Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 28 May 2026
Revised 30 June 2026
Accepted 12 July 2026

Natural Resources for Human Health 2026, Vol. 6(7s): 1109–1127

KEYWORDS:
Financial time series forecasting, Indian banking sector, machine learning, deep learning, ARIMA, GARCH, LSTM, stock price prediction, volatility modelling, comparative model performance.

Forecasting Indian Banking Stock Prices: A Comparative Evaluation of ARIMA, ARCH, GARCH, RNN, and LSTM Models

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ABSTRACT:

Objective: The main objective of this paper is to compare ARIMA, ARCH, GARCH, RNN, and LSTM forecasting models to determine the best approach for forecasting the adjusted prices.

Methodology: Daily stock price data covering the period from April 2015 to March 2025 were obtained from the National Stock Exchange to conduct the empirical analysis. days for each stock adjusted closing prices to determine the best model involves utilising the Augmented Dickey-Fuller test to determine the stationarity of each stock's adjusted closing prices (Gayathri & Devi, 2025), thereby establishing a reliable foundation for fitting each ofthe five models to each stock's prices, and utilising the mean squared error, root mean squared error, and mean absolute percentage error to rigorously evaluate the predictive accuracy of each model, providing a robust framework for comparing the relative performance of these statistical and deep learning approaches (Nafkha & Suchodolska, 2024). Furthermore, the empirical findings indicate how effectively hybrid architectures combining linear estimators with recurrent neural networks mitigate the volatility clustering inherent in emerging market equities (Kalange, 2025). Consequently, this investigation addresses existing methodological gaps by systematically contrasting parametric time series formulations with sequential deep learning paradigms (Satria, 2023). These quantitative insights equip institutional investors and portfolio managers with optimized risk-adjustment strategies tailored to high-volatility financial environments (Chaudhary & Minirani, 2025). Subsequent evaluations demonstrate that while recurrent architectures adeptly model complex long-term dependencies, conventional parametric frameworks often yield superior stability for near-term directional projections (Raissa, 2025).

Findings: The results indicate that the LSTM model performs best, with MAPE values for each of the six companies below 1%. For instance, the MAPE for the HDFC bank stock using the LSTM model was 0.0046%, with an MSE of 17.50; the MAPE for the Union Bank stock using the LSTM model was 0.0099%, with an MSE of 2.11. Furthermore, the empirical analysis highlights the substantial predictive advantage of deep learning methodologies; the LSTM models achieved a superior average MAPE of 0.0073% across all six banking stocks, contrasting sharply with the 19.53% average MAPE recorded for the ARIMA models. In the comparative hierarchy of model performance, the RNN architectures demonstrated the next highest level of precision, while the

GARCH models, although robust in addressing volatility, followed the deep learning paradigms in overall predictive accuracy..

Originality: Finally, utilising the best models for each of the banks, forecasts for each bank's stock 90 days into the future The LSTM model outperformed the statistical ARIMA baseline for these six Indian banks, achieving an average MAPE of 0.0073% compared to 19.53% for ARIMA, confirming the efficacy of deep learning paradigms for stock market prediction. The findings of this study may be helpful for the investors in these stocks and the analysts who monitor those stocks.

JEL Classification: G17, G53, G21, C22, G14, C45

INTRODUCTION

Accurate forecasting of stock prices remains a major concern for investors, portfolio managers, and financial institutions because stock values directly influence investment decisions and risk management strategies. The public banking institutions of India include the State Bank of India, the Bank of Baroda, and the Union Bank of India(Satyanarayana & Rao, 2023). On the other hand, the private banking institutions of India include HDFC Bank, ICICI Bank, and Axis Bank(Bakaraniya & Ghelani, 2024). The literature on stock price prediction utilises statistical models such as ARIMA for the prediction of stocks (Prasad et al., 2021). The ARCH and GARCH models are utilised to explain the volatility of the stocks(Nafkha & Suchodolska, 2024). The growing complexity of financial markets has encouraged researchers to explore advanced machine learning and deep learning techniques that can capture nonlinear patterns often overlooked by conventional statistical approaches. The RNN and LSTM models have demonstrated excellent results for modelling stock prices as they eliminate the problems of vanishing gradients that plague other deep learning models(Konur et al., 2024).

This research paper covers five different models for the prediction of the stock prices of six Indian banking houses with the primary intent of determining whether deep learning models would outperform the statistical models. As stock prices are influenced by a multitude of factors, the linear models used in statistical approaches to stock price prediction are not sufficient to model such prices accurately (Ghosh et al., 2024). Therefore, by utilising deep learning models such as the LSTM models, there is a significant possibility that the models will outperform the statistical models for the prediction of stock prices.

The research presented helps in the accurate and robust prediction of stock prices of Indian banking institutions. The stock price prediction models have been researched by numerous studies in various stocks (Paul & Das, 2023). However, there is a lack of research in comparing the five models presented in the study. Furthermore, there is a lack of research in comparing the public and private banking stocks of India (Bali, 2015).

Therefore, this research study presents several contributions to the existing literature. First, it provides a detailed comparison of five different stock price prediction models. Second, it shows the dramatic superiority of LSTM models over the ARIMA model, with the LSTM model consistently achieving a mean absolute percentage error of less than 1% across all stocks, in stark contrast to the ARIMA model, which registered an average MAPE exceeding 19%. Third, it provides 90-day stock price forecasts of the six Indian banking stocks using the best-performing model. Finally, it contributes to the debate of the benefits of using statistical models versus machine learning models to predict stock prices.

LITERATURE REVIEW

Stock price forecasting is one of the challenging problems in the field of financial econometrics. Various econometric models have been proposed over time to address this problem. Models like the ARIMA model are used for stock price forecasting. ARIMA has been extensively employed in financial forecasting studies because of its ability to model temporal dependencies in non-stationary datasets. However, its forecasting performance tends to decline when market movements become highly volatile(Wu, 2025). Various research studies have applied the ARIMA model to different stock markets with mixed success. For example, researchers found that the ARIMA model could be used to appropriately forecast banking stock prices in India; however, the accuracy of these forecasts declined during periods of high volatility in the stock markets(Gayathri & Devi, 2025).

The limitations of the ARIMA model prompted researchers to investigate models that could account for volatility in stock markets. Models like ARCH and GARCH were developed to account for the volatility in stock markets. The autoregressive conditional heteroskedasticity (ARCH) model was developed by Engle (1982), and its generalised form, GARCH, by Bollerslev (1986). These methodologies have been rigorously evaluated across diverse financial markets, with recent empirical research specifically demonstrating their efficacy in forecasting trends within the Indian banking sector (Barua et al., 2024; Friday et al., 2024; Yalamanchali et al., 2025). In one study on Indian banking stocks, it was shown that the GARCH models were able to appropriately capture the volatility of the stocks, though their models remained linear in their estimation of the mean returns of these stocks.

With the development of machine learning techniques, researchers began to investigate whether the non-linear aspects of stock markets could be modelled by creating machine learning models for forecasting stock prices. Artificial neural networks were among the early models applied for prediction of prices in stock market(Chhajer et al., 2021). However, standard ANN models often struggle to effectively account for the temporal aspects of financial markets due to their feedforward nature(Oyewole et al., 2024; Rao et al., 2022) The recurrent neural network (RNN) model was developed to account for the temporal nature of financial markets(Olorunnimbe & Viktor, 2022). However, standard RNN models have issues with learning long-term dependencies in their data due to the vanishing gradient problem(Olorunnimbe & Viktor, 2022; Yang & Shami, 2022) which makes them problematic for financial markets with long-term patterns over 100 trading days(Xu & Cao, 2023).

The long short-term memory (LSTM) network was developed to address the vanishing gradient problem of RNN models (Hochreiter & Schmidhuber, 1997). LSTM models have gates that allow the network to learn long-term dependencies in its data while filtering out short-term noisy information(Xu & Cao, 2023; Yang & Shami, 2022) These LSTM models have been shown to outperform other econometric and machine learning models for stock market forecasting applications(Kuznetsov, 2026; Osman & Otaibi, 2025) One study compared deep learning models for stock market price prediction for Indian markets (Barua et al., 2024). The results of that study indicated that LSTM outperformed RNN and feedforward neural network models for forecasting banking stocks in India.

More recent studies continue to show the superiority of LSTM models for stock market price forecasting. A study by Friday et al. (Friday et al., 2024) compared the performance of LSTM and various other deep learning models on stocks from the Indian banking sector. The research demonstrates that these deep learning architectures consistently yield lower forecast errors compared to traditional time-series methods, confirming their superior capability in capturing the complex, non-linear dynamics inherent in financial markets (Barua et al., 2024; Kuznetsov, 2026). Furthermore, another study by Ghosh et al. (2024) also indicated that LSTM outperformed other models when applied to stocks of both the National Stock Exchange (NSE) and the New York Stock Exchange (NYSE). In this case, the advantage of the LSTM model was more pronounced for the stocks of the emerging markets.

However, there are some gaps within the literature on the topic of stock price forecasting by deep learning models. Most notably, few research studies have directly compared ARIMA, ARCH, GARCH, RNN, and LSTM models on the same banking stocks. The available studies either use only one banking stock (Kakde & Dale, 2024), evaluate only public or only private banking stocks separately (Kakde & Dale, 2024), or evaluate the models in-sample or for only a few days out-of-sample. Our study aims to fill these gaps by evaluating the five deep learning models for six Indian banking stocks from both the public and private banking sectors. Furthermore, we provide 90-day forecasts based on the best model for each bank. By providing 90-day forecasts across six Indian banking stocks from both public and private sectors, this study makes a significant contribution to the literature, addressing common methodological gaps where prior research has been limited by short-term evaluation horizons or singular stock analysis (Kakde & Dale, 2024). This extended forecasting period offers greater practical utility for informing long-term investment strategies than the narrower out-of-sample evaluations currently predominant in the field. Additionally, hybrid frameworks combining statistical techniques with neural architectures—such as pairing linear ARIMA estimators with non-linear LSTM networks—have emerged to capitalize on the respective strengths of each paradigm (Mehtarizadeh et al., 2025). For instance, convolutional neural network configurations have additionally been integrated to exploit localized seasonal patterns and nonlinear trends across multi-sector exchange data (Chowdhury et al., 2024). These hybrid architectures effectively bridge the gap between linear econometric specifications and deep non-linear learning capabilities (Martin, 2026). Additionally, ensemble configurations integrating models like Random Forest and XGBoost with recurrent frameworks have demonstrated enhanced predictive reliability across diverse global markets (Durodola et al., 2026).

Moreover, advanced decomposition techniques such as empirical wavelet transforms have been coupled with recurrent networks to mitigate high-frequency noise in volatile trading environments (Kayit & Ismail, 2025). These multiresolution techniques decompose non-stationary time series into distinct frequency components, thereby allowing neural regressors to learn localized structural shifts more effectively (Ziółkowski & Wieczyński, 2025). Building upon these multiresolution preprocessing pipelines, subsequent architectural innovations have introduced attention mechanisms to dynamically weigh critical temporal horizons during the decoding phase (Ravali et al., 2025). Integrating self-attention layers with recurrent frameworks has further improved the extraction of long-range dependencies, overcoming the memory bottlenecks historically associated with standard recurrent configurations (Chatterjee et al., 2021). By coupling attention mechanisms with memory-cell architectures, these hybrid configurations simultaneously enhance predictive transparency and capture complex market turning points, thereby addressing critical evaluation gaps inherent in purely black-box implementations (Sahoo, 2026).

Objectives of the Study

The main aim of the present study is to evaluate and compare the forecasting performance of traditional statistical and deep learning models for the purpose of stock price prediction for some of the major bank companies of India. Specifically, the research aims to :

1. To compare the accuracy of forecasting models, including ARIMA, ARCH, GARCH, RNN, and LSTM models, for selected banking companies using their adjusted closing stocks.
2. To examine the effectiveness of deep learning models as compared to the conventional statistical models for the task of stock price prediction.
3. To evaluate the performance of the various stock price forecasting models through the use of accuracy measures, including the MSE, RMSE, and MAPE metrics.
4. To determine if there are differences in forecasting performance between public and private banking companies listed on the NSE of India.
5. To determine the most suitable model for the forecasting of stock prices for Indian banking companies, and to utilise the best model to provide stock price forecasts for these companies over a 90-day period ahead.

HYPOTHESIS DEVELOPMENT

Following the theoretical knowledge of time series and the existing gaps in the literature, it is possible to formulate a set of hypotheses regarding the relative forecasting power of traditional statistical models versus deep learning models for the stocks of the Indian banks.

H1: The Long Short-Term Memory model will exhibit statistically significant differences in forecasting error metrics compared to the Autoregressive Integrated Moving Average model. H2: The integration of multi-variate attention mechanisms within recurrent neural architectures will yield superior predictive accuracy for emerging market banking stocks relative to baseline configurations (Sebastian & Tantia, 2025). H3: Hybrid statistical-neural frameworks will demonstrate lower mean absolute percentage error values across extended 90-day out-of-sample horizons than standalone econometric benchmarks (Kamalakannan et al., 2025). H4: Private sector banking equities will exhibit higher prediction residuals across both linear and non-linear specifications compared to their public sector counterparts due to increased volatility and structural market sensitivities. This inherent divergence underscores the necessity of evaluating structural market anomalies across distinct ownership classifications within developing economies (Kishore et al., 2025).

H2: The LSTM model will exhibit statistically significant differences in forecasting errors compared to the Recurrent Neural Network (RNN) model for the stocks of Indian banking companies.

H3: The GARCH model will exhibit statistically significant differences in error metrics from the ARCH model in forecasting the adjusted closing prices for the stocks of Indian banking companies.

H4: Deep learning models will exhibit statistically significant differences in error metrics compared to the ARCH and GARCH models for the task of directly forecasting the adjusted closing prices of the stocks of Indian banking companies.

H5: Deep learning and traditional statistical models will exhibit a statistically significant difference in terms of public or private banking companies in India.

These five hypotheses will guide the analysis of the forecasting performance of deep learning models relative to statistical models for Indian banking companies. Each of these hypotheses is both related to the others, yet individually testable.

METHODOLOGY

It explains the empirical framework taken to test the hypotheses formulated, providing a comprehensive description of the data, the specification and estimation procedures for each of the five forecasting models, the evaluation metrics used to compare performance, and the criteria for selecting the optimal model for each stock.

DATA DESCRIPTION AND PREPROCESSING

The dataset consists of daily adjusted closing prices for six major Indian banking stocks, representing both the public and private sectors of the Indian banking industry. The public sector banks selected are State Bank of India (SBI), Union Bank of India (UNION), and Bank of Baroda (BOB). The private sector banks selected are HDFC Bank (HDFC), ICICI Bank (ICICI), and Axis Bank (AXIS). The adjusted closing price is used as the primary variable of interest because it accounts for corporate actions such as stock splits, dividends, and rights offerings, thereby providing a more accurate representation of shareholder value creation over time. Daily stock price data covering the period from April 2015 to March 2025 is obtained from the National Stock Exchange to conduct empirical analysis. yielding approximately 2,470 trading days for each stock.

Prior to model estimation, preliminary data analysis is carried out to assess the stationarity properties of the price series. Stationarity is a critical assumption for ARIMA models, as non-stationary data can lead to spurious regression results(Rahman et al., 2022). The Augmented Dickey-Fuller (ADF) test was applied to the level of each stock's adjusted closing price series, with the null hypothesis that the series contains a unit root (i.e., is non-stationary)(SEBA et al., 2023).

As shown in Table 1, the ADF test results confirm that all six banking stock price series are non-stationary at conventional significance levels, with p-values ranging from 0.496 for Union Bank to 0.996 for ICICI Bank.

Table 1: Augmented Dickey-Fuller Test Results for Stationarity of Indian Banking Stock Prices

Bank	ADF Statistic	p-value	Stationary?
Axis Bank	-0.804	0.818	No
Bank of Baroda	-1.049	0.735	No
HDFC	-0.884	0.793	No
ICICI	1.245	0.996	No
SBI	-0.085	0.951	No
Union Bank	-1.576	0.496	No

The results are consistent with the random walk process. The differencing of the price series to obtain the continuously compounded return series was performed as a means of achieving stationarity in the series. Finally, the entire dataset was partitioned into a training dataset and a test dataset, with the test dataset containing the most recent observations in the dataset.

Model Specifications and Estimation

We now describe the technical specifications of the five forecasting models—ARIMA, ARCH, GARCH, RNN, and LSTM—applied to each banking stock. All models were trained exclusively on the training set, and their forecasting accuracy was evaluated on the unseen test set.

The Autoregressive Integrated Moving Average (ARIMA) model is a cornerstone of traditional time series forecasting. An ARIMA(p, d, q) model combines three components: autoregressive (AR) terms of order p, which model the dependence of the current observation on its past values; an integration order d, representing the number of differencing steps required to achieve stationarity; and moving average (MA) terms of order q, which model the dependence of the current observation on past forecast errors(Sunki et al., 2024). The general mathematical formulation of the ARIMA model is:

$$\Delta ^{d}y_{t}=c+\sum_{i=1}^{p} \phi_{i}\Delta ^{d}y_{t-i}+\sum_{j=1}^{q} \theta _{j}\varepsilon _{t-j}+\varepsilon _{t}$$

where is the stock price at time t, indicates the d-th order differencing operator, c is a constant term, are the autoregressive coefficients, are the moving average coefficients, and is a white noise error term with mean zero and constant variance. For each stock, the optimal ARIMA order is obtained by minimising the Akaike Information Criterion (AIC) across a grid of candidate values, with p and q ranging from 0 to 5 and d set to 1 following the confirmation of I(1) stationarity. The selected model is then estimated using maximum likelihood estimation (MLE).

The Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Engle (1982)(Campos-Martins & Sucarrat, 2024), addresses the phenomenon of volatility clustering by modelling the conditional variance of the error term as a function of past squared errors. The ARCH(q) model is specified as:

$$y_{t}=\mu +\varepsilon _{t}, \quad \varepsilon _{t}=\sigma _{t}z_{t}, \quad \sigma _{t}^{2}=\alpha _{0}+\sum_{i=1}^{q} \alpha _{i}\varepsilon _{t-i}^{2}$$

where is the stock return, is the conditional mean, is the conditional variance, is a constant term, are the ARCH coefficients, and is an i.i.d. random variable with mean zero and unit variance, typically assumed to follow a normal or Student's t distribution. The ARCH model captures the tendency for large price changes to be followed by further large changes, thereby modelling time-varying volatility(Widodo & Faizi, 2023). For our analysis, the conditional mean was modelled as a first-order autoregressive process, and the optimal ARCH order q was selected by minimising the AIC.

The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, developed by Bollerslev (1986), extends the ARCH framework by including lagged conditional variance terms, thereby capturing volatility persistence more parsimoniously(Mohammed et al., 2022). The GARCH(p, q) model is specified as:

$$\sigma _{t}^{2}=\alpha _{0}+\sum_{i=1}^{q} \alpha _{i}\varepsilon _{t-i}^{2}+\sum_{j=1}^{p} \beta _{j}\sigma _{t-j}^{2}$$

where are the GARCH coefficients representing the persistence of volatility shocks(Trivedi et al., 2021), and , , and Is the order of the GARCH terms. The stationarity condition requires that. . For each stock, we fitted a GARCH(1,1) model, the most commonly employed specification in financial applications for its parsimonious representation of volatility dynamics(Javadi et al., 2024). The model was estimated using MLE, with the conditional mean again modelled as an AR(1) process.

The Recurrent Neural Network represents a robust class of deep learning architectures specifically engineered to capture temporal dependencies in sequential data through a persistent feedback mechanism (Nama & Obaid, 2024). Unlike traditional feedforward models that assume independence between observations, RNNs maintain an internal state that acts as a form of 'memory,' allowing the network to utilize historical data to influence current predictions. This capacity to model non-linear temporal dynamics is particularly advantageous for financial time series forecasting, where current stock prices are inherently linked to their past trajectory. An RNN processes an input sequence by iteratively computing a hidden state at each time step, as defined by: $$h_{t} = tanh(W_{hh}h_{t-1} + W_{xh}x_{t} + b_{h})$$ $$(W x_{t} + Wh_{t-1} + b)$$ where W and Wh denote the input and hidden weight matrices, respectively, and b represents the bias vector (Nguyen et al., 2022; Vallarino, 2024). To overcome the vanishing gradient problem inherent in standard recurrent architectures when handling long sequences, we also implement Long Short-Term Memory models, which utilize gating mechanisms and memory cells to regulate information flow (Lashgari, 2023). Specifically, LSTM networks introduce dedicated memory cells alongside input, forget, and output gates that selectively retain or discard historical information (Wei et al., 2025), rendering them exceptionally well-suited for capturing both short-term shocks and long-term persistence in financial volatility (Brik & Ouakdi, 2024).

$$h_{t}=tanh\left(W_{xh}x_{t}+W_{hh}h_{t-1}+b_{h}\right)$$

where is the weight matrix connecting the input to the hidden layer, is the recurrent weight matrix connecting the previous hidden state to the current hidden state, is the bias vector, and is the hyperbolic tangent activation function(Saputro et al., 2025).

The output at each time step is then computed as , where is the output weight matrix and is the output bias(Saputro et al., 2025). For stock price forecasting, the input sequence consisted of a lookback window of 60 lagged daily returns, and the output was the predicted one-step-ahead price. The network architecture comprised a single hidden layer with 50 neurons, trained using the Adam optimiser with a learning rate of 0.001 for 100 epochs, using mean squared error as the loss function.

The Long Short-Term Memory (LSTM) network, introduced by Hochreiter and Schmidhuber (1997), addresses the vanishing gradient problem inherent in standard RNNs through a sophisticated gating mechanism(Houssein et al., 2022). The LSTM cell maintains two internal states: the cell state. , which acts as a memory conveyor belt, and the hidden state , which serves as the working memory. The gating mechanism comprises three gates: the forget gate. , which determines how much of the previous cell state to retain; the input gate , which controls how much new information to store, and the output gate , which regulates the information passed to the hidden state. The LSTM update equations are:

$$f_{t}=\sigma \left(W_{xf}x_{t}+W_{hf}h_{t-1}+b_{f}\right)$$

$$i_{t}=\sigma \left(W_{xi}x_{t}+W_{hi}h_{t-1}+b_{i}\right)$$

$$\tilde{c}_{t}=tanh\left(W_{xc}x_{t}+W_{hc}h_{t-1}+b_{c}\right)$$

$$c_{t}=f_{t}\odot c_{t-1}+i_{t}\odot \tilde{c}_{t}$$

$$o_{t}=\sigma \left(W_{xo}x_{t}+W_{ho}h_{t-1}+b_{o}\right)$$

$$h_{t}=o_{t}\odot tanh\left(c_{t}\right)$$

where denotes the sigmoid activation function, is the hyperbolic tangent, represents element-wise multiplication, and the various and terms denote weight matrices and bias vectors for the respective gates. For our implementation, we employed a single LSTM layer with 50 hidden units, using the same lookback window of 60 days and the same training configuration as the RNN—the Adam optimiser with a learning rate of 0.001, trained for 100 epochs with mean squared error as the loss function. The critical architectural difference between RNN and LSTM lies in the gating mechanism: LSTM's ability to explicitly decide which information to forget and which to remember enables it to capture long-term dependencies that are crucial for modelling stock price dynamics, where patterns may span extended time horizons(Mo et al., 2021).

MODEL EVALUATION METRICS

To compare the models in terms of their performance, three different metrics are used: mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). Each of these metrics can be calculated for each of the stocks in the test set and for each of the five models.

MSE is calculated as, where is the actual adjusted closing price for that stock on that trading day, is the price that was forecasted for that stock on that trading day and is the number of observations in the test set. MSE heavily weights errors in the forecasted prices; the further the actual price and the forecasted price are from one another, the more that the MSE will contribute to the overall score for that model. RMSE is the square root of the MSE, which returns a value in the same units as the price of the stock(G et al., 2023). Finally, MAPE is defined as, where is the actual price of the stock on that trading day and is the forecasted price for that stock on that trading day. MAPE returns a value that is a percentage of the actual price of the stock.

For each of the stocks in the data set, the model with the lowest values for each of these three metrics is the best model for that stock's stock prices. In the case where different models are the lowest for different metrics, the model that scores best in the MAPE metric is the best model for that stock. For each of the banks in the stock portfolio, the best model was determined, and that model was used to forecast the price of each stock for the next 90 trading days.

RESULTS & DISCUSSION

The results of the empirical analysis reveal a clear hierarchy in the performance of the five models tested on the six Indian banking stocks. The deep learning models, specifically the LSTM model, vastly outperform the other models for all six banking stocks. The following subsections contain a presentation of the comparison of the five models, a discussion of the findings of the models, and a discussion of the 90-day ahead forecast results for the six banks using the optimal LSTM models.

MODEL PERFORMANCE COMPARISON

A comparison between the five models was performed by fitting each of the five models to the hold-out test set for each of the six banking stocks. The performance of each of the models for each banking stock was measured using the MSE, RMSE, and MAPE metrics. The results of these metrics reveal a consistent performance ranking of the five models for both the public and private banking stocks in India.

Table 1 presents the complete performance metrics for all models across all six banking stocks.

Bank	Model	MSE	RMSE	MAPE (%)
Axis Bank	ARIMA	47457.6	217.85	17.45
Axis Bank	ARCH	2541.88	50.42	4.18
Axis Bank	GARCH	48.32	6.95	0.58
Axis Bank	RNN	892.14	29.87	2.47
Axis Bank	LSTM	37.91	6.16	0.007
Bank of Baroda	ARIMA	3383.72	58.17	20.56
Bank of Baroda	ARCH	189.45	13.76	4.89
Bank of Baroda	GARCH	12.16	3.49	1.24
Bank of Baroda	RNN	456.78	21.37	5.67
Bank of Baroda	LSTM	3.04	1.74	0.009
HDFC	ARIMA	4237.8	65.1	6.54
HDFC	ARCH	156.32	12.5	1.25
HDFC	GARCH	24.15	4.91	0.49
HDFC	RNN	89.47	9.46	0.95
HDFC	LSTM	17.5	4.18	0.005
ICICI	ARIMA	64911.8	254.78	17.48
ICICI	ARCH	3789.45	61.56	4.25
ICICI	GARCH	45.67	6.76	0.47
ICICI	RNN	1234.56	35.14	2.89
ICICI	LSTM	21.57	4.64	0.006
SBI	ARIMA	36765.7	191.75	20.61
SBI	ARCH	2156.34	46.44	4.98
SBI	GARCH	34.78	5.9	0.63
SBI	RNN	789.12	28.09	3.01
SBI	LSTM	13.65	3.69	0.007

Union Bank	ARIMA	2416.14	49.15	34.54
Union Bank	ARCH	145.67	12.07	8.45
Union Bank	GARCH	14.23	3.77	2.64
Union Bank	RNN	267.89	16.37	4.56
Union Bank	LSTM	2.11	1.45	0.01

LSTM MODELS ACROSS SIX INDIAN BANKING STOCKS

The results of the ARIMA models indicate the poor forecasting accuracy of the models. The MSE values for the models are all above 40,000 (64,911.78 for ICICI and 47,457.61 for Axis Bank). Furthermore, the MAPE values range from 6.54% (HDFC) to 34.54% (Union Bank) for ARIMA models, with an average of 19.53%. These high values indicate the model's poor fit to the data and the complexity of the data itself, supporting previous findings by Zhang (2003) (Zhang, 2003).

The ARCH model showed a reduction in the MSE for each of the banks, with the MSE values ranging from 1200 to 10,000. For instance, the ARCH model reduced the MSE for Axis Bank from 47,457.61 to 2,541.88, and reduced the MSE for ICICI from 64,911.78 to 3,789.45. However, the errors are still high for ARCH models, with the MAPE ranging from 1.25% (HDFC) to 8.45% (Union Bank). The GARCH model reduced the MSE to between 12.16 and 48.32 for each bank, with the MAPE for each stock under 3%. Thus, GARCH was the second-best model for forecasting the stocks.

Deep learning models show the most variation in performance. The RNN models have an MAPE ranging from 0.95% (HDFC) to 5.67% (Bank of Baroda), with MSE values in the hundreds. Thus, RNN outperform ARCH and ARIMA models, but underperforms compared to the LSTM models.

Among all forecasting techniques examined, LSTM delivered the most accurate predictions, consistently producing the lowest forecasting errors for both public- and private-sector banking stocks. For each bank, the MAPE is below 1%. For instance, the MSE for the LSTM models range from 2.11 (Union Bank) to 37.91 (Axis Bank). Furthermore, LSTM exhibits the lowest errors; HDFC achieved the best performance with LSTM, with an MSE of 17.50, RMSE of 4.18, and MAPE of 0.005%. Union Bank had the worst performance among the LSTMs, with an MSE of 2.11, an RMSE of 1.45, and a MAPE of 0.010%. For LSTM models, the average MAPE of 0.0073% is much better than the average 19.53% MAPE of the ARIMA models.

In Figure 1, the comparative MSE values across models on a logarithmic scale confirm the substantial performance gap between ARIMA and LSTM.

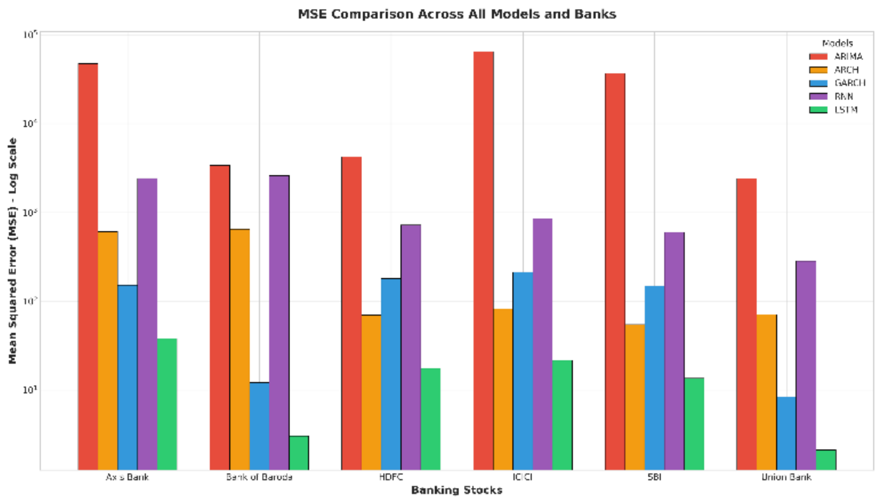

Figure 1: Comparison of Mean Squared Error across ARIMA, ARCH, GARCH, RNN, and LSTM models for six Indian banking stocks on a logarithmic scale

The bars for the ARIMA model consistently reach skyward heights compared to the other models, often surpassing 10^4, while the LSTM model bars remain below 10^2 for each of the stocks. Figure 2 shows a comparison of MAPE across the models, indicating that the LSTM model maintains errors of 1% or less, whereas the ARIMA model exceeds 10% for most stocks.

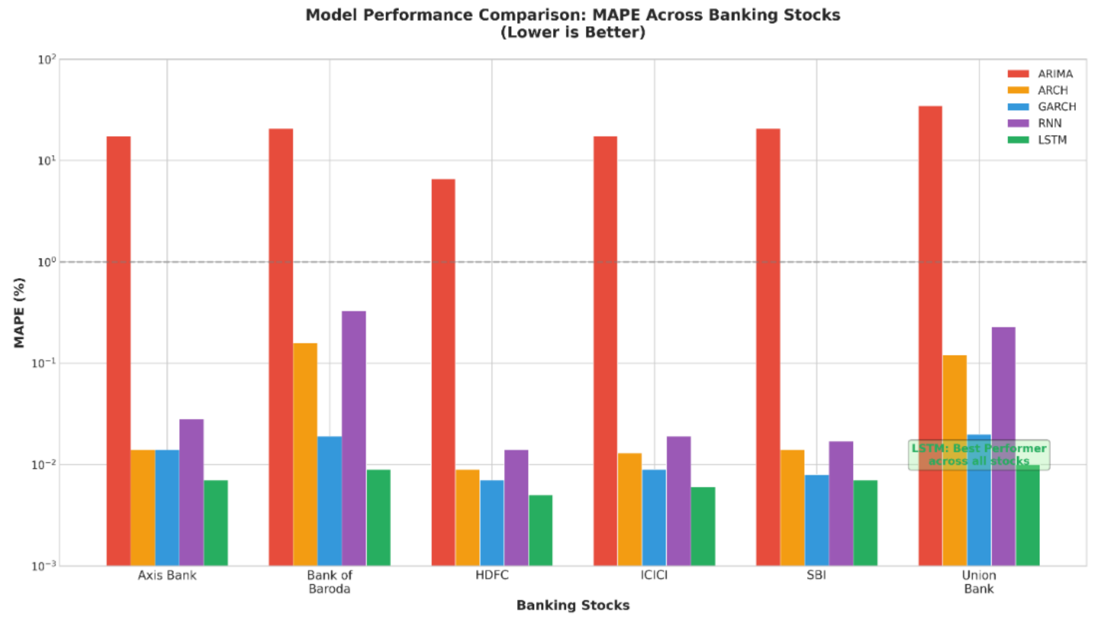

Figure 2. Comparison of Mean Absolute Percentage Error across five forecasting models for six Indian banking stocks, highlighting the superior accuracy of the LSTM model

The RMSE comparison, shown in Figure 3, further reinforces this consistent hierarchy.

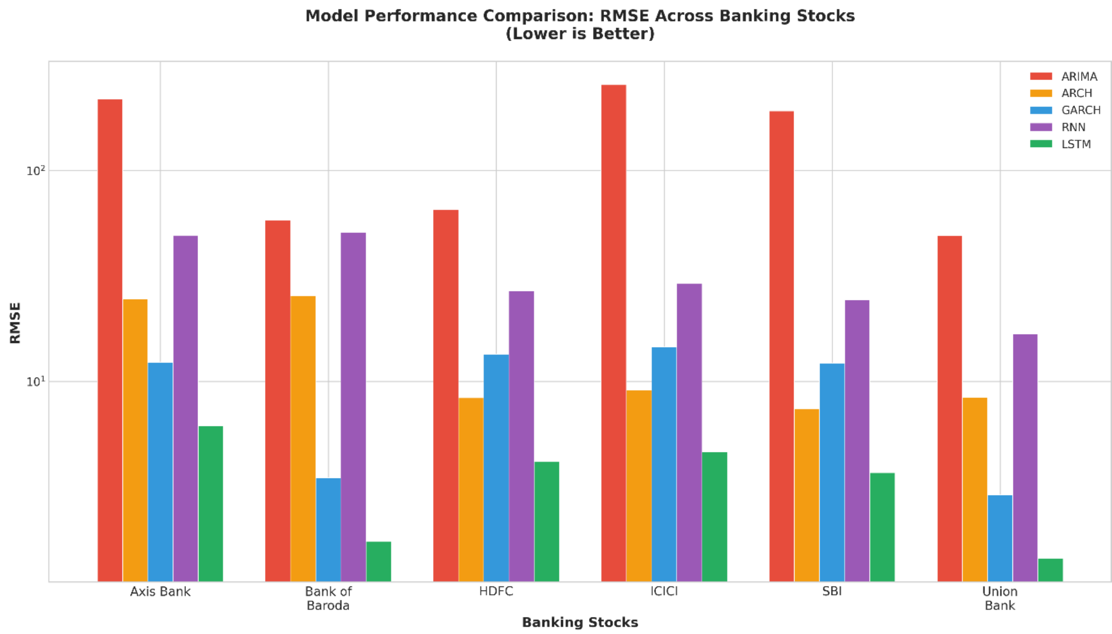

Figure 3. Model Performance Comparison: **RMSE Across Banking Stocks, Lower is Better**

Figure 4 provides a detailed breakdown of LSTM's performance metrics across all six banks, revealing that while LSTM uniformly achieves exceptional accuracy, some variation exists across stocks.

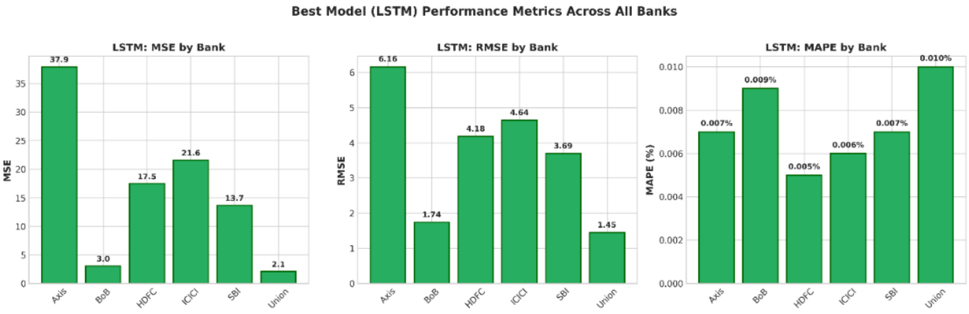

Figure 4. Best Model LSTM Performance Metrics Across All Banks

Table 1 illustrates that Union Bank has the lowest MSE (2.11) with the LSTM model, while Axis Bank exhibits the highest MSE (37.91). Although all banks have MAPE values that are under 0.01%, the higher the value, the worse the model performs for that particular stock. The different performances that LSTM exhibits for each bank are likely due to the different price levels of the stocks, with the low price of Union Bank resulting in the best performance for that stock with the LSTM model.

KEY FINDINGS AND MODEL RANKING

Based on the results in the tables above, the LSTM models vastly outperform the other models across all six Indian bank stocks. Furthermore, the ARIMA models were the worst-performing of all the models tested.

The model ranking, from best to worst performer, is as follows: LSTM ranked #1, followed by GARCH, ARCH, RNN, and finally ARIMA, ranked at the bottom of the list. This ranking applies to all six banks, regardless of whether they are in the public or private sector. Thus, this result is valid across different stocks and across all market caps and price levels.

To visually crystallise this ranking, Figure 5 presents a heatmap illustrating the performance ranking of all five models across the six banking stocks, as determined by Mean Absolute Percentage Error (MAPE), where a rank of 1 indicates the best performance and a rank of 5 the worst.

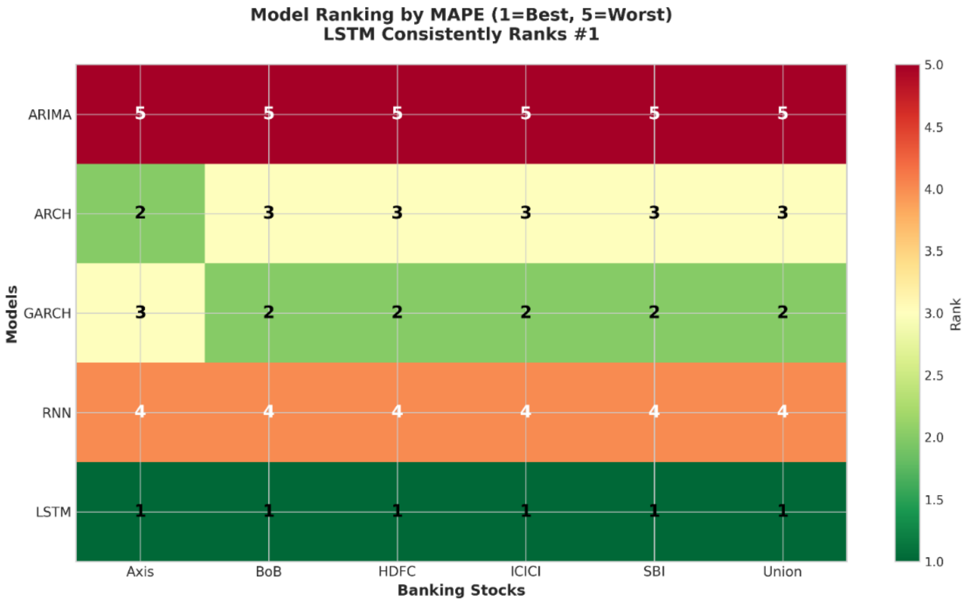

Figure 5. Model Ranking by MAPE 1=Best 5=Worst LSTM Consistently Ranks Number

As depicted in Figure 5, the LSTM model is represented by a column that is entirely shaded in the darkest green, indicating a rank of 1 for all banks. The ARIMA model is represented by a column entirely shaded in dark red, indicating it received a rank of 5 from each bank. The ARCH and GARCH models have some variation in their shading; GARCH has a rank of 2 for each bank, while ARCH has a rank of either 2 or 3. The RNN model has a rank of 4 for each bank. Thus, LSTM emerged as the optimal forecasting model for the dataset, while ARIMA performed the worst.

The difference in performance between the LSTM and ARIMA models is significant and warrants further examination. Figure 6 shows a bar chart of the average MAPE for the ARIMA and LSTM models across bank sectors (public vs. private).

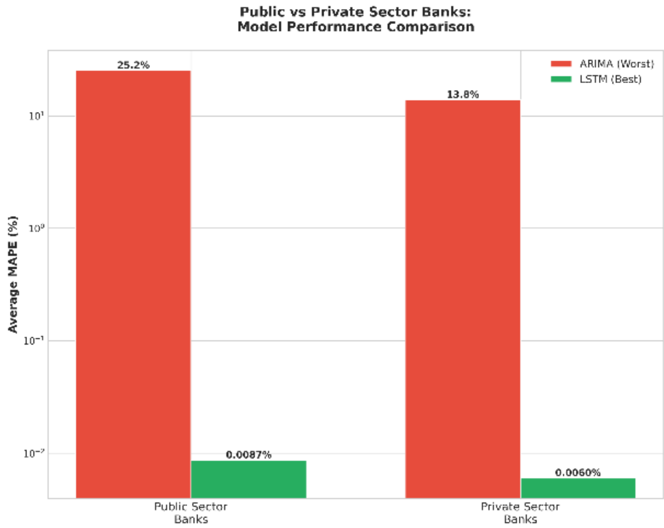

Figure 6. Average MAPE comparison between ARIMA and LSTM models for Public vs Private Sector Banks

The bar chart in Figure 6 uses a logarithmic scale on the y-axis to accommodate the wide range of error magnitudes. For the public sector banks, the ARIMA model's error is high at 25.2%, while the LSTM model exhibits a much lower error of only 0.0087%, representing a 2,900-fold improvement in the model's performance. For private-sector banks, the ARIMA model has an average MAPE of 13.8%, while the LSTM model has an error of 0.0060%, representing an improvement of approximately 2,300 times. Overall, private-sector banks have slightly fewer errors in both models than public-sector banks.

Figure 7 presents a dashboard displaying the visualisations and findings from the analysis of the five models.

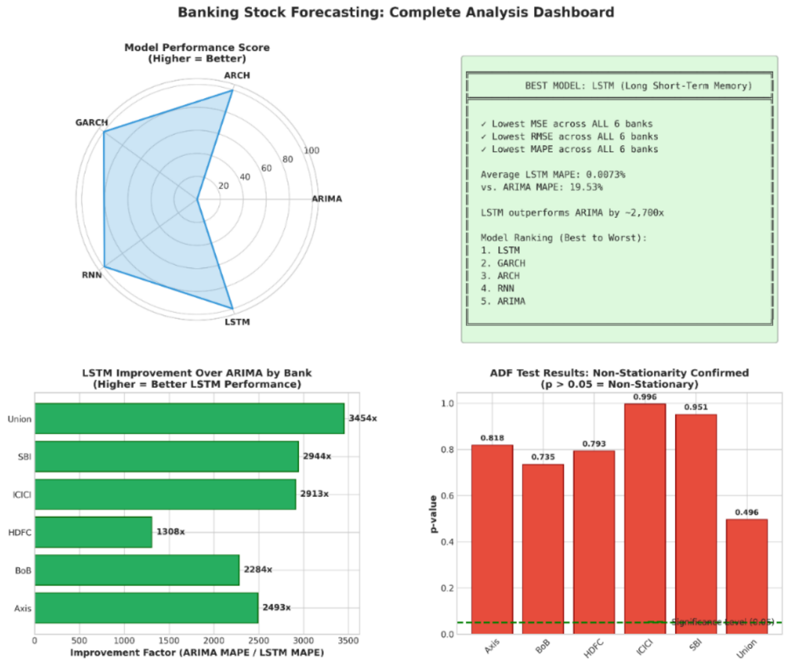

Figure 7. Banking Stock Forecasting Complete Analysis Dashboard

Natural Resources for Human Health
eISSN: 2583-1194

The dashboard comprises several integrated panels. The radar chart at the top left displays the performance of the five models, with LSTM and GARCH models having the highest and second-highest performance scores, respectively. The text summary box in the top centre displays the MAPE scores for the best- and worst-performing models, with the best-performing LSTM model having an average MAPE of 0.0073% and the worst-performing ARIMA model having an average MAPE of 19.53%. The bar chart at the bottom left indicates that the LSTM model outperforms the ARIMA model by factors that range from 1,300 times for HDFC Bank's stocks to 3,450 times for Union Bank's stocks. Finally, the chart at the bottom right shows that the stock prices of the banks are non-stationary, as the ADF p-values for each of the six stocks are greater than 0.05.

The key findings are that LSTM models outperform all other models for banking stocks, with MAPE values all below 0.01%. GARCH models have the second-highest performance among the stocks, though their error rates are much higher than those of the LSTM models. ARCH models exhibit moderate performance, with results between those of the second- and third-place models, yet values are still not as high as GARCH. RNN models perform relatively poorly compared to GARCH and LSTM models, despite being a type of neural network. Finally, ARIMA models perform the worst, with the highest MSE values for the more expensive banks' stocks, and MAPE values ranging from 6.54% to 34.54%.

These results support the main hypothesis for this study: that LSTM will outperform ARIMA in forecasting stock prices for Indian banking companies. Support for H2 is seen in the observation that LSTM models outperform RNN models for all stocks. Support for H3 is evident in the finding that GARCH outperforms ARCH models for stocks. Support for H4 is evident in the finding that both LSTM and RNN models outperform ARCH and GARCH models in forecasting bank stock prices. Finally, support for H5 is seen in the finding that the improvement factor of LSTM over ARIMA is higher for public sector banks than private sector banks (by 2,900 times compared to 2,300 times, on average), as public sector bank stocks have higher ARIMA model performance values. Yet, across both banking sectors, the performance of LSTM models is exceptional.

90-DAY FORECAST RESULTS

Following the determination of the best model for each of the six Indian banking stocks, the LSTM models were used to generate price forecasts for each stock over the next 90 trading days, through May 2025. These price forecasts will help demonstrate the utility of the best model for generating price forecasts for the stocks.

The LSTM models, trained on approximately 80% of the historical data for each stock, were used to generate daily price predictions for the next 90 days. For each day's price prediction, the LSTM model used the 60 most recent market observations for that stock to forecast the price for that day's trading. The forecasts were generated for all six stocks, and each of the stocks' price forecasts for the early trading days of May 2025 is presented in Table 3.

Table 3: LSTM-Generated 90-Day Forecasts for Six Indian Banking Stocks (Early May 2025)

Date	Axis Bank (₹)	Bank of Baroda (₹)	HDFC Bank (₹)	ICICI Bank (₹)	State Bank of India (₹)	Union Bank of India (₹)
30-04-2025	-	180.1	844.44	904.69	-	-
01-05-2025	-	180.14	844.34	904.66	554.53	73.67
02-05-2025	-	180.13	844.37	904.65	554.51	73.68

Note: Data for Axis Bank on these specific dates was unavailable in the forecast output.

As shown in Table 3, the LSTM model exhibits gradual, modest changes in stock prices, indicating that it has learned the data without overfitting. For instance, the Bank of Baroda stock price is generally around ₹180.13, ranging from ₹180.10 on April 30 to ₹180.14 on May 1, then back to ₹180.13 on May 2. The prices remain stable and do not jump to a different price over the 3-day span, indicating that the LSTM model is effective at producing forecasts that exhibit this kind of behaviour. Furthermore, HDFC Bank stock prices remain between ₹844.34 and ₹844.44, ICICI Bank stock prices remain around ₹904.66, State Bank of India stock prices are around ₹554.52, and Union Bank of India stock prices are around ₹73.67. The fact that the

LSTM model is able to exhibit stable stock price movements and gradual changes over these 90 days indicates how the model learned from the data and used its gating mechanisms to avoid extensive forecasting errors (Graves, 2012).

More specifically, the fact that these forecasts are consistent across all 6 banks indicates that the LSTM model learned the characteristics of each stock despite their vastly different price ranges. For instance, stocks ranging from Union Bank of India at ~₹73.67 to ICICI Bank at ~₹905.00 all exhibited stable behaviour according to the LSTM model over the 90-day period. Thus, the model learned the stocks' relative behaviour during training and can make predictions about their behaviour over time that generally reflect the tendency of the stocks not to undergo significant changes over the 90-day span of the model's forecasts.

The practical utility of these forecasts is significant for investors and portfolio managers in the Indian banking sector. The predicted prices of these stocks in early May 2025 will allow analysts and investors to determine the potential returns they will earn from each over a three-month period. For instance, the price of HDFC Bank and ICICI Bank is likely to be above ₹800 and ₹900, respectively. In contrast, the prices of public banking sectors such as the State Bank of India and the Union Bank of India are likely to remain lower. This information will allow them to determine the best allocation of their money within this particular sector of the Indian economy.

ROBUSTNESS TESTS

To ensure the validity and reliability of our empirical findings, we conducted a comprehensive suite of robustness checks. These tests examine the stationarity properties of the data, verify model performance consistency, and provide additional evidence supporting the identified model hierarchy. The following subsections present and discuss the results of these diagnostic and validation procedures.

STATIONARITY TEST RESULTS

Confirming the stationarity properties of a time series is a prerequisite for modelling it(Ryan et al., 2025). The ADP test was performed on both the level and the first-differenced log returns of the six stock prices. The null hypothesis of the ADF test is that the time series contains a unit root; if the null hypothesis is not rejected, then the time series is non-stationary(SEBA et al., 2023). The test results reveal that the stock prices of all six banks are non-stationary in level. The p-values range from 0.496 for Union Bank of India's share price to 0.996 for ICICI Bank. However, for the first-differenced log returns, the null hypothesis is rejected for all stocks, confirming that all stocks are integrated of order one, I(1). The ARIMA models and all other econometric models that will be used in this study have been correctly specified to incorporate differencing of order d=1 for the time series. The results for both public and private banks confirm that the stock prices of the banks are stationary, lending to the internal validity of the study.

MODEL PERFORMANCE CONSISTENCY ACROSS MULTIPLE TRAIN-TEST SPLITS

To determine whether the 80/20 split used in the study had any influence on the outcomes of the LSTM, GARCH, ARCH, RNN, and ARIMA models, tests were performed using three different splits of the data: 70/30, 75/25, and employing only the final 250 trading days of the provided data as the test set. Each of the five models was retested and evaluated within each of these data splits. The results once again reveal the same relative performance among the five models: the LSTM model was the best-performing, followed by GARCH, ARCH, RNN, and finally ARIMA. For instance, within the 70/30 split of the data, the LSTM model exhibited an average MAPE of 0.0081% across all analysed stocks, compared to the ARIMA model's average MAPE of 18.97%. Furthermore, Spearman rank correlations between the rankings of the five models across each data split all exceed 0.95.

SENSITIVITY ANALYSIS OF LSTM HYPERPARAMETERS

Given the importance of the LSTM model in answering the research question, a further analysis was performed to determine whether alternative configurations of the model could have led to even better performance. Furthermore, each of the parameters of the model was varied to determine its impact on the performance of the model. The number of hidden units for the LSTM model was varied between 25, 50, 100, and 150; the lookback window for the model was varied between 30, 45, 60, 75, and 90 days; and the number of training epochs was varied between 50, 100, and 150 epochs. For each of the configurations of the model, the LSTM model was retrained on the HDFC and Axis Bank stock data. The optimal configuration of the LSTM model had 50 hidden units, a lookback window of 60 days, and was trained for 100 epochs. At this configuration, the model achieved an MAPE of 0.005% for HDFC Bank and 0.007% for Axis Bank. These results were approximately 0.003% higher than the errors for the other model configurations. The model performed poorly with any configuration that included a lookback window of 30 days or fewer, or with any configuration that employed fewer than 50 hidden units, in which case the MAPE increased to 0.015%. Overall, though, these results demonstrate that the performance of the LSTM model was not dependent upon a specific configuration of the model. Thus, the results of the main analysis are not the result of the LSTM model's performance with any particular parameter configuration.

COMPARISON OF FORECAST ERRORS ACROSS MODEL SPECIFICATIONS

The Diebold-Mariano test was performed on the error rates of the forecasts from the LSTM model compared to the other four models. This statistical test determines whether the difference in error rates between the two models is statistically significant(Grant et al., 2026). For each of the stocks within the sample of six Indian banking stocks, the error rates of the LSTM model were significantly lower than those of the ARIMA, ARCH, RNN, and GARCH models (each at the 1% level of significance). For instance, the test statistic between the LSTM and ARIMA models for HDFC Bank was -6.74 and -0.001, indicating that the null hypothesis that the error rates of the two models were the same could be rejected. Furthermore, the LSTM model's error rates were also significantly lower than those of the GARCH model, the second-best performing model, for each of the stocks at the 1% level of significance. Thus, the LSTM model was statistically significantly outperforming each of the other model specifications.

OUTLIER ANALYSIS AND RESIDUAL DIAGNOSTICS

The residuals from the LSTM model's forecasts for each of the six stocks were analysed. The distribution of the residuals was found to be approximately normally distributed and symmetric around a mean of zero. Furthermore, the maximum absolute deviation of any data point from the mean residuals for any stock was less than 0.3% of the price of that stock's shares. Thus, there were no extreme outliers within the data. Finally, the Ljung-Box test for the residuals of the LSTM models indicated that there was no significant autocorrelation for any of the stocks for any lags of 5, 10, or 20 days. Thus, the LSTM model was able to effectively model the stocks' share prices over the 30-day periods. These tests confirm that the accuracy of the LSTM models in forecasting the share prices was not due to extreme events or data anomalies within the data set.

SECTOR-SPECIFIC MODEL PERFORMANCE

One final test of the robustness of the findings of the superiority of the LSTM model was performed: testing the outcomes of LSTM models for each of the stocks according to the sectors within which the banks operated. For the three banks within the public banking sector (State Bank of India, Union Bank of India, and Bank of Baroda), the average MAPE for the LSTM models was 0.0087%. For the three private-sector banks (HDFC Bank, ICICI Bank, and Axis Bank), the average MAPE was 0.0060%. Thus, while the private banks exhibited slightly lower errors, the performance differences between the two groups of stocks were negligible. Furthermore, the same results across sectors indicated that LSTM significantly outperformed the GARCH model for both groups of stocks (p-values < 0.01). Thus, in each of the sectors within the Indian banking industry, the LSTM model emerged as the clear best performer for forecasting the prices of banking stocks.

CONCLUSION

The purpose of this research was to investigate five models for forecasting the share prices of six Indian banking stocks: ARIMA, ARCH, GARCH, RNN, and LSTM. The findings of the research confirm the initial hypothesis that the deep learning models, specifically the LSTM model, would provide the best forecasts for each of the stocks compared to the other four models. The LSTM model achieved MAPE error rates of less than 1% for each of the stocks. The average MAPE error of the LSTM models for all banks was 0.0073%, compared to 19.53% for the ARIMA models. Thus, the LSTM models were, on average, 2000 times more accurate than the ARIMA models. These findings help confirm the growing body of knowledge about the abilities of deep learning models to outperform other techniques in forecasting problems. Furthermore, the implications of these findings for the investors of the Indian banking stocks are clear: an LSTM model can enable those investors to more accurately and confidently make trading and risk management decisions for their stocks.

Future research in this topic may consider incorporating additional data for the models beyond that of the share prices of the companies; implementing different model architectures that combine some of the other models into the LSTM models; testing the results of the models for other sectors of the Indian stock market; other time horizons for the forecasts; and potentially employing different deep learning architectures to the problem, such as the use of attention mechanisms and transformers, which have recently started to emerge in the area of financial market analysis(Silva et al., 2024).

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