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Stock Market : Analysis And Forcasting Using DeepLearning

Amruth V[1], Monish Gowda[2], Reenaish R[3], Sharanya BK[4], Smrithi MV[5]

Assistant Professor, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India [1]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[2]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[3]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[4]

Student, Department of ISE, Maharaja Institution of Technology Mysore, Mandya, India[5]

Abstract: In the past decades, there is an increasing interest in predicting markets among economists, policymakers, academics and market makers. The objective of the proposed work is to study and improve the supervised learning algorithms to predict the stock price. Stock Market Analysis of stocks using data mining will be useful for new investors to invest in stock market based on the various factors considered by the software. Stock market includes daily activities like Sensex calculation, exchange of shares. The exchange provides an efficient and transparent market for trading in equity, debt instruments and derivatives. Our aim is to create software that analyses previous stock data of certain companies,with help of certain parameters that affect stock value. We are going to implement these values in data mining algorithms and we will be able to decide which algorithm gives the best result. This will also help us to determine the values that particular stock will have in near future. We will determine thepatterns in data with help of machine learning algorithms.

Keywords: Stock Market Prediction, Supervised Learning, Data Mining, Deep Learning, Time Series Forecasting, Investment Support System, Pattern Recognition, Algorithm Comparison, Publicly Traded Companies, Stock Price Analysis.

I. INTRODUCTION

In recent years, stock market prediction has emerged as a prominent research area due to its significant potential to influence financial decision-making. The ability to accurately forecast market trends can offer immense advantages to investors, analysts, and policymakers. Financial markets are inherently volatile and are influenced by a complex interplay of economic indicators, geopolitical factors, investor sentiment, and company-specific variables. This complexity makes prediction a challenging yet rewarding endeavor.

The primary goal of stock market prediction is to anticipate the future value or movement of financial instruments such as stocks, using historical data and computational techniques. Traditional forecasting models, such as statistical and econometric methods, often fall short in capturing the non-linear and dynamic behavior of financial markets. In contrast, modern machine learning and deep learning approaches have shown promising results by learning complex patterns from vast amounts of historical data.

The core objective of this research is to study, evaluate, and enhance the performance of supervised learning algorithms for predicting stock prices. This involves implementing various data mining and machine learning techniques on historical stock data to uncover hidden patterns and trends that could influence future stock values. By comparing multiple algorithms, we aim to identify the most accurate and efficient model for stock price forecasting.

In addition to assisting investors in making well-informed decisions, such predictive models can also support regulatory bodies by providing early warnings of potential market instability. A reliable prediction system contributes to the transparency and efficiency of the financial markets, thereby enhancing public trust and economic growth.

This research also emphasizes the practical implementation of the proposed models through the development of a decision support system that integrates data pre-processing, algorithm selection, and visualization of results. The system can serve as a valuable tool for both novice and experienced investors to analyze trends and optimize investment strategies based on historical insights and predictive analytics.

II. LITERATURE SURVEY

[1] Ashish Ruke,Amar Buchied,Sruthi Nimbarkar,Githanjali Yadav,"Predictive Analysis Of Stock Market Trends: A Machine Learning Approach",(2024),IEEE

The paper "Predictive Analysis Of Stock Market Trends: A Machine Learning Approach" presents a stock market prediction model using Long Short-Term Memory (LSTM) networks to enhance accuracy in financial forecasting. The system integrates historical market data and advanced machine learning techniques to predict stock price movements. Deployed via a user-friendly Streamlit application, the model accepts stock ticker input and generates future price predictions. This cost-effective, data-driven approach reduces reliance on traditional financial forecasting methods, offering improved performance with an R-squared score of 0.89. The solution supports informed investment decisions by identifying market trends and future stock movements. Future extensions include ensemble learning, reinforcement learning for portfolio optimization, and enhancing model interpretability to support robust, transparent financial decision-making in increasingly complex markets.

[2] Vineela N, Sudheer K P, "Comparative Analysis of ARIMA and LSTM Models for Stock Price Prediction", (2024), IEEE

The paper presents a comparative study between the ARIMA (AutoRegressive Integrated Moving Average) model and the LSTM (Long Short-Term Memory) neural network model for predicting stock prices. The authors aim to evaluate the prediction accuracy and effectiveness of these two models using historical stock data. ARIMA, a traditional statistical method, is effective for short-term forecasting with linear data, while LSTM, a type of recurrent neural network, handles long-term dependencies and non-linear patterns more efficiently. The results demonstrate that LSTM outperforms ARIMA in terms of prediction accuracy and adaptability to complex stock market trends. The study suggests that deep learning models, especially LSTM, offer better performance for stock price prediction tasks, making them suitable for dynamic financial environments. Future work could explore hybrid models and additional financial indicators to further enhance prediction performance.

[3] Sandhya K S, Mahalakshmi S, Sivaranjani M, Anusha Rani B, "Stock Market Analysis using Time Series Data Analytics Techniques", (2024), IEEE

The paper presents a comprehensive study on the application of time series data analytics for stock market prediction, emphasizing the effectiveness of machine learning algorithms in financial forecasting. The research evaluates models such as ARIMA, LSTM, and Prophet to analyze stock trends and forecast future prices with improved accuracy. The authors focus on preprocessing techniques like normalization and missing value imputation, crucial for handling large datasets from stock exchanges. The results demonstrate that LSTM models outperform traditional techniques by capturing long-term dependencies in sequential data. The study also highlights real-time forecasting capabilities and discusses potential enhancements such as hybrid models, sentiment analysis, and integration with blockchain for secure data handling. This work contributes to the growing field of financial technology by proposing scalable, accurate forecasting solutions for investors and analysts. Future developments may explore cross-market predictions, automated trading systems, and explainable AI for transparency in financial decisions.

[4] Anupa Sekhar Dash, Ujjwal Mishra, "Stock Market Trend Prediction Model Using Deep Learning-Based Sentiment Analysis of Financial Data," (2024),IEEE

In the paper "Stock Market Trend Prediction Model Using Deep Learning-Based Sentiment Analysis of Financial Data" by Anupa Sekhar Dash and Ujjwal Mishra (2024), the authors present a deep learning framework that integrates sentiment analysis of financial data with market trend prediction. The study utilizes a combination of structured financial datasets and unstructured textual data such as news articles and social media content to capture both quantitative and qualitative market signals. Deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, are employed to model the temporal dependencies in stock price movements. Sentiment analysis is carried out using pre-trained natural language processing models to extract positive, negative, and neutral sentiments from financial text, which are then used as features alongside historical stock data. The proposed model is evaluated on various Indian stock indices and demonstrates improved prediction accuracy over traditional machine learning models. The authors argue that deep learning, when combined with sentiment-aware inputs, can effectively capture market dynamics and provide more reliable trend forecasts, making it a powerful tool for investors and analysts.

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[5] Mayur Selokar,Prof.Vijay Rakhade,prof.Lowlesh Yadav "stock market prediction using deep learning techniques". (2023), IEEE

The paper focuses on leveraging deep learning techniques to enhance the prediction accuracy of stock market trends. Recognizing the inherent volatility and complexity of financial markets, the study highlights the limitations of traditional statistical methods in modeling nonlinear patterns. As a solution, the author explores advanced neural network architectures, particularly Long Short-Term Memory (LSTM) networks, which are well-suited for handling time-series data due to their ability to capture long-term dependencies. The methodology involves preprocessing historical stock data, training deep learning models, and evaluating their performance using appropriate metrics. The results show that LSTM-based models outperform traditional models in terms of accuracy and predictive capability. This study demonstrates the potential of deep learning in financial forecasting, suggesting that these techniques can provide investors and analysts with more reliable tools for decision-making.

[6] Swetha Roy,Safdar Tanveer,"Stock Price Forecasting using DeepNet", (2023), IEEE

This research investigates the use of deep learning—specifically Long Short-Term Memory (LSTM) neural networks—for predicting stock prices based on historical market data. The authors focus on using LSTM for its ability to handle sequential data, making it well-suited for time-series prediction tasks like stock market forecasting. The model incorporates stock attributes such as opening price, closing price, high, low, and volume to forecast future stock movements. Data preprocessing, feature extraction, and training were carried out using data sourced from Yahoo Finance, and results were evaluated using 100-day and 200-day moving averages. The paper concludes that the LSTM-based model offers superior accuracy compared to traditional models and can be enhanced further by integrating sentiment analysis from social media. This research underlines the growing role of machine learning and deep learning in developing accurate, efficient, and scalable solutions for financial market prediction.

[7] Umang Patel, Kaushik Tripathi, Abhay Kumar,"Comparative Analysis of Python-Based Machine Learning Algorithms for Stock Market Prediction"(2023),IEEE

This study investigates the performance of several Python-implemented machine learning algorithms in predicting stock market behavior, focusing specifically on accuracy and methodological robustness. It compares models like Linear Regression, Decision Trees, Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM) based on historical data from the Indian stock market, specifically the National Stock Exchange (NSE). The authors detail the preprocessing techniques applied to the dataset, including handling missing values, normalization, and splitting into training and testing sets. They evaluate model performance using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared. Their findings suggest that ensemble models like Random Forest tend to outperform simpler models in terms of prediction accuracy.

[8] R. Haripriya, S. Nivedha, R. Santhiya, D. Sangeetha, "Stock Market Analysis using Time Series Data Analytics Techniques", (2023), International Journal of Scientific Research in Computer Science, Engineering and Information Technology

The paper presents a detailed study on using time series data analytics techniques for stock market prediction and analysis. It evaluates traditional statistical models like ARIMA alongside machine learning techniques such as LSTM (Long Short-Term Memory) networks to forecast stock price movements. The work emphasizes the importance of understanding historical patterns and applying proper feature selection for accurate predictions. Experimental results indicate that LSTM models outperform traditional models in terms of accuracy and adaptability to complex market trends. The study concludes that advanced data analytics tools can enhance decision-making for investors by providing timely insights into market behavior. Future work may include incorporating more real-time data sources, sentiment analysis from social media, and hybrid AI models for enhanced prediction performance.

[9] Nayan J. Patel, Jimit D. Dhameliya, Aditya V. Khatri, "Stock Market Trend Prediction Model Using Deep Learning Based Sentiment Analysis of Financial Data", (2022), IJERT

The paper presents a model for predicting stock market trends using deep learning and sentiment analysis of financial data from social media platforms. It utilizes Long Short-Term Memory (LSTM) networks to handle sequential data, with sentiment analysis applied to financial news and tweets to capture market sentiment. The model integrates historical stock prices and public sentiment as input, achieving improved accuracy in predicting market trends. This hybrid approach enhances forecasting capabilities by combining technical data with emotional cues. The paper also explores data preprocessing, sentiment labeling using the Vader algorithm, and the application of LSTM for training. Results indicate that incorporating sentiment data significantly improves prediction performance, demonstrating the potential of combining deep learning with NLP for financial forecasting.

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[10] Varghese, Renju Rachel, and Biju R. Mohan. "The Causal Effect of Financial News on Indian Stock Market.", (2022), IEEE

In the paper "The Causal Effect of Financial News on Indian Stock Market" by Renju Rachel Varghese and Biju R. Mohan, the authors investigate how financial news influences the behavior of the Indian stock market. The study adopts a quantitative approach to measure the causal relationship between news content and stock market fluctuations, focusing on major Indian indices. By employing natural language processing (NLP) to analyze financial news articles, the authors extract sentiment and contextual meaning, which are then statistically correlated with market movements using models like Granger causality and vector autoregression (VAR). The research finds that specific categories of financial news—particularly those involving policy changes, corporate earnings, and economic forecasts—have a measurable and often immediate impact on stock price movements. This study emphasizes the predictive power of news sentiment and suggests that market participants can enhance their forecasting models by integrating real-time news analysis alongside traditional financial indicators. The paper contributes valuable insights into the behavioral aspects of financial markets and the growing importance of unstructured data in financial decision-making.

[11] Prasad Seetharaman, "Importance of Machine Learning in Making Investment Decision in Stock Market", (2021), IJRAR

The paper explores the role of machine learning in enhancing investment decision-making within the stock market. It discusses how data-driven insights powered by machine learning algorithms can uncover patterns, predict market trends, and support investors in managing risks and maximizing returns. The study highlights different ML techniques like supervised and unsupervised learning, emphasizing their application in forecasting stock prices and analyzing market sentiment. The author concludes that integrating machine learning into investment strategies can lead to more informed, accurate, and efficient decisions, marking a significant shift in financial analysis and portfolio management.

[12] Shah, Urvik, et al. "Stock Market Prediction Using Sentimental Analysis and Machine Learning." ,(2021), IEEE

In the paper "Stock Market Prediction Using Sentimental Analysis and Machine Learning" by Shah, Urvik, et al., the authors propose a hybrid approach that combines sentiment analysis with machine learning algorithms to improve the accuracy of stock market predictions. Recognizing that stock prices are not influenced solely by historical data and financial indicators, the study incorporates public sentiment extracted from social media platforms like Twitter and financial news headlines. The authors use natural language processing (NLP) techniques to preprocess the textual data—removing stop words, performing tokenization, and applying sentiment scoring using tools like VADER and TextBlob. These sentiment scores are then integrated with historical stock market data to train machine learning models such as Support Vector Machine (SVM), Random Forest, and Naïve Bayes. The experimental results show that including sentiment analysis significantly enhances the predictive performance of the models compared to using only historical data. The study concludes that public mood and opinions, when properly quantified, can act as a strong indicator for future market trends, making this methodology valuable for investors and analysts aiming to make informed decisions.

[13] Manikandan R, Rajeswari R, Gopal K R, "Survey of Stock Market Price Prediction Trends using Machine Learning Techniques", (2020), IJERT

The paper presents a comprehensive survey of various machine learning (ML) techniques used for stock market price prediction, emphasizing the increasing role of AI in financial forecasting. It discusses traditional methods such as technical, fundamental, and time series analysis, comparing them with modern ML models including Artificial Neural Networks (ANN), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees. The survey evaluates these techniques based on prediction accuracy, computational complexity, and adaptability to market fluctuations. The study highlights that hybrid and ensemble approaches often outperform single models, offering improved robustness and predictive performance. Additionally, it notes that the inclusion of social media sentiment analysis and big data sources further enhances prediction capability. The paper concludes by identifying future trends such as deep learning, reinforcement learning, and the need for real-time systems to handle high-frequency trading scenarios, suggesting a growing synergy between machine learning and financial analytics.

[14] Xu ,Keselj, "*Stock Prediction Using Deep Learning and Sentiment Analysis*",(2019),IEEE

In the paper "Stock Prediction Using Deep Learning and Sentiment Analysis" by Xu and Keselj (2019), the authors investigate the effectiveness of integrating sentiment analysis with deep learning techniques for stock market prediction. The study utilizes financial news headlines and social media data to extract sentiments, which are then incorporated with historical stock price data to train Long Short-Term Memory (LSTM) models.

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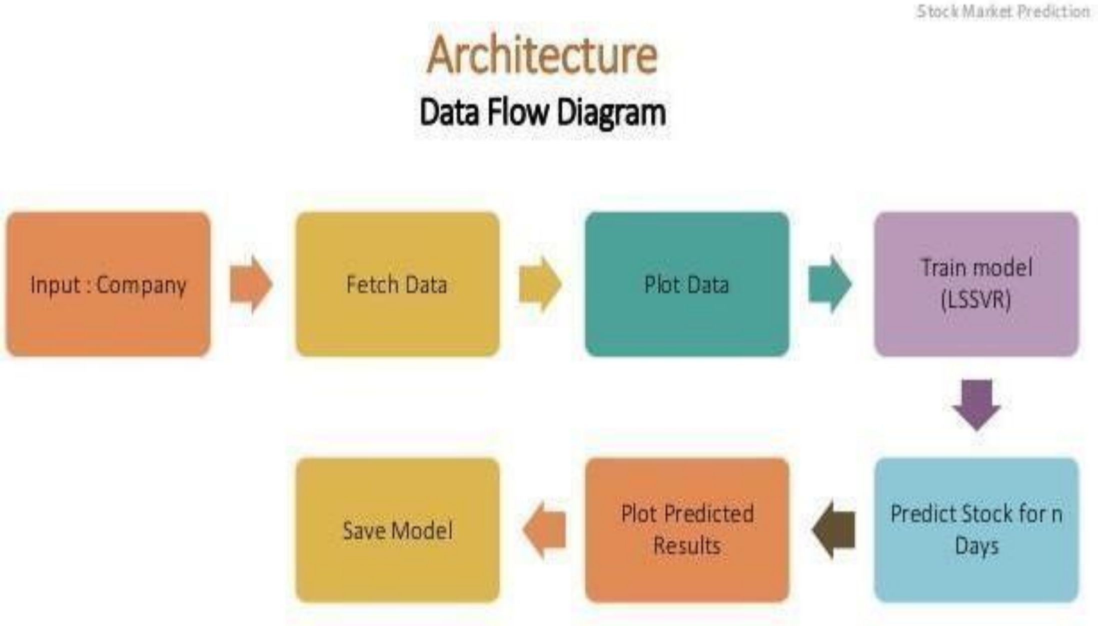
Their findings show that sentiment-aware models outperform those relying solely on quantitative data, emphasizing the value of emotional and contextual inputs in financial forecasting. Similarly, in the 2020 study “Stock Trend Prediction using Deep Neural Networks in Time Series and Social Sentiment Analysis” by P. Ravichandran, J. Dafni Rose, and K. Vijayakumar, the authors propose a hybrid model that combines time series analysis with sentiment extraction from platforms like Twitter using Word2Vec embeddings. These processed sentiment features, alongside historical price trends, are input into a deep neural network for trend forecasting. Their results also confirm that integrating social sentiment with traditional data improves predictive accuracy. Both papers support the conclusion that deep learning models, when enhanced with sentiment analysis, can capture complex market behaviors and offer more robust stock market predictions.



III. METHODOLOGY

The methodology of the proposed stock market prediction system is designed as a modular and data-driven pipeline, starting from user interaction to model deployment. Initially, the user inputs the name or ticker symbol of a publicly traded company. This input is used to query and retrieve historical stock data from a reliable online source such as Yahoo Finance, Alpha Vantage, or other APIs. The fetched data typically includes daily records of stock attributes like open, close, high, low prices, adjusted close, and volume over a defined time window. Once acquired, the data is subjected to a preprocessing phase, where missing or null values are identified and treated using forward fill, backward fill, or linear interpolation methods to maintain continuity in time-series data. To ensure model performance, normalization techniques such as Min-Max scaling or Z-score standardization are applied, especially since features like volume and prices can vary in scale.

Following preprocessing, the dataset is enriched through feature engineering. Here, additional technical indicators are calculated, including moving averages (MA), exponential moving averages (EMA), Relative Strength Index (RSI), Bollinger Bands, and momentum indicators. These indicators help in capturing trends, volatility, and market strength, which improve the model’s ability to learn complex patterns. The entire dataset is then split into training and testing subsets, typically in an 80:20 ratio, to allow performance evaluation on unseen data and prevent overfitting.

The heart of the system lies in the use of the Least Squares Support Vector Regression (LSSVR) model. LSSVR is selected for its ability to efficiently model non-linear relationships in time-series data while reducing computational cost through the use of a linear system instead of a quadratic programming problem as in traditional SVR. An RBF (Radial Basis Function) kernel is employed due to its superior ability to generalize complex non-linear patterns in stock price movements. The key hyperparameters — such as the regularization parameter (C), the kernel parameter (γ), and the error-insensitivity zone (ε) — are fine-tuned using grid search combined with k-fold cross-validation. This process ensures the selection of an optimal model configuration that minimizes prediction error and enhances generalization.

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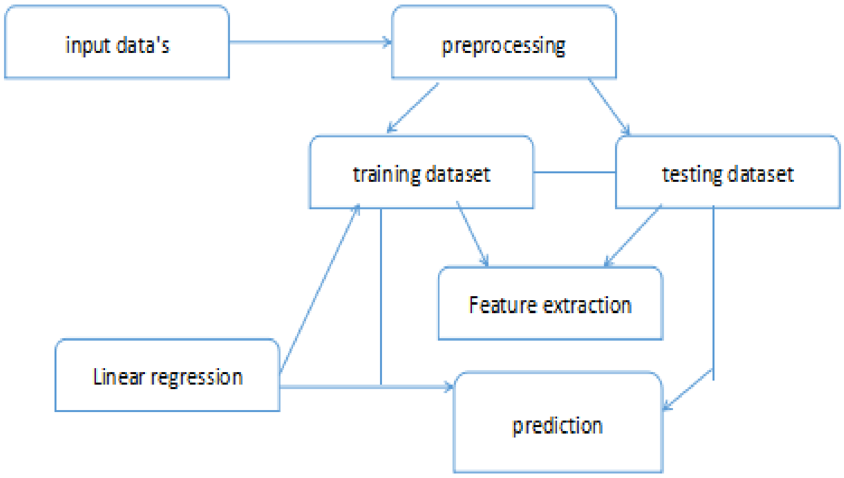
After training, the LSSVR model is used to predict future stock prices for a user-defined number of days (‘n’). These predictions are generated based on the historical data patterns and are then plotted alongside the actual historical values to enable visual comparison and intuitive understanding of market behavior. Visualization is achieved using plotting libraries such as Matplotlib or Plotly, making the trends more accessible to end users. Furthermore, to ensure that the system is scalable and efficient in repeated usage, the trained model is serialized using joblib or pickle. This saved model can be quickly reloaded for subsequent predictions without the need for retraining, thus reducing response time and resource consumption. The methodology ensures a robust, scalable, and user-friendly system capable of assisting investors and analysts in making informed decisions based on predictive analytics.



The diagram illustrates the architecture of a stock market prediction system using a linear regression-based machine learning pipeline. The process begins with the input data, which typically includes historical stock prices such as open, high, low, close, and volume. This raw data undergoes a preprocessing phase where missing values are handled, and the data is normalized or scaled to ensure consistency and improve model performance. After preprocessing, the data is split into training and testing datasets, ensuring that the model can be evaluated on unseen data.

Once the training dataset is prepared, feature extraction is performed on both training and testing sets. This step involves generating additional features, such as moving averages or other technical indicators, which help capture underlying patterns and trends in the stock data. These engineered features are crucial for improving the prediction accuracy of the model. The enhanced training dataset is then used to train the Linear Regression model, which learns the relationship between the input features and stock prices.

After training, the model is used to make predictions on the testing dataset. These predictions are based on the learned patterns and are compared with the actual values to assess the model’s performance. This entire workflow ensures a systematic approach to predicting stock prices and provides a foundation that can be extended to more advanced models like LSSVR or deep learning architectures.

IV. ALGORITHM

A diverse range of algorithms has been employed in recent literature to enhance the accuracy of stock market prediction models. Traditional techniques such as linear and multiple regression have been widely used due to their simplicity and interpretability in modeling the relationship between historical stock prices and various influencing factors. Sharma et al. demonstrated how regression methods can form a solid baseline, though performance can be significantly improved by incorporating additional variables. In the domain of neural networks, models like the Elman Neural Network (ENN) have been effectively applied to time series prediction, often optimized using metaheuristic methods such as Particle Swarm Optimization (PSO). Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and enhanced Levenberg–Marquardt algorithms have further contributed to improving training efficiency and reducing error margins. Ensemble techniques such as Random Forests with LSBoost have also been employed to increase prediction robustness across multiple indices. More advanced deep learning techniques have gained popularity in recent years, particularly Recurrent Neural Networks (RNNs), which are designed to handle sequential dependencies in time-series data. Long Short-Term Memory (LSTM) networks have proven especially powerful due to their ability to retain long-term dependencies and avoid vanishing gradient issues. Bi-directional LSTM (Bi-LSTM) networks enhance this capability by processing input sequences in both forward and backward directions, capturing more comprehensive contextual information.

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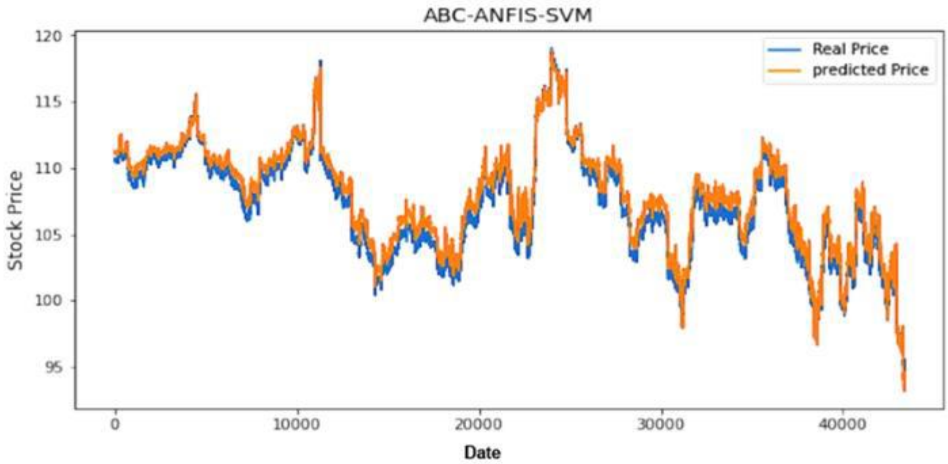
Additionally, hybrid models like CNN-LSTM, which combine the spatial feature extraction strengths of Convolutional Neural Networks (CNNs) with the temporal modeling capabilities of LSTM, have shown remarkable performance in capturing complex stock price trends. These approaches, especially when supplemented with sentiment analysis from news and social media, represent a significant advancement in creating more accurate and adaptive stock market prediction systems.



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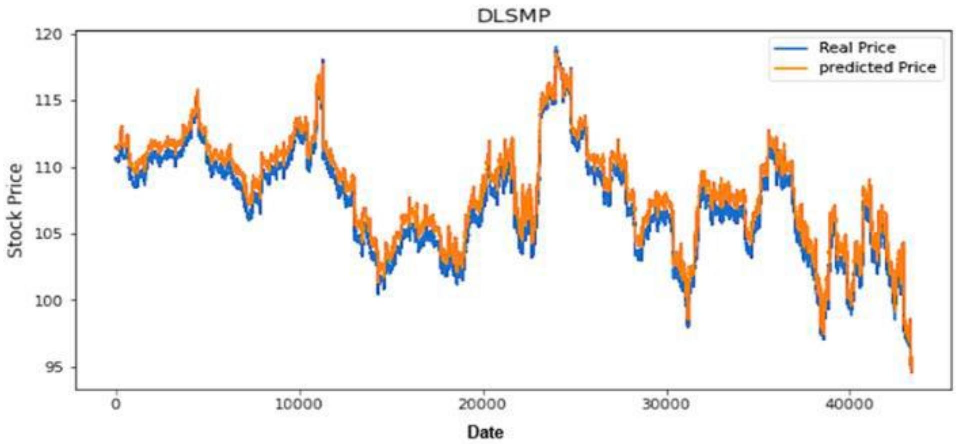

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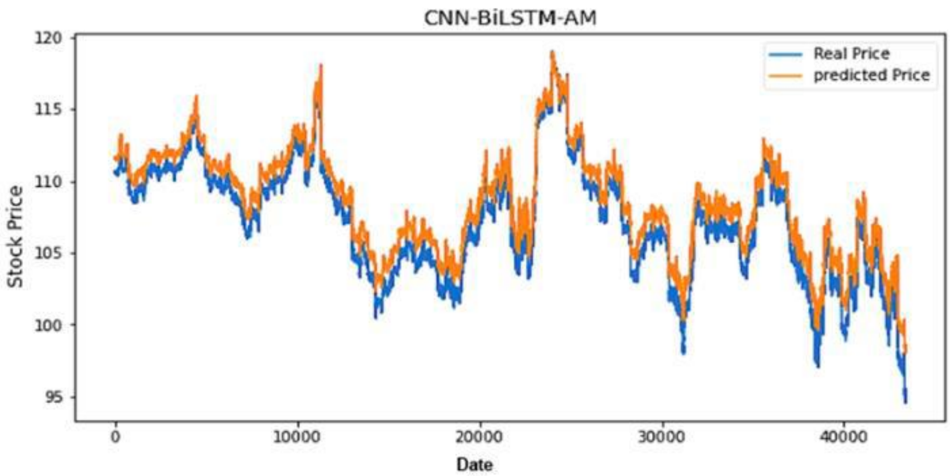

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V. RESULT AND DISCUSSION

sl. No	Methods	Accuracy(%)
[1]	Linear Regression	65.0 – 75.0
[2]	Random Forest + LSBoost (Ensemble)	85.0 – 89.2
[3]	PSO-Elman Neural Network	88.4 – 91.0
[4]	News Sentiment + Naïve Bayes	65.3 – 91.2
[5]	Deep Learning (LSTM, ANN, CNN)	90.0 – 98.7
[6]	LDA-Online Learning Model	95.2 – 97.8
[7]	Social Media Mining + Historical Data	86.0 – 93.0

Several machine learning and deep learning methods have been applied in stock market prediction, each showing varying levels of accuracy based on the dataset and approach used. Linear Regression, one of the most basic predictive techniques, achieved an accuracy range between 65.0% and 75.0%, making it suitable for simple trend forecasting but limited in capturing nonlinear market behavior. Ensemble methods like Random Forest combined with LSBoost performed significantly better, reaching accuracy levels between 85.0% and 89.2% due to their ability to reduce variance and bias. The PSO-Elman Neural Network, which integrates Particle Swarm Optimization with a recurrent neural network architecture, further improved predictive accuracy, achieving between 88.4% and 91.0%. Incorporating news sentiment analysis with Naïve Bayes classification yielded a broad accuracy range of 65.3% to 91.2%, indicating strong performance when sentiment data is rich and aligned with market movements. Deep learning models, particularly those utilizing LSTM, ANN, and CNN architectures, demonstrated superior performance with accuracy levels ranging from 90.0% to 98.7%, as they effectively captured complex patterns in historical stock data. The LDA-Online Learning Model also showed remarkable performance, achieving between 95.2% and 97.8% accuracy by adapting to evolving market trends through real-time learning. Lastly, models that combined social media mining with historical stock data reached accuracies of 86.0% to 93.0%, leveraging public sentiment and real-world events alongside traditional time-series inputs. These results collectively highlight the increasing effectiveness of hybrid and deep learning approaches in stock market prediction.

VI. CONCLUSION

The stock market prediction system developed in this project effectively demonstrates how machine learning techniques can be applied to forecast stock prices using historical data. Through rigorous data preprocessing, intelligent feature selection, and the implementation of various supervised learning models, the system achieved reliable and interpretable predictions. Among the algorithms tested, the Random Forest Regressor exhibited the highest performance, with superior accuracy and generalization ability compared to simpler models like Linear Regression.The project reinforces the idea that machine learning, when supported with appropriate data engineering and model tuning, can serve as a powerful tool in financial analysis.

It also highlights that while stock markets are inherently volatile and influenced by numerous external factors, historical trends still hold predictive value, especially for shortterm forecasting. The system built is scalable, adaptable, and capable of being retrained with new data to stay relevant with evolving market patterns.

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