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Predicting Stock Market Trends Using Machine Learning: A Sector-Wise Comparative Study of ARIMA, Linear Regression, and LSTM Models on NSE-Listed Companies

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Abstract- This study, titled "Predicting Stock Market Trends Using Machine Learning," examines stock price behaviour across five major sectors of the Indian stock market — Information Technology, Banking, Energy, Automobile, and Pharmaceuticals — using historical daily price data of ten companies listed on the National Stock Exchange (NSE). The research problem addressed is the difficulty of achieving accurate stock trend prediction using conventional forecasting methods in a volatile market environment. The objectives were to evaluate stock price trends across the selected sectors, compare prediction performance across companies, develop forecasting models using ARIMA, Linear Regression, and Long Short-Term Memory (LSTM) networks, and identify the most effective technique. Secondary OHLCV data was collected from the NSE, cleaned, and chronologically split 80:20 for training and testing. Trend, volume, and volatility indicators were computed for all ten companies, while detailed model development was carried out for Tata Consultancy Services (TCS) as a representative case. Linear Regression used Open, High, Low, and Volume as predictors of the Closing price; ARIMA was applied to the differenced Closing price series; and the LSTM network was trained on scaled Closing price sequences using a sixty-day look-back window. Performance was assessed using MAE, RMSE, and R^2. The findings reveal clear sectoral divergence, with Information Technology and Banking stocks exhibiting bearish trends while Energy, Automobile, and Pharmaceutical stocks showed upward momentum. Linear Regression outperformed both ARIMA and LSTM, yielding an R^2 of 0.998 compared with 0.959 for LSTM and a negative value for ARIMA, resulting in a SELL recommendation for TCS. The study concludes that the most suitable forecasting technique depends on the nature of the input data and forecast horizon, and that model outputs should support, rather than replace, broader investment judgement.

Keywords: stock market prediction; machine learning; ARIMA; linear regression; long short-term memory (LSTM); NSE; sectoral analysis

I. INTRODUCTION

1.1 Background and Industry Context

The stock market is a regulated platform through which ownership of publicly listed companies is exchanged, and it plays a central role in a country's economic growth. In India this activity is conducted mainly through the BSE and NSE, which provide companies access to long-term capital and offer investors avenues for wealth creation, while supporting price discovery and channelling household savings into productive investment under SEBI's disclosure norms. Forecasting has traditionally relied on fundamental and technical analysis, and on statistical techniques such as ARIMA and regression. The growth of computational power and large financial datasets has since enabled machine learning algorithms — Support Vector Machines, Decision Trees, Random Forests, and Artificial Neural Networks — to capture non-linear relationships that traditional statistical methods cannot easily model, and deep learning architectures such as LSTM have further advanced the field through their capacity to learn from sequential, time-dependent data.

1.2 Problem Statement, Research Gap, and Need for the Study

The dynamic and volatile nature of the stock market makes accurate trend prediction a persistent challenge for traditional forecasting methods. This study compares Linear Regression, ARIMA, and LSTM in predicting NSE stock trends to identify the approach

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best suited to the task. A review of prior research (Chapter 2) shows that most existing studies focus on individual stocks rather than trends across entire economic sectors, and that comparative evaluation of multiple machine learning techniques across sectors remains limited — a gap this sector-wise, multi-technique study seeks to address. Reliable prediction reduces uncertainty in investment decision-making: because prices are shaped by company performance, sentiment, and macroeconomic conditions, forecasting models can help investors identify opportunities and manage risk, a need reinforced by the growing participation of retail investors through online trading platforms.

1.3 Objectives and Scope

The study was conducted with the following objectives: (1) to evaluate the stock price trends of selected companies across different sectors; (2) to compare stock price prediction performance across sectors; (3) to develop prediction models using ARIMA, Linear Regression, and LSTM techniques; and (4) to identify the best-performing model among the techniques used. The study analyses historical data of ten NSE-listed companies from five sectors: Information Technology (TCS, Infosys), Banking and Finance (HDFC Bank, ICICI Bank), Energy (Reliance Industries, ONGC), Automobile (Maruti Suzuki, Mahindra & Mahindra), and Pharmaceuticals (Sun Pharma, Dr. Reddy's Laboratories). Model performance is compared using MAE, RMSE, and R^2 at the sector and company level.

1.4 Significance and Limitations

By combining sector-wise trend analysis with a systematic, multi-model comparison, the study offers practical value to investors, analysts, and portfolio managers, while contributing to the academic literature on machine learning applications in Indian equity markets. The study is confined to ten companies across five sectors, relies on historical secondary data without incorporating sudden market events, examines only ARIMA, Linear Regression, and LSTM without extension to hybrid models, and does not directly incorporate macroeconomic or sentiment variables or account for transaction costs and taxes. Conclusions are specific to the companies and period studied.

II. LITERATURE REVIEW

Stock market prediction has grown in importance for financial risk management and investment decision-making, even though forecasting remains difficult owing to market sentiment, corporate performance, and macroeconomic conditions. Research has progressively shifted from traditional statistical methods towards machine learning and deep learning approaches capable of analysing large volumes of financial data. This section reviews twenty-three studies published between 2016 and 2025, before identifying the specific gap addressed by the present study.

Early comparative work by Usmani et al. [1] evaluated perceptron, radial-basis-function, and SVM models on Karachi Stock Exchange data, finding the Multi-Layer Perceptron most accurate (~77%), though limited by a small dataset. Sharma et al. [2] reviewed regression-based methods and found they generally outperform conventional forecasting techniques. Selvin et al. [3] compared RNN, LSTM, and CNN on NSE data and found CNN produced the lowest error, while Liu et al. [4] proposed a multi-objective Echo State Network for the Shanghai index that reduced overfitting but was limited to a single index. Tantisripreecha and Soonthornphisaj [5] applied an LDA-based online learning model to technology stocks with improved accuracy over ANN, KNN, and Decision Tree baselines, though relying only on price-based indicators. Bustos and Pomares-Quimbaya [6], in a systematic review, confirmed the promise of SVM, ANN, and deep learning while noting a scarcity of price-forecasting studies. Dinesh et al. [7] combined moving averages with machine learning to generate buy/sell signals with ~79–80% accuracy, and Mintarya et al. [8], reviewing about thirty studies, found neural-network models most widely used and among the strongest performers.

A cluster of 2022–2023 studies directly informs the present modelling choices. Mathanprasad and Gunasekaran [9] found a Levenberg–Marquardt Neural Network achieved 94.17% accuracy, outperforming SVM and Random Forest, though it weakened in volatile conditions. Mishra et al. [10] developed LSTM, Random Forest, and Gradient Boosting models, with LSTM strongest but tested only in a simulated environment. Mantravadi et al. [11] compared LSTM and Linear Regression on NSE data and found LSTM captured time-series patterns more accurately, while Srinidhi et al. [12] showed a hybrid CNN–LSTM outperformed either model alone. Addagalla et al. [13] confirmed LSTM/RNN effectiveness for time-series forecasting, and Guntaka et al. [14] integrated sentiment, fundamental, and technical analysis into an LSTM framework with low error but limited real-time validation. Manasa et al. [15] combined technical, sentiment, and macroeconomic predictors with six algorithms, finding SVM most accurate (~87%) once external factors were included. Patidar et al. [16] reported LSTM outperforming Linear Regression via lower MAE, and Kotapati et al. [17], testing nine algorithms on Reliance and IBM data, found the Multi-Layer Perceptron second only to LSTM.

The most recent studies (2024–2025) increasingly favour hybrid and sentiment-augmented approaches. Dubey et al. [18] found hybrid techniques outperformed single models on NSE/BSE data. Kumar et al. [19] applied LSTM to Google stock data with improved accuracy despite overfitting and computational cost. Ahire and Borse [20] combined ARIMA with several machine learning algorithms, finding Linear Regression, Random Forest, and CatBoost performed best within the hybrid framework. Ruke et al. [21] achieved an R^2 of 0.89 using LSTM deployed via Streamlit. Bhardwaj et al. [22] obtained ~99% accuracy using Linear Regression on ICICI Bank data with MAE of 2.18, closely mirroring the Linear Regression performance obtained for TCS in the present study. Agrawal and Mukherjee [23] integrated news and social-media sentiment with Linear Regression, Random Forest, SVM, and LSTM, with a BERT-based model achieving 98.92% accuracy.

2.1 Synthesis and Gap Identification

The literature shows a progression from simple perceptron and regression-based models towards deep learning (RNN, LSTM, CNN) and, more recently, towards hybrid and sentiment-augmented frameworks. While LSTM and CNN often achieve lower error than conventional regression in time-series settings, studies such as Bhardwaj et al. [22] and Mathanprasad and Gunasekaran [9] show that simpler, well-specified models can match or exceed deep-learning performance on structured financial data — a pattern consistent with the present findings. Common limitations across the literature include a narrow focus on single stocks rather than sectors, limited cross-sector comparison, dependence on historical data without real-time validation, and restricted incorporation of macroeconomic or sentiment variables. These gaps motivate the present study, which analyses ten NSE-listed companies across five sectors and applies a common methodology — ARIMA, Linear Regression, and LSTM, evaluated using MAE, RMSE, and R^2 — to determine the most suitable strategy for stock trend prediction.

III. METHODOLOGY

3.1 Research Design and Data Source

The study adopts a quantitative, predictive, time-series research design. It relies entirely on numerical NSE historical stock records; the models are trained on historical data to generate forward-looking forecasts; and both ARIMA and LSTM specifically model temporal dependence, while the regression model exploits same-session relationships among price variables. The conceptual pipeline integrates data collection, preprocessing, exploratory analysis, feature selection, model building, model evaluation, and prediction. Secondary data was obtained from the NSE, supplemented by Yahoo Finance, chosen for authenticity, standardisation, and SEBI's regulatory oversight. Historical daily OHLCV data was extracted in CSV format and imported into Python for analysis.

3.2 Sample Selection and Study Period

Purposive sampling selected ten companies from five major sectors based on sectoral representation, market capitalisation, liquidity, and data availability (Table 1). The study covers approximately five years and three months, from May 2021 to mid-2026, spanning the post-pandemic recovery (2021–2022), global macroeconomic turbulence linked to the Russia-Ukraine conflict and rising interest rates (2022–2023), a stabilisation phase supported by domestic fundamentals (2023–2024), and a recent, technology-driven phase (2024–2026), exposing the models to both trending and volatile conditions.

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Table 1: Sample Companies Selected for the Study

Sector	Company Name	NSE Symbol	Market Cap
Information Technology	Tata Consultancy Services	TCS	Large Cap
Information Technology	Infosys Limited	INFY	Large Cap
Banking & Finance	HDFC Bank Limited	HDFCBANK	Large Cap
Banking & Finance	ICICI Bank Limited	ICICIBANK	Large Cap
Energy & Oil	Reliance Industries Limited	RELIANCE	Large Cap
Energy & Oil	Oil & Natural Gas Corp.	ONGC	Large Cap
Automobile	Maruti Suzuki India Limited	MARUTI	Large Cap
Automobile	Mahindra & Mahindra Limited	M&M	Large Cap
Pharmaceutical	Sun Pharmaceutical Industries	SUNPHARMA	Large Cap
Pharmaceutical	Dr. Reddy's Laboratories	DRREDDY	Large Cap

3.3 Variables, Data Collection, and Preprocessing

The study employs one dependent variable, the closing price, and four independent variables: Open, High, and Low price, and Trading Volume (Table 2). Data collection followed six steps: company selection; downloading OHLCV data from NSE/Yahoo Finance; verification for missing values and inconsistencies; storage in Excel; import into Python via Pandas; and preparation of a consolidated, chronologically sorted dataset. Missing values were treated using forward-fill imputation; duplicates were removed via drop_duplicates(); date fields were parsed with to_datetime() and set as the index. Feature scaling applied Min-Max normalisation prior to LSTM training and Z-score standardisation for the regression model. Additional transformations included lagged closing-price features, 7-day and 30-day rolling averages, and a log transform on trading volume to reduce skewness.

Table 2: Variable Description

Variable	Type	Definition	Role
Closing Price	Dependent	Final traded price at session end	Target (Y)
Open Price	Independent	First traded price of the session	Predictor (X1)
High Price	Independent	Maximum price during session	Predictor (X2)
Low Price	Independent	Minimum price during session	Predictor (X3)
Trading Volume	Independent	Total shares traded in session	Predictor (X4)

3.4 Tools, Analytical Techniques, and Models

Analysis was conducted in Python (Anaconda 3.11+) using Pandas and NumPy for data manipulation, Matplotlib/Seaborn/Plotly for visualisation, Scikit-learn for regression and evaluation metrics, Statsmodels for ARIMA and stationarity testing, and TensorFlow/Keras for the LSTM network; Excel supported initial storage, and Google Colab served as the coding environment. Exploratory analysis used time-series plots, seasonal decomposition, autocorrelation analysis, and outlier detection via box plots and z-scores. Trend analysis used 20-day/50-day (and 50-day/200-day) moving averages, where a shorter average crossing above a longer one signals a bullish ‘Golden Cross’ and the reverse a bearish ‘Death Cross’. Volatility was measured as the

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annualised standard deviation of daily returns; correlation used Pearson's coefficient.

Multiple Linear Regression predicted the closing price as $Y = \beta0 + \beta1X1 + \beta2X2 + \beta3X3 + \beta4X4 + \varepsilon$, using Open, High, Low, and Volume as predictors. ARIMA was applied to the univariate closing-price series after Augmented Dickey-Fuller testing: the original series was non-stationary (ADF = –2.1838, $p = 0.2122$) and became stationary after first-order differencing (ADF = –30.4066, $p < 0.0001$); with pmdarima unavailable, a fallback order of (5,1,0) was used. The LSTM network used two stacked layers of 64 units, dense output layers, a 60-day look-back window, dropout of 0.2, 50 training epochs, the Adam optimiser, and Mean Squared Error loss. Performance was assessed using MAE, RMSE, and R^2, providing a consistent framework for comparing a classical linear model, a classical time-series model, and a deep-learning model under identical data conditions.

IV. RESULTS AND DISCUSSION

4.1 Sector-Wise and Company-Wise Trend Analysis

Table 3 summarises price trend, annualised volatility, average daily return, and technical interpretation for each sample company, based on 20-day/50-day moving-average relationships.

Table 3: Company-Wise Trend Summary and Recommendations

Company	Price Trend	Volatility	Avg. Return	Recommendation
TCS	Downtrend; 20-D MA < 50-D MA	21.09%	-0.0132%	SELL/ HOLD
Infosys	Downtrend; limited recovery	24.69%	0.0018%	SELL/ HOLD
HDFC Bank	Sharp downtrend; no reversal	30.87%	-0.0237%	SELL/ HOLD
ICICI Bank	Long-term uptrend; consolidation	20.49%	0.066 %	HOLD/ BUY
Reliance Ind.	Recovery trend; MA bullish	31.99%	0.0019%	BUY
ONGC	Uptrend with consolidation	31.08%	0.0916%	BUY/HOLD
Maruti Suzuki	Long-term uptrend; recovery	23.35%	0.0679%	BUY/HOLD
M&M	Uptrend; MA crossed bullish	28.00%	0.1327%	BUY/HOLD
Sun Pharma	Long-term uptrend; recovery	20.65%	0.0870%	BUY/HOLD
Dr. Reddy's	Long-term uptrend; consolidation	42.11%	-0.0399%	BUY/HOLD

The results reveal clear sectoral divergence. Both Information Technology stocks, TCS and Infosys, were bearish, with 20-day moving averages below 50-day averages and near-zero or slightly negative returns. Within Banking, HDFC Bank recorded the steepest decline in the sample (–0.0237% daily, 30.87% volatility), while ICICI Bank maintained a long-term uptrend (0.0667%), showing that companies within a sector need not share the same trajectory. Energy was broadly positive: Reliance showed a bullish recovery and ONGC generated the second-highest average return (0.0916%) despite high volatility (31.08%). Both Automobile stocks trended upward, with M&M recording the highest return in the sample (0.1327%). Pharmaceuticals was similarly positive, though Dr. Reddy's recorded the sample's highest volatility (42.11%) alongside a slightly negative return, reflecting a sharp mid-period correction. These findings address Objectives 1 and 2: IT and, to a lesser extent, Banking stocks showed weak short-term momentum, while Energy, Automobile, and Pharmaceutical stocks generally trended upward, consistent with sector-specific drivers identified in the literature.

4.2 Comparative Model Performance for TCS

Detailed model development was carried out for TCS using a chronological 80:20 train-test split (992 training and 248 test observations from 1,240 trading days). Table 4 reports MAE, RMSE, and R^2 for each model on held-out test data.

Table 4: Model Comparison for TCS Closing-Price Prediction

Model	MAE	RMSE	R^2 Score
Linear Regression	10.1699	12.8794	0.9984
ARIMA (5,1,0)	418.9567	522.1621	-1.5792
LSTM	51.9156	66.1317	0.9586

Linear Regression achieved the strongest performance across all three metrics, explaining approximately 99.8% of the variance in TCS's closing price on unseen data. LSTM was second-best ($R^2 = 0.959$), while ARIMA performed markedly worse, with a negative R^2 of –1.579, indicating its forecasts explained less variance than a naive mean-based prediction.

4.3 Discussion

Linear Regression's strong performance stems from its use of same-session Open, High, Low, and Volume values, which are highly correlated with closing price within a trading day — information unavailable to ARIMA or LSTM, both trained purely on historical closing prices. ARIMA's weak performance reflects the limits of a linear, univariate model against TCS's pronounced structural decline (from above ₹4,500 to below ₹2,400 during the test window), a pattern the fixed-order specification struggled to track. LSTM, while more capable of non-linear temporal modelling than ARIMA, still produced higher error than Linear Regression, suggesting that for short-horizon, next-day forecasting the informational advantage of same-day predictors outweighed sequence-learning capacity.

These findings align with Bhardwaj et al. [22], who similarly found Linear Regression near 99% accuracy on ICICI Bank data, and with Mathanprasad and Gunasekaran [9], who showed a well-specified neural network can outperform more complex alternatives on structured data. The result runs counter to Mantravadi et al. [11] and Patidar et al. [16], who found LSTM outperforming regression; the difference lies in predictor choice rather than modelling paradigm, since those regression models relied only on historical closing prices. Practically, Linear Regression of this kind is best suited to same-day or very short-horizon estimation, whereas ARIMA and LSTM remain more appropriate when only past closing prices are available. Combining the model output with the technical picture, TCS's predicted next-day closing price of ₹2,391.12 represented a 0.14% decline from the last actual close of ₹2,394.40, consistent with the bearish technical signals identified in Section 4.1, together supporting a SELL recommendation. At the sector level, companies experiencing sharp trend reversals, such as HDFC Bank and Dr. Reddy's, present a harder forecasting problem than those following a gradual, trend-consistent path, reinforcing that forecasting technique, predictor selection, and market regime jointly determine accuracy, with no single model universally superior.

V. CONCLUSION

5.1 Summary of Key Findings and Achievement of Objectives

The study analysed stock price behaviour across five sectors and developed ARIMA, Linear Regression, and LSTM models to forecast TCS's closing price. Technical analysis revealed a clear sectoral divergence: Information Technology and HDFC Bank were bearish, while Energy, Automobile, and Pharmaceutical companies generally trended positive; ICICI Bank's stronger trend relative to HDFC Bank confirmed that companies within a sector can follow markedly different trajectories. Linear Regression achieved the strongest predictive performance for TCS (MAE = 10.17, RMSE = 12.88, $R^2 = 0.998$), ahead of LSTM ($R^2 = 0.959$) and ARIMA (negative R^2), supporting a SELL recommendation alongside the bearish technical trend. All four objectives were achieved: trends were evaluated across all ten companies (Objective 1); prediction performance was compared through the TCS case study (Objective 2); ARIMA, Linear Regression, and LSTM models were developed under a consistent train-test framework (Objective 3); and Linear Regression was identified as the best-performing model (Objective 4).

5.2 Practical Implications and Limitations

The study demonstrates that machine learning can meaningfully support short-term stock analysis when combined with technical trend indicators, provided model choice reflects the information available to the forecaster: Linear Regression suits same-day estimation, while ARIMA and LSTM remain relevant when forecasts must rely on historical closing prices alone. The divergence between HDFC Bank and ICICI Bank underscores that company-level, not purely sector-level, analysis is essential. The study is limited to ten companies; fundamentals, investor sentiment, and unexpected market events were not incorporated, and detailed comparative modelling was performed primarily on TCS, which may limit generalisation to the other nine companies.

5.3 Scope for Future Research and Concluding Remarks

Future work could extend the detailed model comparison to all ten companies and sectors, incorporate sentiment analysis and macroeconomic variables, and examine hybrid architectures such as ARIMA-LSTM, which the reviewed literature suggests may improve accuracy over longer horizons. Overall, the study demonstrates that machine learning techniques can meaningfully assist stock trend analysis: Linear Regression provided the most accurate results for TCS owing to its use of multiple same-session variables, while LSTM and ARIMA offer complementary value where only historical closing prices are available. In all cases, model outputs are best treated as decision-support tools to be combined with fundamental and technical analysis, rather than as a substitute for broader investment judgement.

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