



## SURVEY ARTICLE

# A review and analysis of deep learning methods for stock market prediction with a variety of indicators

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## Abstract

The stock market is an open forum in which stocks may be exchanged, bought, and sold on a stock exchange or over-the-counter to gain profits. However, the stock market may be impacted by a variety of variables like the business cycle, economic conditions, changing political and government policies, market volatility and so on, resulting in lesser forecast possibilities. Statistical models have difficulty predicting the stock market because of their alternating nature and relying only on previous data does not give optimal future results. In recent years, deep learning (DL) models have gained attention in stock market forecasting. DL models accurately estimate both past and current data to improve prediction outcomes. Various DL models are explored in this study and their application to stock market prediction, specifically how past patterns can be used to anticipate future trends. DL models can reveal previously unseen patterns and connections by using massive datasets, including market prices, transaction amounts, news mood, and macroeconomic indicators. Furthermore, the article compares and contrasts a number of DL algorithms that are part of stock market prediction systems, outlining their advantages and disadvantages. At last, possible improvisations are made to improve the effectiveness and precision of stock market forecasting.

**Keywords:** Stock market, Deep learning, Historical data, Stock prices market activity.

## Introduction

In the global economy, the financial market is quite important as it affects national economies as well as personal income (Srinivasan & Prakasam, 2014). The stock market provides chances to create gains by purchasing stocks at a cheaper cost and selling them at a greater value, therefore acting as a marketplace for investors to swap shares of publicly listed firms (Pollet & Wilson, 2010). The

most prominent stock market networks that build a range of stock alternatives from varied industrial sectors are the New York stock exchange (NYSE), the National Association of Securities Dealers Automated Quotations (NASDAQ), and the London stock exchange (LSE). The Bombay stock exchange (BSE) and the National Stock Exchange of India (NSE) are two of India's most important stock exchanges, alongside their international counterparts. Particularly relevant to China's technology sector are the Shenzhen stock exchange (SZSE) and the Shanghai Stock Exchange (SSE). A major financial center for China and foreign investors alike is also Hong Kong stock exchange (HKEX). Among the many well-known stock exchanges globally are the Tokyo stock exchange (TSE) in Japan, the Australian Securities Exchange (ASX), and Euronext, which runs across several European cities including Amsterdam, Brussels, Dublin, Lisbon, Milan, Oslo and Paris. These platforms include many financial instruments from several industries and give several opportunities for investors all over to participate in the stock market (Baltussen *et al.*, 2019; Al Nasser *et al.*, 2016). Detection of stock markets has many uses that might influence general market behavior, investor choices, and price movements (Iacomin, R. 2015). Commonly utilized for stock market trend prediction include technical, basic, and statistical analysis (Kumar *et al.*, 2021).

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### Technical Analysis

This method examines the previous price movements and trade volumes and assists to analyse and project the future trend of stocks, assets, or markets (Nazário *et al.*, 2017). Forecasts of possible price developments rely on statistical measurements, technical indicators, and chart patterns (Li, A. W., & Bastos, G. S. 2020). The list below the elements of technical analysis.

#### Historical Price Data

Technical analysis is grounded on historical price data including past stock prices, trade volumes, and price swings. Analyzed are price charts and patterns to forecast the next trends (Jishag *et al.*, 2020).

#### Indicators

These help to estimate future price fluctuations by use of historical price and volume statistics. Common examples include moving averages including the simple moving average (SMA) and exponential moving average (EMA), the relative strength index (RSI) for spotting overbought or oversold circumstances, the moving average convergence divergence (MACD), and Bollinger bands (Saud & Shakya, 2024).

- Technical analysis uses metrics such as the Volatility Index (VIX) to evaluate market conditions by means of their capacity to capture uncertainty and possible price movements (Bantwa, 2017).

By utilizing the application of technical analysis, price trends and patterns can be found, thereby offering investors insightful information to guide their best points of view for market entrance and departure. This study is less dependable in certain market situations, however, as it depends only on past price data and ignores the underlying financial elements that could affect the long-term value of a company.

### Fundamental Analysis

In this analysis, the fundamental financial and economic elements of a company, asset, or market are assessed to determine its intrinsic worth (Ahmed *et al.*, 2015). By using the important metrics, economic circumstances, industry efficiency and firm fundamentals are stressed for the core values of the assets (Chen *et al.*, 2013). In helping investors make wise selections, the objective is to determine if an item is priced below or over its actual worth. The following lists elements suggesting the basic analysis:

#### Economic Indicators

Macroeconomic factors include price increases, interest rates, gross domestic product (GDP) and unemployment ratios that affect stock prices and the larger economy (Keswani *et al.*, 2024).

#### Corporate Financials

It depends on the economic stability of a corporation. For example, price-to-earnings (P/E) ratio, earnings per

share (EPS), income growth and dividends and debt levels (FERNIAWAN *et al.*, 2024).

#### Market Indices

These include the major evaluating elements like Standard & Poor's 500 (S&P 500) and Dow Jones industrial average (DJIA) which assists the investors to well-known about the total market updates, that are considered to be a fundamental assessment (Guerard *et al.*, 2022).

#### External Data

The key component of the stock market may be inferred from diverse financial markets, such as bond yields, commodity prices and currency rates. For instance, energy businesses may be impacted by changes in oil prices, which was covered in fundamental analysis (Mbarki *et al.*, 2023).

Fundamental analysis enables investors to comprehend the essential importance of a company by examining its economic health, profits, and economic circumstances, making it valuable for long-term investment choices. However, this evaluation might be resource-intensive, requiring a thorough assessment of economic statistics and other pertinent data that can be time-consuming and difficult, particularly for small financiers.

### Combined Analysis

In defined situations, investors mix technical and fundamental research to acquire a more comprehensive view of the market. The following are some common aspects when both methodologies are used simultaneously.

#### Geopolitical Factors

Events that include political unrest, wars, or legislative changes may influence both technical price movements (short-term responses) and fundamental causes (long-term economic effect on businesses or sectors (Reivan-Ortiz *et al.*, 2023).

#### Market Sentiment

Technical as well as fundamental elements might affect investor attitude in the market. News or earnings releases, for example, could impact the price movement (technical) of the stock as well as its long-term value and growth potential (Dumiter *et al.*, 2023).

#### Economic Cycles

By assessing the GDP growth and interest rates, more general economic cycles are depicted for guiding long-term trends. The technical study provides information on instantaneous price swings within those cycles concurrently (Switzer, L. N., & Picard, A. 2016).

Investors may improve their strategic planning by means of integrated analysis as technical analysis helps to ascertain ideal trade timing and fundamental analysis assesses the inherent worth of a stock or asset over the long run (Nti *et al.*, 2020).

### Statistical Analysis

Using mathematical models and analytical tools, statistical analysis investigates previous data and predicts future stock price patterns (Makridakis *et al.*, 2018). By being routinely used on time-series data, including stock prices, it aids in the identification of patterns, fluctuation, and arrangement. Statistical techniques help investors and financial analysts to predict future behavior and grasp the fundamental framework of stock price fluctuations. Long basic models in financial time-series prediction, autoregressive integrated moving average (ARIMA) (Xiao, D., & Su, J. 2022) and generalized autoregressive conditional heteroskedasticity (GARCH) (Nkoro, E., & Uko, A. K. 2013). have essentially seized trends, seasonality, and instability in stock price data. This study does not, however, account for abrupt changes in the market, non-linear relationships, or severe occurrences, thereby producing erroneous forecasts, particularly in times of great volatility or unusual circumstances.

The emergence of artificial intelligence (AI) especially via machine learning (ML) and DL models has transformed stock market forecasting in recent years (Chopra, R., & Sharma, G. D. 2021). Both these models benefit the technical, fundamental and statistical analysis, which effectively analyze the complex patterns to predict adaptive market conditions (Moghaddam *et al.*, 2016). ML aids institutional traders and investors in optimizing their portfolios and transactions, increasing revenue while reducing risk in the stock market (Mintarya *et al.*, 2023; Kumar *et al.*, 2022). ML models are prone to overfitting, nevertheless, particularly

in cases of too much historical data reliance. Furthermore, challenges for ML models to adjust include the implicit risk of the stock market and other factors such as geopolitical events, natural disasters, and changes in market sentiment, which might result in erroneous forecasts during unstable times. In stock market prediction, DL has shown a quite great potential (Nabipour, M., Nayyeri, P., Jabani, H., Mosavi, A., & Salwana, E. 2020). Stock price movements, market pattern identification, and investment risk assessment are predicted using models such as convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM), and so on (Ji, X., Wang, J., & Yan, Z. 2021). These models help investors respond fast to market swings and make smarter, data-driven judgments, hence improving the accuracy and efficacy of stock market projection (Zhao, R., Lei, Z., & Zhao, Z. 2024). Figure 1 depicts the general outline of DL-based stock market prediction.

This paper presents a wide range of stock market data from several areas by investigating many datasets and platforms used in stock market prediction. Various data sources available on different stock market platforms may be trained in DL models to improve their prediction capability. This work primarily intends to provide an overview of current advancements and ideas in DL-based stock prediction models. Emphasizing their effectiveness and possible enhancements, it addresses the many techniques already used for stock market movement prediction. The study also addresses the implementation of these algorithms on many stock markets and proposes future avenues to improve

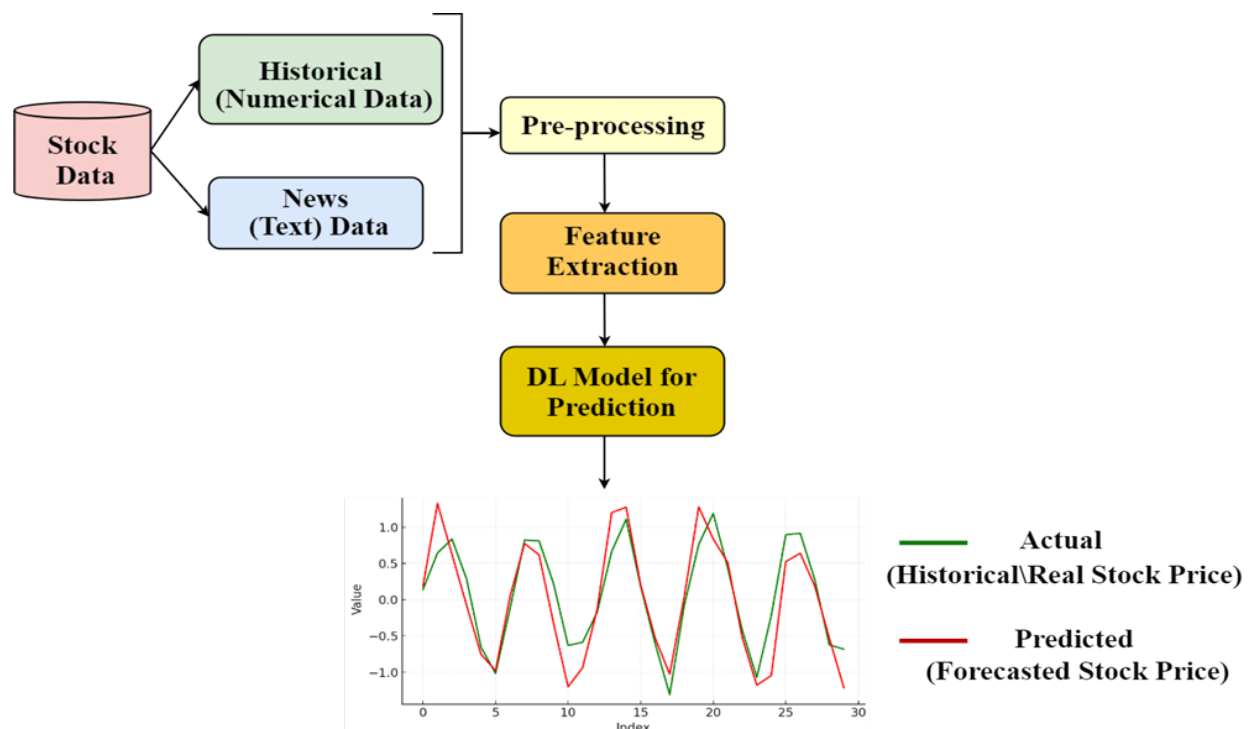


Figure 1: Stock price prediction workflow using DL model

forecast accuracy. The research also looks at creative ideas to solve problems such as data quality and market volatility, which are difficulties in stock market prediction. It ends with some thought on how newly developing technology could improve stock market forecast accuracy.

This work is organized as section II addresses many DL models for stock market prediction. Section III details a thorough comparison of various models. Section IV assesses these models; Section V ends the study with important conclusions and suggests areas of future research to enhance investing methods and strengthen stock market prediction models.

### **Survey On DL-Based Stock Market Prediction System**

The stock prices were predicted using an ML and DL model (Mehtab *et al.*, 2021). This approach uses ML models to find stock pattern correlations like random forest (RF), support vector machine (SVM), and multivariate regression (MVR). This approach used realistic, sequential forecasting with walk-forward validation. Simple univariate LSTM models maximize cost by surpassing intricate topologies. Different multi-variate LSTM models were used for long-term and short-term stock price forecasts.

An evolutionary DL model (EDLA) was presented (Agrawal *et al.*, 2022) to project stock trends and prices by employing stock technical indicators (STIs). Correlation tensor was used to capture intricate interactions across STIs for trend prediction in the livestock market with an eye for Indian banking companies, this model offered short-term fluctuations and long-term trends in the data were caught and used in an LSTM network to find the relationship between STIs and closing prices. Furthermore, employed for performance comparison with the proposed EDLA model were logistic regression (LR) and SVM.

To anticipate the stock prices, many sequential models were examined (Gupta *et al.*, 2023) including LSTM, gated recurrent unit (GRU), stacked LSTM (SLSTM), stacked GRU (SGRU), bidirectional LSTM (Bi-LSTM), bidirectional GRU (Bi-GRU), and hybrid model integrating Bi-LSTM and GRU layers. Using evolutionary algorithms tuned for important hyperparameters like epochs, batch size, dropout, layers, and activation functions, a neuro-evolution method minimizes mistakes. In stock estimate among all three models, Bi-GRU produced the best performance.

Using artificial neural network (ANN) and CNN models, a stock market forecast model was created (Mukherjee *et al.*, 2023). These models continue as long as the dataset is valid by forecasting future stock values founded on prior data in a recursive fashion. CNNs provide accurate forecasting by using 2-D histograms produced from quantized data within designated time frames, hence optimizing predictions.

The deep learning model including MLP, RNN, LSTM, and CNN to forecast stock prices was created (Ghosh *et al.*, 2024) using previously existing data of frequently traded equities

in the automotive, banking, and IT industries. Crucially for market movement prediction, these models are effective at capturing nonlinear trends in financial time series. Whereas RNNs and LSTMs manage sequential dependencies in pricing data, MLPs describe intricate interactions. CNNs using sectoral diversity and nonlinear dynamics enhance prediction by extracting local patterns in stock prices.

A hybrid DL model including peephole LSTM (PLSTM) with a temporal attention layer (TAL) was presented (Latif *et al.*, 2024) to enhance the accuracy of stock market direction predictions. Their method represented markets in the United States, the United Kingdom, China, India, using daily stock data from four main worldwide indexes. TAL was introduced PLSTM to choose relevant information depending on time, therefore improving the performance of the model. The PLSTM efficiently learns and maintains long-range relationships by including TAL, therefore finding important trends in stock market data.

To create a fundamental analysis for predicting stock prices (Khanpuri *et al.*, 2024) utilized LSTM model. Initially, this technique was based on monthly stock closing prices, with a focus on computing moving average. Then, a number of financial indicators were presented, including data from quarterly and annual financial reports, balance sheets, cash flow assessments, and other financial measurements. Finally, an LSTM model is used to forecast stock values, drawing on previous performance data from both annual and quarterly financial outcomes.

An advanced stock market forecasting model was developed (Jagadesh *et al.*, 2024) by applying a dandelion optimization algorithm (DOA)-driven 3D-CNN-GRU classification method. Data pre-processing was applied to eliminate the noises using the wavelet transform technique. In order to maximize feature selection by means of most relevant inputs, DOA is employed. Hybrid 3D-CNN-GRU model was developed by combining a 3D CNN with GRU to examine stock market data. In order to improve the model-predicted accuracy, hyperparameter tweaking was performed using the blood coagulation algorithm (BCA).

A CNN-bidirectional LSTM (BiLSTM)-Attention Model (CNN-BiLSTM-AM) was proposed (Zhang *et al.*, 2023) for the prediction of stocks prices and indices. CNN first helped to extract nonlinear local characteristics from SM data. Then BiLSTM was used to eliminate directional time series aspects of the sequence data. In order to reduce the impact of duplicate information and improve the accuracy of stock price forecasts, the information features of the BiLSTM layer were lastly automatically matched using weight assignments attention technique.

The MS-SSA-LSTM model for stock price prediction, combining diverse data sources, sentiment analysis, and DL techniques was proposed (Mu *et al.*, 2023). The model leveraged posts from the East Money forum to construct a sentiment dictionary and derive a sentiment index. To

improve predictive accuracy, the Sparrow search algorithm (SSA) was utilized for optimizing LSTM hyperparameters. The sentiment index was then integrated with fundamental trading data, and LSTM was applied to predict future stock values.

To enhance the causal relationships that guide the stock price fluctuations, an implicit-causality-exploration-enabled GNN was presented (Li *et al.*, 2024) for stock prediction. Extensive dynamic and stationary feature extraction in this model enhances predicting accuracy. Explicit and implicit links allow the GNN-based stock predictor strike a compromise between interpretability and deep learning capabilities. It improves stock prediction accuracy by using two feature extractors—one for static relations and one for dynamic relations—as well as an undirected Granger causality graph.

A multi-relational dynamic graph neural network (MDGNN) was created (Qian *et al.*, 2024) to forecast stock prices in a broad range. This method utilized discrete dynamic graphs for predicting stock investments. Using a multi-relational embedding layer, every graph snapshot with daily stock and relationship data was assessed to eliminate the stock complexity. The resultant infographic showed all the interconnections between stocks and associated companies. In addition, the accuracy of stock predictions was enhanced by capturing the temporal dynamics of multiplex data using the Transformer architecture.

To forecast stock prices, multilayer graph attention models (ML-GAT) was created (Huang *et al.*, 2022). By integrating LSTM with the BERT module, this model is able to predict the direction of linked equities. Market graphs may benefit from the use of LSTM and BERT, two methods for representing statistical data. After that, ML-GAT was used to filter a number of input sources, resulting in an aggregated graph. This graph included various attention mechanisms at different layers, which were used to extract feature representations of nodes and improve the accuracy of predictions. The model improves stock price predictions by using market characteristics and topological data from stock network graphs.

The deep reinforcement learning (DRL) was applied (Awad *et al.*, 2023) for predicting stock market. The model uses natural language processing (NLP) to glean sentiment from various news sources. In addition, BERT was enhanced by using TF-IDF to get stock data from many platforms' historical records. For the purpose of signal analysis, VMD (variation mode decomposition) was used. DRL generates actions based on market knowledge gathered from high-dimensional data, which handles complicated problems including fast changes and incomplete data. For better stock price forecasting, the DRL algorithm takes sentiment, past data, and news sources into account.

Stock prices were predicted using a Heterogeneous BiLSTM

(He-BiLSTM) with matching backpropagation (Sang *et al.*, 2024). This model's creation made use of the LSTM unit structure to improve data transmission and handling of non-stationary, nonlinear stock data, leading to increased generalizability. Using a novel backpropagation method in conjunction with noise reduction, this model enhances performance. He-BiLSTM provides more accurate stock price predictions, which is useful for financial market projections.

To forecast shifts in stock values, hybrid information mixing module (HIMM) (Choi *et al.*, 2023) were developed when applied to time series and semantic data, it uses GRU and BERT. A multimodal feature was created by merging the two features so that it could more accurately reflect the properties of the two types of data. In order to identify market signals and predict changes in stock prices, the HIMM was developed. It combines a feature and knowledge-based Multi-Layer Perceptron (MLP). This module generates row- and column-level mixed feature predictions for stock price forecasting.

A Generative Adversarial Network and transformer-based attention mechanisms (GAN-TAM) was applied (Li & Xu., 2024) to improve stock price prediction. This method applies GANs to create artificial stock price data by coupling market emotion with instability. In order to help identify important market indicators impacting stock prices, the attention approaches highlighted critical characteristics and patterns. By including social media tales on volatility and emotion, the algorithm enhanced stock price forecasts.

A hybrid BiLSTM (H. BLSTM) strategy was used (Kalra *et al.*, 2024) for stock market forecasting. Previous stock prices were treated as univariate time series, with technical indications tied to a diversified time series architecture. The batch relearning was built in time-to-time portions for continual upgrading in real-time stock trading situations using the twofold training technique. The scenario with variable frequency was handled to address the concerns of dynamic and alternating temporal data for real-time stock market detection.

The Earnings Calls-Driven Heterogeneous Graph Learning (ECHO-GL) model was developed (Liu *et al.*, 2024) to predict stock movements based on earnings calls. To identify the complete stock environment, multimodal and heterogonous graph learning were applied to foresee the transitions of stock trends by retrieving the possible conceptual data from earning calls. Also, ECHO-GL integrates versatile uncertain task impacted by the post-earnings announcement drift (PEAD) to access the up and down shift price paths are modulated to a diversified investment policies for extended period to forecast the real-model stock prices.

## Comparative Analysis

This part determines the comparison study in table 1, providing the benefits, challenges of several DL based stock market forecasting as illustrated in section 2.

**Table 1:** Comparison of Various State-of-the-Art DL Methods for Stock Market Forecasting

| Ref No                              | Techniques                                                                               | Indicators                                    | Merits                                                                        | Demerits                                                                                                              | Dataset                                                                                                             | Performance Metrics                                                                                         |
|-------------------------------------|------------------------------------------------------------------------------------------|-----------------------------------------------|-------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|
| <b>Indian Stock Market Database</b> |                                                                                          |                                               |                                                                               |                                                                                                                       |                                                                                                                     |                                                                                                             |
| 32                                  | Multivariate regression, MARS, regression tree, bagging, XGBoost, RF, ANN, SVM, and LSTM | Technical                                     | Efficient for high-frequency trading systems with real-time applications      | Limited technical indicators cause instability in performance                                                         | NIFTY 50 index values                                                                                               | Best Performance (RF model): Training and Test Correlation: 0.99, Test RMSE: 0.42                           |
| 33                                  | LSTM, LR, SVM                                                                            | Technical                                     | Provides stable correlation between stock price and indices factors           | Limited dataset and more advanced models could be opted for prediction                                                | India's National Stock Exchange (NSE) for HDFC, Yes Bank, and SBI from Nov 16, 2016, to Nov 15, 2018.               | Accuracy: HDFC: 63.59%, Yes Bank: 56.25%, SBI: 57.95%                                                       |
| 34                                  | LSTM, GRU, BI-LSTM, BI-GRU, Hybrid Model (BI-LSTM and GRU)                               | Technical                                     | High scalability, eliminates reliance on manual trial-and-error approaches    | Requires additional data for analyzing stock market volatility                                                        | NIFTY50 stock index (India), covering Jan 1, 2013, to Mar 5, 2023 using Yahoo Finance                               | Best Performance (Bidirectional GRU): MSE = 382.95, MAE = 14.73, RMSE = 19.57, MAPE = 0.32                  |
| 35                                  | ANN, CNN                                                                                 | Technical                                     | Effectively handles overfitting and reduces excessive training cost           | Using 2-D histograms oversimplifies complex stock market patterns                                                     | NIFTY price index data from NSE of India, April 2008 to April 2018                                                  | Accuracy (ANN) = 97.66%, Accuracy (CNN) = 98.92%                                                            |
| 36                                  | MLP, RNN, LSTM, and CNN                                                                  | Technical                                     | Better decision interpretation with easy training process                     | Requires a large amount of data for training                                                                          | NSE of India for Maruti, Axis Bank, Hcltech, and NYSE                                                               | MAPE for Marathi = 21.56%, HCL = 22.7%, Axis Bank = 18.89%                                                  |
| 37                                  | PLSTM-TAL                                                                                | Technical and Statistical                     | Focuses on critical time steps, reduces dimensionality and noise              | Computationally intensive and limited generalizability                                                                | Daily data from Yahoo Finance for stock indices (S&P 500, FTSE 100, SSE, Nifty 50) from Jan 1, 2005 to Mar 31, 2022 | Accuracy: S&P 500 = 85.09%, FTSE 100 = 96.17%, SSE = 88.21%, Nifty 50 = 85.11%                              |
| 38                                  | LSTM                                                                                     | Fundamental                                   | Generates accurate predictions without incorporating sector-based information | Lacks a structured approach for analyzing stocks that exhibit strong inter-dependencies during data training          | NSE India for Reliance Industries Ltd, Tata Consultancy Services ITC Ltd Tata Motors Ltd                            | MAPE Reliance =15.33 TCS= 8.41 ITC =16.8 Tata Motors= 36.68                                                 |
| 39                                  | DOA, 3D-CNN-GRU classification                                                           | Combined (Technical. Fundamental Statistical) | Effectively handles non-linearity and volatility of financial time series     | Limited database does not focus on external variables like economic events, political events and yearly event trends. | Nifty 50 stock market index (Apr 2008–Dec 2018)                                                                     | Accuracy = 99.14%, Sensitivity = 98.68%, Specificity = 92.48%.                                              |
| <b>China Stock Market Database</b>  |                                                                                          |                                               |                                                                               |                                                                                                                       |                                                                                                                     |                                                                                                             |
| 40                                  | CNN-BiLSTM, Attention Model (CBA)                                                        | Technical                                     | Effectively learns bi-directional temporal features                           | Needs more focus on sentiment analysis for emotional indicators                                                       | Chinese stock index - CSI300 index                                                                                  | MAPE = 1.023, RMSE = 0.064848, = 0.985                                                                      |
| 41                                  | MS-SSA-LSTM (MSL)                                                                        | Combined                                      | Lower computational complexity                                                | More overfitting issues and additional data required for secondary markets                                            | China's A-share market, Ruisi Financial database, and stock forum comments from the East Money forum                | MAPE for Petrol China = 0.018216, RMSE = 0.123077, MAPE for Hifuture Technology = 0.029589, RMSE = 0.157564 |

|                                              |                                                |                                               |                                                                                                          |                                                                                  |                                                                                                                                                  |                                                                                                                                                                               |
|----------------------------------------------|------------------------------------------------|-----------------------------------------------|----------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 42                                           | GNN                                            | Technical                                     | Effectively tackles challenges of identifying causal relationships between stocks                        | Less generalizable, harder to apply in dynamic market conditions                 | Chinese stock market from Jan 1, 2019, to Jan 4, 2022 (600 companies)                                                                            | Accuracy = 54.97%, MCC = 0.0821                                                                                                                                               |
| 43                                           | MDGNN discrete dynamic graph model             | Technical and Fundamental                     | Captures both local and global information and temporal changes in multiple stock relationships          | Might overfit on smaller datasets without proper regularization                  | CSI100: 100 stocks, 196 banks, 97 industries, 18,950,706 edges. CSI300: 300 stocks, 202 banks, 191 industries, 62,500,988 edges.                 | CSI 100: CR = 0.2741, Precision@K = 0.5081, CSI 300: CR = 0.9828, Precision@K = 0.5232                                                                                        |
| <b>Global\Combined Stock Market Database</b> |                                                |                                               |                                                                                                          |                                                                                  |                                                                                                                                                  |                                                                                                                                                                               |
| 44                                           | LSTM, BERT, and ML-GAT                         | Combined (Technical. Fundamental Statistical) | Stock connections ensured consistent real-time alignment and predictions                                 | Selects overestimated values in some cases leading to longer training time       | 423 U.S. stocks in the S&P 500 index and 286 stocks in the CSI 300 index                                                                         | Accuracy = 95%, F1-Score = 95%                                                                                                                                                |
| 45                                           | NLP, DRL, VMD                                  | Combined                                      | Effectively captures correlation of dynamic market status                                                | Noisy or incomplete data might degrade prediction accuracy                       | Sentiment Analysis of Commodity News (Gold) accessed on 1 Feb 2023                                                                               | Sharpe ratio = 3, Calmar Ratio = 3, Annualized return rate (ARR) = 1.1                                                                                                        |
| 46                                           | He-BiLSTM                                      | Combined                                      | Performs well during price volatility and stability                                                      | Does not consider external factors like financial reports or geopolitical events | S&P 50 (5000 data points from Jan 26, 2000 – Dec 9, 2019) and Futures data (Gold, 4960 data points from Jan 25, 2005 – Apr 23, 2024)             | Training Accuracy = 95.41%, Testing Accuracy = 94.23%, Training MSE = $6.12 \times 10^{-5}$ , Testing MSE = $1.96 \times 10^{-4}$                                             |
| 47                                           | GRU, BERT, and MLP                             | Combined                                      | Accurately identifies and interprets the relationships within evolving market conditions                 | Needs supplementary data to effectively analyze stock market volatility          | StockNet dataset                                                                                                                                 | Accuracy = 69.20%, MCC = 0.43, F1 score = 76.17%                                                                                                                              |
| 48                                           | GAN and transformer-based attention mechanisms | Combined                                      | Mitigates overfitting, improves generalizability and adaptability                                        | Limited consideration for market anomalies and transaction costs                 | Yahoo Finance (2017–2023) for Apple Inc., Amazon, Microsoft, Google                                                                              | RMSE Apple = 3.3315, Amazon = 2.8974, Google = 2.8437, Microsoft = 3.3665                                                                                                     |
| 49                                           | H.BLSTM, dual learning mechanism               | Technical and statistical                     | Model effectively adapts to new data and has lower error rate                                            | High delays as model requires periodic retraining                                | Nine major stock indices globally, including DJI, SPX, NDX, DXY, NI225, 000001, NIFTY, FTSE DAXEUR                                               | Average RMSE = 26.501; Average MAPE = 0.001; Average forecasting delay = 2s                                                                                                   |
| 50                                           | ECHO-GL PEAD                                   | Combined                                      | Effectively models the stock price trajectories for arbitrary time horizons, enabling diverse investment | Performance may degrade if earnings calls lack clarity or consistency            | Qin's Dataset: Earnings calls 400 from 253 companies Period: 2017–2018. MAEC Dataset: Earnings calls: 2,725 from 963 companies Period: 2015–2018 | Qin's Dataset (for 1, 3, 7, 15, 30 days): F1 Scores = 63.5%, 3.5%, 61.6%, 63.3%, 67.1%; MAEC Dataset (for 1, 3, 7, 15, 30 days) F1 Scores = 54.4%, 54.3%, 54.4%, 54.9%, 57.3% |

Result And Discussion

Table 1 gives a graphical comparison of several models in this area with regard to various performance indicators. The accuracy assessment of several stock estimating techniques utilizing various datasets is shown in Figure 2. According to accuracy metrics, some models perform better than others, indicating their capacity to predict changes in the stock market. The DOA-3D-CNN-GRU [39] model is the outperforming technique that attained 99.14% accuracy on the Nifty 50 stock market dataset.

Figure 3 and Figure 4 provides the comparison analysis of RMSE and MAPE values of diversified prediction models on china dataset. In related to this analysis, the MS-SSA-LSTM (MSL) model surpasses CNN-BiLSTM-AM (CBA) [40] in form of RMSE and MAPE resulting in enhanced market movements prediction. MSL executes significantly reduces error values and emphasizing the models capacity to obtain more suitable predictions.

The Figure 5 depicts the accuracy evaluation of various stock forecasting techniques on global\combined stock market dataset. Figure 6 presents the RMSE analysis of various stock prediction models applied to the Global Stock Market dataset. According to this investigation, He-BiLSTM (Training) [45] outperforms other prediction models in terms of stock prediction on global or combined stock market datasets. In a similar vein, GAN-TAM [48] produced lower RMSE values across all three sectors and various companies than H.BiLSTM [49], which had a significantly higher value.

From the overall analysis, the DOA-3D-CNN-GRU [39] model achieves good accuracy performance than other models. However, this model faces some limitations like trained with limited dataset and does not focus on external variables like economic events. Future models will address these constraints by adapting to diverse datasets from different market platforms to improve the models flexibility to adapt in serious scenarios. A diverged model will be

Accuracy Comparsion of Indian Stock Market Predication Models

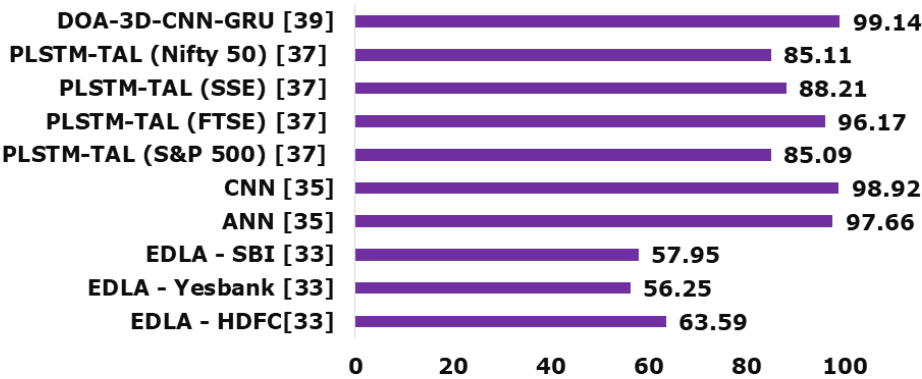


Figure 2: Comparison of Accuracy of Diverse Stock Prediction Models on Indian Dataset

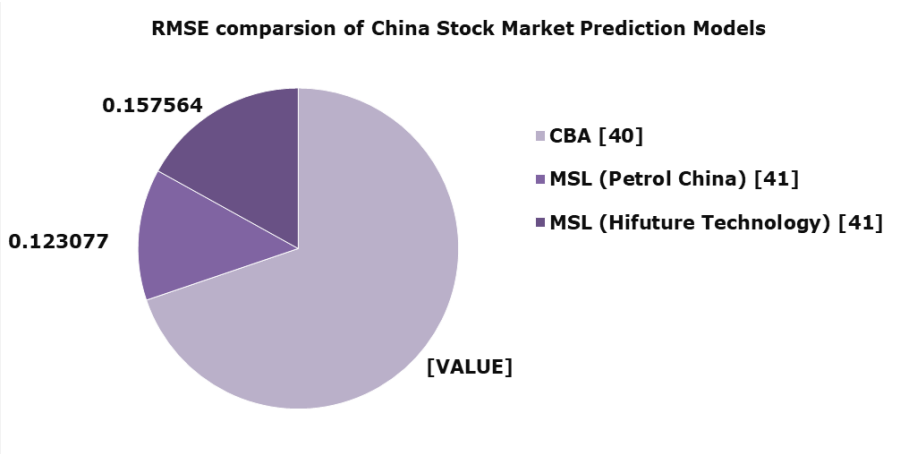


Figure 3: Evaluation of RMSE of Various Stock Prediction Models related to China Dataset

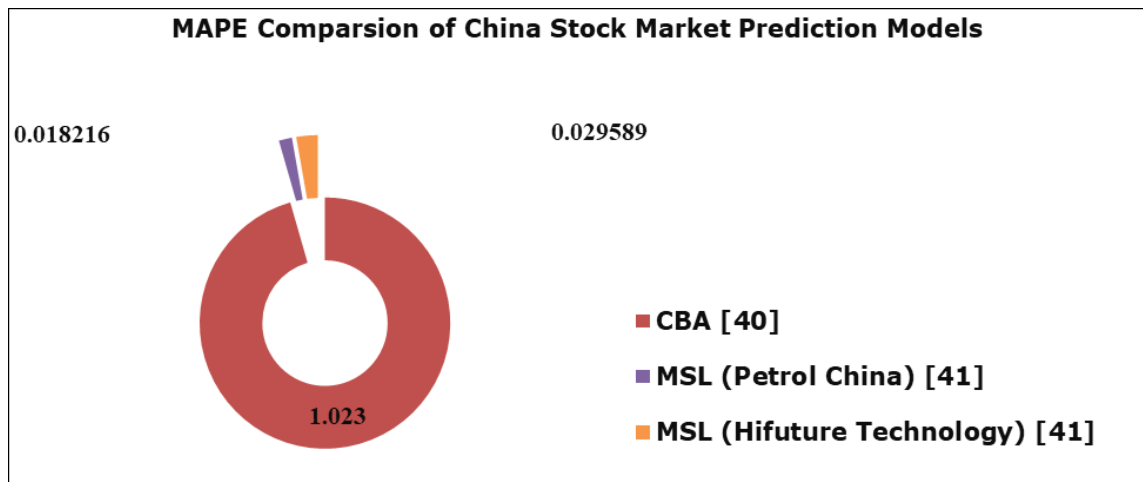


Figure 4: Analysis of MAPE regarding various Stock Prediction Models on China Dataset

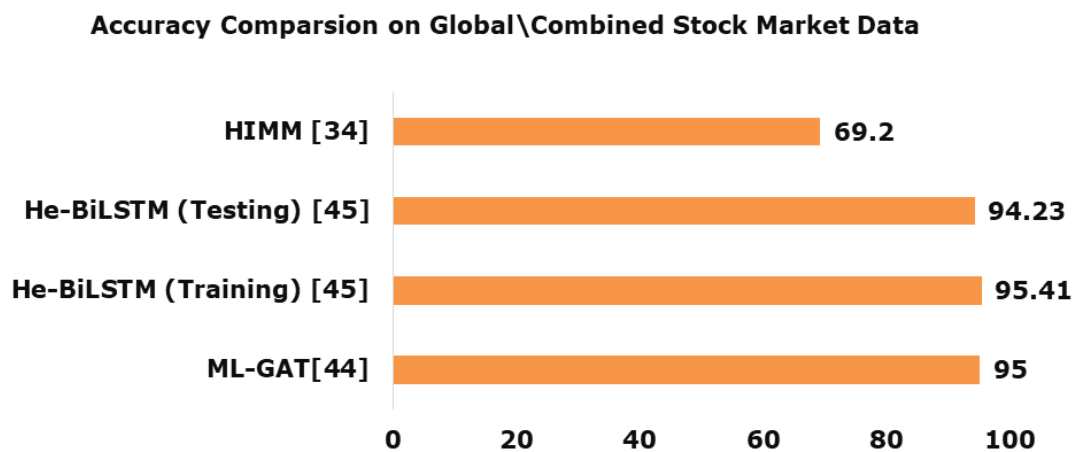


Figure 5: Accuracy Evaluation of Different Stock Prediction Models on Global\Combined Stock Market Dataset

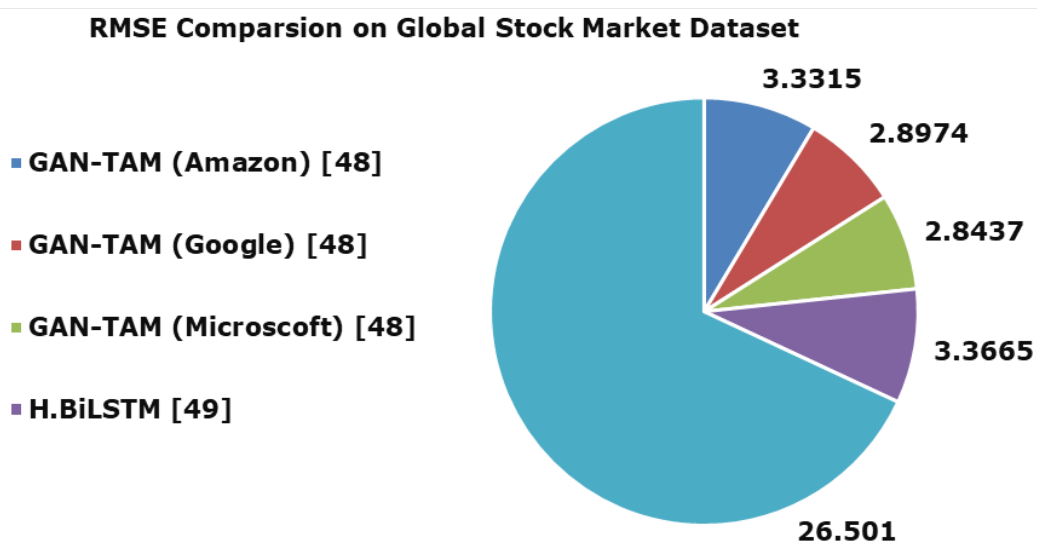


Figure 6: RMSE Evaluation of Various Stock Forecasting Techniques on the Global Stock Market Dataset

developed which combines the peripheral factors indulging macroeconomic information political and government information and typical market environments trends to improvise the performance of stock market forecasting. The future model will be applied in real-time stock market applications by diverging the various data and provide insight evaluation into market patterns, socio-economic factors and more accurate predictions that cope up with current stock market scenarios.

## Conclusion

Accurate stock market prediction is crucial since forecasts are affected by a variety of factors, including market conditions, which reduces performance results. Accurate stock market predictions are essential for making sound trading and investing decisions. DL models have achieved impressive results in stock market forecasting applications. Motivated by this, this research performed a complete analysis of several DL approaches for stock market prediction successes, evaluating their strengths and shortcomings as well as prediction efficiency. Thus, this analysis may assist investors in selecting the most efficient and trustworthy forecasting approaches for detecting past, present, and future trading. The future work will be developed by merging varied stock market datasets and applied in advanced DL models to improve the stock market prediction for analysing future market conditions.

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