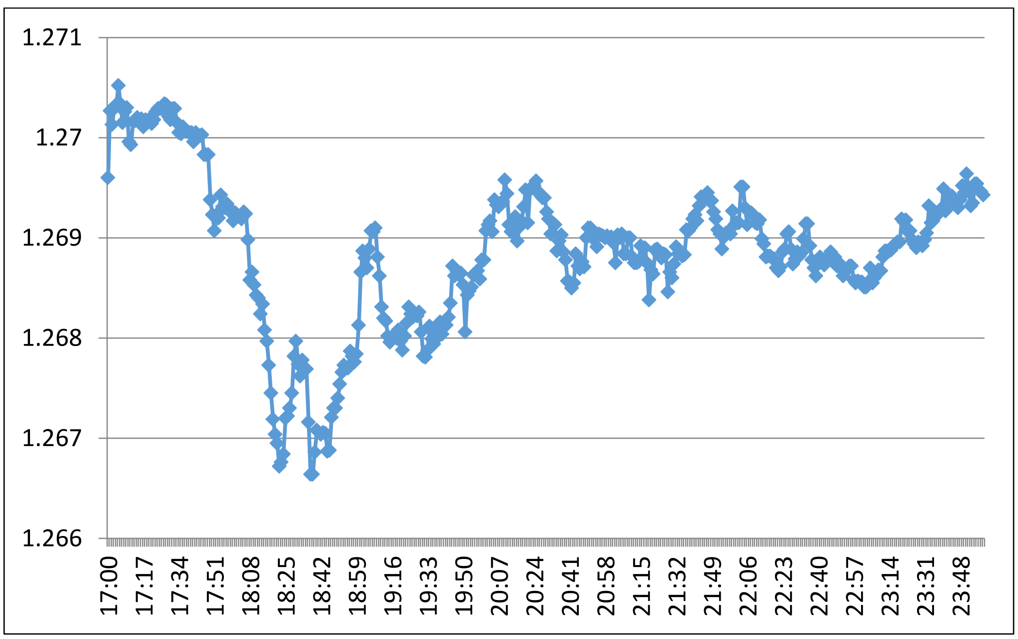


**Figure 1.1 - Example of Financial Time Series Data for Forex Trading**

## 1.3 The Financial Time Series Prediction

Financial time series data is non-stationary, as it is influenced by the variations in supply and demand of investors. It is affected by many correlated factors including economic, political and even psychological ones. The reason is that financial market facilitates exchange between buyers and sellers, and reduces unsecure issues from investment. The operation of financial market has been measured as very important task in global economy field. Therefore, any fluctuation in financial market will affect the market cap of corporation and the economic growth of industries and countries.

There are some risks when investing in financial market due to the uncertainty in movement of financial time series. Investing in financial market that has no prediction and accuracy information for market performance may expose an investor to both high risk of market prediction and improper time estimation for entrance. To avoid these issues, most investors prefer to have a tool with intelligence techniques in order to minimise investment risk so that they would have higher chances in gaining profit from the investment.

Financial time series prediction relates the current economic growth of a society to future business conditions. Prediction concerns likely factors that may affect a prospective business. It also identifies the trends in order to provide decision making about the future prospect of the financial investment. However, financial time series prediction is a non-linear dynamic field due to the non-stationary and noise of time series data as the major challenges. This is because the financial market is affected by both external and internal trading. This also concerns the valuation of assets, and speculation about future events. Traditionally, the time series data obtained does not contain sufficient information to understand the future trends. Therefore, the level of difficulty in predicting the financial time series data is high.

Since 1970s, there are a large amount of intensive researches have been discovered for financial time series prediction. Researchers from the fields of finance and computer science have carried out several techniques in order to accomplish one goal, which is predicting the trend movement to yield profit. In the early stage of the financial field, technical analysis methods such as Exponential Moving Average (EMA), candlestick pattern, OHLC (Open, High, Low and Close) bar chart, stochastic oscillator, Linear Regression Line (LRL) and Moving Average Convergence-Divergence (MACD) have been proposed and implemented by researchers to investigate the financial trends for developing the prediction model (Exponential Moving Average, 2012; Linear Regression Slope Indicator, n.d.; Using Technical Indicators, 2009; Kuepper, 2012). These methods are implemented to assist the investors in identifying the trend patterns based on historical time series data. However, these methods are not reliable; this could be due to lack of ability to learn the patterns and behaviour of time series data.

Due to the rapid growth of computational intelligence, computer science researchers have involved and applied certain Artificial Intelligence (AI) techniques such as Artificial Neural Network (ANN), Fuzzy Logic (FL), Expert Systems (ES), Hidden Markov Model (HMM) and Support Vector Machine (SVM) with the technical analysis methods to predict the movement of financial trend (Cao & Tay, 2001; Charkha, 2008; Enke, Grauer, & Mehdiyev, 2011; Hassan, Nath, & Kirley, 2007; K. H. Lee & Jo, 1999). There are certain trading tools, prediction software and investment management platforms in the industry that can handle information and signals of the financial markets, such as TradeStation, MetaStock and MetaTrader (MetaStock, 1982; MetaTrader, 2000; TradeStation, 2001). These tools utilise AI techniques and technical analysis methods to provide more reliable decision-making for investors. The researchers proved that the combination of AI techniques and technical analysis methods could be a promising approach in identifying the patterns and behaviour of financial trend.

Despite the existence of trading tools and software, as well as the experiments done by past researchers, financial time series prediction models are still a very active topic for development and improvement. Thus, this thesis introduces a proposed framework using LRL for pattern analysis, supported by ANN or SVM as classifiers, and then utilises Dynamic Time Warping (DTW) algorithm to predict the following day of trends.

In the first proposed prediction framework, the candlestick pattern is applied to represent the behaviour and pattern of historical financial time series data. The candlestick pattern is formalised in terms of numeric and nominal values using equations and trading rules. Formalisation is used to represent the candlestick pattern as an input parameter for AI techniques to learn the patterns during learning process. Subsequently, ANN and SVM are implemented as classifiers to predict the movement direction of financial trends based on the selected features. From the preliminary results of this framework, the candlestick pattern is not considered as good features for representing the trend patterns.

To represent the trend patterns in a more reliable way, the implementation of LRL has been utilised for analysing and forming the overall trend patterns based on the historical financial time series data in the second proposed prediction framework. Figure 1.2 illustrates the concept of this framework. The proposed features that consist of starting point, ending point, minimum area and the sequential series of trend are utilised for identifying and segmenting the trend patterns. After the segmentation, clustering algorithm – K-mean (Kanungo *et al.*, 2002) is implemented to cluster the trend patterns into two main classes – “Uptrend” and “Downtrend”.

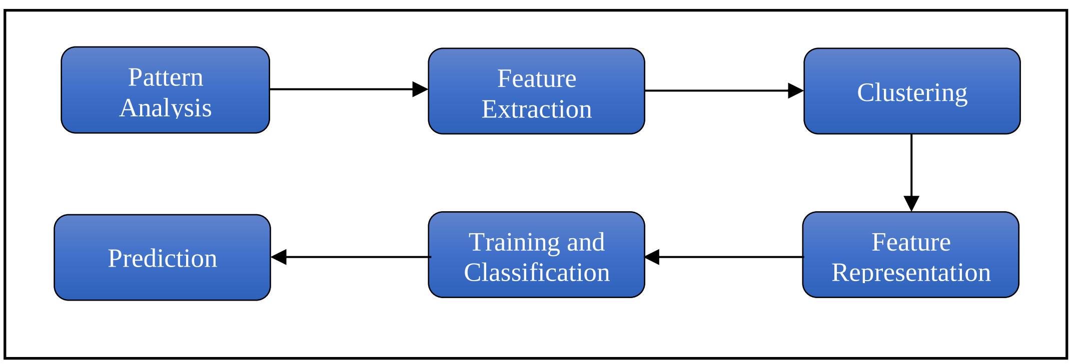


**Figure 1.2 - Structure of Second Proposed Framework**

Sequentially, ANN and SVM are implemented separately as classifiers to learn the trend patterns that are analysed by LRL. The selected features representation of trend patterns that are extracted from “Uptrend” and “Downtrend” are then used in the training process of ANN and SVM. Before the training process of ANN and SVM on the trend patterns, feature selection plays an important role as both machine learning algorithms could not be well-trained without reliable feature representation.

To predict future trends of the financial market, DTW is used to measure the similarity of testing trend patterns and training trend patterns in the proposed prediction model. Once the tested trend patterns have been classified as one of the trained group, DTW is applied in order to compare the tested trend patterns through brute force against the training trend patterns from the database to identify the shortest warping path.

## 1.4 Scope

In this thesis, the US Dollar (*USD*) and other major currencies, particularly the Australian Dollar (*AUD*) and European Union Dollar (*EUR*) are selected as the historical financial time series data, which consists of half-hour closing prices. Based on the historical financial time series data mentioned, LRL is applied to analyse the trend patterns, supported by ANN and SVM as classifiers separately. Then, DTW is implemented to predict the direction of future trends in the financial market.

## 1.5 Problem Statements

Financial time series prediction is a very complex and non-dynamic field that has been characterised by unstructured environment, uncertain motion of financial time series, hidden, noise or non-stationary raw data. There are many factors that influence the process of financial market, such as general economic conditions, supply and demand of the investment. As a result of these factors and effects, the accuracy of financial time series prediction has attracted most research interest in identifying reliability of existing frameworks for financial time series prediction.

Most researchers do not fully utilise the behaviour and patterns of financial time series data in features extraction. Traditionally, researchers from financial fields have started to implement technical analysis methods in order to calculate future trends in prediction model (Grunder *et al.*, 2012). Moreover, technical analysis methods usually proposed a statistical prediction model based on a set of parameters. In other words, these methods require a certain amount of time series data to calculate and identify the trends in modelling. However, financial time series prediction model will not be able to predict the future trends more accurately via these methods, as they are based solely on the statistical result of the financial trends to predict the movement of future trends. Therefore, technical analysis methods are lacking a learning mechanism for identifying the trend patterns (Introduction to Technical Indicators and Oscillators, 2012; Slope, 2012; Sewell, 2007).

On the other hand, the ability to predict the movement of financial market value would be a crucial capability for investors and stakeholders to yield a significant profit. However, the reliability of financial time series prediction model is not satisfactory, due to the lack of effective data analysis of trends over a period of time. As such, researchers may not fully utilise the available information for prediction. Therefore, the accuracy of the prediction model is unsatisfactory and unreliable. It is difficult to determine the usefulness of information from the financial time series data. Furthermore, financial time series data must be identified and eliminated cautiously to avoid the misleading information before the training process of AI techniques (Naeini, Taremia, & Homa Baradaran, 2010; Zhai, Hsu, & Halgamuge, 2007).

## 1.6 Aim and Objectives

According to the limitations and facts which mentioned, this thesis aims to propose a financial time series prediction model for solving the problems using technical analysis method and machine learning algorithm. The proposed prediction model is to improve 1 percent accuracy rate from the existing approach as target in predicting financial trends for investors and stakeholders to understand about the investment and financial growth.

The objectives of this research have been listed as following:

- To identify better features from the historical financial time series data in order to avoid misleading information that has the repeat behaviour and pattern of trends.
- To offer a reliable financial time series prediction model application for the investors and stakeholders using machine learning algorithms.

Therefore, the behaviour and trends movement of financial market are very significant that could be extracted as features for identifying trend patterns in the learning process. Hence, this thesis utilised technical analysis methods to identifying the overall trend patterns from the historical financial time series data, supported by machine learning algorithm to train the cluster patterns and applied DTW to predict the future trends. Furthermore, the proposed prediction model has improved the accuracy rates in predicting financial trends, and able to offer reliable application that is able to provide the trend movement of financial market for investors and stakeholders.

## 1.7 Contributions

This thesis combines technical analysis methods of LRL and machine learning algorithms of ANN or SVM, and DTW to propose a prediction model. The major contributions are:

- Analysing trend patterns from the historical financial time series data using LRL. The proposed segmentation and K-mean clustering algorithms are applied to identify trend patterns as features. The proposed segmentation algorithm demonstrates an effective approach to identify trend patterns that leads promising of clustering results.
- Developing the proposed prediction model using machine learning algorithms as classifiers for the partial trend patterns. Based on the classification results, the proposed features have successfully represented trend patterns for ANN or SVM to learn during the learning process individually.
- DTW has been utilised to predict future trends based on shortest warping path. Experimental result further proves how the proposed framework utilisation of LRL, ANN and DTW yields successful results for predicting future trends.

## 1.8 Thesis Layout

Chapter 2 of this thesis introduces certain background and related work of technical analysis methods and AI techniques that had been implemented to develop the prediction model. Chapter 3 describes the proposed framework that included technical analysis method – candlestick pattern and LRL are implemented to analyse the financial time series data, representing the trends in the form of different types of pattern. Then, the process of machine learning algorithm – ANN and SVM are studied, including the proposed features as input parameter for training and classification. The function of DTW in predicting the future trends is introduced. Then in Chapter 4, it shows the comparison result of different types of technical analysis methods and experimental results of the proposed methods. Chapter 5 concludes the thesis. Future work that indicates for improvement of the prediction model also included.

## 2.0 LITERATURE REVIEW

This chapter reviews on certain existing experiments and researches of financial time series prediction model. Section 2.1 reviews several technical analysis methods, which have been used as feature extraction by researchers from the fields of finance and computer science, to identify trend patterns from financial time series data. Section 2.2 gives a comprehensive review of the existing works that utilise different technical analysis methods with AI techniques for predicting the direction of financial trends.

### 2.1 Feature Extraction of Financial Time Series

Technical analysis methods are the study of financial market actions, which includes the information of price, volume and open interest. It is usually represented in graphical form and records the history of stock price changes in the stock market. These methods are traditional methodology for identifying the movement direction of financial trends, predicting the movement direction of prices and evaluating the security of financial trends by analysing the statistical result through the study of historical financial time series data ( Edwards & Magee, 2007).

These methods are widely used among financial professionals, as well as private and corporate investors for prediction. Technical analysis methods do not provide promising predictions about the movement direction of future financial trends. This is because technical analysis methods are used to identify the financial trends instead of prediction. However, these methods can be utilised as feature extraction to analyse the behaviour of financial trend patterns. Thus, technical analysis methods only capable for the analysis of financial trend patterns that are similar when repeated over time. Therefore, it is also called behavioural finance (Janssen, Langager, & Murphy, 2012).

In this section, technical analysis methods have been categorised into two types – stock chart and technical indicators. This section reviews the basic concept and related work, which have been applied by the researchers from different fields.

### 2.1.1 Financial Time Series: Stock Chart

Stock chart is a graphical plot that represents a sequence of financial time series data over a set of time stamp which shown in Figure 2.1. In statistics, this chart is referred to as a time series plot. It includes the time scale, price scale and the patterns of financial trend. The stock chart usually shows the movement of prices over a period of time, where each point on the chart represents the prices they trade at. Furthermore, a graphical stock chart makes it easier to spot the movement direction of the financial trends and its performance over a period of time (Introduction to Stock Charts, 2009). This category reviews on two popular types of stock chart – candlestick pattern and OHLC bar chart that are used by investors and traders in financial circle today.

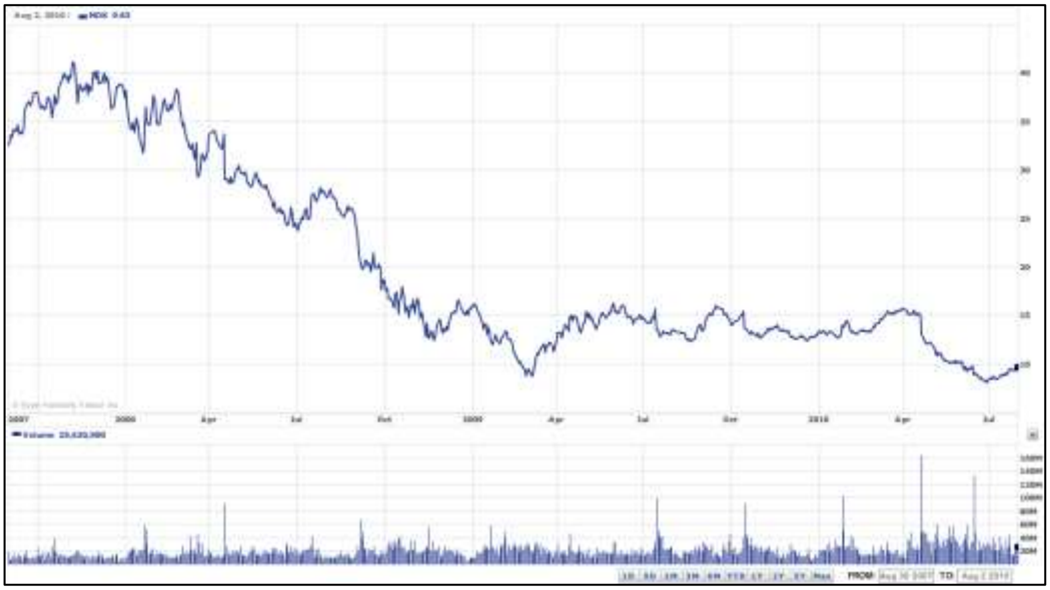

**Figure 2.1 - Example of Stock Chart**

## Candlestick Pattern

A Japanese rice trader Munehisa Homma founded candlestick pattern in the 18$^{th}$ century. It is one of the most popular and oldest types of empirical prediction model which have been used for decision making in stock price, foreign exchange rates, commodity and trading (Introduction to Candlesticks, 2012). The theory of candlestick pattern assumes that the trend of financial time series could be predicted by identifying the patterns. It visualises the financial trend patterns and provides the signal of continuations and inversion about the nature of financial trends (Nison, 1991; Technical Analysis Candlestick charts, 2007).

Candlestick pattern is composed of the thick body (black or white) and shadows. The thick part of candlestick body is called real body (RB), which represents the price range between close and open prices. The vertical lines above and bottom of the real body are called shadows. The shadow above the real body is called upper shadow (US) and the shadow under the real body is called lower shadow (LS), which represent the highest and the lowest prices of the time stamp.

Figure 2.2 shows the illustration of candlestick pattern where the real body of candlestick has two colours – “Black” and “White”. The “Black” real body illustrates that the open price is higher than the close price, which indicates the financial trend is decreasing, vice versa, when the close price is higher than the open price as the “White” real body representing the financial trend is increasing.

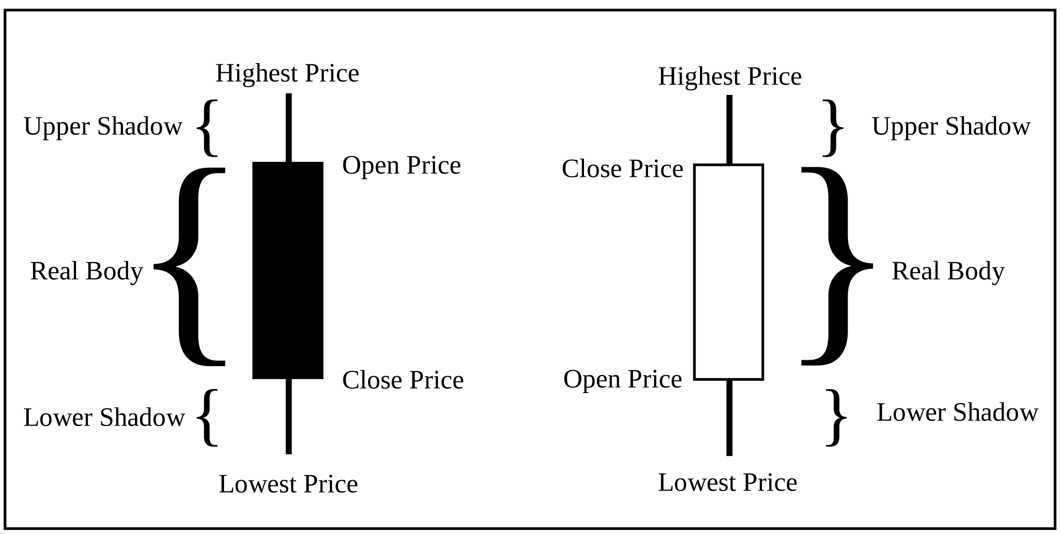


**Figure 2.2 - Structure of Candlestick Pattern**

An experiment which done by Caginalp and Laurent (1998), they had used the statistical method z-test to test the ability of candlestick chart pattern for predicting the changes of stock trend. The percentage of z-test results accuracy for the experiment was 67%.

Based on the research studied by Person (2002), he utilised the candlestick pattern and combined with two technical analysis methods known as Exponential Moving Average (EMA) and Moving Average Convergence-Divergence (MACD) to analyse the trading decision for reducing the risk. The experimental result showed that the first resistance point value of pivot analysis method could determine the next month "potential" price. The author concluded that candlestick pattern helps traders to interpret the changing direction of stock price, and then anticipate the trend signal of the stock.

Lee and Liu (2006) proposed a financial decision model that combined candlestick pattern with fuzzy linguistic variables, and designed an information agent to collect the financial time series data. In the model, the investment knowledge was represented using fuzzy candlestick chart and stored in a pattern base. In the experiment, the authors extracted the financial information and utilised the fuzzy candlestick pattern to identify the rules in the model for developing the financial decision-making. According to the research outcome, they concluded that the fuzzy candlestick patterns provided rich information that could be used to increase the efficiency of the pattern recognition models. They also mentioned that the model could also increase the efficiency of the investing strategies.

According to a research that was done by Shmatov (2012), he found that candlestick chart is able to provide the patterns for machine learning algorithms to learn and recognise the patterns for predicting the stock trend. The prediction model proposed by the author who provided equations to represent candlestick patterns based on different historical time frames for AI techniques to learn and recognise the patterns for predicting the stock trend.

Table 2.1 summarises a review on existing methods that show different conclusive results of experiments in each case. Overall, the research outcomes proved that the candlestick patterns as a reliable feature extraction method for identifying financial trends.

**Table 2.1 - Review of Financial Time Series Prediction Model using Candlestick Pattern**

| **Authors** | **Year** | **Features and Methods** | **Research Outcome** |
|---|---|---|---|
| Caginalp and Laurent | 1998 | • Statistic method z-test had been used to test the ability of candlestick chart pattern for predicting. | The z-test result accuracy of experiments was 67%. |
| Person | 2003 | • Utilised the candlestick chart and combined with other technical analysis method - pivot point analysis to analyse the trading decision.<br>• Formula:<br>Pivot Point = (High + Low + Close) / 3 | The combination techniques of candlestick chart and pivot point analysis were able to calculate and identify the buying and selling signal. |
| Lee and Liu | 2006 | • Combined candlestick chart with fuzzy linguistic variables to develop the financial decision model. | The proposed model - fuzzy candlestick patterns provided rich information that can be used to increase the efficiency of the pattern recognition models. |

| | | | |
|---|---|---|---|
| Shmatov | 2012 | • The proposed equations are used to identify the candlestick patterns based on different historical time stamps. | The author introduced few equations as feature for identifying the candlestick patterns as input parameters for machine learning algorithms to learn. |

OHLC Bar Chart

OHLC bar chart is another type of stock chart, which illustrates the direction of the financial trend. The bar chart includes four separate financial time series data price information:

- Open: Opening price of that current time stamp.
- High: The highest price of that current time stamp.
- Low: The lowest price of that current time stamp.
- Close: Closing price of that current time stamp.

OHLC chart shows the trend of the stock price in different time stamp. The horizontal line in Figure 2.3 represents the price range (open and close price) and the vertical line at the top and bottom represents the highest and lowest price within a time stamp, such as a day or an hour (Bar Charts (OHLC), 2001).

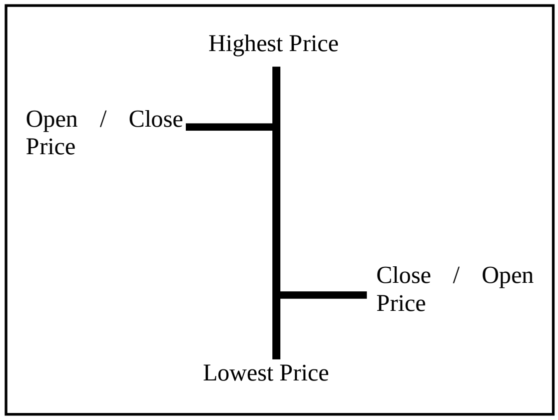


**Figure 2.3 - Structure of OHLC Bar Chart**

OHLC bar chart generated four types of rules to identify the direction of financial trends. Figure 2.4 shows the concept classify the position of the OHLC bar into four types: up, down, inside and outside. If the highest and lowest prices of current bar are higher than previous bar, then is called an “**Up Bar**”. If the highest and lowest prices of current bar are lower than previous bar, then is called a “**Down Bar**”. If the highest price of current bar is higher than previous bar and the lowest price of current bar is lower than the lowest price of previous bar, then current bar is termed as an “**Outside Bar**”. If the highest price of current bar is lower than the highest price of previous bar and the lowest price of the current bar is higher than the lowest price of the previous bar, then the current bar is termed as an “**Inside Bar**”.

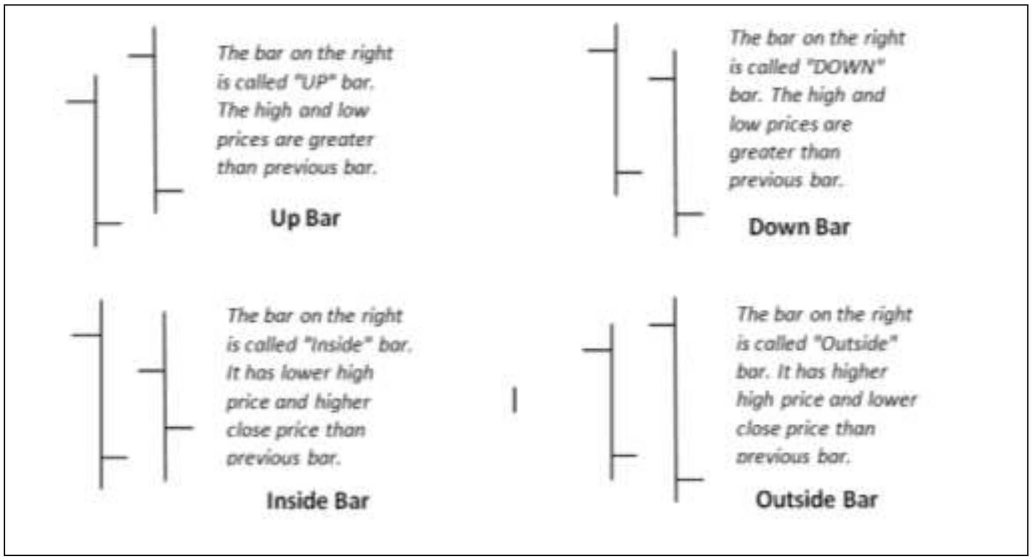


**Figure 2.4 - Concept of Trend Position**

Along with Ge's (1998) study, he introduced hierarchical piecewise linear representation to segment the trend pattern of OHLC bar chart into two groups – uptrend and downtrend, and build up the decision tree of trend patterns. Once the decision tree was done, he utilised pattern matching algorithm to match the pattern of time series data with the decision tree for predicting stock trend. This algorithm computed the probability values to certain patterns that have been occurred. He believed that the matching method could easily go up and down the hierarchy for suitable segments in decision tree that was used for predicting the trend patterns.

Another research done by Kuepper (2012) has applied the trading rules with several technical analysis methods to improve accuracy rate of prediction, and easily position the "stop-loss" and "take profit" points. He found that using the position of OHLC bar chart could assist the investors to understand the overall trend of the financial market.

Table 2.2 summarises research outcome drawn by two prominent researches. These authors found that trading strategy and rules could be combined with OHLC bar chart to represent financial trends for investigating the movement direction.

**Table 2.2 - Review of Financial Time Series Prediction Model using OHLC Bar Chart**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Ge | 1998 | • Hierarchical piecewise linear representation is used to segment the trend pattern of OHLC bar chart into two groups – uptrend and downtrend.<br>• Built up the decision tree of trend patterns.<br>• Matched the pattern of time series data with the decision tree for predicting stock trend. | The research computed the stock trend patterns for investigating how those patterns could help in predicting. |
| Kuepper | 2012 | • Applied trading rules with several technical analysis methods. | OHLC Bar chart could view the overall of stock trend and investigate the "stop-loss" and "take-profit" points. |

As a conclusion, the candlestick pattern shows a more informative way to interpret the overall trend of financial time series compared to the OHLC bar chart. This is because the candlestick pattern utilises the RB colour to interpret the representation of open and close prices relationship for different time stamps.

### 2.1.2 Financial Time Series: Technical Indicators

In the financial field, the technical indicators utilise a series of data point, which are derived by applying formulas to calculate the movement of financial time series over the specified time stamp. It uses to identify the future price levels, investigate the financial trend direction and security by looking at the historical information of stock (Using Technical Indicators, 2009). Technical indicators serve for three important functions – “to alert”, “to confirm” and “to predict” (Introduction to Technical Indicators and Oscillators, 2012).

This category discusses certain technical indicators that include Exponential Moving Average (EMA), Linear Regression Line (LRL), Moving Average Convergence-Divergence (MACD) and stochastic oscillator.

Exponential Moving Average (EMA)

EMA is used to analyse and keep track of the trend changes of financial time series. It provides an element of weighting with each previous day. Furthermore, EMA can determine that a slope of financial trend is positively related with the stock price. It always decreases when price closes below the moving average of stock price and always increases when the price is increased (Exponential Moving Average, 2012). The EMA is calculated with the following equation:

$$EMA_{current} = Price_{current} * k + EMA_{yesterday} * (1 - k) \tag{2.1}$$

where $k$ is defined as 2 / ( Number of days + 1).

Edward and Magee (2007) implied that EMA was relatively easy to use the equation 2.1 for calculating the predictions of stock trend. They found that EMA indicator has the power of support and resistance level to assist the investors for analysing the trend patterns based on the historical data. They also concluded that EMA indicator could show the trend for prediction easily.

Based on a research which done by Tanaka-Yamawaki *et al.* (2009), they utilised the pattern recognition approach that was combined with EMA to create the prediction model. In the experiment, EMA was applied to recognise the pattern of uptrend and downtrend of stock price by using a two dimension metric format, and then utilised those patterns for EMA in order to predict the price range. They had successfully improved the rate of prediction accuracy above 67%.

According to the experiment done by Dzikevicius and Saranda (2010), they found that EMA was adequate to analyse the financial trend. From their tracking signal, they concluded that EMA was less risky to identify the direction of financial trend instead of predicting the direction.

Table 2.3 summarises the experimental outcome and discussion that carried out by few authors. Each of these works successfully identifies the trend; however, it fails to capture the nonlinear pattern in data. Such approach could usually fail in predicting future trends via EMA. This method works similar to statistical methods in defining current financial trend directions.

**Table 2.3 - Review of Financial Time Series Prediction Model using EMA**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Edward and Magee | 2007 | • Implied that EMA to calculate direction of stock trend. | It could easily show the financial trends for prediction. |
| Tanaka-Yamawaki *et al.* | 2009 | • Utilised the pattern recognition approach to recognise the pattern of uptrend and downtrend of stock price by using 2-dimension metric format.<br>• Utilised those patterns for EMA in order to predict the price range. | The rate of prediction accuracy was 67%. |
| Dzikevicius and Saranda | 2010 | • Used S&P 500 and OMX Baltic Benchmark data as features.<br>• Applied buy-and-sell strategies and specific rules with EMA.<br>• Find out the appropriate value of Constanta to apply EMA rule. | The tracking signal result done by the authors showed that EMA can identify the financial trend with fewer errors. |

<u>Linear Regression Line (LRL)</u>

LRL is a statistical tool that is used to calculate the slope value of regression line. A straight line is drawn through the time-series data to identify the distances between the prices of different time frame and trendlines (Linear Regression Line, 2012). The slope is used to identify two major trend patterns; a positive slope is defined as an uptrend whilst a negative slope is defined as a downtrend. The following equation defines a straight line, which is used to identify the trends over the historical data:

$$y = mx + b \tag{2.2}$$

where $y$ is defined as price, $m$ is defined as slope, $x$ is defined as different period of time and $b$ is defined as intercept.

Figure 2.5 shows the basic concept of linear regression line using the equation 2.2 to identify the direction of financial trends in a certain period of time. Financial experts concluded that when the price is under the LRL (solid line shown in Figure 2.5), it is considered as buy signal, and when the price is above the LRL, it is considered as a sell signal.

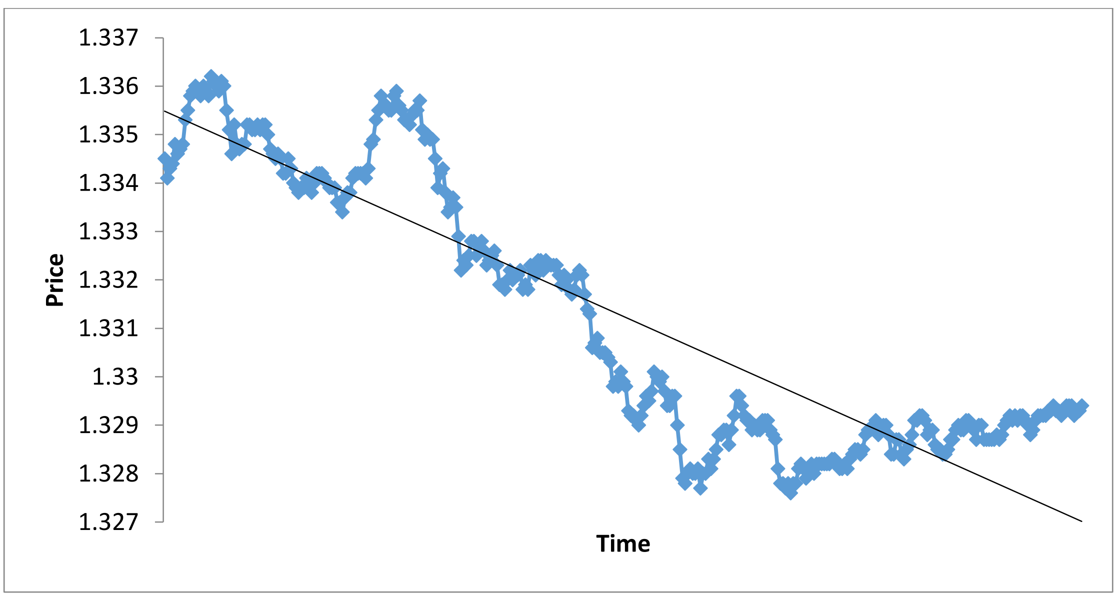


**Figure 2.5 - Example of Linear Regression Line**

Traditionally, the LRL approach has been applied to many real-world situations and the model is easy to develop and implement. Zhang (2001) explained that the limitations of price prediction based on LRL in terms of complex time series data requirement. This is because the LRL approach only analysed the trend patterns from the financial time series data. Moreover, the experiment results show that the ANN can be a satisfactory solution for complex time-series prediction.

According to Rinechart (2003), he had implemented Regression Trend Channel (RTC) technique, which includes LRL, upper trendline channel and lower trendline channel in order to analyse the trends for identifying two major trend patterns. In the experiment, he applied Pearson Correlation Coefficient to detect the desirable trend patterns which proved that LRL was working well in identifying trend patterns.

In Ahangar *et al.* (2010)'s paper, the trend patterns were identified using macro-economic variables and financial variables as selected features. Subsequently, the LRL approach was implemented to predict the direction of future trends. The limitations regarding price prediction based on LRL are highlighted in this paper, such as being unable to predict the price directly. Furthermore, the authors suggested combining LRL with machine learning algorithms in order to improve the prediction process. Similar work had been done by Naeini *et al.* (2010), which applied the lowest, highest and average value of stock market from the historical financial time series data as input features for prediction. The authors found that LRL was able to identify the direction of current and past trend changes for features extraction rather than being able to predict future trends directly.

Another research conducted by Olyaniyi *et al.* (2011) had fully utilised LRL to generate new knowledge from the time-series data, and successfully identified the trend patterns involved. They proved that LRL could be used as a technique to describe trend patterns for prediction purposes.

Table 2.4 summarises the research outcome of few authors. According to these findings, LRL is tip as the better approach to feature extraction. In addition, these approaches provide a useful marker to assess changes over time stamp.

**Table 2.4 - Review of Financial Time Series Prediction Model using LRL**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Zhang | 2001 | • LRL was implemented to analysis the trend patterns.<br>• Utilised the patterns as input features for machine learning algorithm to predict the price. | The author explained that LRL could be a satisfactory solution for identifying the financial trends through complex time-series data. |
| Rinehart | 2003 | • RTC technique – the linear regression line, the upper trendline channel and the lower trendline channel have been applied to identify the stock trend.<br>• The Pearson's value is used to identify and detect the desirable stock price movement. | The author proved that the combination of RTC technique and Pearson values were fitting well for identifying stock trends. |
| Ahangar *et al.* | 2010 | • Identified the trends using macro-economic variables and financial variables are implemented as key features.<br>• Developed the prediction model using LRL. | The authors found that the ANN algorithm was better than LRL approach in prediction. |

| | | | |
|---|---|---|---|
| Naeini *et al.* | 2010 | • Applied the lowest, highest and average value of stock market from the historical financial time series data as input features.<br>• Normalised the value of stock market into the range [-1, 1] for ANN and LRL to predict the price. | The authors found that LRL able to identify the direction of current and past trend changes. |
| Olaniyi *et al.* | 2011 | • LRL was implemented to generate new knowledge from the historical stock data.<br>• Identified the patterns that described the stock trends. | This research utilised LRL as data mining method to identify the trend patterns from historical data. |

<u>Moving Average Convergence-Divergence (MACD)</u>

MACD is developed by Gerald Appel, which used to spot the changes, direction and momentum of stock trend. It consists of using two different periods of EMAs – short period EMA (12 days) and long period EMA (26 days) to identify a stock trend reversal or continuation of a stock trend, and then using a signal line to determine buy or sell the stock. The basic trading rule is to sell when the MACD line falls below the signal line (Moving Average Convergence-Divergence (MACD), 2012).

Figure 2.6 shows the example of the MACD indicator graph. The MACD histogram and line spots the divergences into "Bullish" and "Bearish". "Bullish" divergence occurs when the MACD is making new highs while prices fail to reach new highs, which determines buy signal. "Bearish" divergence occurs in reverse, the MACD is making new lows while prices fail to reach new low that determines sell signal.


**Figure 2.6 - MACD Indicator**

According to Tanaka-Yamawaki and Tokoukas' (2007) study, they mentioned that MACD did not perform well in their experiment. They had proved and concluded that MACD had to combine with other types of indicators to improve the prediction average rate up to 66%. An experiment conducted by Fernandez-Blanco *et al.* (2008) shown that the parameters of MACD can be implemented as a feature to improve their evolutionary algorithm for stock prediction.

Table 2.5 summarises selected research outcomes by few authors. From these findings, MACD could be utilised as the reliable feature to identify the buying and selling signals. However, MACD does not improve accuracy of prediction, as it requires certain amount of time series data to calculate and identify the trends during modelling.

**Table 2.5 - Review of Financial Time Series Prediction Model using MACD**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Tanaka-Yamawaki and Tokouka | 2007 | • Employed genetic algorithm with EMA and MACD as features.<br>• Generated the decision tree structure using selected features.<br>• The decision tree is used to predict the direction of financial trend. | The result showed that the combinations of MACD with other type of indicators had improved the accuracy rate of prediction to 66%. |
| Fernandez-Blanco *et al* | 2008 | • Utilised MACD as input parameters for evolutionary algorithm to develop the prediction model. | The authors proved that their prediction model that used the input parameters of MACD could be improved with evolutionary algorithm. |

Stochastic Oscillator

Stochastic oscillator is developed by George C.Lane in the late 1950s, which used to track the momentum of stock market and gives a warning signal of the stock trend. It shows the location of current closing price that relative to the range of high and low prices over a set of time stamp. It is displayed in two lines – main line is called "%K" and the second line is called "%D" (Singh & Kumar, 2011). %K line compares the latest closing price with the recent time stamp trading. %D is a signal line calculated by smoothing %K line.

Figure 2.7 shows the concept of stochastic oscillator. The %K is displayed as a solid line and %D is displayed as a dotted line. To understand the trend rules in this indicator, the concept is defined as "buys when the %K line rises above the %D line and sells when the %K line falls below the %D line" (Achelis, 1995; Singh & Kumar, 2011).

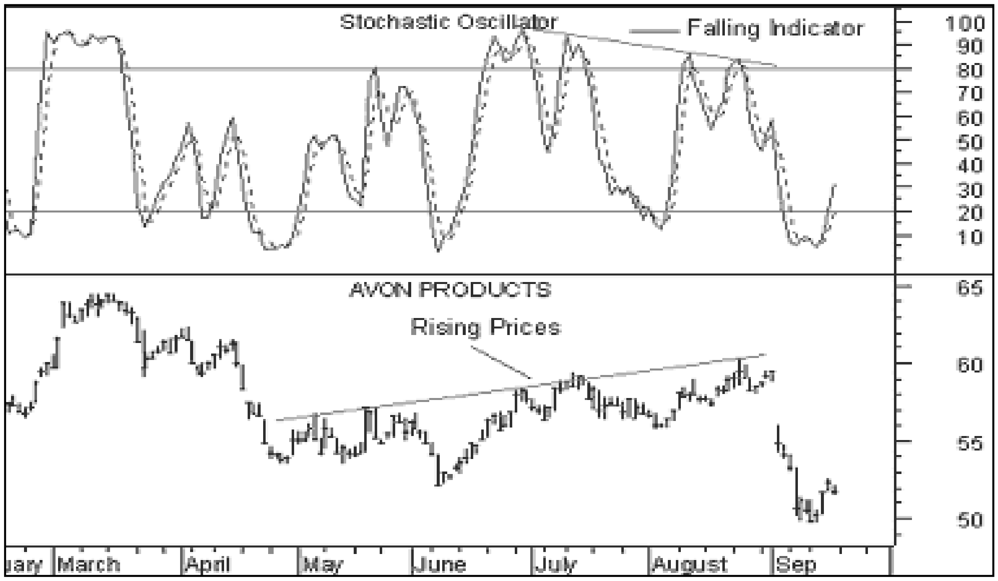


**Figure 2.7 - Stochastic Oscillator**

An article which done by Ng (2007), he mentioned that stochastic oscillator has the ability to show the clear "Bullish" and "Bearish" signals. Thus, he utilised the ability of stochastic oscillator to combine with another indicator known as Guppy Multiple Moving Average (GMMA) to analyse the signals and predict the stock trend. Dharmik Team had implemented the concept of stochastic oscillator - %K and %D lines for their case studies. They utilised the %K and %D values as parameter to identify the correct time to generate profit from investment. They concluded that stochastic oscillator correctly used and followed, it can offer complex and correct information for investment (Norris, n.d.).

From reviews, the LRL shows the result of analysing the financial trends in more consistent compared to other indicators approach. LRL calculates a "best-fit" line through the financial time series and provides a slope to identify the trends. It also has the ability to avoid the unbiased fit in the data.

## 2.2 Prediction Techniques – Artificial Intelligence (AI) Techniques

An AI technique is the study of designing computer systems, which shows characteristics that associate with intelligent human behaviour. The concept of AI technique is that a computer can be developed to assume some capabilities normally thought like human intelligence, such as adapting, self-learning and self-correction. AI research is not an easy task because a computer must be able to do many things in order to be called “Intelligent” (Kok *et al.*, 2009).

Since 1990s, researchers from computer science sector have implemented AI techniques with technical analysis methods to develop more accurate financial time series prediction model. In this section, AI techniques will be categorised into three categories: Expert System (ES), machine learning algorithms and hybrid intelligence systems, which reviews the feature of financial trend patterns for AI techniques to learn, and the combination of technical analysis methods and AI techniques for financial time series prediction.

### 2.2.1 Expert System (ES)

An ES is a type of computer software that mimics the behaviour and knowledge of human domain experts in specific areas, in order to provide a higher quality of decision-making and advice for users. ES has often been used to advise non-experts in situations when human domain experts are unavailable. ES operate through asking the user questions about the given problem, through which they will then supply the best answer possible to support decision making (Anjaneyulu, 1998; Butuza & Hauer, 2010).

The structure of an ES is designed in three parts: user interface, inference engine and knowledge base. A user interface allows an operator to query and receive advice from the ES. The knowledge base of ES is designed based on compiling human domain experts' knowledge, and is transformed into rule conditions that are then used by ES. The structure of inference engine in ES is designed to produce reasoning based on the rules within the ES. The inference engine of ES will detect the contradictions within the rules and refine the problem, and it will provide the user with information, which is similar to the way of human expert's thinking. Figure 2.8 shows the basic structure of an ES.

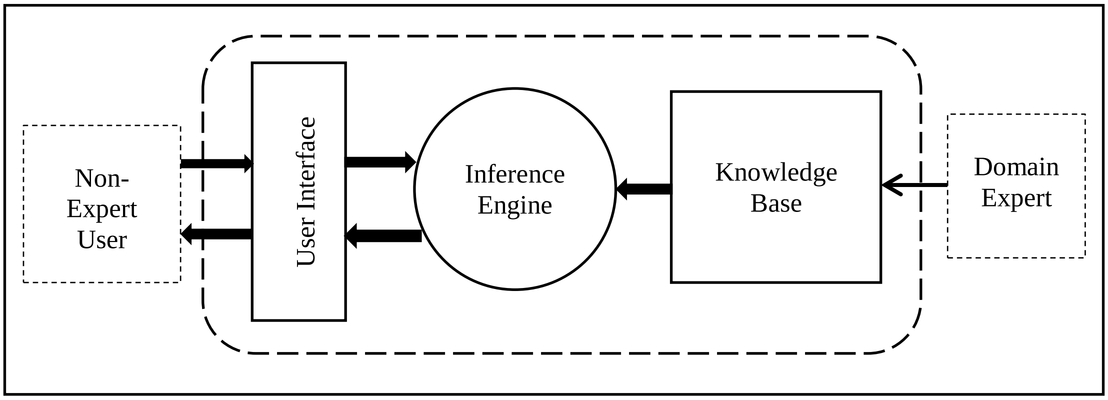


**Figure 2.8 - Basic Structure of an ES**

Based on the research which conducted by Kim and Park (1996), they found that rule induction algorithm is a good solution to generate the rules in ES compared to former ES approach. They consulted domain experts for data features selection, and then categorised the data collection by using Iterative Dichotomiser 3 (ID3) approach to discover the decision tree. The casual model of ES shows the effect value based on the induced rules that had been fired, and then provides the explanation of the ES conclusion and information about the stock prediction for investors whether to accept or reject. The author found that ES does not always generate a successful explanation of the classification rules.

According to Lee and Jo’s (1999) research, they applied candlestick pattern to develop an ES to predict the timing to buy or sell stock. During the development of their ES, they had interviewed investment domain experts to create the rule-based and used candlestick pattern to visualise the stock price movement for predicting stock price. The

ES based on the candlestick patterns and the rule-based to predict the movement of stock price which was constructed from various patterns and suggests the information and decision of stock price to investors. They proved that candlestick pattern was very useful as the feature, and concluded that the limitation of their system was lack of automated learning.

Along with Chang and Liu’s (2008) study, they utilised stepwise regression to choose suitable selected features from six technical indexes and used k-mean method to cluster into different groups. To prove the proposed method, they setup the fuzzy rules-based with simulated annealing method to search the optimal value for rule parameters of fuzzy rules-based. They used the training data for experiment as well as to map with the most similar rules from fuzzy rules-based to predict the stock trend.

Table 2.6 summarises the research outcomes done by few authors. The limitation of ES is that the inability to offer automated learning. Reason could be that the implementation of rules is not directly applicable to constantly changing scenarios. To solve these issues, ES has to generate new rules to adapt and to solve different scenarios.

**Table 2.6 - Review of Financial Time Series Prediction Model using ES**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Kim and Park | 1996 | • Used historical transactions data.<br>• Interviewed with domain experts for data collection.<br>• Used induction algorithm (ID3) to create decision tree.<br>• Generated the inducted rules for explanation of the result with casual model. | The author found that ES does not always generate a successful explanation of the classification rules. Furthermore, the decisions for certain cases are inconsistent with the prediction of classification rules. |
| Lee and Jo | 1999 | • Analysed stock data in candlestick pattern.<br>• Represented trading rules from financial experts.<br>• Collected real invested result which was used to fine tune the knowledge.<br>• Adjusted the knowledge after analysed market trends from case base.<br>• Utilised the candlestick chart as key information to develop the ES. | The experiment conducted by the authors had an average hit ratio 72% as prediction result. |
| Chang and Liu | 2008 | • Utilised linear regression as selected features.<br>• Used stepwise regression to identify the suitable selected features, then used k-mean method to cluster the parameters into few groups.<br>• Setup the fuzzy rules-based.<br>• Used the training dataset to attempt and map with the most similar rules to predict the stock trend. | The experiment proved that the combination of linear regression with ES has greatly improved the ability of prediction. |

### 2.2.2 Machine Learning Algorithms

In this category, it reviews a certain machine learning algorithms such as Artificial Neural Network (ANN), Hidden Markov Model (HMM) and Support Vector Machine (SVM) that are implemented in the experiments of financial time series prediction model which conducted by researchers.

Artificial Neural Network (ANN)

ANN is a mathematical model that inspired by the neural network that forms the human brain. Human brains consist of few hundred billions of neurons, with each neuron acting as an independent biological information processing unit. This concept contributes a strong inspiration for building an intelligent neural model which known as ANN. This model functions by simulating the functioning of brain for problem solving on a computer system (Alvarez, 2006).

ANN acts as a black box to classify an output based on patterns recognised from a given input. Figure 2.9 illustrates the basic structure of ANN. It consists of an input layer, hidden layer and output layer. All the nodes of each layer are connected to each node in the next layer. During the learning and training process, the training inputs are presented at the input layer, with connections within the hidden layer used to acquire classification, while the desired output is presented at output layer. Moreover, ANN trains based on the given input value features, and classifies the outcomes appropriately.

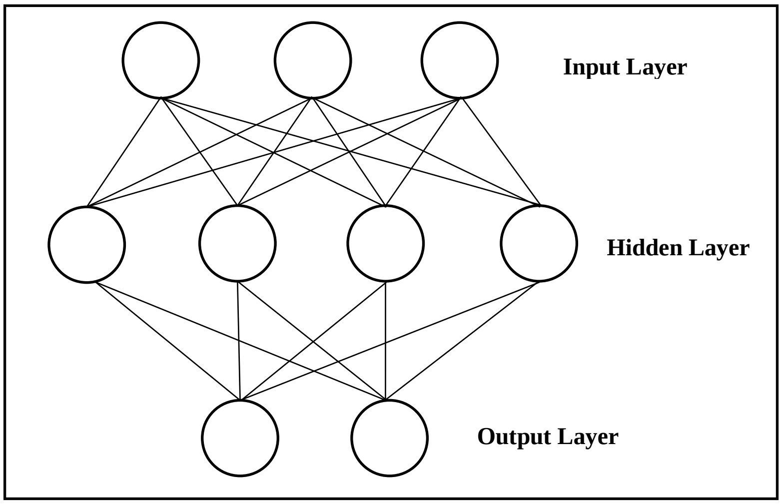


**Figure 2.9 - The Concept and Structure of ANN algorithm**

According to Kamijo and Tanigawa's (1990) research, they utilised the candlestick pattern and used the extracting triangle approach to mark resistance lines on the trend pattern for recognition. The authors found that ANN is able to identify and recognise candlestick patterns in the learning and training stage. Goswamil *et al.* (2009) also utilised the ability of candlestick patterns as selected features to analyse the raw data of stock price and capture it in a database. Then, the authors utilised Self – Organising Map (SOM) and Case – Based Reasoning (CBR) to predict the stock price. SOM is used to train with the candlestick patterns from database, and then CBR is used to find out the best pattern matching with the new inputs (open, close, high and low prices) and existing patterns from the database to predict the short-term stock price and market timing. The authors concluded that the proposed method could identify the patterns for predicting the stock trend.

Along with the experiment done by Lawrence (1997), he utilised the technical analysis method – EMH (Efficient Market Hypothesis) as feature to test with ANN for stock price prediction. Since the result of prediction model did not perform well, he concluded that feature of stock trend must be fully understood so that ANN will learn the correct pattern to predict the stock trend.

Yao and Tan (2000) proposed a prediction model that used technical indicators and financial time series data as selected features, then utilised ANN to capture the movement of currency exchange rates. The authors proved that the combination of ANN with a simple technical analysis method was a good approach for predicting exchange rates. To enhance the prediction model, they suggested that trading strategies were needed to be considered as extra features for prediction.

In Kamruzzaman and Sarkers' (2003) first studies, they implemented the historical Forex rates and moving average as selected features for the ANN algorithm and ARIMA model to predict the future trends of exchange rates. The author concluded that the ANN algorithm could predict the exchange rates more closely than ARIMA. According to another experiment done by them, they had applied five technical indicators as selected features to identify the trend patterns of exchange rates. Then, ANN – Back propagation algorithm and Scaled Conjugate Gradient (SCG) has been implemented to develop the prediction model. In the experiment results, the authors proved that the proposed model is more capable to predict the trend direction of exchange rates closely than their previous ANN prediction model (Kamruzzaman & Sarker, 2004).

Mehrara *et al.* (2010) applied Simple Moving Average (SMA) and EMA indicators respectively as input features for ANN to recognise trend patterns. According to the experiment results, the authors proved that EMA was a better choice compared to SMA for ANN to predict stock trends. The limitation of this model was that the number of hidden layers has been initialised to 2 in ANN.

Another experiment that conducted by Charkha, the author applied normalisation technique to scale the four days' stock closing price in a range between interval values -1 to 1, and utilised ANN to train with the analysed data in the prediction stage. He concluded that the results of prediction observed that ANN is more consistent in recognising the patterns (Charkha, 2008).

Based on the research which done by Enke *et al.* (2011), they utilised Multiple Regression Analysis method to select the features of the data, and then clustered the selection data by using fuzzy "IF-THEN" rules. They used the clustered data as input parameters for ANN to learn and predict the stock trend. The authors concluded that the suggested prediction model resulted in lower prediction error compared to other approach.

Kardos and Cwiok (2011) implemented two technical indicators - EMA and MACD as input features, and ANN had been applied to train with input features for recognising the buy and sell signals in the prediction. In the experiment results, the authors proved that ANN had successfully recognised the signals for predicting the financial trends using EMA and MACD as selected features.

Desai *et al.* (2013) mentioned that the selection of input variables is a critical factor in the performance of ANN because it contains important hidden information. In the experiments, the authors implemented data preprocessing technique to analyse the trend patterns based on the historical data, and then utilised ANN to train. They also proved that ANN has the ability to learn hidden trend patterns and predict the direction of the stock trends.

Table 2.7 summarises the techniques and research outcome done by few authors. Each has stress the relevance of feature extraction in representing trend patterns. Moreover, utilising incorrect selected features as input parameters, to train ANN could mislead results.

**Table 2.7 - Review of Financial Time Series Prediction Model using ANN**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Kamijo and Tanigawa | 1990 | • Used candlestick patterns to represent the stock price.<br>• Extracted triangle by drawing resistance lines in candlestick, (Resistance line was marked on basis of high and low prices for candlestick – as input data).<br>• Used cluster analysis that applied to context vector (generated in first hidden layer at recognition stage).<br>• Used neural network approach to train and classify the pattern. | The authors concluded that the proposed method could identify the patterns for predicting the stock trend. |
| Lawerence | 1997 | • Used EMH to represent the stock trend.<br>• Applied ANN to train with the features. | The result showed 51% for the prediction rate. |

| | | | |
|---|---|---|---|
| Yao and Tan | 2000 | • Technical Indicators and time series data are implemented as selected features.<br>• Utilised ANN algorithm to capture the movement of currency exchange rates. | The authors prove that the combination of ANN with a simple technical analysis method is a good approach for predicting exchange rates. |
| Kamruzzaman and Sarker | 2003 | • The historical data and moving average technical indicator are applied as input features.<br>• Utilised ANN and ARIMA model to train with the input features for prediction. | The authors concluded that ANN prediction model can predict the Forex rates closely than ARIMA model. |
| Kamruzzaman and Sarker | 2004 | • Five technical indicators are applied as selected features to identify the trend patterns of exchange rates.<br>• Utilised ANN – Back propagation algorithm and Scaled Conjugate Gradient (SCG) to develop the prediction model.<br>• SCG approach is used to minimise the step size of learning process for ANN. | The authors proved that the proposed model is more capable to predict the trend direction of exchange rates more accurate than normal ANN. |
| Charkha | 2008 | • Used Normalisation technique to analyse the four days' stock closing price.<br>• Trained the normalised data with ANN to predict the stock price. | The experiment results show that ANN is more consistent in recognising the patterns. |
| Goswamil *et al.* | 2009 | • Used candlestick standard pattern as selected features.<br>• Manipulated the usage of SOM for pattern training.<br>• Used CBR to detect the most suitable pattern matching case from database.<br>• Combined the matching case with the output and derived a decision support. | This research had proven that the SOM and CBR could be sued to identify the patterns for predicting the stock trend. |
| Mehrara *et al.* | 2010 | • Implemented technical indicators – simple moving average and EMA as input features.<br>• Two types of ANN – Multi-Layered Feed Forward (MLFF) and Group Method of Data Handling (GMDH) are applied to recognise the patterns for prediction. | The experiment results show that the combination of GMDH and EMA has a better response in predicting the stock trends. |

| | | | |
|---|---|---|---|
| Enke *et al.* | 2011 | • Used Multiple Regression Analysis for the selection process of financial data.<br>• Applied Differential Evolution Optimisation-based Fuzzy type-2 clustering to generate the "IF-THEN" rules.<br>• Used Type-2 Fuzzy Inference Neural Network (five layers) to train. | The proposed prediction model resulted in lower prediction error compared to other approaches. |
| Kardos and Cwiok | 2011 | • EMA and MACD have been applied as input variables in the training process of ANN algorithm.<br>• ANN is implemented to train in recognising the buy and sell signals. | In the experiment results, the authors proved that ANN has successfully recognised the signals for predicting the financial trends using EMA and MACD as selected features. |
| Desai *et al.* | 2013 | • Data preprocessing technique is implemented to analyse the historical data as input features.<br>• Utilised ANN to train with input features for prediction. | The authors proved that ANN has the ability to learn hidden trend patterns and predict the direction of the stock trends. |

Hidden Markov Model (HMM)

HMM is a statistical tool for modelling a wide range of time series data. HMM is used in pattern recognition such as speech, words, gesture and other related tasks. The preliminary phase in HMM is to specify the number of hidden states and initialise a sequence of observations. Subsequently, HMM will be evaluating with a set of data to learn and locate patterns in predicting the most likely states. In HMM, the state is hidden, but output is visible. Each state has a probability distribution over the possible output state. As a result, the sequence of states that are generated by an HMM that gives some information through the output state (Blunsom, 2004; Schuster-Böckler & Bateman, 1986). Figure 2.10 shows the basic concept and structure of HMM.

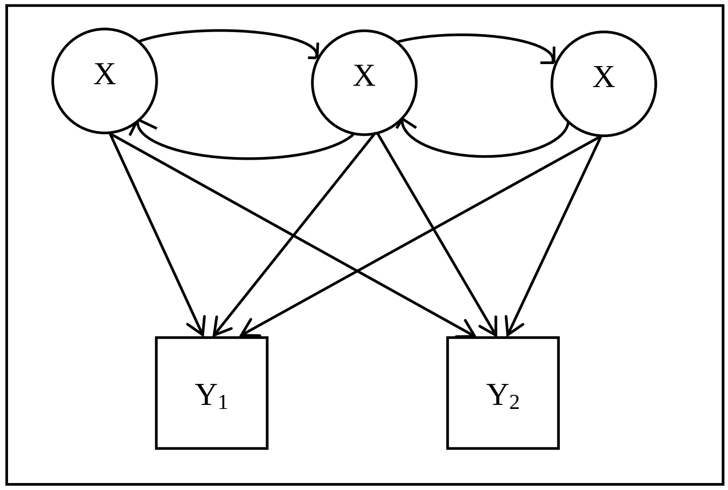


**Figure 2.10 - Structure of HMM**

To define an HMM, it needs to be characterised as the following:

1) States $Q$: a number of states N.
2) Observations $O$: a sequence of observations as $\{o_1, o_2, \ldots\ldots o_i\}$
3) Transition Matrix $A_{N \times N}$ = {$a_{ij}$} where $a_{ij}$ represent the probability of transition from state $i$ to $j$.
4) Observation Emission Matrix B = {$b_j(O_t)$} where $b_j(O_t)$ represent the probability of observing $O_t$ at state $j$.
5) Prior Probability $\pi_{N \times 1}$: π represents the probability of being in state $i$.

Theoretically, an HMM is denoted as λ:

$$\lambda = (\pi, \mathrm{A}, \mathrm{B}) \tag{2.3}$$

where $\pi$ is defined as prior probability, $A$ is defined as transition matrix and $B$ is defined as observation matrix.

An experiment was performed by Hassan and Nath (2005) for both HMM and ANN to predict the future stock closing price. The experiment was being carried out using four variables – 'open', 'high', 'low' and 'close' prices as an input information to predict the result. ANN can be utilised as a well method that has successfully predicted time series data. Thus, the authors discovered that HMM is a more accurate technique since it could provide a better result in predicting the direction of stock market. Based on the experiment result, they also found that HMM prediction model has predicted a more precise prophecy compare to ANN in predicting the future stock prices.

Nobakht *et al.* (2010) had applied a scaling approach to analyse the historical stock within the specific range -1 to 1 as input features for HMM to train. The input features included open, high, low and close prices. In the HMM, the model have computed the likelihood values of the previous day in the desired range for prediction. The authors concluded that the proposed prediction model has successfully predicted the future of trends.

According to an experiment which conducted by Angelis and Paas (2010), they found that the number of states has to be clearly defined and characterised in HMM so that the model can be useful in predicting future stock prices. The reason is that stock markets change their prices abruptly from time to time and its often characterised by the regime of frequently changes. One of the benefits presented by HMM is that, it has the ability to cluster the time observation values according to the similarity of time periods with different regimes to train.

An experiment was carried out by Rao and Hong (2010) by applying HMM, Baum-Welch algorithm was performed to compute the unobserved parameters by instructing to the following HMM model. Before the implementation of Baum-Welch algorithm to train the model in the experiment, they had used k-mean to cluster the data into 5 hidden states – 'big price movement up', 'small price movement up', 'no movement', 'small price movement down' and 'big price movement down'. Followed by Viterbi algorithm, it was to detect the most likely state that could be used to provide an accurate result with the model. They believed that HMM is prospective as providing a better result in predicting future values in time series data and direction of stock market.

Gupta and Dhingra (2012) conducted an experiment that used continuous HMM based MAP (Maximum a Posteriori) estimator. In their experiment, they applied daily stock data in form of 4-dimentional vector (fractional change, fractional high and fractional low) for observation values and used k-mean for clustering so that can divide between the states to obtain initial emission probabilities in HMM. The result of the prediction showed that continuous HMM based MAP approach with selected features which represented the stock trends provided better performance compared to other approaches.

Table 2.8 reviews the research outcomes done by few authors. The number of states and observational sequences has to be clearly defined for HMM modelling task and prediction.

**Table 2.8 - Review of Financial Time Series Prediction Model using HMM**

| **Authors** | **Year** | **Features and Methods** | **Research Outcome** |
|---|---|---|---|
| Hassan and Nath | 2005 | • Used open, close, high and low prices as data input.<br>• Implemented left-right approach to observe the data input as pattern.<br>• Applied HMM and ANN to learn the observed pattern for predicting the next day close price | The authors proved that HMM has predicted the future of stock price more accurate compare to ANN. |
| Nobakht *et al.* | 2010 | • Analysed the historical data using scaling approach in a specific range [-1, 1].<br>• Open, High, Low and close prices of the historical data were applied as input features for HMM to train.<br>• Computed the likelihood values of the previous day in the desired range for prediction. | The authors concluded that HMM has successfully predicted the future of trends. |
| Angelis and Paas | 2010 | • Used S&P 500 Index as input feature.<br>• Investigated and analysed the stock market.<br>• Used HMM to train the stock price. | The author found that the number of states had to been clearly defined and characterised in HMM. |
| Rao and Hong | 2010 | • MACD and EMH are utilised to analyse the data information as input features.<br>• Clustered the data into several of categories.<br>• Implemented HMM to train with the data. | The accuracy rate of the proposed prediction model is about 60%. |

| | | | |
|---|---|---|---|
| Gupta and Dhingra | 2012 | • Applied observations by using daily stock data in form of 4-dimentional vector (fractional change, fractional high and fractional low).<br>• Used k-mean to cluster the Gaussian mixture component in HMM.<br>• Computed MAP estimate with possible vectors (fractional change, fractional high and fractional low), and found the maximum to predict. | The authors found that continuous HMM based MAP approach with selected features that represented the stock trend provided better performance compared to other approaches. |

Support Vector Machine (SVM)

SVM is a supervised learning method developed based on the foundations of statistical learning theory in 1995 by Vladimir Vapnik (Boswell, 2002). In the past few years, it has become one of the most popular methods to analyse data, learn and recognise patterns with many potential applications in the science and engineering sectors. As a learning method, SVM is often used to classify data points using a kernel-based function (Fletcher, 2009; Sullivan & Luke, 2007). Figure 2.11 shows the structure of SVM with a kernel function.

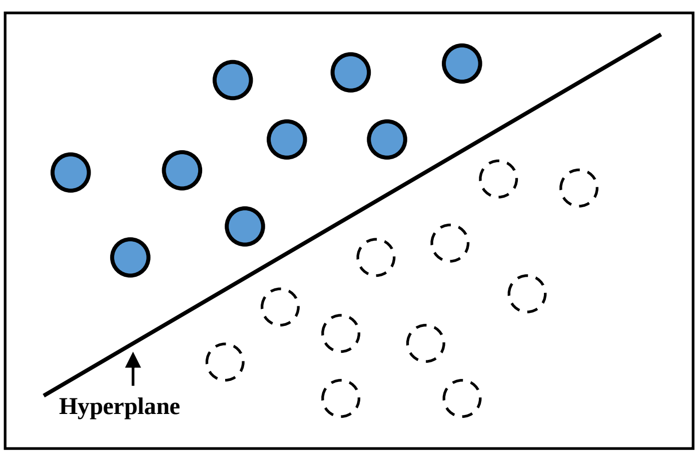


**Figure 2.11 - Structure of SVM with a Kernel Function**

In SVM, the hyperplane (kernel function) shown in Figure 2.11 is used for classification and regression in separating the data to the nearest training data point which is based on the categories that provided by the SVM training algorithm. SVM utilises a set of input data to build a model in dividing the data into separated categories with a clearly gap. A hyperplane is denoted as:

$$w \,.\, x - b = 0 \tag{2.4}$$

where $w$ is defined as the normal vector to the hyperplane, $x$ is defined as data point and $b$ is determined the offset of the hyperplane. The following equations are defined to separate the data points using hyperplane:

$$\begin{cases} w \,.\, x - b = 1 \\ w \,.\, x - b = -1 \end{cases} \tag{2.5}$$

According to the experiment conducted by Cao and Tay (2001), it was proved that SVM has the ability for recognising patterns with the selected features known as RDP, EMA, MACD, OBV and volatility in the learning stage. Based on Kim's (2003) experimental result, the *C* value (*C* is essentially a regularisation parameter to avoid misclassifying) and kernel parameter values of the kernel function are critical for the stock prediction performance of SVM. Thus, optimal values for those parameters in SVM are crucial to its effectiveness. Kamruzzaman *et al.* (2003) also found that the performance of SVM is sensitive with the parameters selection of the kernel functions. In the experiment results, the authors suggested that radial basic and polynomial kernel functions are the better choice for SVM to analyse the Forex data in the prediction.

Zhai *et al*. (2007) proposed a prediction model that combined the related news and utilised the technical indicators to analyse the stock trends for SVM to train and predict the direction of stock price. The experiment results showed that the proposed prediction model are enhanced and provided 70% accuracy rate to predict the direction of stock price. The authors also found that the prediction model only performed better when the radial basic kernel function of *C* value is set to 20, while standard deviation and *d* (The degree values of polynomial) are set to 3.

Based on the experiments that were done by Rao and Hong (2010), Abirami and Vijaya (2012), they had built a model by applying SVM and radial kernel function, to be tested in their new experiment. The primary functionality of radial kernel is used to determine the influential area of data by separating them into two categories. From their experiments, it shown that by using technical analysis methods to analyse data as input pattern for SVM to learn, the model can represent more accurate prediction results. Another experiment found by Ni *et al.* (2011) had proven that the selected features from the raw data of stock price must first be constructed, only then can SVM utilise these features as the input parameters to train and predict the stock.

Table 2.9 reviews research outcomes of financial time series prediction models using SVM. SVM is sensitive to features selection during training. Moreover, it relies on the values of kernel function to build its parameters.

**Table 2.9 - Review of Financial Time Series Prediction Model using SVM**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Cao and Tay | 2001 | • Used S&P 500 index stock values as feature.<br>• Used RDP, EMA, MACD, OBV and Volatility to transform the historical data of stock price.<br>• Utilised those values as input parameters for SVM to train. | The authors have concluded that SVM provide a promising alternative to predict the stock price. |
| Kamruzzaman *et al.* | 2003 | • Simple moving average is applied as feature to analyse the currency exchange rates.<br>• Applied SVM as classifier using different kernel functions: linear, polynomial and radial basic. | The authors found that the performance of SVM is sensitive with parameters selection of the kernel functions. |
| Kim | 2003 | • Used Daily Korea composite stock price index data.<br>• Analysed data with 12 technical indicators as input parameters.<br>• Used the SVM, BP and CBR to train and learn the analysed input parameters to predict the next day stock price index. | The accuracy of prediction using SVM was 64.75%. |
| Zhai *et al.* | 2007 | • Seven technical indicators were selected to analyse the history data.<br>• Implemented a text mining approach to analyse the news as feature selection.<br>• Utilised the news and stock price as input features for SVM to train and predict the stock price. | The accuracy of the prediction model was 70%. |
| Rao and Hong | 2010 | • MACD and EMH are applied to analyse the data information as input features.<br>• Implemented RBF to categorise the pattern for SVM to learn and train. | The accuracy rate of prediction was about 70%. |

| | | | |
|---|---|---|---|
| Ni *et al.* | 2011 | • Used dataset from Shanghai Stock Exchange Index.<br>• Provided fractal dimension for dataset.<br>• Applied the few technical analysis methods as features by using feature selection algorithm.<br>• Constructed the dataset with the selected features.<br>• SVM is implemented to train with the selected features. | The accuracy rate of prediction was 64%. |
| Abirami and Vijaya | 2012 | • Used data analysis method to analyse the historical data.<br>• Applied RBF, Polynomial, and Linear Regression as kernel function for SVM to train and learn the patterns. | The authors found that SVM worked with the RBF kernel method, which showed an increase in efficiency for predicting the stock price with selected features. |

### 2.2.3 Hybrid Intelligence System

Since 1990s, hybrid intelligence systems have become a very important problem solving methodology in the areas of science, computing technology, business and commerce. In 1995, Lotfi A. Zadeh introduced some hierarchies among the individual AI techniques and utilised their abilities to develop a hybrid intelligence system (Gavrilov, 2007). A hybrid intelligence system is designed by combining within different paradigms of knowledge representation and reasoning such as ANN, genetic algorithm, fuzzy logic, rules, semantic nets and so on to construct more robust and reliable problem solving models (Rudas & Fodor, 2008).

In Abraham *et al.* (2001) studies, they applied principal component analysis method to analyse the historical data as input features for ANN with scaled conjugate algorithm to train with input features. Neuro-fuzzy system is applied to provide details for trend analysis of individual stock. The authors proved that the proposed prediction model can assist the investors to provide detailed information for better understanding of the stock market performance.

Hassan *et al.* (2007) proposed a hybrid prediction model using ANN to transform the historical data as input features and utilised genetic algorithm to optimise the initial parameters. Then, HMM is used to identify and recognise the trend patterns from the optimised input features to predict the stock price. Although the authors proved that the prediction model is better than other approaches, the limitation of the model is that the number of states as the number attributes in the observation vectors may not be suitable for some historical data.

According to the research which conducted by Hassan (2009), he proposed a new prediction model using HMM and fuzzy rules. In the experiments, the author implemented HMM to train with the historical data, then calculated the likelihood values based on the historical data to analyse the trend patterns and stored the patterns in different buckets. A recursive divide and conquer algorithm is used to generate fuzzy rules for the stock price prediction. According to the experiment results, the authors found that the current proposed prediction is more accurate compared to the previous prediction model using the combination of ANN, genetic algorithm and HMM.

Hadavandi *et al.* (2010) proposed a stock price prediction model that utilised SRA to choose the key variables that are to be considered, supported by ANN to divide the data into different clusters based on the key variables and reduce the complexity of the historical data. All the clusters were fed into with the ability of fuzzy rule base extraction for predicting the stock price. The authors found that the proposed prediction model is outperformed that other approaches and concluded that can be used as a suitable prediction tool to deal with stock price prediction problems.

Table 2.10 reviews different types of financial time series prediction models using hybrid intelligence systems. Hybrid intelligence systems rely on rules-based algorithm to utilise trading rules and strategies. These are further combined with machine learning algorithms to build the model. The trading rules and strategy could be unreliable when a new situation is discovered.

**Table 2.10 - Review of Financial Time Series Prediction Models using Hybrid Intelligence Systems**

| Authors | Year | Features and Methods | Research Outcome |
|---|---|---|---|
| Abraham *et al.* | 2001 | • Principal component analysis method is applied to analyse the historical data as input features.<br>• Utilised ANN with scaled conjugate algorithm to train with input features.<br>• Neuro-fuzzy system is applied to provide details for trend analysis of individual stock. | The empirical result of the proposed hybrid system is very promising. It provides information for better understanding of the stock market performance. |
| Hassan *et al.* | 2007 | • ANN is implemented to transform the historical data that become input features for HMM.<br>• Utilised genetic algorithm to optimise the initial parameters of HMM.<br>• HMM is used to identify and discover the similar patterns in the historical data. | The authors proved that the proposed hybrid prediction model is slightly better than ARIMA models. |

| | | | |
|---|---|---|---|
| Hassan | 2009 | • Utilised HMM to train with the historical data.<br>• Calculate the HMM likelihood values based on the training data to analyse the patterns and store in different buckets.<br>• A recursive divide and conquer algorithm is used to generate fuzzy rules for prediction. | The authors found that the proposed prediction is more accurate compared to the previous prediction model using the combination of ANN, genetic algorithm and HMM. |
| Hadavandi *et al.* | 2010 | • Used Stepwise Regression Analysis (SRA) to choose the key variables that are to be considered.<br>• ANN is applied to divide the data into different clusters and reduce the complexity of the historical data.<br>• All the clusters were fed into with the ability of fuzzy rule base extraction. | The experiment results showed that the proposed prediction model could be considered as a suitable tool for stock price prediction. |

## 2.3 Dynamic Time Warping (DTW) Algorithm

DTW is an algorithm that measures the optimal alignment between two time series data by warping the distance. The warping between two time series data can be used to determine the similarity between themselves. It is a robust technique that has often been used in speech recognition to identify two different waveforms that represent the same spoken phrase. DTW has also been applied in other fields which included data mining, handwriting recognition and face recognition, where similarity of shapes is desired (Albrecht & Muller, 2009; Niels, 2004; Salvador & Chan, 2007).

Figure 2.12 shows an example of a warping between two time series data. Each vertical line connects a point in one time series to its correspondingly similar point in the other time series, while the bold solid line ($W_{ki}$) and bold dotted line ($W_{kj}$) represents a distinct time series. The warping path distance is a measurement of the difference between two time series data, which is measured by the sum of the distances between each pair of points connected by the vertical lines in Figure 2.12. Euclidean distance is an efficient distance measurement that can be used to calculate the warping path distance. The Euclidian distance between two time series is simply the sum of the squared distances from each point in one time series data to the other points in the other time series data.

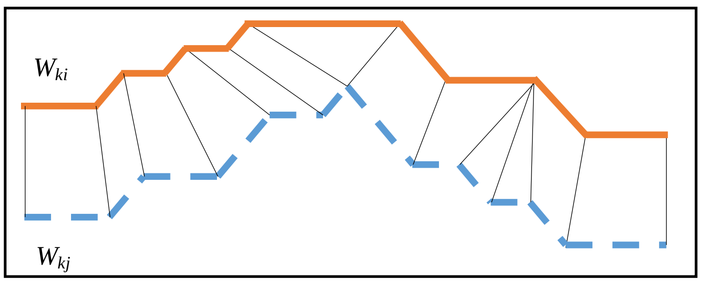


**Figure 2.12 - A warping path between two time series data**

To find an optimal warp path from two sets of time series data, the following equation shows the idea:

Given two time series $T_1$, and $T_2$ that represents as following,

$$T_1 = x_1, x_2, x_3, \dots, x_m \tag{2.6}$$

$$T_2 = y_1, y_2, y_3, \dots, y_n \tag{2.7}$$

A warp path *W* is constructed by the time series $T_1$ and $T_2$ which shows as,

$$W = w_1, w_2, w_3, \dots, w_k \tag{2.8}$$

where $k$ is defined as the length of warp path. To represent the $k^{th}$ warp path between both data point from two time series $T_1$ and $T_2$,

$$w_k = (i, j) \tag{2.9}$$

where $i$ is defined as an index from time series $T_1$ and $j$ is defined as an index from time series $T_2$.

An optimal warp path from two sets of time series $T_1$ and $T_2$ shows as,

$$Dist(W) = \sum_{k=1}^{k=K} Dist(w_{ki}, w_{kj}) \tag{2.10}$$

where $K$ is defined as numbers of warp path, $Dist(W)$ is the distance of warp path for $W$ and $Dist\left(w_{ki}, w_{kj}\right)$ is the distance between two set of time series data point (from bold solid line and from bold dotted line shown in Figure 2.12).

According to an experiments which conducted by Berndt and Clifford (1994), they implemented the DTW algorithm to find the matched patterns with different time series data. Based on the results, the authors found that this technique could be encouraging for further investigation. Yu *et al.* (2011) found that the path constraint of DTW is learned for optimization of the alignment of time series by implementing the equation 2.10. From the experimental results, the authors concluded that DTW could strongly select different vector values for identifying the similarities between different patterns.

## 2.4 Review Summary

This chapter presented the general form of technical analysis methods, AI techniques and other related works. The accuracy of various prediction models done by other researchers is unsatisfactory, as the AI techniques could not classify the patterns correctly for prediction.

Hypothetically, the trend pattern of a financial time series data repeats itself at different time stamp. According to the reviews, candlestick patterns and LRL are widely used as features to represent the trend patterns. Researchers also proved that these methods provide an informative way to identify trend patterns. This thesis proposed two frameworks that used different methods - candlestick patterns and LRL as feature extraction. Moreover, the proposed frameworks investigated the performance of both features in representing trend patterns.

Furthermore, the proposed frameworks applied ANN and SVM as classifiers to learn the trend patterns. From the reviews, the learning performance of HMM and hybrid intelligence system are not flexible compared to ANN and SVM. This is because the parameters of HMM needed certain adjustments that depends on the HMM model was trained. Likewise, a hybrid intelligence system mostly implemented trading rules and strategies with machine learning algorithms in developing the prediction model. Those trading rules and strategies could be unreliable when a new situation is discovered. This is because the knowledge representation of the system is required to be updated to fulfil the new requirements.

Thus, this research applied the proposed features by using LRL and proposed segmentation algorithm, supported by machine learning algorithms and DTW to improve the accuracy of prediction model.

## 3.0 PROPOSED FRAMEWORK

This chapter describes the proposed framework for developing a financial time series prediction model. Figure 3.1 shows the process of two proposed framework in analysing the trend patterns as input features using machine learning algorithms. The models utilise ANN or SVM as classifiers separately to train the patterns. A new dataset is used to evaluate both prediction models.

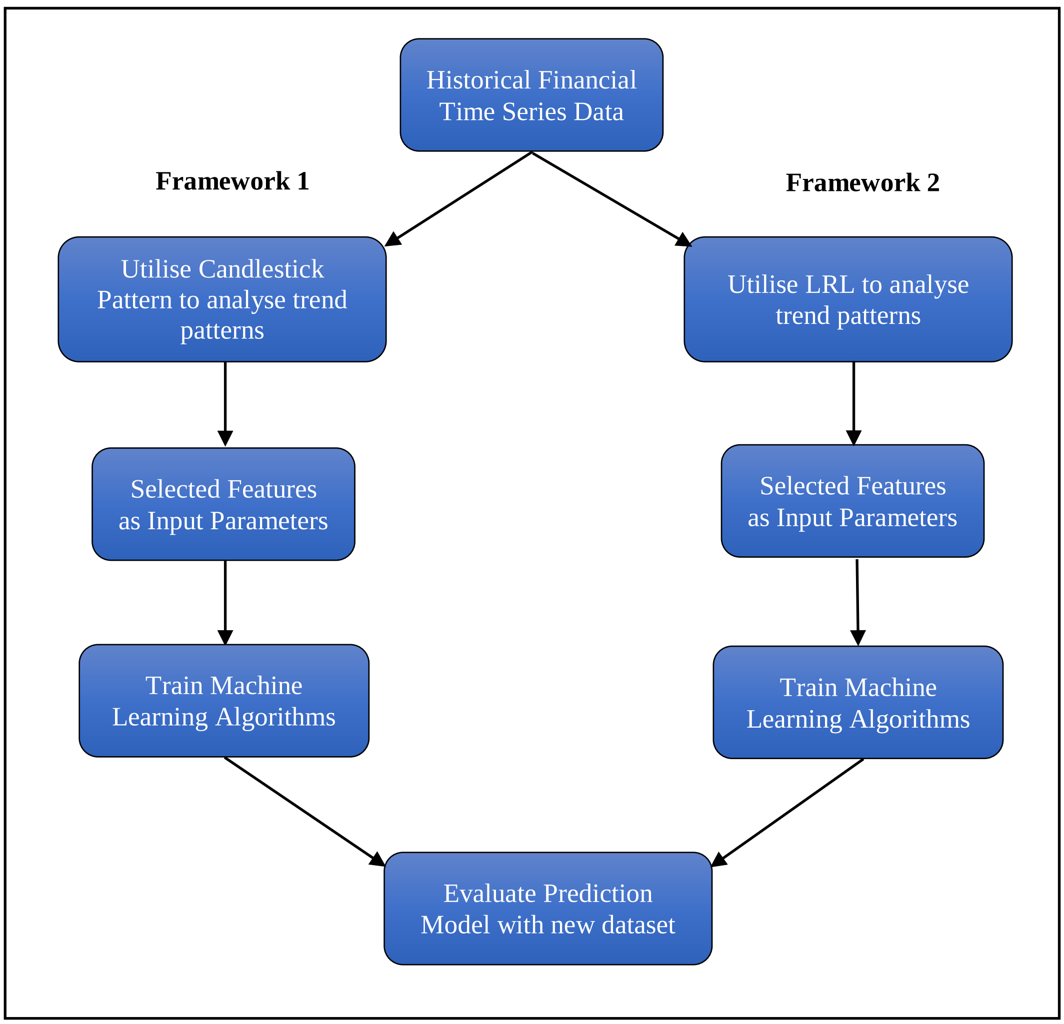


**Figure 3.1 - General Ideas of Proposed Frameworks**

The first proposed framework utilises candlestick pattern as selected features for analysing the financial time series data. Both ANN and SVM separately classify relevant features for patterns learning and predicting of future trends. This research investigates either ANN or SVM is efficient and it can be used to automate a significant classification with the features. In the second proposed framework, the LRL has been utilised as a feature to analyse the trend patterns, and then using ANN or SVM as classifiers for learning patterns and classifying the unique groups of uptrend and downtrend patterns. Based on the classification results of machine learning algorithms, DTW is implemented to predict the trend movement of the next day.

The main purpose of both proposed models is to find out which technical analysis methods is suitable as selected features for machine learning algorithms to learn the patterns. In addition, this study investigates the behaviour and pattern of financial trends for avoiding potential misleading information from the historical financial time series data. At the same instant, the proposed framework tries to investigate the performance of machine learning algorithms could be better classifiers in identifying the trend patterns.

## 3.1 Candlestick Chart and Machine Learning Algorithms

This section introduces the first proposed framework using ANN and SVM algorithms, supported by candlestick patterns. The framework could be divided into two stages: Pattern Analysis, Training Process of Machine Learning Algorithms. In the first stage, candlestick pattern is applied to analyse and form the general trend patterns. Implementation of ANN and SVM for trend classification forms the second stage.

### 3.1.1 Candlestick Pattern as Pattern Analysis method

This section describes the candlestick pattern process for representing financial trends. Candlestick pattern is used for identifying patterns in financial trends, based on a historical financial time series data. Figure 3.2 shows a general structural design for this approach. This framework utilises certain equations, which explains in the following sections to calculate the candlestick patterns based on a historical financial time series data, basic attributes are highlighted in Table 3.1. Then, the framework implements the concept earlier described in chapter 2 to identify the position of financial trend as selected features.

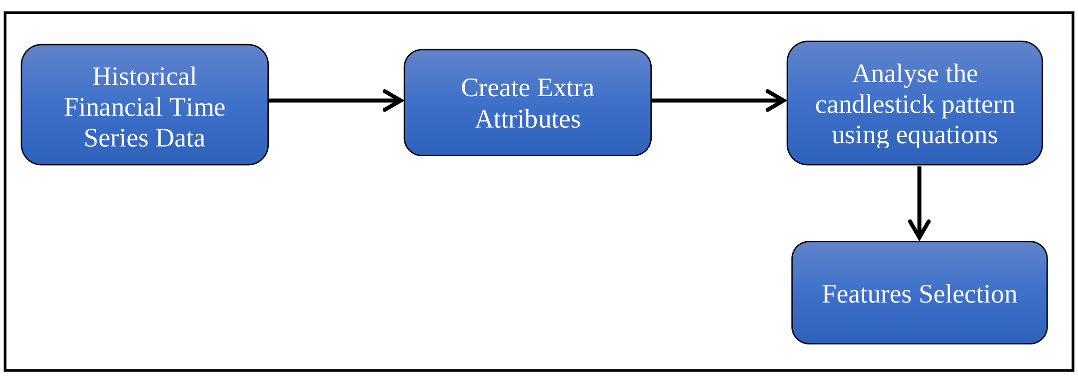


**Figure 3.2 - The Proposed Framework of Financial Time Series Analysis using Candlestick Chart**

**Table 3.1 - Attributes of Financial Time Series Data**

| Attributes | Description |
|---|---|
| Time | The time frame of the current financial time series |
| Volume | The number of investor |
| Open | The opening price of the current financial time series |
| High | The highest price of the current financial time series |
| Low | The lowest price of the current financial time series |
| Close | The closing price of the current financial time series |

The basic idea behind the candlestick pattern shown in Figure 2.1 is to utilise as selected features. The features include real body (RB), upper shadow (US), lower shadow (LS), real body colour (Colour) and the position of candlestick pattern (CP). Candlestick chart can be formalised in numeric and nominal values that should be expressed in relative unit.

RB can be converted by using the following equation:

$$RB = \frac{|(C-O)|}{O} * 100\% \tag{3.1}$$

where *C* is defined as close price, *O* is defined as open price.

While the close price is greater than open price in the candlestick pattern, the US and LS values can be converted as the following equations:

$$US = \frac{(C-O)}{(H-O)} * 100\% \tag{3.2}$$

$$LS = \frac{(C-O)}{(C-L)} * 100\% \quad (3.3)$$

where *C* is defined as close price, *O* is defined as open price, *H* is defined as high price and *L* is defined as low price in candlestick pattern.

While the open price is greater than close price in the candlestick pattern, the US and LS value can be converted as the following equations:

$$US = \frac{(O-C)}{(H-C)} * 100\% \quad (3.4)$$

$$LS = \frac{(O-C)}{(O-L)} * 100\% \quad (3.5)$$

where *C* is defined as close price, *O* is defined as open price, *H* is defined as high price and *L* is defined as low price in candlestick pattern.

To determine the colour of the RB in candlestick pattern, the basic concept that described in chapter 2 has been implemented based on the open price and close price. The following rules shown in Figure 3.3 are used for identifying the colour of RB:

IF **open price** *is greater than* **close price**
    THEN RB Colour is "Black";
ELSE
    THEN RB Colour is "White";

**Figure 3.3 - Rules for identifying the Colour of RB**

To identify the position of candlestick pattern, four types of rules that identified the direction of financial trends constructed by OHLC bar chart as earlier mentioned have been utilised. The rules in Figure 3.4 describe the concept for identifying position of candlestick patterns. These rules utilises the highest and lowest price of current and previous time stamp to identify the position as “Up”, “Down”, “Inside” and “Outside” in each case. The mean value of 50 calculated from the finding is utilised as average percentage for the position. Thus to distinguish the positions as either “Large” or “Small” status, the mean 50 is utilised as the target average, as the framework could represent the direction of trend patterns more efficiently.

IF **current high price** *is greater than* **previous high price** AND **current low price** *is greater than equal* **previous low price**<br>
    IF **up state** *is greater than equal* **50**<br>
        THEN Position of candlestick is “Large Up”;<br>
    ELSE<br>
        THEN Position of candlestick is “Small Up”;<br>
ELSE IF **current low price** *is less than* **previous low price** AND **current high price** *is less than equal* **previous high price**<br>
    IF **down state** *is greater than equal* **50**<br>
        THEN Position of candlestick is “Large Down”;<br>
    ELSE<br>
        THEN Position of candlestick is “Small Down”;<br>
ELSE IF **current high price** *is greater than* **previous high price** AND **current low price** *is less than equal* **previous low price**<br>
    IF **outside state** *is greater than equal* **50**<br>
        THEN Position of candlestick is “Large Outside”;<br>
    ELSE<br>
        THEN Position of candlestick is “Small Outside”;<br>
ELSE IF **current high price** *is less than equal* **previous high price** AND **current low price** *is greater than equal* **previous low price**<br>
    IF **inside state** *is greater than equal* **50**<br>
        THEN Position of candlestick is “Large Inside”;<br>
    ELSE<br>
        THEN Position of candlestick is “Small Inside”;

**Figure 3.4 - Rules for Identifying the Position of Candlestick Pattern**

Candlestick Representation algorithm shown in Figure 3.5 is utilised for analysing a historical financial time series data as follows. This algorithm calculates the numeric values of RB, US and LS that represent the candlestick patterns, and followed by using the rules as earlier mentioned in Figure 3.3 to identify the colour of RB. Once the calculation is completed, the rules mentioned in Figure 3.4 has been utilised to identify the position of candlestick pattern.

```
Input: Historical Financial Time Series Data T
Output: RB, US, LS, Colour and CP

T ← {X1, X2, ..., Xi} // Time Series Data
Initialise the candlestick features as 0
for k ← 0 to T do
    CurrClosePrice = Xk ← ClosePrice
    CurrOpenPrice = Xk ← OpenPrice
    CurrHighPrice = Xk ← HighPrice
    CurrLowPrice = Xk ← LowPrice
    PrevClosePrice = Xk-1 ← ClosePrice
    PrevOpenPrice = Xk-1 ← OpenPrice
    PrevHighPrice = Xk-1 ← HighPrice
    PrevLowPrice = Xk-1 ← LowPrice
    RB = [ ( | CurrClosePrice – CurrOpenPrice | ) / CurrOpenPrice ] * 100
    if CurrOpenPrice < CurrClosePrice then
        US = [ ( CurrClosePrice – CurrOpenPrice ) / (CurrHighPrice – CurrOpenPrice ) ] * 100
    else
        US = [ ( CurrOpenPrice – CurrClosePrice ) / ( CurrHighPrice – CurrClosePrice ) ] * 100
    end if
    if CurrClosePrice > CurrOpenPrice then
        LS = [ ( CurrClosePrice – CurrOpenPrice ) / ( CurrClosePrice – CurrLowPrice ) ] * 100
    else
        LS = [ ( CurrOpenPrice – CurrClosePrice ) / ( CurrOpenPrice - CurrLowPrice ) ]  * 100
    end if
    if CurrOpenPrice >= CurrClosePrice then
        Colour = "Black"
    else
        Colour = "White"
    end if
    if  CurrHighPrice > PrevHighPrice and CurrLowPrice >= PrevLowPrice then
        Up_Stat = [ ( CurrHighPrice – PrevHighPrice ) / (CurrHighPrice – PrevLowPrice ) ] *
```

```
100
          if Up_Stat >= 50 then
                CP = "Large Up"
          else
                CP = "Small Up"
        end if
     else if CurrLowPrice < PrevLowPrice and CurrHighPrice <= PrevHighPrice then
        Down_Stat = [ ( PrevHighPrice – CurrHighPrice ) / ( PrevHighPrice – CurrLowPrice ) ]
* 100
        if Down_Stat >= 50 then
              CP = "Large Down"
        else
              CP = "Small Down"
        end if
     else if CurrHighPrice > PrevHighPrice and CurrLowPrice < PrevLowPrice then
        Outside_Stat = [ ( CurrHighPrice – PrevHighPrice ) / ( CurrHighPrice - CurrLowPrice) ]
* 100
        if Outside_Stat >= 50 then
              CP = "Large Outside"
        else
              CP = "Small Outside"
        end if
     else
        Inside_Stat = [ ( PrevHighPrice – CurrHighPrice ) / ( PrevHighPrice – PrevLowPrice ) ]
* 100
        if Inside_Stat >= 50 then
              CP = "Large Inside"
        else
              CP = "Small Inside"
        end if
     end if
  end for
```

**Figure 3.5 - Candlestick Representation Algorithm**

Traditionally, after the features are represented as candlestick chart, features including, RB, US, LS, Colour of RB and the position of candlestick chart are then selected as input parameters for machine learning algorithms – ANN and SVM. The next stage is followed by training and identifying the candlestick patterns.

### 3.1.2 Learning Process and Evaluation using Machine Learning Algorithms

In this stage, the selected features - candlestick pattern previously introduced in the preceding section is presented as input parameters for machine learning algorithms to train and classify. The ANN algorithm - Multi-Layer Perceptron (MLP) and the SVM algorithm - Sequential Minimal Optimisation (SMO) are selected as classifiers, which were carried out from WEKA open source library. Figure 3.6 shows the learning and evaluation processes of the prediction model.

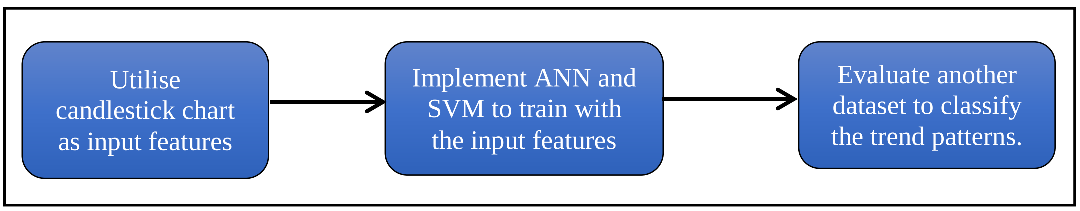


**Figure 3.6 - The Learning and Evaluation Processes of the Prediction Model**

In the learning process of both machine learning algorithms, candlestick patterns are used to represent the trend patterns. These are later utilised as input parameters for both machine learning algorithms for pattern training. All the input features representing the different time stamp of candlestick patterns are listed in Table 3.2. The input features are analysed using Candlestick Representation algorithm in the previous.

**Table 3.2 - Candlestick Chart as Input Parameters**

| Input Features | Description |
|---|---|
| Time Stamp_RB | The real body of candlestick pattern at current time stamp |
| Time Stamp _US | The upper shadow of candlestick pattern at current time stamp |
| Time Stamp _LS | The lower shadow of candlestick pattern at current time stamp |
| Time Stamp _Colour | The real body colour of candlestick pattern at current time stamp |
| Time Stamp _Up_Status | The up status of candlestick pattern at current time stamp |
| Time Stamp _Down_Status | The down status of candlestick pattern at current time stamp |
| Time Stamp _Inside_Status | The inside status of candlestick pattern at current time stamp |
| Time Stamp _Outside_Status | The outside status of candlestick pattern at current time stamp |
| Time Stamp _CP | The trend position of candlestick pattern at current time stamp |

Based on the input features shown in Table 3.2, both machine learning algorithms – ANN and SVM are implemented to train with the input features and classify the position of candlestick pattern at the future time stamp. In the training process, the dataset that represented the six days candlestick chart are split into training and testing in 7:3 ratios. To justify the learning process of ANN and SVM with minimum error, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used. Once the model has been trained well, another dataset is implemented for evaluation to ensure the model can classify the future trends effectively for prediction. Figures 3.7 and 3.8 respectively describe the learning process of ANN and SVM with candlestick pattern separately and the classification of machine learning algorithms.

**Input:** Candlestick pattern
**Output:** the position of candlestick chart at the next time stamp

$F \leftarrow \{X_1, X_2, \ldots, X_i\}$ // Selected Features which analysed by Candlestick Representation Algorithm
**for** k $\leftarrow$ 0 to $F$ **do**
    InstanceTraining = F.size * ( 70 / 100) // Training Data
    InstanceTesting = F.size – InstanceTraining.size // Test Data
    ModelMLP = MLP(InstanceTraining) // Implementing ANN algorithm from WEKA library to train with the trainingData
    ModelSMO = SMO(InstanceTraining) // Implementing SMO algorithm from WEKA library to train with the trainingData
    TestMLP( ModelMLP, InstanceTesting) // Test the testingData with MLP model
    TestSMO( ModelSMO, InstanceTesting) // Test the testingData with SMO model
**end for**

**Figure 3.7 - Learning Process with Candlestick Pattern Algorithm**

**Input:** New dataset for candlestick pattern
**Output:** Predict the position of candlestick pattern at the next time stamp

$NewF \leftarrow \{X_1, X_2, \ldots, X_i\}$ // Selected Features which analysed by Candlestick Representation Algorithm
**for** k $\leftarrow$ 0 to *NewF* **do**
    Instance = *NewF*
    EvalauteMLP( ModelMLP, Instance) // Evaluate the data with MLP Model
    EvalauteSMO( ModelSMO, Instance) // Evaluate the data with SMO Model
**end for**

**Figure 3.8 - Classification of Candlestick Pattern Algorithm**

## 3.2 LRL, K-Mean and Machine Learning Algorithms

This section introduces the second proposed prediction framework using ANN and SVM, supported by LRL and DTW. The framework could be divided into three stages: Pattern Analysis, Training Process of Machine Learning Algorithms and DTW Prediction. In the first stage, LRL is applied to analyse and form the general trend patterns. Implementation of ANN and SVM for trend classification forms the second stage. Lastly, DTW is used to determine the degree of similarity based on the trained model.

### 3.2.1 Pattern Analysis method

This section describes the general process of financial time series data analysis using technical analysis method - LRL and the proposed features. LRL is applied for analysing financial trend patterns based on the historical financial time series data. The proposed features are utilised to represent the trend patterns. Figure 3.9 shows the proposed framework for the financial time series analysis and features selection.

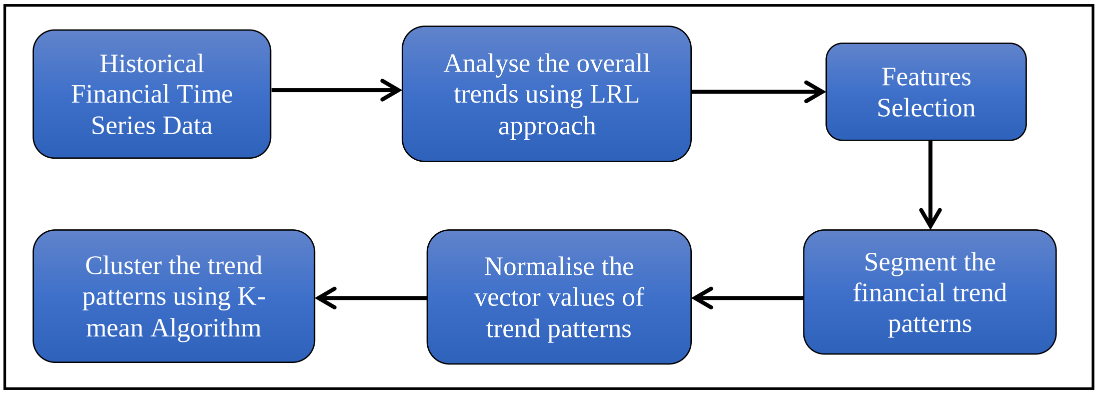


**Figure 3.9 - The Proposed Framework of Financial Time Series Analysis using LRL**

In financial sector, LRL has been an approach for modelling the relationship between prices and time stamp. Moreover, LRL has also been utilised for identifying the direction of financial trend to generate buying and selling signals. In this section, the implementation of LRL had been applied for analysing and forming general trend patterns for the historical financial time series data.

The LRL approach is implemented to analyse the historical financial time series data and identify the financial trend that represents in the form of patterns. The equation 2.2 has been applied to derive a straight line through the historical financial time series data in order to identify the overall financial trends. Figure 3.10 shows the implementation of LRL approach using the equation 2.2.

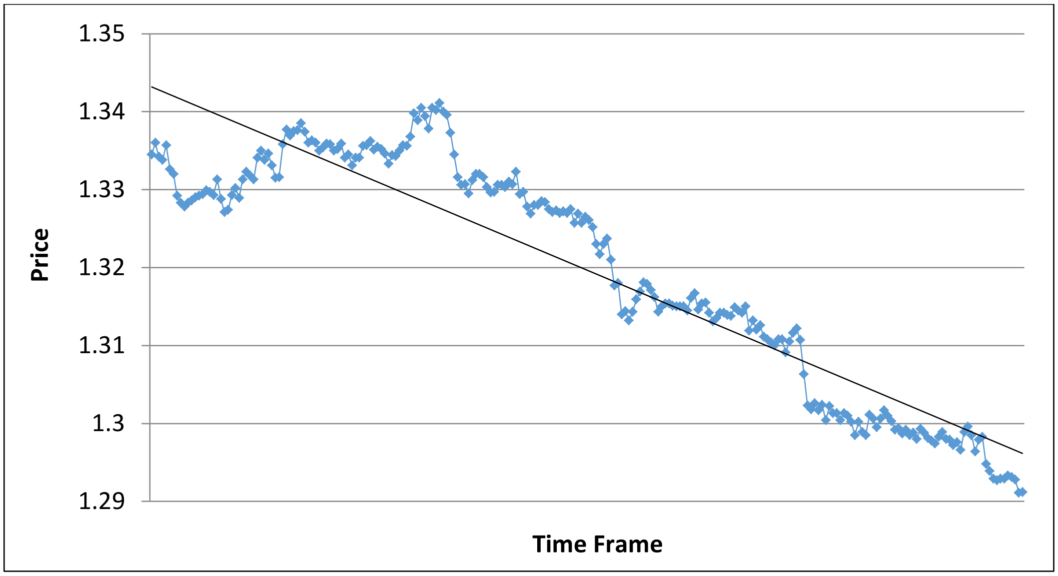


**Figure 3.10 - Implementation of Equation 2.2**

Once the overall trends have been identified, a proposed algorithm namely Pattern Segmentation is implemented to identify and segment the trends shown in Figure 3.11, fitting them into two general archetypes, and storing the values of the trend patterns vector for recognising the patterns. In addition, Pattern Segmentation algorithm utilised the proposed features shown in Figure 3.12 that consist of starting point, ending point, minimum area and the sequential series of trend patterns as input features. In the next step, the values of segmented trend patterns is normalised between the ranges -1 to 1.

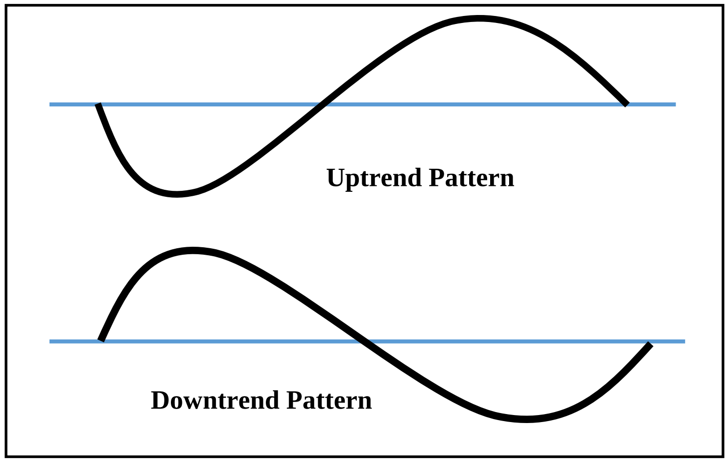

**Figure 3.11 - Different Types of Trend Patterns**

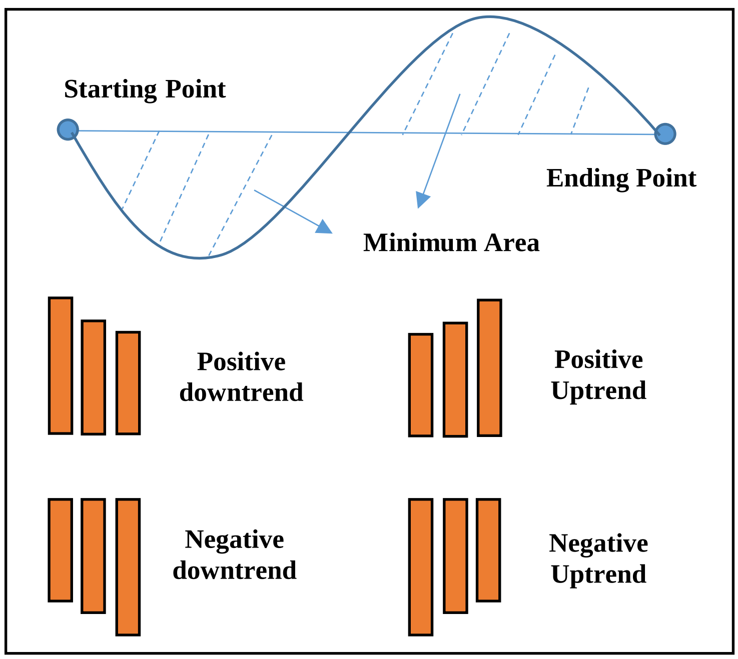

**Figure 3.12 - Proposed Features**

The following Figure 3.13 describes the implementation of Pattern Segmentation algorithm. This algorithm utilises certain rules in calculating the minimum areas to segment the trend patterns from the financial time series data. Furthermore, the rules (see Figure 3.13) begin from the starting point of trends to segment the different types of trend patterns, fitting the two archetypes shown in Figure 3.11, storing the values of the resultant trend vector.

**Input:** Historical Financial Time Series Data *T*
**Output:** Trend patterns

```
T ← {X_1, X_2, ..., X_i} // Time Series Data
P ← { } // Storing the trend patterns
negativeCount = 0 // Initialise as counter
positiveCount = 0 // Initialise as counter
for k ← 0 to T do
    if X_k < 0 then
        P(k) ← X_k
        negativeCount++
        continue
    else if X_k > 0 then
        P(k) ← X_k
        positiveCount++
        continue
    else
        if negativeCount < minArea then
            P(k) ← X_k
            negativeCount = 0
            positiveCount++
        else if negativeCount >= minArea then
            P(k) ← X_k
            negativeCount = 0
            positiveCount++
        else if positiveCount < minArea then
            P(k) ← X_k
            positiveCount = 0
            negativeCount++
        else if positiveCount >= minArea then
            P(k) ← X_k
            positiveCount = 0
```

```
                negativeCount++
            end if
        end if
end for
```

**Figure 3.13 - Pattern Segmentation Algorithm**

After segmentation, K-mean algorithm has been applied to cluster trend patterns into two main classes – “Uptrend” and “Downtrend”. The K-mean clustering algorithm is utilised from WEKA open source library. To represent the trend patterns as input parameters for clustering, the selected features representation of trend patterns are listed in Table 3.3.

**Table 3.3 - Proposed Features**

| Features | Description |
|---|---|
| Feature 1 | The starting point of the trend patterns |
| Feature 2 | The highest/lowest values to changing point |
| Area 1 | The area between starting point and changing point |
| Feature 3 | The changing point to highest/lowest point |
| Feature 4 | The ending point of the trend patterns |
| Area 2 | The area between changing point and ending point |
| Length | The length of the trend patterns |

According to the features that are listed in Table 3.3, Figure 14 illustrates the ideas of the feature representation. As can be seen, the values of “Feature 1”, “Feature 2”, “Feature 3” and “Feature 4” are identified as 1 - Up, 2 - Normal and 3 - Down. The value of “Area 1” is sum from starting point vector value to exchange point vector value. The value of “Area 2” is sum from exchange point vector value to ending point vector value. The value of “Length” is length of the trend patterns. The proposed algorithm named as “Features Creation” shown in Figure 3.15 is used to identify the values of “Feature 1”, “Feature 2”, “Feature 3” and “Feature 4”, and calculates the values of “Area 1” and “Area 2”.  Figure 3.16 describes the implementation of K-mean algorithm for clustering cluster the trend patterns into two groups: “Uptrend” and “Downtrend” in the database.

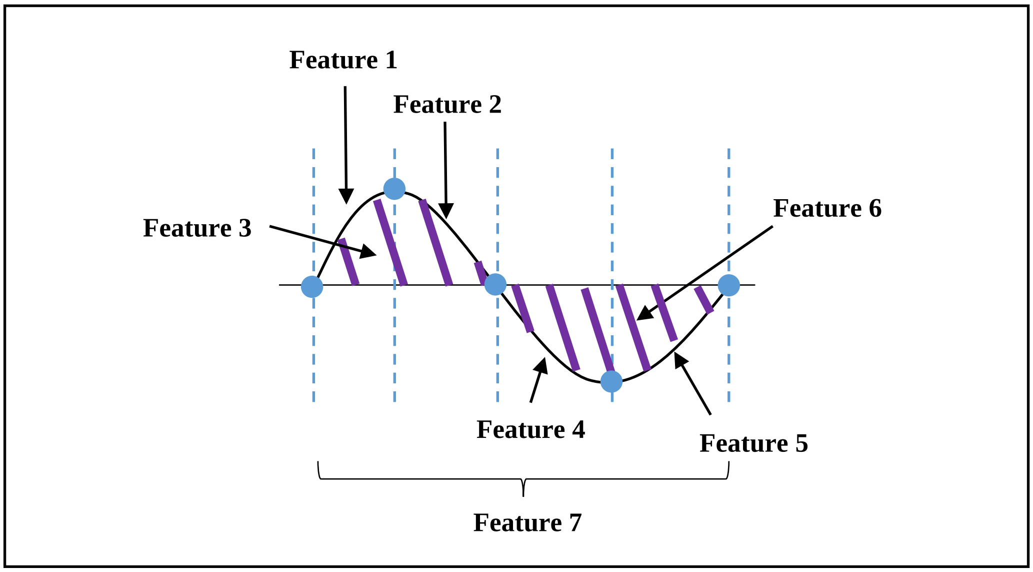


**Figure 3.14 - Illustration of Proposed Features**

**Input:** Vector values of trend pattern
**Output:** Selected features of trend pattern

```
Initialise Features As 0
P ← {X1, X2, ..., Xi} // The vector values of trend patterns
for k ← 0 to P do
    if X1 > 0 then
        if highest_point > X1 then
            P1 = 1
        else if highest_point == X1 then
            P1 = 2
        end if
        if highest_point > exchange_point then
            P2 = 3
        else if highest_point == exchange_point then
            P2 = 2
        end if
        if exchange_point > lowest_point then
            P3 = 3
        else if exchange_point == lowest_point then
            P3 = 2
        end if
        if Xk > lowest_point then
            P4 = 1
        else if Xk == lowest_point then
            P4 = 2
        end if
        Area1 = Area1 + | Xk |
    else if X1 < 0 then
        if X1 == lowest_point then
            P1 = 2
        else if X1 > lowest_point then
            P1 = 3
        end if
        if exchange_point > lowest_point then
            P2 = 1
        else if exchange_point == lowest_point then
            P2 = 2
        end if
        if highest_point > exchange_point then
            P3 = 1
        else if highest_point == exchange _point then
            P3 = 2
        end if
        if highest_point > Xi then
```

```
            P4 = 3
        else if highest_point == X_k then
            P4 = 2
        end if
        Area2 = Area2 + | X_k |
    end if
end for
```

**Figure 3.15 - Features Creation Algorithm**

```
Input: Selected features of trend patterns
Output: Clusters

P ← {X_1, X_2, ..., X_i} // Initialise the vector values of selected features
K ← {C_1, C_2} // Cluster Group
for k ← 0 to P do
    K ← k-mean (X_i) // Implement WEKA k-mean algorithm to cluster the trend patterns
    if K assigns as "Uptrend" then
        X_k as "Uptrend Group"
    else
        X_k as "Downtrend Group"
    end if
end for
```

**Figure 3.16 - K-mean Algorithm**

After the clustering, the trend patterns are stored in the database based on the clustering result. The proposed features are utilised as input features for ANN and SVM to learn the patterns. The learning and classification processes of machine learning algorithms are described in the next stage.

### 3.2.2 Classification Process of Machine Learning Algorithms

After the pattern analysis stage, ANN and SVM are implemented as classifier to train with the selected features, which analysed using LRL and the proposed features. Table 3.4 lists the selected features representation of trend patterns that is extracted from “Uptrend” and “Downtrend” shown in Figure 3.11. Figure 3.17 shows the learning process of machine learning algorithms – ANN and SVM.

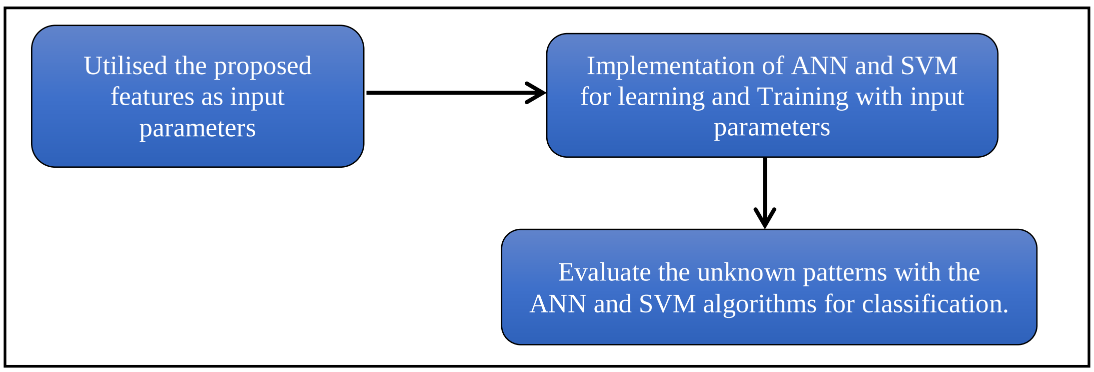


**Figure 3.17 - Classification Process of Machine Learning Algorithms**

In the training process, the input features shown in Table 3.4 are implemented as input parameters. Then, ANN and SVM train with the input parameters to classify the unknown trend patterns as either “Uptrend” or “Downtrend”.

**Table 3.4 - Selected Features Representation**

| Attributes | Description | Value |
|---|---|---|
| Feature 1 | Distance between starting point to turning point | 1 – Up, 2 – Normal, 3 - Down |
| Feature 2 | Distance between turning points to exchange point | 1 – Up, 2 – Normal, 3 - Down |
| Feature 3 | The area between starting point to exchange point | 1 - 10 |
| Feature 4 | Distance between exchange point to turning point | 1 – Up, 2 – Normal, 3 - Down |
| Feature 5 | Distance between turning points to ending point | 1 – Up, 2 – Normal, 3 - Down |
| Feature 6 | The area between exchange point and end point | 1 - 10 |

The training dataset that has analysed by the proposed Pattern Representation algorithm to represent the trend patterns, are split into training and testing in 7:3 ratios. In order to calculate the minimum error of training process for both ANN and SVM, MAE and RMSE are used in the proposed models. Figure 3.18 describes the implementation of selected features as input parameters for ANN and SVM to learn with the patterns.

**Input:** Selected features of trend patterns
**Output:** Type of trend patterns

```
P ← {X_1, X_2, …, X_i} // Initialise the vector values of selected features
for k ← 0 to F do
    InstanceTraining = F.size * ( 70 / 100)  // Training Data
    InstanceTesting = F.size – InstanceTraining.size  // Test Data
    ModelMLP = MLP(InstanceTraining) // Implementing ANN to train with the trainingData
    ModelSMO = SMO(InstanceTraining) // Implementing SVM to train with the trainingData.
    TestMLP( ModelMLP, InstanceTesting) // Test the testingData with MLP model
    TestSMO( ModelSMO, InstanceTesting) // Test the testingData with SMO model
end for
```

**Figure 3.18 - Learning Process with Selected Features Algorithm**

Once the model has been trained well, another dataset is implemented for evaluation to classify the future trends effectively for prediction. Then, DTW is utilised to search for the shortest warping path that matched against the patterns in the group based on the classification results that belongs to either “Uptrend” or “Downtrend” groups. Figure 3.19 describes the evaluation of ANN and SVM to classify with the unknown trend patterns separately.

**Input:** Unknown Trend pattern
**Output:** Type of trend patterns

```
P ← {F1, F2, ..., Fi}// The vector values of selected features for the unknown trend pattern
MLPClassificationResult = MLP(P) // Classify the pattern with the trained ANN model
SMOClassificationResult = SMO(P) // Classify the pattern with the trained SVM model
if MLPClassificationResult == “Uptrend” then
      applyDTWwithUptrend (P)
else if MLPClassificationResult == “Downtrend” then
      applyDTWwithDowntrend(P)
end if
if SMOClassificationResult == “Uptrend” then
      applyDTWwithUptrend (P)
else if SMOClassificationResult == “Downtrend” then
      applyDTWwithDowntrend(P)
end if
```

**Figure 3.19 - Classification of Trend Patterns Algorithm**

### 3.2.3 DTW Prediction

DTW is implemented to match the unknown patterns against train patterns from the models by measuring the points of similarity between both patterns. Figure 3.20 shows the idea of using DTW for predicting the next movement of test trend patterns against train patterns.

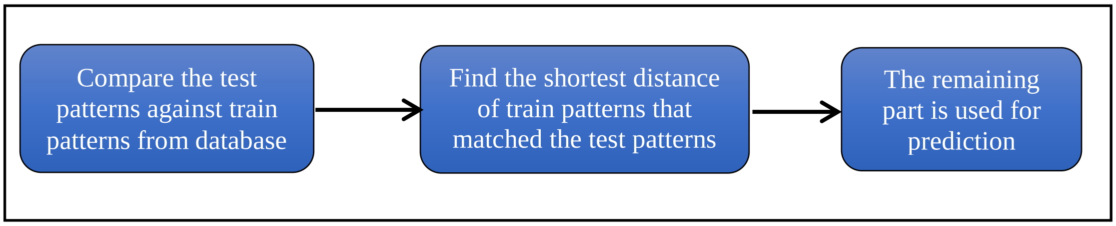


**Figure 3.20 - Implementation of DTW for Prediction**

In this stage, DTW is applied in order to compare the test patterns through brute force against the train patterns from the database to identify the shortest warping path. The equation 2.10 has been utilised to find the shortest path distance of the train pattern.

After the shortest distance between the test and train patterns is found, DTW generates the cost matrix. The equation 2.10 is utilised to sum up the minimum values from the cost matrix to represent the matched sequence elements for both test and train patterns. The result of matrix table indicates that in order to predict future trends, DTW based identification of the test patterns using the train patterns is carried out, and the remaining sequence elements between the two trend patterns are used for prediction. Figure 3.21 describes the implementation of calculating the shortest warping path between two trend patterns using the equation 2.10.

**Input:** Test trend pattern and train trend pattern
**Output:** Shortest warping path

```
P1 // The vector values of test trend pattern
P2 // The vector values of train trend pattern
for k ← 0 to P1 do
      TimeSeriesA = { Pk }
end for
for j ← 0 to P2 do
      TimeSeriesB = { Pj }
end for
shorestWarp = DTW(TimeSeriesA, TimeSeriesB, EuclideanDistance) // Calculate the shortest warping path
```

**Figure 3.21 - Optimising the Shortest Warping Path using DTW**

Based on the remaining part of sequence elements that is found in the cost matrix table, a 2 × 2 Structure Elements shown in Figure 3.23 is applied to identify the diagonal direction. The result obtained in original matrix table is traced by 2 × 2 structure elements in order to achieve a pattern representative table shown in Figure 3.23. Figure 3.24 illustrates the steps of using 2 × 2 Structure Elements to identify the diagonal direction from the original matrix table. Once diagonal direction is found, the proposed rules and condition are applied to find the matched sequence elements between the patterns. The remaining sequence elements are utilised to predict the future of financial trends. Figure 3.22 describes the implementation of 2 × 2 Structure Elements to identify the diagonal direction.

```
Input: Cost Matrix Table
Output: Shortest warping path with diagonal direction

M // Cost Matrix Table of the shortest warping path
for k ← 0 to M do
      for j ← 0 to M do
            if k == 0 and j == 0 then
                  Pattern as "1"
            else if k == 0 and j == 1 then
                  Pattern as "2"
            else if k == 1 and j == 0 then
                  Pattern as "3"
            else if k == 1 and j == 1 then
                  Pattern as "4"
            end if
      end for
end for
```

**Figure 3.22 - 2 × 2 Structure Elements Algorithm**

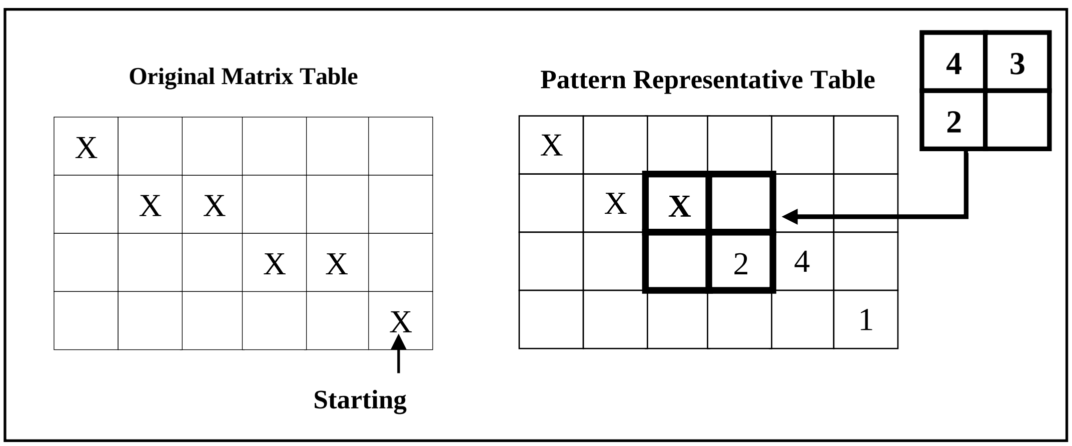


**Figure 3.23 - Basic Idea for Identifying the Diagonal Direction**

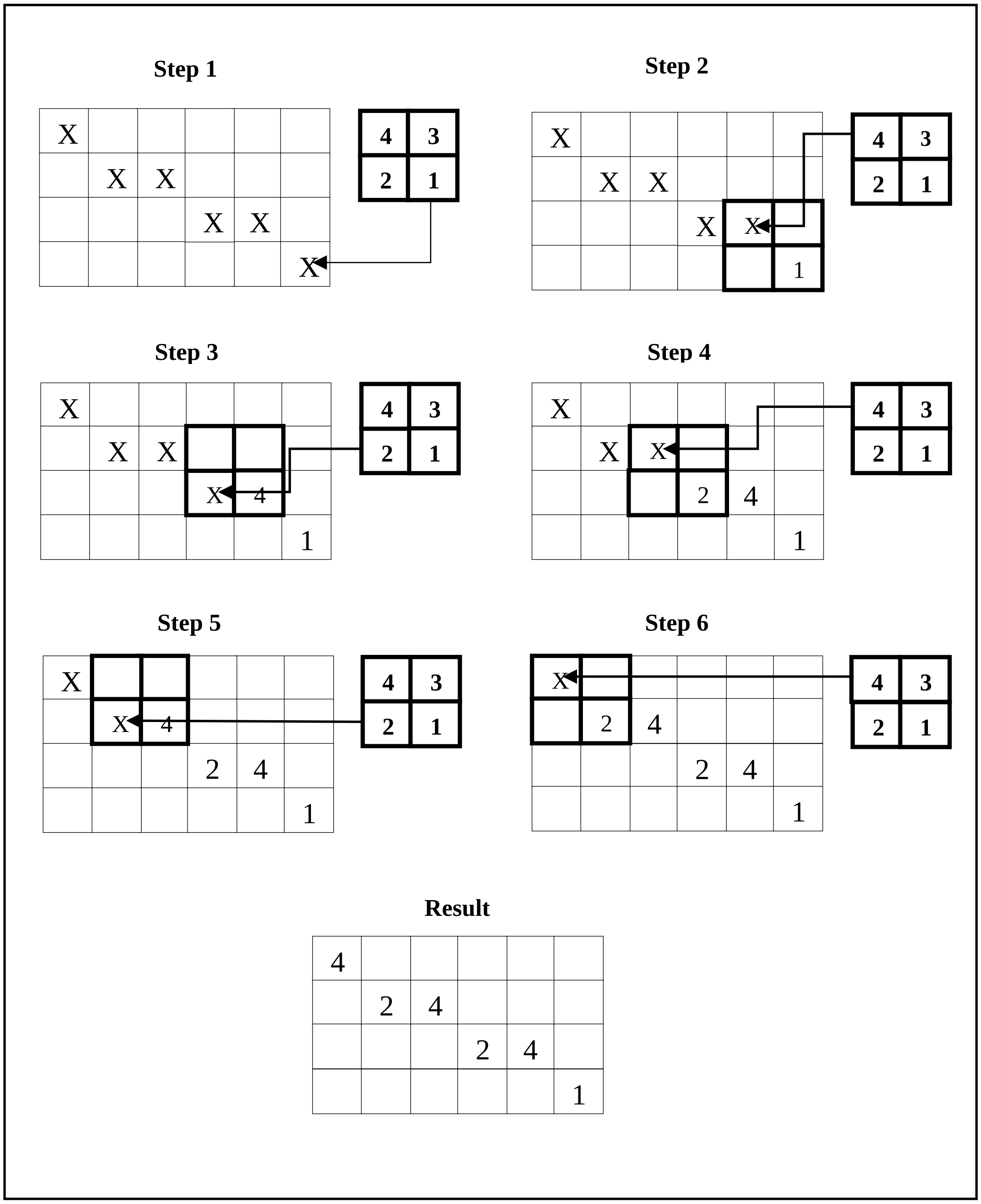


**Figure 3.24 - The Steps of Using 2 × 2 Structure Elements to Identify the Diagonal Direction**

# 4.0 EXPERIMENTAL RESULT AND DISCUSSION

This chapter presents the experiment results for two proposed frameworks. First proposed frameworks utilises candlestick pattern as data analysis method, followed by machine learning algorithms as classifiers. In the second proposed frameworks, LRL and K-mean algorithm are utilised as data analysis method, followed by machine learning algorithms as classifiers, and then utilise DTW as prediction technique. The machine learning algorithms, ANN and SVM are utilised as two separate classifiers.

The financial time series data used in this research is the foreign exchange rate of *AUD* and *EUR* against *USD*. *USD* is a benchmark in current Forex market that trades against other major currencies especially *AUD* and *EUR*. These financial time series data employed in the experiments consists of half-hour closing prices. The dataset encompasses the time range from 2nd January 2011 until 31st December 2012. The data is collected from Free Forex Historical Data website (Free Forex Historical Data, 2013).

## 4.1 Candlestick Pattern and Machine Learning Algorithms

### 4.1.1 Pattern Analysis

This section describes utilisation of the candlestick pattern to produce trend patterns from historical financial time series data. Analysing the candlestick position is more reliable because it provides supported information for an investment strategy. As reflected in the candlestick pattern shown in Figure 4.1, it follows that equations, 3.1 to 3.5 earlier described in chapter 3 could be utilised to represent the patterns.

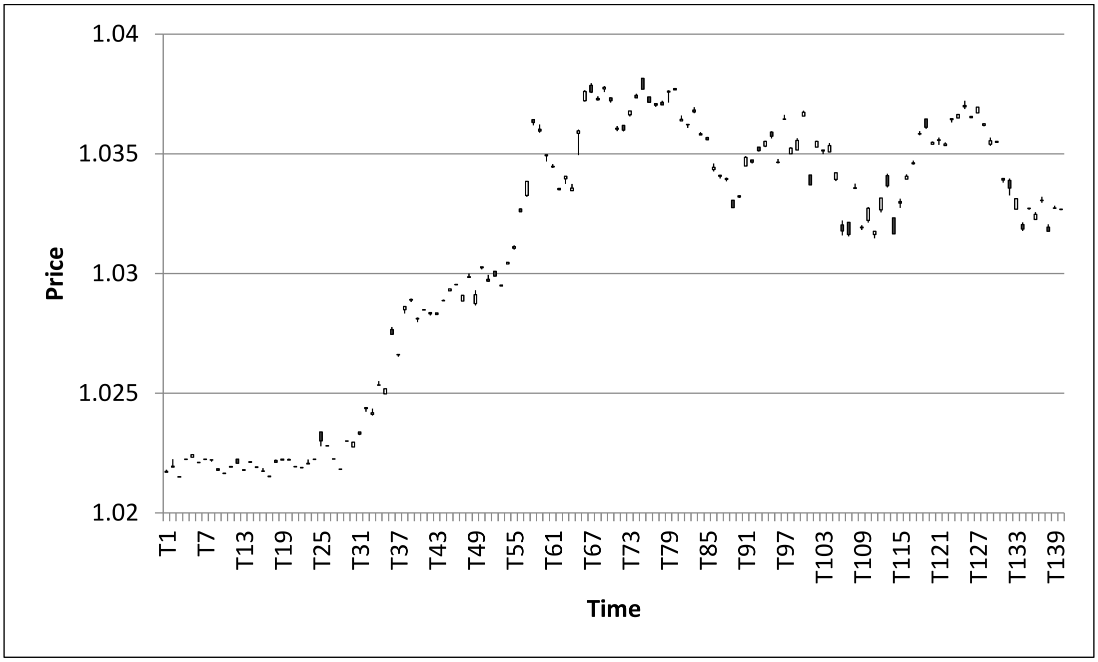


**Figure 4.1 - Financial Time Series Data *AUD – USD* in January 2011**

In this framework, two cases are presented for study. The first case is designed to utilise half an hour of candlestick pattern as input. For the second case, it extended the parameters by 2.5 hours with 30 minutes interval of candlestick pattern that represents the financial trend. This experiment concentrates on financial time series data split as 7:3 ratios of training and testing sets respectively. The objective is to find out which among those cases that could present the trend patterns with the best features possible for financial trend analysis. The values of RB, US and LS of the candlestick patterns are calculated in each case. Then, applied the rules to define the colour of RB as well as the position of the candlestick patterns.

The justification for the choice of two cases – half an hour candlestick pattern and 2.5 hours with 30 minutes interval candlestick pattern is ascertain possible disparities in the changes of trend patterns for each giving time stamp. Technically, this could explain how clear the trend patterns are discriminated.

Table 4.1 shows the first case results of the candlestick pattern in numeric values as selected features with the position of candlestick patterns also defined. The values of RB, US and LS at T1 are undefined; this is because T1 is the starting time, and the equations (3.1 to 3.5) depend on the previous historical data in calculating RB, US and LS. Thus, Candlestick Representation algorithm and rules stated earlier in Figure 3.4 are then utilised the features, **U_Stat, D_Stat, O_Stat** and **I_Stat** to identify the position of candlestick pattern corresponding.

It is vital illustrating the position of candlestick patterns to demonstrate any significant effects based on the selected features. Figure 4.2 to Figure 4.9 show the different positions of candlestick samples, Figure 4.2 shows the concept of large uptrend patterns between two different time stamp whereas, Figure 4.4 reflects small uptrend patterns. Figures 4.3 and 4.5 on the other hand, shows the large downtrend and small downtrend patterns respectively from another time stamp. Figures 4.6 and 4.8 show the small and large inside trend patterns respectively. Figures 4.7 and 4.8 depict the small and large outside patterns respectively. Invariably, the results obtained in each case show how the trend patterns do not provide clear and smoothness in its distinctiveness.

To attain a more clear smoothness in the trend patterns status, a 3 hours candlestick pattern has been suggested earlier on in case 2. Table 4.2 shows the sample numeric results and positions of 3 hours candlestick patterns. It clearly seen, each sample presents six distinctive half-hourly intervals of candlestick patterns to analyse the financial trends. The calculation for each candlestick patterns for a single sample correlates with the first case. Knowledge and ideas gained from these findings could be extended to represent the financial trend patterns, thus achieving a better smoothness.

**Table 4.1 - Sample Result of Candlestick Chart in Numeric Format**

| T | Open | High | Low | Close | RB | US | LS | COL | U_Stat | D_Stat | O_Stat | I_Stat | P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| T1 | 1.02211 | 1.02211 | 1.02211 | 1.02211 | - | - | - | - | - | - | - | - | - |
| T2 | 1.02225 | 1.02225 | 1.02223 | 1.02225 | 0 | 0 | 0 | Black | 80 | 0 | 0 | 0 | L Up |
| T3 | 1.02222 | 1.02222 | 1.02214 | 1.0222 | 0.001957 | 100 | 25 | Black | 0 | 97.333 | 0 | 0 | L Down |
| T4 | 1.02184 | 1.02184 | 1.02177 | 1.02177 | 0.00685 | 100 | 100 | Black | 97.36842 | 0 | 0 | 0 | L Up |
| T5 | 1.02165 | 1.02165 | 1.02165 | 1.02165 | 0 | 0 | 0 | Black | 100 | 0 | 0 | 0 | L Up |
| T6 | 1.02194 | 1.02194 | 1.02191 | 1.02191 | 0.002936 | 100 | 100 | Black | 0 | 100 | 0 | 0 | L Down |
| T7 | 1.02224 | 1.02224 | 1.02207 | 1.02207 | 0.01663 | 100 | 100 | Black | 100 | 0 | 0 | 0 | L Up |
| T8 | 1.0218 | 1.0218 | 1.02176 | 1.02177 | 0.002936 | 100 | 75 | Black | 0 | 27.27272 | 0 | 0 | S Down |
| T9 | 1.02211 | 1.02214 | 1.0221 | 1.02214 | 0.002935 | 100 | 75 | White | 0 | 84.44444 | 0 | 0 | L Down |
| T10 | 1.02192 | 1.02192 | 1.02189 | 1.0219 | 0.001957 | 100 | 66.66667 | Black | 0 | 100 | 0 | 0 | L Down |
| T11 | 1.02175 | 1.02187 | 1.02175 | 1.02175 | 0 | 0 | 0 | White | 100 | 0 | 0 | 0 | L Up |
| T12 | 1.02151 | 1.02153 | 1.02151 | 1.02153 | 0.001958 | 100 | 100 | White | 90.90909 | 0 | 0 | 0 | L Up |
| T13 | 1.02219 | 1.02223 | 1.02211 | 1.02211 | 0.007826 | 66.66667 | 100 | Black | 0 | 91.66667 | 0 | 0 | L Down |
| T14 | 1.02225 | 1.02225 | 1.02221 | 1.02221 | 0.003913 | 100 | 100 | Black | 89.47369 | 0 | 0 | 0 | L Up |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| T15 | 1.02221 | 1.02227 | 1.0222 | 1.02223 | 0.001957 | 33.33333 | 66.66667 | White | 0 | 88 | 0 | 0 | L Down |
| T16 | 1.02194 | 1.02195 | 1.02193 | 1.02193 | 0.000979 | 50 | 100 | Black | 0 | 29.41177 | 0 | 0 | S Down |
| T17 | 1.02189 | 1.02189 | 1.02189 | 1.02189 | 0 | 0 | 0 | Black | 0 | 94.44444 | 0 | 0 | L Down |
| T18 | 1.02204 | 1.02203 | 1.02203 | 1.02207 | 0.002935 | 15.78947 | 75 | White | 97.22222 | 0 | 0 | 0 | L Up |
| T19 | 1.02224 | 1.02224 | 1.02223 | 1.02223 | 0.000978 | 100 | 100 | Black | 14.28571 | 0 | 0 | 0 | S Up |
| T20 | 1.02338 | 1.02338 | 1.02278 | 1.02301 | 0.036155 | 100 | 61.66667 | Black | 0 | 0 | 28.57143 | 0 | S Out |

* **T** – Time, **Col** – Colour, **U_Stat** – Up Status, **D_Stat** – Down Status, **I_Stat** – Inside Status, **O_Stat** – Outside Status, **P** - Position
* L UP – Large Up, L DOWN – Large Down, L OUT – Large Outside, L IN – Large Inside, S UP – Small Up, S DOWN – Small Down, S OUT – Small Outside, S IN – Small Inside

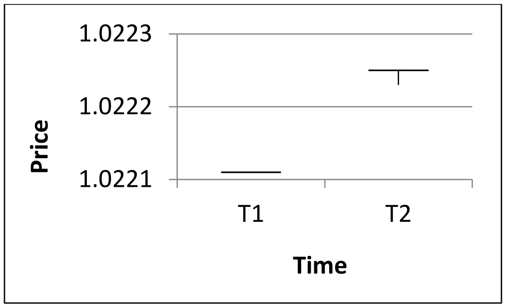


**Figure 4.2 - Large Up Position**

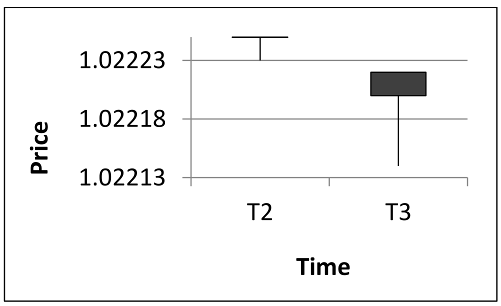


**Figure 4.3 - Large Down Position**

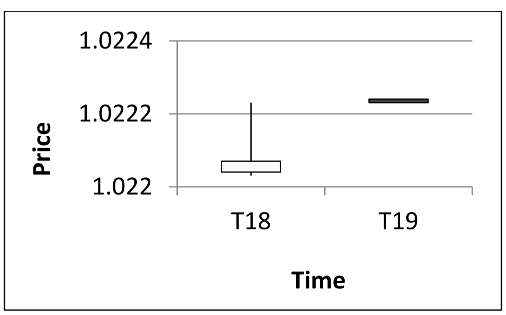


**Figure 4.4 - Small Up Position**

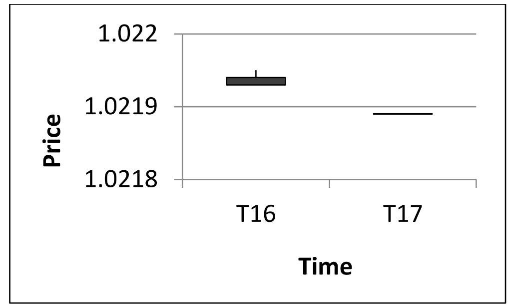


**Figure 4.5 - Small Down Position**

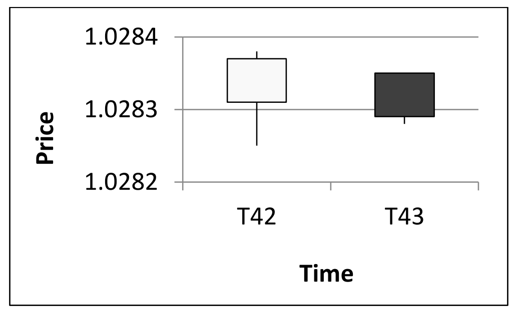


**Figure 4.6 - Small Inside Position**

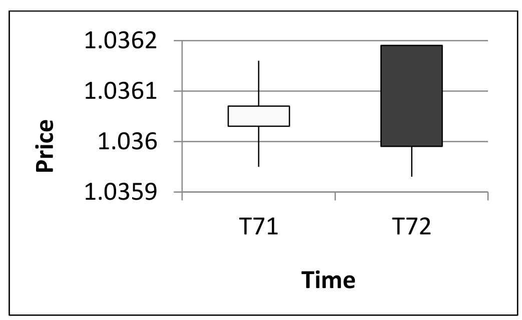


**Figure 4.7 - Small Outside Position**

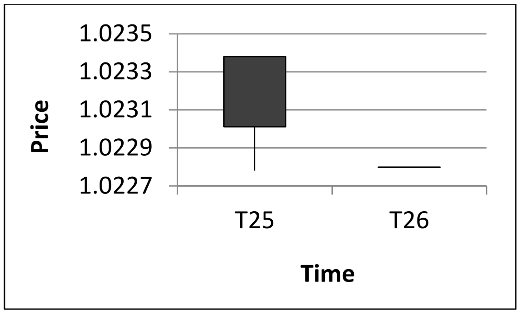


**Figure 4.8 - Large Inside Position**

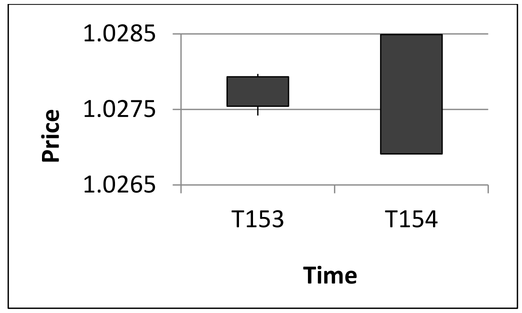


**Figure 4.9 - Large Outside Position**

**Table 4.2 - Sample Results of Second Case**

| Sample / Input Features | Sample 1 | Sample 2 | Sample 3 | Sample 4 |
|---|---|---|---|---|
| **Day_1_RB** | - | 0.007495 | 0.007484 | 0.037481 |
| **Day_1_US** | - | 50 | 50 | 100 |
| **Day_1_LS** | - | 50 | 100 | 83.333333 |
| **Day_1_Colour** | - | White | White | White |
| **Day_1_Up_Status** | - | 90.625 | 50 | 66.666667 |
| **Day_1_Down_Status** | - | 0 | 0 | 0 |
| **Day_1_Inside_Status** | - | 0 | 0 | 0 |
| **Day_1_Outside_Status** | - | 0 | 0 | 0 |
| **Day_1_CP** | - | Large Up | Small Up | Large Up |
| **Day_2_RB** | 0.007495 | 0.014984 | 0.007486 | 0 |
| **Day_2_US** | 33.333333 | 100 | 100 | 0 |
| **Day_2_LS** | 33.333333 | 100 | 100 | 0 |
| **Day_2_Colour** | Black | White | White | White |
| **Day_2_Up_Status** | 0 | 70 | 0 | 0 |
| **Day_2_Down_Status** | 77.272727 | 0 | 80 | 100 |
| **Day_2_Inside_Status** | 0 | 0 | 0 | 0 |
| **Day_2_Outside_Status** | 0 | 0 | 0 | 0 |
| **Day_2_CP** | Large Down | Large Up | Large Down | Large Down |
| **Day_3_RB** | 0.007498 | 0.007497 | 0 | 0.007495 |
| **Day_3_US** | 33.333333 | 50 | 0 | 100 |
| **Day_3_LS** | 100 | 100 | 0 | 100 |
| **Day_3_Colour** | White | Black | Black | White |
| **Day_3_Up_Status** | 0 | 0 | 0 | 100 |
| **Day_3_Down_Status** | 62.5 | 83.333333 | 81.818182 | 0 |
| **Day_3_Inside_Status** | 0 | 0 | 0 | 0 |
| **Day_3_Outside_Status** | 0 | 0 | 0 | 0 |

| | | | | |
|---|---|---|---|---|
| **Day_3_CP** | Larger Down | Larger Down | Large Down | Large up |
| **Day_4_RB** | 0.007487 | 0.007492 | 0 | 0.007495 |
| **Day_4_US** | 50 | 50 | 0 | 100 |
| **Day_4_LS** | 100 | 100 | 0 | 100 |
| **Day_4_Colour** | White | Black | White | Black |
| **Day_4_Up_Status** | 85.714286 | 80 | 66.666667 | 0 |
| **Day_4_Down_Status** | 0 | 0 | 0 | 0 |
| **Day_4_Inside_Status** | 0 | 0 | 0 | 1 |
| **Day_4_Outside_Status** | 0 | 0 | 0 | 0 |
| **Day_4_CP** | Large Up | Large Up | Large Up | Small Inside |
| **Day_5_RB** | 0 | 0.007502 | 0.007486 | 0.007487 |
| **Day_5_US** | 0 | 100 | 100 | 100 |
| **Day_5_LS** | 0 | 50 | 100 | 100 |
| **Day_5_Colour** | White | White | White | Black |
| **Day_5_Up_Status** | 0 | 0 | 66.666667 | 93.75 |
| **Day_5_Down_Status** | 96.969697 | 89.473684 | 0 | 0 |
| **Day_5_Inside_Status** | 0 | 0 | 0 | 0 |
| **Day_5_Outside_Status** | 0 | 0 | 0 | 0 |
| **Day_5_CP** | Large Down | Large Down | Large Up | Large Up |
| **Day_6_RB** | 0 | 0.022536 | 0 | 0.014976 |
| **Day_6_US** | 0 | 100 | 0 | 66.666667 |
| **Day_6_LS** | 0 | 75 | 0 | 100 |
| **Day_6_Colour** | Black | White | White | Black |
| **Day_6_Up_Status** | 0 | 0 | 0 | 0 |
| **Day_6_Down_Status** | 83.333333 | 80 | 0 | 0 |
| **Day_6_Inside_Status** | 0 | 0 | 100 | 0 |
| **Day_6_Outside_Status** | 0 | 0 | 0 | 33.333333 |
| **Day_6_CP** | Large Down | Large Down | Large Inside | Small Outside |

### 4.1.2 Classification

Following the outcomes from the data analysis stage, it becomes possible to train and test machine learning algorithms utilising the selected features as input parameters. This experiment investigates the performance of learning process for both cases. The machine learning algorithms, ANN and SVM are adopted from the WEKA open source library. ANN in WEKA library utilises the concept of Multi-Layer Perceptron (MLP).

For the SVM, the Radial Basic Function (RBF) kernel has been utilised to maximise the margin hyperplane.

In Tables 4.3 and 4.4, 3717 of candlestick patterns from the data *AUD – USD* in 2011 and 3672 of candlestick patterns from the data *EUR – USD* in 2011 are experimented. The learning process results of the first case candlestick patterns achieve 96.6% (3591 successes out of 3717 attempts) for ANN and 96% (3568 successes out of 3717 attempts) for SVM based on the data *AUD – USD* in 2011. For the data *EUR – USD* in 2011, the results of using candlestick patterns achieves 94.4% (3466 successes out of 3672 attempts) for ANN and 94.3% (3464 successes out of 3672 attempts) for SVM. From Table 4.4, the learning process results using second case candlestick patterns show 97% (3605 successes out of 3717 attempts) for ANN and 96.5% (3586 successes out of 3717 attempts) for SVM based on the data *AUD – USD* in 2011. The results using the data *EUR – USD* in 2011 on the other hand achieves 95.7% (3515 successes out of 3672 attempts) and 94.3% (3463 successes out of 3672 attempts) for ANN and SVM respectively.

**Table 4.3 - First Case Candlestick Patterns as Input Parameters**

| **Financial Time Series Data** | **Classifier** | **Number of Dataset** | | **Training Result** | | **Classification Testing Result** |
|---|---|---|---|---|---|---|
| | | *Training* | *Testing* | *MAE* | *RMSE* | |
| *AUD – USD* in 2011 | ANN | 8670 | 3717 | 0.033 | 0.0849 | 96.6% |
| | SVM | 8670 | 3717 | 0.0094 | 0.0957 | 96% |
| *EUR – USD* in 2011 | ANN | 8568 | 3672 | 0.024 | 0.093 | 94.4% |
| | SVM | 8568 | 3672 | 0.031 | 0.1252 | 94.3% |

**Table 4.4 - Second Case Candlestick Patterns as Input Parameters**

| Financial Time Series Data | Classifier | Number of Dataset | | Training Result | | Classification Testing Result |
|---|---|---|---|---|---|---|
| | | *Training* | *Testing* | *MAE* | *RMSE* | |
| *AUD – USD* in 2011 | ANN | 8670 | 3717 | 0.009 | 0.0761 | 97% |
| | SVM | 8670 | 3717 | 0.0187 | 0.0929 | 96.5% |
| *EUR – USD* in 2011 | ANN | 8568 | 3672 | 0.0135 | 0.0994 | 95.7% |
| | SVM | 8568 | 3672 | 0.0214 | 0.1052 | 94.3% |

Going by the classification results of each case, the candlestick patterns successfully analysed the financial time series data, utilising the selected features. It could be added here, that the study selects both cases as features, train and test machine learning algorithms for representing the financial trend patterns.

This is followed by testing other financial time series data with the trained model to validate individual results of classifications by ANN and SVM. 40 datasets are randomly selected from each of the historical financial time series data: *AUD – USD* and *EUR – USD* that encompasses the time range of 2012 are used to evaluate the selected features. The evaluation results shown in Table 4.5 and 4.6 are rather unsatisfactory in predicting the future of financial trends.

**Table 4.5 - Evaluation Result using Candlestick Patterns as Features for First Case**

| Sampling Data | Classifier | Number of Evaluation Dataset | Classification Result |
|---|---|---|---|
| | | | *Candlestick Pattern* |
| *AUD – USD* in 2012 | ANN | 40 | 47.5% |
| | SVM | | 45% |
| *EUR – USD* in 2012 | ANN | 40 | 42.5% |
| | SVM | | 40% |

**Table 4.6 - Evaluation Result using Candlestick Patterns as Features for Second Case**

| Sampling Data | Classifier | Number of Evaluation Dataset | Classification Result |
|---|---|---|---|
| | | | *Candlestick Pattern* |
| *AUD – USD* in 2012 | ANN | 40 | 57.5% |
| | SVM | | 60% |
| *EUR – USD* in 2012 | ANN | 40 | 55% |
| | SVM | | 57.5% |

In the first case, the accuracy rates for ANN and SVM in predicting for *AUD – USD* in 2012 are 19 successes out of 40 attempts as 47.5% and 18 successes out of 40 attempts as 47.5% respectively, and EUR – *USD* in 2012 are 17 successes out of 40 attempts as 41% and 16 successes over 40 attempts as 40% respectively. In the second case, the accuracy rates for ANN in predicting for *AUD – USD* in 2012 and *EUR – USD* in 2012 are 57.5% (23 successes over 40 attempts) and 60% (24 successes over 40 attempts) respectively. That for SVM, on the other hand are 55% (22 successes over 40 attempts) and 57.5% (23 successes over 40 attempts) accordingly for the two datasets.

According to the results shown in Tables 4.5 and 4.6, using the candlestick patterns as input features for ANN and SVM for classifying the trend patterns did not provide satisfactory results. This is because the selected input features are complexed to represent the trend patterns, as ANN and SVM are not being trained appropriately. Due the unsatisfactory result, this thesis proposes a second framework in the next section that utilises seven features for ANN and SVM as input parameters to learn the trend patterns.

## 4.2 LRL, K-Mean and Machine Learning Algorithms

This section proposes LRL to analyse the overall financial trends based on the historical financial time series data. The Pattern Segmentation and K-Mean clustering algorithms are implemented to identify the different types of trend patterns through the overall financial trends.

### 4.2.1 Pattern Analysis

This experiment collects the financial time series data in weekly format with half-hourly intervals. Based on the historical financial time series data, the equation 2.2 has been utilised to analyse the overall trend. This equation only concentrates on the close price from the financial time series data to analyse the financial trends. This is because the close price provides a useful marker to assess changes over time stamp. In other words, the close price of the current time stamp could be compared to the previous time stamp in order to measure market sentiment for a given security over trading.

Figures 4.10 to 4.13 show the sample results using the equation 2.2. The LRL approach could analyse the overall financial trend patterns from the historical financial time series data with a clear and smoothness results compare to the previous method.


**Figure 4.10 - Financial Trend in Histogram Chart: *AUD – USD* 2nd Week in January 2011**

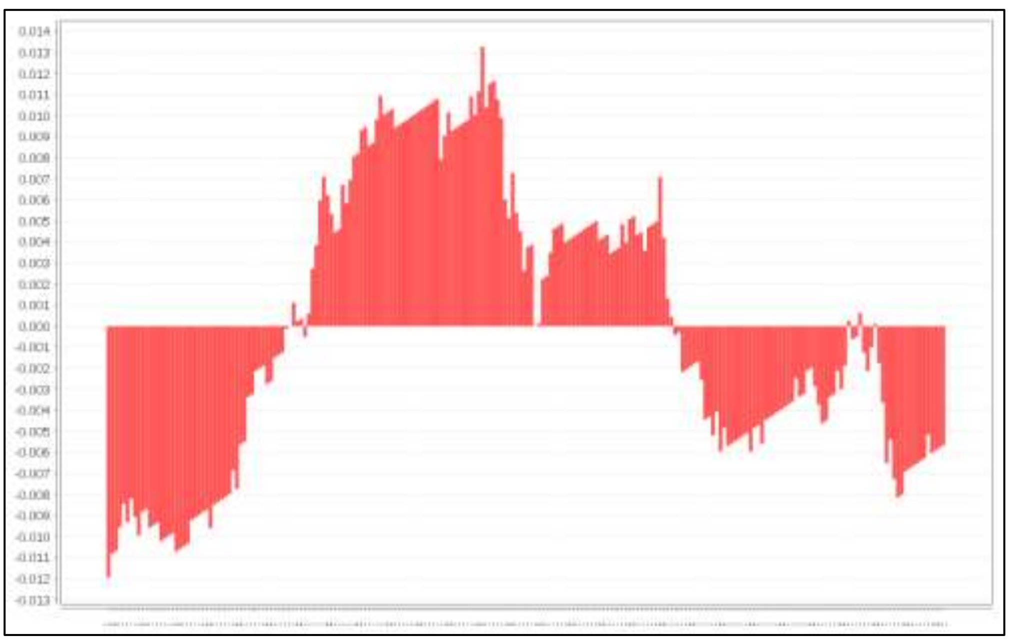


**Figure 4.11 - Financial Trend in Histogram Chart: *AUD – USD* 4th Week in April 2011**

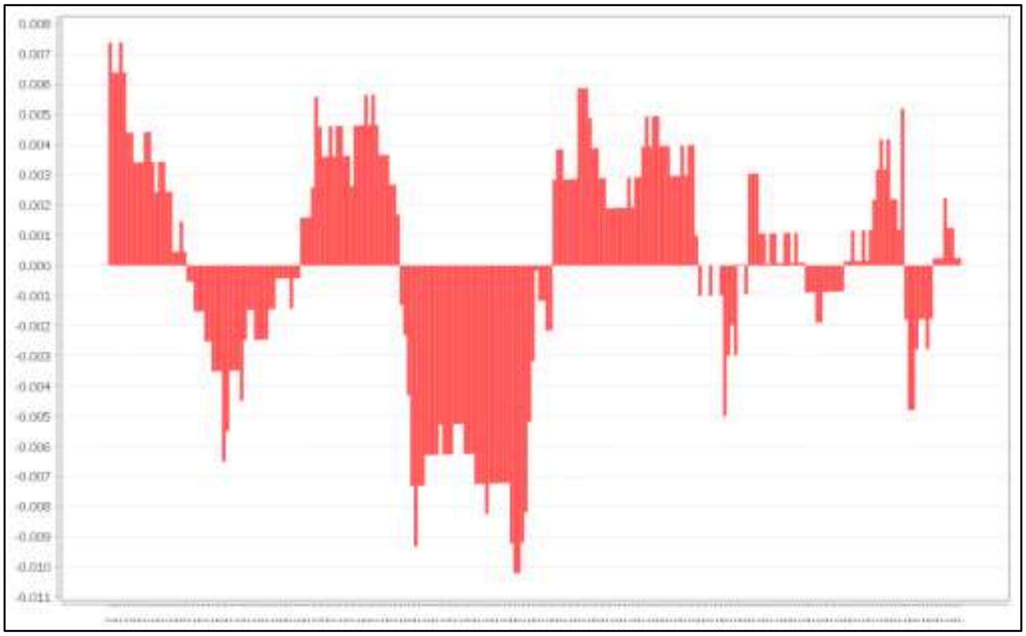

**Figure 4.12 - Financial Trend in Histogram Chart:** ***EUR – USD*** **3nd Week in July 2011**

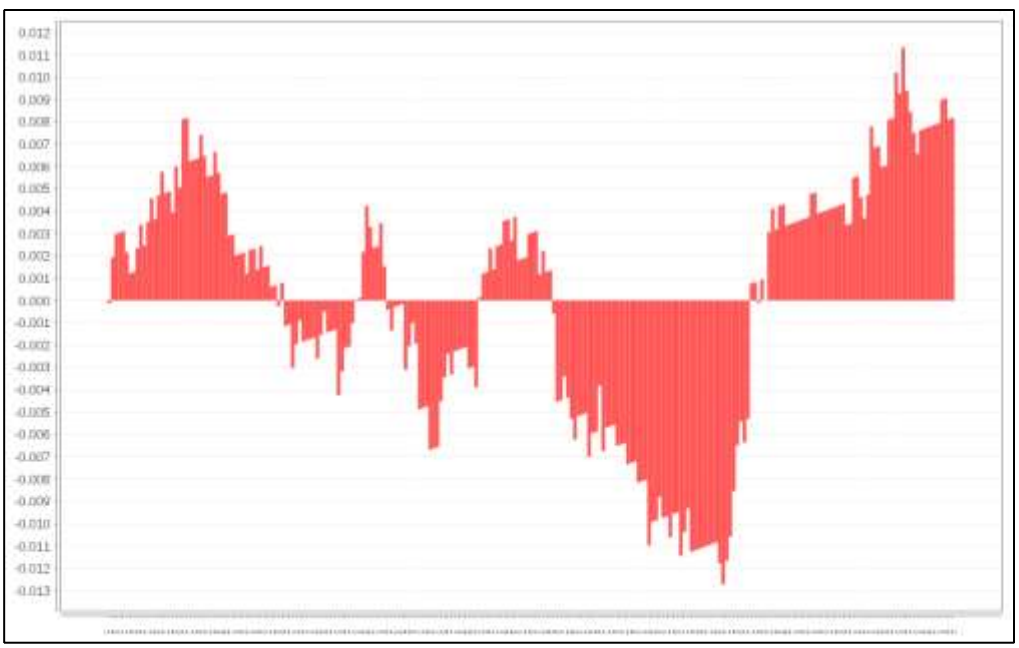

**Figure 4.13 - Financial Trend in Histogram Chart:** ***EUR – USD*** **4nd Week in September 2011**

In the following steps, the overall trend patterns could be identify as two general archetypes of trend patterns shown in Figure 3.3. This is because the trend patterns could be used to ascertain the underlying market conditions. The patterns also give a good idea of the direction in which an investment's value might move. In this experiment, Pattern Segmentation algorithm and the rules earlier described in chapter 3, has been implemented to identify the trends as either “Uptrend” or “Downtrend” patterns.

Figures 4.14 to 4.16 present three samples of “Downtrend” patterns, and Figures 4.17 to 4.19 show three types of “Uptrend” patterns. Experimental results from pattern representation, proves that Pattern Segmentation algorithm could reliably presents different types of trend patterns efficiently to unveil certain trends direction any given time stamp.

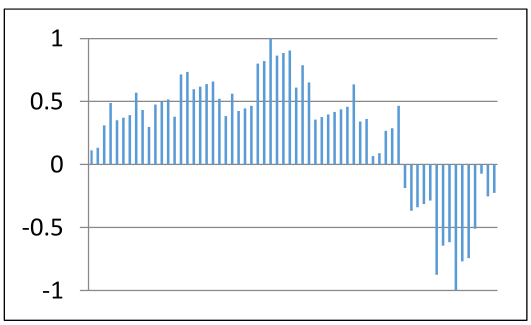


**Figure 4.14 - Downtrend Sample 1**

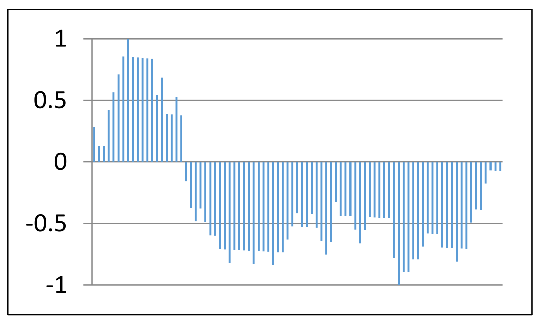


**Figure 4.15 - Downtrend Sample 2**

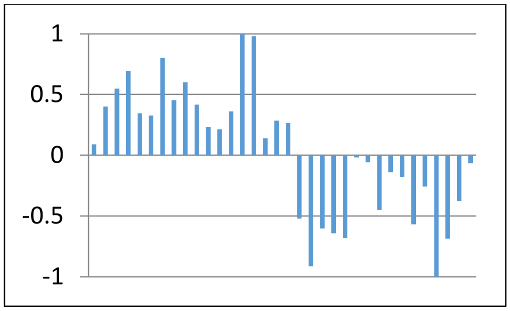


**Figure 4.16 - Downtrend Sample 3**

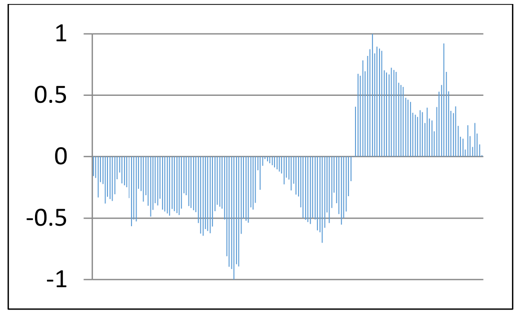


**Figure 4.18 - Uptrend Sample 2**

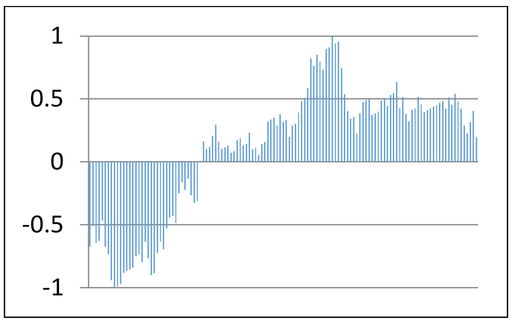


**Figure 4.17 - Uptrend Sample 1**

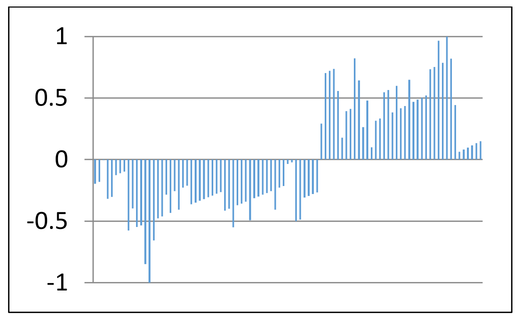


**Figure 4.19 - Uptrend Sample 3**

The proposed selected features described in Table 3.3 are utilised as input vectors representing the trend patterns as shown in Figures 4.14 to 4.19. Figure 4.20 illustrates the representation for the selected features from Table 3.3. “Feature 1”, “Feature 2”, “Feature 3” and “Feature 4” indicated three feature values: a movement up is represented as 1, while 2 indicates normal, 3 represents down. The value of the Area 1 and Area 2 defines the areas of trend patterns. Table 4.7, shows these vector values for the proposed selected features to be identified. Appendix 3 shows the sample outcome of clustering.

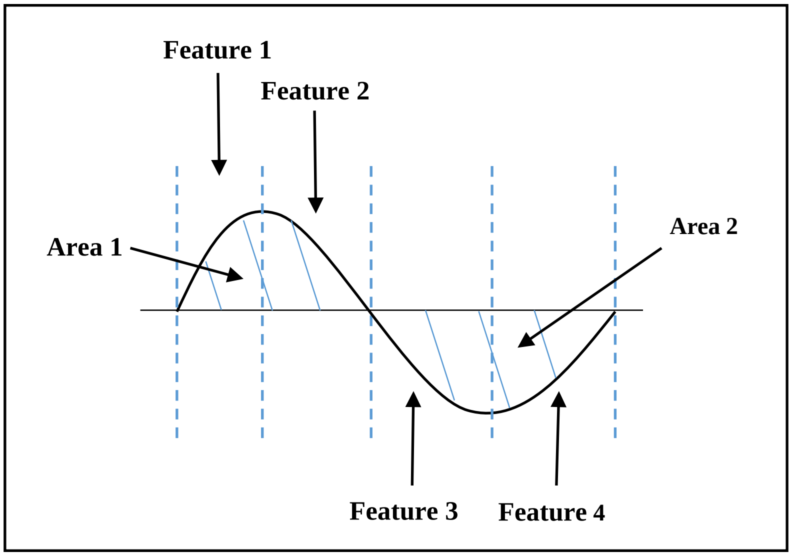


**Figure 4.20 - Concept of Selected Features**

**Table 4.7 - Sample of Clustering Result using Proposed Features**

| **Feature 1** | **Feature 2** | **Area 1** | **Feature 3** | **Feature 4** | **Area 2** | **Length** | **Cluster** |
|---|---|---|---|---|---|---|---|
| 3 | 1 | 3.8 | 1 | 3 | 6.2 | 126 | Cluster_2 |
| 3 | 1 | 5.9 | 1 | 3 | 4.1 | 9 | Cluster_2 |
| 1 | 3 | 6 | 2 | 1 | 4 | 9 | Cluster_1 |
| 1 | 3 | 3.8 | 3 | 1 | 6.2 | 75 | Cluster_1 |
| 3 | 1 | 6.3 | 1 | 3 | 3.7 | 163 | Cluster_2 |
| 1 | 3 | 9.1 | 2 | 1 | 0.9 | 58 | Cluster_1 |
| 1 | 3 | 5.3 | 3 | 1 | 4.7 | 33 | Cluster_1 |
| 3 | 1 | 2.6 | 1 | 3 | 7.4 | 58 | Cluster_2 |
| 3 | 1 | 5 | 1 | 2 | 5 | 11 | Cluster_2 |
| 1 | 2 | 1.5 | 3 | 1 | 8.5 | 44 | Cluster_1 |
| 3 | 1 | 7.7 | 1 | 3 | 2.3 | 32 | Cluster_2 |
| 1 | 3 | 4.9 | 3 | 1 | 5.1 | 28 | Cluster_1 |
| 3 | 1 | 3 | 2 | 3 | 7 | 11 | Cluster_2 |
| 1 | 3 | 9.1 | 3 | 1 | 0.9 | 57 | Cluster_1 |
| 3 | 1 | 4.6 | 1 | 3 | 5.4 | 11 | Cluster_2 |
| 1 | 3 | 3.8 | 3 | 1 | 6.2 | 16 | Cluster_1 |

* Cluster_1 – Downtrend Cluster Group, Cluster_2 – Uptrend Cluster Group

K-mean algorithm described in previous chapter have been implemented for clustering under two main classes namely, “Uptrend” and “Downtrend”. Figures 4.14 to 4.19 illustrate this based on the selected features. Results presented in Table 4.7, shows how the algorithm clusters the trend patterns perfectly for the given dataset. The purpose of implementing clustering algorithm is to group the trend patterns in the database, so as to increase the performance of machine learning algorithms during the learning stage.

According to the results shown in Figures 4.10 to 4.13, the LRL approach successfully distinguishes the financial trends. The results of pattern representation shown in Table 4.7 and Figures 4.14 to 4.19 further prove that the Pattern Segmentation and K-mean algorithms represent the trend patterns efficiently compared to first framework.

### 4.2.2 Classification

An implementation of ANN or SVM using WEKA open source library is described in this section. ANN in WEKA library utilises the MLP concept for classification. The RBF kernel of SVM has been implemented to maximise the margin hyperplane. During the training process, the dataset is partitioned into two – training set and testing set, in a 7:3 ratio. Other sets of financial time series data are tested with the proposed model to validate the classification. Appendix 4 shows the sample outcome of classification.

Table 4.8 shows the results on utilisation of these proposed features as input parameters in the learning process. Performance achieved by both ANN and SVM is 100% for the AUD – USD and EUR – USD in 2011, dataset. It could be pointed here that the proposed features achieves better performance compared to when candlestick pattern are utilised as selected features.

**Table 4.8 - Proposed Features as Input Parameters**

| **Financial Time Series Data** | **Classifier** | **Number of Dataset** | | **Training Result** | | **Classification Testing Result** |
|---|---|---|---|---|---|---|
| | | *Training* | *Testing* | *MAE* | *RMSE* | |
| *AUD – USD* in 2011 | ANN | 118 | 51 | 0.00 | 0.00 | 100% |
| | SVM | 118 | 51 | 0.00 | 0.00 | 100% |
| *EUR – USD* in 2011 | ANN | 139 | 60 | 0.00 | 0.00 | 100% |
| | SVM | 139 | 60 | 0.00 | 0.00 | 100% |

This is followed by random selection of 40 datasets from each of the historical financial time series data: *AUD – USD* and *EUR – USD* that encompasses the time range of 2012 for evaluation. Table 4.9, shows the evaluation results for both ANN and SVM in this regard. Performances for both algorithms, is 100% in classifying the trend patterns using the proposed features. Clearly seen from the results, this study proves how the proposed features could be a better preference over candlestick patterns for effective classification of trend patterns. Additionally, this study also proves that the proposed features could be utilises in representing the trend patterns to train well both machine learning algorithms.

**Table 4.9 - Using Proposed Features as Input Features for Classification**

| Sampling Data | Classifier | Number of Evaluation Dataset | Classification Result |
|---|---|---|---|
| | | | *Proposed Features* |
| *AUD – USD* in 2012 | ANN | 40 | 100% |
| | SVM | | 100% |
| *EUR – USD* in 2012 | ANN | 40 | 100% |
| | SVM | | 100% |

### 4.2.3 Prediction

In the following section, 40 datasets randomly selected from each of the historical financial time series data: *AUD – USD* and *EUR – USD* in the previous classification stage that used ANN. These are considered as partial unknown patterns for predicting the future trends. DTW is utilised to predict those unknown patterns within the model.

As shown in Figure 4.21 a partial unknown uptrend pattern is presented. It is left for model prediction stage to discover the trend pattern group for the shortest warping path for which the unknown belong to. Based on the findings from DTW, Figure 4.22 shows the matching trend patterns for an unknown pattern shown in Figure 4.21.

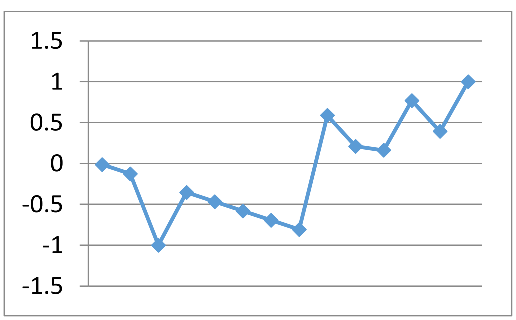


**Figure 4.21 - Partial Unknown Pattern**

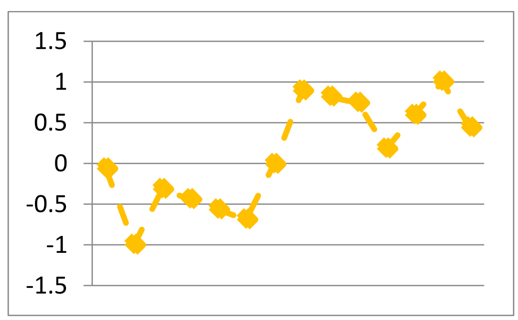


**Figure 4.22 - Full Train Pattern**

A cost matrix table is generated using DTW in Table 4.10. This calculates each points of the shortest warping path between the two trend patterns. To identify the shortest warping path, DTW traces the minimum value from the starting point (right bottom in Table 4.10) to the ending point (top right in Table 4.10).

Figure 4.23 demonstrates the concept of DTW in tracing the minimum value from the cost table. This follows a direction - bottom right from the cost table. The algorithm searches for the minimum value from neighbourhood values until the end of the cost table. Once this search is completed, DTW then acquires the shortest warping path that has been highlighted as Table 4.10. Figure 4.24 is an illustration result of this acquisition cost matrix with minimum distance warp path between the partial uptrend pattern and an uptrend pattern.

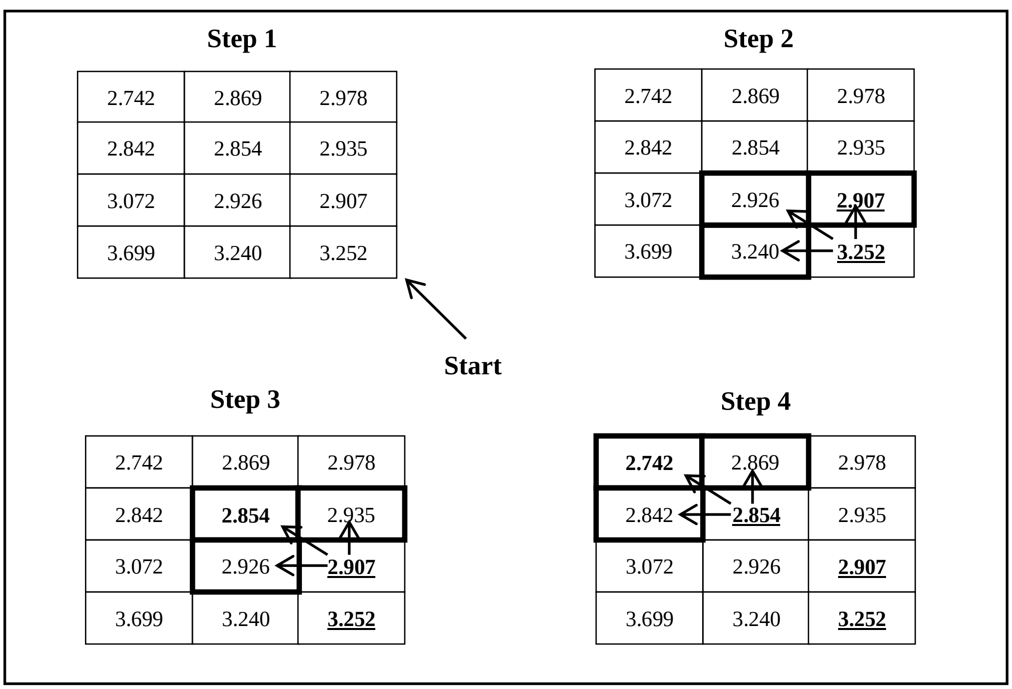


**Figure 4.23 - Demonstration in Tracing Minimum Value**

**Table 4.10 - Cost Matrix Table**

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0.031** | **0.044** | **0.102** | **0.746** | **0.892** | 1.625 | 2.401 | 3.222 | 3.545 | 3.912 | 4.865 | 4.940 | 5.359 | 5.747 | 6.480 | 7.183 |
| 1.015 | 0.971 | 0.94 | 0.411 | 1.218 | **1.113** | 1.29 | 1.422 | 2.053 | 2.639 | 2.639 | 3.668 | 5.040 | 6.382 | 7.434 | 8.136 |
| 1.922 | 1.834 | 1.759 | 0.643 | 1.142 | 1.257 | **1.213** | 1.268 | 1.822 | 2.332 | 2.409 | 3.360 | 4.655 | 5.920 | 7.530 | 9.012 |
| 2.752 | 2.62 | 2.501 | 0.799 | 1.297 | 1.208 | 1.231 | **1.234** | 1.711 | 2.144 | 2.298 | 3.172 | 4.390 | 5.578 | 7.111 | 8.613 |
| 3.506 | 3.329 | 3.166 | 0.877 | 1.375 | 1.218 | 1.263 | 1.330 | **1.634** | **1.990** | **2.221** | 3.018 | 4.160 | 5.271 | 6.726 | 8.151 |
| 3.643 | 3.510 | 3.391 | 1.689 | 1.191 | 2.092 | 2.163 | 2.252 | 1.82 | 2.169 | 3.111 | **2.314** | 2.565 | 2.785 | 3.350 | 3.884 |
| 3.808 | 3.720 | 3.645 | 2.529 | 1.533 | 2.119 | 3.064 | 3.180 | 2.339 | 2.383 | 3.318 | 2.435 | **2.537** | 2.730 | 3.267 | 3.774 |
| 4.371 | 4.326 | 4.296 | 3.767 | 2.272 | 2.859 | 3.489 | 4.478 | 3.255 | 3.299 | 3.93 | 2.954 | 2.609 | **2.742** | 2.869 | 2.978 |
| 4.961 | 4.961 | 4.975 | 5.032 | 3.039 | 3.626 | 4.257 | 4.931 | 4.199 | 4.243 | 4.873 | 3.500 | 2.812 | 2.842 | **2.854** | 2.935 |
| 5.579 | 5.623 | 5.668 | 6.268 | 3.834 | 4.421 | 5.051 | 5.726 | 5.170 | 5.214 | 5.845 | 4.074 | 3.041 | 3.072 | 2.926 | **2.907** |
| 6.595 | 6.639 | 6.728 | 7.358 | 5.026 | 5.613 | 6.244 | 6.919 | 6.539 | 6.583 | 7.214 | 5.046 | 3.669 | 3.699 | 3.240 | **3.252** |

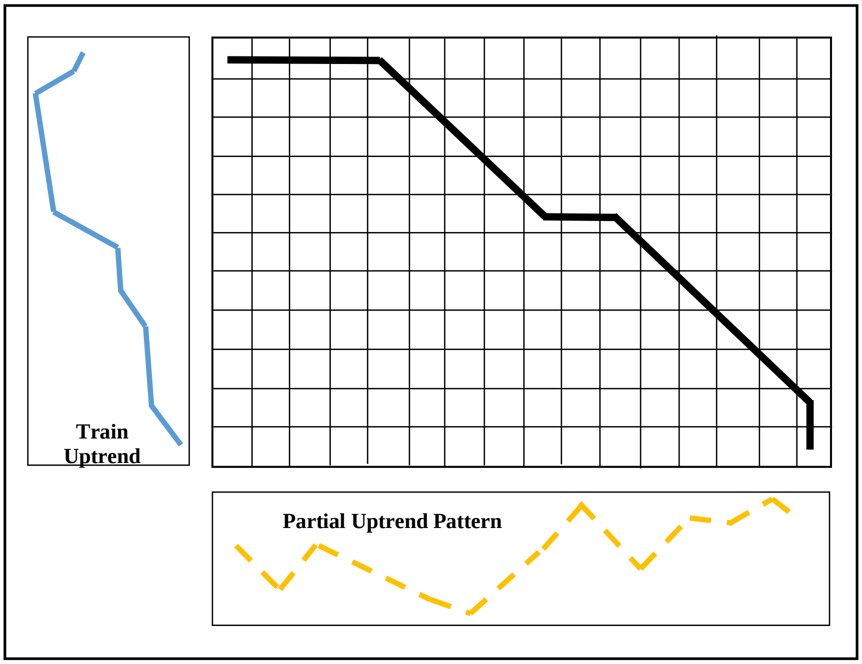


**Figure 4.24 - Shortest Warping Path**

The proposed 2 × 2 Structure Elements algorithm is utilised for predicting the future trends based on the cost matrix with minimum distance warp path. One bottleneck of the DTW is that it does not extend capability from cost matrix table to further unmatched part. On the contrary, the 2 × 2 Structure Elements algorithm would find the remaining part that predicts the direction of future trends. Figures 4.25 to 4.29 show the sample prediction results using the 2 × 2 Structure Elements algorithm. Appendix 5 shows the sample of prediction outcome.

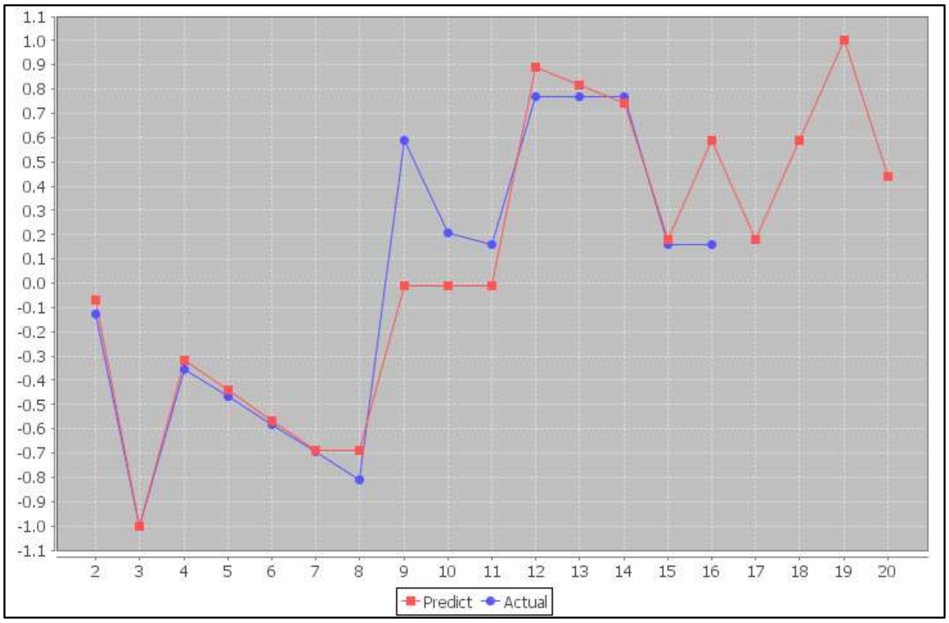


**Figure 4.25 - Sample 1 Prediction Result for *AUD – USD* in 2012**

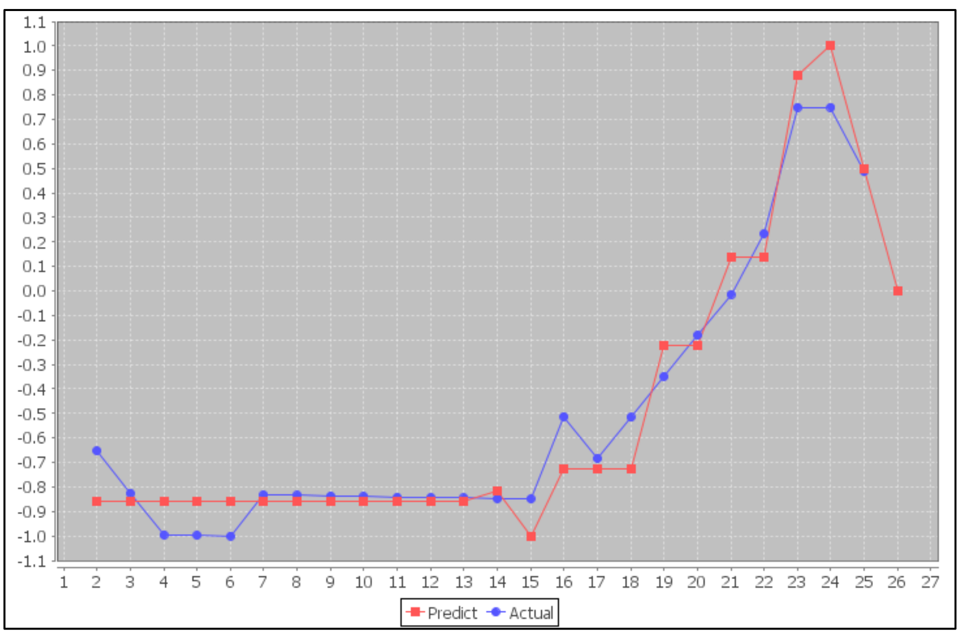


**Figure 4.26 - Sample 2 Prediction Result for *AUD – USD* in 2012**

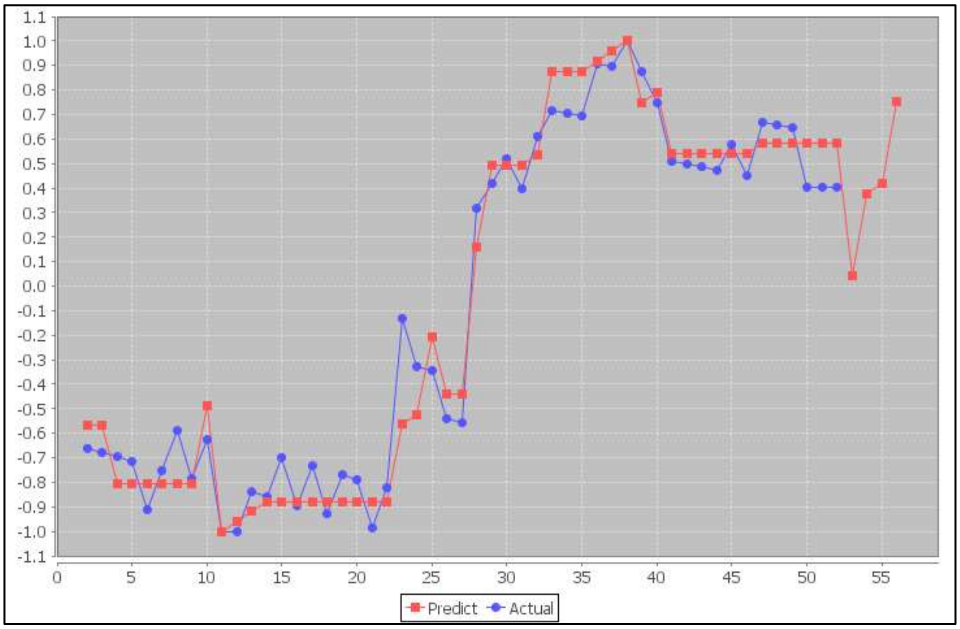


**Figure 4.27 - Sample 3 Prediction Result for *AUD – USD* in 2012**

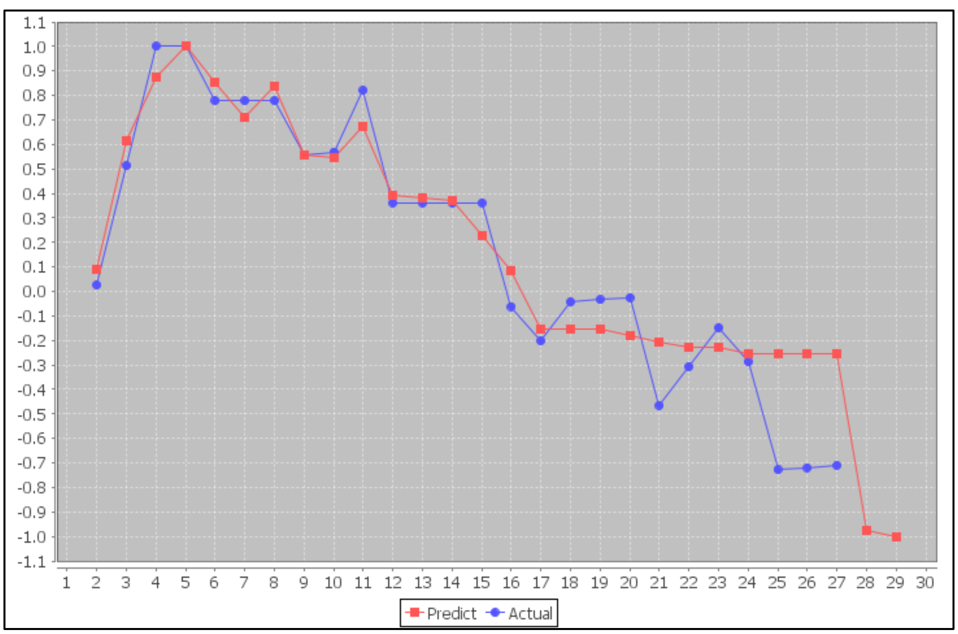


**Figure 4.28 - Sample 4 Prediction Result for *EUR – USD* in 2012**

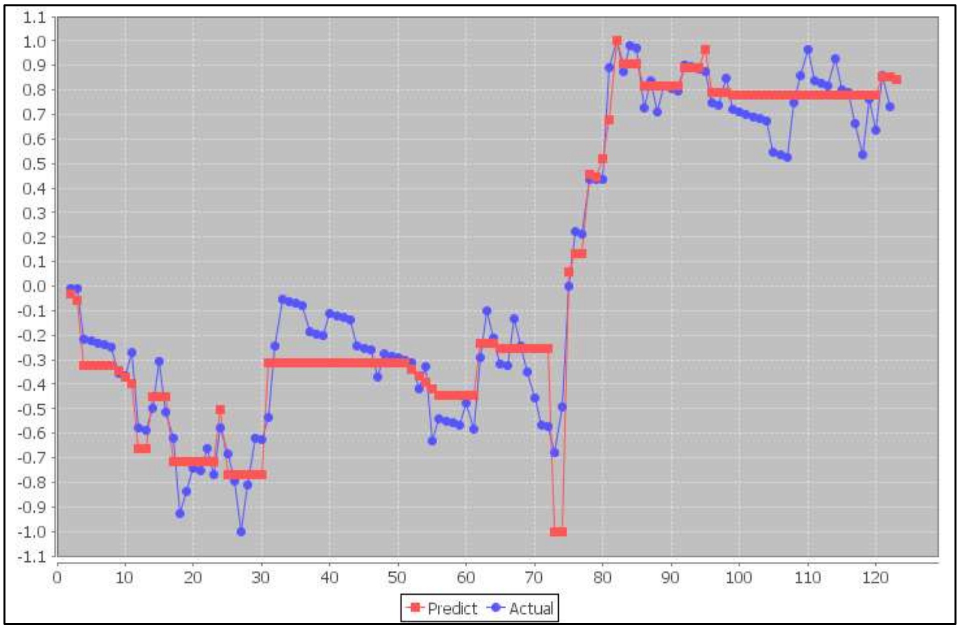


**Figure 4.29 - Sample 5 Prediction Result for *EUR – USD* in 2012**

Table 4.11 shows this prediction results using *AUD – USD* in 2012. Altogether, there are 23 uptrend and 17 downtrend samples. The proposed algorithm utilises the remaining part to predict the direction of future trends as 17 successes out of 23 attempts for uptrends and 11 successes out of 17 attempts for downtrend. The accuracy result shows 70% (28 successes out of 40 attempts) accuracy as reflected in Table 4.13. Table 4.12 on the other hand shows another prediction results using *EUR – USD* in 2012. In this case, there are 20 samples each for uptrend and downtrend. Prediction results show the direction of future trends as 13 successes out of 20 attempts for uptrends and 17 successes out of 20 attempts for downtrend. The accuracy result shows 72.5% (29 successes out of 40 attempts) accuracy as reflected in Table 4.13.

This framework proposes seven features that are shown in Table 3.3 based on LRL, K-mean and proposed segmentation algorithms to represent the trend patterns. Table 4.9 shows that our proposed features can be classified using ANN and SVM. The experimental result of the proposed feature in the second framework outperforms the candlestick feature representation for trend identification.

**Table 4.11 - Confusion Matrix Table for Future Trend Prediction Result of 40 cases using *AUD – USD* data in 2012**

**Predicted**

| Actual | Up | Down |
|---|---|---|
| **Up** | 17 | 5 |
| **Down** | 6 | 11 |

**Table 4.12 - Confusion Matrix Table for Future Trend Prediction Result of 40 cases using *EUR – USD* data in 2012**

**Predicted**

| Actual | Up | Down |
|---|---|---|
| **Up** | 13 | 7 |
| **Down** | 4 | 16 |

**Table 4.13 - Accuracy of Prediction**

| Experiment Data | Number of Tested Dataset | Accuracy Result |
|---|---|---|
| *AUD – USD* in 2012 | 40 | 70% |
| *EUR – USD* in 2012 | 40 | 72.5% |

## 4.3 Experiment Summary

From the experimental results of first proposed framework, it could be interpreted here that a match of the selected features with candlestick patterns yields poor performance in representing the financial trends. This is especially apparent when evaluated for both classifiers. The reason is due to the incorrect utilisation of selected features as input parameters, the classification of machine learning algorithms could not classified correctly with new dataset using the trained model.

According to the second proposed framework of experimental results, LRL performs well in producing trend patterns from historical financial time series data. The finding of this research has proven that the proposed features achieves better performance for classification compared to when candlestick pattern.

From the literature review, there are different types of input features were used in Kim (2003), Ni *et al*. (2011), Zhai *et al*. (2007), Rao and Hong (2010) to develop the prediction model. Overall, the accuracy rates of the prediction models are between 65% and 70%. In this research, the second framework shows that the proposed feature vector outperforms the others feature representation for identifying trend patterns in all the tests. The proposed framework has provided 71.2% accuracy (57 successes out of 80 attempts) in predicting the future trends. Furthermore, this proposed framework has proven that a fusion of technique with DTW can achieve a good prediction result.

## 5.0 CONCLUSION AND FUTURE WORK

This chapter concludes the thesis, which shows the findings through the experiments, and indicate the possible improvements for the proposed prediction model.

### 5.1 Conclusion

According to the experiment results of data analysis, it has been proven that the technical analysis method – LRL can successfully analyse trend patterns from the historical financial time series. Based on the proposed Pattern Segmentation algorithm, the results show that the algorithm has successfully identified 40 cases of different trend patterns. From the investigation, the experiment has found that the trend patterns have repeated itself in different time stamp. Hypothetically, this research also proves that the proposed framework utilised the proposed features to identify the hidden patterns in order to avoid misleading information in the prediction model.

According to experimental results for features selection, this has proven to be very important for the learning process of machine learning algorithms. This is because the machine learning algorithms are sensitive to the input parameters in the training process. The proposed features are fully utilised for providing a useful marker to identify the trend patterns as “Uptrend” and “Downtrend” over time stamp. The experimental results prove that ANN and SVM have effectively classified the patterns 100% correctness with the proposed features rather than using candlestick patterns as selected features.

The prediction experimental results have proved that the DTW and $2 \times 2$ Structure Elements algorithms have successfully predicted the following day of trends. In summary, the proposed prediction model has successfully predicted the future trend with 1.2% increase in the accuracy rate. As can be seen, the proposed prediction model significantly improves performance of the prediction, thus achieving greater accuracy.

## 5.2 Future Work

From the trend patterns, each of the “Uptrend” and “Downtrend” groups contains different types of patterns, such as “Skew Left”, “Skew Right” and “Normal”. Clustering these types of patterns into different groupings would assist the machine learning algorithms to classify the trend patterns more efficiently and with better performance. Furthermore, clustering algorithm would be implemented to cluster the different types of patterns in each group to improve performance in the learning process.

In the proposed prediction model, the performance of DTW in the prediction will be considered to be through an optimal process instead of using brute force computation to identify patterns from the database. Machine learning algorithms will be utilised to classify unknown patterns through the extension cluster groups, which will optimise the performance of DTW to calculate the shortest warping path from the database.

Since different financial time series data have different characteristics, different type of patterns will be discovered. It will be interesting to apply the proposed prediction model to predict the occurrence of these patterns. This study will be able to investigate the features selection and the behaviour of trend patterns for the performance of prediction.

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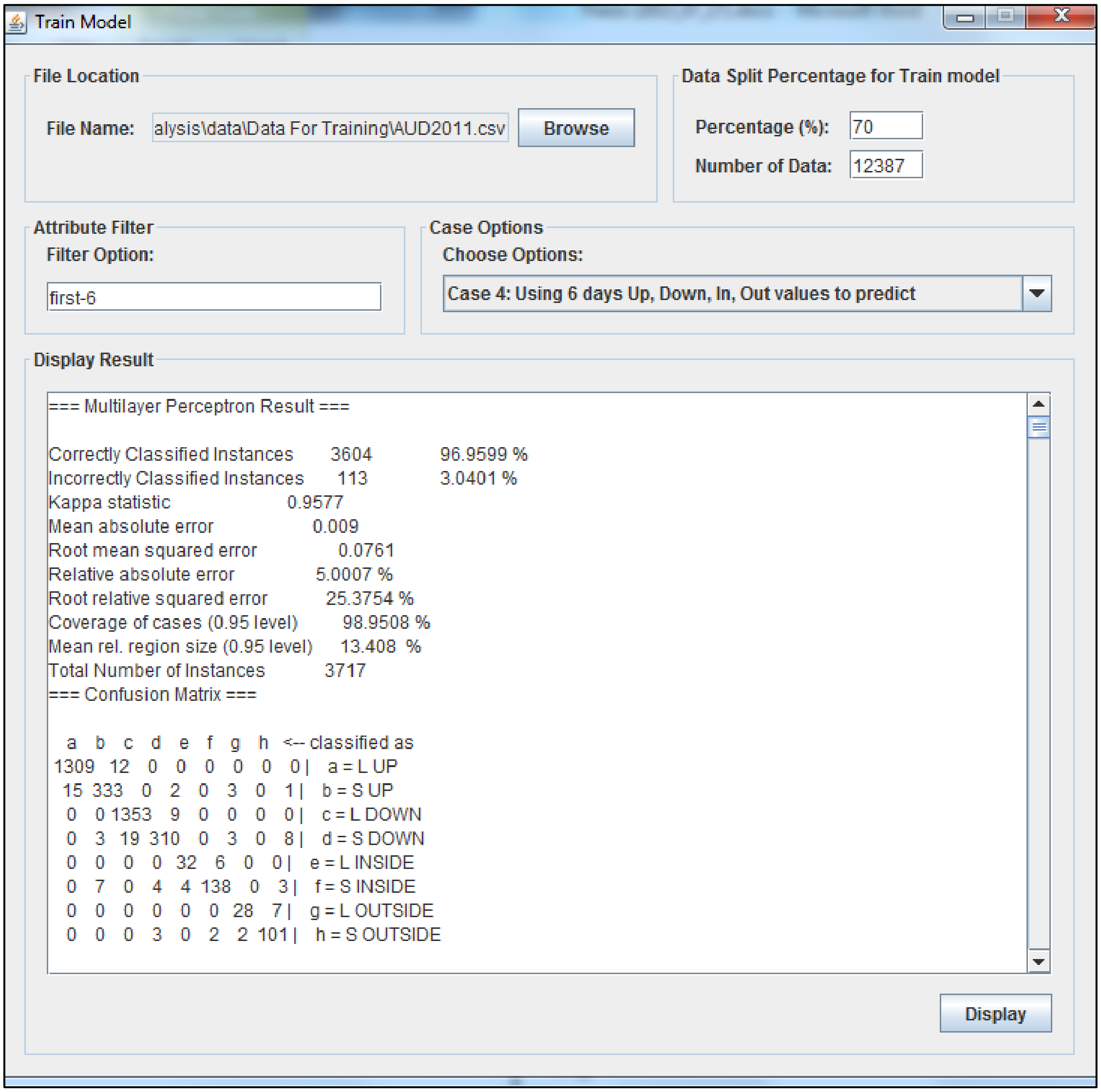
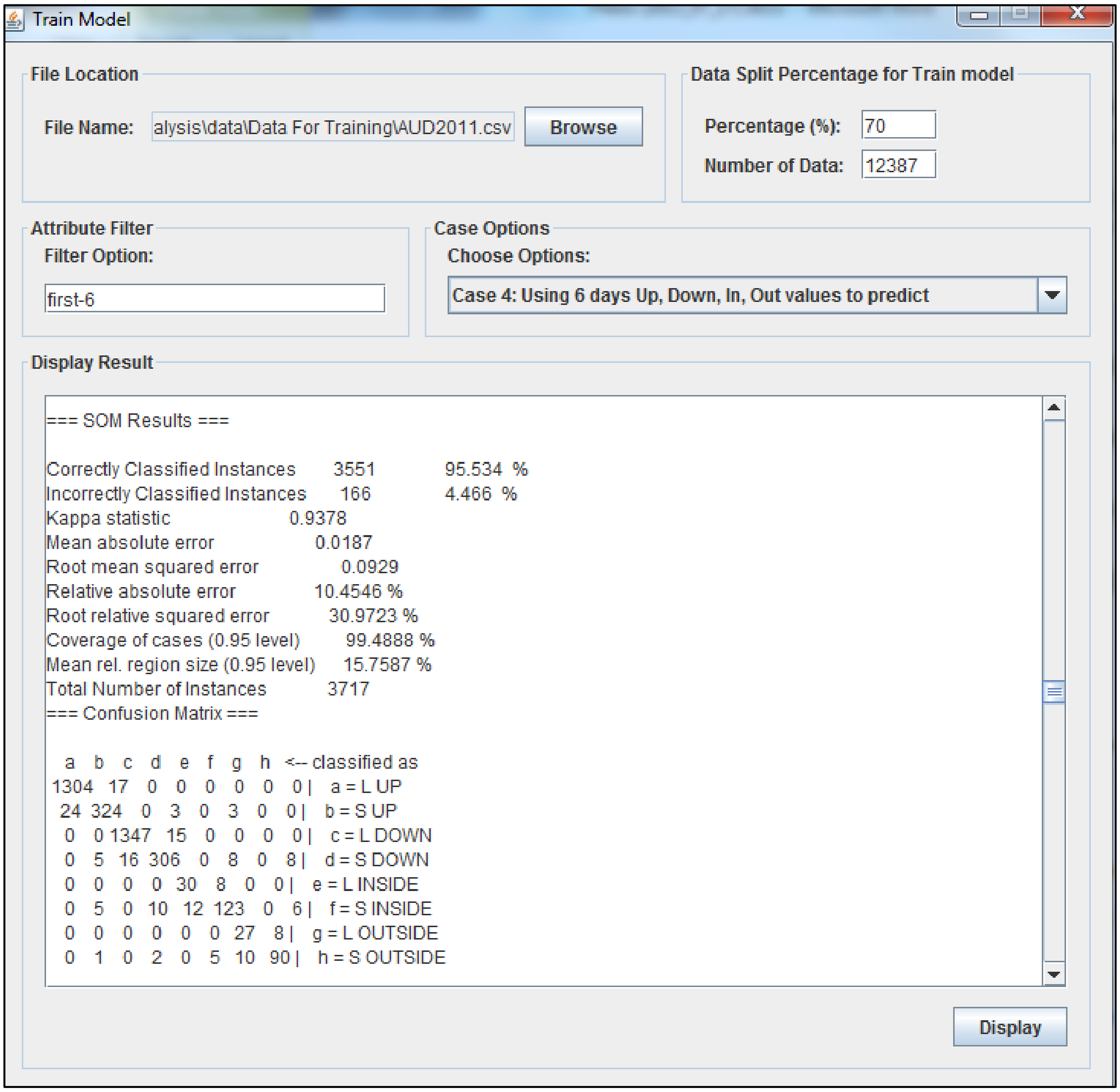
# APPENDIX

## Screen Shot – Preliminary Prediction Model

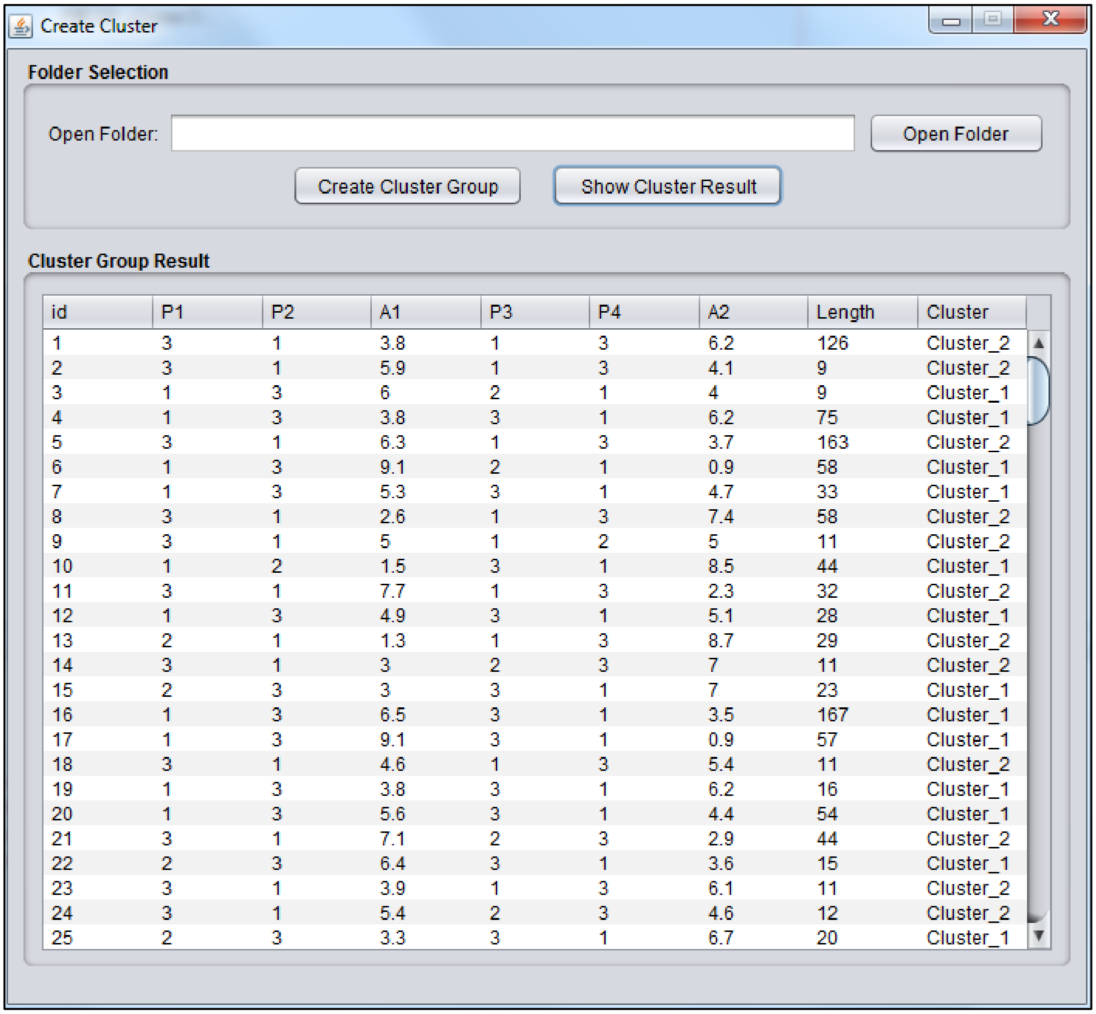



**Appendix 1 - The Learning Process of ANN using Candlestick Pattern as Features**



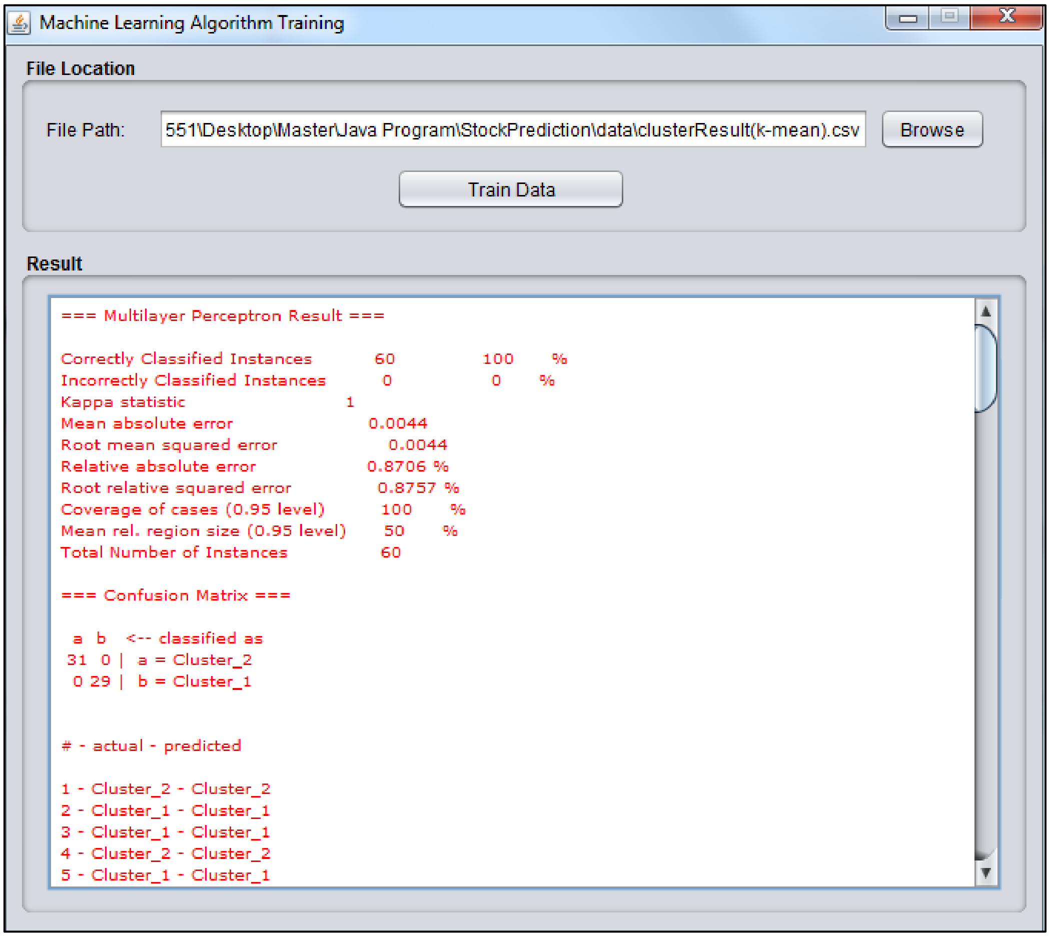

**Appendix 2 - The Learning Process of SVM using Candlestick Pattern as Features**

## Screen Shot – Proposed Prediction Model

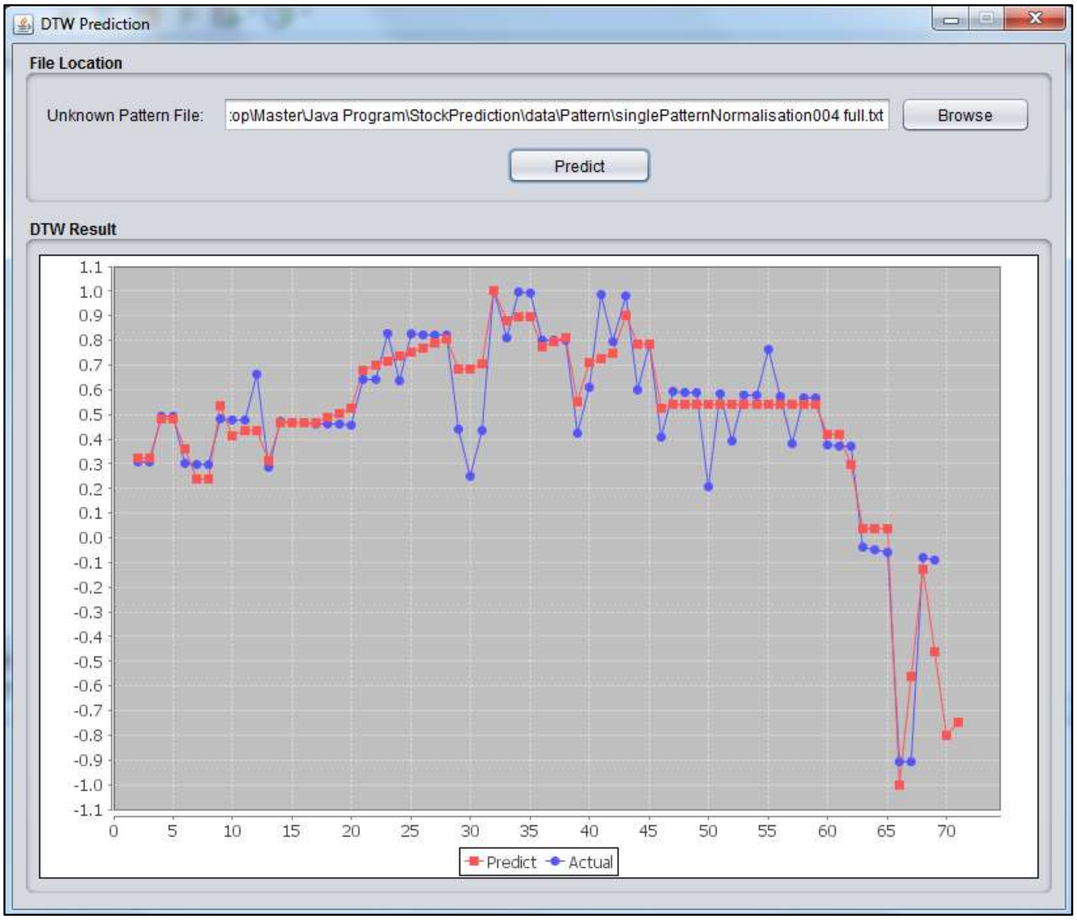



| id | P1 | P2 | A1 | P3 | P4 | A2 | Length | Cluster |
|---|---|---|---|---|---|---|---|---|
| 1 | 3 | 1 | 3.8 | 1 | 3 | 6.2 | 126 | Cluster_2 |
| 2 | 3 | 1 | 5.9 | 1 | 3 | 4.1 | 9 | Cluster_2 |
| 3 | 1 | 3 | 6 | 2 | 1 | 4 | 9 | Cluster_1 |
| 4 | 1 | 3 | 3.8 | 3 | 1 | 6.2 | 75 | Cluster_1 |
| 5 | 3 | 1 | 6.3 | 1 | 3 | 3.7 | 163 | Cluster_2 |
| 6 | 1 | 3 | 9.1 | 2 | 1 | 0.9 | 58 | Cluster_1 |
| 7 | 1 | 3 | 5.3 | 3 | 1 | 4.7 | 33 | Cluster_1 |
| 8 | 3 | 1 | 2.6 | 1 | 3 | 7.4 | 58 | Cluster_2 |
| 9 | 3 | 1 | 5 | 1 | 2 | 5 | 11 | Cluster_2 |
| 10 | 1 | 2 | 1.5 | 3 | 1 | 8.5 | 44 | Cluster_1 |
| 11 | 3 | 1 | 7.7 | 1 | 3 | 2.3 | 32 | Cluster_2 |
| 12 | 1 | 3 | 4.9 | 3 | 1 | 5.1 | 28 | Cluster_1 |
| 13 | 2 | 1 | 1.3 | 1 | 3 | 8.7 | 29 | Cluster_2 |
| 14 | 3 | 1 | 3 | 2 | 3 | 7 | 11 | Cluster_2 |
| 15 | 2 | 3 | 3 | 3 | 1 | 7 | 23 | Cluster_1 |
| 16 | 1 | 3 | 6.5 | 3 | 1 | 3.5 | 167 | Cluster_1 |
| 17 | 1 | 3 | 9.1 | 3 | 1 | 0.9 | 57 | Cluster_1 |
| 18 | 3 | 1 | 4.6 | 1 | 3 | 5.4 | 11 | Cluster_2 |
| 19 | 1 | 3 | 3.8 | 3 | 1 | 6.2 | 16 | Cluster_1 |
| 20 | 1 | 3 | 5.6 | 3 | 1 | 4.4 | 54 | Cluster_1 |
| 21 | 3 | 1 | 7.1 | 2 | 3 | 2.9 | 44 | Cluster_2 |
| 22 | 2 | 3 | 6.4 | 3 | 1 | 3.6 | 15 | Cluster_1 |
| 23 | 3 | 1 | 3.9 | 1 | 3 | 6.1 | 11 | Cluster_2 |
| 24 | 3 | 1 | 5.4 | 2 | 3 | 4.6 | 12 | Cluster_2 |
| 25 | 2 | 3 | 3.3 | 3 | 1 | 6.7 | 20 | Cluster_1 |

**Appendix 3 - Clustering Result using K – mean Algorithm**




**Appendix 4 - The Learning Process of Machine Learning Algorithms**




**Appendix 5 - Prediction Result**