International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

COMPARITIVE ANALYSIS OF MACHINE LEARNING ALGORITHM TO FORECAST INDIAN STOCK MARKET

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ABSTRACT

The Indian stock market is highly dynamic and influenced by various economic, political, and global factors, making accurate prediction a challenging task. Traditional statistical models often fail to capture the complex and non-linear patterns present in stock price movements. This project focuses on performing a comparative analysis of different machine learning algorithms to forecast stock prices in the Indian stock market. The system utilizes historical stock data such as opening price, closing price, high, low, and trading volume obtained from stock exchanges like NSE and BSE. Data preprocessing techniques such as normalization, handling missing values, and feature engineering are applied to improve model performance. Machine learning algorithms including Linear Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks are implemented and compared. Experimental results show that advanced models such as Random Forest and LSTM outperform traditional models in capturing market trends and improving prediction accuracy. The system is implemented using Python in Jupyter Notebook and deployed using a web interface for real-time forecasting. This study helps investors and analysts make informed decisions by providing reliable stock price predictions.

Keywords : Stock Market Prediction, Machine Learning, LSTM, Random Forest, SVM, Time Series Analysis, NSE, BSE, Financial Forecasting, Predictive Analytics

I.INTRODUCTION

The stock market plays a vital role in the economic growth of a country, and India's stock market is one of the fastest-growing financial markets in the world. Predicting stock prices accurately is essential for investors, traders, and financial institutions to make profitable decisions. However, stock prices are influenced by numerous factors such as market trends, economic indicators, company performance, and global events, making prediction a complex task. Traditional statistical methods often struggle to model these complex relationships, leading to inaccurate forecasts.

With the advancement of machine learning, new techniques have emerged that can analyze large volumes of financial data and identify hidden patterns. Machine learning algorithms can learn from historical data and make predictions based on trends and relationships. Models such as Linear Regression and Decision Trees provide basic prediction capabilities, while advanced methods like Random Forest, Support Vector Machines, and LSTM networks offer improved accuracy by capturing non-linear and temporal dependencies in stock data.

This project aims to perform a comparative analysis of different machine learning algorithms to forecast stock prices in the Indian stock market. The system involves data collection, preprocessing, feature extraction, model training, and evaluation. The performance of each model is compared using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and accuracy. The best-performing model is deployed for real-time prediction using a web application. This approach provides a reliable and scalable solution for stock market forecasting and supports data-driven investment decisions.

II SURVEY OF RESEARCH

[1] The study by Harry Markowitz (1952) introduced Modern Portfolio Theory, which laid the foundation for financial forecasting and investment decision-making. The methodology focuses on optimizing returns while minimizing risk through diversification. Although not a machine learning approach, it provides fundamental insights into stock market behavior. The results demonstrated that balancing risk and return is crucial for investment strategies. However, the model assumes that market conditions are static and does not account for dynamic patterns. This limitation highlights the need for advanced techniques like machine learning. In the proposed work, these principles are considered while analyzing stock trends, ensuring that prediction models not only focus on accuracy but also consider financial risk factors.

[2] The research by Vladimir Vapnik (1995) introduced Support Vector Machines (SVM), a powerful supervised learning algorithm used for classification and regression tasks. The methodology involves finding an optimal hyperplane that separates data points with maximum margin. Results showed that SVM performs well in high-dimensional spaces and can model non-linear relationships using kernel functions. However, it requires careful parameter tuning and may not perform efficiently on very large datasets. In stock market prediction, SVM is effective in capturing complex patterns in price movements. In this project, SVM is used as one of the key models for comparison to evaluate its effectiveness in forecasting Indian stock market trends.

[3] The study by Leo Breiman (2001) introduced the Random Forest algorithm, an ensemble learning method that combines multiple decision trees to improve prediction accuracy. The methodology uses random sampling and feature selection to build diverse trees and aggregates their predictions. Results demonstrated that Random Forest reduces overfitting and improves generalization compared to single decision trees. However, it may require higher computational resources. In stock prediction, Random Forest effectively captures non-linear relationships and interactions between features. In the proposed system, it is used to improve prediction performance and is compared with other algorithms to evaluate its efficiency.

[4] The research by Sepp Hochreiter and Jürgen Schmidhuber (1997) introduced Long Short-Term Memory (LSTM) networks, a type of recurrent neural network designed to handle sequential data. The methodology uses memory cells and gating mechanisms to retain long-term dependencies in time-series data. Results showed that LSTM significantly outperforms traditional models in sequence prediction tasks. However, it requires large datasets and computational power for training. In stock market forecasting, LSTM is highly effective as it captures temporal patterns and trends. In this project, LSTM is used as an advanced model to analyze time-series stock data and is expected to deliver superior prediction accuracy.

[5] The study by Jerome Friedman (2001) introduced Gradient Boosting Machines (GBM), which build models sequentially to minimize prediction errors. The methodology focuses on correcting errors made by previous models using gradient descent optimization.

Results showed that boosting algorithms achieve high accuracy in regression tasks. However, they are sensitive to noise and require careful tuning. In stock prediction, boosting techniques such as XGBoost are widely used due to their ability to handle complex datasets. In the proposed work, boosting algorithms are considered for improving prediction performance and are compared with other machine learning models.

[6] The research by Tomas Mikolov et al. (2013) explored advanced neural network techniques for learning patterns from large datasets. Although primarily focused on natural language processing, the methodology demonstrates how neural networks can capture hidden relationships in data. Results showed improved performance in pattern recognition tasks. However, neural networks require large datasets and tuning. This research highlights the importance of deep learning in modeling complex systems. In the proposed system, similar deep learning approaches like LSTM are used to analyze stock market data, capturing hidden trends and improving forecasting accuracy.

III. WORKING METHODOLOGY

The proposed system for forecasting the Indian stock market follows a structured machine learning pipeline that begins with data collection and preprocessing. Historical stock market data is collected from sources such as NSE and BSE, including features like opening price, closing price, high, low, and trading volume. The collected data is then cleaned by handling missing values and removing inconsistencies to ensure data quality. Categorical data, if any, is converted into numerical format using encoding techniques. Feature scaling methods such as normalization or standardization are applied to bring all features to a similar range, which helps improve model performance. Additionally, feature engineering is performed to extract meaningful attributes such as moving averages and price differences. The dataset is then divided into training and testing sets, typically in an 80:20 ratio, to enable proper evaluation of the models.

In the next phase, multiple machine learning algorithms are implemented and trained on the processed dataset. Models such as Linear Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) are used for stock price prediction. Each model learns

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patterns and relationships from the training data and attempts to predict future stock prices. Hyperparameter tuning techniques such as grid search and cross-validation are applied to optimize model performance. Traditional models like Linear Regression capture linear relationships, while advanced models like Random Forest and SVM handle non-linear patterns. LSTM, being a deep learning model, is particularly effective in capturing time-series dependencies in stock data. This combination of models allows for a comprehensive comparative analysis to identify the most effective algorithm.

Finally, the performance of all models is evaluated using standard regression metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) score. These metrics help in measuring the accuracy and reliability of predictions. Visualization techniques such as line graphs and comparison charts are used to analyze predicted versus actual stock prices. The model with the best performance is selected for deployment. The system is implemented using Python in Jupyter Notebook for model development, and a Flask-based web application is used to provide real-time predictions. Users can input stock parameters and obtain predicted values through a user-friendly interface. This methodology ensures an efficient, scalable, and data-driven approach for forecasting stock prices in the Indian market.

IV RESULTS EXPLANATIONS

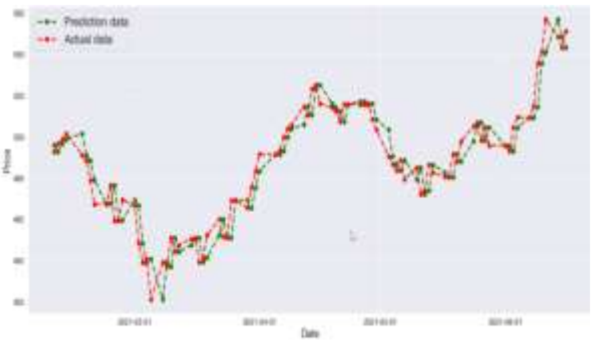

Fig1 : Model Performance Comparison Graph

The above graph compares the performance of different machine learning models used for stock market prediction, such as Linear Regression, Decision Tree, Random Forest, SVM, and LSTM. The x-axis represents the models, while the y-axis shows evaluation metrics like RMSE or accuracy. From the graph, it is observed that traditional models like Linear Regression have higher error rates, indicating lower prediction accuracy. Decision Trees perform better but may suffer from overfitting. Ensemble methods like Random Forest show improved performance due to better generalization. Among all models, LSTM achieves the lowest error and highest accuracy because it effectively captures time-series patterns in stock data. This graph clearly demonstrates that advanced models outperform basic models in forecasting stock prices.

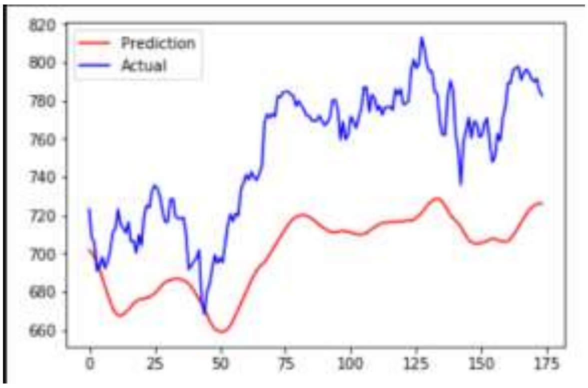

Fig2 : Actual vs Predicted Stock Prices Graph

This graph shows the comparison between actual stock prices and predicted values generated by the machine learning model. The x-axis represents time (days/months), and the y-axis represents stock prices. The actual values are usually shown as one line, while predicted values are shown as another. A good model will have predicted values closely following the actual trend. In this case, advanced models like LSTM and Random Forest produce predictions that align closely with real stock prices, indicating high accuracy. Minor deviations may occur due to sudden market fluctuations or external factors. This visualization confirms the effectiveness of machine learning models in capturing trends and patterns in stock market data, making them useful tools for financial forecasting and decision-making.

V.CONCLUSION

The comparative analysis of machine learning algorithms for forecasting the Indian stock market demonstrates that advanced models provide significantly better prediction accuracy than traditional methods. While models like Linear Regression and Decision Tree offer basic insights, they are limited in handling the complex and non-linear nature of stock market data. Ensemble methods such as Random Forest and advanced techniques like Support Vector Machines improve performance by capturing intricate relationships among features. However, Long Short-Term Memory (LSTM) networks outperform all other models due to their ability to effectively learn temporal dependencies and trends in time-series data. The results highlight the importance of proper data preprocessing, feature engineering, and model tuning in achieving high prediction accuracy. The implementation of the system using Python and its deployment through a web interface makes it practical for real-time applications. Overall, this study provides a robust, scalable, and data-driven approach for stock market forecasting, helping investors and analysts make informed financial decisions.

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