Int. J. Nonlinear Anal. Appl. 14 (2023) 1, 2587–2600
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.27602.3660

Forecasting financial time series trends by pattern recognition

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(Communicated by Madjid Eshaghi Gordji)

Abstract

Stock and price index prediction are among the main challenges for market players, traders, and economic analysts. Pattern recognition is one of the most common methods for analyzing complex data such as financial data. Elliot waves are used as one of the most robust models for predicting many markets, and it works based on a hypothesis that argued that upward and downward market price action always showed up in the same repetitive patterns. The need for expert knowledge and skills to detect these waves makes using it difficult for many traders. So far, little research has been done on the automatic identification of these waves. In this paper, we have attempted to recognize these patterns automatically and use them in predicting future upward/downward trends in prices. For this purpose, twelve patterns have been selected as representing Elliot waves. These patterns are stored in a self-organized map neural network and the network is used to identify the waves in the target stock. The proposed algorithm has been tested with several stocks from the Forex financial market. The results have an average accuracy of 93.94 percent in predicting stock trends and it indicates an improvement in prediction accuracy compared to other works.

Keywords: Elliott wave recognition, Self-organizing map neural network, Pattern recognition, Forex market
2020 MSC: 68T07, 92B20

1 Introduction

Predicting the trend of financial markets, especially the stock market, is known as one of the main goals of scientific and industrial research. To advance this aim various methods such as technical analysis [17, 21], machine learning [22, 28] and identification Pattern [18] are used. Among these methods, pattern recognition is one of the most widely used techniques in dealing with complex financial data. Pattern recognition is a branch of machine learning that receives raw data and then categorizes it according to similarities and differences. In other words, pattern recognition can be defined as data classification based on the features extracted from the original data [11]. This method is used in any field of science and engineering that studies the structure of observations. Handwriting recognition systems [10], automatic speech recognition [23], fingerprint recognition [2], medical signal analysis [12], and time series prediction [19] are examples of the most critical applications of pattern recognition.

Time series is one of the types of data that pattern recognition methods are commonly used to analyze. A time series is a collection of observations recorded over time at discrete or continuous intervals. In recent years, pattern recognition and extraction for stock forecasting as examples of time series have been widely studied and used. Most of the patterns used to forecast stocks have been extracted and exploited by stock analysts concerning stock price

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Received: February 2022 *Accepted:* June 2022

fluctuations. One of the oldest of these patterns is Japanese candles which are divided into two general categories of continuation patterns (stock continues its up/down trend) and reversal patterns (stock has the opposite behavior of the first category patterns).

Triangular, rectangular, and flag patterns are examples of continuation patterns. head & shoulders patterns, double stops, and double bottoms are examples of reversal patterns. Researches in various markets show the success of these patterns in stock forecasting. Wu et al. [26] reviewed the daily data of 25 different stocks on the Taiwan Stock Exchange and showed that these patterns have a strong ability to predict stocks. Lu and Shiu [15] also independently examined the Taiwanese markets with different characteristics and concluded that the continuous and return patterns can be used to determine the appropriate time to buy or sell stocks in the next two to three days. Research on the Shanghai Stock Exchange [27] and China [5] also show the success of these models in predicting the short-term stock market trend.

Despite the great success of these templates and their widespread use by users in stock forecasting, these templates have insurmountable shortcomings and flaws. The most significant drawback of these patterns is the incorrect performance for predicting some stocks. Marshall et al. [16] showed these patterns have no informational value and are not able to predict Dow Jones stock price. Horton [13] also examined the performance of these patterns in eight different markets and concluded that these patterns would not lead to acceptable results for predicting prices in these markets.

Other models have been proposed to solve non-responsiveness of reversal and continuation patterns problems in some markets. In 1938, based on his observations and research, Ralph Nelson-Elliott [6] proposed a theory based on price changes. He explained price movements in the form of distinct and repetitive wave patterns. These patterns are called Elliott waves. From Elliott's point of view, the characteristics of financial market movements are based on emotional, intellectual, ambiguity, and group logic. Elliott believed everything that happens in the market has its roots in the past and by analyzing past repetitive patterns, they can be linked to the present and the future [1].

The primary use of Elliott Waves is to predict future stock prices as well as to determine whether their market is bear or bull. Akdemir and Yu in [1] have anticipated the future stock price using Elliott waves and the multilayer perceptron network. Volna, Kotyrba, and Jarusek in [24], with the help of two error backpropagation neural networks, first identify the waves and then, according to the identified wave, announce that in the future, the market will be up or down. Later in [14] and [25], the same methods were used to predict the future of the stock market. In another study [20], Hopfield networks were used to identify Elliott waves and predict stock prices. In [4], a method based on fuzzy control and output-to-input feedback is presented. This method has provided one of the highest reported accuracies in stock forecasting. In [3], the combination of the ANFIS neuro-fuzzy system and Elliott waves have been used to predict stock orientation. In [30], three types of multilayer artificial neural networks with backpropagation integrated neural networks with differential evolution, and synthesized pseudo neural networks have been used to identify Elliott waves and predict stock.

In this study, Elliott waves are taught to the SOM neural network. Then in a new financial time series, Elliott waves are extracted automatically. Finally, according to the extracted patterns, the stock orientation of the next day would be predicted.

This article is organized as follows. In the second part, the basic concepts are briefly described. In the third and fourth sections, the proposed method and obtained results are presented, respectively. Finally, in the fifth section, conclusions and suggestions for future works are presented.

2 Research background

2.1 Elliott waves

The mass behavior of people is recognizable in patterns of market trends and returns. Elliott called this recognizability the law of waves. The basic principle of waves is based on five motives (impulse) marked by numbers and three corrective waves represented by letters (Figure 1). Motive waves are waves that move the price of a stock in a specific direction.

Each motive wave consists of five microwaves, which consist of three impulse microwaves and two corrective microwaves. The corrective wave also includes three microwaves, two of which are impulse and one is corrective. Impulse waves are always in the direction of the motive or corrective wave, which is one degree larger than them. It means that if an impulse wave, for example, is part of an uptrend, it is also an uptrend. Each Elliott wave is part of another higher degree wave and contains lower degree waves (Figure 2). Elliott used 9 degrees in the division of

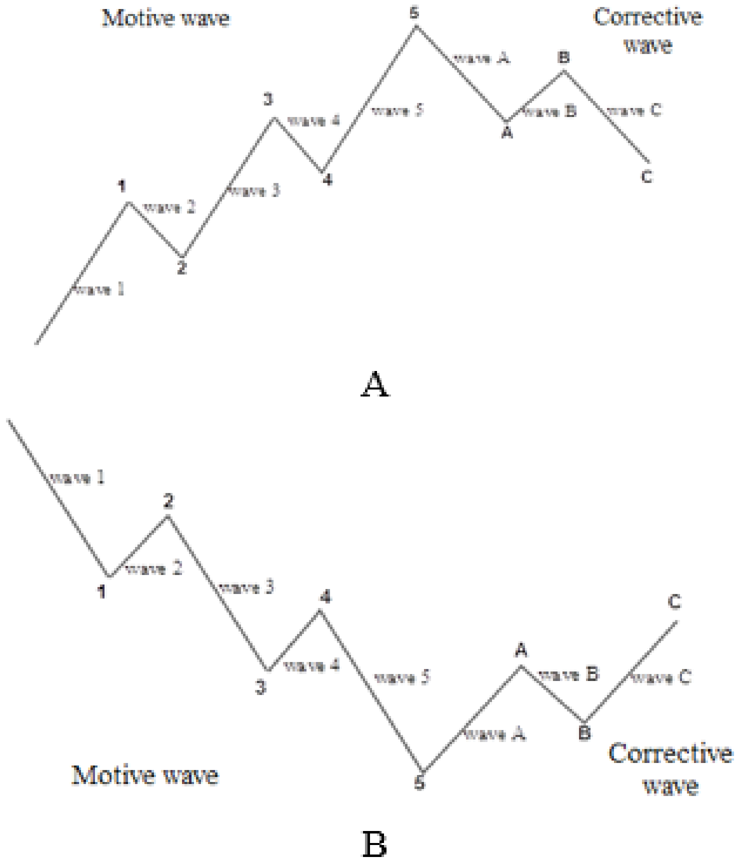

Figure 1: The complete cycle of the Elliott wave [6] : A) The primary wave (ascending), B) The reverse wave (descending)

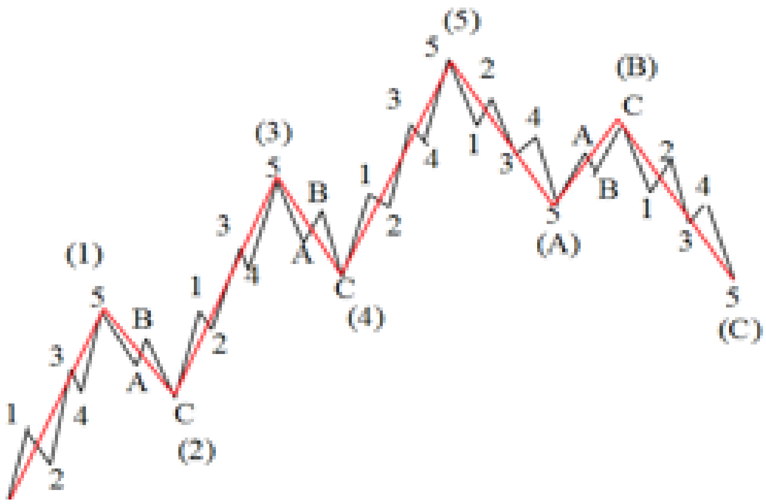

Figure 2: Different wave degrees [6]

waves for naming and identification. These degrees range from small movements in a one-hour chart to activities over several years. Later, his students and followers raised these 9 degrees in detail to 15 degrees.

Elliott waves have seven main properties to detect waves [1, 29].

Wave one: Wave one is rarely recognizable at the beginning of its operation. When a new wave starts, fundamental analysts are pessimistic about the market and do not predict a change in market trends. The previous downtrend still looks firmly ahead. Fundamental analysis still estimates lower revenue. Trading prices are likely to increase as prices rise, but this increase is not enough to alert most technical analysts.

Wave two: Wave two is the correction of the first wave, but can never go beyond the starting point of wave one. Typically in this wave, market news is still negative. Falling prices again quickly evoke previous negative emotions. However, there are some positive signs. The trading volume should be less than the trading volume in wave one. Prices usually do not fall more than 61.8% of the Wave 1 (Fibonacci relationships). Then prices enter the third wave pattern.

Wave three: Wave three is usually the largest and most powerful wave in a trend (although some research suggests that wave five is the largest in the commodity market). During this wave, positive market news and fundamental analysts begin to raise revenue estimates. Price increases are rapid, and reforms are short-lived and shallow. When wave three starts, the news is probably still bad, and most traders have a negative view of the market. But by reaching the midpoint of the wave, three more people are joining the new trend. Wave three often grows up to 1.618% of wave one.

Wave four: Wave four is clearly corrective. Wave four typically drops to less than 38.2% of wave three. The trading volume is good but less than the trading volume in the third wave. This is an excellent time to buy stocks.

Wave five: Wave five is the final wave in the direction of the prevailing trend. The market news is all positive. Unfortunately, this is precisely when many ordinary investors start buying just before reaching the maximum price. Trading volume is often lower in wave five than wave three. After a strong uptrend, we will face a downtrend.

Wave A: In Wave A, market news is usually still positive. Many analysts see the decline as a correction in the bullish market. Some technical indicators indicate growth in trading volume, an increase in implicit fluctuations in the market and possibly a turnaround in the market's future.

Wave B: A higher reverse price, which many see as a resumption of the bullish market. Those familiar with technical analysis may see the end of this wave as the right shoulder of a reversal head-to-shoulder pattern. The volume of trades in wave B should be less than wave A.

Wave C: Prices are falling rapidly. Trading volume has increased and by the end of Wave C, everyone knows that a bear market has begun. The minimum wavelength of C is equal to wave A and its maximum is usually equal to or greater than 1.618% of wave A.

It is challenging to correctly detect Elliott waves, and prices do not behave exactly according to these patterns.

2.2 General methods to identify Elliott

It is difficult to detect Elliott waves in a time series for which there are three main methods [24, 30] .

2.2.1 Detection of Elliott waves by rules

The first method of detecting Elliott waves was developed by Dostál and Sojka [30]. This method gradually divides the waves from the smallest to the largest wave. This process begins with finding a single wave and then combining the waves to create higher degree waves. Seven rules are used to detect waves grouped according to the ratio of neighboring wavelengths. These rules are written using Fibonacci ratios with a possibility of deviation of 5% of the ratios. This method is accurate but time-consuming.

2.2.2 Identify units and separate them

The second method is to classify large pieces of Elliott waves and then break them down into smaller pieces. The pattern of motive waves can be identified more accurately than corrective patterns.

One drawback of this method is that only the motive pattern can be detected directly while the corrective pattern must be derived. Another weakness is that when a large wave is detected, its internal structure is unknown.

2.2.3 Identification of Elliott waves by patterns

The third way is to limit the search to a few specific patterns of waves according to Elliott's theory. Therefore, this method is not limited to identifying single waves. One of the drawbacks of this method is that we can find many patterns of Elliott waves on the input, which is time-consuming. In this method, it is necessary to select the correct patterns for identification, and also, a suitable amount of data must be available for testing.

Due to the shortcomings of the first two methods and the strength and flexibility of pattern recognition methods, in this study, the third method has been used to identify Elliott waves. Neural networks are one of the best ways to identify patterns in different data. The advantage of a neural network is direct learning from data without the need to estimate their statistical characteristics. In this research, because of having some features such as the possibility of learning with/without an observer, the possibility of defining neighborhoods for similar categories, defining low initial parameters, and also relevant results in identifying similar data, a self-organized mapping neural network has been used.

2.2.4 Self-Organizing Map (SOM)

SOM or Kohonen networks [31] are a particular class of artificial neural networks often used to analyze the complex space of data. The basis of the operation of such networks is to convert an input with an arbitrary dimension to a smaller dimension. For this reason, such networks are considered a tool to reduce dimension.

The SOM network generally has a two-layer structure with one input layer and one output layer.

The input layer neurons are responsible for transmitting data to the network and in general, their number is equal to the input dimensions. The output layer also consists of a set of neurons arranged next to each other in a one-dimensional or two-dimensional space. The number of neurons in the output layer depends on the problem and is determined by the user. Each output neuron produces a binary number. If a neuron wins a competition for resources, it will be assigned a value of one and the output of the other neurons will be zero. For each input, the winning neuron is declared to have the most similar weight to this input. The following formula shows how to select the winning unit [3]. q Indicates the number of neurons in the output layer.

$$c = argmin_{j=1,\ldots,q} \|x_i - w_j\| \tag{1}$$

The weight vector of the winning neuron and its neighbors are modified as they move toward the current input. The weight of other neurons remains unchanged. Formula 4 shows how to update SOM weights.

$$w_j(n+1) = \begin{cases} w_j(n) + \mu_n \chi_n & j \in neihbor(c) \\ w_j(n), & otherwise \end{cases} \tag{2}$$

Variable μ_n is a learning function and usually decreases over time. The structure of a self-organizing map is shown in Figure 3. In this figure, the output neurons are in a two-dimensional space.

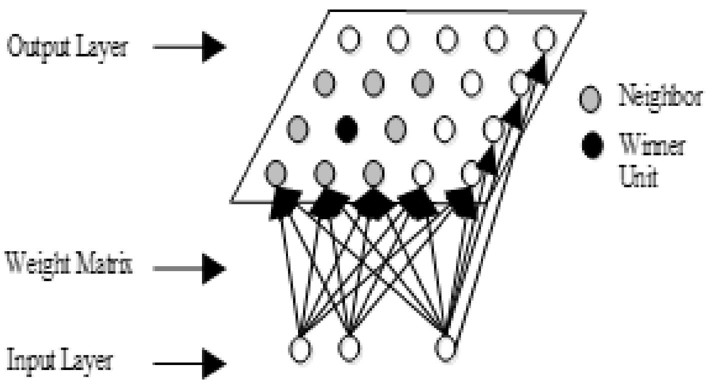

Figure 3: SOM network

3 The proposed method

The proposed system utilizes patterns to identify Elliott waves. The system consists of a preprocessing and three main parts including training, pattern identification and predicting the trend or direction of stock movement in the future. Figure 4 shows an overview of the proposed solution.

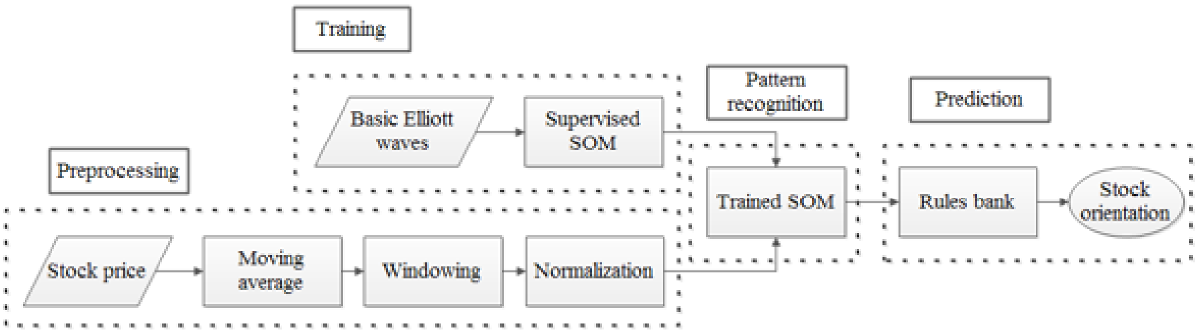

Figure 4: The proposed method

3.1 Preprocessing

The preprocessing section includes input data changes, ie, prices correction. In this research, the moving average (MA) of prices is used instead of the pure prices. The reason for this alternation is to reduce price fluctuations and to be able to predict price trends. Equation (3) is used to determine the MA, in which N displays the number of points, M represents the mean calculation interval, and P expresses the prices.

$$MA(N,M) = \frac{\sum_{i=N-M}^{N} P_i}{N-M} \tag{3}$$

Each proposed Elliott wave pattern consists of 10 consecutive points, each point having values between 0 and 1 (details are discussed in Section 3.2). Thus, the input data is divided into 10-day intervals by the sliding windowing technique, and each interval differs from the previous interval by only one day (Figure 5). Each interval will then be mapped to values between 0 and 1 by normalization. Equation (4) shows the normalization method in this research.

$$Normal(P_i) = \frac{P_i - Min(P)}{Max(P) - Min(P)} \tag{4}$$

P represents the desired price, the Min and Max function also represents the minimum and maximum price values in the studied range, respectively.

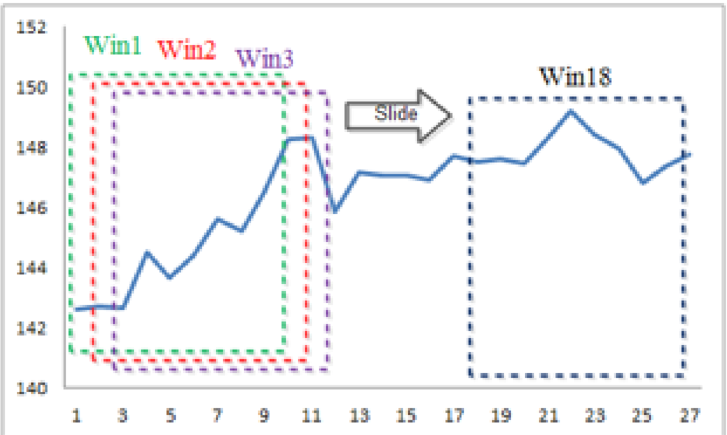

Figure 5: Sliding window

3.2 Training

The training section includes determining the appropriate patterns of Elliott waves and teaching Elliott wave patterns to the neural network, each of which is described below.

3.2.1 Determining the appropriate patterns of Elliott waves

Determining the acceptable training patterns for developing a wave detection system is an essential task that, if done incorrectly, can cause confusion and increase system error. After classifying the different Elliott waves identified in the Forex market, Volna et al. [24] proved 12 main patterns for the waves are obtained. Figure 6 shows an example of these patterns. These patterns are normalized in the range [1 0] and their complete list with letters P1 to P12 is shown in Table 1. Five motivational patterns named P2, P5, P6, P8 and P10 and four corrective patterns called P1, P7, P9 and P11. Two particular triangular patterns are corrective patterns called P3 and P4 and the primary Elliott full-wave pattern market shows with P12.

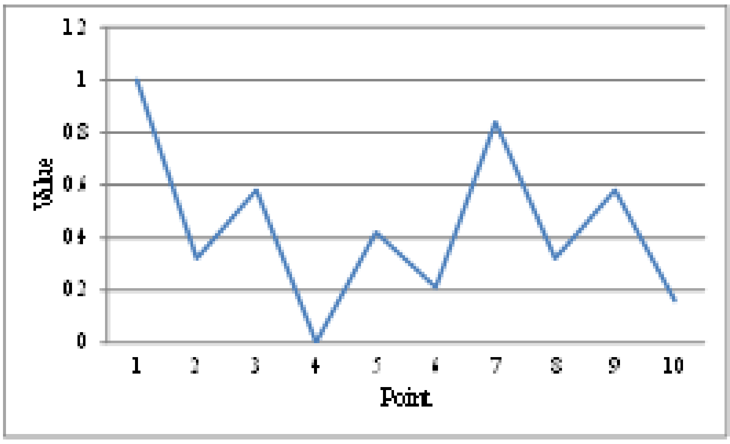

Figure 6: An example of a corrective pattern

3.2.2 Training Elliott wave patterns to the neural network

The heart of the proposed Elliott Wave Detection System is a Supervised SOM (SSOM) that trains the 12 patterns defined in table 1 and then identifies the trained patterns in the stock.

Table 1: Different types of Elliott waves [24]

	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10
P1	1	0.32	0.58	0	0.42	0.21	0.84	0.32	0.58	0.16
P2	0	0.68	0.42	1	0.58	0.79	0.16	0.68	0.42	0.84
P3	0	0.46	1	0.15	0.85	0.31	0.69	0.38	0.62	0.46
P4	0	0.33	0.17	0.67	0.50	1	0.50	0.75	0.42	0.67
P5	0	0.63	0.50	1	0.63	0.75	0.38	0.63	0.50	1
P6	0	0.39	0.13	0.58	0.45	0.74	0.61	0.87	0.71	1
P7	1	0.71	0.87	0.61	0.74	0.45	0.58	0.13	0.39	0
P8	0	0.31	0.10	0.42	0.35	0.58	0.48	0.69	0.56	1
P9	1	0.56	0.69	0.48	0.58	0.35	0.42	0.10	0.31	0
P10	0	0.24	0.12	0.36	0.24	0.48	0.33	0.83	0.64	1
P11	1	0.64	0.83	0.33	0.48	0.24	0.36	0.12	0.24	0
P12	0	0.38	0.19	0.51	0.83	0.54	1	0.71	0.90	0.64

The proposed SSOM has 10 neurons in the input layer, 12 neurons in the middle layer, and one output unit. Each output neuron, like the base SOM, has a binary output value. If a neuron wins a competition, it takes one and the output of the other neurons is zero. To better understand the proposed method, its differences with the basic SOM are described below.

1- For each input, the winning neuron is announced that its weight is the most similar to this input. Unlike the base SOM, which uses the Euclidean distance to select the most similar neurons, the proposed method measurs the similarity between the input and the desired pattern by Correlation Coefficient (CC) metric. Equation (5) shows how to calculate this criterion, in which x and w are the input and the desired pattern, and and are the averages of the inputs and patterns, respectively.

$$CC(x,w)=\frac{\sum\sum(x-\overline{x})(w-\overline{w})}{\sqrt{(\sum\sum(x-\overline{x})^2)(\sum\sum(w-\overline{w})^2)}} \tag{5}$$

The reason for using this criterion is related to the properties of Elliott waves. As described in Section 1-2, each wave experiences a percentage of change or slope relative to the previous wave. The above criterion compares the same amount of slopes instead of measuring peer-to-peer distances.

Figure 7 shows the proposed SSOM network. As shown in the figure, the P1 pattern is stored in the weights of the first neuron of the middle layer. Similarly, other patterns are stored in the network.

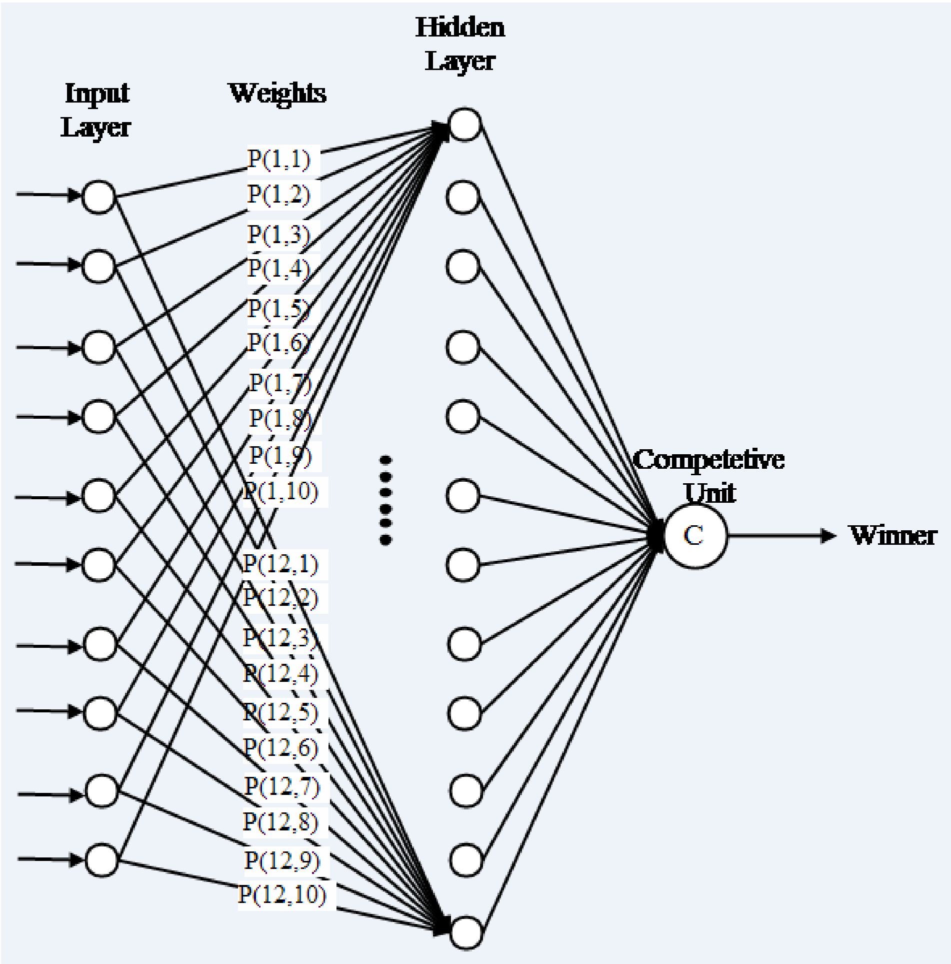

Figure 7: Internal structure of the proposed SSOM network

If the number of the winning neuron is equal to the number of the input pattern, it means that the correct neuron has won. In this case, the weight of the winning neuron and its neighboring neurons are updated as the base SOM (Equation 2). Otherwise the update will not be done. This way of weight updating acts like an observer.

3-Unlike the basic SOM, where neighborhoods are determined by how neurons are arranged, in the proposed SSOM, the definition of the neighborhood is based on the characteristics of patterns in four categories. The first neighborhood is related to motivational patterns, the second neighborhood is related to corrective patterns. The third and fourth neighborhoods also include Elliott triangular patterns and the full-wave pattern, respectively. Neurons 2, 5, 6, 8, and 10 are in the motivational neighborhood, neurons 1, 7, 9, and 11 are in the corrective neighborhood, and neurons 3 and 4 are in the triangular neighborhood. Neuron 12 also belongs to the last neighborhood alone.

4- The learning function $\mu(n)$ is also defined in the proposed method according to Equation 6.

$$\mu(n+1) = \begin{cases} 0.8 & n = 1 \\ 0.8\mu(n) & otherwise \end{cases} \tag{6}$$

The variable n represents the repetition number in the offered neural network training process.

3.3 Recognizing patterns in stocks

To recognize patterns, a ten-day period of the preprocessed stock is given as input to the SSOM network. The most similar pattern stored in the SSOM network to the input is selected as the winner. If the input similarity with the winning pattern is more than a value of α threshold, the diagnostic pattern is verified and stored, and the patterns are searched further in the share. If this similarity is less than the threshold value, no pattern is assigned to the input, and the next window, which is selected one day later than the current interval, is considered as the input.

3.4 Predicting stock trends in the future

To predict the stock trend, it is necessary to specify what trend is observed after viewing each pattern. A bank of rules is used for this purpose. Each law consists of two parts, condition and result, and can be expressed as:

If $X = P_i$ then $Y = T_j$ In this expression, X and P are the input vector the winning pattern respectively, Y is the output, and T is the stock trend. The trend can have one of two ascending or descending values. Table 2 shows the bank of rules used in this research. This bank is extracted based on the characteristics of Elliott waves.

Table 2: Rules bank for predicting stock orientation based on the discovered pattern [24]

P	P1	P2	P3	P4	P5	P6	P7	P8	P9	P 10	P 11	P 12
T	1	0	1	1	0	0	1	0	1	0	1	1

After extracting Elliott waves by the neural network from the target stocks, the stock trend is elicited the next day by the rules of the law bank, in which 1 means predicting the uptrend and 0 means the downtrend. In order to check the accuracy of the obtained results, it is necessary to examine the real trend of stocks and compare it with the desired forecast.

There are several methods for determining stock orientation. In this research, one of the most potent methods called Piecewise Linear Regression (PLR) has been used. In the PLR method, the time series under study is divided into several parts and each part is approximated separately. The number of these divisions increases until the error of approximation of each piece becomes less than a threshold value. The slope of these approximated lines shows the tendency of time series at any point [32].

3.5 Research findings

Our case study stock is a thirteen-year period from 2001 to 2014 of the AUDJPY, AUDUSD, EURGBP and EURJPY indices listed on the Forex database [9]. The Forex (also known as foreign exchange market, FX, or the currencies market) is an over-the-counter global marketplace that determines the exchange rate for currencies around the world [8]. Some of these currency exchanges are used to buy and sell goods and services, travel expenses and investments of individuals in the country. The most enormous volume of foreign exchange is done to make a profit from the difference between the purchase and sale price [7]. AUDJPY, AUDUSD, EURGBP and EURJPY show the exchange rates of the Australian dollar against the Japanese yen, the Australian dollar against the US dollar, the Euro against the British pound and the Euro against the Japanese yen, respectively. Figure 8 shows, for example, the price of the EURJPY index in the intended period.

The proposed method has three essential components including α, M and similarity criterion. In this case, after some experiments, the threshold value of α is 0.9, the mean duration M is 40 days and the similarity criterion, as

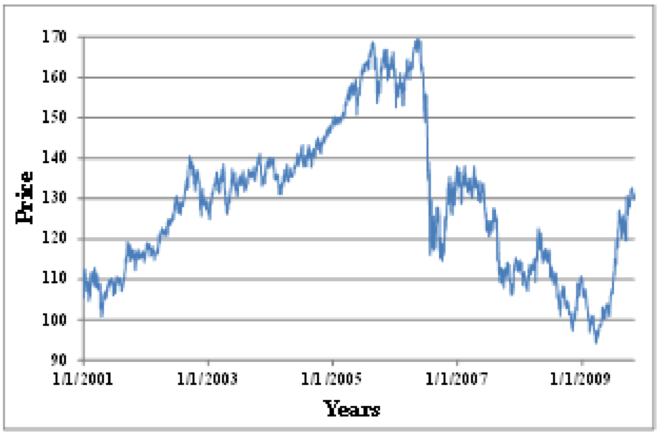

Figure 8: EURJPY stock index

mentioned earlier, is CC (Equation 5). How to quantify these values and their effect on the final results will be discussed later.

As mentioned earlier, the purpose of this system is extracting Elliott waves automatically from the price signal and predict stock trends according to these patterns. For this purpose, using a slider window with a length of 10, the prices are windowed, and each window is given to the neural network to select the winning pattern. If the similarity is greater than the threshold value of 0.9, the final winning pattern is established. Figure 9 shows four examples of selected patterns. The red line shows the main pattern and the blue line indicates the prices in the window under study. It should be noted that the use of averages instead of the original data has caused smoother price fluctuations than patterns.

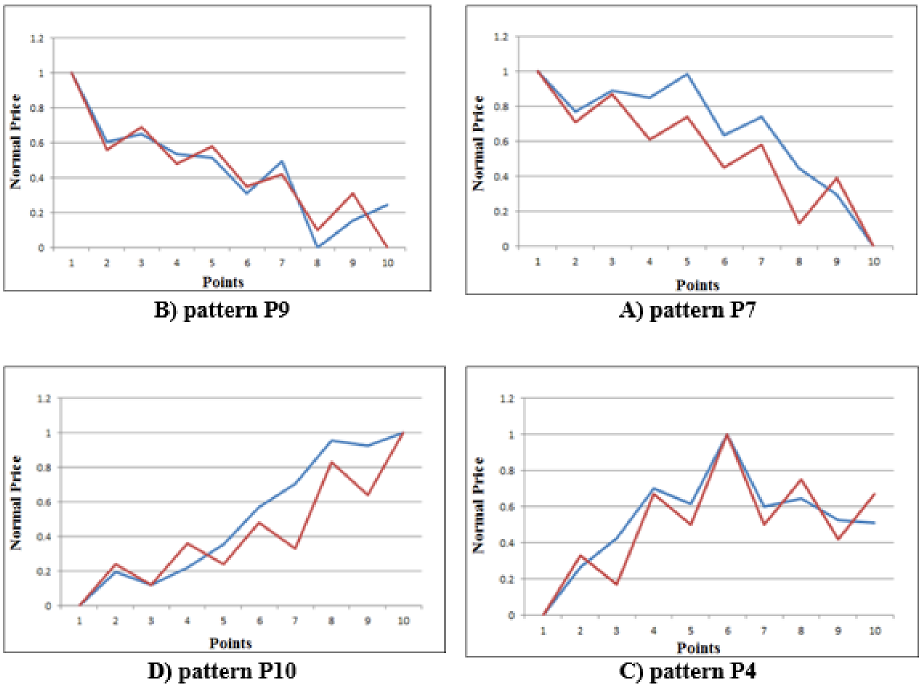

Figure 9: Four examples of patterns extracted from the price signal

Table 3 demonstrates the number of patterns extracted with respect to different values of α as well as the total number of windows studied for all stocks looked. This table shows how many windows are examined. By the proposed neural network, their similarity to the patterns is greater than the value of α. The last two rows of the table show the total extracted patterns for a particular α value and the extracted patterns for the total number of windows, respectively. As can be inferred from the table, the ratio of the extracted patterns decreases with the raising of the value of α. This decrease is significant at $\alpha = 0.9$. On the other hand, the selected value of α also affects the accuracy. This effect will be investigated later, so the value of α is chosen according to the accuracy instead of the number of extracted patterns. Table 4 shows the results obtained in forecasting stock trends. Equation (7) has been used to calculate the accuracy of the predictions.

$$Accuracy = \frac{T}{A} \tag{7}$$

In the above formula, T represents the number of correct predictions, and A means the total made predictions.

Table 3: Number of extracted patterns according to different values of α

	α=0.5	α=0.6	α=0.7	α=0.8	α=0.9	α=0.95	The total number of examined windows
AUDJPY	3458	3395	3305	3141	1577	0	3586
EURGBP	3421	3335	3224	3029	1447	0	3586
AUDUSD	3478	3423	3364	3229	1698	1	3587
EURJPY	3435	3363	3268	3096	1589	1	3587
Sum	13792	13516	13161	12495	6311	2	14346
Percentage of extracted patterns	96.03	94.17	91.62	86.99	43.94	0.01	

Table 4: Accuracy of predicting stock orientation by the proposed method

Share	AUDJPY	EURGBP	AUDUSD	EURJPY
Number of patterns extracted	1577	1447	1698	1589
The number of correct patterns predicted	1483	1370	1576	1498
Accuracy	94.04	94.67	92.81	94.27

According to Table 4, the average accuracy obtained for all stocks is 93.94%. Table 5 compares these results with the results obtained in the work of others. This comparison illustrates a significant improvement in the results using the proposed method.

Table 5: Average accuracy of stock trend prediction

Proposed method	[24]	[3]
93.94	62.4	75

4 Discussion

Many problem-solving methods have several parameters and initial components which affect the final results. In the following, how to select the components of the proposed method is examined.

4.1 The impact of threshold value

Threshold value parameter α measures the degree of similarity between the pattern and the window understudy if their degree of similarity is less than the threshold value, there is no winning pattern and the next window is examined. Table 6 shows the prediction accuracy for different values of α. As α increases, the accuracy of the prediction increases. For values greater than 0.9, according to Table 3, the number of extracted patterns is greatly reduced and almost zero, so it can be concluded from these two tables that the best value of α is equal to 0.9 in which both numbers of extracted patterns and accuracy are acceptable.

Table 6: Accuracy of stock trend prediction concerning different values of α

	α=0.5	α=0.6	α=0.7	α=0.8	α=0.9
AUDJPY	84.74	85.25	85.66	87.11	94.04
EURGBP	83.16	87.46	87.82	88.97	94.64
AUDUSD	87.50	83.13	83.87	85.64	92.81
EURJPY	85.31	84.66	86.19	86.98	94.27
Average	85.18	85.12	85.88	87.17	93.94

4.2 The impact of moving average

As mentioned earlier, a moving average price is used instead of raw prices to reduce price fluctuations. The mean interval M is one of the parameters that affect the final accuracy. Table 7 shows the accuracy of the stock trend prediction for different M values. As the value of M increases, the accuracy of the forecast also increases, but on the other hand, due to the smoothing of the stock signal, the stock trend is less sensitive to price changes. Also, after the interval of 40, the amount of differences in accuracy is relatively minor and negligible, so the value of M = 40 in this study has been selected as the optimal value.

Table 7: Accuracy of forecasting stock trend concerning different values of M

	M=0	M=10	M=20	M=30	M=40	M=50
AUDJPY	54.29	81.98	90.1	93.8	94.04	94.84
EURGBP	50.98	81.44	90.82	93.78	94.64	94.89
AUDUSD	49.15	78.18	89.12	90.73	92.81	93.81
EURJPY	42.86	78.18	91.87	92.12	94.27	95.66
Average	49.32	79.94	90.48	92.61	93.94	94.8

4.3 The impact of similarity criteria

To investigate the effect of the similarity criterion on the prediction accuracy, the correlation coefficient criterion was compared with three well-known criteria in comparing signals, namely cosine distance, Dynamic Time Warping (DTW) criterion, and Euclidean distance. To obtain the best results of each criterion, α is selected as 0.9. The results in Table 8 show that in the above problem, the use of CC criteria has led to better results.

Table 8: Accuracy of predicting stock orientation according to similarity criteria

	CC	Cosine	DTW	Euclidean
AUDJPY	94.04	89.55	87.55	92.12
EURGBP	94.64	90.88	89.37	92.36
AUDUSD	92.81	86.6	86.6	89.96
EURJPY	94.27	87.79	87.79	92.24
Average	93.94	88.7	87.83	91.67

5 Conclusions and suggestions

In this research, a method for the automatic detection of Elliott waves is presented. The proposed method is a combination of different methods of artificial intelligence. In this study, twelve different patterns of Elliott waves have been sought in stocks. The proposed SOM neural network has been used to detect these waves. The final accuracy of the proposed method is 93.94% for the four selected stocks of the Forex market.

In future research, other pattern recognition methods can be used to find patterns instead of the SSOM neural network. In addition, other stock forecasting patterns such as continuing and reversing patterns can be identified in stocks. Other stock forecasting methods such as indicators can also be used as contributing factors to increase forecasting accuracy.

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