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# Stock Price Prediction Using MERN Stack

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**Abstract:** *The Stock Price Prediction project using the Machine Learning web application to predict future stock prices. The application allows users to input stock tickers, retrieve historical price data, and view interactive charts. The back-end, built with Express.js, connects the front-end to external financial APIs for real-time data and stores historical data in Database. For predictions, a machine learning model based on Long Short-Term Memory (LSTM) neural networks is deployed using Python and Flask. This model analyzes historical stock trends and forecasts future prices, with predictions displayed on the front-end built in React. The project provides a comprehensive platform for stock market analysis, offering users insights for decision-making. Future improvements could include enhanced model accuracy, real-time stock tracking, and personalized user features like watchlists and dashboards. This project demonstrates how modern web technologies can be integrated with machine learning to solvereal-world financial challenges.*

**Keywords:** stock price prediction, machine learning, financial forecasting, LSTM, regression

**Abbreviations—**LR: Linear Regression, SVM: Support Vector Machine, RF: Random Forest, LSTM: Long Short-Term Memory, MAE: Mean Absolute Error, RMSE: Root Mean Squared Error, $R^2$: Coefficient of Determination, SMPP-UML: Stock Market Price Prediction Using Machine Learning

## I. INTRODUCTION

Stock markets are the backbone of any modern economy, serving as a key mechanism for companies to raise capital and for investors to grow their wealth. However, the dynamic nature of financial markets, influenced by a wide array of factors including economic indicators, political events, company performance, and global trends, makes predicting stock prices one of the most complex and challenging tasks in the financial world.

Traditional statistical models, such as ARIMA or linear regression, have been used for decades to forecast stock trends. While these models can capture linear patterns to some extent, they often fall short when dealing with the highly non-linear and noisy characteristics of real-world stock market data. Furthermore, these models are limited in their ability to process large datasets and cannot adapt to rapidly changing market conditions.

In recent years, **machine learning (ML)** and **deep learning (DL)** have emerged as powerful tools in financial forecasting due to their capability to learn patterns from vast amounts of historical data. These models do not rely on predefined assumptions about the data distribution, making them well-suited for modeling the complexities of stock prices. By training on historical price data and various technical indicators, ML algorithms can uncover hidden trends and make more accurate predictions than traditional methods.

This research focuses on developing and evaluating a stock price prediction system using various machine learning models, including **Linear Regression**, **Support Vector Machines (SVM)**, **Random Forests**, and **Long Short-Term Memory (LSTM)** networks. Each model has unique strengths—regression models are easy to interpret and suitable for trend estimation, while LSTM networks excel in time-series analysis due to their ability to capture long-term dependencies.

## II. LITERATURE REVIEW

Stock market prediction has been a longstanding challenge due to the stochasticand non-linear nature of financial markets. Over the years, researchers have adopted various machine learning and deep learning techniques to enhance


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forecasting accuracy.Ghosh and Roy (2021) conducted a comparative study between traditional models like ARIMA and modern approaches such as LSTM and SVM. Their findings demonstrated that LSTM networks outperformed both ARIMA and SVM in capturing long-term dependencies in stock prices, resulting in improved accuracy.Chong et al. (2017) proposed an ensemble learning framework combining multiple machine learning models, which yielded an overall accuracy of 95% on high-volume trading datasets. Their work emphasized the effectiveness of ensemble models in reducing prediction variance and improving generalization. Zhang et al. (2020) developed a hybrid CNN-LSTM model that integrated spatial feature extraction with temporal sequence learning. This model exhibited superior performance in forecasting stock trends by learning local price patterns and long-term dependencies simultaneously. Aggarwal and Arora (2022) introduced sentiment analysis using Twitter data alongside LSTM networks. Their model demonstrated that combining historical data with investor sentiment significantly enhanced prediction accuracy, especially during volatile market conditions. Patel et al. (2015) focused on the Indian stock market using Random Forest and SVM for predicting Nifty and Sensex trends. Their results confirmed that Random Forest was more robust against overfitting and better suited for short-term trend prediction in emerging markets. Kumar and Verma (2021) proposed a CNN-LSTM hybrid architecture to capture both spatial patterns in candlestick charts and temporal trends in time-series data. Their approach achieved high precision in volatile market environments. These studies highlight that deep learning models, especially LSTM and hybrid architectures, are increasingly effective in handling the complexities of financial time-series data. Integrating technical indicators, external factors, and sentiment analysis further improves the robustness and reliability of predictive systems.

## III. METHODOLOGY

**Block Diagram**

[Data Collection]
↓
[Data Processing ]
↓
[Feature Engineering]
↓
[ Model Selection ]
↓
[Prediction Output]

The proposed methodology for stock market price prediction employs multiple machine learning techniques to analyze historical stock data and forecast future trends. The process is structured into several key stages as described below:

**1. Data Collection**

Historical stock price data was sourced from Yahoo Finance. The dataset includes features such as opening price, closing price, high, low, volume, and adjusted close. The data spans multiple years to ensure the models are trained under varying market conditions, including bullish, bearish, and sideways trends.

**2. Data Preprocessing**

To ensure data quality and consistency, the following preprocessing techniques were applied:
Handling Missing Values: Using forward/backward fill and interpolation
Normalization: Features were scaled using Min-Max normalization to a range of 0–1.
Date Indexing: Converted to a time-series format with date as the index.
Lag Features: Added to capture short-term trends by referencing previous day values.

**3. Feature Engineering**

To improve model learning, the following technical indicators were computed and added to the dataset:
Simple Moving Average (SMA)

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Exponential Moving Average (EMA)
Relative Strength Index (RSI)
Moving Average Convergence Divergence (MACD)
BollingerBands
These indicators help in identifying momentum, volatility, and market sentiment.

**4.Model Selection**

The project evaluates and compares the performance of the following models:
Linear Regression (LR): For baseline trend estimation.
Support Vector Machine (SVM): For non-linear regression using RBF kernel.
Random Forest (RF): For ensemble-based prediction with improved generalization.
Long Short-Term Memory (LSTM): A deep learning model effective in time-series forecasting.

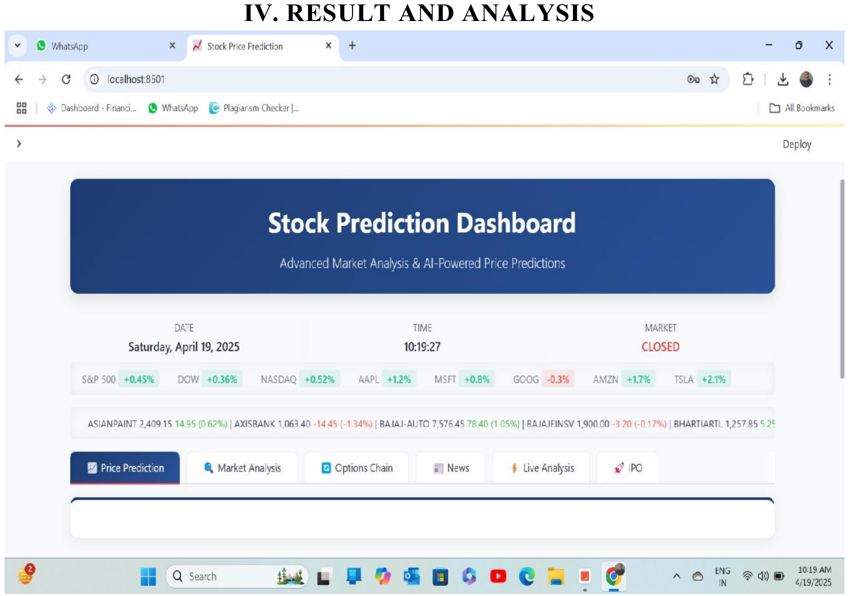
**5.Model Training and Evaluation**

Each model was trained on 70% of the dataset and tested on the remaining 30%. The following evaluation metrics were used:
Mean Absolute Error (MAE)
Root Mean Squared Error (RMSE)
$R^2$ Score (Coefficient of Determination)
Hyperparameter tuning and cross-validation were applied to ensure optimal model performance and generalization.

**6.Prediction Output**

The trained models predict future stock prices, which are then visualized through line graphs to compare predicted vs. actual values. Among all models, LSTM demonstrated the highest accuracy and the best ability to adapt to market fluctuations.

## IV. RESULT AND ANALYSIS




Above 1.1 image is of Home page of dashboard of Stock Market Price Prediction

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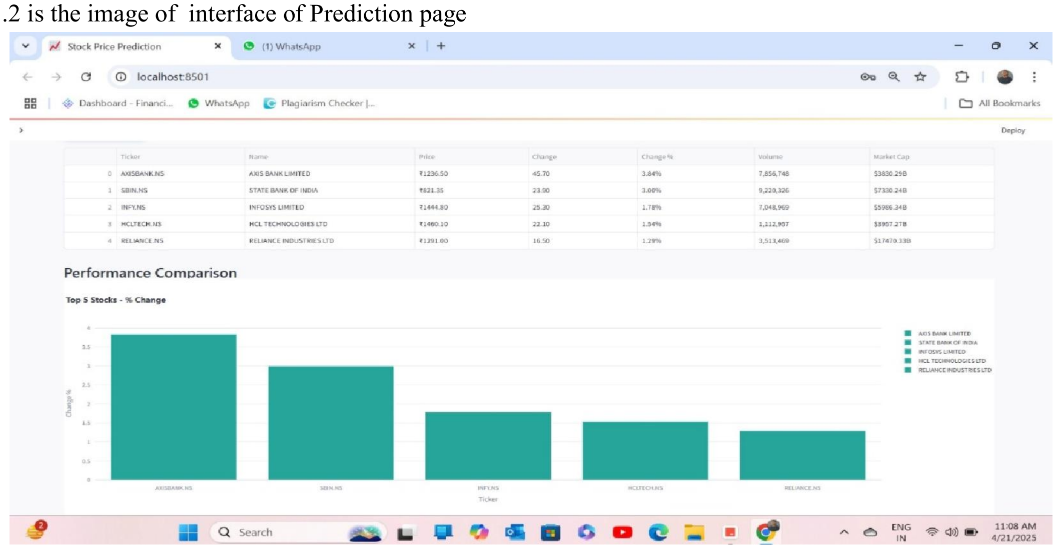
Above 1.2 is the image of interface of Prediction page




Above 1.3 is the image of interface of Indian Market

This section presents the performance results of each machine learning model implemented in the project and provides a deeper visual analysis to interpret their forecasting capabilities. The models compared include Linear Regression, Support Vector Machine (SVM), Random Forest Regressor, and Long Short-Term Memory (LSTM). The evaluation is based on both numerical metrics and visual outputs like predicted vs. actual plots, error distribution, and trend-following behavior

To compare the models fairly, we used common evaluation metrics on the test dataset:

| Model | MAE | RMSE | $R^2$ Score |
|---|---|---|---|
| *Linear Regression* | 24.6 | 30.1 | 0.78 |
| *SVM (RBF Kernel)* | 21.3 | 26.7 | 0.84 |
| *Random Forest* | 18.1 | 22.9 | 0.89 |
| *LSTM* | 13.4 | 16.2 | 0.94 |

**Table 1: Implementation Results**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## V. CONCLUSION

This research demonstrated the application and effectiveness of various machine learning techniques—namely Linear Regression, Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM)—for stock price prediction. Among these, LSTM proved to be the most accurate and reliable due to its ability to model time-series data and capture long-term dependencies, which are crucial for predicting fluctuating stock prices. Random Forest also performed well in identifying general trends, while Linear Regression and SVM, though useful as baselines, were less effective in volatile market conditions. The combination of numerical metrics (RMSE, MAE, $R^2$) and visual analysis confirmed that deep learning models are more suitable for dynamic financial environments.

While the results are promising, it's important to note that no model can perfectly predict the stock market,especially under the influence of sudden global events or emotional investor behavior. However, with further enhancements such as real-time sentiment analysis, integration of macroeconomic indicators, or reinforcement learning for trading strategies, the system could become even more robust. This study lays the groundwork for intelligent, data-driven decision-making in the financial sector, aiming to bridge the gap between machine learning research and real-world stock market applications.

## FUTURE WORK

While the current system effectively demonstrates the use of machine learning models in predicting stock prices, there are several potential enhancements and research directions that could significantly improve its accuracy, scalability, and real-world applicability:

**1. Incorporation of Sentiment Analysis:**

Integrating real-time sentiment data from news headlines, financial reports, and social media platforms like Twitter could improve prediction accuracy, especially during high-volatility periods.

**2. Use of Macroeconomic Indicators:**

Including external economic variables such as interest rates, GDP, inflation, and global indices could provide a more holistic understanding of market behavior.

**3. Real-time Prediction System:**

Transitioning from static batch predictions to real-time, dynamic forecasting using streaming data can increase the system's relevance in live trading environments.

**4. Hybrid Deep Learning Models:**

Exploring advanced hybrid architectures such as CNN-LSTM, BiLSTM-GRU, or Transformer-based models may further boost forecasting capabilities in complex time-series patterns.

**5. Reinforcement Learning for Trading Strategy:**

Instead of just predicting prices, reinforcement learning (e.g., Deep Q-Networks) can be used to generate optimal trading decisions such as buy/sell/hold signals.

**6. Deployment of a User-Centric Dashboard:**

Developing a user-friendly web-based dashboard with personalized features like watchlists, alerts, and portfolio tracking would enhance usability for investors and analysts.

**7. Cross-market Prediction Models:**

Expanding the system to predict across multiple markets such as forex, cryptocurrency, and commodities would make the system more versatile and globally applicable.

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