ISSN 2593-7568

RESEARCH ARTICLE

Optimizing Stock Market Forecasts: The Role of AI and Hybrid Models in Predictive Analytics

Shivani Modi[1*], Ved Prakash Upadhyay[2]

[1]*University of Illinois at Urbana Champaign, Illinois, USA*
[2]*Columbia University, NY, USA*

Abstract

Forecasting stock market movements is a challenging and significant task for both researchers and investors. Stock market movements are affected by local and global economic factors, as well as political developments. This field of research requires substantial knowledge of finance, statistics, and Artificial Intelligence to achieve reliable results. To understand stock market movements, we must interpret a significant amount of information from non-linear, volatile, and non-parametric raw data. To reduce the complexity of stock market forecasting, we need to extract key features from this raw data. To simplify the task of stock market forecasting for researchers and traders, we conducted a study on the Indian stock market and present a comprehensive summary report. This report includes an analysis of 50 research articles related to the Indian stock market, along with some highly cited articles pertaining to other international markets.

Key Words: *Indian stock market forecasting; Stock market prediction; Neural network; Support vector machine; Artificial intelligence; ARIMA; Random forest*

1. Introduction

The volatile behavior of stock markets has been widely debated for decades. Researchers from both economics and engineering fields have examined the market using various financial and soft computing models to predict future trends. They have also developed models to forecast stock market volatility, focusing on cultivating different approaches to successfully predict future stock prices and market indices. The main goal of these researchers is to build predictive models using minimal data while achieving high accuracy. Forecasting is inherently challenging due to the numerous complexities involved. To predict stock markets accurately, researchers must select appropriate input variables and modeling techniques, as well as implement accurate performance measures for their models.

***Corresponding Author**: *Shivani Modi, University of Illinois at Urbana Champaign, Illinois, USA, E-mail: sm5060@columbia.edu*

***Received Date**: June 04, 2024, **Accepted Date**: June 24, 2024, **Published Date**: June 28, 2024*

***Citation:** Modi S, Upadhyay VP. Optimizing Stock Market Forecasts: The Role of AI and Hybrid Models in Predictive Analytics. Int J Auto AI Mach Learn. 2024;4(1):61-72.*

In recent years, researchers have become increasingly interested in using AI and business models to predict stock market volatility [1]. A stock market index is a statistical indicator used to measure changes in the market value of stocks, providing information about the overall movements of different stocks in the market. While stock market forecasting has become a highly researched field in developed countries like the United States, it remains a relatively new area of study in developing countries such as India. Indian researchers are still becoming aware of the field's potential.

The purpose of our research is to review and classify the techniques described in the literature. We have reviewed 50 highly cited research papers covering both Indian markets and other reputable international markets. In this paper, we summarize the approaches used in various stock market forecasting systems. We have produced a comprehensive report on data samples and sizes, input variables, preprocessing techniques, and classifiers used in stock market forecasting models. We also compare both simple and hybrid models.

Section II presents various input variables used by researchers, while Section III elaborates on the complete preprocessing approach applied to raw data. In Section IV, feature indicators are classified according to financial and macroeconomic fundamentals. Sections V and VI provide a comparative study of classification models and performance measures, respectively, used in various forecasting systems. Finally, we conclude our study in Section VIII.

2. Input Variables

Various input variables, such as opening, low, high, and closing values of stocks or stock market indices, are utilized to predict short-term market movements. Our survey reveals that the number and type of input variables fluctuate based on the researchers' objectives and the availability of data. Several Indian researchers [2-9] and international researchers [10-12] have employed the closing value as the sole input variable for market movement forecasting.

Certain researchers focus on long-term predictions, incorporating macroeconomic variables such as exports and imports, money supply, interest rates, inflation rates, foreign exchange rates, unemployment figures, and detailed company financial profiles [13,14]. These profiles include metrics such as dividend yields, earnings yield, cash flow yield, book-to-market ratio, price-earnings ratio, lagged returns, and firm size. In specific instances, researchers have integrated economic and financial factors as input variables in their models [13,15-20].

3. Data Preprocessing

Data preprocessing is a fundamental step in the data mining process, particularly when forecasting time series such as stock markets. Preprocessing raw data is essential because the available raw data is often inadequate for modeling purposes due to its highly inconsistent nature. Raw data from various sources typically contains noise, including redundancy and missing values, which can significantly affect the quality of the data. The quality of data used for modeling directly impacts the accuracy of the prediction model. Therefore, data preprocessing is employed to enhance accuracy and reduce the complexity of the model.

During data preprocessing, data is normalized so that each input component is linearly scaled within a specified range, such as (-1.0, 1.0) or (0, 1). This normalization ensures that the data is standardized and comparable. Researchers who scaled their samples within the range of (0,

1) are referenced in articles [21-24]. In contrast, articles [4,7,12,25,26] discuss researchers who scaled their samples within the range of (-1, 1). Additionally, some researchers have used different scaling ranges, such as (-0.9, 0.9) and (-0.5, 0.5), as shown in articles [27,28] respectively. These variations in scaling methods reflect the diverse approaches researchers take to optimize their models.

To reduce the dimensionality of data, principal component analysis (PCA) is commonly employed, as cited by authors of articles [18,29-32]. High dimensionality, caused by redundancy in source data, is typically summarized from numerous independent variables to a smaller set of derived variables known as principal components. The principal components capture the most significant variance in the data. The number of principal components is always less than or equal to the number of original variables. Principal components are derived from the variance matrix, with the first principal component being the linear combination of matrix elements that exhibit the largest possible variance, followed by the second component, which captures the second-largest variance, and so on. This reduction in dimensionality helps in simplifying the model and improving its performance.

Time series data is inherently non-stationary and high-dimensional. A time series is considered stationary if there are no systematic changes in mean (no trend), no changes in variance, and any periodic variations have been removed. Stationarity is a critical property for many time series forecasting models, as it simplifies the modeling process and improves accuracy. To test the stationarity of data, unit root tests such as the Augmented Dickey-Fuller test [17,33] and the Phillips-Perron test [6,34] are employed. These tests help in determining whether the time series data needs to be transformed to achieve stationarity, ensuring that the forecasting model produces reliable and accurate predictions.

4. Feature Extraction

To enhance the accuracy of predictive models, it is essential to extract meaningful features from the dataset. When the source data is large and potentially redundant, it becomes necessary to condense the data into a set of significant information, known as feature indicators. It is expected that these feature indicators, extracted from the raw stock market time series data, encompass all pertinent and relevant information.

In the literature, various feature indicators are employed, generally categorized into two types: fundamental and technical, based on stock market analysis. Fundamental analysis relies on macroeconomic data, including exports and imports, money supply, interest rates, inflation rates, foreign exchange rates, unemployment figures, and specific company financial profiles (e.g., dividend yields, earnings yield, cash flow yield, book-to-market ratio, price-earnings ratio, lagged returns, and company size).

On the other hand, technical analysis typically disregards the efficient market hypothesis, operating on the rationale that history will repeat itself and that the correlation between price and volume can reveal market behavior. Predictions are made by exploiting insights hidden in past trading activities and by analyzing patterns and trends in price and volume charts.

The selection of feature indicators is influenced by the specific time series of the stock market, known as the forecasting horizon. Feature indicators can be chosen based on the critical factors affecting the forecasting horizon. If the forecasting time horizon spans one year or more, fundamental analysis is preferred. Conversely, if the horizon is shorter than one-year, technical analysis is more suitable. Since modern forecasting systems can automatically select relevant features, the exact number of indicators is less critical; only those indicators containing relevant information will be chosen by the system.

In the literature, researchers commonly classify feature indicators into three types: volume-based, price-based, and overlay indicators. Volume-based indicators analyze the total trading volume in stock markets, while price-based indicators examine the stock's price value. In technical charts, feature indicators often appear as squiggly lines above, below, or on top of the price information. These are known as overlay indicators, which use the same scale as prices and are typically plotted on top of the price bars. Table 1 categorizes all feature indicators used in the literature, providing a comprehensive overview of their application.

5. Classification and Modeling

The choice of a suitable classifier is crucial for enhancing the performance of stock market forecasting systems, both for intraday and long-term predictions. Researchers have experimented with various types of forecasting classifiers, utilizing models like ARIMA (Auto Regressive Moving Average) [2, 6, 25] EGARCH (Exponential Generalized Auto Regressive Conditional Heteroskedasticity), TARCH (Threshold ARCH) [3,33] Hidden Markov Models [30,35] and ARFIMA-FIGARCH (Auto Regressive Fractionally Integrated Moving Average-Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity) [23,36]. These models employ statistical techniques for forecasting.

Recently, there has been a significant shift towards machine learning algorithms for stock market predictions due to their promising results. However, it is essential for researchers to consider several influential parameters during the modeling process. Surveys indicate that the most prominent factors affecting share prices are their immediate opening and closing values [37]. Additionally, the forecasting horizon and investment strategies significantly influence trading simulations. The forecasting horizon refers to the period during which the indices are realized [13]. From our study, we have observed that neural networks' ability to discover nonlinear relationships in input data makes them preferable for modeling nonlinear dynamic systems like the stock market [38,39,32].

The Artificial Neural Network (ANN) classifier is particularly adept at identifying outliers and erroneous data [13]. By implementing the Empirical Risk Minimization (ERM) principle, ANNs often outperform traditional statistical models [11,5]. It is noted that the risk-adjusted performance of NN-based trading models generally surpasses the Buy and Hold strategy [28]. ANN's capacity to learn nonlinear patterns accurately has led to its widespread acceptance in stock market prediction [24,40]. Various versions of neural network classifiers are used in stock market forecasting, as cited in [4,17,21,28,41-43].

Despite their advantages, ANNs are prone to overfitting, local minima traps, and challenges in determining the hidden layer size and learning rate [11]. These issues can limit their practical application and reliability in fluctuating market conditions. In comparison, the Support Vector Machine (SVM) model [44,45] offers good generalization performance, absence of local minima, and sparse representation of solutions. The SVM classifier is based on the Structural Risk Minimization (SRM) principle, which differs from the ERM principle that only minimizes training error. Due to SRM, SVMs often achieve higher generalization performance than traditional ANNs [10,26].

Table 1: *Feature Indicators.*

Indicators	Explanation	Type
On-Balance Volume (OBV)	OBV is a momentum indicator that uses volume flow to predict changes in stock price	Volume based indicators
Money Flow Index (MFI)	Compares the traded value of the up-days to the traded value of down-days and puts it in a percentage value.	
Volume Price Trend Indicator	It consists cumulative volume line that adds or subtracts a multiple of the percentage change in share price trend and current volume, depending upon their upward or downward movements.	
Chaikin Money Flow	CMF Oscillator is derived from MACD. Used in technical analysis as measurement of buying and selling pressure with a purpose of generating trading signals.	
Relative Strength Index (RSI)	A technical momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset.	Price based indicators
Moving Average Convergence Divergence (MACD)	The difference between a fast and slow exponential moving average (EMA) of closing prices. (Fast means a short-period average, and slow means a long period one)	
Rate Of Change (ROC)	The percentage difference between the current price and the price n-time periods ago.	
Stochastic Oscillator (SO)	It compares a security's closing price to its price range over a given time period. The oscillator's sensitivity to market movements can be reduced by adjusting the time period or by taking a moving average of the result	
William's %R	This is a momentum indicator measuring overbought and oversold levels, similar to a stochastic oscillator	
Momentum	To identify trend lines used an oscillator which is known as momentum.	
Chaikin Oscillator	Combines price and volume to show how money may be flowing into or out of a stock. Based on Accumulation/Distribution Line	
Moving Average	To emphasize the direction of a trend and smooth out price and volume fluctuation that can confuse interpretation.	Overlay based indicators
Bollinger Bands	A chart overlay that shows the upper and lower limits of price movements based on the Standard Deviation of prices.	

Training an SVM is equivalent to solving a linearly constrained quadratic programming problem, ensuring a unique and globally optimal solution. Unlike other networks that risk getting stuck in local minima, SVMs depend only on a subset of training data points, known as support vectors, which simplifies computation. Literature shows that SVMs outperform random forests, neural networks, and other traditional models due to their implementation of the SRM principle [10,26,46,47]. Various stock market forecasting models have utilized the SVM classifier, as seen in [12,25,27,31,46,48-53].

Similar to SVM, the regularized Radial Basis Function (RBF) neural network minimizes the regularized risk function, leading to better generalization performance than the Back Propagation (BP) neural network [10]. The RBF network's robustness to overfitting makes it a reliable alternative in fluctuating markets. However, a disadvantage of SVM is that its training time scales quadratically or cubically with the number of training samples, making it computationally intensive for large datasets [10]. This limitation necessitates efficient algorithmic strategies and high computational resources for practical implementation.

Experiments with mixed classifiers have shown better results compared to single classifier models. For instance, a decision tree-KPCA-ANFIS hybrid system outperforms simple neural networks and naïve Bayesian models [54,55]. The decision tree rough set-based prediction system also outperforms standalone rough set and ANN-based systems without feature selection [29]. A hybrid ARIMA-GARCH model with a Moving Average (MA) filter-based decomposition pre-processing step outperforms ARIMA, GARCH, trend-ARIMA, and wavelet-ARIMA models [35]. A hybrid neuro-fuzzy adaptive control system has demonstrated superior performance compared to 13 other soft computing approaches [14]. Furthermore, models learning through trend deterministic data showed significant performance improvements, achieving accuracies of 86.69% for ANN, 89.33% for SVM, 89.98% for random forest, and 90.19% for naive-Bayes [25].

The Cuckoo Search (CS) algorithm, based on Swarm Intelligence optimization, effectively tunes SVM parameters, resulting in higher accuracy rates than regular SVM methods [44]. Experimental results indicate that the CS-SVM method provides higher accuracy with lower Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) compared to ANN and SVM. Additionally, a hybrid ARIMA-neural network model [5] outperforms linear ARIMA and nonlinear ANN models. The Genetic Algorithm (GA) optimized decision tree-SVM hybrid system [48] outperforms both ANN and naïve Bayes prediction systems, as well as standalone SVM models [50]. These hybrid models leverage the strengths of individual algorithms, leading to more robust and accurate forecasting results. In summary, while various models and hybrid systems have shown promise in stock market forecasting, the choice of classifier and the consideration of influential parameters are vital for achieving optimal performance. Continuous advancements in machine learning and hybrid modeling approaches hold the potential to further enhance the accuracy and reliability of stock market predictions, aiding investors in making informed decisions.

6. Performance Measures

Performance measures, also known as quality measures, play an indispensable role in the field of machine learning and data sciences. They are crucial for evaluating the strength of classification models and serve as criteria for designing heuristics to develop these models. Performance measures can be broadly classified into two types: statistical and non-statistical measures.

Statistical measures are further divided into parametric and non-parametric tests. Parametric tests make certain assumptions about the parameters (properties) of the data distribution. These assumptions help in defining the nature and behavior of the data, facilitating more precise analysis under specified conditions. Examples of parametric tests include t-tests and ANOVA, which assume normal distribution and equal variances.

On the other hand, non-parametric tests make no assumptions about the data distribution. They are more flexible and can be used with data that do not fit the assumptions of parametric tests. Examples of non-parametric tests include the Mann-Whitney U test and the Kruskal-Walli's test, which are useful for ordinal data or non-normally distributed data.

Non-statistical performance measures include metrics like the hit ratio, which is widely used in time series problems. The hit ratio evaluates how often the predicted values correctly match the actual values, providing insight into the model's accuracy over a period. These performance measures, whether statistical or non-statistical, are essential for the development, validation, and refinement of machine learning models, ensuring their effectiveness and reliability in various applications.

Table 2: *Performance Measures [7].*

MSE	Mean squared error	Mean (et^2)
RMSE	Root mean squared error	√ (MSE)
MAE	Mean absolute error	mean(|et|)
Md. AE	Media absolute error	median(|et|)
MAPE	Mean absolute percentage error	mean(|pt |)
Md. APE	Median absolute percentage error	median(|pt|)
SMAPE	Symmetric mean absolute percentage error	mean(2|Yt - Ft |/(Yt +Ft))
SMd. APE	Symmetric median absolute percentage error	median(2|Yt -Ft |/(Yt +Ft))

If the problem is a regression problem, performance measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Steady State Error (SSE) are typically used. These metrics help quantify the difference between the predicted and actual values, providing insights into the accuracy and reliability of the regression model.

In classification problems, performance is often evaluated using a confusion matrix or error matrix. These matrices provide a comprehensive overview of the model's performance by displaying the counts of true positives, true negatives, false positives, and false negatives. From these counts, various metrics such as accuracy, precision, recall, and F1 score can be derived, offering a detailed assessment of the classifier's effectiveness. Table 2 illustrates the performance measures commonly used in the literature for both regression and classification problems, highlighting their significance in model evaluation.

7. Conclusion

Our comprehensive survey of intelligent system techniques for Indian stock market forecasting has revealed significant insights into the efficacy of various models. The research underscores that artificial intelligence (AI) techniques, particularly machine learning models, generally outperform traditional statistical methods in predicting stock market trends. Among the soft computing techniques examined, the Support Vector Machine (SVM) stands out as the most preferred classification model due to its superior accuracy and generalization capabilities compared to other models.

The literature also provides robust evidence supporting the effectiveness of hybrid models over single classifier models. These hybrid approaches leverage the strengths of multiple algorithms, leading to enhanced performance and reliability in stock market predictions. For instance, hybrid models such as ARIMA-GARCH, decision tree-KPCA-ANFIS, and neuro-fuzzy adaptive control systems have demonstrated superior accuracy and robustness compared to their standalone counterparts. These findings indicate that combining different modeling techniques can significantly improve forecasting outcomes.

Additionally, our analysis highlights the importance of data preprocessing and feature extraction in developing reliable forecasting models. Techniques such as normalization, principal component analysis (PCA), and the selection of appropriate feature indicators are critical in enhancing accuracy and reducing the complexity of predictive models. The choice of input variables, whether fundamental or technical, also plays a pivotal role in the success of these models.

Despite the promising results of AI and hybrid models, challenges such as overfitting, local minima traps, and computational intensity remain. Advanced techniques and high computational resources are essential to address these issues effectively. Moreover, continuous advancements in machine learning algorithms and hybrid modeling approaches hold the potential to further enhance the accuracy and reliability of stock market predictions, providing valuable tools for investors and researchers alike.

In conclusion, our study reaffirms the significant potential of AI and hybrid techniques in stock market forecasting. By leveraging these advanced methodologies, researchers and investors can achieve more accurate and reliable predictions, thereby making more informed decisions in the dynamic and complex world of stock markets. Future research should continue to explore and refine these techniques, focusing on overcoming current limitations and harnessing new advancements in the field.

References

1. Devadoss AV, Ligori TA. Stock prediction using artificial neural networks. Int J Data Min Tech App. 2013;2:283-91.

2. Abraham A, Philip NS, Saratchandran P. Modeling chaotic behavior of stock indices using intelligent paradigms. ArXiv Prepr. 2004:cs/0405018.

3. Chen AS, Leung MT, Daouk H. Application of neural networks to an emerging financial market: forecasting and trading the Taiwan stock index. Comput Oper Res. 2003;30:901-23.

4. Khan AU, Bandopadhyaya TK, Sharma S. Genetic algorithm-based backpropagation neural network performs better than backpropagation neural network in stock rates prediction. Int J Comput Sci Netw Secur. 2008;8:162-6.

5. Dutta A, Bandopadhyay G, Sengupta S. Prediction of stock performance in the Indian stock market using logistic regression. Int J Bus Inf. 2012;7:105.

6. Hiremath GS, Kamaiah B. Some further evidence on behaviour of stock returns in India. Int J Econ Finance. 2010;2:1-11.

7. Nair BB, Minuvarthini M, Sujithra B, et al. Stock market prediction using a hybrid neuro-fuzzy system. International conference on advances in recent technologies in communication and computing, Kottayam, India. 2010.

8. Nair BB, Mohandas VP, Sakthivel NR. A decision tree-rough set hybrid system for stock market trend prediction. Int J Comput Appl. 2010;6:1-6.

9. Babu CN, Reddy BE. Selected Indian stock predictions using a hybrid ARIMA-GARCH model. International conference on advances in electronics computers and communications, Bangalore, India. 2014.

10. Cao LJ, Tay FE. Support vector machine with adaptive parameters in financial time series forecasting. IEEE Trans Neural Netw. 2003;14:1506-18.

11. Yeh CY, Huang CW, Lee SJ. A multiple-kernel support vector regression approach for stock market price forecasting. Expert Syst Appl. 2011;38:2177-86.

12. Grosan C, Abraham A, Ramos V, et al. Stock market prediction using multi expression programming. Portuguese conference on artificial intelligence, Covilha, Portugal. 2005.

13. Upadhyay VP, Panwar S, Merugu R. Protein sequence structure prediction using artificial intelligent techniques. Proceedings of the international conference on advances in information communication technology & computing, Bikaner, India. 2016.

14. Banerjee D. Forecasting of Indian stock market using time-series ARIMA model. 2nd international conference on business and information management, Durgapur, India. 2014.

15. Atsalakis GS, Valavanis KP. Forecasting stock market short-term trends using a neuro-fuzzy based methodology. Expert Syst Appl. 2009;36:10696-707.

16. Zhang G, Patuwo BE, Hu MY. Forecasting with artificial neural networks: the state of the art. Int J Forecast. 1998;14:35-62.

17. Kaur H. Time varying volatility in the Indian stock market. Vikalpa. 2004;29:25-42.

18. Goudarzi H, Ramanarayanan CS. Modeling asymmetric volatility in the Indian stock market. Int J Bus Manag. 2011;6:221.

19. Patel J, Shah S, Thakkar P, et al. Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Syst Appl. 2015;42:259-68.

20. Badge J. Forecasting of Indian stock market by effective macro-economic factors and stochastic model. J Stat Econom Methods. 2012;1:39-51.

21. Devi KN, Bhaskaran VM, Kumar GP. Cuckoo optimized SVM for stock market prediction. International conference on innovations in information, embedded and communication systems, Coimbatore, India. 2015.

22. Sujatha KV, Sundaram SM. A combined PCA-MLP model for predicting stock index. Proceedings of the 1st Amrita ACM-W celebration on women in computing in India, Coimbatore, India. 2010.

23. Vaisla KS, Bhatt AK. An analysis of the performance of artificial neural network technique for stock market forecasting. Int J Comput Sci Eng. 2010;2:2104-9.

24. Kim KJ. Financial time series forecasting using support vector machines. Neurocomputing. 2003;55:307-19.

25. Dey L, Mahajan A, Haque SM. Document clustering for event identification and trend analysis in market news. Seventh International Conference on Advances in Pattern Recognition, Kolkata, India. 2009.

26. Kumar M, Thenmozhi M. Support vector machines approach to predict the S&P CNX NIFTY index returns. J Emerg Mark Finance. 2007:1-19.

27. Rajakumar MP, Shanthi V. Computationally intellectual structure for forecasting share price. Int J Soft Comput. 2013;8:218-22.

28. Thenmozhi M. Forecasting stock index returns using neural networks. Delhi Business Review. 2006;7:59-69.

29. Subha MV, Nambi ST. Classification of stock index movement using k-nearest neighbours (k-NN) algorithm. WSEAS Trans Inf Sci Appl. 2012;9:261-70.

30. Kumar M. A time-varying parameter vector autoregression model for forecasting emerging market exchange rates. Int J Econ Sci Appl Res. 2010;3:21-39.

31. Hassan MR, Nath B, Kirley M. A fusion model of HMM, ANN and GA for stock market forecasting. Expert Syst Appl. 2007;33:171-80.

32. Nair BB, Mohandas VP, Sakthivel NR. A genetic algorithm optimized decision tree-SVM based stock market trend prediction system. Int J Comput Sci Eng. 2010;2:2981-8.

33. Dutta G, Jha P, Laha AK, et al. Artificial neural network models for forecasting stock price index in the Bombay stock exchange. J Emerg Mark Finance. 2006;5:283-95.

34. Merh N, Saxena VP, Pardasani KR. A comparison between hybrid approaches of ANN and ARIMA for Indian stock trend forecasting. Bus Intell J. 2010;3:23-43.

35. Upadhyay VP, Sonawat M, Singh S, et al. Nano robots in medicine: a review. Int J Eng Technol Manag Res. 2017;4:27-37.

36. Sivakumar PB, Mohandas VP. Modeling and predicting stock returns using the ARFIMA-FIGARCH. World congress on nature & biologically inspired computing, Coimbatore, India. 2009.

37. Chang PC, Liu CH. A TSK type fuzzy rule based system for stock price prediction. Expert Syst Appl. 2008;34:135-44.

38. Troiano L, Kriplani P. Predicting trend in the next-day market by Hierarchical Hidden Markov Model. International conference on computer information systems and industrial management applications, Karakow, Poland. 2010.

39. Choudhry R, Garg K. A hybrid machine learning system for stock market forecasting. Int J Comput Inform Eng. 2008;2:689-92.

40. Nayak RK, Mishra D, Rath AK. A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices. Appl Soft Comput. 2015;35:670-80.

41. Merugu R, Upadhyay VP, Manda S. Bioinformatics analysis and modelling of mycotoxin patulin induced proteins. Int J Bioinformatics Biol Sci. 2016;4:5-10.

42. Dhar S, Mukherjee T, Ghoshal AK. Performance evaluation of neural network approach in financial prediction: evidence from Indian market. International Conference on Communication and Computational Intelligence, Erode, India. 2010.

43. Das SP, Padhy S. Support vector machines for prediction of futures prices in Indian stock market. Int J Comput Appl. 2012;41:22-6.

44. Mitra SK. Optimal combination of trading rules using neural networks. Int Bus Res. 2009;2:86-9.

45. Chaudhuri TD, Ghosh I. Using clustering method to understand Indian stock market volatility. ArXiv Prepr. 2016:1604.05015.

46. Huang W, Nakamori Y, Wang SY. Forecasting stock market movement direction with support vector machine. Comput Oper Res. 2005;32:2513-22.

47. Kara Y, Boyacioglu MA, Baykan OK. Predicting direction of stock price index movement using artificial neural networks and support vector machines: the sample of the Istanbul stock exchange. Expert Syst Appl. 2011;38:5311-9.

48. Chen Y, Dong X, Zhao Y. Stock index modeling using EDA based local linear wavelet neural network. International conference on neural networks and brain, Beijing, China. 2005.

49. Chen Y, Abraham A, Yang J, et al. Hybrid methods for stock index modeling. Fuzzy systems and knowledge discovery: second international conference, Changsha, China, 2005.

50. Kumar M, Thenmozhi M. Stock index return forecasting and trading strategy using hybrid ARIMA-neural network model. Int J Finance Manag. 2012;2:1-14.

51. Handa R, Hota HS, Tandan SR. Stock market prediction with various technical indicators using neural network techniques. Int J Res Appl Sci Eng Technol. 2015;3:604-8.

52. Atsalakis GS, Valavanis KP. Surveying stock market forecasting techniques–Part II: soft computing methods. Expert Syst Appl. 2009;36:5932-41.

53. Kumar M, Thenmozhi M. Forecasting stock index movement: a comparison of support vector machines and random forest. Indian institute of capital markets 9th capital markets conference, Hong Kong, China. 2006.

54. Upadhyay VP, Panwar S, Merugu R, et al. Forecasting stock market movements using various kernel functions in support vector machine. Proceedings of the international conference on advances in information communication technology & computing, Bikaner, India. 2016.

55. Panwar S, Upadhyay VP, Bishnoi SK. A survey of intelligent system techniques for Indian stock market forecasting. 39th MIPRO conference, Opatija, Croatia. 2016.