RNNLBL : A Recurrent Neural Network and Log Bilinear based Efficient Stock Forecasting Model

Uma Prashant Gurav, S. Kotrappa

***Abstract:** Recent years have seen the wide use of Time series forecasting (TSF) for predicting the future price stock, modeling and analyzing of finance time series helps in guiding the trades and investors decision. Moreover considering the stock as the dynamic environment, it is pronounced as the non-linearity of time series which affects the stock price forecast immediately. Hence, in this research work we propose intelligent TSF model, which helps in forecasting the early prediction of stock prices. The proposed stock price forecasting model employed both short-term (i.e. recent behavior fluctuation) using log bilinear (LBL) model and long-term (i.e., historical) behavior using recurrent neural network (RNN) based LSTM (long short term memory)model. Subsequently, this model is mainly helpful for the home brokers since they do not possess enough knowledge about the stock market. Proposed RNNLBL hybrid model shows the satisfying forecasting performance, these results in overall profit for the investors and trades. Furthermore, proposed model possesses a promising forecasting in case of the non-linear time series since the pattern of non-linear pattern are highly improbable to capture through these state-of-art stock price forecasting models.*

***Keywords :** Recurrent Neural Networks, Long short term memory ,Log Bilinear model, machine learning, prediction system, stock price forecasting, time series.*

I. INTRODUCTION

Financial markets generates large amount of data every day and considered as highly volatile, moreover the investment can be defined as the commitment of any resources such as money for future return and stock is one of them. Stock has been very popular in past few decades and it is one of the popular financial market, however it changes on a rapid manner [1]. The definition of stock is given through the various organization; moreover, the stock can be defined as the capital participation of any enterprise or an individual in a company. Stock market gives an opportunity for companies and broker on the neutral ground [2]. Moreover, stock price is predicted mainly to determine the company's future value or the other financial assets that can be marketed on the exchange [3][7].

Revised Manuscript Received on February 28, 2020.
* Correspondence Author
Mrs. Uma Gurav*, Assistant Professor, Department of Computer Science and Engineering, V.T.U , Belgaum, India.
Dr. Kotrappa S., Professor, Department of Computer Science and Engineering, K L E's Dr MSS College of Engineering & Technology, Belgaum, India.

Meanwhile it is also observed that the stock market is heavily characterized through the various properties such as high frequency MC (Multi-polynomial Component), nonlinearities and discontinuities since fluctuations occurs due to the various scenario such as political changes, Country economic conditions and the expectation of traders[4][17], hence it is highly improbable to predict the stock values.
Moreover the investors buy the stocks which deals with the infrastructure projects, construction firms, contractors hiring, paperwork handling. Furthermore, if the market directions are predicted absolutely then the investors can get better guidance and receive the substantial monetary rewards. However, considering the today's dynamic environment prediction has become an essential part of the stock market. Furthermore, prediction of the stock prices are also important considering the sudden decline in the market.
Time series data plays an important role in investment and financial research, hence these data needs to be analyzed carefully. In recent, several researchers have taken the various approaches to elaborate the financial data, one of the approach is modeling approach. Modeling approach gives the way to learn the data and make predictions [5]. The data used here is known as modeling FTS (Financial Time series)-data, this is similar to the modeling signals used in the engineering applications. For instance, during the noise presence, filtering approach such as particle filter and Kalman filters are applied to the financial data [6], [7]. Meanwhile signal-processing community has come up with the modified modeling approach named as Bayesian nonparametric modeling; this can provide us more flexibility like other model such as CP (Copula Process) [8], and GP (Gaussian Process) [9]. Moreover in last decades, researchers have more focused on the volatility modeling, it is one of the active financial time series [10], the main advantage of volatility modeling is that it can be applicable for both i.e. academic researcher as well as finance market practitioners. Volatility modeling can be calculated as SD (Standard Deviation) of the asset return and it can easily describe the variability in FTS (Financial Time Series)-Data [11]. In [12], time series forecasting represents the information providence and supporting subsequent decision, furthermore the time series analysis mainly focuses on dependence relationship in historical data. Forecasting model can be categorized as linear and non-linear. Traditional statistical models which were followed in past were linear, and uses the statistical mode in time series forecasting.

Several conventional modeling techniques namely Box-Jenkins AIM (Auto Integrated Moving) average were used, however they were not accurate in SMP (Stock Market Price) forecasting [13].

Machine Learning has played crucial role in almost every area including some of the critical application, the algorithm such as SVM (Support Vector Machine) gives the various feature and perform the fast computation when compared to the ANN (Artificial Neural Network). Moreover, SVM not only tolerates the chaotic components and noise but also they are non-sensitive for assumption in error terms. Some of the research have also indicated the superiority of LSSVR over SSVR to estimate the cost of product [14] and the energy utilization [15], it is observed that LSSVR focuses on solving the linear equations and it is more preferable for LSR (Large Scale Regression) [16], since TSD (Time Series Data) is computed through the regression analysis. However LSSVR efficiency depends on the tuning parameter, tuning parameters are kernel function and regularization parameter. Meanwhile any inappropriate setting in parameter leads to the disaster performance of model; hence, parameter setting is the real scenario optimization problem. Moreover, to address this issue, [17] proposed the direction forecasting loss and forecasting error loss and it is observed that GA (Generative Adversarial) training can be applied to integrate the loss parameter for obtaining the sustaining outcomes. Moreover, this prediction architecture is named as GAN for forecast error loss and direction prediction loss aka GAN-FD. The GAN-FD uses CNN (convolution neural network) and LSTM (long and short term model) for forecasting stock price. However, they fails to bring a good learning tradeoff performance of modeling both long and short market behavior context. Thus, the GANFD suffers significantly when markets behavior are extremely volatile in nature. For overcoming research problems, this paper present an efficient stock forecasting model using behavior pattern of stock market. First, the RNN is used to model long-term behavior pattern of stock market and LBL is used for modeling short term behavior pattern of stock market.

The contribution of research work are as follow.

- This paper presented efficient stock forecasting model RNNLBL by combining RNN with LBL for modeling both long and short term behavior pattern of stock market, respectively.
- Experiments are conducted on Chinese stock market data. The outcome shows the proposed RNNLBL stock forecasting model based LBL attain better performance than existing stock forecasting models in terms of RMSRE and DPA.

II. RNN-LBL: EFFICIENT STOCK PRICE FORECASTING MODEL USING BEHAVIOR PATTERN OF STOCK MARKET

This section present RNNLBL based efficient stock price forecasting model using behavior pattern of stock market. The work aims to build an efficient stock forecasting model for stock market that models both short-term and long-term context considering stock market volatility behavior with respect to time. First, the system model of proposed RNNLBL stock market forecasting model is described. Second, describe the detail of RNN model and how it is used to model long-term context. The behavior of market changes rapidly (short-term) when it is exposed to certain external factors. That is, circulation of fake news of certain stock, wars, social media reviews of a product etc. Thus, RNN model cannot be applied to model such short-term context. Then, this work describes the working structure of Log Bilinear (LBL) model for modeling short-term context in dynamic behavior pattern of stock market. Further, this work describe the stock market behavior pattern modeling considering both short and long context. Lastly, this paper describes how Bayesian personalized ranking (BPR) is used for learning recurrent neural network for predicting behavior pattern of stock market.

A. Problem statement and System model

Under the high-frequency trading environment, high-quality one-step forecasting is usually of great concern to algorithmic traders, providing significant information to market makers for risk assessment and management. In this article, we aim to forecast the price movement of individual stocks or the market index one step ahead, based solely on their historical price information. Our problem can be mathematically formalized as follows. Let $\boldsymbol{X_t}$ represent a set of basic indicators and Y denote the closing price of one stock for a 1-minute interval at time t is described as follows

$$t = 1, 2, \ldots, T \tag{1}$$

where T is the maximum lag of time. Given the historical basic indicators information $\boldsymbol{X}$ as described in below equation

$$\boldsymbol{X} = \{\boldsymbol{X_1}, \boldsymbol{X_2}, \ldots, \boldsymbol{X_T}\} \tag{2}$$

and the past closing price $\boldsymbol{Y}$ as described in below equation

$$\boldsymbol{Y} = \{\boldsymbol{Y_1}, \boldsymbol{Y_2}, \ldots, \boldsymbol{Y_T}\} \tag{3}$$

Our goal is to predict the closing price $\boldsymbol{Y_{T+1}}$ for the next 1-minute time interval. Let considers a set of stock market and set of stock within stock market as follow

$$\mathcal{U}\{u_1, u_2, \ldots\}, \tag{4}$$

$$\mathcal{V} = \{v_1, v_2, \ldots\}. \tag{5}$$

This work considers stock market environment, which is composed of following stock volatility behavior such as

$$\mathcal{C} = \{c_1, c_2, c_3, c_4\}. \tag{6}$$

Similarly, in the stock performance pattern there exist,

$$\mathcal{C} = \{c_1, c_2, c_3\} \tag{7}$$

behavior. Then, the task is to predict what will be future score/price of a particular stock within a stock market will be done using RNNLBL forecasting model.

B. RNNLBL Stock Forecasting model:

The RNN model is composed of an input layer, multiple hidden layers, output layers, along with inner weight matrices. The activation parameter of the hidden layers are obtained as follows

$$i_\ell^v = f\left(\mathcal{X} i_\ell^v + \mathcal{D} s_{w_\ell^v}\right), \tag{8}$$

where, $i_l^v \in S^e$ depicts the hidden illustration of stock v at time instance (i.e., position) l in a series, $s_{w_l^v} \in S^e$ depicts the illustration of the l^{th} input stock of a particular stock market v. The activation function (AF) is represented by $f(i)$ and transition matrix (TM) of present stock is represented as follows

$$D \in S^e \tag{9}$$

and previous status is represented as follows

$$W \in S^e. \tag{10}$$

D can obtain stocks present volatility (i.e., behavior pattern) and X can propagate time series signals. The Eq. (8) is executed iteratively to obtain or compute the status of each time instance in a time series sequence. The architecture of recurrent neural network is shown in Fig. 1.

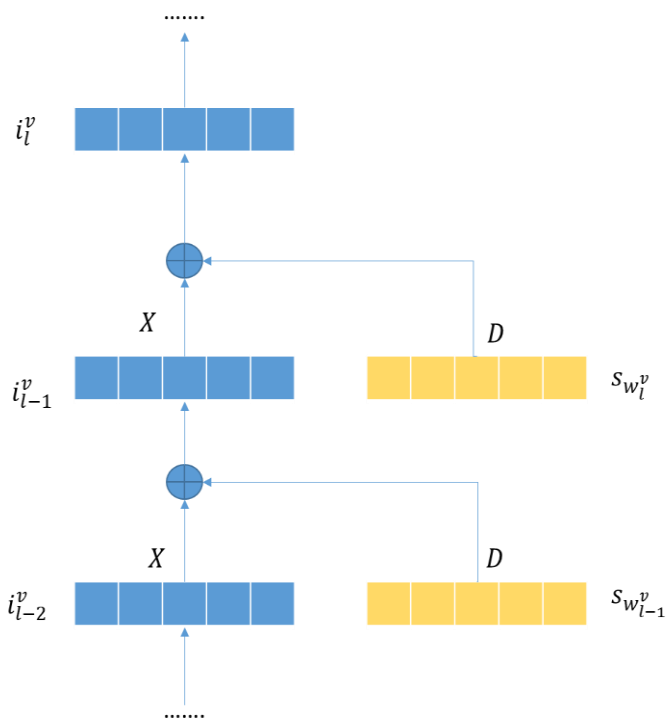

Fig. 1. Architecture of RNN-LBL model.

RNN-LBL architecture is composed of multiple hidden layers. The hidden layer information of recurrent neural network are dynamic in nature with respect to stock market behavior sequence, where the pattern is repetitive. Thus, recurrent neural network faces problems in learning short-term pattern in stock market behavior sequence. For addressing, this work present Log bilinear (LBL) model with a single linear hidden layer. Therefore, in this work it is considered as deterministic model. Using LBL for stock market behavior sequence forecasting problem, the absolute forecasting representation of time sequence is constructed based on stocks market score/price input and transition matrices at each time instance. The next time instance is a linear forecasting can be depicted using following equation

$$i_l^v = \sum_{j=0}^{o-1} D_j s_{w_{l-j}^v}, \tag{11}$$

where $D_j \in S^{e*e}$ depicts the TM for the respective time instance in a stock market score behavior sequence, and o is the number of element modeled in a time sequence. The architecture of proposed LBL model to model short-term contexts in stock market behavior sequences is shown in Fig. 2.

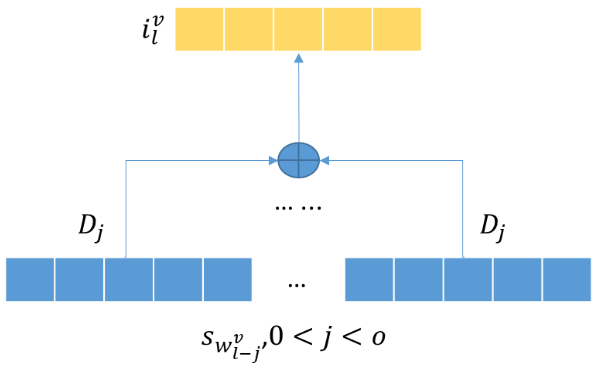

Fig. 2. Architecture of LBL model

In LBL each position in time sequence is modeled with a precise transition matrix. In general, LBL finds difficulty in efficiently learning long-term contexts in stock market behavior sequence.For addressing above stock forecasting research problems this work present a stock behavior model that capture both long and short term context in past data sequences simultaneously, rather than one component in each hidden layer in recurrent neural network. This work model multiple component in each hidden layer and add position-centric matrices into RNN structure, which is described in Fig. 3.

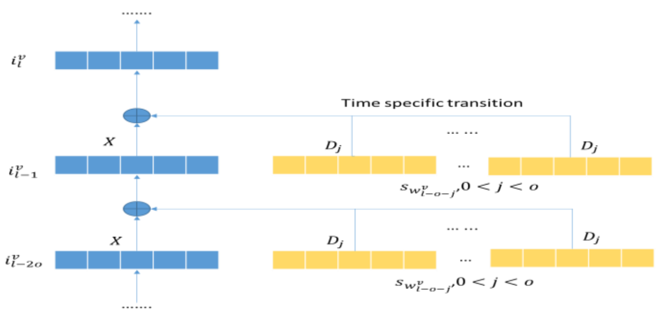

Fig. 3. Architecture of proposed RNNLBL stock forecasting model.

Architecture of stock forecasting model is modeled to capture both short-term and long-term context in stock market behavior sequence.

Let consider a stock v, the hidden description of the stock at the time instance ℓ in a sequence can be evaluated as follow

$$i_\ell^v = \mathcal{X} i_{\ell-1}^v + \sum_{j=0}^{o-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \tag{12}$$

where o is the number of input stock scores considered or used in each layer of proposed RNNLBL stock forecasting model, which in this work we call it as adaptive size. The position-centric transition matrices is depicted as follows

$$\mathcal{D}_j \in \mathbb{S}^{e*e} \tag{13}$$

obtains the influence factor of short term contexts, that is, the j^{th} stock score in each layer of proposed RNNLBL stock forecasting model, on stock market behavior, and the feature of stock market's long term history are learned using recurrent neural network architecture. Additionally, if we consider only one input for each layer and set the adaptive size $o = 1$, the outcome of proposed RNNLBL stock forecasting model will be similar to RNN neglecting the non-linear activation function. An important things to be seen here is, when the sequences is shorter than the adaptive size or the predicted time instance is at very initial segment of a sequences, that is, $\ell < o$. Therefore, the Eq. (12) can be reformulated as follows

$$i_\ell^v = \mathcal{X} i_0^v + \sum_{j=0}^{\ell-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \tag{14}$$

where $i_0^v = u_0$, representing the preliminary status of stock markets. The preliminary status of entire stock market must be the similar. Since individual stock information does not come into picture when model does not select a stock. This consideration v_o aid in addressing cold start problem (i.e., for forecasting new entrant in stock market). Bayesian personalized ranking model [20] is a pair wise ranking method used for the implicit feedback information. Bayesian personalized ranking has been used as an objective parameter that is widely applied for learning recurrent neural network for forecasting stock market behavior sequence of particular stock market. In general Bayesian personalized ranking considers that a customer desires a chosen set than a negative one (i.e., it aims to maximize the probability). Experiments are conducted to evaluate the outcome of RNNLBL forecasting model shows significant performance which is experimentally proven in next section.

III. SIMULATION RESULTS AND ANALYSIS

This section present performance evaluation of proposed RNNLBL stock market forecasting model over existing stock market forecasting model [17]. The existing model is designed using convolution neural network. On other side the proposed model combined RNN with LBL. Then, the RNN learning is performed with maximizing objective function using BPR [19], [20]. The proposed RNNLBL stock market forecasting model and existing model is designed using Microsoft DotNet framework 4.5, C# and python programming language. The experiment is conducted on Windows 10, 64-bit operating system, I-7 Intel class 64 bit quad core processor, 16 GB RM, 4 GB dedicated CUDA enabled graphic card. The performance of proposed RNNLBL model and existing stock forecasting model is evaluated in terms of (Root Mean Squared Relative Error) RMSRE and Direction Prediction Accuracy (DPA). The experiment is conducted using china stock exchange (CSE) data used in [17] which composed of extreme volatility and accidental event extremely impacting stock price. The CSE data ranges from January 1, 2016 to December 31st, 2016 that composed of total 244 trading days and each day is composed of 242-minute sessions with respect to 59048 time periods. The RMSRE is evaluated by considering training data size $M = 10$ and testing data size $N = 5$ .Here $\{5,10, and\ 20\}$ depicts one week, two week, and one month, respectively. For making forecasting for real-time environment, first the training data is selected for first M days and next N data is chosen as testing data. After carryout forecasting operation, the time window is moved forward to N days (i.e., $(N+1)^{th}$ day to the $(M+1)^{th}$ day as training dataset and $(M+N+1)^{th}$ to the $(M+2N)^{th}$ as testing dataset. The process is repeated till the entire stock data is forecasted (i.e., N can be used to updated the learning model and M depicts the size of respective training stock dataset). More details of dataset can be obtained from [17]. Experiments are conducted for different stock considering time t, a forecasting is done for next interval of time $t+1$ using proposed learning methods. Let's consider that the total number time interval the forecasting is done as T_0. The actual stock value is described as Y_t and forecasted value is described as $\hat{Y}_t$. The RMSRE is evaluated using following equation

$$RMSRE = \sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}\left(\frac{\hat{Y}_{t+1} - Y_{t+1}}{Y_{t+1}}\right)^2}. \tag{15}$$

A lower RMSRE value indicates the forecasting is good (i.e., it aggress with actual data). This work computed the RMSRE value of all stock similar to [17]. The RMSRE performance of proposed stock forecasting model and existing stock forecasting model is shown in TABLE I, Fig. 4, and Fig. 5. From result attained it can be seen GAN-FD stock forecasting model [17] attain much better performance than earlier existing stock forecasting models in terms of RMSRE considering varied training data size with RMSRE of 0.0098 and 0.0079 considering $M = 10\ and\ N = 5$ and $M = 20\ and\ N = 5$ as shown in Fig. 4, and Fig. 5, respectively. Similarly, the proposed stock forecasting model attain much improved RMSRE than GAN-FD model [17] with RMSRE of 0.0071 and 0.0064 considering $M = 10\ and\ N = 5$

and $M = 20\ and\ N = 5$ as shown in Fig. 4, and Fig. 5, respectively. Thus, proposed RNNLBL stock forecasting model reduces forecasting error by 27.55% and 18.987% over GAN-FD considering $M = 10\ and\ N = 5$ and $M = 20\ and\ N = 5$, respectively. An average RMSRE performance improvement of 23.26% is attained by proposed forecasting model over GAN-FD.

TABLE I: RMSRE performance of proposed and existing stock forecasting models

Method used	For M=10 and N=5	For M=20 and N=5
ARIMA-GARCH	0.0419	0.0406
ANN	0.0419	0.0485
SVM	0.0512	0.0450
GAN-F	0.0151	0.0155
GAN-D	0.0422	0.0304
LSTM-FD	0.0200	0.0194
GAN-FD	0.0098	0.0079
Proposed Model	**0.0071**	**0.0064**

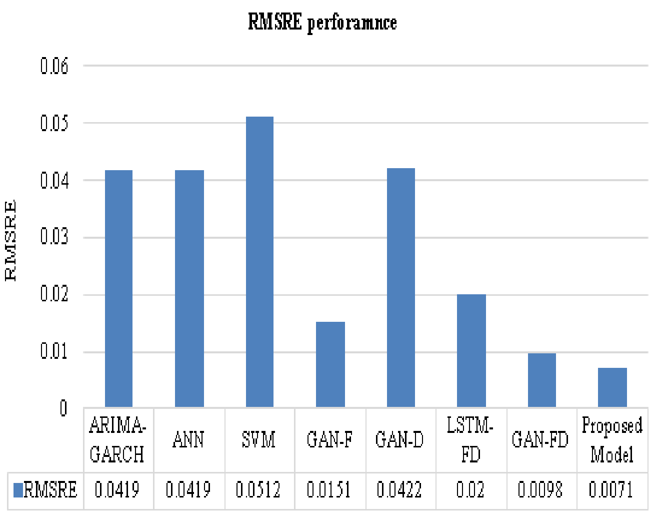

Fig. 4. RMSRE performance considering M=10 and N=5

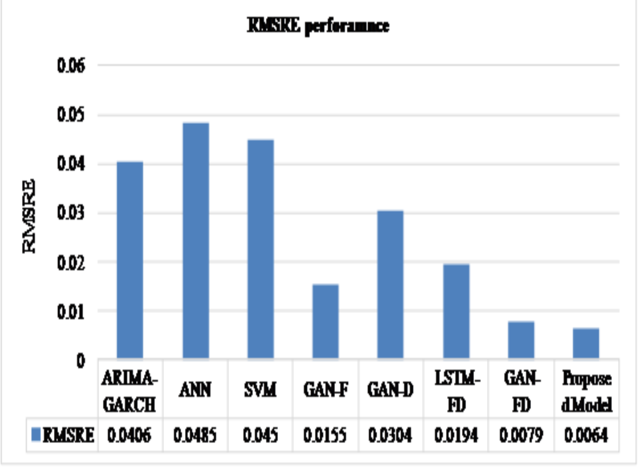

Fig. 5. RMSRE performance considering M=20 and N=5

Further, the performance stock forecasting model is evaluated in terms of DPA. The DPA metric is a measure of accuracy in terms of percentage. A higher DPA defines better profit. The DPA is evaluated using following equation

$$DPA = \frac{100}{T_0}\sum_{t=1}^{T_0} I_t, \quad (16)$$

where

$$I_t = \begin{cases} 1\ if\ (Y_{t+1} - Y_t)(\hat{Y}_{t+1} - Y_t) > 0 \\ 0\ otherwise \end{cases}. \quad (17a)$$

The DPA performance of proposed stock forecasting model and existing stock forecasting model is shown in TABLE II, Fig. 6, and Fig.7. From result attained it can be seen GAN-FD stock forecasting model [17] attain much better performance than existing earlier stock forecasting models in terms of DPA considering varied training data size with DPA of 0.676 and 0.696 considering M=10 and N=5 and M=20 and N=5, respectively. Similarly, the proposed stock forecasting model RNNLBL attain much improved DPA than GAN-FD model [17] with DPA of 0.7746 and 0.7898 considering M=10and N=5 and M=20 and N=5 as shown in Fig. 6, and Fig. 7, respectively. Thus, proposed RNNLBL stock forecasting model improves forecasting performance by 12.716% and 11.93% over GAN-FD considering M=10 and N=5 and M=20 and N=5 as shown in Fig. 6, and Fig. 7, respectively. An average DPA performance improvement of 12.31% is attained by proposed forecasting model over GAN-FD. From overall result attained it can be seen proposed aid in minimizing forecasting error and also aid in achieving high return.

TABLE II: DPA performance of proposed and existing stock forecasting models

Method used	For M=10 and N=5	For M=20 and N=5
ARIMA-GARCH	0.5464	0.5479
ANN	0.5456	0.5978
SVM	0.5715	0.5490
GAN-F	0.5347	0.5507
GAN-D	0.6220	0.6399
LSTM-FD	0.6340	0.6506
GAN-FD	0.6761	0.6956
Proposed Model	**0.7746**	**0.7898**

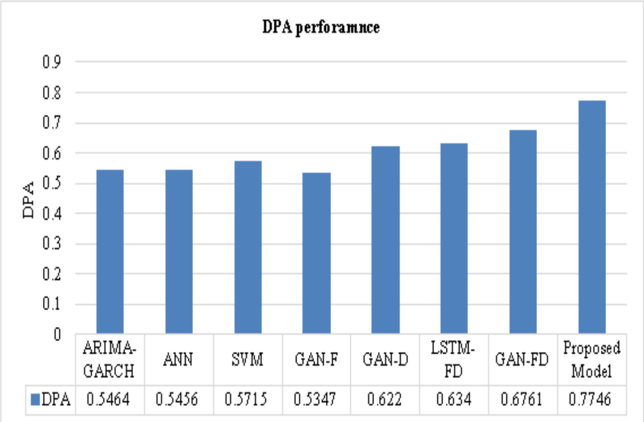

Fig. 6. DPA performance considering M=10 and N=5

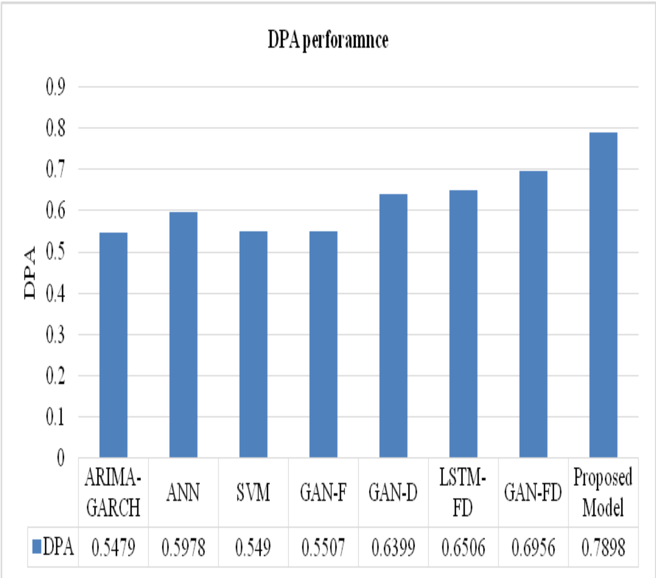

Fig. 7. DPA performance considering M=20 and N=5

IV. CONCLUSION

Forecasting stock price under highly dynamic and volatile stock market environment is challenging. This work first conducted extensive study of various existing stock market forecasting models. From study it is seen Deep learning based techniques aid in improving the classification accuracy of stock market forecasting. However, these existing stock forecasting models are not efficient when applied to different market and when market stock price are volatile in nature. This is because these models are trained considering long-term (i.e., historical) data and any fluctuations in stock price impacting forecasting accuracy. Thus are not efficient in capturing market behavior/pattern efficiently. For addressing this research problem, this paper presented RNNLBL based stock market forecasting model for forecasting stock price considering highly volatile stock market environment. The model applied RNN for learning long-term stock data and used LBL for learning short-term information. Further, combined both the model together to learn both long and short-term market behavior in order to carryout forecasting operation. Experiments are conducted on Chinese stock market data. An average RMSRE reduction of 23.265% and DPA performance improvement of 12.31% is attained by RNNLBL stock forecasting model over existing stock forecasting model. From overall result attained it can be seen proposed attain superior forecasting performance i.e., will aid in attaining higher stock returns even under highly volatile and dynamic market including new market. Future work will consider evaluating the model considering other performance parameter and carryout comparative analysis over various state-of-art stock price forecasting models.

REFERENCES

1. Neha Bhardwaj, MD Akil Ansari, "Prediction of Stock Market using Machine Learning Algorithms," IRJET, May 2019
2. G. H. Chen, K. Xiao, J. Sun, and S. Wu, "A double-layer neural network framework for high-frequency forecasting," ACM Transactions on Management Information Systems *(TMIS,)*, vol.7 ,2018
3. Gurav Uma., Sidnal N. Predict Stock Market Behavior: Role of Machine Learning Algorithms. In: Bhalla S., Bhateja V., Chandavale A., Hiwale A., Satapathy S. (eds) Intelligent Computing and Information and Communication. Advances in Intelligent Systems and Computing, vol 673. Springer, Singapore, 2018
4. Uma Gurav, Prof. Dr. Nandini Sidnal ," Adaptive Stock Forecasting Model using Modified BackPropagtion Neural Network (MBNN)",IEEE Xplore,CTEMS' 2018
5. Z. Ghahramani, "An introduction to hidden markov models and bayesian networks," International Journal of Pattern Recognition and Artificial Intelligence, vol. 15, no. 01, pp. 9–42, 2001.
6. T. Rajbhandary, X.-P. Zhang, and F. Wang, "Piecewise constant modeling and kalman filter tracking of systematic market risk," in Global Conference on Signal and Information Processing (GlobalSIP), 2013 IEEE, Dec 2013, pp. 1144–1144.
7. L. Vo, X.-P. Zhang, and F. Wang, "Multifactor systematic risk analysis based on piecewise mean reverting model," in Global Conference on Signal and Information Processing (GlobalSIP), 2013 IEEE, Dec 2013, pp. 1142–1142.
8. A. Wilson and Z. Ghahramani, "Copula processes," in Advances in Neural Information Processing Systems, 2010, pp. 2460–2468.
9. C. E. Rasmussen, Gaussian processes for machine learning. MIT Press, 2006.
10. C. Brownlees, R. Engle, and B. Kelly, "A practical guide to volatility forecasting through calm and storm," Journal of Risk, vol. 14(2), pp. 1–20, 2011.
11. R. Tsay, Analysis of financial time series. Wiley, 2010.
12. D. Saini, A. Saxena, and R. C. Bansal, "Electricity price forecasting by linear regression and SVM." pp. 1-7.
13. J. Wang, R. Hou, C. Wang, and L. Shen, "Improved v -Support vector regression model based on variable selection and brain storm optimization for stock price forecasting," Applied Soft Computing, vol. 49, pp. 164-178, 2016.
14. S.-G. Deng, and T.-H. Yeh, "Using least squares support vector machines to the product cost estimation," Journal of Chung Cheng Institute of Technology, vol. 40, no. 1, pp. 1-16, 2011.
15. F. Kaytez, M. C. Taplamacioglu, E. Cam, and F. Hardalac, "Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines," International Journal of Electrical Power and Energy Systems, vol. 67, pp. 431-438, 2015.
16. J. A. K. Suykens, "Nonlinear modelling and support vector machines." pp. 287-294.
17. Zhou, Xingyu & Pan, Zhisong & Hu, Guyu & Tang, Siqi & Zhao, Cheng. (2018). Stock Market Prediction on High-Frequency Data Using Generative Adversarial Nets. Mathematical Problems in Engineering. 2018. 1-11. 10.1155/2018/4907423, 2018.
18. I. J. Goodfellow, J. Pouget-Abadie, M. Mirza et al., "Generative adversarial nets," in Proceedings of the 28th Annual Conference *on Neural Information Processing Systems 2014, NIPS 2014*, pp. 2672–2680, can, December 2014.

19. Y. He, C. Wang and C. Jiang, "Correlated Matrix Factorization for Recommendation with Implicit Feedback," in IEEE Transactions on Knowledge and Data Engineering. doi: 10.1109/TKDE.2018.2840993, 2017.
20. Rendle, S., Freudenthaler, C., Gantner, Z., Schmidt-Thieme, L. BPR: Bayesian personalized ranking from implicit feedback. In: Proceedings of the 25th Conference on Uncertainty in Artificial Intelligence, UAI'09, pp. 452–461, 2009.
21. J. P. He, L. Cai, P. Cheng, and J. L. Fan, "Optimal Investment for Retail Company in Electricity Market," Ieee Transactions on Industrial Informatics, vol. 11, no. 5, pp. 1210-1219, Oct, 2015.
22. M. Göçken, M. Özçalıcı, A. Boru, and A. T. Dosdoğru, "Integrating metaheuristics and Artificial Neural Networks for improved stock price prediction," Expert Systems with Applications, vol. 44, pp. 320-331, 2016.
23. Y. Perwej, A. Perwej, and "Prediction of the Bombay Stock Exchange (BSE) market returns using artificial neural network and genetic algorithm," Journal of Intelligent Learning Systems and Applications, vol. 4, pp. 108-119, 2012.
24. A. A. Arafah, and I. Mukhlash, "The Application of Fuzzy Association Rule on Co-movement Analyze of Indonesian Stock Price," Procedia Computer Science, vol. 59, pp. 235-243, 2015/01/01, 2015.
25. M. Göçken, M. Özçalıcı, A. Boru, and A. T. Dosdoğru, "Integrating metaheuristics and Artificial Neural Networks for improved stock price prediction," Expert Systems with Applications, vol. 44, pp. 320-331, 2016

AUTHORS PROFILE

Mrs. Uma Gurav currently pursuing P.H.D in Computer Science and Engineering in V.T.U , Belgaum, INDIA, presently working as Assistant Professor in Department of CSE, K.I.T's College of Engineering,Kolhapur.Her Area of research includes Algorithms, Data Sciences (AI/ML), Artificial Neural Networks, Deep Learning .

Dr. Kotrappa S. , Professor received Doctoral Degree (Ph.D) in Computer Science & Engineering(CSE), from Walchand College of Engineering, Sangli, under Shivaji University Kolhapur , Maharashtra .He is presently working as Professor, Department of CSE, K L E's Dr MSS College of Engineering & Technology, Belgaum. His current research interests includes Big Data Analytics, Data Science (including AI/ML/DL), Block chain Technology and Software engineering (Agile, Design Patterns, OOMD, and AOSD/AOP).