FOREX TRADING PREDICTION USING LINEAR REGRESSION LINE, ARTIFICIAL NEURAL NETWORK AND DYNAMIC TIME WARPING ALGORITHMS

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ABSTRACT. Forex prediction has become a challenging task in the Forex market since the late 1970s due to uncertainty movement of exchange rates. In this paper, we utilised linear regression equation to analyse the historical data and discover the trends patterns in Forex. These trends patterns are modeled and learned by Artificial Neural Network algorithm, and Dynamic Time Warping algorithm is used to predict the near future trends. Our experiment result shows a satisfactory result using the proposed approach.

Keywords: Forex Trading Prediction; Forex Trend Patterns; Artificial Neural Network; Linear Regression Line; Dynamic Time Warping

INTRODUCTION

In the past decade, many investors were worried that their investments may not profit due to factors such as erroneous prediction, information and estimation of time. Therefore, the request has been made for prediction techniques to get better odds of profit from investments. The price in any exchange never represents the fair value in financial market due to variations in supply and demand from investors. Thus, Forex and stock prediction has become a challenging task to the Artificial Intelligence (AI) community.

Generally, the most common issue in Forex and stock prediction is that most investors are usually unaware of the behaviour and patterns of price within historical data. Since the late 1970s, researchers from the financial sector have used technical analysis methods to analyse trends for prediction (Dzikevičius & Šaranda, 2010; Maknickienė & Maknickas, 2012; Tanaka-Yamawaki & Tokuoka, 2007). However, the implementation of trends patterns as a prediction factor is suggested for improving the existing prediction result. This leads to observe the potential of historical data that discovered a unique cluster of trends patterns.

Due to the rapid growth of computing technology, AI techniques such as Artificial Neural Network (ANN), Expert Systems (ES), Hidden Markov Model (HMM) and Genetic Algorithms (GA) have been applied as classifiers in financial market to learn and predict the prices by researchers from computer science sector. These AI techniques have yielded good results over technical analysis methods, and proved that these techniques have a better approach in learning patterns and behaviours of prices for prediction (Gupta & Dhingra, 2012; Hassan, Nath, & Kirley, 2007; Lee & Jo, 1999; Yao & Tan, 2000).

Based on the history of previous experiments done in the literature, Forex and stock prediction models are still an active topic for development and improvement. This paper proposes a prediction model using machine learning algorithm – ANN, supported by

Dynamic Time Warping (DTW) algorithm and Linear Regression Line (LRL). The proposed method is to improve the existing prediction models. In this approach, LRL is utilised to analyse the trends patterns and formed general patterns of Forex trends. Then, trends patterns models are implemented by using ANN algorithm. For predicting the future trends, DTW is used to measure the similarity based on the train models.

BACKGROUND AND RELATED WORK

Linear Regression Line (LRL)

LRL is a statistical tool that uses the slopes' value of regression to identify the distance between the prices of timeline and the trend line. Slopes can be used to identify trends; a positive slope is defined as an uptrend whilst a negative slope is defined as a downtrend (Barbara Rockefeller, 2011). The following equation defines a straight line to describe the trend:

$$y = mx + b \tag{3}$$

where y – closing price, m – slope, x – the number of time frame and b – y intercept. Figure 1 shows Eq. (1) to identify the trend.
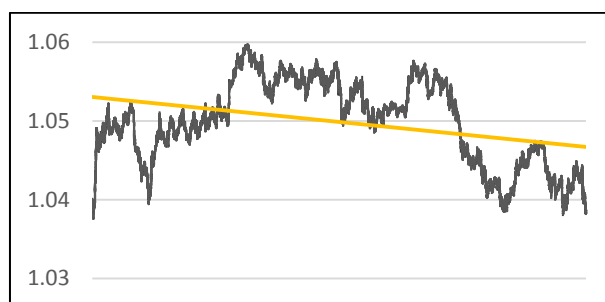
Figure 1. The Concept of LRL

According to Rinehart's experiment, he utilized regression trend channel (RTC) technique that includes linear regression line, the upper trend line channel and the lower trend line channel to analyse the stock trend for recognising the trend patterns (Rinehart, 2003). Another experiment which was conducted by Olaniyi, Adewole & Jimoh used linear regression line to generate new knowledge from historical data, and identified the patterns that describe the stock trend (Olaniyi, Adewole, & Jimoh, 2011). Both results concluded that LRL was able to identify the pattern of trend for prediction.

Artificial Neural Network (ANN) Algorithm

ANN is a field of computational science that have different methods which try to solve problems in real world by offering strong solutions. ANN has the ability to learn and generate its own knowledge from the surroundings (Alvarez, 2006). But sometimes the model can be intimately associated with a particular learning algorithm or learning rule. Generally, ANN is acts as a black box that able to classify an output pattern when it recognizes a given input pattern. Basically, ANN will learn and train based on the input values features and classify the outcome values appropriately.

According to Kamijo and Tanigawa, they had found that the ANN algorithm is able to identify and recognise candlestick patterns in the learning and training stage (Kamijo & Tanigawa, 1990). Other experiments were done by Charkha, Yao & Tan, Tiong, Ngo & Lee

and Maknickienė & Maknickas, which have shown significant results through implementing the ANN, and proved that, ANN is more consistent in recognising the patterns of stock price and Forex exchange rates (Charkha, 2008; Maknickienė & Maknickas, 2012; Tiong, Ngo, & Lee, 2012). Along with the experiment done by Lawerence, he utilised the technical analysis method – EMH (Efficient Market Hypothesis) as a source feature for ANN to test for stock price, and found that the features of stock trend must be fully understood so that ANN will learn the correct pattern for prediction (Lawrence, 1997).

Dynamic Time Warping (DTW) Algorithm

In 1983, Joseph Kruskal and Mark Liberman introduced a new technique "*time warping*" to compare and calculate the distance of curves. DTW is a time-series alignment algorithm for measuring two sequences of vector values by warping the distance until an optimal match between the sequences. Formerly, DTW has been successfully implemented in speech recognition, handwriting recognition and data mining fields in order to compare different patterns (Niels, 2004).

(a) Pattern 1   **(b) Pattern 2**

(c) Matrix of Matching Path
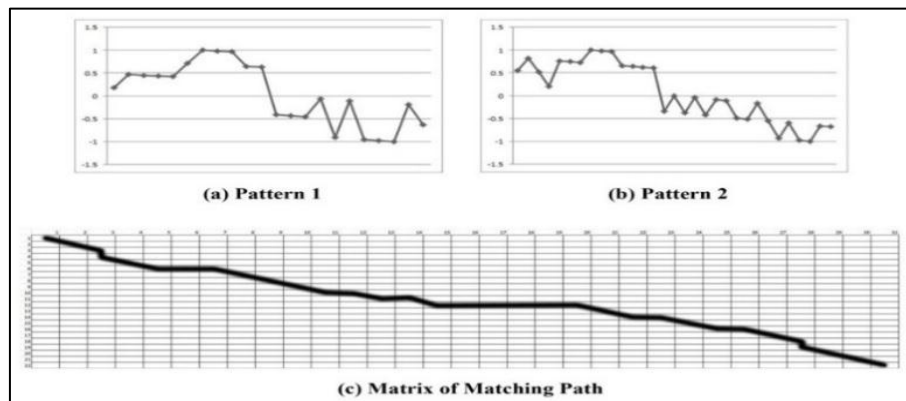
Figure 2. The Concept of Dynamic Time Warping

Figure 2 illustrates the idea and concept of DTW algorithm. Figure 2 (a) and (b) shows the examples Pattern 1 and Pattern 2 and utilised DTW to find the matching path. To calculate the warping path, DTW firstly initialises the matrix table and calculates the accumulated cost matrix by using a distance function (Albrecht & Muller, 2009). From the matrix table Figure 2 (c), it showed the result of warping path between both patterns and proves that the patterns are matched.

EXPERIMENT AND RESULT

Data Analysis Stage

In our experiment, we have selected the historical data of *Currency Exchange AUD – USD* and *EUR - USD* from the beginning of 2012 until the end of 2012 in Free Forex Historical Data website. Figure 3 showed the structure of data analysis stage.
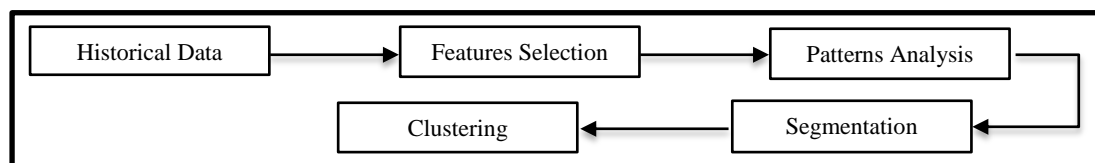
Figure 3. Structure of Data Analysis Stage

In this stage, linear regression line was implemented to analyse the dataset, representing the trend in the form of a pattern. Eq. (1) has been applied to derive a straight line through the

exchange rates of different time frames to identify the overall trend. To identify the trend, the model will utilise certain rules to segment the trend, fitting the two archetypes shown in Figure 4 and store the values of the resultant trend vector.

After the segmentation, K-Mean clustering algorithm had been applied to cluster the trend patterns into two main clusters - "Uptrend" and "Downtrend". We utilised the selected features which are shown in Table 1 to represent the patterns of trends for clustering. To identify the different types of "Uptrend" and "Downtrend" patterns showed in Figure 5 and 6, we used certain rules and conditions to cluster them.
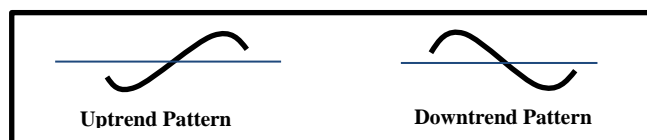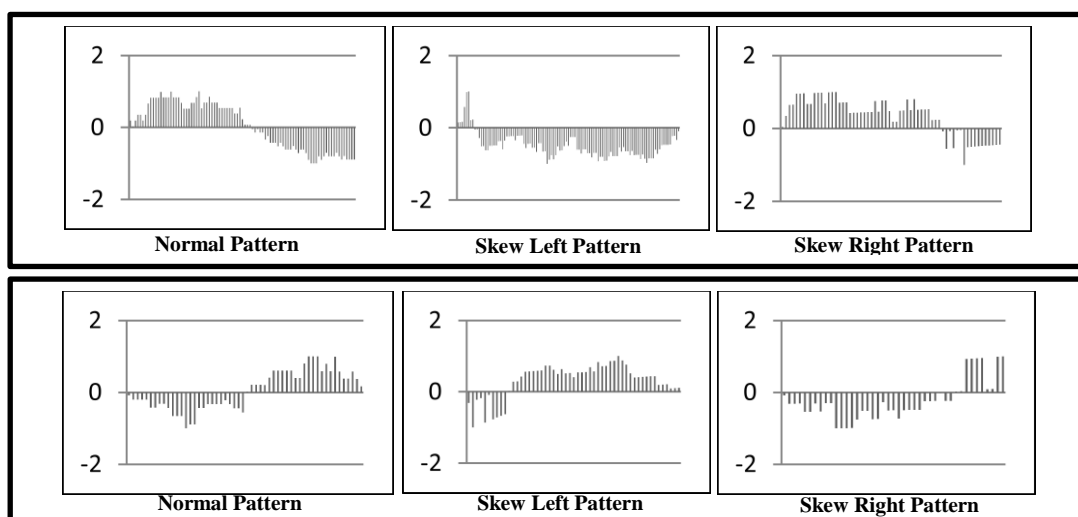

Figure 4. Example of Trend Patterns

**Figure 5. Different Types of Downtrend Patterns**

Table 6. Details of Selection Features

Attributes	Description
Feature_1	Distance between starting point to highest/lowest point.
Feature_2	Distance between highest/lowest points to changing point 1.
Feature_3	The area between starting point to changing point 1
Feature_4	Distance between changing point 2 to highest/lowest point.
Feature_5	Distance between highest/lowest points to ending point.
Feature_6	The area between changing point 2 and end point.
Feature_7	The Length of the Pattern.

Learning and Training Stage

Since the previous stage had successfully analysed the exchange rates trend patterns, we utilised ANN algorithm as classifier to learn and train with the trend patterns. Figure 7 showed the structure of learning and training stage. To determine two main clusters - "Uptrend" and "Downtrend", we implemented ANN algorithm – Multi-layer Perceptron from WEKA open source library to learn and train for the trend patterns. In our experiment, we had split the dataset into a training set and testing set, in a 7:3 ratio. In each of these clusters, we also applied ANN algorithm to learn different types of "Normal", "Skew Left" and "Skew Right" patterns. From the results of ANN classification which shown in Table 1 and 2, we used Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to prove that our ANN model can classify the patterns with the selected features.

In the experiments, we have selected the historical partial data of *Currency Exchange AUD – USD* and *EUR - USD* from the beginning of January 2013 until the end of March 2013 as unknown patterns. To predict the future exchange rate trends, we had utilized the ANN model to classify the unknown patterns belong to the specific group, and used DTW algorithm to find the matching path between the patterns. The accuracy of prediction shown
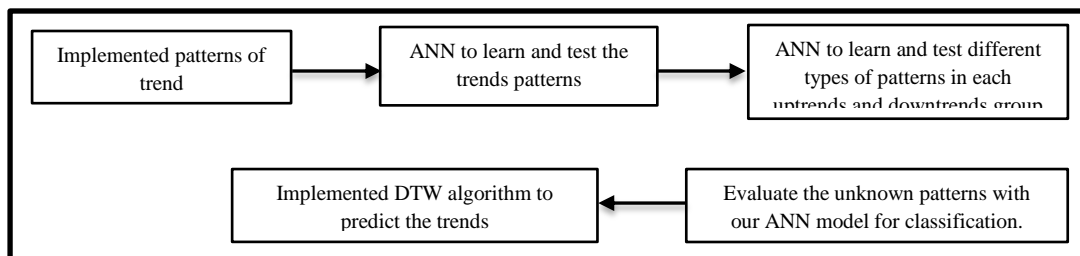
Figure 5. Structure of Learning and Training Stage

in Table 4 had successfully warped the similarity across the patterns to predict the trends.

Table 7. Result of ANN Model for classifying "Uptrend" and "Downtrend" patterns

Data	Number of Dataset		Result	
	Training	*Testing*	*MAE*	*RMSE*
AUD – USD 2012	139	60	0.005	0.0054
EUR – USD 2012	134	58	0.0048	0.005

Table 8. Result of ANN Model for classifying different types of patterns in each group

Data	Trend Group	Result	
		MAE	*RMSE*
AUD – USD 2012	Uptrend	0.0454	0.1939
	Downtrend	0.081	0.2501
EUR – USD 2012	Uptrend	0.013	0.0614
	Downtrend	0.0642	0.2283

Table 9. DTW algorithm Prediction

Experiment	Dataset	Accuracy Rate
1	AUD – USD 2013 (Jan – March)	70%
2	EUR – USD 2013 (Jan – March)	72%

CONCLUSION

The analysis method LRL that we proposed in this paper successfully analysed the trend from historical Forex data. Our experiment had shown that ANN model can classify the patterns of uptrend and downtrend, and stored the values of the resultant trend vector for DTW algorithm to predict the future exchange rates trends. In addition to this study, the selected features we used in analysis stage are very important due to the non-stationary raw data for ANN model to learn and train the trends patterns.

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