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"STOCK MARKET PREDICTION: A COMPREHENSIVE REVIEW"

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ABSTRACT

In recent years, stock market prediction has emerged as a vital research domain due to its potential to enhance investment strategies, mitigate financial risks, and support data-driven decision-making. The inherent volatility, non-linearity, and dynamic behavior of stock markets make accurate forecasting a highly challenging task. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has demonstrated significant promise in tackling these challenges by leveraging large volumes of historical and real-time data. Advanced models now integrate time-series signals, technical indicators, and sentiment analysis from news and social media to capture hidden patterns that often remain undetected by human experts. Accurate and reliable predictions are crucial, as they may yield substantial financial benefits, while erroneous forecasts can lead to severe economic losses. This survey presents a comprehensive review of current ML and DL approaches applied to stock market prediction, examining benchmark datasets, evaluation metrics, and comparative results across various architectures. Furthermore, it highlights the challenges and limitations in deploying these models, including over fitting, generalization to unseen market conditions, and data scarcity. The paper concludes with future research directions aimed at improving reliability, robustness, and interpretability of predictive models in highly volatile financial environments.

Key Words: *Stock market prediction, machine learning, deep learning, time-series forecasting, sentiment analysis, financial data analytics.*

I. INTRODUCTION

The stock market is among the most volatile and uncertain fields, affected by various elements like worldwide occurrences, economic metrics, corporate performance, and investor mood. Forecasting stock price fluctuations has been a persistent challenge for analysts, traders, and economists because of the highly non-linear and random characteristics of financial time series data. Precise forecasting models can offer considerable benefits to investors and policymakers by minimizing risks, aiding informed choices, and improving financial stability.

In recent years, the progress of machine learning (ML) and deep learning (DL) methods has sparked significant research in financial forecasting. Conventional methods like Linear Regression and Autoregressive Integrated Moving Average (ARIMA), despite their common use, frequently fail to capture the nonlinear trends in stock data. In contrast, ML algorithms like Support Vector Machines (SVM), Random Forests, and Gradient Boosting have shown enhanced performance in managing high-dimensional features and intricate dependencies. Recently, DL architectures like Convolution Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) have surfaced as effective techniques for modeling temporal sequences and identifying significant patterns in financial

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data. Additionally, hybrid models that integrate historical stock prices with external information sources—such as financial news, social media sentiment, and macroeconomic indicators—have attracted interest for their capacity to deliver more comprehensive and precise predictions. These models show that adding real-time, unstructured data can enhance conventional numerical data in analyzing the stock market.

This document offers a comprehensive literature review of methods for stock market prediction, emphasizing approaches based on machine learning and deep learning. The aim is to offer information on frequently utilized datasets, methods, assessment metrics, and results from prior research. Through examining existing studies, the paper seeks to emphasize significant contributions, recognize limitations, and propose avenues for future investigation in financial forecasting

II. BACKGROUND

The stock market is essential to the global economy by enabling capital creation and investment options. Precise prediction of stock prices has continued to be a persistent difficulty because of the extremely volatile, dynamic, and nonlinear characteristics of financial markets. Conventional statistical and econometric models like Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been extensively applied in time-series prediction. Nevertheless, these techniques frequently struggle to capture intricate nonlinear relationships and abrupt changes in financial data.

Due to the swift progress in computational capabilities and access to extensive financial datasets, machine learning (ML) and deep learning (DL) methods have become significant in predictive modeling. These methods can autonomously identify complex patterns from past data and adjust to nonlinear connections, rendering them appropriate for predicting stock market trends. Models like Support Vector Regression (SVR), Random Forests (RF), and Decision Trees (DT) have been utilized for forecasting financial time series, demonstrating enhanced results compared to traditional techniques. Likewise, deep learning architectures, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks excel at managing sequential data, allowing them to grasp temporal relationships present in stock price fluctuations.

Artificial intelligence (AI), including ML and DL as branches, improves decision-making by utilizing computational techniques to analyze extensive and intricate datasets. Figure 2 depicts the hierarchical connection among AI, ML, and DL, highlighting their link in predictive analytics. In the realm of financial markets, these technologies assist investors, analysts, and policymakers in making better-informed decisions by minimizing uncertainty and enhancing the precision of stock price forecasts

Fig 1: Stock Market in India

(Source: World Federations of Exchanges)

The illustration shows a comparison of stock market performance between Hong Kong and India, emphasizing that although Hong Kong faced more significant ups and downs (surge and decline), India exhibited consistent and strong growth.

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III. RELATED WORK

Stock market prediction has been a widely studied area due to the highly volatile and nonlinear nature of financial data. With advancements in artificial intelligence and computational power, machine learning (ML) and deep learning (DL) models have been increasingly applied to forecast stock prices more accurately.

In [1], Artificial Neural Networks (ANN) and Random Forests were employed to predict next-day closing prices for companies from different sectors. Input variables were derived from financial indicators such as opening, high, low, and closing prices. The models were evaluated using RMSE and MAPE, where both approaches demonstrated low error rates, indicating strong predictive capability.

The study in [2] compared traditional time-series and econometric models with machine learning and deep learning models. Using stock data from Infosys, ICICI, and SUN PHARMA (2004–2019), Holt-Winters, ARIMA, Random Forest, MARS, RNN, and LSTM models were tested. Results showed that MARS achieved the best overall performance across IT, banking, and healthcare sectors, while LSTM was the most effective deep learning model.

A machine learning-based survey of stock data for American Airlines was presented in [3], where Decision Trees (DT), Support Vector Regression (SVR), Random Forest (RF), and ANN were implemented using Python. The dataset spanned five years, with a 70–30 split between training and testing. Simulation results demonstrated that RF outperformed other models, highlighting its potential for real-time implementation.

Several comparative studies have also evaluated combinations of ML and DL algorithms. For instance, the authors in [4] compared SVR, SVM, LR, NN, and Genetic Algorithms, noting varied performances depending on the data. In [12], CNN outperformed MLP, RNN, and LSTM in stock forecasting, while [13] found SVR to yield superior regression-based predictions. Additionally, [5] showed that Neural Networks surpassed SVM and Case-Based Reasoning (CBR). A hybrid framework was proposed in [18], combining historical and real-time market data with news sentiment analysis, where LSTM demonstrated improved results by integrating textual and numerical information.

Collectively, the reviewed studies highlight that while traditional models such as ARIMA remain useful for linear dependencies, advanced ML and DL models—particularly RF, MARS, CNN, and LSTM—offer more robust performance for capturing complex nonlinear stock market patterns.

IV. CHALLENGES & RESEARCH GAP

Even though machine learning and deep learning methods have demonstrated encouraging outcomes in predicting stock markets, various challenges and research voids remain. A significant challenge pertains to the quality and accessibility of data [20]. Stock market data are naturally unstable, erratic, and affected by external elements like worldwide economic conditions, political happenings, and investor feelings, rendering precise forecasts challenging. Another issue is over fitting and the constrained generalization capability of models such as LSTM, CNN, and other combined methods, which frequently excel on training datasets but struggle to preserve accuracy when used on new or unseen data [18]. Furthermore, many studies concentrate solely on numerical and historical data, overlooking unstructured sources like financial news, social media sentiment, and macroeconomic indicators that greatly influence market dynamics. Computational complexity poses a challenge, since deep learning models need substantial datasets and significant processing power, restricting their application in real-time scenarios. Moreover, the absence of interpretability in many prediction models leads to a “black-box” issue [14], diminishing their trust among financial professionals and investors. Even with these initiatives, there has been minimal research into hybrid and ensemble models that combine the advantages of various methods. Additionally, cross-market forecasting, integrating multi-source data, and explainable AI are still inadequately examined, underscoring significant gaps and prospects for upcoming studies [12]

V. CONCLUSION

This survey provides a comprehensive overview of current machine learning and deep learning approaches for stock market prediction. While AI-driven models, including LSTM, GRU, CNN, hybrid CNN-LSTM, and attention-based architectures, have demonstrated promising predictive performance, challenges remain due to the inherent volatility, non-linearity, and noise in financial markets. Integrating alternative data sources such as news sentiment, social media

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signals, and macroeconomic indicators has shown potential in enhancing forecast accuracy, yet issues like over fitting, data quality, and model interpretability persist. The literature reveals that while significant progress has been made, there is no single universally robust model, and predictive performance often varies across datasets and market conditions. Future research should focus on developing hybrid and ensemble methods, improving generalization to unseen market scenarios, and incorporating explainable AI techniques to ensure transparency and reliability in decision-making. Addressing these challenges is essential to building robust predictive systems that can support informed investment strategies and risk management in dynamic financial environments.

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