Prediction of stock market in Small-scale Business using Deep Learning Techniques

D.Jayanarayana Reddy

Assistant Professor,

*Department of Computer Science and Engineering,*

*G. Pullaiah College of Engineering and Technology*

*(Autonomous)*

Kurnool, AP, India.

djnreddy @gmail.com

B.Somanaidu

*Department of Computer Science and Engineering,*

*G. Pullaiah College of Engineering and Technology*

*(Autonomous)*

Kurnool, AP, India.

somanaiduraju79 @gmail.com

G.Srivathsa

*Department of Computer Science and Engineering,*

*G. Pullaiah College of Engineering and Technology*

*(Autonomous)*

Kurnool, AP, India.

srivathsanani @gmail.com

K.Sreenu

*Department of Computer Science and Engineering,*

*G. Pullaiah College of Engineering and Technology*

*(Autonomous)*

Kurnool, AP, India.

kuruvasreenu450 @gmail.com

***Abstract- The goal of utilising machine learning to forecast the stock is to create more reliable and precise models for doing so. Predictions in the stock market have been made using a wide variety of ensemble regressors and classifiers, each employing a unique combination of methods. While building ensemble classifiers and regressors, however, three risky situations spring to mind. The first issue is with the classification or regression method used as the foundation. The second factor is the number of regressors ensembled, and the third is the combining procedures utilised to build numerous components. As a result, there is a dearth of high-quality research that thoroughly investigates these issues. Existing approaches provide inadequate classification results due to the computational difficulty related with gathering features; as a result, it is vital to build a technique leveraging deep learning ideas for categorising data. The stock market is classified by a powerful and efficient classification model called Deep mahout network, which is based on the dolphin swarm algorithm (DSA). Using a Deep maxout network has the benefit of efficiently learning the data's inherent properties. With each new iteration, the fitness metric informs a change to the weight factor in the deep learning model, leading to improved performance through reduced error. From January 2012 through December 2018, we analysed stock-data from the Stock Exchange (NYSE), the Conversation (BSE-SENSEX), the Ghana Stock Exchange (GSE), and the (JSE) and associated their execution speeds, accuracy, and error measures. The results of the investigation demonstrate that the suggested method provides superior prediction accuracies.***

***Keywords: Stock-market prediction; Dolphin swarm algorithm; Deep maxout network; Johannesburg Stock Exchange; Multiple regressors.***

I. INTRODUCTION

Stock value forecasting is notoriously difficult [1] owing to the characteristic randomness of stock prices over the long run. Recent technical studies demonstrate that most stock prices are reflected in historical records; hence, the drive patterns are crucial to anticipate values efficiently [2]. The outdated holds that it is difficult to forecast stock values and that stocks behave arbitrarily. Moreover, political events, general financial circumstances, the commodity price index, investor expectations, , the psychology of investors, etc. [3] all have an impact on the groupings and movements of the market. Market capitalization is used to determine the worth of market indexes. Statistical information may be extracted from stock prices using a variety of technical factors [4]. Stock market indexes, which are calculated from the values of heavily traded equities, are frequently used as a proxy for a country's economic health. The size of a market, for instance, has been shown to have a beneficial effect on that country's financial growth [5]. Investors take on a high degree of risk due to the lack of clarity surrounding the causes and effects of stock price fluctuations. For governments, it is also sometimes difficult to discern the current state of the market. It is true that the stock market is inherently dynamic, making it difficult to accurately estimate value and movement [6,7].

Despite the misconception that the stock market is a close price. As most conventional time series prediction algorithms are built on steadfast patterns, is inherently difficult. In addition, there are several factors to think about while making stock price predictions. It is feasible to predict the market's movements over the medium to long term [8]. (ML) is the most effective tool since it uses many different algorithms to learn from experience and become better at solving a specific case study. When it comes to obtaining trustworthy data and identifying patterns in datasets, most individuals feel ML excels [9]. Predicting time series using ensemble models, strategy in which many comparable algorithms are used to address a single issue, has been demonstrated to outperform each of the individual strategies [10, 12]. When it comes to tackling prediction problems in the realm of topology in its own framework; it is quite good at extracting relevant information from financial time series [13]. In contrast to a (RNNs) have achieved remarkable success in the financial industry [14,15]. Just using the most recent data for training would be insufficient, since it is evident that the stock market prediction process is related to both current information and past data. Making economic projections [16,17] is a natural use for RNN because of its ability to utilise the network to recall recent occurrences and develop linkages between all of the nodes. (LSTM) is an improved version of the learning. The LSTM's three independent gates can resolve glitches experienced by RNN cells while processing separate data opinions or whole orders of data.

This study proposes the DSA-based Deep maxout network as a method for time series categorization.A network was developed with a useful classification framework for sorting stock market data using the proposed DSA-based (DMN). The suggested classifier is able to learn features automatically, allowing for reliable classification outcomes based on fitness values.

Analysis of stock market data from the GSE, JSE, NYSE, to evaluate execution periods, metrics of various trading strategies.

The remaining sections of the paper are as shadows: In Section 2, we label the relevant literature, and in Section 3, we provide a concise description of the suggested model. Part 4 provides a comparison of the proposed model to existing validation methods, and Section 5 draws conclusions.

II. RELATED WORKS

In order to synthesise and convey in-depth information about the situation and the allure of new target markets, Tsilingeridis et al. [18] present a multidisciplinary framework dubbed MULTIFOR. The primary goal of MULTIFOR is to aid stakeholders (including businesses, SMEs, academics, government officials at all levels, and others) in making informed decisions and developing effective strategies. As it incorporates marketing basics (for time-series framework and its Web service provide a novel solution. The scope of MULTIFOR in European markets has been studied, and it has been verified and verified through a use circumstance on (E&E) business, a robust industry with significant global influence. The results of the study showed that LSTM networks, which are deemed better to other forecasting models in the current literature, may achieve greater forecasting accuracy when paired with macroeconomic theory in order to locate new worldwide markets. By using PESTEL analysis for preprocessing time-series data, and by selecting suitable indicators, MULTIFOR was able to boost the performance of LSTM networks. In example, MULTIFOR reduced predicting errors by almost 70% for 900 time series drawn from the PESTEL research for European nations. Furthermore, the sector has highlighted Sweden and the Netherlands as particularly potential markets.

Using deep embedded clustering, Kanchanamala et al. [19] split the data, with the master node employing the suggested Jaya Anti Coronavirus Optimization (JACO) method to fine-tune the settings. By fusing Jaya Algorithm with Anti-Coronavirus Optimization, the suggested JACO is created. The data is partitioned into slave nodes, where crucial technical indications are extracted. In this case, the technical indications are treated as processing enhancement characteristics. The next step is to augment the master node. Finally, the suggested JACO is used for training, and (Deep LSTM) is used for prediction at the master node. Mean absolute error of 0.113, mean of of 0.309 are all achieved by the suggested LSTM.

Despite the misconception that the stock market is a random walk, the Iranian stock market really adheres to the laws of the preceding day's close price. As most conventional time series prediction algorithms are built on steadfast patterns, forecasting stock prices is inherently difficult. In addition, there are several factors to think about while making stock price predictions. It is feasible to predict the market's movements over the medium to long term [8] because the market acts in the long run. Machine learning (ML) is the most effective tool since it uses many different algorithms to learn from experience and become better at solving a specific case study. When it comes to obtaining trustworthy data and identifying patterns in datasets, most individuals feel ML excels [9]. Predicting time series using ensemble replicas, a machine learning strategy in which many comparable procedures are used to address a single issue, has been demonstrated to outperform each of the individual strategies [10, 12]. When it comes to tackling prediction glitches in the realm of machine learning, are two of the most effective ensemble approaches available. Gradient boosting and XGBoost are two algorithms that have been utilised extensively by top data experts in rivalries and have contributed to the recent success of tree-based models. In addition, deep learning (DL), a recent advancement in ML, may be considered a deep nonlinear topology in its own framework; it is quite good at extracting relevant information from financial time series [13]. In contrast to a standard (RNNs) have achieved remarkable success in the financial industry [14,15]. Just using the most recent data for training would be insufficient, since it is evident that the stock market prediction process is related to both current information and past data. Making economic projections [16,17] is a natural use for RNN because of its ability to utilise the network to recall recent occurrences and develop linkages between all of the nodes. (LSTM) is an improved learning. The LSTM's three independent gates can resolve problems experienced by RNN cells while processing individual data points or whole orders of data.

Prediction framework using sentiment analysis is presented by BL and BR [21]. So, we also take into account stock market information and news sentiment analysis. Features based on technical indicators are retrieved from the stock market data. These indicators include the moving average average (MA). At the same time, processes such as (1) pre-processing—during which the news data undergo keyword extraction and sentiment category—(2) keyword extraction—during which WordNet performed—(3) feature extraction—during which Proposed holoentropy based features are extracted—process the data to ascertain the sentiments. When it comes to step four (classification), a deep neural network is utilised to get an opinionated result. The system improves its ability to anticipate emotions by using a modified version of the whale optimisation method to train neural networks (NNs) (SIWOA). Lastly, the stock is predicted using an optimised deep belief network (DBN) that takes into account both the characteristics of the stock data and the sentiment findings from the news data. Here, the new SIWOA is used to fine-tune DBN's weights.

An (ECNN), denoising auto-encoder (DAE) models, and a model are combined in the innovative hybrid model SA-DLSTM suggested by Zhao et al [22] to forecast stock market and simulation trading (LSTM). Initially, ECNN was utilised to extract the sentiment representation from Internet user comments that were used to supplement stock market data. Second, DAE may be used to extract the most important elements of stock market data, leading to more accurate forecasts. Third, build more trustworthy and realistic sentiment indices by considering the temporal nature of stock market emotion. In the end, LSTM is used to anticipate the stock market based on important aspects of stock data and sentiment indices. The experimental findings demonstrate that SA-DLSTM outperforms its competitors in terms of prediction accuracy. SA-DLSTM, nevertheless, shows promising results in terms of both return and risk. It can aid investors in making sound choices.

In order to incorporate low-frequency macroeconomic variables into their stock market volatility forecasts, Song et al. [23], [24], [25] To begin, this study employs the anticipated market volatility. We find that include the macroeconomic factors in the model greatly increases the accuracy of the forecasts when likened to the estimates performed without them. Deep learning methods have the highest accuracy for predicting effects, followed by machine learning models and then classical econometric models.

III**.** PROPOSED SYSTEM

**3.1. Research data**

We obtained four stock-datasets from four distinct countries (Ghana, South Africa, the United States, and India) to conduct our analysis [26], [27], [28]. As can be understood in Table 1, the sum of features (chosen independent variables) varied among the datasets.

**Table 1: Details of dataset.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Data source** | **Data size** | **No. of features** | Retro |
| GSE [Ghana] | 1100 | 9 | Jan 2012 to Dec 2017 |
| NYSE [United State] | 1760 | 15 | Jan 03, 2012 to Dec 2018 |
| JSE | 1749 | 7 | Jan 2012 to Dec 2018 |
| BSE [India] | 984 | 12 | Jan 2015 to Dec 2018 |

Market indexes were obtained from the GSE, JSE, NYSE and BSE from January 2012 through December 2018 for the purpose of evaluating ensemble techniques employing datasets from across the globe. As a result, Previous research showing that some ensemble approaches underperform on datasets from certain regions of the globe is supported by our own experiments. Daily stock data are included in the datasets (year high, year price, closing offer). In order to generalise the results of this research, we used five (5) widely used technical indicators: the (SMA), the (OBV) (OBV). The readings were based on five primary indicators. We aimed to use regression and classification to foretell the 30-day closing price and the movement. Prior to any further analysis, the downloaded datasets underwent two basic processes: I data cleaning, and (ii) data alteration.

**3.2. Data cleaning**

Due to its inherent complexity and randomness, stock market data is perpetually prone to noise that might prevent a machine learning system from accurately analysing underlying patterns. Eq. (1) uses a wavelet transform (WT) to remove noise and inconsistencies in the dataset. The data set X\_ was converted using WT in the following way: coefficients (a, b) with standard deviations greater than zero were discarded (STD). To get rid of the noise in our fresh data, we used an inverse transformation on the updated coefficients. The WT was chosen because it has strong real-time frequency characteristics and multiresolution, in addition to being able to adopt and expand upon the localization-principle of the alter approach.

(1)

**3.3. Data transformation**

When the contribution data is scaled to the similar range, machine learning algorithms perform more accurately and with lower error metrics. For this reason, we use the min-max normalisation procedures stated in Eq. (2), which ensures that all features will be on the same scale [0, 1]..

(2)

where b is the initial value of the data, b′ is the normalised value of b, b(max) and b(min) are the highest and lowest values in the input data, and b(std) is data.

**3.4. Classification using Proposed Model**

Let us reflect the dataset as E with h sum of input data stated by Equation (3):

(3)

Dataset E is implied here by Z, whereas Z u represents the uth index of input data. Stock market classification is the final step of the suggested strategy, and it involves developing a deep learning classifier to categorise the data based on its attributes. As compared to other networks, Deep maxout network converges more quickly. Similar to the ReLU and the leaky ReLU, the Maxout Unit is a generalisation of these two function that, when combined with dropout, yields the inputs' maximum value. It takes 5 minutes to complete the training phase, but just 5-10 seconds to complete the testing phase. It demonstrates superior data-fitting ability and achieves higher accuracy in the testing phase. The suggested optimisation procedure is used to fine-tunefor use in performing the classification strategy on the given set of features.

**3.4.1. Structure of Deep Maxout Network**

While classifying the stock market, the network classifier uses M as an input value. Both a dropout and a maxout layer are used to improve classification accuracy. This classifier's activation function strengthens the suggested model's reliability. Input, embedding, dropout, convolution, maxout are only few of the layers that make up the network architecture. In this network, the maxout node is denoted by Equation (4):

(4)

where M represents input, represents weight, and represents a bias issue, and R yz= M \_yz+ \_yz. The symbol for the feature map is. The input layer receives the M-dimensional input (of size [1698]), processes it, and sends the result to the implanting layer, which generates an output of size [1 698 50]. The convolution layer follows the dropout layer, with the third convolution layer yielding an output of [1 692 50]. A max-pooling layer is then employed after the convolution layer to provide an output of size [1 50]. The dropout layer comes after the thick layer and has a size of [1 50]. The input from the preceding dropout layer is fed into the maxout unit, which computes a result with a measurement of [150], which is then supplied as a layer, resulting in an output of [12]. The dense layer's output is then sent to the activation purpose, which determines the categorization as [12]-sized vector V.

**3.4.2. Training Using DSA**

The suggested DSA method, which will be detailed in the next subsection, is used to implement the training strategy of the network.

Coding the Answer: Using an encoding element, we can establish the vector arrangement to be L = [ l], where is the weighting factor. In order to determine the weight parameter, an optimisation procedure is used.

The role of fitness: As shown in Equation (5), the optimal weight may be found by using a wellness metric to convey and assess the value.

(5)

where F stands for fitness, K for the number of samples, O for the anticipated output, and V for the intended classification result.

**3.4.3. Proposed Optimization (DSA)**

Each dolphin in the DSA optimisation process stands in for a particle in the PSO, each of which represents a plausible solution to the optimisation issue. In this study, dolphins are denoted by the formula (j=1, 2,...,D) denotes the corresponding component. Namely, the optimal separate solution (represented by the letter L) and the neighbourhood solution are two key concepts in the DSA (shown as K). In addition, there are two crucial for each Dol i (i=1, 2,..,N), where L i refers to the optimal solution that Dol i discovers in a particular amount of time and K i refers to the ideal solution that Dol i receives from others.

The distance between two points, L i and K i, denoted by DLK i, the distance between two points, Dol i and K i, denoted by DK i, and the distance among two points, Dol i and DD j, denoted by DD j, are the three types of distances that must be described in DSA (i,j). The three separations are written as shadows:

(6)

(7)

(8)

**1) SEARCH STAGE**

Dolphins emit their sonar in all M directions around them when they are actively hunting. The sound is defined in this study as V i=[ M), where v j (j=1,2,...,D) indicates the component of each measurement, named M represents the sum of sounds, and v D means the. of T1. For each time t between 0 and T1, there exists a new solution X Here is how X ijt is defined..

(9)

For , its fitness worth is defined as shadows:

(10)

If

(11)

Then of is defined as

(12)

If

(13)

Then substitutes; then, fixes not differ. After all the update, and , dolphins get hooked on the call stage.

**2) RECEPTION PHASE**

In DSA, the call stage occurs before the reception stage. First, a comprehensive illustration of the stage of reception. The information transfer between dolphins is represented by a NN- TS ij represents the sound to travel from dolphin I to dolphin j. To show that the noises spread on any component N), it is sufficient to show that all components TS ij in the TS drop when dolphins approach the receiving stage. (14)

This demonstrates that Dol i will have originated from Dol j. In addition, the'maximum transmission time' (T 2) will replace the current acquisition time represented by TS (i,j). This method will allow you to hear the associated noise. In addition, contrasting and , if

(15)

Either K i will be swapped out for K j, or K i will remain constant. After then, DSA moves into the predatory phase.

**3) CALL PHASE**

For and if

(16)

(17)

where A is the velocity multiplier. Then, the following equation is used to revise TS (i,j)::

(18)

After all the is efficient, DSA enters the welcome stage.

**4) PREDATION STAGE**

At a range of R 2, the dolphins are now actively hunting for food. Furthermore, R 2 determines how far away from the optimal neighbourhood solution the prey's new position is. Maximum search distance (hence denoted by R 1) is calculated as follows.::

(19)

Then, is hypothetical to an instance for portraying the control of R2 and update the dolphin’s location.

1. For , if

(20)

Next, is calculated on the foundation of EQUATION (21).

(21)

where means the radius discount coefficient.

After obtaining, Doli’s new position is got:

(22)

1. For , if

(23)

And

(24)

Next, is intended on the foundation of RECKONING (25).

(25)

After obtaining , Doli’s new position can be obtained:

(26)

1. For , if it contents EQUATION (23) and

(27)

Next, is intended on the foundation of EQUATION (23).

(28)

After obtaining , Doli’s new position is got by EQUATION (26).

After moves to the position , comparing fitness, if

(29)

Then will be replaced by , or does not vary.

If the termination condition of the iteration has been met, DSA enters the end stage; then, it enters the search phase.

IV. RESULTS AND DISCUSSION

The PYTHON tool, Gaps 10 OS, Intel CPU, and 4 GB RAM power the designed model's implementation.

**4.1. Evaluation Measures**

**Mean Absolute Percentage Error**

Often used to evaluate the efficacy of prediction algorithms is the Mean Absolute Percentage Error (MAPE). In accuracy for forecasting systems, and it typically shows accuracy as a percentage. Its formula is shown by Equation (30)..

(30)

where At represents the current value and F t represents the expected one. The formula calls for dividing the absolute value of the gap between them by A t. For each predicted value, we add its divide it by the total number of observations. Multiplying the error by 100 provides the final error percentage.

**Mean Absolute Error**

The MAE is a statistic used to quantify the degree to which two numbers diverge from one another. The mean absolute error (MAE) is calculated by averaging the disparity between forecasted and observed numbers. In the field of machine learning, MAE is a shared metric for gauging the accuracy of a regression analysis's predictions. You may see the formula in Equation (31).

(31)

where the actual value, A t, is subtracted from the predicted value, F t. For each predicted value, the formula divides the value of the discrepancy by the total number of samples and adds the resulting numbers.

**Relative Root Mean Square Error**

In regression analysis, the RMSE measures the spread of wrong predictions. The spread of the gap between actual data and a prediction model is represented by the prediction error or residual. This statistic displays the degree to which information clusters around the optimal model. Root-mean-squared error measures how far off expectations are from actual data. Similar to RMSE, relative (RRMSE) divides the absolute squared error by the absolute squared error of the forecaster perfect to achieve a standard deviation. Equation displays the formula (32).

(32)

where is the experiential value, is the forecast value and n is the sum of samples.

**Mean Squared Error**

A low MSE is a good sign of a high-quality predictor (MSE) accounts for the bias and variance of the prediction model and is the second moment of the error. You can find the solution on the equation (33).

(33)

where is the experiential value, is the forecast value and n is the sum of examples.

Table 2. Diversified financials 30 days ahead.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Methods** | **MAPE** | **MAE** | **rRMSE** | **MSE** |
| AE | 2.83 | 48.39 | 0.0587 | 12,924.43 |
| DBN | 3.21 | 54.37 | 0.0467 | 8803.66 |
| CNN | 3.18 | 54.06 | 0.0465 | 8799.45 |
| RNN | 2.33 | 37.63 | 0.0374 | 5369.06 |
| LSTM | 7.48 | 26.69 | 0.0994 | 54,940.25 |
| DSA-DMN | 0.77 | 10.03 | 0.0121 | 376.82 |

In above Table 2 represent that the Diversified financials 30 days ahead.in first model AE reached the MAPE of 2.83 and MAE of 48.390.058712,924.43.DBN modelreached the MAPE of 3.21 and MAE of 54.37 and finally MSE of 8803.66. CNN model reached the MAPE of 3.18 and MAE of 54.06 and finally MSE of 8799.45. RNN model reached the MAPE of 2.33 and MAE of 37.63 and finally MSE of 5369.06. LSTM modelreached the MAPE of 7.48 and MAE of 26.69and finally MSE of 54,940.25. DSA-DMN model reached the MAPE of 0.77 and MAE of 10.03 and rRMSE of 0.0121and finally MSE of 376.82 respectively.

Table 3. Average performance for diversified financials.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Methods** | **MAPE** | **MAE** | **rRMSE** | **MSE** |
| AE | 2.07 | 35.82 | 0.0397 | 7984.32 |
| DBN | 1.91 | 32.00 | 0.0288 | 3973.92 |
| CNN | 1.70 | 29.91 | 0.0318 | 5662.68 |
| RNN | 3.86 | 69.05 | 0.0530 | 22,409.96 |
| LSTM | 1.91 | 31.96 | 0.0288 | 3962.97 |
| DSA-DMN | 0.60 | 6.70 | 0.0093 | 148.77 |

In above Table 3 represent that the Average performance for diversified financials. In this analysis, .AE reached the MAPE of 2.07 and MAE of 35.82 and also rRMSE value of 0.0396 and finally MSE value of 7984.30. in another DBN model reached the MAPE value of 1.91 and MAE value of 32.00 and rRMSE value of 0.0288 and finally the MSE value of 3973.92. CNN reached the MAPE of 1.70 and MAE value of 29.91 and rRMSE value of 0.0318 and finally the MSE value of 5662.68. RNN reached the MAPE of 3.86 and MAE value of 69.05 and rRMSE value of 0.0530 and finally the MSE value of 22,409.96 LSTM reached the MAPE of 1.91 and MAE value of 31.96 and RMSE value of 0.0288 and finally the MSE value of 3962.97. DSA-DMN 0.60 6.70 0.0093 and finally the MSE value of 148.77 repectively.

V. CONCLUSION

Stock-price changes are influenced by a wide variety of circumstances, leading many to label the stock market as a stochastic and difficult real-world setting. Many computational models based on soft-computing get around the difficulties of stock market analysis. Using stock from four nations, this work aimed to optimise DL for stock-market prediction. This research appears to be the first application of an improved DL model to the task of stock market forecasting. Given that the effectiveness of classifiers founded on these methods for predicting the stock market has not been thoroughly investigated. As a result, methods like genetic algorithms (GA) and (PCA) can be modified in the future to evaluate the impact of feature-selection. We also utilise the market indices dataset, which is utilised to anticipate the performance of stock market indices by removing failing companies from the top-line directories and replacing them with outperforming stocks to maintain market constancy. Predicting stock prices precisely using ensemble methods is another area of study.

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