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Machine Learning and Deep Learning Approaches for Stock Market Prediction: A Comprehensive Study

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Abstract. *Stock market forecasting has emerged as a critical area of research due to its profound influence on national economies, industries, and individual investors. The inherently volatile, non-stationary, and noisy nature of stock market data makes accurate prediction a challenging task. This paper presents a comprehensive study of machine learning (ML) and artificial intelligence (AI) techniques applied to stock market prediction, integrating both structured data (historical prices, indices) and unstructured data (financial news, investor sentiment). Various models, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) models, Deep Neural Networks (DNN), and Reinforcement Learning, are explored for their effectiveness in identifying hidden patterns and trends. A special emphasis is placed on the role of feature selection, dimensionality reduction, and pre-processing, which significantly impact model performance. The study also reviews the unprecedented effect of COVID-19 on global financial markets, highlighting how ML techniques such as SVM, KNN, Naïve Bayes, and ensemble methods have been employed to capture pandemic-driven volatility. Comparative analyses reveal that hybrid approaches combining market data and textual sentiment data yield superior performance compared to single-source models. The findings underline both the potential and limitations of AI-driven stock market forecasting, emphasizing challenges such as non-stationarity, interpretability, and retraining frequency. Ultimately, this work provides a consolidated view of the methodologies, challenges, and emerging directions in stock market prediction research, with implications for investors, policymakers, and researchers.*

Keywords: *:* Stock market prediction, Machine Learning, Deep Learning, CNN, RNN, Long Short-Term Memory (LSTM).

Introduction

The stock market is a highly dynamic and complex system influenced by a multitude of factors, including macroeconomic conditions, political events, global crises, and investor psychology. Traditional statistical approaches, while effective to some extent, often fail to capture the nonlinear and volatile patterns inherent in financial markets. With the rapid advancements in computational power and artificial intelligence, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for financial forecasting. Algorithms such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Deep Neural Networks (DNN), and

Reinforcement Learning (RL) have demonstrated significant potential in predicting market movements by learning from historical data and extracting complex patterns.

In addition to price and volume data, the integration of sentiment analysis, news feeds, and social media inputs has enhanced the predictive capability of hybrid models, offering more robust and accurate forecasting. This multidimensional approach has gained greater relevance in recent years, especially during the COVID-19 pandemic, when traditional models struggled to adapt to sudden market shocks. Furthermore, feature selection techniques and optimization strategies play a critical role in improving model performance, reducing computational overhead, and addressing overfitting issues. Given the growing importance of accurate stock market forecasting for investors, policymakers, and financial institutions, this study reviews and analyzes the effectiveness of various ML and DL models, highlights their comparative performance, and discusses emerging trends and challenges. The aim is to provide a comprehensive understanding of how artificial intelligence can contribute to more reliable and efficient decision-making in financial markets.

Significance of Stock Market Prediction

By investing in the stock market, investors demonstrate their desire to make money. The stock market has attracted stockholder attention due to sophisticated bids that can help predict profitable market forecasts [10]. Accurately forecasting stock market changes requires previous information. Stock market prediction apparatuses can help monitor and regulate the market to make the best selections. The stock market should manage several industrial stock data points that span the entire financial market. Investors adjust their sales and purchases based on the state of the firm.

Figure 1: Processes in Stock Market Price Prediction.

Market position is influenced by events such as management changes, earnings news releases, and future income projections [11]. Precise stock market forecasting helps investors make wiser choices. Using ML techniques, investors can increase their profits despite the high risk involved. The procedures in predicting stock market price are portrayed in Figure 1. Primarily, real-world information is acquired from several sources, like internet sites and historical databases like NASDAQ according to their price index. A subdivision of the stock market, the price index allows investors to calculate performance by evaluating the present price level with previous market values. Following data collection, the information is pre-processed to eliminate noise and other variables. Forecasting the stock market can thus benefit from pre-processed data. Some features are chosen from a vast information using attribute selection techniques. Current and forecast details are the two divisions into which particular information analyzer functions or user-friendly apps separate the dataset. Better stock market selections may be made with the help of these facts.

General Scheme for Stock Market Price Prediction

Figure 2 describes the generic process involved in SMP. The process starts with the collection of the data, and then pre-processing that data so that it can be fed to a machine learning model. The prediction models generally use two types of data: market and textual data. SMP systems can be classified according to the type of data they use as the input. Most of the studies used market data for their analysis. Recent studies have considered textual data from online sources as well. In this section, the studies are classified based on the type of data they use for prediction purposes. Market data are the temporal historical price-related numerical data of financial markets. Analysts and traders use the data to analyze the historical trend and the latest stock prices in the market. Textual data is used to analyze the effect of sentiments on the stock market. Public sentiments have been proven to affect the market considerably. The most challenging part is to convert the textual information into numerical values so that it can be fed to a prediction model. Furthermore, the extraction of textual data is a challenging task. The textual data has many sources, such as financial news websites, general news, and social platforms [12].

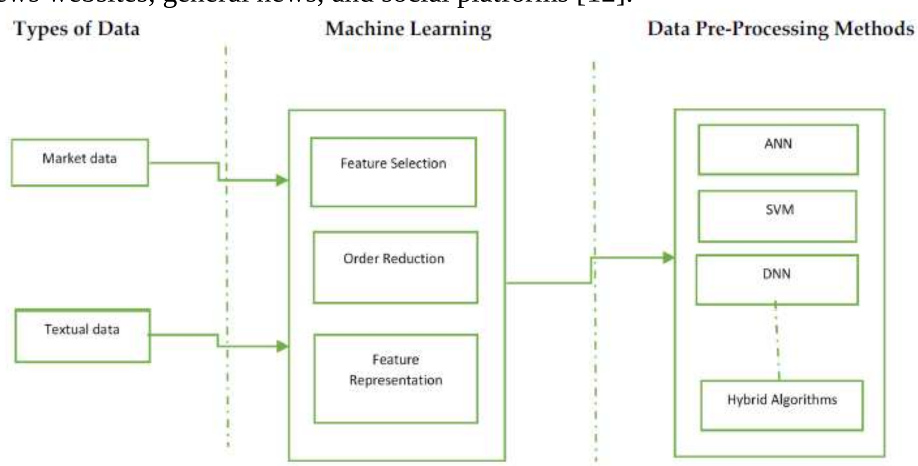

Figure 2: Generic Scheme for SMP (Stock Market Prediction).

Feature selection is a crucial step in textual data processing. Most of the studies on SMP have used basic feature extraction techniques such as Bag of Words, where the text is broken into words and each word is converted into a numeric feature. The feature selection depends on the number of occurrences of a word. The feature selection process for the textual data leads to an increase in the number of features. High dimensional features are extremely difficult to process, and leads to the poor efficiency of most of the learning algorithms [6]. This phenomenon is known as the curse of dimensionality [7]. Lower numbers of features will decrease the training complexity of the algorithms. Feature representation is one of the important factors for the efficient training of machine learning algorithms. Once the number of required features is determined, the input data is converted to a numeric representation so that machine learning algorithms can readily process it.

Operational Flow of Stock Prediction

The stock market is one of the most important parts of every country; It fluctuates the economic growth of the country and also provide a huge effect on many fields, such as employment and industry etc. According to research only 10% of people of every country take a risk to invest in the stock market, it is very difficult to invest because of its dynamic nature, non- stationary, noisy and non-parametric nature [1]. Stock price changes due to political problems, the financial economic crisis and many other factors affecting the market.

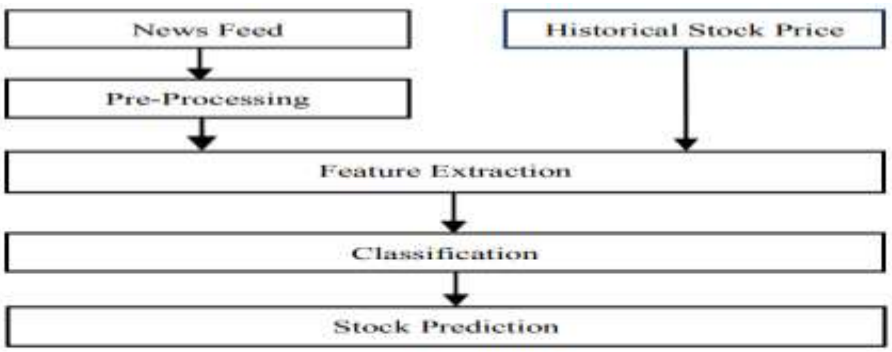

Figure 3: Operational flow of Stock Prediction.

Market forces adjust stock prices on a daily basis. Stock prices fluctuate as a result of supply and demand. The price of a stock increases when there are more people who want to buy it (demand) than there are people who want to sell it (supply). If more people wanted to sell a stock than buy it, the supply would exceed the demand, causing the price to drop [2]. To achieve a better result or accuracy, most researchers concluded that both structured and unstructured data sets are used. Many machine learning techniques are used in stock price prediction like Naive Bayesian, Support Vector Machine, K-Nearest Neighbor, Artificial neural network, Random Forest and the important branch of machine learning algorithm, Neural network (NN), Deep neural networking (DNN). The main aim of this research is to provide a detailed analysis using different methodologies of stock market forecasting to predict future trends and stock returns. This paper explains many of the current stock market prediction tools and techniques adapted to the recant research works [3]. An overview of how the stock price predicted from sentiments can be seen in Figure 3.

Stock Market Prediction Using AI

Stock market prediction or forecasting using historical time series has become a technique widely used by researchers and investors to obtain financial profits in stock trading. These predictions, initially carried out by statistical methods, have been increasingly performed by Artificial Intelligence algorithms. Therefore, AI applied to investments constitutes a recent research area that has already achieved a large number of publications. Since 1965, many researchers have defended the hypothesis of an efficient market [10], which states that the market incorporates all the information that all market participants have and their expectations, so that the price changes are completely random and unpredictable. In contrast to the efficient market hypothesis, other researchers believe that the market prices fluctuate with a trend. Considering this hypothesis, two schools of market analysis can be regarded as:

1) technical analysis, which defends trends in stock price movements and tries to predict them through historical asset prices; and

2) fundamental analysis, which argues that the socioeconomic context of a company interferes with its future stock price and, therefore, provides information that can be used for forecasting future asset prices [8].

The general framework for an Artificial Intelligence prediction model applied to financial forecasting is presented in Figure 4. The first step is the acquisition of all the necessary data to train and test the predictive model. These data can be treated, transformed, or reduced to remove noisy information and highlight important information. Then, the predictor uses the treated data to train its model, in which its hyperparameters can be optimized in a validation step. Finally, the trained model's performance with tuned hyperparameters needs to be evaluated in a test step.

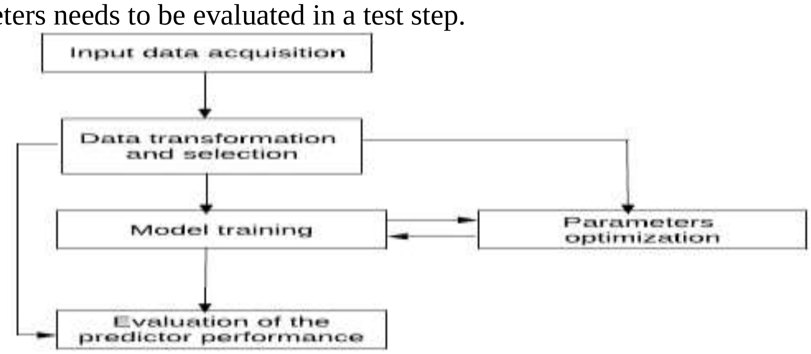

Figure 4: Flowchart for general financial forecasting with AI model predictions.

Stock Price Prediction Techniques

Convolutional Neural Network (CNN)

CNN was widely used in the field of image recognition because of its powerful pattern recognition ability; its use was also extended to the field of economic prediction. Similar to the traditional neural network, CNN is composed of multiple neurons connected by a hierarchical structure, and the weights and bias between layers can be trained. CNN is different from the network structure of a fully connected network such as deep brief network (DBN), Sparse Autoencoder (SAE), backpropagation (BP), as the CNN can share the weight among the neurons in each layer of the network. Hence, the model significantly reduces the weight of the network and avoids falling into dimensional disaster and local minimization [6]. If the characteristics of the stock market at a specific time point are regarded as a feature graph, CNN has the potential to extract the characteristics of the stock market at the corresponding period from these feature graphs. Therefore, CNN can be used to build a timing-selection model and can ultimately be used to complete the construction of the timing-selection strategy.

Recurrent Neural Network (RNN)

RNN belongs to the neural network, and it is good at modelling and processing sequential data. The specific expression is that the RNN is able to memorize the previous state, and the previous state can be used in the current state calculation. The different hidden layers are non-independent, and the input of the current hidden layer includes not only the output of the input layer but also the output of the previously hidden layer as shown in figure 5.

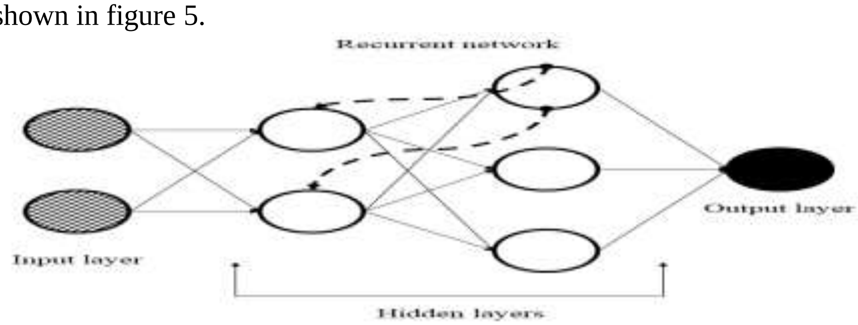

Figure 5: Architecture of Recurrent Network.

For this reason, RNN has a good performance in dealing with sequential data. The advantage of RNN is that it considers the context of data in the process of training, which is very suitable for the scenario of stocks and Forex because the fluctuation at a particular time often contains some connection to the previous trend.

Deep Neural Network (DNN)

DNN is a neural network with at least one hidden layer. It provides modelling for complicated nonlinear functions and has a high-level abstraction ability, which means that the fitting power of the model is significantly improved. Meanwhile, it is a kind of discriminant model which could be trained through the backpropagation algorithm. Since the DNN is good at dealing with prediction problems with sizable data and complicated nonlinear mapping relations, an intelligent stock and Forex prediction system can be designed based on a DNN to predict stock and Forex trends [9]. Hopefully, the model is able to achieve far higher accuracies than human beings.

Reinforcement Learning

Reinforcement learning is one of the deep learning methods that focuses on how to act according to the current situation to profit maximization. In reinforcement learning, there are two basic elements: state and action. A strategy is defined as performing a particular action in a specific state. All the learner has to do is learn a good strategy by continually exploring and learning. If the state is regarded as the attribute and the action is the label, it is easy to know that both supervised learning and reinforcement learning try to find a map and to infer the label/action from the known attribute/state. In this way, the strategy in reinforcement learning is equivalent to the classification/regression in supervised learning. However, in practical problems, reinforcement learning does not have such labelling information as that of supervised learning, and the results are often obtained after an attempt of the action. Therefore, reinforcement learning continuously adjusts the previous strategy through feedback from the results; for this reason, this algorithm would learn in which state one should take which step to have the most beneficial result.

Long Short-Term Memory (LSTM Model)

The Long Short-Term Memory (LSTM) model is a sophisticated data mining technique designed to identify fundamental trends and analyse complex patterns in unstructured data. LSTM model is implemented as a neural network composed of LSTM units, each consisting of a cell state, input gate, forget gate and output gate. These essential components collaboratively interact with the input layer, incorporating features such as historical stock prices, date/time information, and relevant market indicators. The input gate determines the information to be stored in the long-term memory cell, the forget gate decides what to retain or discard from the past, and the output gate shapes the final output based on the current input and stored information. This dynamic interaction enables LSTMs to effectively capture and retain crucial patterns and dependencies in sequential data, establishing their suitability for predicting stock market prices. The specific number of LSTM units is subject to variation based on task complexity and dataset characteristics, often determined through iterative experimentation and turning in the model development process. Basic architecture of LSTM is shown in figure 6.

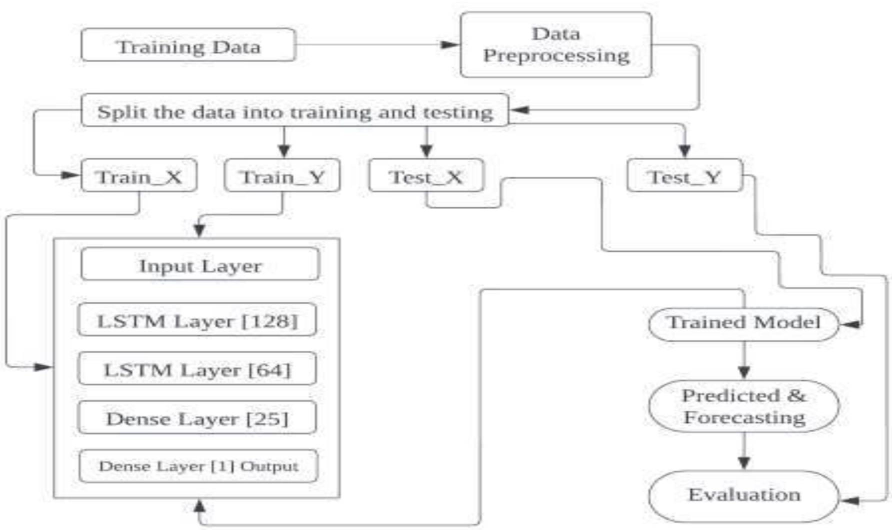

Figure 6: Proposed Recurrent Neural Network (LSTM).

Summary of Ml Techniques for Prediction of Covid-19 Impact on Stock Market

The primary objective of this section is to present a study on the impact of COVID-19 on Stock Market Prediction (SMP). Several studies have utilized machine learning (ML) techniques, including Support Vector Machines (SVM), to forecast market prices during the COVID-19 pandemic. Tiwari et al. [4] employed SVM alongside Naïve Bayes and Linear Regression to predict trends across various markets. However, the effectiveness of SVM in predicting stock performance during COVID-19 has varied across studies. Interestingly, some research suggests that alternative models may outperform SVM in specific scenarios. For instance, in post-COVID-19 forecasting, SaifMohamm et al. [5] demonstrated that K-Nearest Neighbors (KNN) combined with Particle Swarm Optimization (PSO) outperformed other models, including SVM, in predicting power consumption during the pandemic. This research includes a tabulated summary of the most relevant literature, as presented in Table 1.

Table 1: Comparison of Existing Methods

Reference	**Methodology**	**Impact of COVID-19 on Stock Market Performance**	**Prediction Model & Dataset Used**
[1] Kulal et al.	Event Study	Significant negative impact on Nifty 50 index due to COVID-19 announcements	Nifty 50 dataset, event study methodology
[2] Ahmed et al.	Comparative Analysis	Examines performance disparities in stock and commodity markets across South Asia	Statistical analysis, datasets from multiple South Asian countries
[3] Ben Hamadou et al.	Machine Learning	Investigates investor sentiment's effect on Bitcoin returns	Machine learning algorithms, Bitcoin price data
[4] Tiwari et al.	Machine Learning	Analyzes global effects of COVID-19 on various sectors, including finance	Various machine learning techniques, sector-specific datasets
[5] Al-azzawi et al.	Hyperparameter Optimization	Focuses on electricity load forecasting during lockdowns	Regression model, electrical load data
[6] Bora &Basistha	Volatility Analysis	COVID-19 caused increased volatility in stock markets	Econometric modeling, stock market data from affected economies
[7] Varma et al.	Short-Term Analysis	Short-term declines observed in Indian stock market indices	Statistical analysis, Indian stock market data
[8] Salman & Ali	Comparative Study	Negative impact on GCC stock markets; increased volatility	Statistical analysis, GCC stock market data
[9] Ullah et al.	Quantile-on-Quantile Analysis	Economic policy uncertainty exacerbated negative impacts on China's stock returns	Causality-in-quantiles approach, Chinese stock market data

[10] Basuony et al.	Dynamic Modeling	Global stock markets exhibited high volatility and bad state probabilities	Dynamic modelling techniques, global stock market data
[11] Ji et al.	Event Study	Stock market reactions varied significantly across different countries during the pandemic	Event study methodology, cross-country stock market data
[12] Chaudhary et al.	Performance Analysis	Indian stock market showed significant downturns during COVID-19	Statistical analysis, Indian stock market data
[13] Jelilov et al.	Nexus Testing	Analyzed the relationship between stock returns and inflation, noting COVID-19's effects	Econometric analysis, Nigerian stock market data
[14] Ganie et al.	Comparative Analysis	COVID-19 negatively impacted stock markets in select economies	Statistical analysis, datasets from various economies
[15] Thapa et al.	Analytical Study	Documented the impact of COVID-19 on the Indian stock market	Statistical analysis, Indian stock market data
[16] Alam et al.	Event Study	Analyzed stock market responses during lockdown periods in India	Event study methodology, Indian stock market data
[17] Birau et al.	High-Frequency Data Analysis	Short-term forecasting of stock prices during the pandemic	High-frequency trading data, forecasting models
[18] Ahmed et al.	Comparative Analysis	Evaluated sustainability and performance of stock and commodity markets	Statistical analysis, datasets from South Asian countries

The table 1 highlights key aspects of each reference, facilitating a clearer understanding of the methodologies employed, the observed impacts of COVID-19 on stock market performance, and the prediction models and datasets used.

Challenges and Limitations in Stock Price Prediction

1) Market Volatility and Noise- Stock prices are extremely volatile and influenced by unpredictable factors such as news events, political changes, and investor sentiment. This randomness creates “noise” that makes it difficult for models to distinguish between meaningful patterns and short-term fluctuations.
2) Non-Linear and Dynamic Relationships- The connection between input features (like volume, sentiment, or indicators) and future stock prices is rarely linear. Financial markets behave in complex and evolving ways, requiring sophisticated models that can adapt to changing patterns over time.

3) Data Quality and Availability- Historical data may include missing values, outliers, or inaccuracies that can degrade model performance. Moreover, access to high-quality, high-frequency data is often restricted or expensive, limiting the ability of many to build effective models.
4) Overfitting- Many models perform well on historical (training) data but fail to generalize to future unseen data. This is because they may overfit—learning noise instead of signal—leading to poor real-world predictive performance.
5) Feature Selection Complexity- Choosing the right set of predictive features is challenging. Adding too many features can introduce noise, while omitting key variables may cause the model to miss important trends. Balancing relevance and redundancy is crucial.
6) Influence of External, Unquantifiable Events- Unpredictable events such as natural disasters, policy decisions, or geopolitical tensions often impact stock prices, but these events are hard to model due to their qualitative nature and lack of structured data.
7) Latency and Real-Time Processing- In high-frequency trading, every millisecond counts. Even a highly accurate model may become ineffective if it cannot process data and make predictions quickly enough to act in real-time.
8) Lack of Interpretability in Complex Models- Advanced models like deep learning or ensemble methods often operate as "black boxes," making it difficult to understand how they arrive at predictions. This lack of transparency can be problematic for trust, accountability, and compliance.
9) Non-Stationarity of Market Data- Market behavior changes over time, meaning the patterns learned by a model today may not hold in the future. Models must be frequently retrained and monitored to stay relevant in evolving market conditions.
10) Ethical and Legal Constraints- Stock prediction models must operate within regulatory and ethical boundaries. Using insider information, violating privacy rules, or developing manipulative trading strategies can lead to legal consequences and reputational damage.

Conclusions and Future Scope

This study demonstrates that stock market prediction is a dynamic and multi-faceted problem that requires the integration of diverse data sources and advanced computational models. The review of existing literature and techniques confirms that machine learning and AI-based models especially CNNs, RNNs, LSTMs, and reinforcement learning outperform traditional statistical approaches by capturing nonlinear and temporal dependencies in stock market data. Moreover, the incorporation of textual sentiment analysis significantly enhances predictive power, reflecting the growing importance of investor psychology in financial markets. The COVID-19 pandemic further exposed the vulnerability of stock markets to external shocks, highlighting the need for robust, adaptable models capable of handling volatility and uncertainty. However, several challenges persist, including overfitting, feature selection complexity, limited interpretability of deep learning models, and the non-stationarity of financial data. Future research must focus on hybrid architectures, interpretable AI models, and efficient retraining strategies to cope with rapidly evolving market conditions. Overall, this paper concludes that while perfect prediction may remain elusive due to the stochastic nature of financial markets, machine learning provides powerful tools to improve forecasting accuracy, support decision-making, and reduce investment risks in increasingly complex and uncertain environments.

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