Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

A Prototype Classification Algorithm for Stock Price Prediction using Optimized Variance of Attributes

Jayshree Bhangre[1], Anurag Jain[2]

sdmeet@gmail.com[1], anurag.akjain@gmail.com [2]

Department of Computer Science & Engineering[12]

Madhyanchal Professional University, Bhopal, India[12]

Article Info

Page Number: 1574 - 1586

Publication Issue:

Vol 71 No. 4 (2022)

Article History

***Article Received**: 25 March 2022*

***Revised**: 30 April 2022*

***Accepted**: 15 June 2022*

***Publication**: 19 August 2022*

Abstract

The advancement of machine learning algorithms increases the prediction of stock prices. The enhanced prediction ratio moves the stock market into the mode of stability and attacks investors to invest in the stock market. This paper proposed a prototype classification algorithm for the prediction of stock price. The prototype classification algorithm bags a clustering algorithm and classification algorithm. The bagging of the algorithm improves the data normalization factors and reduces the variance of attributes of stock data. The employed support vector machine uses rank factors of an improved clustering algorithm and increases class voting. The proposed algorithm is implemented in MATLAB tools for data analysis. The results of the proposed algorithm compared with SOM neural network model and SVM. The study of effects represents that the proposed algorithm is very efficient in SBI bank data sets. The evaluation of performance estimates in RMSE, NMSE, MAR and MI.

Keywords: Stock Price, Prediction, SVM, K-Means, Classification SBI Bank

Introduction

The variation of attributes in stock price prediction is the most critical factor in financial sectors. The interpretation of attributes changes the market's stability, and the growth of economic sectors is declining. On the other hand, the strength of the stock market provides financial growth in demand and increases the financial gain of the nation. The tracking of stock variation depends on various market factors, and the conventional prediction model is compromised. Therefore, investors are constantly looking for new and inventive ways to forecast stock movements to maximize profits. Recently, there has been an increase in a desire to use powerful Machine Learning (ML) based methods [1,2,3] that consider all accessible information sources, such as past prices or news, to forecast stock price motions. This study focuses on development in this environment. Development of a reliable and accurate information fusion-based stock Framework for movement prediction In terms of historical data and other technical and macroeconomic factors, stock prices are nonlinear [4,5]. Before neural networks were found, many academics chose to employ time-series analyses, which are used to forecast future occurrences based on existing data. Support vector machine (SVM), autoregressive integrated moving average (ARIMA), autoregressive conditional heteroskedasticity (ARCH) model, and generalized autoregressive conditional heteroskedasticity (GARCH) model are among the most well-known models among the methods [7]. Furthermore, regression analysis and artificial neural networks (ANNs) have been widely employed for forecasting and classification [6,7,8] to deal with these nonlinear interactions. Systems based on technical analysis, including expert systems, hybrid systems, and other forms of computational intelligence, have also been proposed [8,9,10]. Researchers' interest in using artificial intelligence to anticipate SM index direction continues to grow. The prediction methodologies are often quite complicated due to the nonlinear structures of the issues, necessitating the development of effective solution methods for such models. Technical analysts use various data, technological tools, and, in particular, technical indicators to determine price patterns and market trends based on price and volume conversions in the market [11,12,13]. Despite various prediction models, the stock price prediction is still a major issue. This paper proposed a prototype classification algorithm for predicting the stock market. The prototype classification algorithm encapsulates two machine learning algorithms: one improves k-means algorithms (IKM), and the other is a support vector machine. The improved k-means algorithm groups the data and normalizes the variance factors of the option price. The support vector machine algorithm scales the vector machine and increases the data sample for the voting of the classification algorithm. The depreciation of variation factors increased the classification ratio and normalized the nonlinear function of data. The rest of the paper is organized as in section II related works, section III proposed methodology, section IV experimental analysis, section V conclusion & future work.

II. Related Work

In this [1] author examines each dataset, variable, model, and outcomes. RMSE, MAPE, MAE, MSE, accuracy, Sharpe ratio, and return rate are the most commonly used performance metrics in the survey. We discovered that recent models integrating LSTM with additional approaches, such as DNN, have received a lot of attention. Reinforcement learning and other deep learning algorithms produced excellent results. We conclude that the use of deep-learning-based approaches for financial modelling has increased dramatically in recent years.

In this [2] author propose the GA was used to reach a simultaneous optimal of the SVM's many design variables. The suggested GASVM had a prediction accuracy of 93.7 percent, compared to 82.3 percent for the RF, 75.3 percent for the DT, and 80.1 percent for the 80.1 percent. As a result of the consequences, it can be determined that the suggested technique provides a realistic approach to feature selection and parameter optimization of the various design characteristics of the SVM, obviating the necessity for labor-intensive parameter optimization.

In this [3] author propose the PSO is employed iteratively as a global optimization technique to optimise Random forest for stock price prediction. Plot all of the data from the findings as well as the training part. Based on surveys and comparisons with all other machine learning models for stock price prediction using Twitter, Random Forest is the most affordable model for assessing and predicting based on public mood using sentimental analysis.

In this [4] author proposed a novel sentiment analysis method with deep neural networks was developed, and estimated sentiment information was applied to stock movement forecasts For stock comments. Our deep sentiment classification method outperformed the logistic regression algorithm by 9% and delivered an appropriate sentiment extractor for the following prediction phase, according to the empirical results.

In this [5] author presents two CNNbased regression models and three LSTM network-based predictive models. The results show that, while all of the models are capable of forecasting the NIFTY, the univariate encoder-decoder convolutional LSTM with data from the previous two weeks is the most accurate. On the other hand, a univariate CNN model with prior one week's data as input is proved to be the fastest model in terms of speed.

In this [6] author propose Walk-forward validation was used in conjunction with a multi-step prediction technique. In this approach, the open values of the NIFTY 50 index are forecasted over a one-week time horizon, and after a week, the actual index values are added to the training set before the model is retrained and forecasts for the following week are created. For all of our proposed models' forecasting accuracies, we provide detailed findings.

In this [7] author used ANN, RNN, and long short-term memory, as well as decision trees, bagging, random forest, adaptive boosting, gradient boosting, and eXtreme gradient boosting. Each of the prediction models was given ten technical indicators as inputs. Finally, four metrics were used to display the results of the forecasts for each technique. LSTM produces the most accurate findings and has the best model fitting capabilities of all the algorithms employed in this paper. Furthermore, for tree-based models, Adaboost, Gradient Boosting, and XGBoost are frequently in competition.

In this [8] author present a new machine learning model for forecasting the BIST index's movement MLP–GA and MLP–PSO were used to model Tanh and the default Gaussian function as the output function in two scenarios. To compare the accuracy and performance of the created models, the RMSE, MAPE, and correlation coefficient values are used. With RMSE of 0.732583 and 0.733063, MAPE of 28.16 percent, 29.09 percent, and correlation coefficients of 0.694 and 0.695, respectively, MLP–PSO with population size 125 and MLP–GA with population size 50 gave improved testing accuracy.

In this [9] author proposes stock price movement prediction, the framework for Noisy Deep Stock Movement Prediction Fusion was created. A two-level attention layer is used to uncover significant phrases with the highest correlation and effects on stock trends, which are then integrated with historical price data to complete the prediction task. The performance of the proposed ND-SMPF framework is evaluated using a real dataset, which shows that it beats previously developed alternatives.

In this [10] author presents a collection of deep learning-based regression models that accurately predict stock prices. Using this incredibly granular stock price data, the suggested method developed four CNN and five LSTM-based deep learning models for trustworthy future stock price prediction. Furthermore, this study endeavour gives extensive results on forecasting accuracies of all supplied models based on their execution duration and RMSE values.

In this [11] author uses the algorithms Long Short Term Memory, Extreme Gradient Boosting, Linear Regression, Moving Average, and Last Value Model were used to construct a prediction model for forecasting stock price using more than twelve months of historical stock data. The MAPE measurement is utilised to compare the models, and the LSTM methodology beats all other methods with a MAPE of 0.635. Furthermore, of the five models in our circumstance, Moving Average has the largest error rate.

In this [13] author propose the time series PSR technique is used to rebuild financial product pricing data as a one-dimensional series produced by projecting a chaotic system made of numerous components into the time dimension. A DNN-based prediction model is constructed utilising the PSR technique and LSTMs for DL to forecast stock prices. Using the specified and extra prediction methodologies, multiple stock indexes for various periods are projected. When the results are compared, the proposed prediction model clearly has a better prediction accuracy.

In this [14] author propose a deep learning-based stock market forecast model that takes emotional tendencies into account. The emotional propensity of investors has been proven to improve projected results the addition of EMD can increase inventory sequence prediction and the attention mechanism can aid LSTM in efficiently extracting specific information and current mission objectives from the information ocean.

In this [15] author propose Convolutional layers' capacity to extract meaningful knowledge and learn the internal representation of time-series data, as well as LSTM layers' competence in distinguishing short-term and long-term dependencies, are combined in the suggested model. In a series of experiments, we compared the proposed model to state-of-the-art deep learning and machine learning models. The use of LSTM layers in combination with extra convolutional layers considerably improved forecasting capacity, according to preliminary experimental studies.

In this [16] author proposes a new framework structure that blends CNN and Long–Short–Term Memory Neural Network to achieve a more accurate stock price forecast. It generates a sequence array of historical data and its leading indicators, feeds the array into the CNN framework, extracts particular feature vectors via the convolutional layer and the pooling layer, then feeds the vector into the LSTM.

In this [17] author propose the different methodologies discovered in these publications were divided into three categories: technical, fundamental, and combined analysis. The following criteria were used to group the datasets the nature of the dataset and the number of data sources used, the data timeframe, the machine learning methods employed, the machine learning task, accuracy and error metrics used, and modelling software packages. In terms of data sources, single sources were utilised in 89.34 percent of documents evaluated, while two and three sources were used in 8.2 percent and 2.46 percent of documents, respectively.

In this [18] author investigates the topic of stock market stock closing price forecasting. Two new prediction models based on clustering have been developed, based on existing two-stage fusion models in the literature, where the k-means clustering approach is used to cluster various common technical indicators. The use of k-means clustering on stock technical indicators can improve the ensemble learning's forecast accuracy.

In this [19] author propose the long short-term memory neural network with automatic encoder and the deep long short-term memory neural network with embedded layer We use the embedded layer and the automatic encoder, respectively, to vectorize the data in these two models in order to forecast the stock using a long short-term memory neural network. In the experiments, the deep LSTM with embedded layer performs better.

In this [20] author Create a three-stage framework for strategic marketing planning that includes mechanical AI for automating repetitive marketing operations and activities, thinking AI for data processing and decision-making, and feeling AI for analysing interactions and human emotions. Throughout the marketing action stage, mechanical AI can be used for standardisation, thinking AI for personalization, and feeling AI for relationalization.

In this [21] author despite the importance of three multiple influence factors, feature selection, preprocessing of the carbon price and its four exogenous variables, multi-objective intelligence optimization, and kernel-based 5 models in improving prediction validity, current carbon trading price forecasting research ignores the importance of three multiple influence factors, which may result in unfavourable 6 forecasting performance.

In this [22] author propose multi-filters neural network (MFNN) is a revolutionary end-to-end model designed exclusively for feature extraction on financial time series samples and price movement prediction. The multi-filters structure is built using both convolutional and recurrent neurons, allowing information from various feature spaces and market viewpoints to be acquired. In terms of accuracy, profitability, and stability, our network beats classical machine learning models, statistical models, and single-structure (convolutional, recurrent, and LSTM) networks.

In this [23] author use efficient categorization approaches for predicting price movement patterns, and we use various regression techniques for determining actual closing values. Logistic regression, SVM, ANN, Random Forest, and ensemble learning approaches have all been used (Bagging, Boosting). We also employ the LSTM deep learning technique to predict stock closing prices, and then superimpose the accuracy metrics by comparing the LSTM results with the results of the other machine learning models.

In this [24] author propose RNN model, often known as the LSTM model, and the BI-LSTM model are used to create a novel stock price prediction framework. According to the simulation results, our suggested scheme may accurately estimate future stock trends utilising these RNN models, namely LSTM and BI-LSTM, with correct hyper-parameter tuning.

In this [25] author For predicting the next day trend of equities, support vector machines, perceptrons, and logistic regression are used. For the experiment, a dataset of around fifty stocks from the NIFTY 50 index of the Indian National Stock Exchange was gathered, stock data was collected, and technical indicators were calculated.

III. Proposed Methodology

The proposed prototype classification algorithm for option price prediction uses improved K-means algorithms and a support vector machine. The improved k-means algorithm generates the pattern of a similar group of data. The generation of patterns reduces the variation of attributes. The reduced attributes and noise factor increase the quality of data normalization. The phase of the support vector machine trained the data of clusters and defined the class level of the option price. The bagging of K-means and support vector machine (SVM) reduces the noise variance, increases class vectors, and increases the classification ratio. The processing of the algorithm is described in two algorithms, such as algorithm1 for the processing of data and algorithm2 for the bagging of SVM[14,15].

Algorithm-1

The improved K-means algorithm form cluster of given data of stock price. The formation of cluster based on random selection of center point. The selection of center point uses the theory of rank order and minimized the randomness of cluster and reduces the iteration. The processing of clustering algorithm is

- $k - number\ of\ cluester\ (p)$: the number of cluster value put initial
- $Rank\ of\ centers\ (\frac{D}{N}K)$ rank of centers decides by the size and ratio of number of attributes here D is size of data, N is number of attributes and K is rank attribute in data.
- $estimate\ the\ cluester\ mean$

$$mean(K) = \left(\sum_{D \in N_{(x,k)}} Xi - dist_k(Xj)\right)^{-}$$

  where $N_{(x,k)}$ is the number of cluster and x is data point?
- $intermidate\ cluster$

$$clust(imt) = \sum_{K \in N_{(X,k)}} (Xk + Xk2 + \cdots, Xkn)$$

Final formation of cluster

$$clust(final) = \sum_{K \in N_{(X,k)}} (k1, k2, k3 \ldots \ldots \ldots \ldots, kn)$$

Algorithm-2

Algorithm-2 describes the processing of support vector machine with input data of cluster and finally produces the prediction of option price. The support vector machine algorithm uses non-linear kernel function and bagged to cluster data as pattern. The processing of algorithm describes here.

1. Input: number of clusters = $\{k_1, \ldots \ldots, kn\}$
2. Output: prediction rate of option price
3. $Train\ data \leftarrow 0$;
4. for all $k_t \in D$do
5. $level(k_t) \leftarrow$ data of cluster
6. if the data is set now call kernel function of machine
7. $kernal^s \leftarrow \{k_{s\frac{c}{2}+margin}\ \}$
8. $\left(C^i, k^i\right) \leftarrow K$or
9. for all $C_l^{ik} \in\ V$do
10. measure $confusion\ matrix$

11. end for
12. estimate evaluation parameters

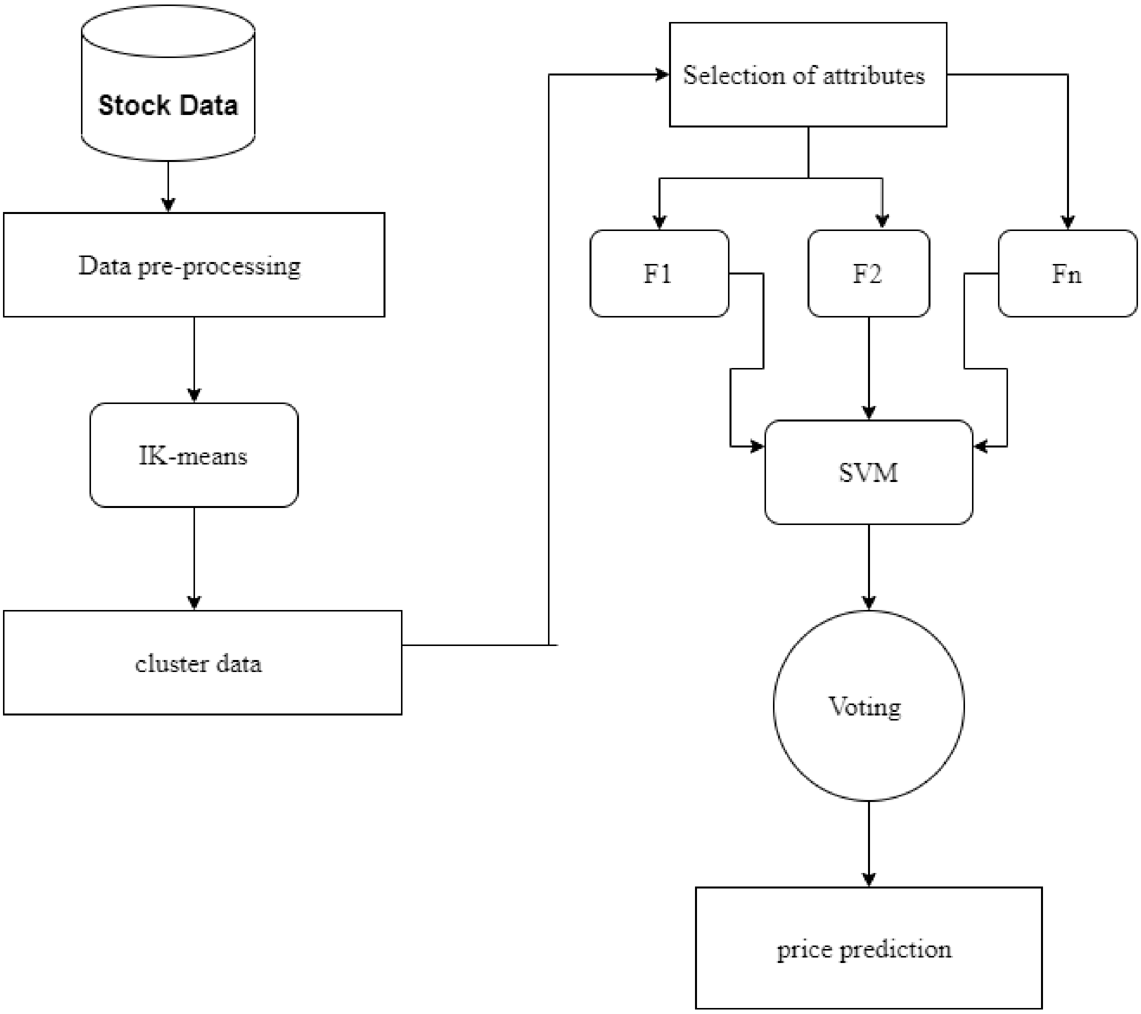

Figure 1 proposed model of prototype classification algorithm using SVM and IKM

IV. Experimental analysis

To analyse the performance of machine learning algorithms for stock price prediction, use MATLAB tools. The system configuration of the machine is an I7 processor, 16GB of RAM, and a 1TB HDD. The algorithms of machine learning are implemented as SOM, SVM and proposed algorithm. MATLAB tools provide the library file and create some functions for the processing and mapping of data. The performance of algorithms is estimated in terms of RMSE, NMSE, MI, and MAE. Data collection from Indian stock exchanges from bank sectors record of data is the last 10 years of SBI Bank [22,23,24].

Data collection

Table 1: Input Data taken from National Stock Exchange of India (NSE) Stock option of SBI bank

Symbol	Strike Price	Settle Price	Underlying Value
SBIBANK	310	0.2	190.75
SBIBANK	300	0.05	192
SBIBANK	310	0.05	198.45
SBIBANK	300	0.05	193.55
SBIBANK	310	0.35	204.05
SBIBANK	300	0.15	199.25
SBIBANK	280	0.05	187
SBIBANK	270	0.05	183
SBIBANK	300	0.25	203.5
SBIBANK	270	0.2	184.8
SBIBANK	280	0.05	192
SBIBANK	300	0.15	207.25
SBIBANK	280	0.05	193.55
SBIBANK	280	0.1	196.6
SBIBANK	260	0.3	183
SBIBANK	270	0.15	190.05
SBIBANK	280	0.05	198.45
SBIBANK	280	0.05	198.8

Evaluation Parameters

We evaluate prediction performance using four measures: normalized mean squared error (NMSE), root mean squared error (RMSE), mean absolute error (MAE), and mutual information (MI)[24,25,26,27].

A. Normalized Mean Squared Error, NMSE

Given a set of target returns and their predicted values, $\{r_{t+1}^{n}, r\wedge_{t+1}^{n}\}_{n=1}^{N}$, NMSE is defined as

$$NSME = \frac{1}{N}\frac{\sum_{n=1}^{N}(r_{t+1}^{n} - r\wedge_{t+1}^{n})^2}{var(r_{t+1}^{n})}$$

where $var(\cdot)$ denotes variance. Recall that $var(r_{t+1}^{n}) = min_c \frac{1}{n=1}(r_{t+1}^{n} - C)^2$; NMSE is a mean squared error (MSE) normalized by the least MSE obtained from a constant prediction.

B. Root Mean Squared Error, RMSE

RMSE is the square root of MSE, defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(r_{t+1}^{n} - r\wedge_{t+1}^{n})^2}$$

C. Mean Absolute Error, MAE

MAE is defined as follows:

$$MAE = \frac{1}{N}\sum_{n=1}^{N} |r_{t+1}^{n} - r\hat{\ }^{n}_{t+1}|$$

Note that inequality holds for the last two measures, $MAE \leq RMSE \leq \sqrt{N}\, MAE$; both error measures are known to informative, e.g., while MAE gives the same weight to all error amounts, RMSE is more sensitive to outliers, and is more suit for normal distributed error. For more interpretations, see Chai and Draxler, 2014.

D. Mutual Information, MI

MI measures dependency between r_{t+1} and u_t, and is defined as follows:

$$MI(r_{t+1}; u_t) = \sum_{r_{t+1}; u_t} p(r_{t+1}, u_t)\ log \frac{p(r_{t+1}, u_t)}{p(r_{t+1})P(u_t)} \approx \frac{1}{N}\sum_{n=1}^{N} \log \frac{p(r_{t+1}^{n} \mathrm{l}\, u_t^{n})}{p(r_{t+1}^{n})}$$

$MI(r_{t+1}; u_t)$is zero when the two variables are independent, and bounded to the information entropy, $H(r_{t+1}) = -\sum_{r_{t+1}} p(r_{t+1})\ log\, p(r_{t+1})$, when the two variables are fully dependent. From the assumption made earlier, we have $r_{t+1}\mathrm{l}u_t \sim N(r^{\wedge}{}_{t+1}, \beta)$. With an additional assumption, $r_{t+1} \sim N(\mu,\ \sigma)$ timate the parameters $\beta, \mu\ and\ \sigma$ from the sample and evaluate MI from (20).

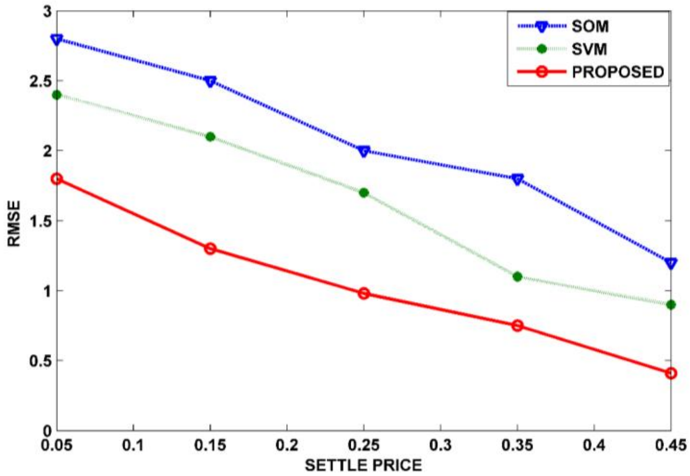

Fig 2 : Results of RMSE and settle price of stock

In this graph indicates the variation of root mean square error betweenself-organizedmap, support vector machine and proposed method for the SBI Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.35, 0.45 the variation indicates the value of RMSE is optimized due to the process of optimization and better prediction of proposed method. According to the settle price (2.8, 2.5, 2, 1.8, 1.2) support vector machine method RMSE values are 2.4, 2.1, 1.7, 1.1, 0.9 and similarly in self organized machines RMSE value are 2.8, 2.5, 2, 1.8, 1.2 and in proposed method RMSE values are 1.8, 1.3, 0.98, 0.75, 0.41.

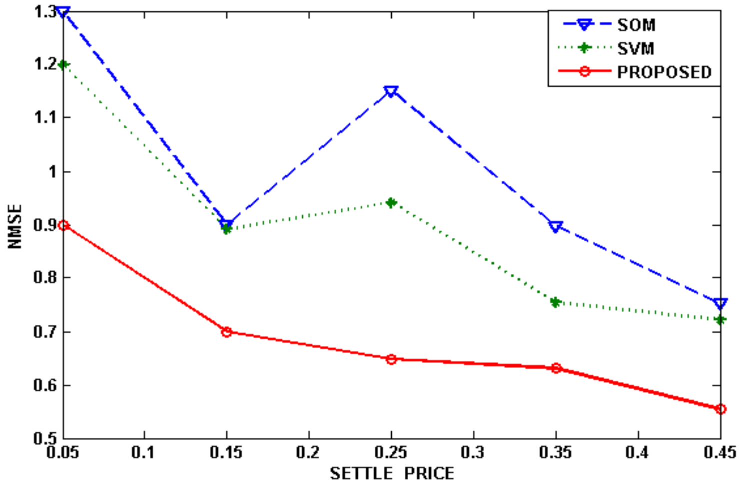

Fig 2 : Results of NMSE and settle price of stock

In this graph indicates the variation of normalized mean square error betweenself-organized map, support vector machine and proposed method for the SBI Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.35, 0.45 the variation indicates the value of NMSE is optimized due to the process of optimization and better prediction of proposed method. According to the settle price (0.05, 0.15, 0.25, 0.35, 0.45) in support vector machine method NMSE values are 1.2, 0.891, 0.941, 0.754, 0.721 and similarly in self organized machines NMSE value are 1.3, 0.9, 1.15, 0.897 0.752 and in proposed method NMSE values are 0.9, 0.699, 0.648, 0.631, 0.554.

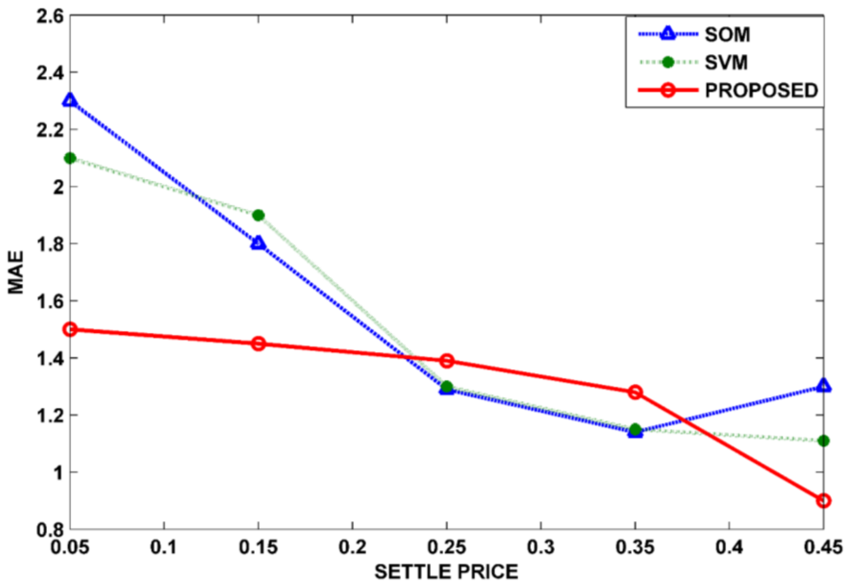

Fig 3 : Results of MAE and settle price of stock

In this graph indicates the variation of mean absolute error between self organized map, support vector machine and proposed method for the SBI Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.35, 0.45 the variation indicates the value of MAE is optimized due to the process of optimization and better prediction of proposed method. According to the settle price (0.05, 0.15, 0.25, 0.35, 0.45) in support vector machine method MAE values are 2.1, 1.9, 1.3, 1.15, 1.11 and similarly in self organized machines MAE value are 2.3, 1.8, 1.29, 1.14, 1.3 and in proposed method MAE values are 1.5, 1.45, 1.39, 1.28, 0.9.

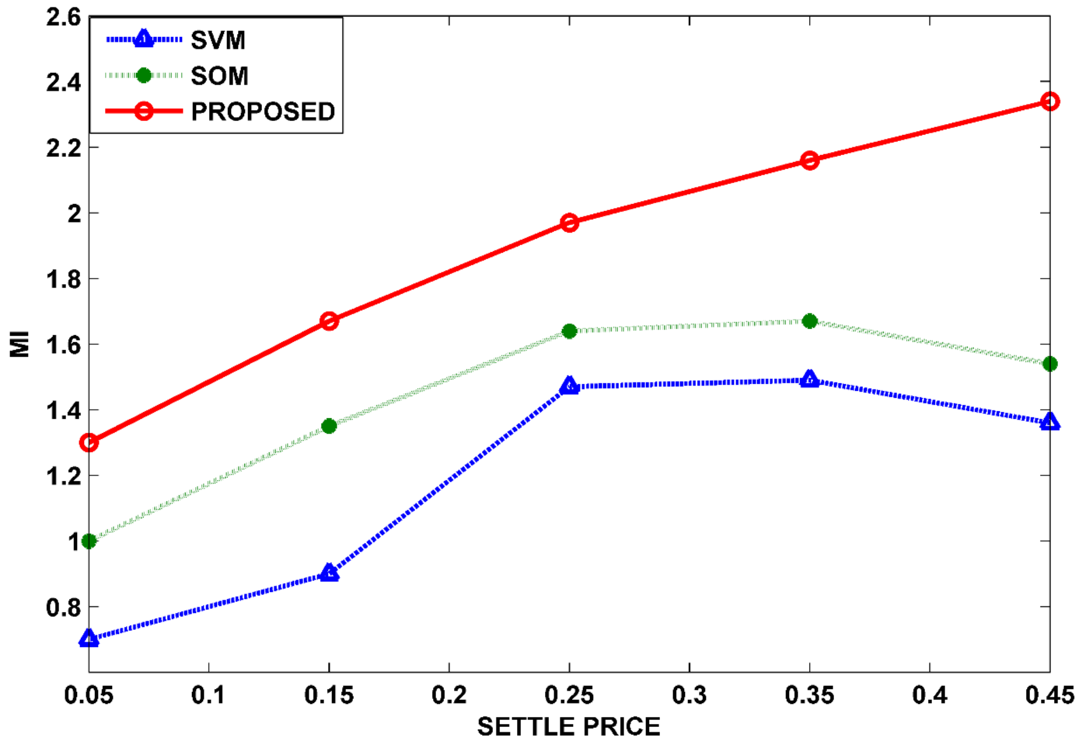

Fig 5 : Results of MI and settle price of stock

.In this graph indicates the variation of mutual information between self-organized machines, support vector machine and proposed method for the SBI Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.35, 0.45 the variation indicates the value of MI is optimized due to the process of optimization and better prediction of proposed method. According to the settle price (0.05, 0.15, 0.25, 0.35, 0.45) in support vector machine method MI values are 0.7, 0.9, 1.47, 1.49, 1.36 and similarly in self organized machines MI value are 1, 1.35, 1.64, 1.67, 1.54 and in proposed method MI values are 1.3, 1.67, 1.97, 2.16, 2.34.

V. Conclusion & Future Work

This paper proposed a prototype classification algorithm for stock price prediction. The proposed algorithm bags the Ik-means algorithm and support vector machine. The K-means algorithm improves the rank function and increases the centre selection of the clustering process. The bag of clustering algorithm and classification algorithm enhances the performance of stock price prediction. The proposed algorithm is tested on MATLAB software and validated with the SBI bank dataset. The SBI bank dataset is a record of the last ten years. The proposed algorithm compares the support vector machine and SOM neural network model. The variation of results in the case of SOM and SVM is maximum. The maximum deviation of results indicates the instability of the stock market. The current study exclusively used an IK-Means algorithm for data normalization; the process of data normalization reduces the noise and data unbalancing factors. As a result, additional research should look into adopting different possibilities. Again, stock price movement is influenced by past stock data and fundamental data such as consumer satisfaction with the company's market and online news. As a result, future studies might look at the impacts of user emotion and web financial news on stock price movement.

Reference

[1]. Hu, Zexin, Yiqi Zhao, and Matloob Khushi. "A survey of forex and stock price prediction using deep learning." Applied System Innovation 4, no. 1 (2021): 9.

[2]. Nti, Isaac Kofi, Adebayo Felix Adekoya, and Benjamin Asubam Weyori. "Efficient stock-market prediction using ensemble support vector machine." Open Computer Science 10, no. 1 (2020): 153-163.

[3]. Reddy, Niveditha N., E. Naresh, and Vijaya Kumar BP. "Predicting Stock Price Using Sentimental Analysis Through Twitter Data." In 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), pp. 1-5. IEEE, 2020.

[4]. Shi, Yong, Yuanchun Zheng, Kun Guo, and Xinyue Ren. "Stock movement prediction with sentiment analysis based on deep learning networks." Concurrency and Computation: Practice and Experience 33, no. 6 (2021): e6076.

[5]. Mehtab, Sidra, and Jaydip Sen. "Stock price prediction using CNN and LSTM-based deep learning models." In 2020 International Conference on Decision Aid Sciences and Application (DASA), pp. 447-453. IEEE, 2020.

[6]. Sen, Jaydip, Sidra Mehtab, and Gourab Nath. "Stock price prediction using deep learning models." Lattice-The Machine Learning Journal 1, no. 3 (2020): 34-40.

[7]. Nabipour, Mojtaba, Pooyan Nayyeri, Hamed Jabani, Amir Mosavi, and Ely Salwana. "Deep learning for stock market prediction." Entropy 22, no. 8 (2020): 840.

[8]. Ecer, Fatih, Sina Ardabili, Shahab S. Band, and Amir Mosavi. "Training multilayer perceptron with genetic algorithms and particle swarm optimization for modeling stock price index prediction." Entropy 22, no. 11 (2020): 1239.

[9]. Ronaghi, Farnoush, Mohammad Salimibeni, Farnoosh Naderkhani, and Arash Mohammadi. "ND-SMPF: A noisy deep neural network fusion framework for stock price movement prediction." In 2020 IEEE 23rd international conference on information fusion (FUSION), pp. 1-7. IEEE, 2020.

[10]. Mehtab, Sidra, Jaydip Sen, and Subhasis Dasgupta. "Robust analysis of stock price time series using CNN and LSTM-based deep learning models." In 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), pp. 1481-1486. IEEE, 2020.

[11]. Biswas, Milon, Atanu Shome, Md Ashraful Islam, Arafat Jahan Nova, and Shamim Ahmed. "Predicting stock market price: A logical strategy using deep learning." In 2021 IEEE 11th IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE), pp. 218-223. IEEE, 2021.

[12]. Chen, Wei, Haoyu Zhang, Mukesh Kumar Mehlawat, and Lifen Jia. "Mean–variance portfolio optimization using machine learning-based stock price prediction." Applied Soft Computing 100 (2021): 106943.
[13]. Yu, Pengfei, and Xuesong Yan. "Stock price prediction based on deep neural networks." Neural Computing and Applications 32, no. 6 (2020): 1609-1628.
[14]. Jin, Zhigang, Yang Yang, and Yuhong Liu. "Stock closing price prediction based on sentiment analysis and LSTM." Neural Computing and Applications 32, no. 13 (2020): 9713-9729.
[15]. Livieris, Ioannis E., Emmanuel Pintelas, and Panagiotis Pintelas. "A CNN–LSTM model for gold price time-series forecasting." Neural computing and applications 32, no. 23 (2020): 17351-17360.
[16]. Wu, Jimmy Ming-Tai, Zhongcui Li, Norbert Herencsar, Bay Vo, and Jerry Chun-Wei Lin. "A graph-based CNN-LSTM stock price prediction algorithm with leading indicators." Multimedia Systems (2021): 1-20.
[17]. Nti, Isaac Kofi, Adebayo Felix Adekoya, and Benjamin Asubam Weyori. "A systematic review of fundamental and technical analysis of stock market predictions." Artificial Intelligence Review 53, no. 4 (2020): 3007-3057.
[18]. Xu, Ying, Cuijuan Yang, Shaoliang Peng, and Yusuke Nojima. "A hybrid two-stage financial stock forecasting algorithm based on clustering and ensemble learning." Applied Intelligence 50, no. 11 (2020): 3852-3867.
[19]. Pang, Xiongwen, Yanqiang Zhou, Pan Wang, Weiwei Lin, and Victor Chang. "An innovative neural network approach for stock market prediction." The Journal of Supercomputing 76, no. 3 (2020): 2098-2118.
[20]. Huang, Ming-Hui, and Roland T. Rust. "A strategic framework for artificial intelligence in marketing." Journal of the Academy of Marketing Science 49, no. 1 (2021): 30-50.
[21]. Hao, Yan, and Chengshi Tian. "A hybrid framework for carbon trading price forecasting: the role of multiple influence factor." Journal of Cleaner Production 262 (2020): 120378.
[22]. Long, Wen, Zhichen Lu, and Lingxiao Cui. "Deep learning-based feature engineering for stock price movement prediction." Knowledge-Based Systems 164 (2019): 163-173.
[23]. Mondal, Saikat, A. Dutta, and P. Chatterjee. "Application of Deep Learning Techniques for Precise Stock Market Prediction." In National Conference on Machine Learning and Artificial Intelligence. 2020.
[24]. Sunny, Md Arif Istiake, Mirza Mohd Shahriar Maswood, and Abdullah G. Alharbi. "Deep learning-based stock price prediction using LSTM and bi-directional LSTM model." In 2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES), pp. 87-92. IEEE, 2020.
[25]. Parray, Irfan Ramzan, Surinder Singh Khurana, Munish Kumar, and Ali A. Altalbe. "Time series data analysis of stock price movement using machine learning techniques." Soft Computing 24, no. 21 (2020): 16509-16517.