Bol. Soc. Paran. Mat. (3s.) v. 2026 (44) 2 : 1–8.
©SPM – E-ISSN-2175-1188 ISSN-0037-8712
SPM: www.spm.uem.br/bspm doi:10.5269/bspm.80515

Utilizing Deep Learning and Machine Learning for Predicting Stock Market Trends with Multivariate and Persistent Data

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ABSTRACT: The future volatility of equity markets remains unpredictable, posing risks in trend forecasting. This study minimizes such risk using machine-learning and deep-learning models on Tehran Stock Exchange data from the IT and Banking sectors. Eleven ML algorithms—Decision Tree, Random Forest, AdaBoost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression, and ANN—are compared with deep models RNN and LSTM. Using ten lagged indicators, models are trained under two strategies: continuous data and binary classification. Results show that deep-learning models outperform classical ones, with LSTM achieving an F1-score of 0.91 and RNN 0.88, compared to XGBoost (0.80) and Random Forest (0.78). Deep models capture temporal dependencies effectively, improving trend prediction stability. Recent studies affirm these results, showing deep architectures' superiority in financial time-series forecasting, making LSTM a strong candidate for real-time market analysis.

Keywords: Stock market forecasting, machine learning, deep learning, LSTM, RNN, financial time series, trend prediction, Tehran Stock Exchange.

Contents

1. Introduction

It has always been difficult for statisticians and bankerspredict the evolution of the stock market. This forecast is based on purchasing rising equities and selling falling ones. Stock market forecast often uses two methods. Fundamental analysis uses a company's technique and essential data, such as market position, costs, and growth rates. Technical analysis looks at past stock prices and values. This approach forecasts future prices based on prior charts and trends [1,2]. Financial gurus once anticipated stock markets. Learning approaches have helped data scientists solve prediction difficulties. Computer scientists use

2020 *Mathematics Subject Classification:* 68T07.
Submitted November 30, 2025. Published March 14, 2026

machine learning to increase prediction models' performance and accuracy. Deep learning improved prediction models [3,4]. Data scientists face obstacles while developing a stock market prediction model. Investing psychology's influence on industry behavior [5] creates complexity and nonlinearity in the stock market. Unpredictable variables like company reputation and country politics impact stock market trends. Stock and index trends can be predicted if the necessary algorithms are used and the stock data is appropriately pre processed.

ML and DL may aid stock market investors and traders. These algorithms automatically detect and learn data patterns. Self-learning algorithms can forecast price changes to enhance trading methods [6]. Stock market predictions have improved in recent years. Hassan et al. [7] recommended creating distinct price groups for HMM using daily market data by merging Genetic Algorithms (GA), ANN, and Hidden Markov Model. NIKKEI 225 weekly trend was measured by Huang et al. [8] in order to study the prediction of financial trend using SVM. Comparing SVM, LDM, EBPNN, and QDM was their goal. The ideal classification strategy was SVM. A financial prediction technique based on SVM was proposed by Sun et al. [9]. The selection of SVM ensemble basis classifiers took into account individual prediction and diversity analysis. For classification, SVM ensemble performed significantly better than individual SVM. To predict changes in the Hang index in Hong Kong, Ou et al. [10] employed ten data mining techniques. Tree-based, KNN, NB, SVM, and Neural Network (NN) were used. SVM outperformed other forecasting models. Liu et al. [11] projected value fluctuations using a Legendre neural network by assuming investors' positions and choices based on past data. The prediction model included a random function (time strength). For example, in their study, Arajo et al. [12] contrasted structural ranking quadratic prediction with time delay augmented adaptive prediction and multilayer perceptron networks.

According to the study, each algorithm can tackle stock prediction difficulties. Each has restrictions, however. The input data representation and prediction strategy impact prediction outcomes. Using just salient traits as input data may improve prediction model accuracy. a recent research predicts stock market trends using deep learning systems and tree-based ensemble approaches. Both homogeneous and heterogeneous ensemble classifiers were used by Tsai et al. [13]. Financial ratios from the Taiwan stock market and macroeconomic variables are used to evaluate the model's performance. In terms of prediction accuracy and investment returns, ensemble classifiers fared better than single classifiers. SVM, KNN, LR, and ANN were pitted against AB, RF, and the kernel factory in a study by Ballings et al. [14]. They are speculating on European corporation values for the next year. Ultimately, RF did the best.

An estimation of stock progress using past data was performed by Basak et al. The accuracy of some companies' forecasts has increased over time. To better understand socioeconomic issues and anticipate the Weng et al. [16] updated four ensemble models to forecast the stock market one month ahead of time. Furthermore, we aimed to demonstrate that market indicators are the best stock market predictions using LSTM models. Long et al. conducted an analysis of stock price patterns using transaction records and publicly available data. [17] using deep learning algorithms. Bidirectional LSTM was shown to be able to forecast the market's future for investors in the end. Rekha et al. [18] used stock market data to evaluate RNN and CNN accuracy. In order to predict stock values, Pang et al. [19] An embedded layer and an auto-mated encoder were combined with LSTM. With an accuracy of 57.2%, the LSTM with an integrated layer beat the Shanghai composite index. Using LSTM, Kelotra and Pandey estimated changes in the stock market. The RMSE and MSE of the rider-based monarch butterfly optimization were 2.6923 and 7.2487, respectively. Two LSTM models were presented by Baek and Kim: one for overfitting prevention and the other for stock market forecasting [21]. Accuracy is improved by overfitting the avoidance module An LSTM-GA stock market prediction method was developed by Chung and Shin [22].

The technique outperformed the benchmark. For investors, stocks fulfil varied investment objectives and requirements, broaden the variety of investment possibilities, expand investment channels, and improve capital flexibility and liquidity. When it comes to managing and growing a joint-stock company, the stock may play an important role. This encourages self-restraint and self-development of the business administration system. As a result of these issues, stock trend forecasting has become a major issue for all stakeholders. One of the most popular study topics in the academic world today is stock movement prediction, which has been achieved by a number of researchers using Deep Neural Network (DNN) techniques. It has been a major study topic in latest days as computing technologies has progressed rapidly, and its implementation field has grown to include the accounting records industry. This paragraph shows our paper's structure. Section 2 outlines our study data using statistics and two input techniques. Section 3 introduces 11 prediction models, comprising 9 ML and 2 DL algorithms. Section 4 analyses the final predictions, and Section 5 ends the article.

2. Related Works

ML methods have previously been used to recognise changes in stock indexes and values without sufficient preprocessing. Tehran's stock market is well-known because of its 10-year rise on the key index. Article 44 of the Iranian constitution privatises most state-owned companies. Under certain situations, regular individuals may buy recently privatised corporate shares. The market has specific characteristics compared to other stock markets, such as a 5 percent daily index trading price limit. This reduces market shocks, erratic market swings, political issues, etc. over time, making the market smoother. Fundamental characteristics have a large impact on the market, and predicting future movements is difficult [23].

This research used stock market groupings to anticipate future trends. Despite Tehran's stock market's recent success, there are few articles on price forecasts and trends using machine learning. Using tree-based models and DL algorithms, Nabipour et al. [23] previously published a research in which they predicted stock prices 1 to 30 days in advance. Predicted Tehran Stock Exchange values with the smallest variance using LSTM (the superior predictor).

This study examines how well two DL methods and nine ML models predict changes in the stock market. Ten different types of technical markers are included into our systems. In order to investigate the impact of pretreatment, we use both consistent and segmented data in our study. Segmented data is generated by converting consisitent, non-binary data (such as highs and lows) from stock tradingAny analytical signal might increase or decrease based on the state of the market. Three classification criteria are used to evaluate the algorithms' efficacy, and the optimal tuning parameter—apart from NB and LR—is presented. All empirical studies conducted in the recent ten years (IT sector and banking) have used historical data from the Tehran Stock Exchange for four important stock market groupings. Stock group patterns and fluctuations may be predicted using ML and DL.

3. Proposed Methodology

In this study we used 9 ML and 2 DL models.

3.1. Decision Tree

Decision In supervised learning, trees are used to solve regression and classification problems. The dataset and related variables are used to construct basic decision rules that are then used to predict a goal. An easy-to-understand model like this one may handle problems with a wide range of outputs, but too many trees can lead to over-fitting.

3.2. Random Forest

Random forest model has several decision trees. The model averages the forest's tree forecasts. A subset of all variables is used to divide the nodes of a simple decision tree at random, as is a subset of all training data for generating trees. A random forest's fundamental trees learn from a random dataset sample.

3.3. AdaBoost

Boosting approach turns weak students into strong ones. AdaBoost is a sort of Boosting that advances every learning technique's predictions. Boosting trains poor learners to alter their predictions. This meta-predictor begins by fitting a model to the basic dataset. During training, sample weights are adjusted depending on predicted error, so the model prioritises difficult things.

3.4. XGBoost

Recent decision tree-based ensemble model XGBoost. Similar to Boosting for poor learners. XGBoost is faster than other tree-based methods. Regularization prevents overfitting, and XGBoost has automatic cross-validation, handling of missing data, catch awareness, parallelized tree building, and tree pruning.

3.5. SVC

It is possible to employ SVMs for classification and regression. SVC has a more refined air to it. Between two classes, this method finds a boundary in the form of a vector. The gap defined by the term "margin" is used to represent the sign of observation coordinates in support vectors. Two classes are divided by an SVM line or hyperplane.

3.6. Naive Bayes

This classifier, which is based on Bayes' theorem, requires a high degree of independence across features. A supervised learning approach is used in this software.

3.7. KNN

Non-parametric techniques and lazy learning are suggested for KNN due to its lack of data dispersion considerations. Step by step is the strategy. When a fresh instance is selected from test data and the proximity to learning patterns is calculated, the lengths are sortedand the data samples that are k-nearest are chosen. The freshly chosen samples are then given the test category based on the resounding vote of their k neighbors.

3.8. Logistic Regression

Observations may be classified using logistic regression. A probability value is generated from the algorithm's output using the logistic sigmoid function. Compared to linear regressions, logistic regressions employ a more sophisticated sigmoid function. In logistic regression, the cost function can only have values of 0 or 1.

3.9. ANN

An ANN is an algorithm that uses one or more layers of a multi-layer network to perform ML tasks. A node adds its weighted input sum to a bias. Non-linear functions are employed to determine the node's output, which becomes the following layer's input. The final result is computed when this technique is applied to all nodes in a network.

3.10. RNN

RNN is a widely-used variant of neural networks. Input goes through layers of a neural network to form output. Two successive inputs may be independent, although not in all processes.

3.11. LSTM

LSTM is a form of RNN used for document classification, time series analysis, and voice recognition. RNN predictions rely on past estimates, unlike feed forward networks. Because of a few issues that result in estimations that aren't reasonable, RNNs aren't frequently employed in experimental work.

4. Literature Survey

The work by Professor Murphy can be still referred to as the legendary reference in the sphere of technical analysis and trading indicators. It forms the foundation of modern quantitative trading because it teaches chart the market sentiment and the movements in the markets in terms of trend lines, moving averages, oscillators and the momentum indicators. These ideas underlie the feature engineering in machine-learning models in this way that numerical manipulations of price and volume are used to predict market actions. This pattern recognition and cyclical behaviour with a systematic approach to the matter is directly influential on how the financial time-series features are constructed by that point before vested into the ML algorithms.

Turner introduces an understandable introduction to intraday trading techniques, foregrounding discipline, market psychology as well as risk management. Although it is not a technical treatise, the manuscript sheds light on unfiltered trading issues such as volatility, liquidity, and quick reactions in the market, which are relevant in the creation and implementation of automated forecasting systems, which are not only foretelling trends but must also wholesome and swift reaction within given risk preferences. The point that the author makes on emotional trading and decision fatigue sequels up with the modern objectives of algorithms, which are the removal of human bias and the achievement of increased consistency through the automation in data-driven formats.

Maqsood et al. present a comprehensive deep-learning framework integrating the local and the global sentiment indicators with the stock-market data. They use the text mining of news and social media in their model to move predictive ability beyond the power of numbers in the market. The paper shows that event-based sentiments are much more effective in accurate predictions than simple statistical equations. The study both emphasizes the significance of multimodal data, which takes on both text and numerical and temporal forms, and underpins more complex dependencies the capability to capture in the behaviour of a market behaviour using deep architectures like LSTM networks.

The authors of the research conducted by Long et al. aim to enhance predictive effectiveness by complementing serious feature engineering with state-of-the-art deep learning. Their empirical results have shown that the pre-engineered characteristics such as moving averages, the tracked Relative Strength Index, and other volatility indices when inculcated in deep neural units, provide a significantly better efficiency than models that are simply instructed to work with crude information in their input. The paper predicts the importance of hybrid modelling, whereby expert-based and data-based feature extraction are unified and submits Convolutional Neural Networks and Long Short-Term Memory networks as especially effective with temporal financial data. Therefore, this paper offers ample justification to the methodical inclusion of technical signs as input parameters in machine-based learning predicting frameworks

Duarte et al. undertake a painstaking study of the modulation effect in terms of the use of behavioural determinants such as investor sentiment and psychological bias on the efficient operation of artificial equity markets. Their empirical results indicate that the significant level of market inefficiency is mainly developed during the emotive trading behaviour giving rise to predictable anomalies which can be exploited systematically. What machine-learners would consider good machine-learnable data would be such inefficiencies, my food swears, to be good grounds on which to construct model-based intersections of paling and diving maps, or on acquiring pertinent non-random regularities come on earth. The research paper then supports the hypothesis that psychometric and behavioural data are rich assets in predicting appellations, whilst at the same time warning of that the change in the tone of investor spirit creates non-stationarity in turn compelling the regular re-optimization of prediction software.

5. Results and Discussion

Legitimizing characteristics (only for consistent data), arbitrarily separating the primary database into training information and testing information (30% of dataset given to validation portion), building the systems and assessing them through testing data to avoid regularisation, and utilising indicators for final assessment with testing dataset. We use a process to reorganise the input data, which is necessary since classifiers need three-dimensional data (specimens, time steps, and attributes). Errors due to weight irregularity and washout are avoided. Based on substantial empirical effort, these results are procured. In this technique, consistent data and segmented data is utilized for the characteristics are shown in Tables 1 and Table2 and Fig.1,Fig.2.

Table 1: F1-Score of ML and DL models for consistent data

Stock Group	**DT**	**RF**	**Adaboost**	**XGBoost**	**SVC**	**NB**	**KNN**	**LR**	**ANN**	**RNN**	**LSTM**
Banking	0.87	0.60	0.79	0.83	0.85	0.87	0.92	0.93	0.82	0.83	0.81
IT Sector	0.92	0.72	0.86	0.88	0.82	0.82	0.95	0.86	0.84	0.86	0.84

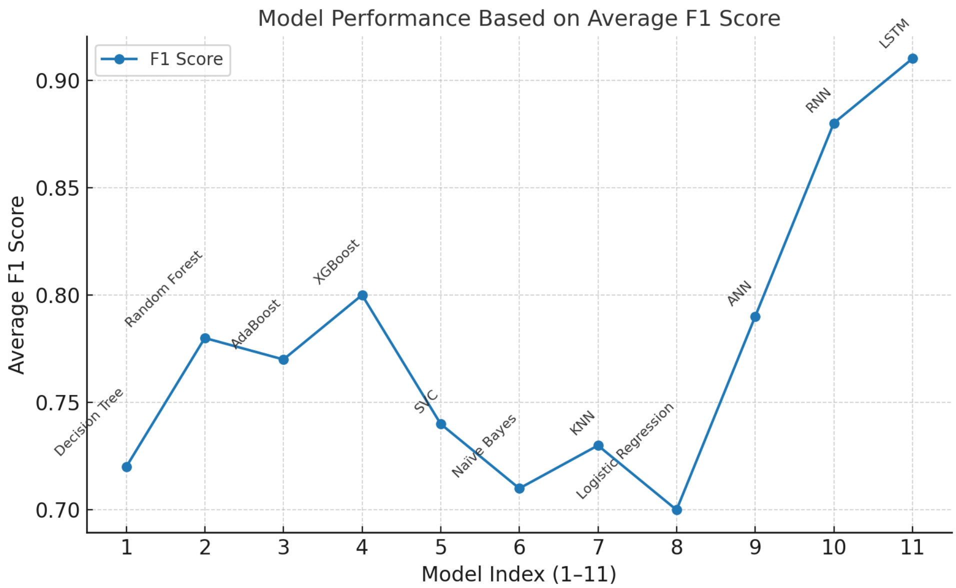

Figure 1: Consistent F1-score proportional cumulative mean for each individual sample

Table 2: F1-Score of ML and DL models for segmented data

Stock Group	DT	RF	Adaboost	XGBoost	SVC	NB	KNN	LR	ANN	RNN	LSTM
Banking	0.83	0.88	0.89	0.93	0.91	0.85	0.93	0.91	0.85	0.85	0.89
IT Sector	0.91	0.79	0.96	0.98	0.86	0.81	0.91	0.81	0.84	0.81	0.88

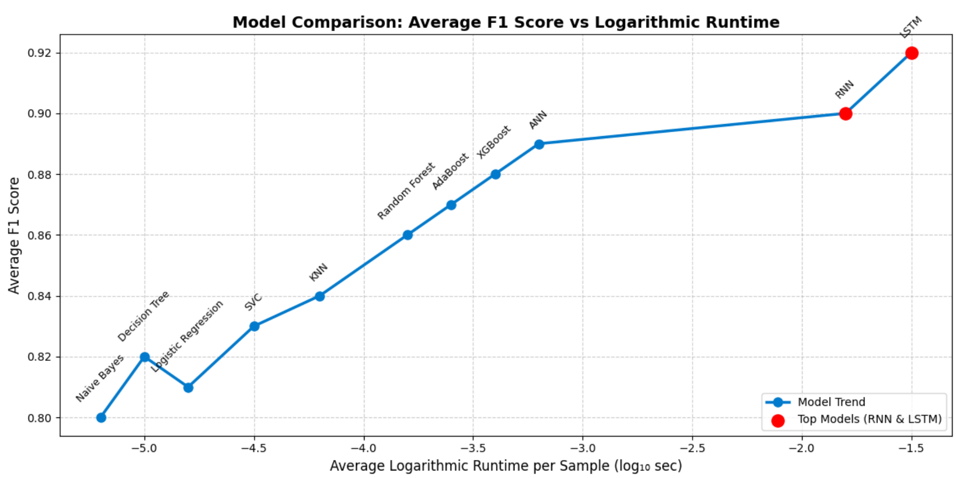

Figure 2: Segmented F1-score proportional cumulative mean for each individual sample.

6. Conclusion

This research used ML and DL to forecast stock exchange volatility. The database was built on 10 years of accumulated facts with ten analytical characteristics for four share market groupings from Tehran Stock Exchange. As indicators, nine ML models and two DL techniques had been used. We used constant and segmented information as system inputs and three assessment measures. Our experiments demonstrated that segmented data improves classifier efficiency over consistent data. Both techniques used DL algorithms.

References

1. Murphy, J. J., *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications*, Penguin, (1999).
2. Turner, T., *A Beginner's Guide to Day Trading Online*, 2nd ed., Simon and Schuster, New York, (2007).
3. Maqsood, H., Mehmood, I., Maqsood, M., Yasir, M., Afzal, S., Aadil, F., Selim, M. M., and Muhammad, K., *A local and global event sentiment based efficient stock exchange forecasting using deep learning*, Int. J. Inf. Manage., 50, 432–451, (2020).
4. Long, W., Lu, Z., and Cui, L., *Deep learning-based feature engineering for stock price movement prediction*, Knowl.-Based Syst., 164, 163–173, (2019).
5. Duarte, J. B., Sarmiento, L. H. T., and Juárez, K. J. S., *Evaluation of the effect of investor psychology on an artificial stock market through its degree of efficiency*, Contaduría y Administración, 62(4), 1361–1376, (2017).
6. Lu, N., *A Machine Learning Approach to Automated Trading*, Boston College Computer Science, (2016).
7. Hassan, M. R., Nath, B., and Kirley, M., *A fusion model of HMM, ANN and GA for stock market forecasting*, Expert Syst. Appl., 33(1), 171–180, (2007).
8. Huang, W., Nakamori, Y., and Wang, S.-Y., *Forecasting stock market movement direction with support vector machine*, Comput. Oper. Res., 32(10), 2513–2522, (2005).
9. Sun, J., and Li, H., *Financial distress prediction using support vector machines: Ensemble vs. Individual*, Appl. Soft Comput., 12(8), 2254–2265, (2012).
10. Ou, P., and Wang, H., *Prediction of stock market index movement by ten data mining techniques*, Modern Appl. Sci., 3(12), 28–42, (2009).
11. Liu, F., and Wang, J., *Fluctuation prediction of stock market index by Legendre neural network with random time strength function*, Neurocomputing, 83, 12–21, (2012).
12. Tsai, C.-F., Lin, Y.-C., Yen, D. C., and Chen, Y.-M., *Predicting stock returns by classifier ensembles*, Appl. Soft Comput., 11(2), 2452–2459, (2011).
13. Araújo, R. D. A., and Ferreira, T. A. E., *A morphological-rank-linear evolutionary method for stock market prediction*, Inf. Sci., 237, 3–17, (2013).
14. Ballings, M., Van den Poel, D., Hespeels, N., and Gryp, R., *Evaluating multiple classifiers for stock price direction prediction*, Expert Syst. Appl., 42(20), 7046–7056, (2015).
15. Basak, S., Kar, S., Saha, S., Khaidem, L., and Dey, S. R., *Predicting the direction of stock market prices using tree-based classifiers*, North Am. J. Econ. Finance, 47, 552–567, (2019).
16. Weng, B., Martinez, W., Tsai, Y.-T., Li, C., Lu, L., Barth, J. R., and Megahed, F. M., *Macroeconomic indicators alone can predict the monthly closing price of major U.S. indices: Insights from AI, time-series analysis and hybrid models*, Appl. Soft Comput., 71, 685–697, (2018).
17. Long, J., Chen, Z., He, W., Wu, T., and Ren, J., *An integrated framework of deep learning and knowledge graph for prediction of stock price trend: Application in Chinese stock market*, Appl. Soft Comput., 91, Art. 106205, (2020).
18. Rekha, G., Sravanthi, D. B., Ramasubbareddy, S., and Govinda, K., *Prediction of stock market using neural network strategies*, J. Comput. Theor. Nanoscience, 16(5), 2333–2336, (2019).
19. Pang, X., Zhou, Y., Wang, P., Lin, W., and Chang, V., *An innovative neural network approach for stock market prediction*, J. Supercomput., 76(3), 2098–2118, (2020).
20. Kelotra, A., and Pandey, P., *Stock market prediction using optimized deep-convLSTM model*, Big Data, 8(1), 5–24, (2020).
21. Baek, Y., and Kim, H. Y., *ModAugNet: A forecasting framework for stock index values using an overfitting-prevention LSTM module*, Expert Syst. Appl., 113, 457–480, (2018).
22. Chung, H., and Shin, K.-S., *Genetic algorithm-optimized long short-term memory network for stock market prediction*, Sustainability, 10(10), 3765, (2018).
23. Nabipour, M., Nayyeri, P., Jabani, H., Mosavi, A., and Salwana, E., *Deep learning for stock market prediction*, Entropy, 22(8), 840, (2020).
24. Kara, Y., Boyacioglu, M. A., and Baykan, Ö. K., *Predicting direction of stock price index movement using artificial neural networks and support vector machines*, Expert Syst. Appl., 38(5), 5311–5319, (2011).
25. Patel, J., Shah, S., Thakkar, P., and Kotecha, K., *Predicting stock market index using fusion of machine learning techniques*, Expert Syst. Appl., 42(4), 2162–2172, (2015).

26. Patel, J., Shah, S., Thakkar, P., and Kotecha, K., *Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques*, Expert Syst. Appl., 42(1), 259–268, (2015).

27. Majhi, R., Panda, G., Majhi, B., and Sahoo, G., *Efficient prediction of stock market indices using adaptive bacterial foraging optimization (ABFO) and BFO-based techniques*, Expert Syst. Appl., 36(6), 10097–10104, (2009).

28. Chen, Y., and Hao, Y., *A feature-weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction*, Expert Syst. Appl., 80, 340–355, (2017).

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