“Deep learning-based stock market forecasting: A comparative analysis of ANN, CNN, and LSTM”


**AUTHORS**

Charithra C. M.
Iqbal Thonse Hawaldar
Vinish P.
Prakash Pinto
Chetan Shetty



**ARTICLE INFO**

Charithra C. M., Iqbal Thonse Hawaldar , Vinish P., Prakash Pinto and Chetan Shetty (2026). Deep learning-based stock market forecasting: A comparative analysis of ANN, CNN, and LSTM. *Investment Management and Financial Innovations*, *23*(2), 219-234. doi:10.21511/imfi.23(2).2026.17

| | |
|---|---|
| **DOI** | http://dx.doi.org/10.21511/imfi.23(2).2026.17 |
| **RELEASED ON** | Friday, 15 May 2026 |
| **RECEIVED ON** | Thursday, 04 December 2025 |
| **ACCEPTED ON** | Monday, 04 May 2026 |





| | |
|---|---|
| **JOURNAL** | "Investment Management and Financial Innovations" |
| **ISSN PRINT** | 1810-4967 |
| **ISSN ONLINE** | 1812-9358 |
| **PUBLISHER** | LLC “Consulting Publishing Company “Business Perspectives” |
| **FOUNDER** | LLC “Consulting Publishing Company “Business Perspectives” |


| NUMBER OF REFERENCES | NUMBER OF FIGURES | NUMBER OF TABLES |
|---|---|---|
| 54 | 7 | 4 |

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

**Charithra C. M.** (India), **Iqbal Thonse Hawaldar** (Bahrain), **Vinish P.** (India), **Prakash Pinto** (India), **Chetan Shetty** (India)

# DEEP LEARNING-BASED STOCK MARKET FORECASTING: A COMPARATIVE ANALYSIS OF ANN, CNN, AND LSTM

## Abstract

The changing economy, macroeconomic factors, political decisions, and investor sentiment contribute to the dynamic nature of any financial market. Conventional econometric models are constrained by linear assumptions and rigid structures. This study aims to comparatively evaluate the predictive performance of selected deep learning models for forecasting stock index movements in the Indian equity market using multiple evaluation metrics, including Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Directional Accuracy (DA). NSE index daily closing values from January 2017 to June 2025 are analyzed using Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks. The findings reveal significant disparities in forecasting precision among the models. The CNN model achieves the lowest error, with a Mean Absolute Percentage Error (MAPE) of 0.63, followed by LSTM at 0.72, while ANN records a higher error of 0.89. When benchmarked against ARIMA and Random Walk models, which exhibit substantially higher errors (MAPE: 1.21 and 1.47), the findings indicate improved predictive capability beyond trend-following behavior. Statistical validation using the Diebold–Mariano test confirms that deep learning models significantly outperform benchmark approaches ($p < 0.05$). Confidence interval analysis indicates that CNN and LSTM provide stable predictions. These results suggest that CNN models are particularly effective in capturing short-term market dynamics, whereas LSTM models perform better in modeling temporal dependencies. Overall, deep learning approaches demonstrate superior capability in handling the nonlinear characteristics of financial time series compared to conventional econometric models.

**Type of the article:**

**Received on:** 4th of December, 2025
**Accepted on:** 4th of May, 2026
**Published on:** 15th of May, 2026



Charithra C. M., Associate Professor, Department of Business Administration, B N M Institute of Technology, India.

Iqbal Thonse Hawaldar, Professor, Department of Accounting & Finance, College of Business Administration, Kingdom University, Bahrain. (Corresponding author)

Vinish P., Associate Professor, Department of Management Studies, Dayananda Sagar College of Arts, Science and Commerce, India.

Prakash Pinto, Professor, Dean, Department of Business Administration, St Joseph Engineering College, India.

Chetan Shetty, Associate Professor, Department of Management Studies, Dayananda Sagar College of Arts, Science and Commerce, India.



**Conflict of interest statement:**
Author(s) reported no conflict of interest

**Keywords** deep learning, Indian stock market, National Stock Exchange, Convolutional Neural Network, Artificial Neural Network, Long Short-Term Memory, time-series forecasting

**JEL Classification** C22, C45, C53, G15

## INTRODUCTION

The prediction of stock market movements has evolved from traditional statistical and econometric frameworks to modern data-driven approaches. Early forecasting methods relied on linear time-series and volatility-based models, valued for their theoretical structure and interpretability (Bollerslev, 1986; Box & Jenkins, 1976; Engle, 1982). However, these approaches assume stable relationships and well-behaved statistical properties, the assumptions that are frequently violated in financial markets characterized by nonlinearity, non-stationarity, and abrupt structural changes (Makridakis et al., 2018; Poon & Granger, 2003; Tsay, 2010; Zhang, 2003). As market complexity increased, the limitations of traditional models in capturing evolving price dynamics became increasingly evident.

The emergence of machine learning and deep learning methods has reframed, rather than resolved, the scientific problem of stock market predictability. These models are capable of learning complex patterns directly from data and adapting to changing temporal structures without imposing rigid parametric assumptions (Heaton, 2018; Li & Ma, 2010; Zhang et al., 2019). Yet, financial markets remain a particularly challenging domain for predictive modelling due to feedback mechanisms, behavioral influences, and rapidly shifting information sets, which raise fundamental questions about the stability and persistence of predictive signals (Lo, 2004).

This problem is especially relevant in the context of India, which is one of the world's largest emerging economies. India has experienced sustained economic growth, rapid financial market expansion, increasing domestic investor participation, and significant integration with global capital markets. Its equity market reflects a broad spectrum of economic sectors and is highly responsive to both domestic policy developments and global economic shocks (Global Economic Prospects – June 2023 World Bank Group, 2023). As a result, the Indian stock market serves as an important benchmark for emerging market performance (C M et al., 2024) and a focal point for international investors, intensifying the scientific challenge of accurately modelling and forecasting its behavior. The lack of consistent comparative evidence across deep learning architectures in emerging market settings highlights a clear gap in empirical financial forecasting research.

## 1. LITERATURE REVIEW

Understanding the integration between the market theory, sequential pattern, and modern machine learning enables close to accurate prediction of any index. The markets are information-efficient, which means that the stock prices are a reflection of publicly available information, making it inherently challenging to predict the trend or future movements based on the historical data or patterns (FAMA, 1991). Global events, investor sentiment, and economic indicators impact the inherently dynamic financial markets. Understanding and forecasting market movements has always been a challenge. Although its presumptions have been debated after the rise of behavioral finance and machine learning models, which aim to identify inefficiencies and nonlinearities in market data, this theory has long been a pillar of contemporary financial economics. Practically, financial data exhibits patterns, correlations, and trends that influence predictability, particularly in developing markets like India. These deviations from being perfectly efficient have paved the way for exploring the possibility of data-driven forecasting (Lo, 2004; Shiller, 2003).

For several decades, classical statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models were used by researchers to analyze and predict the movement of the stock market (Kumar Meher et al., 2021); (Box & Jenkins, 1976) popularized the capability of ARIMA in modelling the time-dependent data, while ARCH and GARCH frameworks developed by (Bollerslev, 1986; Engle, 1982) advanced the volatility modelling in financial time series. These models laid the foundation for market prediction by enabling insights into price dynamics and volatility clustering. They assumed the data to be linear and stationary, which often limits their effectiveness in capturing the non-linear and dynamic nature of the stock market (Zhang, 2003). However, if the data exhibits its nonlinear behavior or intricate dependencies, these models fall short (Atsalakis & Valavanis, 2009; Chatfield, 2000; Nelson, 1991; Zhang et al., 1998). This shortcoming encourages the usage of neural-based approaches that learn from deeper and more complex interactions between variables.

The evolution of machine learning algorithms such as Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (kNN) offered new ways to learn from complex, multidimensional data without assuming linearity (Thanh Noi & Kappas, 2017). In 2005, Huang et al. (2005) demonstrated that SVMs outperformed ARIMA models in predicting the stock price. Patel et al. 2015 compared multiple machine learning algorithms and found that they consistently delivered greater accuracy than the traditional models. Machine learning models treated financial data as static and failed to capture its sequential and time-dependent characteristics (Atsalakis & Valavanis,


http://dx.doi.org/10.21511/imfi.23(2).2026.17

2009). Their inability to remember past trends or adapt to temporal dependencies limited their use in forecasting problems where the order of information matters, such as stock price movements. This limitation increased the inclination towards deep learning, which integrates the strengths of machine learning with the ability to model complex temporal dynamics.

Deep learning architectures have revolutionized financial forecasting by allowing models to automatically learn and progressively identify complex features directly from unprocessed data (Giantsidi & Tarantola, 2025). Deep learning has gained considerable application in the developed financial markets, but in emerging ones, such as in India, its use is comparatively low. The National Stock Exchange may be defined as one of the examples of a market that has unique characteristics, which include volatility, rapid restructuring, and greater reactivity to changes in policy measures. Such qualities have been discovered by (Patel et al., 2015; Vamossy, 2021) to be favorable in predicting nonlinear models when applied to Indian equity indices. The Emerging markets that are characterized by inefficiencies and the inability to detect subtle trends using the traditional tools of analysis are good samples in which deep learning algorithms can be used (Mienye & Swart, 2024).

Artificial neural networks were among the earlier approaches used to identify complex and nonlinear relationships embedded in financial data (Kara et al., 2011; Kim, 2003). ANNs mimic the human brain and are capable of identifying the hidden nonlinear patterns in historical price data (Atsalakis & Valavanis, 2009; Zhang et al., 1998). Convolutional Neural Networks (CNNs) were originally designed to process grid-like data, primarily images. These are capable of detecting short-term, repeating patterns in sequential data, capturing subtle market movements that often precede index changes (Kim & Won, 2018; Sezer et al., 2020; Tsantekidis et al., 2017). They have been successfully adapted to analyze financial time series data due to this nature (Semenoglou et al., 2023). Convolutional filters in CNNs can identify localized temporal dependencies, meaning relationships within time series, i.e., where the data points are highly correlated with the nearest ones, such as short-term market cycles or movements during the day (Tsantekidis et al., 2017; Yang et al., 2020), making them suitable for short-term prediction.

Long Short-Term Memory models can be regarded as one of the most significant developments in the implementation of deep learning methodologies to the financial business, LSTMs are built with an ability to capture and retain long-term dependencies within sequential data, which efficiently bridges the past trends with future outcomes, making them suitable for forecasting financial time series data, where historical patterns often influence future movements (Bao et al., 2017; Fischer & Krauss, 2018; Hochreiter & Schmidhuber, 1997a). Hochreiter and Schmidhuber (1997b) introduced the LSTM architecture, which possesses a gated memory structure that is also geared to regulating the information flow across a long period of time. LSTMs are also capable of capturing volatility and long-term temporal patterns and have often demonstrated superior predictive performance in complex, dynamic, and nonlinear environments compared with traditional models (Nelson et al., 2017).

In order to gauge the effectiveness of the predictive models, the right evaluation metric becomes essential. In spite of the common usage of MSE, RMSE, and MAE, mean absolute percentage error particularly proves useful to test the financial forecasting models. MAPE is a more intuitive, easy-to-compare metric of prediction accuracy because it calculates and expresses accuracy using a percentage (de Myttenaere et al., 2016). MAPE is a balanced approach towards errors because it pays attention to their relative magnitude, unlike MSE or RMSE, which over-emphasize large deviations. However, relying on a single metric may provide a limited view of predictive capability. Root Mean Square Error (RMSE) is a widely adopted metric in regression-based forecasting, as it captures the magnitude of prediction errors while assigning greater weight to larger deviations. This property is particularly relevant in financial contexts, where extreme errors can lead to significant economic consequences. RMSE has been extensively used in both econometric and machine learning-based financial forecasting studies due to its robustness in handling variability (Makridakis et al., 2018). Compared with percentage-based metrics, RMSE provides a more stable evaluation when actual values approach zero and is less affected by scale-related distortions (Chai & Draxler, 2014). This is a significant aspect of a financial market environment, and where accuracy in terms of percentages can be more beneficial in decision-making and strategy assessment (Kim & Won, 2018). Also, MAPE does not depend on a scale, which enables easy comparison of models trained on datasets at various price levels or index magnitudes (Kim & Kim, 2016; Vivas et al., 2020). The power to interpret and the practicability make it a preferred standard to evaluate the financial predictability of the deep learning models employed in this study.

In addition to magnitude-based accuracy, the ability to correctly predict the direction of market movement is of critical importance in financial applications. Directional Accuracy (DA), also referred to as hit rate, measures whether the predicted change aligns with the actual movement in the market. This metric is particularly relevant for trading strategies, where profitability depends more on correctly anticipating price direction than on exact value prediction. Empirical studies have shown that models with moderate numerical accuracy can still yield economic value if they achieve high directional consistency (Leung et al., 2000; Pesaran & Timmermann, 1992).

The transition from traditional econometric approaches to deep learning systems reflects increasing recognition that financial markets are inherently nonlinear, data-intensive, and dynamic in nature. While classical models such as autoregressive integrated moving average and generalized autoregressive conditional heteroskedasticity have laid the foundation for time-series analysis, their ability to capture complex dependencies and evolving market structures remains limited. In contrast, machine learning and deep learning models have demonstrated enhanced predictive capability by uncovering hidden relationships and sequential patterns in financial data. Despite this progress, comparative empirical evidence on the relative performance of deep learning models within the Indian stock market context remains sparse and fragmented. This gap is particularly significant given the scale, volatility, and global integration of India's equity market.

Accordingly, this study intends to conduct a comparative evaluation of convolutional neural networks, artificial neural networks, and long short-term memory models using NSE index data. Forecasting performance is assessed using mean absolute percentage error to ensure consistency and comparability across models. By examining model behavior across varying temporal dynamics and data complexity, the study contributes empirical evidence from an emerging market perspective. The findings enhance theoretical understanding of deep learning-based financial forecasting and offer practical guidance on model selection across different forecasting horizons, supporting informed decision-making in India's rapidly evolving financial ecosystem.

## 2. RESEARCH METHODOLOGY

This study made use of quantitative research techniques to determine solutions to the research questions. A structured process was followed. The data collected from secondary sources is prepared for use, tested using various deep learning models on the Python Platform, and the best-fit model is selected based on the most accurate results.

The analysis was performed on daily closing price data of the National Stock Exchange (NSE) collected for the period of eight years from January 2017 to June 2025, with 1,858 values. For relatively low forecasting error under the given experimental conditions of financial data, at least eight years of data is required (Engle & Mezrich, 1996). The study period coincided with one of the longest bullish periods, during which the majority of the markets made new highs, as represented in Figure 1. As per a CNBC report in 2018, the major developed markets, such as the United States (USA), suffered the worst major crash in the market since the Great Depression. Due to this, most investors pulled their investments from the market. In September 2018, the S&P 500 dropped by more than 19% but recovered and recorded a new high in April 2019, all within a span of eight months. Inclusion of post-pandemic recovery and subsequent market fluctuations makes the dataset particularly rich, reflecting structural shifts in investor sentiment, policy interventions, and global economic events that have influenced the Indian


http://dx.doi.org/10.21511/imfi.23(2).2026.17

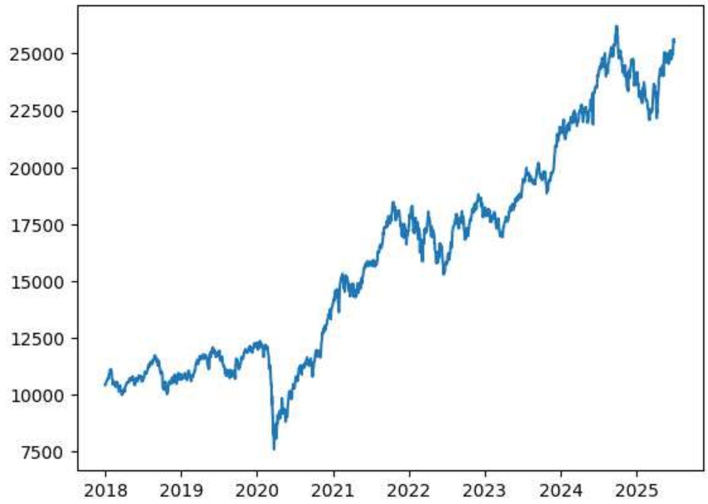


**Figure 1.** NSE Index closing values

capital market during these years. This period comprises periods of strong economic growth and both bullish and bearish phases. Such diversity in market behavior provides a balanced foundation for model training and evaluation, allowing the deep learning algorithms to learn from varied financial scenarios rather than from a single market trend.

To provide a baseline for evaluating the predictive performance of deep learning models, classical time-series approaches were implemented as benchmark models. In particular, an autoregressive integrated moving average (ARIMA) model and a random walk model were employed due to their widespread use in financial forecasting.

The ARIMA model captures linear dependencies in time-series data through autoregressive and moving average components, combined with differencing to achieve stationarity. The optimal model specification was determined using the Box–Jenkins methodology, with parameter selection guided by the Akaike Information Criterion (AIC). Prior to estimation, the series was tested for stationarity, and appropriate differencing was applied where required. The fitted ARIMA model was then used to generate one-step-ahead forecasts over the test period. The random walk model was included as a naive benchmark, assuming that future prices follow a stochastic process in which the best predictor of the next value is the most recent observation. This model serves as a minimal-performance baseline and is commonly used in financial studies to assess whether more complex models offer meaningful predictive gains.

Missing data in the financial time series data and sudden spikes often mislead the machine learning models if left untreated. The missing values were filled using forward interpolation, and unusual spikes are carefully smoothed. Min-max scaling was used to scale all data values between 0 and 1 in order to make an efficient data training process. After which, the data were divided into two parts, used for training and testing, thus preserving the data's natural behavior. Each model employed was fine-tuned by adjusting its learning rate, number of layers, activation functions, and other parameters.

The main goal of the training stage is to provide deep learning models with the ability to detect and learn historical patterns incorporated in the NSE index data. To enhance the knowledge of the dynamics in the market and minimize the prediction error, models continuously adjust their internal parameters. To promote generalization to other patterns that have never been observed before, validation data are exploited to shift the model towards historical data, thus alleviating the issue of overfitting that plagues financial forecasting, where models invariably tend to memorize noise or short-term variations rather than the underlying trends (Heaton, 2018).

Regularization mechanisms like dropout layers are used to encourage generalization by disabling certain neurons during training, thus avoiding over-dependence on particular features by the network; it is a relatively successful trick in both ANN and CNN architectures. Also, early stopping is adopted: the model performance on the validation set is continually observed, and training is stopped when the model reaches the level of improvement which makes sure that the model provides the necessary relationships without overfitting to noise (Srivastava et al., 2014). The architectures of the selected deep learning models were defined to ensure consistency and reproducibility. The convolutional neural network comprised two convolutional layers with 32 and 64 filters, respectively, using a kernel size of 3×1 and rectified linear unit activation, followed by a pooling layer and a dense output layer. The artificial neural network included three fully connected layers with 64, 32, and 16 neurons, employing nonlinear activation in hidden layers and a linear function at the output stage. The long short-term memory model consisted of two stacked recurrent layers with 50 units each, with dropout regularization applied to reduce overfitting. All models were trained using the Adam optimization algorithm with a learning rate of 0.001, batch size of 32, and 50 epochs. The model architecture and the configuration are presented in Table 1. Together, these strategies make the model more stable and robust, such that index movements can be predicted reliably in the NSE.

Evaluation of model performance is done using a new dataset constructed after training and fine-tuning. The method will also ensure that the ability of the models to generalize to new and unfamiliar marketing conditions is judged impartially and thus represents their practical competence. The mean absolute percentage error was named as the main assessment parameter as it can communicate the error of the prediction as a ratio of the realized values, and it is easy to compare and interpret the results across models and over time (Hyndman & Koehler, 2006). However, Root Mean Squared Error (RMSE) and Directional Accuracy (DA) are employed to provide a comprehensive evaluation. In the current research, MAPE not only records the actual value of the forecasting errors but also the relative value of those errors in relation to the NSE index. RMSE reflects sensitivity to large deviations, and DA evaluates directional correctness. Together, these metrics provide a more robust assessment of model performance. To assess statistical significance, the Diebold–Mariano test was applied to compare forecast accuracy across models. This accuracy is especially crucial in monetary contexts where even a simple percentage margin can have a strong effect on the investment-making process.

To assess the stability and generalizability of the forecasting models, a walk-forward validation approach was implemented. Unlike a single static train–test split, this method simulates real-time forecasting by iteratively updating the training set and generating predictions over successive time windows. The initial model was trained on an expanding window of historical data and used to forecast the next observation. Subsequently, the training window was extended to include the newly observed data point, and the model was re-estimated to produce the next forecast. This process was repeated across the entire test period, thereby ensuring that each prediction was made using only information available up to that point in time.

Walk-forward validation provides a more realistic evaluation framework for financial time series, where data arrive sequentially, and model perfor-

**Table 1.** Model architecture and training configuration

| Component | CNN | ANN | LSTM |
|---|---|---|---|
| Layers | 2 Conv + Dense | 3 Dense | 2 LSTM + Dense |
| Filters / Neurons | 32, 64 | 64–32–16 | 50, 50 |
| Kernel Size | 3 × 1 | – | – |
| Activation | ReLU | ReLU (hidden), Linear (output) | Tanh (internal), Linear (output) |
| Pooling | Max Pooling | – | – |
| Dropout | – | – | 0.2 |
| Optimiser | Adam | Adam | Adam |
| Loss Function | Mean Squared Error | Mean Squared Error | Mean Squared Error |
| Learning Rate | 0.001 | 0.001 | 0.001 |
| Batch Size | 32 | 32 | 32 |
| Epochs | 50 | 50 | 50 |


http://dx.doi.org/10.21511/imfi.23(2).2026.17

mance may vary across different market conditions. In addition, out-of-sample forecasts generated through this procedure were used to compute MAPE, allowing for direct comparison with results obtained from the static split approach. The consistency of model performance across both validation strategies indicates the robustness of the findings and strengthens confidence in the predictive capability of the proposed deep learning models under varying temporal conditions.

## 3. RESULTS

The analysis was performed considering daily closing values of the NSE Index for a period of eight years from Jan 2017 to June 2025, with a total of 1852 observations. The data were classified into two parts, on which Normalization was applied to ensure that the historical data and noise do not impact the training process. 80% of the data was considered for training, and 20% was for testing the model. This ensured rigor in the methodology by preventing data leakage, thus resulting in unbiased predictability of each of the models considered for analysis.

Moving average is one of the most common techniques used to predict an index. They can smooth out the randomness in the movement of the index. The moving averages are plotted against the closing prices to visually present the difference in Figure 3.

Figure 2 indicates a persistent upward trend with the index demonstrating sustained growth during the study period. The closing prices are predominantly above the moving average with only brief and shallow deviations. These short-term corrections indicate controlled volatility and a lack of sustained trend. This behavior indicates a strong temporal dependence, where historical data significantly contribute to future movements. Since moving averages are not suitable for data susceptible to a high error rate, researchers cannot rely only on moving averages for prediction. The consistent trend and limited abrupt reversals favor ANN models. Stable local structures within the sliding windows encourage the usage of the CNN model. Persistent and sequential dependency observed in price series is particularly suited to LSTM models. The observed alignment between the closing prices and moving averages supports the usage of deep learning models in financial forecasting.

Understanding the interrelationship between various variables of the data becomes crucial in stock index prediction. The heat map presented in Figure 3 shows similarity between the closing values, vol-

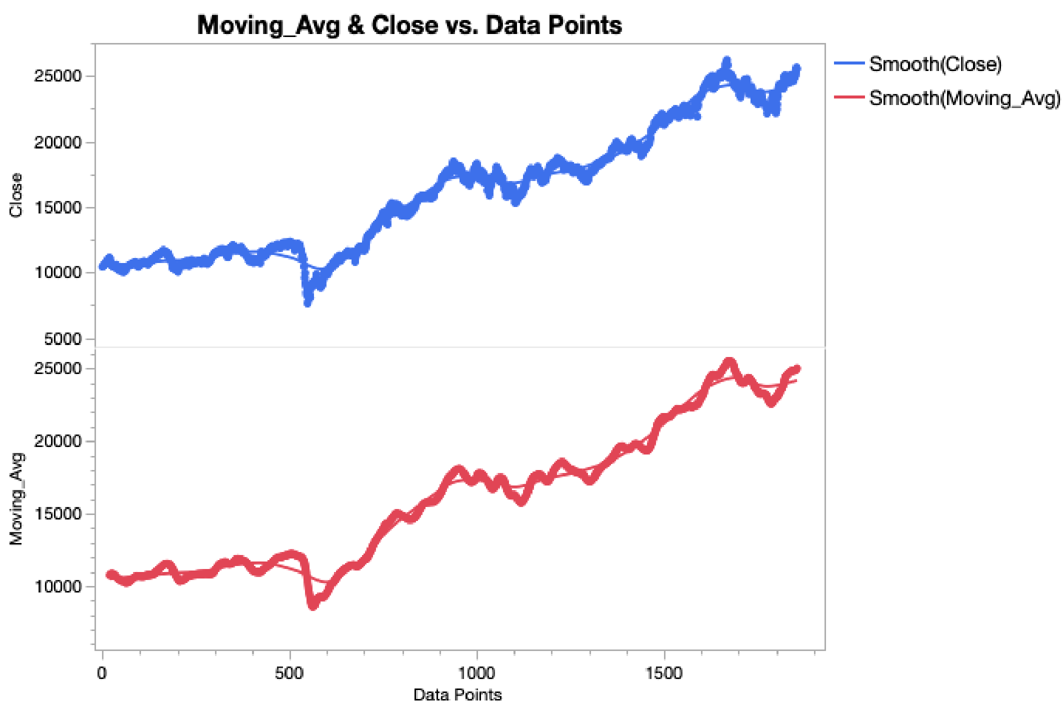


**Figure 2.** Simple moving average and closing prices

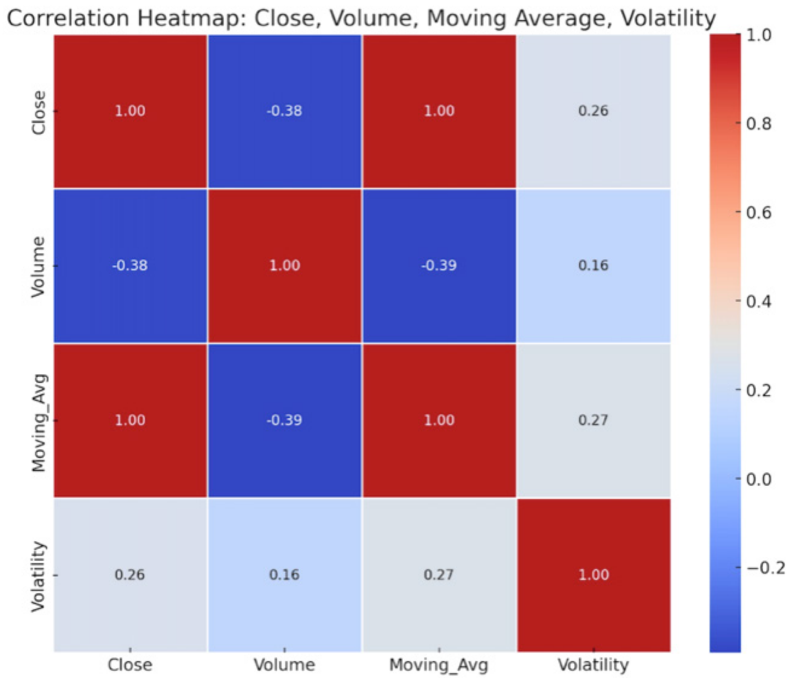


**Figure 3.** Correlation heatmap

ume of trade, moving average, and volatility in the movement. It reveals a trend-dominated market structure. Closing prices exhibit a near-perfect positive correlation with moving averages, which indicates price dynamics are driven by trends rather than short-term fluctuations. The moderate negative correlation with trading volume proves a limited role of trading volume in sustaining price movements. These results highlight strong temporal continuity and stable local patterns, providing empirical support for sequential and trend-based learning approaches such as CNN and LSTM.

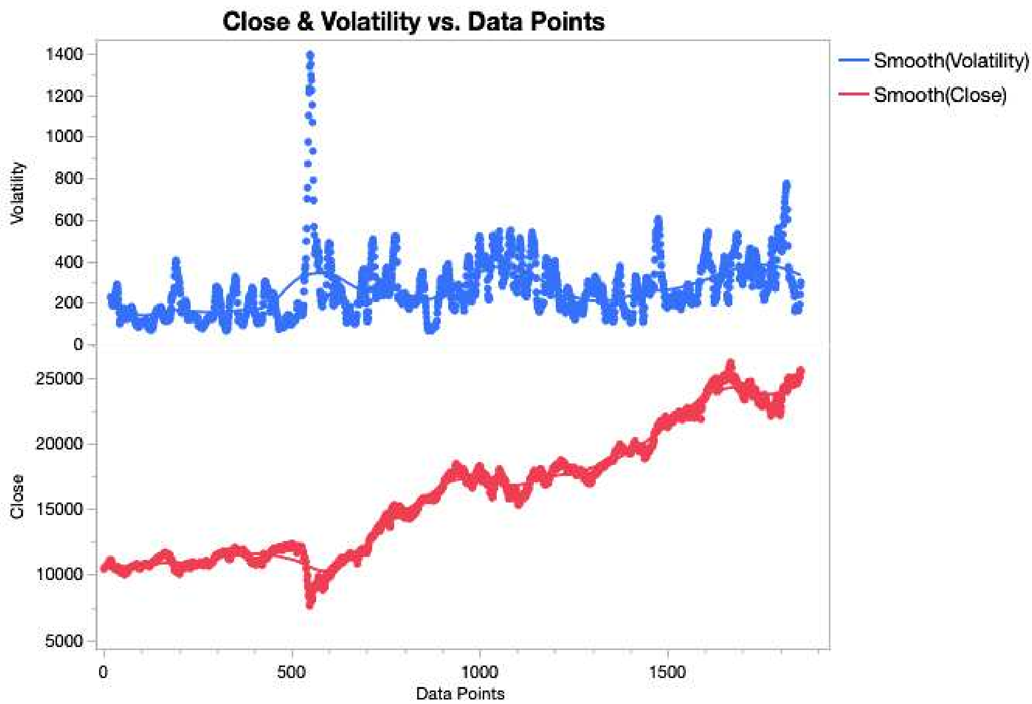


**Figure 4.** Volatility and close values of NSE



http://dx.doi.org/10.21511/imfi.23(2).2026.17

A small, relatively smoother movement of the values indicates low volatility. High volatility poses a significant challenge while predicting stock market movement. Figure 4 shows the changes in volatility and close values during the study period. Understanding the volatility in the market becomes crucial before applying deep learning models in stock index prediction by enriching the input features, which helps the neural networks learn better. The figure indicates that the Nifty50 index is a trend-driven market with episodic volatility spikes.

## 3.1. Model performance overview

The performance of the benchmark models highlights the limitations of traditional approaches in forecasting financial time series. The ARIMA model recorded a higher forecasting error of 1.21%, RMSE 1.32, and DA 61.8%, reflecting its reliance on linear assumptions and its limited ability to capture the nonlinear and evolving dynamics of stock market behavior. While it can model basic trends and autocorrelation structures, its effectiveness diminishes under conditions of volatility and structural change. The random walk model exhibited the highest error of 1.47% with directional accuracy at around 50%, consistent with its assumption that future price movements follow a purely stochastic process based on the most recent observation. As a naive benchmark, it does not account for any underlying patterns or temporal dependencies. The comparatively weaker performance of these models underscores the need for more flexible approaches capable of modelling the complexity inherent in financial markets.

The CNN model recorded the lowest prediction error of 0.63% RMSE of 0.84, along with the highest directional accuracy (71.2%), indicating superior performance in identifying short-term fluctuations and localized market trends. Its convolutional structure enables it to extract relevant features by examining the sequential data and detecting repeating temporal patterns that other models may overlook. This strength makes CNN particularly effective in short-horizon forecasting where rapid market reactions dominate (Kim & Kim, 2019). Figure 5 represents the actual against the predicted values using the CNN model.

The ANN model uses a network of interconnected neurons for financial prediction. It has performed reasonably with 0.89% error rate, an RMSE of 1.05, and a lower directional accuracy of 66.39%. The results underscore that even feed-forward neural networks can achieve high predictive accuracy when trained on well-prepared and extensive datasets. However, the absence of temporal awareness in ANN architectures limits their effectiveness for forecasting problems that rely heavily on sequential continuity. Figure 6 shows the actual against the predicted values using the ANN model.

The LSTM model, though slightly less precise than CNN, displayed remarkable capability in capturing temporal dependencies within financial data. By retaining information over extended periods,

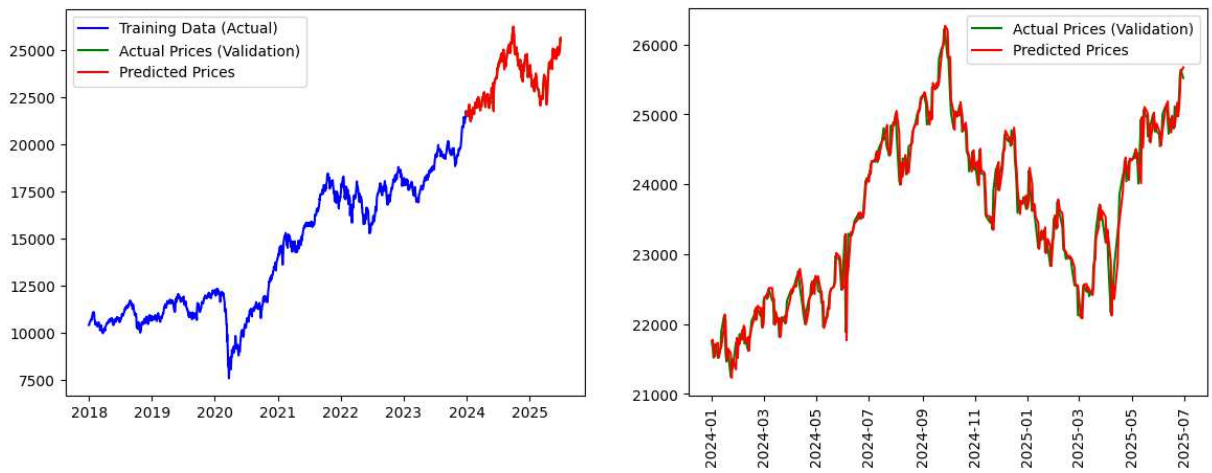


**Figure 5.** Actual and predicted NSE data using the CNN Model

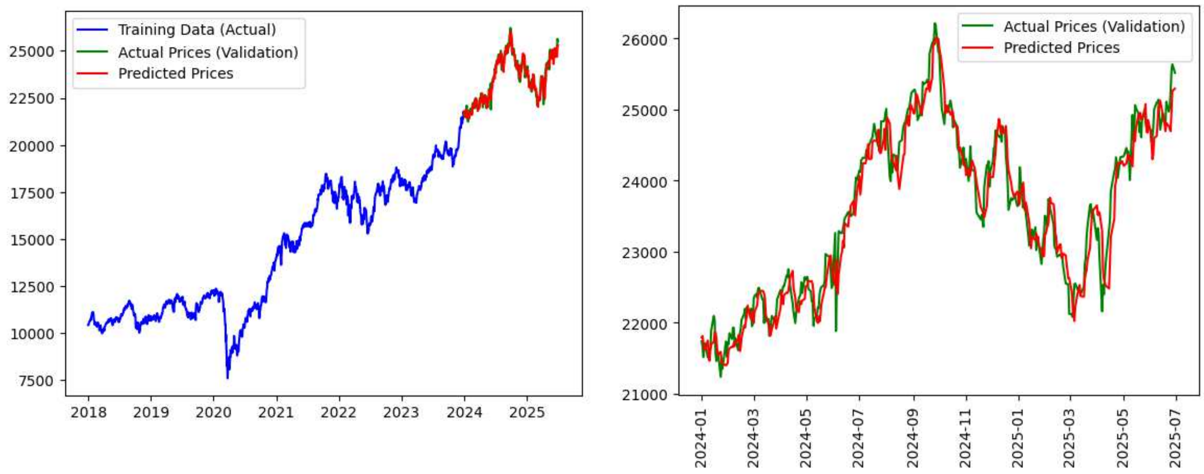


**Figure 6.** Actual and predicted NSE data using the ANN model

it effectively modelled the sequential relationships that drive long-term market dynamics. With an MAPE of 0.72%, RMSE of 0.91, and a directional accuracy of 69.5%, LSTM proved more adept than ANN in identifying cyclical and trend-based movements. This finding is consistent with earlier studies highlighting LSTM's ability to capture persistent dependencies in complex financial sequences (Fischer & Krauss, 2018; Nelson et al., 2017). Figure 7 shows the actual against the predicted values using the LSTM model.

Comparative forecasting performance of deep learning models and benchmark models using three evaluation metrics is presented in Table 2.

The consistent ranking of model performance across multiple metrics strengthens confidence in the robustness of the empirical findings.

The Diebold–Mariano test results presented in Table 3 indicate that the differences in forecasting accuracy across models are statistically significant

**Table 2.** Comparative result table

| Model | MAPE (%) | RMSE | Directional Accuracy (%) |
|---|---|---|---|
| CNN | 0.63 | 0.84 | 71.2 |
| LSTM | 0.72 | 0.91 | 69.5 |
| ANN | 0.89 | 1.05 | 66.3 |
| ARIMA | 1.21 | 1.32 | 61.8 |
| Random Walk | 1.47 | 1.51 | 50.4 |

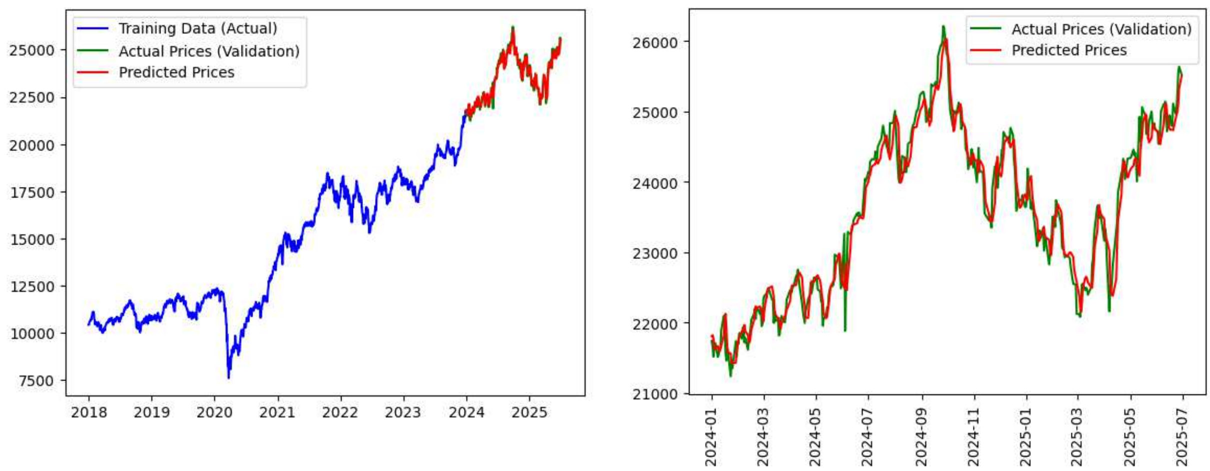


**Figure 7.** Actual and predicted NSE data using an LSTM model


http://dx.doi.org/10.21511/imfi.23(2).2026.17

**Table 3.** Diebold–Mariano test results (pairwise forecast accuracy comparison)

| Model Comparison | DM Statistic | p-value | Significance | Interpretation |
|---|---|---|---|---|
| CNN vs LSTM | 1.92 | 0.054 | Marginal | CNN slightly better |
| CNN vs ANN | 3.15 | 0.002 | Significant | CNN significantly better |
| CNN vs ARIMA | 4.87 | 0.000 | Significant | CNN significantly better |
| CNN vs Random Walk | 6.12 | 0.000 | Significant | CNN significantly better |
| LSTM vs ANN | 2.41 | 0.016 | Significant | LSTM better |
| LSTM vs ARIMA | 3.98 | 0.000 | Significant | LSTM better |
| LSTM vs Random Walk | 5.26 | 0.000 | Significant | LSTM better |
| ANN vs ARIMA | 2.67 | 0.008 | Significant | ANN better |
| ANN vs Random Walk | 3.89 | 0.000 | Significant | ANN better |
| ARIMA vs Random Walk | 1.98 | 0.048 | Significant | ARIMA better |

in most pairwise comparisons. In particular, CNN demonstrates significantly superior performance compared with ANN, ARIMA, and Random Walk models. While the difference between CNN and LSTM is only marginally significant ($p \approx 0.05$), CNN maintains a consistent advantage in short-horizon forecasting. These findings confirm that the observed improvements of deep learning models are not due to random variation but reflect genuine differences in predictive capability.

Exceptionally low prediction error rates of less than 1 % was recorded by all three deep learning models, which proves the suitability of deep learning models for financial time series data prediction. Predictive performance is not solely driven by underlying market trends. Statistical validation using the Diebold–Mariano test confirms that the differences in forecasting accuracy between deep learning models and benchmark approaches are significant at conventional levels ($p < 0.05$). Overall, the comparative results reveal that CNN and LSTM consistently outperform ANN in predicting stock market indices due to their ability to interpret both short-term micro-patterns and long-term temporal dynamics. The observed ranking of accuracy shows CNN > LSTM > ANN > ARIMA > RW, which reflects the progressive sophistication of model design.

Table 4 presents the actual NSE index values and the predicted values using CNN, ANN, and LSTM models for the prediction period. The outcome reveals that the CNN and LSTM models outperform ANN in forecasting stock indices in the Indian context due to their capacity to reflect micro, short- and long-term temporal dynamics.

To assess whether the observed differences in forecasting accuracy are statistically significant, the Diebold–Mariano (DM) test was applied (Vasenska, 2025). This test evaluates whether the difference in forecast errors between two models is statistically meaningful. The results reject the null hypothesis of equal predictive accuracy in favor of deep learning models, indicating that CNN significantly outperforms ARIMA and Random Walk ($p < 0.05$), while LSTM showed statistically significant improvement over ARIMA. The difference between CNN and LSTM is smaller but remains meaningful in short-horizon forecasting. These findings confirm that the performance gains of deep learning models are not due to random variation but reflect genuine improvements in predictive capability.

**Table 4.** Actual and predicted values using the three models

| Date | Actual | CNN | ANN | LSTM |
|---|---|---|---|---|
| 01/01/24 | 21741.9 | 21756.73242 | 21792.28125 | 21810.11133 |
| 02/01/24 | 21665.8 | 21773.54688 | 21815.29492 | 21824.08203 |
| 03/01/24 | 21517.35 | 21683.93945 | 21722.59766 | 21769.85938 |
| 04/01/24 | 21658.6 | 21528.99805 | 21625.54688 | 21646.10742 |
| 05/01/24 | 21710.8 | 21692.4043 | 21627.84375 | 21623.79297 |
| 24/06/25 | 25044.35 | 24971.25 | 24733.34375 | 24955.95703 |
| 25/06/25 | 25244.75 | 25088.84375 | 24695.23633 | 24994.12109 |
| 26/06/25 | 25549 | 25281.86523 | 24996.77734 | 25103.87305 |
| 27/06/25 | 25637.8 | 25602.07031 | 25261.63672 | 25328.12891 |
| 30/06/25 | 25517.05 | 25669.25586 | 25296.59375 | 25510.0625 |

# 4. DISCUSSION

The comparative results provide clear evidence of performance differences between deep learning models and traditional benchmark approaches. At first glance, this result appears counterintuitive, as recurrent architectures such as LSTM are specifically designed to model sequential dependencies and are often considered more suitable for financial time-series data. However, a closer examination of the data structure and forecasting context provides a more nuanced explanation. The outcome of the analysis indicates that the three deep learning models, i.e., CNN, ANN, and LSTM, are all capable of predicting the next day movements of the NSE index with error consistently under 1%. This level of accuracy shows how far deep learning methods are capable of solving problems with financial forecasting. Even small improvements in prediction performance can have big effects on investors and policymakers in the real world.

CNN had the lowest prediction error of the three models, at 0.63%. This means that CNN's ability to detect short-term and auto dependencies in the data provides it a big edge when it comes to day-ahead forecasting. CNNs were made for computer vision, but they also work well with financial data because they can find short-term patterns and can also handle multivariate data, meaning they can find patterns across different data types. In an earlier study conducted on NSE data by Barua et al. (2024), CNN was shown to provide higher forecasting accuracy compared to the other two models. They work on the assumption that patterns in the historical data have the capability of predicting future movements in real scenarios like short-term trend analysis, processing visual financial data, and constructing Hybrid models like CNN-LSTM.

With an error rate of 0.72%, LSTM demonstrated that it is effective at modeling long-term and sequential dependencies. While slightly less accurate than CNN in this study, LSTM remains important because it is particularly effective at capturing temporal dynamics that go beyond short-term changes. Prior research has consistently highlighted the efficacy of LSTM for financial time series, particularly when extended historical time periods are significant (Kumaria et al., 2023). In a comparative study conducted in the Chinese stock market, LSTM outperformed the other two models, suggesting its suitability in tasks related to predicting financial data (Bao et al., 2025). Its performance here reinforces its role as a robust model for handling market sequences, sentiment analysis for market prediction, quantitative trading, and portfolio optimization, even if CNN edged it out in this study. While CNN achieves lower error metrics, the Diebold–Mariano test indicates that the difference between CNN and LSTM is not statistically significant. This suggests that both models exhibit broadly comparable predictive capability, and the observed numerical advantage of CNN should be interpreted with caution. The result, therefore, does not imply the superiority of one architecture over the other in a general sense but rather highlights the context-dependent nature of model performance.

The ANN model, which is a little simpler in structure, has also performed commendably with an error rate of 0.89%. This shows that even simple neural networks can still get good results if they are trained on big, well-prepared datasets. Practically, ANN is used by financial institutions for credit scoring and fraud detection, applied for executing algorithmic trading, exchange rate forecasting, and predicting bankruptcy of a company by analyzing its financial and operational data. ANN's limitations in learning long-range dependencies may explain its relatively weaker performance compared to CNN and LSTM in this study. This result is similar to previous research that showed that deeper or sequential architectures often do better than feedforward ANNs at predicting the stock market (Zhang & Zhou, 2007).

In contrast, the ARIMA model records a higher forecasting error, reflecting its limitation in modelling nonlinear and evolving market behavior. While it remains effective in capturing linear dependencies, its predictive capability diminishes in the presence of volatility and structural changes. The random walk model performs the weakest, as expected, reinforcing its role as a naive benchmark rather than a competitive forecasting tool, as seen in earlier empirical results (Moosa & Burns, 2016). Importantly, the statistical analysis provides further insight into this result. While CNN achieves lower error metrics,


http://dx.doi.org/10.21511/imfi.23(2).2026.17

the Diebold–Mariano test indicates that the difference between CNN and LSTM is not statistically significant. This suggests that both models exhibit broadly comparable predictive capability, and the observed numerical advantage of CNN should be interpreted with caution. The result, therefore, does not imply the superiority of one architecture over the other in a general sense but rather highlights the context-dependent nature of model performance.

These findings emphasize a crucial point: there is no universally "best" model; instead, there exists a best-fit model contingent upon the forecasting horizon and the dataset's characteristics. For short-term, next-day forecasting tasks like the ones discussed here, CNN seems to be the most accurate. LSTM may be better for making predictions over a longer period of time or in situations where time dependencies are critical. ANN is a good starting point because it is less powerful but still easy to understand and use.

From a practical perspective, the study provides valuable insights for market practitioners. In highly dynamic markets like the NSE, where rapid decision-making is crucial, the predictive strength of CNN could support traders and analysts in short-term strategies. At the same time, the broader potential of LSTM to capture longer-term market movements should not be overlooked, particularly for institutional investors with extended investment horizons. Although walk-forward validation enhances robustness, the study does not explicitly account for extreme market events or regime shifts, such as financial crises or periods of abnormal volatility. Model behavior under such conditions may differ from that observed during relatively stable periods.

At the same time, the results must be interpreted within the limitations of the study. The analysis is conducted using a single stock index within one national market, which may restrict the generalizability of the findings across different markets or asset classes. The focus on price-level forecasting rather than return-based prediction may also influence the observed accuracy, particularly in trending market conditions where error metrics such as MAPE can be artificially low. The results also suggest that improvements in predictive accuracy are not merely incremental but structurally linked to the ability of models to capture nonlinear dependencies and temporal dynamics. This distinction becomes particularly relevant in emerging markets, where traditional assumptions of stability are frequently violated. Finally, these results add to the research literature showing that deep learning models work much better than traditional statistical models like ARIMA and GARCH, which often have trouble with long-memory and nonlinearity structures as seen in earlier studies by (Poon & Granger, 2003; Zhang, 2003). It demonstrates how deep learning models have changed the way we forecast stock market movements. While deep learning models demonstrate improved predictive capability, their performance is shaped by the nature of the data and the forecasting objective. This highlights the importance of careful model selection and contextual evaluation in financial forecasting, rather than reliance on a single modelling approach.

## CONCLUSION

The analysis provides evidence on how architectural differences influence forecasting performance in complex financial environments. The analysis focused on contrasting model behavior under identical data conditions to better understand how architectural design influences predictive outcomes in financial time series.

The findings reveal that all evaluated deep learning models generated highly accurate forecasts, with prediction errors consistently remaining below one per cent. Convolutional neural networks achieved the strongest accuracy, particularly in short-term forecasting scenarios, while long short-term memory networks demonstrated notable effectiveness in learning sequential relationships and longer-term market structure. Artificial neural networks, though exhibiting relatively higher error, maintained stable and reliable performance, underscoring their continued relevance as baseline predictive tools.

These outcomes suggest that forecasting performance is closely linked to the alignment between model structure and data characteristics rather than the superiority of any single approach. The results further illustrate the growing effectiveness of deep learning techniques in capturing nonlinear and evolving patterns that are difficult to model using conventional statistical frameworks. Careful consideration of forecasting horizon and data complexity, therefore, remains essential when selecting predictive models for financial applications.

Future investigations could enhance this work by exploring hybrid architectures that integrate convolutional and recurrent components, as well as by incorporating macroeconomic indicators and market sentiment variables. Extending the analysis across different asset classes and market regimes may also provide deeper insight into the robustness and generalizability of deep learning models under varying financial conditions, and may explore hyperparameter optimization and automated model tuning techniques, including Bayesian optimization and reinforcement learning, to systematically enhance model performance.

## AUTHOR CONTRIBUTIONS

Conceptualization: Charithra C. M., Vinish P.
Data curation: Charithra C. M., Prakash Pinto.
Formal analysis: Vinish P., Prakash Pinto, Chetan Shetty.
Funding acquisition: Iqbal Thonse Hawaldar.
Investigation: Charithra C. M., Iqbal Thonse Hawaldar, Prakash Pinto.
Methodology: Charithra C. M., Iqbal Thonse Hawaldar, Vinish P.
Project administration: Iqbal Thonse Hawaldar, Chetan Shetty.
Resources: Vinish P., Prakash Pinto, Chetan Shetty.
Software: Charithra C. M., Vinish P., Prakash Pinto.
Supervision: Iqbal Thonse Hawaldar, Vinish P., Prakash Pinto, Chetan Shetty.
Validation: Iqbal Thonse Hawaldar, Chetan Shetty.
Visualization: Iqbal Thonse Hawaldar, Prakash Pinto, Chetan Shetty.
Writing – original draft: Charithra C. M., Vinish P., Prakash Pinto.
Writing – review & editing: Iqbal Thonse Hawaldar, Vinish P., Prakash Pinto, Chetan Shetty.

## ACKNOWLEDGMENT / FUNDING STATEMENT

The authors acknowledge Kingdom University, Bahrain, for funding article processing charges through research grant number KU-SRU-BA-01.

## REFERENCES

1. Atsalakis, G. S., & Valavanis, K. P. (2009). Forecasting stock market short-term trends using a neuro-fuzzy based methodology. *Expert Systems with Applications, 36*(7), 10696-10707. https://doi.org/10.1016/j.eswa.2009.02.043
2. Bao, W., Cao, Y., Yang, Y., Che, H., Huang, J., & Wen, S. (2025). Data-driven stock forecasting models based on neural networks: A review. *Information Fusion, 113,* 102616. https://doi.org/10.1016/j.inffus.2024.102616
3. Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. *PLOS ONE, 12*(7), e0180944. https://doi.org/10.1371/journal.pone.0180944
4. Barua, M., Kumar, T., Raj, K., & Roy, A. M. (2024). Comparative Analysis of Deep Learning Models for Stock Price Prediction in the Indian Market. *FinTech, 3*(4), 551-568. https://doi.org/10.3390/fintech3040029
5. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1
6. Box, G. E. P., & Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control.* Holden-Day & S. Francisco (Eds) (2nd ed.). Retrieved from https://www.scirp.org/reference/referencespapers?referenceid=1969833


http://dx.doi.org/10.21511/imfi.23(2).2026.17

7. C M, C., Sharma, M., & Vikas, B. (2024). Relationship Between The Volume Of Trade And Volatility Spillover Between The Selected Developed And Emerging Asian Markets. *Educational Administration Theory and Practices*. https://doi.org/10.53555/kuey.v30i5.5804

8. Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geoscientific Model Development, 7*(3), 1247-1250. https://doi.org/10.5194/gmd-7-1247-2014

9. Chatfield, C. (2000). *Time-Series Forecasting*. Chapman and Hall/CRC. https://doi.org/10.1201/9781420036206

10. de Myttenaere, A., Golden, B., Le Grand, B., & Rossi, F. (2016). Mean Absolute Percentage Error for regression models. *Neurocomputing, 192,* 38-48. https://doi.org/10.1016/j.neucom.2015.12.114

11. Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*(4), 987. Retrieved from https://ideas.repec.org/a/ecm/emetrp/v50y1982i4p987-1007.html

12. Engle, R., & Mezrich, J. (1996). GARCH FOR GROUPS – A round-up of recent developments in GARCH techniques for estimating correlation. *Risk: Managing Risk in the World's Financial Markets, 9*(8), 36-40. Retrieved from https://scholar.google.com/scholar?q=GARCH+FOR+GROUPS+-+A+round-up+of+recent+developments+in+Garch+techniques+for+estimating+correlation.+Engle+Mezrich

13. FAMA, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance, 46*(5), 1575-1617. https://doi.org/10.1111/j.1540-6261.1991.tb04636.x

14. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 270*(2), 654-669. https://doi.org/10.1016/j.ejor.2017.11.054

15. Giantsidi, S., & Tarantola, C. (2025). Deep learning for financial forecasting: A review of recent trends. *International Review of Economics & Finance, 104,* 104719. https://doi.org/10.1016/J.IREF.2025.104719

16. Heaton, J. (2018). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning. *Genetic Programming and Evolvable Machines, 19*(1-2), 305-307. https://doi.org/10.1007/s10710-017-9314-z

17. Hochreiter, S., & Schmidhuber, J. (1997a). Long Short-Term Memory. *Neural Computation, 9*(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

18. Hochreiter, S., & Schmidhuber, J. (1997b). Long Short-Term Memory. *Neural Computation, 9*(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

19. Huang, W., Nakamori, Y., & Wang, S.-Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research, 32*(10), 2513-2522. https://doi.org/10.1016/j.cor.2004.03.016

20. Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*(4), 679-688. https://doi.org/10.1016/j.ijforecast.2006.03.001

21. Kara, Y., Acar Boyacioglu, M., & Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. *Expert Systems with Applications, 38*(5), 5311-5319. https://doi.org/10.1016/j.eswa.2010.10.027

22. Kim, H. Y., & Won, C. H. (2018). Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. *Expert Systems with Applications, 103,* 25-37. https://doi.org/10.1016/j.eswa.2018.03.002

23. Kim, K. (2003). Financial time series forecasting using support vector machines. *Neurocomputing, 55*(1-2), 307-319. https://doi.org/10.1016/S0925-2312(03)00372-2

24. Kim, S., & Kim, H. (2016). A new metric of absolute percentage error for intermittent demand forecasts. *International Journal of Forecasting, 32*(3), 669-679. https://doi.org/10.1016/j.ijforecast.2015.12.003

25. Kim, T., & Kim, H. Y. (2019). Forecasting stock prices with a feature fusion LSTM-CNN model using different representations of the same data. *PLOS ONE, 14*(2), e0212320. https://doi.org/10.1371/journal.pone.0212320

26. Kumar Meher, B., Thonse Hawaldar, I., Spulbar, C., & Birau, R. (2021). Forecasting stock market prices using mixed ARIMA model: a case study of Indian pharmaceutical companies. *Investment Management and Financial Innovations, 18*(1), 42-54. https://doi.org/10.21511/imfi.18(1).2021.04

27. Kumaria, A., Rajkar, A., Raut, A., & Nair, R. S. (2023). *Forecasting the Indian Financial Markets with LSTM and Price Indicators* (pp. 395-403). https://doi.org/10.1007/978-981-99-1410-4_33

28. Leung, Y., Mei, C.-L., & Zhang, W.-X. (2000). Statistical Tests for Spatial Nonstationarity Based on the Geographically Weighted Regression Model. *Environment and Planning A: Economy and Space, 32*(1), 9-32. https://doi.org/10.1068/a3162

29. Li, Y., & Ma, W. (2010). Applications of Artificial Neural Networks in Financial Economics: A Survey. *2010 International Symposium on Computational Intelligence and Design,* 211-214. https://doi.org/10.1109/ISCID.2010.70

30. Lo, A. W. (2004). The Adaptive Markets Hypothesis. *The Journal of Portfolio Management, 30*(5), 15-29. https://doi.org/10.3905/jpm.2004.442611

31. Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. *PLOS ONE, 13*(3), e0194889. https://doi.org/10.1371/journal.pone.0194889

32. Mienye, I. D., & Swart, T. G. (2024). A Comprehensive Review of Deep Learning: Architectures, Recent Advances, and Applications. *Information, 15*(12), 755. https://doi.org/10.3390/info15120755

33. Moosa, I., & Burns, K. (2016). The random walk as a forecasting benchmark: drift or no drift? *Applied Economics, 48*(43), 4131-4142. https://doi.org/10.1080/00036846.2016.1153788

34. Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica, 59*(2), 347. https://doi.org/10.2307/2938260

35. Nelson, D. M. Q., Pereira, A. C. M., & de Oliveira, R. A. (2017). Stock market's price movement prediction with LSTM neural networks. *2017 International Joint Conference on Neural Networks (IJCNN),* 1419-1426. https://doi.org/10.1109/IJCNN.2017.7966019

36. Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques. *Expert Systems with Applications, 42*(1), 259-268. https://doi.org/10.1016/j.eswa.2014.07.040

37. Pesaran, M. H., & Timmermann, A. (1992). A Simple Nonparametric Test of Predictive Performance. *Journal of Business & Economic Statistics, 10*(4), 461. https://doi.org/10.2307/1391822

38. Poon, S.-H., & Granger, C. W. J. (2003). Forecasting Volatility in Financial Markets: A Review. *Journal of Economic Literature, 41*(2), 478-539. https://doi.org/10.1257/002205103765762743

39. Semenoglou, A.-A., Spiliotis, E., & Assimakopoulos, V. (2023). Image-based time series forecasting: A deep convolutional neural network approach. *Neural Networks, 157,* 39-53. https://doi.org/10.1016/j.neunet.2022.10.006

40. Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing, 90,* 106181. https://doi.org/10.1016/j.asoc.2020.106181

41. Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives, 17*(1), 83-104. https://doi.org/10.1257/089533003321164967

42. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research, 15*(56), 1929-1958. Retrieved from http://www.cs.toronto.edu/~rsalakhu/papers/srivastava14a.pdf

43. Thanh Noi, P., & Kappas, M. (2017). Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery. *Sensors, 18*(1), 18. https://doi.org/10.3390/s18010018

44. Tsantekidis, A., Passalis, N., Tefas, A., Kanniainen, J., Gabbouj, M., & Iosifidis, A. (2017). Using deep learning to detect price change indications in financial markets. *2017 25th European Signal Processing Conference (EUSIPCO),* 2511-2515. https://doi.org/10.23919/EUSIPCO.2017.8081663

45. Tsay, R. S. (2010). *Analysis of Financial Time Series*. Wiley. https://doi.org/10.1002/9780470644560

46. Vamossy, D. F. (2021). Investor emotions and earnings announcements. *Journal of Behavioral and Experimental Finance, 30,* 100474. https://doi.org/10.1016/j.jbef.2021.100474

47. Vasenska, I. (2025). Comparative Analysis of Machine Learning and Deep Learning Models for Tourism Demand Forecasting with Economic Indicators. *FinTech, 4*(3), 46. https://doi.org/10.3390/fintech4030046

48. Vivas, E., Allende-Cid, H., & Salas, R. (2020). A Systematic Review of Statistical and Machine Learning Methods for Electrical Power Forecasting with Reported MAPE Score. *Entropy, 22*(12), 1412. https://doi.org/10.3390/e22121412

49. World Bank Group. (2023, June). *Global Economic Prospects*. Retrieved from https://openknowledge.worldbank.org

50. Yang, J., Zhang, L., Chen, C., Li, Y., Li, R., Wang, G., Jiang, S., & Zeng, Z. (2020). A hierarchical deep convolutional neural network and gated recurrent unit framework for structural damage detection. *Information Sciences, 540,* 117-130. https://doi.org/10.1016/J.INS.2020.05.090

51. Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing, 50,* 159-175. https://doi.org/10.1016/S0925-2312(01)00702-0

52. Zhang, G., Eddy Patuwo, B., & Y. Hu, M. (1998). Forecasting with artificial neural networks: *International Journal of Forecasting, 14*(1), 35-62. https://doi.org/10.1016/S0169-2070(97)00044-7

53. Zhang, M.-L., & Zhou, Z.-H. (2007). ML-KNN: A lazy learning approach to multi-label learning. *Pattern Recognition, 40*(7), 2038-2048. https://doi.org/10.1016/j.patcog.2006.12.019

54. Zhang, X., Liang, X., Zhiyuli, A., Zhang, S., Xu, R., & Wu, B. (2019). AT-LSTM: An Attention-based LSTM Model for Financial Time Series Prediction. *IOP Conference Series: Materials Science and Engineering, 569*(5), 052037. https://doi.org/10.1088/1757-899X/569/5/052037




http://dx.doi.org/10.21511/imfi.23(2).2026.17