

# Stock Price prediction using LSTM and SVR

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**Abstract**—Stock price movement is non-linear and complex. Several research works have been carried out to predict stock prices. Traditional approaches such as Linear Regression and Support Vector Regression were used but accuracy was not adequate. Researchers have tried to improve stock price prediction using ARIMA. Due to very high variations in stock prices, deep learning techniques are applied due to its proven accuracy in various analytics fields. Artificial Neural Network was deployed to predict stock prices but as stock prices are time-series based, recurrent neural network was applied to further improve prediction accuracy. In RNN, there is limitation of not able to store high dependencies and also vanishing gradient descent issue exists. Therefore, data scientists and analysts applied LSTM to predict stock price movement. In this paper, LSTM is compared with SVR using various stock index data such as S& P 500, NYSE, NSE, BSE, NASDAQ and Dow Jones industrial Average for experiment analysis. Experiment analysis proves that LSTM provides better accuracy as compared to SVR.

**Keywords**—Stock Price prediction, Deep Learning, LSTM, RNN, SVR

## I. INTRODUCTION

Stock market is non-linear and volatile and it is very difficult to extract the valuable information from patterns. Stock market is one of the most important institutions of any economy [1]. In the past, several researchers have proposed innovative approaches to predict stock prices. Researchers have used Linear regression, Support Vector Machines [2], ARIMA(Auto Regressive Integrated Moving Average) and traditional machine learning techniques for stock price prediction. The limitations of these approaches are that accuracy is not adequate. There is need of better approach which can predict high variations prices with significant accuracy. In this research paper, deep learning is applied on different stock index datasets to predict stock prices. Experiment analysis have proved that accuracy is better as compared to existing approaches.

Artificial Neural Network is used to extract information from non-linear data. Existing ANN is not able to provide adequate accuracy [3]. Researchers have used LSTM (Long Short Term Memory) in [4], RBM in [5] and ANN in [6]. As stock prices are time-based i.e. today's price is dependent on previous days prices. Therefore, Recurrent Neural Network is most suitable for stock price predictions. In RNN, states of many hidden layers cannot be saved, so accuracy is degraded. In this paper, LSTM is used to predict stock prices.

LSTM can save cell state in long-term dependencies. It can predict stock prices in effective way as previous day stock prices can be saved. Input gate, Forget gate and Output gate are used in LSTM for verifying previous states.

In this research work, time period from Jan 2015 to Jan 2020 is used for prediction. Window size of 30 days is used for training and testing purpose. Sigmoid activation function

and adam optimizer are used. Furthermore, dropout of 0.2 is used.

In this paper, Support Vector Regression is applied to predict stock prices. SVM is used by researchers to achieve high precision for financial market prediction [7]. SVR is same as SVM in principle and ultimate goal is to minimize error [8]. SVR (Support Vector Regression) is machine learning technique which is efficient for predicting time-series based data [9]. The remainder of the paper is structured as follows. In Section II, several research works in deep learning and traditional techniques based stock price prediction are discussed along with comparative analysis. Section III covers LSTM and SVR techniques in detail. Experiment analysis is covered in Section IV and finally Section V concludes the paper with future directions.

## II. RELATED WORK

In [10], LSTM and CNN are applied on NYSE(NewYork Stock Exchange) and NSE (National Stock Exchange of India) stock indexes. It is mentioned in this paper that forecasting algorithms can be categorized into linear (ARIMA, ARMA) and non-linear (GARCH, Neural Network). Stock prices of one company from NSE were used as training and five companies stock prices were used for testing purpose. It is concluded in this paper that both stock markets i.e. NSE and NYSE are of common dynamics. Furthermore, it is concluded that CNN (Convolutional Neural Network) is outperforming other models and neural network based approaches outperform ARIMA model. There are various factors in Stock market prediction such as company news, industry performance and sentiments as mentioned in [11]. Deep convolutional network and candlestick charts are applied for stock market prediction. Approximately 92% accuracy is achieved on different stock markets. In [12], it is stated that due to non-linear stock market price movement, machine learning and deep learning based approaches are applied to predict stock prices. In this paper, cross-sectional stock market prediction framework is proposed for daily basis. Deep Neural Network is compared with RF (Random Forest) and RR (Ridge Regression). It is concluded that DNN provides better turnover ratio as compared to RF and RR. In [13], it is mentioned that machine learning and linear techniques were proposed for stock market prediction. Deep learning is very popular technique for stock market prediction. In this survey paper different data sources, neural networks and implementation are discussed. Various stock market indexes such as S&P 500, Dow Jones Industrial Average, NASDAQ, NYSE, BSE are mentioned in this paper as most commonly used by researchers. Different techniques such as ARIMA, Logistic Regression, GARCH, LSTM, RNN, CNN are explained in detail. Several evaluation metrics such as Accuracy, MAE, RMSE, Precision, Recall, F1 score are discussed. Several research works using these models and evaluation metrics are categorized in this paper. Existing deep learning solutions are focused on classification or regression for stock price

prediction as stated in [14]. These solutions are not optimized for target of investment. In this paper, historical data is used as input for LSTM and then sequential embedding is revised using Graph Convolution. Proposed approach is validated on NYSE and NASDAQ markets and it is proved in experiment analysis that return ratio is improved significantly. In [15], statistical models are used to predict future stocks. ARIMA model is applied for forecasting and mean percentage error is improved. In [9], SVR is used for predicting stock price movement. In this research, different techniques are applied to preprocess data. It is mentioned that if parameters are determined efficiently, prices can be predicted with adequate accuracy. Mean Absolute Percentage Error (MAPE) is used as evaluation metrics in this paper. In [8], SVR, hybrid SVR-ANN and SVR-RF is applied for stock market prediction. Nifty and BSE stock indices data are used for experiment analysis. In this research, it is observed by researchers that SVR is of same properties as SVM as motive is to reduce the error between actual and predicted values. MAPE, MAE and RMSE values are used as evaluation metrics. It is concluded that SVR-ANN performs better as compared to ANN and SVR models. In [16], hybrid model is proposed to improve prediction accuracy. It is also observed in this research work that RNN performs better than linear models. Furthermore, hybrid model outperforms RNN. Mean Absolute Error is used as evaluation metric and BSE stock index data is used for experiment analysis. In Table I, different approaches with evaluation metrics and dataset used are compared.

### III. TECHNIQUES FOR STOCK MARKET PREDICTION

Several linear and non-linear approaches are proposed by researchers and data scientists over the years to improve stock price prediction. In traditional approach, accuracy is not adequate. In this paper, LSTM is applied on different stock indexes and compared with linear regression and ARIMA.

#### A. LSTM

LSTM (Long Short Term Memory) is modified version of RNN (Recurrent Neural Network). RNN is best suitable for stock price prediction as it can analyze time-series patterns. The limitation of RNN is that it cannot save state for long-term dependencies. In RNN, values are backpropagated and slope becomes small which results in vanishing gradient issue [17]. LSTM overcomes this limitation by saving states in cell state. Furthermore, there is Forget gate available in LSTM which filters whether previous state information is relevant or not. If Forget gate output is 1, cell state saves the information and if output is 0, cell state ignores the information. Input and Output gates are also used in LSTM.

TABLE I. COMPARATIVE ANALYSIS OF DIFFERENT APPROACHES

Approaches	Technique used	Evaluation metrics used	Pros and Cons
[M Hiransha]	LSTM, CNN	Mean Absolute Percentage Error	Pros: Model is trained using one dataset and deployed on other dataset. Cons: Comparative analysis is not extensive.
[R Kusuma]	Deep Convolution	Accuracy	Pros: Candle chart is fed to CNN to improve

	Network		accuracy.
			Cons: In Experiment analysis, there is need of using more dataset.
[M Abe]	Deep Neural Network, Ridge Regression, Random Forest	Turnover Ratio	Pros: Daily management is covered. Cons: In Experiment analysis, there is need of using more dataset.
[F Feng]	LSTM, Graph Convolution	Return Ratio	Pros: Temporal graph convolution is proposed. Cons: In Experiment analysis, there is need of using more dataset.
[S Idrees]	ARIMA	Mean Percentage Error	Pros: Statistical model is proposed to predict future stock prices. Cons: Comparative analysis is not extensive.

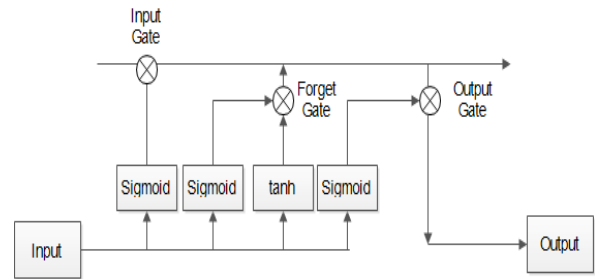


Fig. 1. LSTM Architecture

It is clearly depicted in Fig. 1 that Input, Forget and Output gates are deployed in LSTM. Input gate filters the information from previous layers and output gate filters output that is to be sent to next layer. Cell state in LSTM is

$$c_t = F_t * c_{t-1} + I_t * \bar{c}_t \quad (1)$$

Where  $c_t$  is current cell state and  $c_{t-1}$  is previous cell state.  $F_t$  is forgotten state and  $I_t$  is Input state.

#### B. Support Vector Regression

SVR is applied to predict using training values and target labels. SVR is effective for real-value function [18]. SVR is regression technique to minimize error using most suitable hyperplane. Different kernel functions such as linear, RBF, Sigmoid and Polynomial are used and selecting kernel function is significant for regression [19]. Minimum Loss function is used to improve prediction accuracy.

$$f(x) = W^T \phi(x) + b \quad (2)$$

Where  $W^T$  is weight vector,  $b$  is bias and  $\phi(x)$  is mapping function.

$$\min \frac{1}{2} \|w\|^2 \quad (3)$$

Where  $w$  is normal vector. SVR tries to minimize distance between predicted and actual values.

## IV. EXPERIMENT ANALYSIS

In this paper, LSTM with 7 hidden layers are deployed. Adam optimizer and sigmoid activation function is used. Furthermore, dropout of 0.2 is considered. Epochs are set to 100. Keras[20], Scikit-learn[21], Pandas[22], Numpy[23] and Matplotlib[24] Python library are used for experiment setup. These experiments are deployed on Google Colab GPU.

NYSE, NSE, NASDAQ, Dow Jones Industrial Average and S & P 500 stock indexes are used. Time period from Jan 2015 to Jan 2020 is considered in which Jan 2015 to June 2019 is used for training and July 2019 to Jan 2020 is used for testing and validation. Window size of 30 is used as stock prices are dependent on previous day prices.

Mean Absolute Percentage Error (MAPE) is average percentage of predicted value minus actual value divided by actual value as shown in Equation.

$$MAPE = \frac{1}{n} \sum_{j=0}^n \left| \frac{Y_{actual,j} - Y_{predicted,j}}{Y_{actual,j}} \right| * 100 \quad (5)$$

where,  $y_{actual}$  is actual value and  $y_{predicted}$  is predicted value.

In Table II, Mean Absolute Percentage Error of LSTM and SVR are compared using various stock index such as NSE, BSE, NASDAQ, NYSE, S&P 500 and Dow Jones Industrial Average. It is proved that LSTM outperforms SVR and performs better to provide better prediction accuracy.

TABLE II. MAPE OF LSTM AND SVR

MAPE		
	LSTM	SVR
NSE	0.86	1.44
BSE	0.78	1.32
NASDAQ	1.91	2.54
NYSE	0.84	1.42
S & P 500	0.75	1.30
Dow Jones Industrial Average	1.09	1.78
Nikkei 225	0.78	1.32



Fig. 2. Stock Price prediction for NSE



Fig. 3. Stock Price prediction for BSE



Fig. 4. Stock Price prediction for NASDAQ



Fig. 5. Stock Price prediction for NYSE

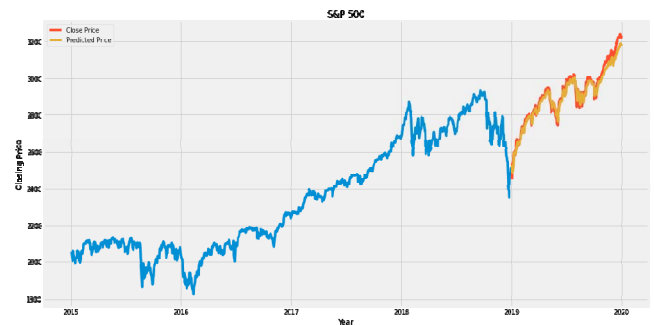


Fig. 6. Stock Price prediction for S &amp; P 500

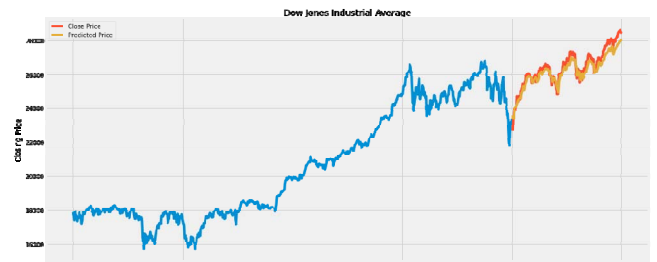


Fig. 7. Stock Price prediction for Dow Jones Industrial Average



Fig. 8. Stock Price prediction for Nikkei 225

In Table II, it is clearly shown that MAPE values of LSTM are less as compared to SVR. In Fig. 2 to Fig. 8, prediction of stock prices on NSE, BSE, NASDAQ, NYSE, S & P 500, Dow Jones Industrial Average and Nikkei 225 using LSTM are predicted. Close price and predicted price curves are overlapping which signifies that LSTM is able to predict with high accuracy. It is clear that LSTM is able to predict non-linear and high variations price movement with adequate prediction accuracy.

## V. CONCLUSION AND FUTURE WORK

Stock market is highly volatile and non-linear. Traditional machine learning techniques cannot predict stock prices with adequate accuracy. In this research work, deep learning is applied to improve prediction accuracy. LSTM is used with adam optimizer and sigmoid activation function. Mean Absolute Percentage Error is used as evaluation metric. Our neural network set up using LSTM is compared with Support Vector Regression. Experiment is conducted on different stock index such as S&P 500, NYSE, NSE, BSE, Dow Jones Industrial Average and NASDAQ. Experiment analysis proves that LSTM outperforms SVR and provides better prediction accuracy. In future, various deep learning techniques such as CNN and hybrid models will be applied to analyze the prediction accuracy. Furthermore, different evaluation metrics such as RMSE and MAE will be used for evaluation of prediction accuracy.

## REFERENCES

- [1] J. Eapen, D. Bein, and A. Verma, "Novel deep learning model with CNN and bi-directional LSTM for improved stock market index prediction", In 2019 IEEE 9th annual computing and communication workshop and conference (CCWC) (pp. 0264-0270). IEEE, 2019.
- [2] W. Huang, Y. Nakamori, and S.Y. Wang, "Forecasting stock market movement direction with support vector machine", *Computers & operations research*, 32(10), pp.2513-2522, 2005.
- [3] R. Singh, and S. Srivastava, "Stock prediction using deep learning", *Multimedia Tools and Applications*, 76(18), pp.18569-18584, 2017.
- [4] T. Fischer, and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions", *European Journal of Operational Research*, 270(2), pp.654-669, 2018.
- [5] C. Zhu, J. Yin, and Q. Li, "A stock decision support system based on dbns", *Journal of Computational Information Systems*, 10, pp. 883-893, 2014.
- [6] X. Zhong, and D. Enke, "Forecasting daily stock market return using dimensionality reduction", *Expert Systems with Applications*, 67, pp. 126-139, 2017.
- [7] M. Nikou, G. Mansourfar, and J. Bagherzadeh, "Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms", *Intelligent Systems in Accounting, Finance and Management*, 26(4), pp.164-174, 2019.
- [8] J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock market index using fusion of machine learning techniques", *Expert Systems with Applications*, 42, 2162-2172, 2015.
- [9] P. Meesad, and R.I. Rasel, "Predicting stock market price using support vector regression". In 2013 International Conference on Informatics, Electronics and Vision (ICIEV) (pp. 1-6). IEEE, 2013.
- [10] M. Hiransha, E.A.Gopalakrishnan, V.K Menon, and K.P Soman, "NSE stock market prediction using deep-learning models", *Procedia computer science*, 132, pp.1351-1362, 2018.
- [11] R.M.I Kusuma, T.T Ho, W.C Kao, Y.Y Ou, and K.L. Hua, "Using deep learning neural networks and candlestick chart representation to predict stock market", *arXiv preprint arXiv:1903.12258*, 2019.
- [12] M. Abe, and K. Nakagawa, "Cross-sectional Stock Price Prediction using Deep Learning for Actual Investment Management", *arXiv preprint arXiv:2002.06975*, 2020.
- [13] W. Jiang, "Applications of deep learning in stock market prediction: recent progress", *arXiv preprint arXiv:2003.01859*, 2020.
- [14] F. Feng, X. He, X. Wang, C. Luo, Y. Liu, and T.S. Chua, "Temporal relational ranking for stock prediction", *ACM Transactions on Information Systems (TOIS)*, 37(2), pp.1-30, 2019.
- [15] S.M. Idrees, M.A. Alam, and P. Agarwal, "A prediction approach for stock market volatility based on time series data", *IEEE Access*, 7, pp.17287-17298, 2019.
- [16] A.M Rather, A. Agarwal, and V.N Sastry, "Recurrent neural network and a hybrid model for prediction of stock returns", *Expert Systems with Applications*, 42(6), pp.3234-3241, 2015.
- [17] H.Y Kim, and C.H. Won, "Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models", *Expert Systems with Applications*, 103, pp.25-37, 2018.
- [18] M. Awad, and R. Khanna, 2015, "Support vector regression", In *Efficient learning machines*, pp. 67-80, Apress, Berkeley, CA, 2015.
- [19] G. Chniti, H. Bakir, and H. Zaher, "E-commerce time series forecasting using LSTM neural network and support vector regression", In *Proceedings of the International Conference on Big Data and Internet of Thing*, pp. 80-84, 2017.
- [20] <https://keras.io/>
- [21] <https://scikit-learn.org/>
- [22] <https://pandas.pydata.org/>
- [23] <https://numpy.org/>
- [24] <https://matplotlib.org>