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ELLIOTT WAVE PRINCIPLE WITH RECURRENT NEURAL NETWORK FOR STOCK MARKET PREDICTION

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ABSTRACT

Nowadays, academics and finance industries are being discussed highly in the domain of stock market trading due to which the improvement in economic globalization. Connections of stock markets are seen among various countries that develop risk factors associated with the market. Everyday rise and fall in the stock market make it a challenging area yet an important one. The increasing dynamic features and complexity of stock markets show difficulty in the industry of finance. The existing methods of inflexible trading were developed by researchers who had utilized larger features of the stock market and failed to establish effective outcomes during different scenarios of markets. Further, the existing data mining methods were inefficient and incomplete in predicting the stock market. To overcome such an issue, a stock market recommendation method based on the Elliott Wave Principle (EWP) with Recurrent Neural Network (RNN) was proposed. The proposed EWP-RNN identifies the impulse waves that sets the pattern and opposes the larger trend using EWP. The RNN assists the traders regarding the future stock trends to enhance the investment profit of a lesser period of time. The proposed EWP-RNN method utilizes the Fibonacci Series (FS) with EWP and RNN to analyze the future trends in the finance market. The proposed method achieved accuracy of 98.67% for the stock market prediction, whereas the existing BPNN showed accuracy of 92.55%.

Keywords: *Elliott Wave Theory, Data Mining method, Recurrent Neural Network, Fibonacci Series, Stock Market.*

1. INTRODUCTION

The stock market prediction indices led to difficulty in creating the financial time series for the investors and the researchers [1]. There was a difficulty caused generally by the stock market facts including the complex system of dynamic change, unstable, non-linear which are affected with various conditions such as economic policy, variation in political condition, investor's psychology, future economy [2]. The economic exchange performed amongst the countries has become better because of the financial acceleration of the global economy [3]. It is a very vast and dynamic field which makes it considerably difficult for prediction within the finance market. According to people, financial markets show high complexity due to presence of statistical and mathematical approaches that have more indices for making the trading system much effective [4]. There were certain gaps present in the financial systems of the developing countries such as India, China, and Brazil which are required to be filled [5].

With the incoming of lower interest rates, the stock market investments, provide higher rates of returns. But, the stock markets showed volatility and investors gained the excess returns by trading in real-time [6]. The stocks markets prediction tends to be a difficult task for undertaking the financial time series. The statistical model used the convention techniques but they were not having proper stock trends such as non-stationary and non-linearity in the stock markets due to which these models failed to forecast [7]. The market agent's profit-seeking action has disrupted the pattern of predictability which was raised in the time series for some time [8]. The characteristics of profit seeking includes analyzing of time series in the market for the non-stationary that is harder to forecast the temporary and the predictable model [9]. The forecasting method is used for ceasing in the stock market reached an effective hypothesis that carried out financial forecasting methods thereby making the conventional method successful [10]. Hence, a stock market recommendation system based on the EWP with RNN was proposed. The proposed EWP-RNN method informs the traders regarding the future stock trends to enhance the investment profit of a lesser period of time. The research work contributions are as follows:

- To identify the impulse waves that sets the pattern and opposes the larger trend using EWP.
- To develop RNN as it uses the sequential model for overcoming the complexity in computation.
- To hybridize Elliot Wave principle with RNN which evaluates with respect to real time series datasets to show an effective improvement and to overcome the problem of computation.

Thus, the proposed EWP-RNN method obtained accuracy of 98.67% and MAE of 0.22 better when compared to the existing models such as AG-LSTM that obtained accuracy of 90.42 % and MAE of 0.480. Similarly, the existing models showed large variations of accuracy using Generative Adversarial network (GAN) obtained accuracy of 57.10%, LSTM of 96 %, and ANN of 97.36 %.

The structure of the research paper is as follows: the section 2 is the literature review of the existing researches, section 3 is the proposed method, section 4 is the results and discussions provided for the proposed method. The section 5 is the conclusion for the present research work.

2. LITERATURE REVIEW

The existing methods that are involved for stock market prediction is reviewed in the present section. The present research includes information of similar case reports based on the stock prediction using Yahoo dataset.

Pang et al. [11] developed a deep LSTM neural network with the embedding layer for the prediction of the stock market. The developed LSTM method obtained effective information from time series of stock and predicted the immature stock markets. The developed LSTM method that showed performance lower due to non-utilization of text information fully.

Kumar et al. [12] developed a Generative Adversarial network (GAN) and Enhanced Root Mean Square Error (ERMSE) based on the deep learning model to predict the stock market price. The developed model utilized the generic model which consisted of Phase-space Reconstruction (PSR) method for the reconstruction of the price series that combined CNN and GAN model. The adversarial training forecasted the stock market which generated the new instances of LSTM based on historical data from where the information is extracted. The information is extracted and the CNN is used for the estimation whether the data predicts to be real or fake. The sufficient accuracy and low processing time was the major factor considered which affected the stock market predicting value.

Selvamuthu et al. [13] utilized Artificial Neural Network (ANN) for the prediction of the Indian stock market. The developed ANN method achieved higher accuracy in predicting, as the working of the neural networks was based on different learning algorithms like Scaled Conjugate Gradient, Levenberg-Marquardt and Bayesian Regularization, to perform stock market prediction. The result obtained from the 15 minutes of dataset showed poor performance in comparison with the tricky data.

Mndawe et al. [14] developed a framework for the stock price prediction based on the intelligent media based on the technical analysis. The text classifier was used for performing sentiment analysis based on the news data and the social media. The machine technique is used in investigation for increasing or decreasing the selected company stock on the basis of sentiment score. The results showed that machine learning model analysed and LSTM architecture included developed for technical analysis.

Albahli et al. [15] developed a novel DenseNet Model with an Auto encoder (AEI-DNET) for the Stock Market Predictions. The developed model focused on the prediction which was closer for the stock prices using the Yahoo Finance data renowned by DebseNet and AE. The Stock Technical Indicators (STIs) were initially fed as an input for the auto encoder which performed dimensionality reduction that results with lesser correlation. The investigation was needed and required fine grained historical stock market data that was unavailable with that of the current data. However, the task demand is implemented and showed an appreciable separate investigation to distinct set of experiments were needed to be performed.

Deepika and Bhat [16] developed an Accelerated Gradient Long Short Term Memory (AG-LSTM) to predict the stock market. The extracted data investigated the stock values on the basis of technical indices. The data was taken from the company's stock value in twitter, which was extracted to analyse the sentiment. The developed model used Kalman filter for the reduction of data errors that had shown sudden peaks in the data. The noise errors were smoothened by using data training and filtering approaches. The output generated is analyzed with the Kalman filter or without Kalman filter as it has increased the performances of the stock market. Yet, the model required correlation weighting features to show the improvement in terms of efficiency.

From the existing approaches, the stocks markets prediction tends to be a difficult task. The statistical model used the convention techniques but they were not having proper stock trends such as non-stationary and non-linearity in the stock markets because the models failed to forecast. The market agent's profit-seeking action has disrupted the pattern of predictability that showed lesser prediction performances.

3. PROPOSED METHODOLOGY

The theory of the Elliott Wave plays a major part in the research of the stock market field due to the capability of interpreting the psychological aspects which appear on the behavior of the market. By considering that prices of stocks are according to trends and are necessary to know the current trend direction and when it changes. The proposed EWP-RNN method is to identify the correlation among outcomes of diverse techniques together with combining for improving the results which make better forecasting for future trends in the market. The process of the proposed research work is as follows:

3.1. Dataset

Yahoo Finance is the platform of media that provides news about finance, information about stock quotes, releases from the press, and report on financial sectors. The data provided by yahoo finance are available freely. The yahoo finance Application Programming Interface (API) is utilized by yahoo to fetch the financial details. Yahoo depicted the API of finance in the year 2017. The python library “yfinance” provides the temporary fix to problems by obtaining the data from yahoo. Yahoo finance gives the access to utilize more than five years of daily Open-High-Low-Chart (OHLC) data price and also can obtain the minutes OHLC information of recent days. The yahoo finance API provides details about a summary of finance like balance sheet, earnings and stock historical prices and actions.

3.2. Elliott Wave Principle & Stock Market Forecasting

Once the data is acquired proposed EWP-RNN method performs the stock market prediction which involves the following steps:

3.2.1. Profitable Methods Based on Technical Analysis

The prediction of the stock market has become an important research topic for many years. The research scholars utilized the technical analysis oscillators and indicators to identify an effective way to predict the particular moment for buying or selling in the stock market. The technical analysis based on profitable methods is considered as Gap Analysis Patterns (GAP), Breakout Systems (BS), Market’s Mode (MM) and Momentum Precedes Price Concept (MPPC).

3.2.2. Gap Analysis Pattern

GAP is considered as a domain where trading did not occur. The GAP can give the signal of important events that occurs in the finance market based on fundamental information or the crowd’s psychology which accompanies the movement of the market. When any change occurs in the stock market or any breaking news is observed, GAP starts signaling. If information is true and stock prices evolve in the gap direction, then two possible moves are considered as Buying can be done when the gaps of market fall beyond the low in open as well as cross a day before above level. Selling can be done when the market’s gap rises above a day before high in open as well as crosses yesterday’s below close. Buying or selling can be also done when the market’s gaps go higher or lesser at some particular range of yesterday’s bellow or above the open. Hence, GAP is considered a good tool to forecast the lesser and medium stock market trends.

3.2.3. Break out System: Yahoo Finance Stock Market Data

The BS is considered among the superior methods in the technical analysis due to its capability of bearing the stocks greater than the breakout order of point for users to obtain gain on the market. The 2 classifications are distinguished in the system of breakout such as channel breakout that takes place when the trading of the stock was provided in the channel when trading begins at a higher cost than the top of the channel. Breakout volatility of buying or selling the markets breaks out system above or below the open with a specific percent of close range of previous day.

3.2.4. Market Mode

The MM includes finds market's condition such as if a particular stock is trending it will continue to consolidate or trend. The technical analysis indicators are used to make assumptions of stock markets. The most utilized indicator is Average Directional Movement (ADM) that signals the status of the market when it goes higher or lesser than the level set.

3.2.5. Momentum Precedes Price Concept

This MPPC provides whether the possible change in price will occur or not. According to the movement of the market in a single direction, it can be possible for prices to further continue in a similar direction. The single buying or selling moment takes place if the oscillator momentum is set as new higher or lower and if it is set above or below zero.

3.3. Elliot Wave Principle

Market evolves as per the patterns along with ratio which human's behavior in the trend of stock price. By considering this fact, the EWP is bilateral direction of waves such as impulse as well as corrective waves. The impulse wave is a sequence of five wave-like $1 - 2 - 3 - 4 – 5$ which follows the direction of a trend. Corrective wave consists of sequence of 3-wave such as $a - b - c$ which is in counter direction of impulse wave. The impulsive and corrective waves are utilized in the prediction of shorter and longer-term due to the establishment of the same patterns in larger or shorter scales. The Elliott has developed a hierarchy of waves according to the degrees such as Cycle, Supercycle, Grand Super cycle, Minor, Primary, Intermediate, Minute, Minuette, and Sub-Minuette. The hierarchy is considered to analyze the trends of the stock market in a shorter and medium period of time. By forecasting the trends of the stock market it is possible to identify the position of patterns by considering the following rules:

- The 2nd wave in EWP shouldn't surpass 1st wave's length, also shouldn't be able to return the price lesser than the 1st wave that is set in the beginning.
- The 3rd wave should not include a lesser length as compared with 1st and 5th waves.
- The 4th wave should not give a lesser price than the 1st wave's closing price.
- The 2nd and 4th wave includes the alternate forms.
- The 1st, 2nd and 3rd waves should include the same direction and the 2nd, and 4th waves should have opposite directions.

The impulse waves are classified as the extended wave, i.e., one of the waves such as 1st, 3rd, and 5th are extended into the structure of Elliott wave and sub-wave. When 5th wave is on a similar line with 2nd and 4th waves, the diagonal triangle occurs. 5th wave fails when the length does not surpass 3rd wave's length which results in the double top of trends.

3.4. Fibonacci within Financial Markets

EWP developed by Elliott includes an association with FS because of series which defines the static and dynamic system's behavior. Fibonacci series is series of numbers that are derived from starting 2 initial values such represented by using the below Eq. (1).

$$F_n = F_{n-1} + F_{n-2} \tag{1}$$

Where $n > 1$

The ratios evaluated by using the Fibonacci series are considered in the proposed EWP-RNN method. From 5th element, 1.618 as the ratio will be obtained if the recent number is divided by the former number. Ratio of 0.618 will be obtained if recent number is divided by next one within sequence. If the current number is divided with the previous two positions number, the ratio of 2.618 will be obtained. If the current number is divided with a number in the sequence that proceeds with two positions, then the ratio of 0.382 will be obtained. It is called Fibonacci ratios and in the EWP, the ratios are considered as primary factors in the extent of price and movements of the time in the finance market. The obtained ratios are utilized to explain the behavior of the market and to identify the waves. By applying the EWP, the ratios include the behavior such as The 2nd wave corrects 50% to 62% of 1st wave, the 4th wave corrects 24% to 28% of 3rd wave, the 3rd wave includes the length of 1.62, 2.62, 4.25 of 1st wavelength, the 5th wave depends on the 1st wave or on the length of initial 1st wave 1 that ends with 3rd wave.

3.5. Agent-Based Architecture

The architecture of proposed EWP-RNN system, on the basis of 3 important agents, is shown in Fig. 1 and the Fig. 2 is the structure of RNN. First agent blends technical forecasting techniques' series according to the breaking news or the alterations that occur within market environment with the historical information to identify the better period for buying or selling the stocks in the market and to know the status of the market.

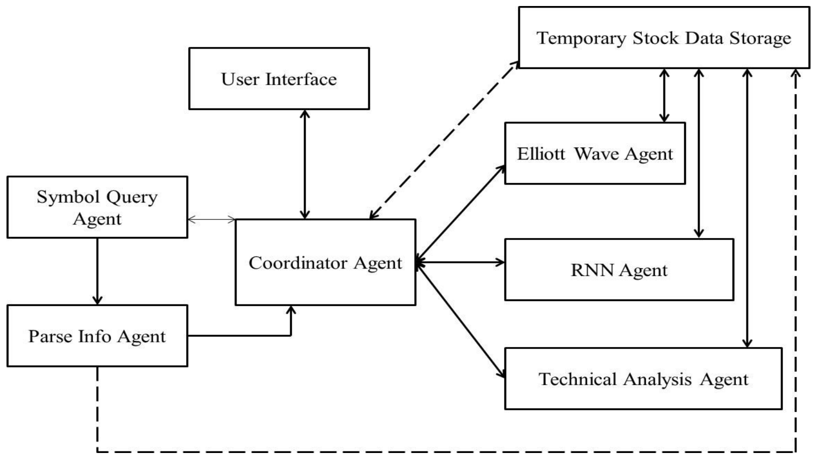

Figure 1: The System Architecture of the proposed EWP-RNN method for stock market prediction.

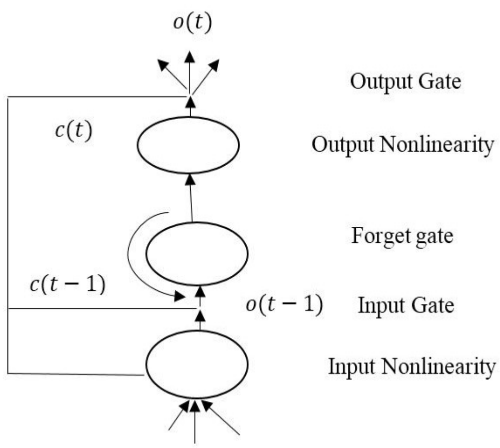

Figure 2: Structure of RNN

The second agent considers the sequential patterns in the prices of the market and identifies psychological aspects of the market's environment to forecast the trends in market. The third agent utilizes the neural networks approach which recognizes and searches for the patterns from previous information to make effective forecasting in present data.

3.5.1. Co-ordinator Agent (CA)

CA is the strength of EWP-RNN which coordinates actions and signals from other agents. Every other agent will pass their collected results to CA for effective and accurate interpretation which means that these agents will not be interpreting the outcome instead it just sends the information. The goal of CA is to establish the buying or selling signal as early as possible and to generate the prediction of a trend that makes the profit for investors in maximum approaches.

3.5.2. Symbol Query Agent (SQA)

CA begins forecasting by sending the signal to SQA by querying the database servers in stock regarding the specific shares. The service given by the SSIFBroker.ro is utilized as it is simple for downloading the previous data from Bucharest Stock Exchange Market (BSE) by utilizing Hyper Text Transfer Protocol (HTTP) portals and Comma Separated Variable (CSV) files. Market's symbol along with time period are specified in HTTP's address and the SQA is utilized to modify the downloading data from the webserver of BSE.

3.5.3. Parse Info Agent (PIA)

Then, loaded information is utilized by PIA for parsing important data as well as saving it in Temporary Stock Data Storage (TSDS). The information of stock is utilized by the other agents for forecasting the markets. When the PIA completes its task, the CA sends the signal to EWA. Technical Analysis Profitable Methods Agent (TAPMA) as well as Recurrent Neural Network Prediction Agent (RNNPA) to analyze previous data.

3.5.4. Elliott Wave Agent (EWA)

After CA provides forecasting signal, EWA analyzes the collected information from PIA in the form of the cycle and tries to analyze the trends of the market by searching for extreme higher and lower values in prices. The link of EWP forms 3rd and 5th wave structure which is utilized to predict the size or lengths of stock markets. By separating the waves and structure of waves, the

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application of EWP is formed in the pattern of recognition.

3.5.5. RNNPA

RNNPA employs a multi-layer perceptron approach with a different number of layers for the prediction of tomorrow's change in the finance market. Because of the variable layers in the network, it is easy to calculate the predicted values more accurately. By utilizing the value of maximum difference among today's close and generated value to become 1%.

Beginning from the 1st hidden layer, the RNNPA analyzes present-day's range. If 1% is unsatisfactory, then number of the hidden layer increase by one. Example: The share of a different stock from the different types of industry is required in various numbers for the layers to evaluate today's range and it is used for forecasting the upcoming values.

The RNN model has the ability to convert all the activations into dependent activations based on the same weights and the biases from all the layers. It reduces the complexity of the parameters thereby memorizing previous outputs. Each output is obtained when the input is processed in the hidden layers, into a single recurrent layer, that is represented in the Eq. (2)

$$h_t = f(h_{t-1}, x_t) \quad (2)$$

h_t is known as the current state
h_{t-1} is known as the previous state
x_t is the input state

The Activation function $\tan h$ is applied using the below Eq. (3).

$$h_t = \tan h\,(W_{hh}h_{t-1} + W_{xh}x_t) \quad (3)$$

Where,
W_{hh} is known as the recurrent neuron for the weight.
W_{xh} is the weight of the input neuron
The output is calculated by using following formula (4)

$$Y_t = W_{hy}h_t \quad (4)$$

Where Y_t is known as the output
W_{hy} is the weight at the output layer

3.5.6. TAPMA

TAPMA utilizes the interpreters of information along with various tools for identifying security which includes rising and period. TAPMA predicts the next periods by forecasting the previous information and not by pattern search. The data interpreters such as GAP, BS, MM and MPPC are utilized as technical analysis agents. Each interpreter functions in parallel mode and will not communicate with one another. After finishing the analysis, TAPMA will be responsible for the intermediate result interpretation. The GAP analysis provides the important event, BS analysis provides a signal if the moment is good for buying or selling, MM analysis provides the signal when the market is consolidating and MPPC analysis provides the signal if the price continues further similar direction.

4. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the experimental results of the proposed EWP-RNN method are described. The proposed method is applied on a computer with 8GB RAM with 2.2 GHz using Python 3.7.3. The dataset considered to evaluate the proposed EWP-RNN method is Yahoo finance stock market data which is explained in this section. The performance metrics and performance analysis for the pedagogical content classification against the existing approaches are explained as follows:

4.1. Performance metrics

To evaluate the performance of the proposed EWP-RNN method for stock market prediction. The proposed EWP-RNN method is compared with the existing techniques and it is estimated by using the various parameters that are used to check the property of the model. The performance metrics considered in the proposed EWP-RNN method is explained as follows:

Accuracy: Accuracy is defined as the total number of predictions correctly classified to the total number of overall predictions. The evaluation of classification accuracy of the model is expressed as shown in the Eq. (5).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{overall\ predictions} \quad (5)$$

Precision: Precision is defined as the truly predicted positive observations to the overall number of observations that are positive. The precision is explained in Eq. (6).

$$Precision = \frac{TP}{TP+FP}$$
(6)

Recall: Recall is defined as the number of relevant documents that are retrieved, to the total number of searches existed in the relevant documents. It is expressed in Eq. (7).

$$Recall = \frac{TP}{TP+FN}$$
(7)

F-score: F-score evaluates the accuracy of the model which is a combination of recall and precision, and is defined in Eq. (8).

$$F - score = \frac{TP}{TP+ \ /2(FP+FN)}$$
(8)

Mean Absolute Error (MAE): MAE measures all of the errors between the paired observations that express the same phenomenon. The MAE is expressed using the Eq. (9).

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$
(9)

Root Mean Square Error (RMSE): RMSE calculates the residual difference among the truth and prediction between each data points that computes the norm of residual at each data point. It computes the mean of residuals and takes the square root of that mean.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2}{N}}$$
(10)

Mean Absolute Percentage Error (MAPE): MAPE is known as the average absolute percent error which is subtracted from the time period of every instance with actual values.

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$
(11)

Where
y_i prediction value
x_i is the true value
n is the total number of data points

4.2. Quantitative Analysis

The quantitative analysis of the proposed EWP-RNN method for stock market prediction is provided in this section. The evaluation results of the proposed EWP-RNN method for stock market prediction, are shown in terms of accuracy, precision, recall and f-measure in table 1.

Table 1: The proposed EWP-RNN method results for stock market prediction.

Metrics	Proposed RNN
Accuracy	98.67
Precision	94.32
Recall	95.54
F-score	96.29

Table 2 is the quantitative analysis for the proposed EWP-RNN method in stock market prediction. The performance is evaluated in terms of accuracy, precision, recall and f-score. The proposed EWP-RNN method for stock market prediction achieved accuracy of 98.67%, precision of 94.32%, recall of 95.54% and an f-score of 96.29%. The RCNN classifier is a simple process and constructs the subsets of example that classifies the original data correctly. The graphical representation of quantitative analysis of the proposed method is shown in Fig.3.

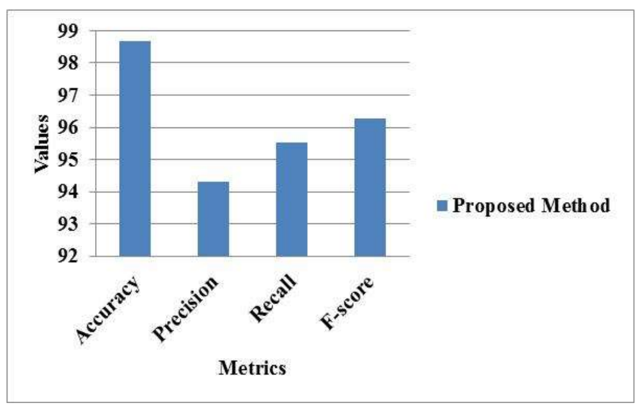

Figure 3: The quantitative analysis graphical representation of proposed EWP-RNN method for stock market prediction

Table 2: The quantitative analysis of the proposed EWP-RNN method for stock market prediction with existing techniques such as CNN, ANN.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)	MAE
CNN	89.45	86.38	87.93	88.57	0.44
ANN	90.25	87.80	88.54	89.73	0.38
Proposed EWP-RNN	98.67	94.32	95.54	96.29	0.22

Table 3: The quantitative analysis of the proposed EWP-RNN method for stock market prediction in terms of RMSE, MAPE, and AMAPE

Methods	RMSE	MAPE	AMAPE
CNN	0.542	0.45	0.37
ANN	0.523	0.43	0.36
Proposed EWP-RNN	0.022	0.40	0.35

Similarly, table 3 shows the results for the proposed EWP-RNN method stock market prediction, which are evaluated in terms of RMSE, MAPE, and AMAPE. The proposed EWP-RNN achieved accuracy of 98.67%, precision of 94.32%, recall of 95.54%, and F-measure of 96.29%. The existing Convolutional Neural Network (CNN) in the quantitative analysis showed the accuracy of 89.45%, precision of 86.38%, recall of 87.93% and F-measure of 88.57%. The existing Artificial Neural Network (ANN) in quantitative analysis showed accuracy of 90.25%, precision of 87.80%, recall of 88.54% and F-measure of 89.73%. The recurrent neural network remembers every detail effectively through the time which is utilized in times series prediction for the previous levels of inputs also. So, the proposed EWP-RNN achieved higher performance in quantitative analysis compared to existing methods. The quantitative comparison of the proposed EWP-RNN with existing methods is shown in Fig. 4 as a graphical representation.

4.3. Comparative Analysis

Table 4 shows results of the comparative analysis of existing model and the proposed method. The existing models such as GA-CNN [12] and Back-Propagation Neural Network (BPNN) [14] were compared to the proposed approach. The sufficient accuracy and low processing time was the major factor considered which affected the stock market predicting value.

Table 2 shows the results obtained by the existing models with the proposed method evaluated in terms of performance metrics such as accuracy, precision, recall and f-score. The proposed EWP-RNN method for stock market prediction is compared with existing methods such as [12] and [14] for the stock market prediction. The proposed EWP-RNN method for stock market prediction achieved accuracy of 98.67%, precision of 94.32%, recall of 95.54% and f-score of 96.29%.

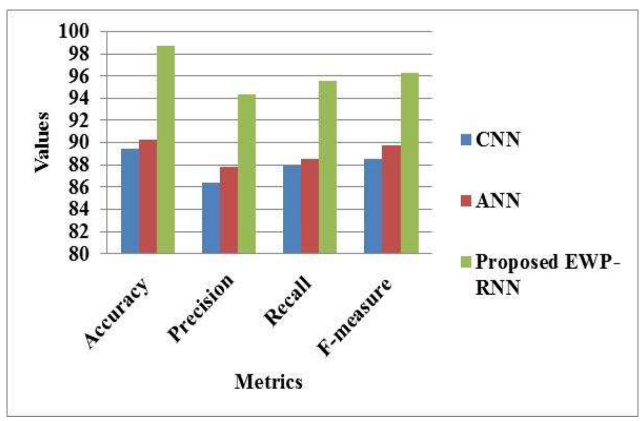

Figure 4: The graphical representation of quantitative analysis of proposed method with the existing method.

Table 4: The comparison results of the proposed method with existing methods.

Methods	Dataset	Days	Accuracy (%)	MAE	RMSE	MAPE	AMAPE
GAN and Enhanced Root Mean Square Error [12]	Yahoo Finance dataset	-	57.10	-	0.0295	-	-
ANN [13]		30	97.36	-	-	-	-
Long Short Term Memory [14]		20	96	-	0.023	-	-
AEI-DNET [15]		75	-	8.12	12.13	0.4236	0.3933
AG-LSTM [16]		-	90.42	0.2941	0.3864	-	-
Proposed EWP-RNN		20	96.27	0.54	0.0188	0.50	0.70
		30	98.67	0.22	0.022	0.40	0.35
		75	99.02	0.20	0.020	0.35	0.25

Also, the sufficient accuracy and low processing time was the major factor considered which affected the stock market predicting value thus obtained 57.10% of accuracy. Also, the task demand is implemented and showed an appreciable separate investigation to distinct set of experiments were needed to be performed obtained an accuracy of 96%. Also, [15] model required correlation weighting features required still more improvement in terms of efficiency obtained 8.12 of MAE value. Therefore, the proposed method achieved higher accuracy of 98.67 % for 30 days and 99.02% for 75 days, MAE of 0.22 better compared with the existing method.

5. CONCLUSION

With the help of the proposed EWP-RNN architecture, a novel method for analyzing previous information of the stock market is presented and it is done by combining pattern recognition techniques (such as EWP and RNN with technical analysis agents). This method proved that it can be also utilized to predict trends and buying or selling signals. By utilizing the neural network, the movement of price in the next day, as well as the buying or selling signal, is forecasted which maximizes the profits. Further, by utilizing the EWP, the investors can get a warning at the beginning of the 5th wave. By employing the architecture of multi-gent, it is possible to integrate the agents of pattern recognition which interact with each other. The Elliot wave principle map take cares of recurrent long-short term price patterns which are related to persistent changes among the sentiment. The model identifies the impulse waves that sets the pattern and oppose the larger trend. With Elliot, RNN uses the sequential model for overcoming the complexity in computation. The combination of Elliot Wave principle with RNN overcame the problem of computation evaluates the results on real time series datasets validated the effectiveness. Thus, the proposed method obtained accuracy of 98.67% and MAE of 0.22 better when compared to the existing models such as AG-LSTM that obtained accuracy of 90.42 % and MAE of 0.480. Similarly, the existing models showed large variations of accuracy using Generative Adversarial network (GAN) obtained accuracy of 57.10%, Long Short Term Memory of 96 %, and ANN of 97.36 %. Such an approach produces a more accurate yet generalized model that can be used for the prediction of the stock market.

6. LIMITATIONS AND FUTURE WORK

The work for the future will be continued in the area of the stock market in multiple ways. The incorporation of wavelet transform can be very informative for extracting new features. Additionally, an investigation of the performance of different models can be used instead of RNN.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

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