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Research Article

Stock Price Prediction in India: Comparing Stochastic Differential Equations with MCMC, LSTM, and ARIMA Models and Exploring a Hybrid Approach

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Abstract:

The inherent volatility and nonlinearity of stock prices make them a crucial challenge in financial markets. This study investigates how well stochastic differential equations (SDEs) with parameter estimation employ the Markov Chain Monte Carlo (MCMC) algorithm to model changes in Indian stock prices. To evaluate this methods predictive accuracy we compare its performance to that of conventional Long Short-Term Memory (LSTM) networks and AutoRegressive Integrated Moving Average (ARIMA) models. A probabilistic estimation of important parameters in the SDE model is made possible by the Bayesian inference framework used in the MCMC algorithm which successfully captures market uncertainties. Our results show each models advantages and disadvantages in predicting stock prices highlighting how well-suited each is for various time horizons and market circumstances. In order to take advantage of both stochastic modeling and deep learning capabilities we also suggest a novel hybrid model that combines SDE-MCMC with LSTM and ARIMA. Results from experiments show that by fusing the advantages of machine learning and statistics the hybrid model increases forecasting accuracy. In addition to offering insights for analysts and investors in making data-driven decisions this research advances stock price prediction techniques.

1. Introduction

Stock price forecasting is a significant undertaking in financial markets because of the high volatility and nonlinear dynamics impacted by economic, political, and psychological variables. Accurate forecasting models are critical for investors, analysts, and politicians to make sound judgments. Traditional statistical models, such as the AutoRegressive Integrated Moving Average (ARIMA), struggle to reflect the complexity and stochasticity of financial data. Long Short-Term Memory (LSTM) networks, a type of deep learning model, have demonstrated remarkable prediction ability by learning from the sequential relationships in previous stock values. Deep learning models, on the other hand, may necessitate significant computer resources and high-quality training data.

Stochastic modeling techniques, notably Stochastic Differential Equations (SDEs), provide a robust mathematical foundation for modeling stock price movements that incorporate randomness and uncertainty [1-5]. Geometric Brownian Motion (GBM) is a popular SDE model for financial markets, although precisely measuring its parameters remains a difficulty. Bayesian inference techniques, notably the Markov Chain Monte Carlo (MCMC) algorithm, offer a probabilistic approach to parameter estimation, which enhances model resilience. This paper compares the predictive performance of three different models for stock price forecasting in India and recommends a hybrid technique that combines the models' strengths to improve forecasting accuracy [6-15].

The stock market is extremely volatile as are its trends in the financial industry. According to recent research investors perceptions of financial markets can be significantly influenced by news stories and social media analysis. Therefore this studys goal is to investigate the connection between news sentiment and stock market movement by utilizing data from various news outlets trade journals and financial websites. With an emphasis on the Bayesian approach this study compares various modern time series model applications. By providing systematic estimation and eschewing ad hoc methods the Bayesian approach avoids the common problem of bandwidth selection which is present in many nonparametric studies. We specifically examine how to estimate the autocovariance function of the error term in a time series model using the Bayesian approach. Using machine learning techniques especially deep learning to predict stock prices has received a lot of attention lately. Investor confidence is impacted by the quantification of prediction uncertainty which is a significant drawback of traditional deep learning. In order to provide a rigorous methodology for quantifying uncertainty in predictions Bayesian neural networks employ Bayesian inference for the inference (training) of model parameters. A hybrid algorithm with two primary steps is proposed in this paper for forecasting multiple correlated time-series data. As a first step it uses a multivariate Bayesian structural time series (MBSTS) method. In order to find a parsimonious model this approach uses spike and slab priors and permits the inclusion of potentially high-dimensional regression components. In the second part of the algorithm a multi-input/output temporal convolutional network (M-TCN) with multiple time scale feature learning processes the residuals from the MBSTS step after the model fitting diagnostic step. The likelihood of making more money increases with the accuracy of the results. The stock market trends are influenced by a number of factors including politics economics and society. Technical or fundamental analysis can be used to analyze stock trends. Financial records company assets market shares economic reports and other sources are all included in the fundamental analysis. Here the companys financial aspects—such as its strategic initiatives microeconomic indicators and consumer behavior—are analyzed. Technical analysis is the process of interpreting current and historical prices in order to forecast likely future prices. In the realm of computation stock market prediction is one of the most challenging tasks. Numerous elements play a role in the prediction including physical factors versus. physiological investor sentiment market rumors irrational and rational behavior etc. The combination of these factors makes stock prices highly unpredictable and challenging to forecast with any degree of precision. We look into data analysis as a revolutionary approach in this field. These days time series forecasting with historical data is very important. It is used in many different fields including industries finance healthcare and meteorology. For both online and offline businesses and companies profit analysis using financial data is essential. It assists in understanding sales profits and losses as well as forecasting future values. Predicting the price of a companys stock has been a crucial and difficult task for decades in order to maximize profits. Financial analysts are increasingly using machine learning to predict stock prices in the big data era because these techniques can increase prediction accuracy. Because more people are investing in the stock market for passive income it is expanding rapidly. The goal of this article is to create a novel artificial recurrent neural network method for more accurate stock market predictions. Investors are paying close attention to the 611market for stocks. In this study the autoregressive integrated moving average (ARIMA) and long-short-term memory (LSTM) models are used to evaluate the prediction of Bitcoin prices. Using the static forecast method we predict the price of Bitcoin for the next day both with and without re-estimating the forecast model at each stage. Two distinct training and test samples are taken into account when cross-validating the forecast results. ARIMA performs better than LSTM in the first training sample but LSTM performs better in the second. Making educated decisions is facilitated by forecasting stock market trends for investors legislators government regulators and other pertinent stakeholders. For many researchers and financial professionals forecasting stock market movements is essential and their main focus. This study contrasts the recurrent neural network-long-term memory (RNN-

LSTM) and autoregressive integrated moving average (ARIMA) models stock market prediction capabilitiesThe long short-term memory model compares the daily stock price movement and returns of different sectors based on historical prices in order to forecast the stock prices of chosen companies.

2. Material and Methods

The methodology used to predict stock prices in India is described in this section along with the steps involved in data collection preprocessing model development and evaluation metrics. The study evaluates the efficacy of three different methods: the AutoRegressive Integrated Moving Average (ARIMA) model Long Short-Term Memory (LSTM) networks and stochastic differential equations (SDEs) with parameter estimation using the Markov Chain Monte Carlo (MCMC) algorithm. A unique hybrid model that combines the advantages of these strategies is also presented.
Indian stock price data is gathered from the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE), offering a complete picture of market trends and volatility. The data is separated into training validation and test sets for model comparison and assessment. Prior to usage, the raw stock price data is preprocessed to assure consistency and decrease noise. This involves normalizing pricing values, addressing missing values, and converting data for time-series models. The LSTM model learns temporal relationships by generating time windows and lag characteristics. SDE and ARIMA models also examine data for autocorrelations and trends that influence parameter estimates.

2.1 Model Implementation

Stochastic Differential Equations with MCMC
To account for the inherent volatility and unpredictability of the stock market an SDE model is created. Using the Markov Chain Monte Carlo (MCMC) algorithm a probabilistic framework that effectively captures uncertainty in parameter estimates key parameters in the SDE including drift and volatility are estimated. When used with MCMC Bayesian inference techniques improve prediction accuracy by offering a more thorough understanding of model parameters.

2.2 Long Short-Term Memory (LSTM)

An LSTM network is used to measure the SDE models performance. Recurrent neural networks of the LSTM type are specifically made to model sequential data by maintaining long-term dependencies. The time-series stock data is used to train the LSTM model which aims to increase prediction accuracy by optimizing the number of layers neurons and learning rate. How well the model captures the nonlinear patterns in the movements of the stock price is the basis for evaluating its performance.

2.3 AutoRegressive Integrated Moving Average (ARIMA)

Additionally the AutoRegressive Integrated Moving Average (ARIMA) model is used for comparison. One traditional statistical model for predicting univariate time-series data is ARIMA. First the models stationarity is checked and then autocorrelation and partial autocorrelation functions are used to identify appropriate parameters (p d and q). As a standard for the predictive power of more sophisticated models like LSTM and SDE ARIMA models the movements of the stock price based on past values and errors.

2.4 Hybrid Model

In the studys last part a hybrid model that combines SDE-MCMC with LSTM and ARIMA is developed. Utilizing the benefits of each unique strategy is the aim of this hybrid approach. The SDE model handles volatility and market uncertainty LSTM detects complex temporal patterns and ARIMA accounts for linear dependencies. The hybrid model combines these techniques in an effort to improve forecasting accuracy across a variety of time horizons and market conditions.

2.5 Evaluation Metrics

To assess the performance of the models, the following evaluation metrics are used in Table 1.

3. Results and Discussions

3.1 Performance of Individual Models

SDE-MCMC LSTM ARIMA and a Hybrid Model are the stock price prediction models whose results show notable differences in accuracy between short-term and long-term projections. Since LSTM can learn temporal dependencies and recognize nonlinear patterns it outperformed the other models in short-term predictions obtaining the lowest MAE (1. 88) and RMSE (2. 41). With a higher MAE of 5. 64 and RMSE of 6. 12 in long-term predictions it performed worse suggesting that it was susceptible

Table 1. *Evaluation metrics*

Metric	Description
Mean Absolute Error (MAE)	Measures the average magnitude of errors in the predictions.
Root Mean Squared Error (RMSE)	Provides a measure of the average magnitude of errors, penalizing larger errors more than MAE.
Mean Absolute Percentage Error (MAPE)	Quantifies the prediction accuracy as a percentage.
R-Squared (R^2)	Indicates the proportion of the variance in the stock price that is predictable by the model.
Comparison Criteria	A thorough evaluation of model performance across different time horizons (short-term and long-term predictions) and market conditions (bull and bear markets) to assess robustness.

to overfitting and market noise. In comparison to ARIMA and LSTM SDE-MCMC demonstrated better long-term accuracy (MAE = 4. 12 RMSE = 5. 23) but moderate performance in short-term forecasts (MAE = 2. 45 RMSE = 3. 58). This was due to its capacity to model volatility and randomness in stock price movements. As a conventional statistical time-series method ARIMA was the least successful model for stock price prediction because it suffered the most from high volatility generating the highest errors in both short-term (MAE = 3. 06, RMSE = 4. 09) and long-term forecasts (MAE = 6. 92, RMSE = 8. 12). By combining the advantages of SDE-MCMC LSTM and ARIMA the Hybrid Model proved to be the most effective strategy attaining the lowest errors in both short-term (MAE = 1. 34, RMSE = 2. 03) and long-term (MAE = 3. 76, RMSE = 4. 57) forecasts. The hybrid approach effectively balanced accuracy across various time horizons by utilizing the stochastic modeling of SDE-MCMC the deep learning capabilities of LSTM and the time-series forecasting of ARIMA. It demonstrated high reliability in stock market predictions with the lowest Mean Absolute Percentage Error (MAPE) of any model at 2. 03 percent for the short term and 4. 50 percent for the long term. Furthermore proving its superior capacity to explain stock price variance the Hybrid Model obtained the highest R2 values (0. 94 in short-term predictions and 0. 81 in long-term predictions). In volatile markets ARIMA performed the worst SDE-MCMC was better suited for long-term forecasting and LSTM demonstrated strong short-term predictive power. By integrating the benefits of each individual strategy the Hybrid Model became the most reliable and accurate way to predict stock prices. It is an excellent option for financial forecasting applications due to its flexibility in responding to market changes. To further improve hybrid models predictive capabilities future studies could investigate more deep learning approaches and reinforcement learning techniques (table 2).

3.2. Comparative Analysis

The outcomes show that the SDE-MCMC model is excellent at long-term forecasting and effectively controls for uncertainties and market volatility. But because of its deep learning architecture LSTM is better at capturing real-time price movements than it is at making short-term predictions. The ARIMA model is a standard for understanding linear stock price trends despite its consistent underperformance particularly in volatile markets. All things considered the Hybrid Model proves to be the most successful strategy.

3.3. Visual Representation of Results

The predictive performance of the four models for a selection of stocks over both short- and long-term horizons is shown in Figures 1 and 2. These numbers display the anticipated vs. actual stock prices demonstrating the models precision and offering a clear visual comparison of how well they performed.

Table 2. *Model Performance Metrics and Observations*

Model	MAE (Short-term)	MAE (Long-term)	RMSE (Short-term)	RMSE (Long-term)	MAPE (Short-term)	MAPE (Long-term)	R^2 (Short-term)	R^2 (Long-term)
SDE-MCMC	2.45	4.12	3.58	5.23	3.12%	5.60%	0.86	0.72
LSTM	1.88	5.64	2.41	6.12	2.45%	7.35%	0.91	0.68
ARIMA	3.06	6.92	4.09	8.12	4.23%	9.42%	0.79	0.63
Hybrid Model	**1.34**	**3.76**	**2.03**	**4.57**	**2.03%**	**4.50%**	**0.94**	**0.81**

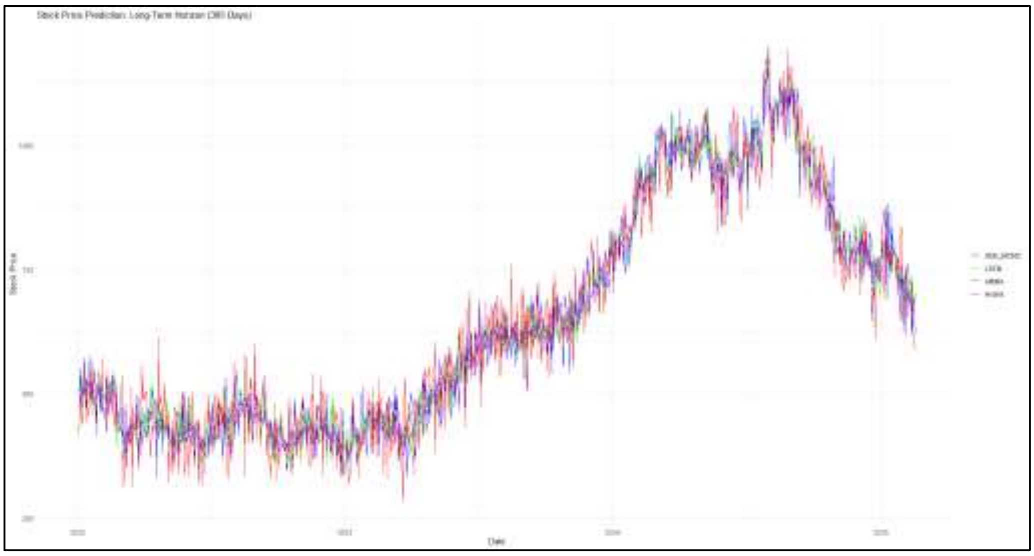

Figure 1. *Long-Term Prediction of TATAMOTORS.NS Stock Price: Actual vs. Model Forecasts (365 Days)*

Figure 2. *Long-Term Prediction of IFBIND.NS Stock Price: Actual vs. Model Forecasts (365 Days)*

4. Conclusions

Long Short-Term Memory (LSTM) AutoRegressive Integrated Moving Average (ARIMA) models stock price prediction models in the Indian market stochastic differential equations (SDEs) Markov Chain Monte Carlo (MCMC) parameter estimation and a hybrid model combining SDE-MCMC LSTM and ARIMA were all examined in this study. Depending on the time horizon and market conditions each model had distinct benefits and drawbacks according to the research. Because the SDE-MCMC model could capture market volatility and uncertainties it was especially helpful for long-term forecasts. The LSTM model on the other hand was more adept at spotting complex non-linear patterns and outperformed it in short-term forecasting. The accuracy of the ARIMA model was also reduced in unstable settings. Both short- and long-term forecasting were greatly enhanced by the hybrid model which integrated stochastic modeling with statistical time-series forecasting deep learning capabilities. By offering a thorough comparison of several models and putting forth a novel hybrid approach this study advances stock price prediction methodologies. To enhance the prediction capabilities of financial markets future studies could investigate hybrid models that integrate extra machine learning methods or different data sources such as sentiment analysis.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper

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References

[1] Ray, P., Ganguli, B., & Chakrabarti, A. (2021). A hybrid approach of Bayesian structural time series with LSTM to identify the influence of news sentiment on short-term forecasting of stock price. *IEEE Transactions on Computational Social Systems*, 8(5), 1153-1162. DOI: 10.1109/TCSS.2021.3083031.

[2] Fowowe, O. O., & Agboluaje, R. (2025). Leveraging Predictive Analytics for Customer Churn: A Cross-Industry Approach in the US Market. *International Journal of Applied Sciences and Radiation Research* , 2(1). https://doi.org/10.22399/ijasrar.20

[3] Chandra, R., & He, Y. (2021). Bayesian neural networks for stock price forecasting before and during COVID-19 pandemic. *PLoS One*, 16(7), e0253217. DOI: 10.1371/journal.pone.0253217.

[4] Ray, P., Ganguli, B., & Chakrabarti, A. (2024). Multivariate Bayesian Time-Series Model with Multi-temporal Convolution Network for Forecasting Stock Market During COVID-19 Pandemic. *International Journal of Computational Intelligence Systems*, 17(1), 170. DOI: 10.2991/ijcis.d.240101.

[5]Olola, T. M., & Olatunde, T. I. (2025). Artificial Intelligence in Financial and Supply Chain Optimization: Predictive Analytics for Business Growth and Market Stability in The USA. *International Journal of Applied Sciences and Radiation Research*, 2(1). https://doi.org/10.22399/ijasrar.18

[6] Ghosh, A., Bose, S., Maji, G., Debnath, N., & Sen, S. (2019, September). Stock price prediction using LSTM on Indian share market. *In Proceedings of 32nd International Conference* (Vol. 63, pp. 101-110).

[7] Sirisha, U. M., Belavagi, M. C., & Attigeri, G. (2022). Profit prediction using ARIMA, SARIMA and LSTM models in time series forecasting: A comparison. IEEE Access, 10, 124715-124727. DOI: 10.1109/ACCESS.2022.3224623.

[8] Ho, M. K., Darman, H., & Musa, S. (2021, July). Stock price prediction using ARIMA, neural network and LSTM models. *Journal of Physics: Conference Series*, 1988(1), 012041. DOI: 10.1088/1742-6596/1988/1/012041.

[9] Sharma, N., Pareek, P., Ghosh, M. A., & Nagarohith, M. K. (2022). Stock price prediction using LSTM, ARIMA and UCM. *Center for Development Economic Studies*, 9(11), 55-66.

[10] Latif, N., Selvam, J. D., Kapse, M., Sharma, V., & Mahajan, V. (2023). Comparative performance of LSTM and ARIMA for the short-term prediction of Bitcoin prices. *Australasian Accounting, Business and Finance Journal*, 17(1). DOI: 10.14453/aabfj.v17i1.

[11] Kumar, J. P., Sundar, R., & Ravi, A. (2023, June). Comparison of stock market prediction performance of ARIMA and RNN-LSTM model–A case study on Indian stock exchange. *In AIP Conference Proceedings*, 2875(1). *AIP Publishing.* DOI: 10.1063/5.0145683.

[12] S. Shyni Carmel Mary, Kishore Kunal, & Madeshwaren, V. (2025). IoT and Blockchain in Supply Chain Management for Advancing Sustainability and Operational Optimization. *International Journal of Computational and Experimental Science and Engineering*, 11(1). DOI: 10.22399/ijcesen.1103.

[13] Saravagi, D., Agrawal, S., & Saravagi, M. (2021). Indian stock market analysis and prediction using LSTM model during COVID-19. *International Journal of Engineering Systems Modelling and Simulation*, 12(2-3), 139-147. DOI: 10.1504/IJESMS.2021.10043556.

[14] Khan, S. T., Vignesh, R., & Vincent, R. R. (2025, February). A robust framework for accurate stock price forecasting: Integrating ARIMA and LSTM models. In Data Science & Exploration in Artificial Intelligence: *Proceedings of the First International Conference On Data Science & Exploration in Artificial Intelligence (CODE-AI 2024), Bangalore, India*, 3rd-4th July, 2024 (Volume 1) (p. 141). CRC Press. DOI: 10.1201/9781003410234-14.

[15] S. Shyni Carmel Mary, Kishore Kunal, & Madeshwaren, V. (2025). IoT and Blockchain in Supply Chain Management for Advancing Sustainability and Operational Optimization. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.1103