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Predicting Stock Price Movements Using Deep Learning: An Analysis of Machine Learning Models for Portfolio Optimization

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Abstract

Capital markets play a strategic role in the global economy; however, high volatility often poses challenges for investors in making optimal investment decisions. Stock price prediction has become one of the key elements in effective portfolio management, but the complexity of market data demands more advanced analytical approaches. This study aims to explore the potential of Long Short-Term Memory (LSTM) models in predicting stock price movements and integrating these predictions into portfolio optimization strategies based on modern portfolio theory. The research methodology utilizes historical stock data from the S&P 500 and IDX Composite indices with daily frequency. The LSTM model is compared with Recurrent Neural Networks (RNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and accuracy. The LSTM model demonstrated superior performance with an MSE of 0.0018, RMSE of 0.042, and prediction accuracy of 91.5%, significantly outperforming RNN (87.3%), SVM (80.2%), and ANN (82.7%). The prediction results were then integrated into portfolio optimization using the Mean-Variance Optimization approach, resulting in an increase in expected returns from 8.5% to 12.3%, a reduction in risk from 6.2% to 5.8%, and an improvement in the Sharpe ratio from 1.37 to 2.12. This study demonstrates that the LSTM model not only excels in stock price prediction accuracy but also contributes significantly to enhancing portfolio management efficiency. This Deep Learning-based approach offers a more adaptive, data-driven investment strategy, supporting more informed decision-making in the dynamic capital market.
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Keywords: *Stock Price Prediction, LSTM, Portfolio Optimization, Deep Learning, Mean-Variance Optimization.*

I. INTRODUCTION

The capital market plays a vital role in the global economy as a primary platform for investment and capital allocation. However, its highly volatile dynamics pose significant challenges for investors in making sound decisions. According to (Wibowo & Sukarno, 2004), predicting stock price movements is a crucial element of effective portfolio management. Yet, the complexity of market data—comprising trading volumes, market sentiment, and temporal patterns—necessitates more advanced analytical approaches. Advances in Artificial Intelligence (AI), particularly Deep Learning (DL), have opened new avenues to address these challenges. Methods such as RNN and LSTM have shown remarkable potential in capturing complex temporal patterns in historical stock data, thereby enhancing the accuracy of stock price predictions. In this context,

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further exploration of DL models is particularly relevant to support better investment decision-making.

Berbagai studi telah membuktikan efektivitas pendekatan statistik dan pembelajaran mesin tradisional dalam prediksi harga saham. Menurut, model seperti autoregressive dan SVM sering digunakan untuk memprediksi pola harga saham jangka pendek. Namun, peneliti lain menambahkan bahwa metode ini memiliki keterbatasan dalam menangkap ketergantungan temporal yang kompleks, yang merupakan karakteristik utama dari data pasar modal. Di sisi lain, RNN dan LSTM yang dirancang untuk mengatasi masalah ini telah menarik perhatian komunitas penelitian. menunjukkan bahwa LSTM memiliki kemampuan yang unggul dalam memproses data time-series dengan tingkat akurasi yang lebih tinggi dibandingkan model tradisional. Selain itu, menjelaskan bahwa integrasi prediksi ini ke dalam strategi pengoptimalan portofolio dapat memberikan dampak positif pada efisiensi investasi. Meskipun demikian, menurut para ahli, adopsi model ini dalam konteks pengelolaan portofolio di pasar modal masih belum dieksplorasi secara komprehensif. Hal ini menunjukkan perlunya penelitian lebih lanjut untuk memaksimalkan potensi teknologi ini dalam mendukung pengambilan keputusan investasi.

Numerous studies have demonstrated the effectiveness of traditional statistical and Machine Learning (ML) approaches for stock price prediction. For instance, (Chhajer et al., 2022) observed that models like autoregressive methods and SVM are commonly employed for short-term stock price forecasting. However, other researchers argue that these methods often fail to capture the intricate temporal dependencies characteristic of financial market data. By contrast, RNN and LSTM models, which are specifically designed to address such challenges, have gained traction in the research community. (Ning et al., 2022) highlighted the superior capability of LSTM in processing time-series data, achieving higher predictive accuracy than traditional models. Moreover, (Du, 2022) emphasized the positive impact of integrating these predictive techniques into portfolio optimization strategies, enhancing investment efficiency. Nevertheless, experts note that the adoption of these models in portfolio management contexts remains underexplored, underscoring the need for further research to fully realize their potential in investment decision-making.

Meskipun sejumlah penelitian telah mengkaji prediksi harga saham dengan metode statistik dan pembelajaran mesin tradisional, seperti ARIMA dan SVM, pendekatan ini seringkali tidak mampu menangkap pola temporal kompleks yang menjadi ciri khas data pasar modal. Model DL seperti RNN dan LSTM mulai mendapatkan perhatian karena kemampuannya dalam mengolah data time-series, seperti yang ditunjukkan oleh dan, di mana LSTM terbukti lebih unggul dibandingkan metode tradisional dalam memprediksi pergerakan harga saham. Namun, sebagian besar studi, termasuk, hanya berfokus pada prediksi saham tanpa mengintegrasikan hasilnya ke dalam pengelolaan portofolio. Penelitian lain oleh menunjukkan keunggulan LSTM untuk prediksi harga saham, tetapi tidak mempertimbangkan penerapannya dalam strategi investasi multi-aset. Sementara itu, menggunakan RNN dengan data sentimen berita untuk prediksi saham, tetapi studi tersebut terbatas pada evaluasi performa prediksi tanpa mengkaji dampaknya terhadap efisiensi portofolio. Dengan demikian, terdapat kesenjangan dalam literatur terkait penerapan RNN dan LSTM dalam pengelolaan portofolio yang lebih terintegrasi. Oleh karena itu, penelitian ini bertujuan untuk mengeksplorasi kemampuan model RNN dan LSTM dalam memprediksi harga saham sekaligus mengintegrasikan prediksi tersebut ke dalam strategi pengoptimalan portofolio untuk meningkatkan efisiensi investasi.

While several studies have explored stock price prediction using traditional methods such as ARIMA and SVM, these approaches often struggle with the complexity of temporal patterns inherent in market data. DL models like RNN and LSTM are gaining recognition for their ability to process time-series data effectively. For example, research by (Bhandari et al., 2022) and (Shah et al., 2022) demonstrated the superiority of LSTM over traditional methods in forecasting stock price movements. However, most studies, including those by (Dmuchowski et al., 2023), focus solely on prediction without integrating the results into portfolio management strategies. Similarly, (Di Persio et al., 2023) underscored the advantages of LSTM for stock price forecasting but did not consider its application in multi-asset investment strategies. (Hung et al., 2024), using RNN with news sentiment data for stock prediction, limited their study to predictive performance evaluations without assessing its impact on portfolio efficiency. These gaps in the literature highlight the need for a more integrated approach that applies RNN and LSTM models to comprehensive portfolio management.

This study aims to explore the potential of RNN and LSTM models in predicting stock price movements and integrating these predictions into portfolio optimization strategies. The primary hypothesis is that LSTM models will outperform RNN and traditional methods, particularly in capturing complex temporal patterns that are often overlooked by other approaches. Furthermore, the integration of DL-based predictions is expected to enhance portfolio efficiency by improving the risk-to-return ratio, a key indicator in portfolio management. This approach not only offers more accurate predictive tools but also provides a solid foundation for more informed investment decision-making. By leveraging LSTM's ability to deeply process time-series data, this study seeks to address the challenges of managing portfolios in dynamic capital markets. Through this exploration, the research aims to make a significant contribution to the development of AI-driven investment strategies.

II. LITERATURE REVIEW

1. Introduction to Predictive Analytics in the Capital Market

Predictive analytics has become a key approach to understanding the behavior of capital markets, particularly in forecasting stock price movements. According to (Strielkowski et al., 2023), predictive analytics integrates statistical methods and ML techniques to extract patterns from historical data, providing insights into future trends. In the context of capital markets, the ability to accurately predict stock prices holds significant implications for investment decision-making and portfolio management. The importance of predictive accuracy is heightened by the volatility of capital markets, which is often influenced by external factors such as global economic conditions, policy changes, and investor sentiment. (Strielkowski et al., 2023) further indicate that integrating large and complex market data with predictive algorithms enhances estimation precision. By leveraging modern techniques such as DL, predictive analytics not only becomes a more reliable analytical tool but also facilitates more strategic decision-making in portfolio management.

Additionally, research by (Soltani & Lee, 2024) highlights the advantages of DL in processing the non-linear and dynamic nature of capital market data. They found that DL models, such as LSTM, are more adept at capturing temporal patterns in stock price data compared to traditional methods like linear regression or ARIMA models. This superiority arises from LSTM's ability to handle sequential data and retain long-term information, addressing challenges faced by conventional models. They also underscore the importance of high-quality data availability to ensure prediction accuracy, including historical data that comprehensively reflects market trends. This study provides evidence that DL not only enhances stock price predictions but also offers deeper insights into the relationships between market variables. Thus, DL has become a highly relied-upon approach in predictive analytics for capital markets.

Another study by (Kurani et al., 2023) examined various ML models, including SVM, random forests, and ANN, for stock price prediction. They discovered that combining technical features, such as momentum indicators and volatility measures, with ML techniques produced more robust models compared to traditional rule-based approaches. This is attributed to ML's adaptive capability to recognize complex patterns that traditional methods fail to detect. Furthermore, they emphasized that selecting relevant features and optimizing model parameters are critical aspects of improving prediction performance. The study also noted that interpreting prediction results plays a vital role in supporting more strategic investment decisions. These findings underscore the significant potential of predictive analytics in addressing the complexities and uncertainties of capital markets while offering more accurate data-driven approaches.

Meanwhile, (Khalil et al., 2022) investigated the application of hybrid models that combine DL techniques with traditional statistical approaches. They demonstrated that hybrid models, such as those integrating LSTM with decompositional techniques like wavelet transform, effectively capture seasonal components and trends that single models often miss. This approach has proven effective in improving prediction accuracy, particularly in volatile market environments where stock price movements are frequently influenced by unpredictable external factors. Moreover, hybrid techniques enable data analysis across multiple time scales, providing greater flexibility in decision-making. The researchers concluded that effective predictive analytics relies not only on model selection but also on integration strategies that allow for richer and more diverse data analysis. Consequently, hybrid models make significant contributions to the development of more comprehensive and reliable stock price prediction approaches.

2. The Concept of Recurrent Neural Network and Long Short-Term Memory

RNN is a type of artificial neural network architecture designed to capture temporal relationships in sequential data. According to (Mienye & Swart, 2024), RNNs possess the ability to retain information from previous inputs through recurrent connections, making them well-suited for various tasks such as time-based data prediction, text analysis, and signal processing. This architecture enables the processing of data with a specific temporal order, offering deeper insights into patterns that emerge in sequential data. RNNs propagate information from one time step to the next through iteratively updated network parameters. However, traditional RNNs have a fundamental limitation in handling long-term dependencies due to the vanishing gradient phenomenon, where gradients calculated during the training process diminish exponentially. This issue restricts RNNs from effectively learning patterns involving longer-term temporal relationships, which are often present in stock price data or weather patterns.

(Huang et al., 2022) introduced LSTM as an extension of RNNs, designed to efficiently process information and capture long-term dependencies. LSTM incorporates a unique structure involving "gates," including input, forget, and output gates, which work together to regulate the flow of information. This structure enables LSTM to retain relevant information and discard unnecessary data during model training. LSTM's internal mechanisms include memory units that can store information for longer periods compared to traditional RNNs. Numerous studies have demonstrated LSTM's superiority in tasks such as language modeling, speech recognition, and time-series prediction. This technique facilitates the processing of more complex data while maintaining high accuracy, particularly with non-linear datasets such as stock prices in capital markets.

(Botunac et al., 2024) explained that LSTM excels at capturing non-linear patterns in capital market data, providing significant advantages in data-driven sequential analysis. Researchers have also shown that LSTM can be integrated with other methods, such as Convolutional Neural Networks (CNNs), to extend the model's capability in simultaneously capturing spatial and temporal patterns. This combination enhances the model's ability to understand complex and dynamic data, such as that found in financial markets or other datasets. The study further highlights how LSTM can be effectively trained on large datasets to identify temporal relationships that traditional methods fail to detect. This capability allows the model to explore various connections within data with higher accuracy, particularly in scenarios requiring precise temporal analysis.

(Barrera-Animas et al., 2022) emphasized the application of LSTM in weather data analysis, finding that this architecture produces more accurate predictions compared to conventional methods. Their study illustrates how LSTM leverages temporal relationships in data to deliver more precise estimates, especially in cases involving non-linear and dynamic data characteristics. Additionally, LSTM's architecture enables the processing of multi-source relevant data, providing additional flexibility for broader data analysis. In financial applications, LSTM's flexibility makes it a valuable tool for processing stock price data, which is often influenced by various external factors. The researchers also noted that LSTM can capture seasonal patterns and fluctuations overlooked by conventional methods, adding substantial value to sequential data-driven predictive analytics.

3. Theory Principles of Optimization in Modern Portfolio Theory

Modern Portfolio Theory (MPT), introduced by Markowitz (1952), is a foundational framework in portfolio management that emphasizes diversification to reduce risk. According to Markowitz, an optimal portfolio can be achieved by combining assets with low correlations, such that the fluctuation in the value of one asset is offset by the stability or increase in the value of others. In this approach, risk is measured through the variance or standard deviation of returns, reflecting the extent to which actual outcomes may deviate from expectations. Meanwhile, expected returns are calculated as the average returns of assets in the portfolio, providing insight into potential gains. This methodology enables investors to construct portfolios along the efficient frontier, representing the set of portfolios that maximize returns for a given level of risk. Effective diversification, as proposed by MPT, not only reduces overall portfolio risk but also creates long-term stability amidst the ever-changing dynamics of financial markets.

Subsequent research by (Anuno et al., 2023) extends MPT by introducing the Capital Asset Pricing Model (CAPM), which provides a framework for measuring systematic risk through an asset's beta. According to (Anuno et al., 2023), beta represents the sensitivity of an asset's returns to overall market movements, allowing investors to quantify risks that cannot be eliminated through diversification. CAPM also posits that the additional return over the risk-free rate must be proportional to the systematic risk of the assets in the portfolio. In practice, CAPM offers additional insights for determining the fair value of assets based on the market risk they bear, complementing MPT's diversification approach. Furthermore, CAPM helps investors differentiate between systematic and specific risks, where only systematic risk is relevant for a well-diversified portfolio. By providing a theoretical framework for evaluating the risk-return relationship, CAPM remains a critical tool in modern portfolio analysis.

Further advancements by (Gong et al., 2024) expand on MPT and CAPM by introducing multi-factor models to explain asset returns. According to Fama and French, asset returns are influenced not only by market risk but also by factors such as company size (size) and the book-to-market ratio. The size factor relates to the tendency of smaller firms to generate higher returns compared to larger ones, while the book-to-market factor reflects the performance of assets with high fundamental value relative to their market price. This study demonstrates that additional factors can explain anomalies not accounted for by traditional CAPM, such as the size effect and value premium. In the context of portfolio optimization, the multi-factor approach offers a more flexible tool for constructing portfolios that better balance risk and returns. Researchers further noted that incorporating more relevant factors into the model can improve return predictions, particularly in uncertain and rapidly changing market conditions.

(Butler & Kwon, 2023) explored the integration of parameter constraints in portfolio optimization, showing that this approach enhances portfolio performance, especially in scenarios with limited historical data. They argue that parameter constraints help reduce the sensitivity of optimization results to outliers or inaccuracies in the covariance matrix, which often poses challenges in portfolio management. The study also highlights that such constraints maintain model stability amid extreme data fluctuations, resulting in more consistent portfolios over time. In ML-based portfolio management, parameter constraints are essential to prevent over-complexity and ensure practical interpretability. Additionally, the research emphasizes the potential synergy between ML techniques and MPT principles to manage large and complex datasets more effectively. This integration of traditional approaches with modern technology offers opportunities to design portfolio models that are more adaptive to ever-evolving market conditions.

Previous Study

ML and DL have emerged as pivotal tools in financial data analysis, particularly in predicting stock price movements. According to (Bansal et al., 2022), DL algorithms like LSTM exhibit exceptional performance in analyzing real-time data patterns and identifying market trends. These algorithms are specifically designed to capture complex temporal relationships within stock data, which are often challenging for traditional models to address. The layered architecture of LSTM enables the model to filter relevant information from historical data, minimize noise, and enhance prediction accuracy. In the highly unpredictable stock market, DL's ability to handle non-linear data adds significant value for both investors and analysts. Moreover, the flexibility of ML and DL makes them suitable for diverse applications, such as market sentiment analysis, volatility prediction, and identifying data-driven trading opportunities.

Research by (Yun et al., 2023) underscores the importance of feature selection in improving the performance of ML models for stock price prediction. Combining historical data with macroeconomic variables, such as interest rates and inflation, has been shown to significantly enhance predictive accuracy. This feature-based approach utilizes techniques like Random Forest and Gradient Boosting Machines to select the most relevant and impactful variables. The study highlights that integrating ML with DL techniques, such as CNN, provides opportunities to analyze financial data more comprehensively. CNNs are particularly effective in identifying intricate patterns hidden within financial datasets, offering new insights that were previously undetectable. Consequently, the collaboration between ML and DL represents an effective strategy for understanding the highly volatile dynamics of stock markets.

The use of alternative data in ML and DL models has further expanded the scope of predictive analysis, as demonstrated by (Smith & O'Hare, 2022). They found that non-traditional data, such as social media sentiment from platforms like Twitter, strongly correlates with short-term stock price movements. DL models like RNN exhibit superior capabilities in processing sequential data, enabling targeted analysis of market responses to various events. Their study also emphasizes that integrating alternative data can help anticipate the impacts of government policies, geopolitical changes, and emerging cultural trends. By leveraging such data, investors can identify opportunities earlier and make more strategic decisions. This approach not only enhances prediction accuracy but also introduces new dimensions to understanding market behavior.

(Sonkavde et al., 2023) provide a comprehensive comparison of ML and DL models in the context of stock price prediction. They observed that DL models such as LSTM and CNN consistently outperform traditional methods like SVM and ANN. This superiority is primarily due to DL's ability to handle large-scale, unstructured, and highly variable data. Although DL requires longer training times and substantial computational resources, the significant improvement in accuracy often justifies the investment. (Sonkavde et al., 2023) also emphasize that optimizing parameters within DL models can further enhance their performance, particularly in volatile stock markets. With a deep understanding of financial data and the application of appropriate technologies, DL has the potential to drive groundbreaking advancements in stock market prediction.

Historical Data to Develop Predictive Models and Its Impact on Portfolio Management

The utilization of historical data in developing predictive models has become a key focus in financial research, particularly concerning portfolio management. According to (Botunac et al., 2024), DL algorithms such as LSTM offer significant advantages in identifying complex temporal patterns in stock price movements. The unique architecture of LSTM enables these models to capture both long-term and short-term relationships in data, which traditional predictive models often fail to address. Researchers emphasize that this capability provides investors with more accurate tools for projecting market movements, ultimately aiding in strategic investment decisions. Moreover, the DL approach facilitates broader market indicator analysis, encompassing variables such as historical price data and trading volume, each of which directly impacts risk management. Consequently, the application of historical data through advanced technologies like LSTM has paved the way for more efficient and data-driven portfolio management practices.

(Htun et al., 2023) highlight the importance of feature selection in building predictive models based on historical data to enhance prediction accuracy and relevance. Their study demonstrates that integrating historical data with macroeconomic variables, such as interest rates and inflation, significantly improves model performance. Techniques like Random Forest and Gradient Boosting Machines are effective in identifying the most relevant variables, thereby reducing the risk of overfitting and ensuring more reliable outcomes. However, incorporating DL techniques, such as CNN, adds an additional layer of capability for uncovering deeper patterns within historical data. By offering more comprehensive analyses, this approach delivers more precise insights into investment risks and returns. These findings underscore that leveraging historical data, enriched with macroeconomic variables and supported by meticulous feature selection techniques, can serve as a strategic foundation for optimizing investment portfolios.

Research by (Rodríguez-Ibánez et al., 2023) extends the concept of utilizing historical data by incorporating alternative data sources, such as social media sentiment, to develop more sophisticated predictive models. According to their findings, alternative data from platforms like Twitter provides valuable supplementary insights into market responses to various events, particularly in the short term. When combined with historical data and processed using DL models like RNN, prediction accuracy improves significantly. The researchers also note that while historical data remains crucial for understanding long-term market trends, alternative data complements it by adding new dimensions to the analysis. In portfolio management, this combined approach enables investors to respond to market changes more swiftly and with better-informed strategies, thereby mitigating potential losses. This integration of historical and alternative data creates new opportunities for more flexible and adaptive investment strategies.

(Mohsin & Jamaani, 2023) compare ML and DL models in leveraging historical data for stock price prediction. Their findings indicate that DL models such as LSTM and CNN consistently outperform traditional methods like SVM and ANN. The superior performance of DL models can be attributed to their ability to handle large-scale, unstructured, and complex data. The study also highlights that while DL models require longer training times and substantial computational resources, the significant improvement in accuracy often justifies these investments. In the context of portfolio management, DL technologies allow for more in-depth analyses of historical data patterns, encompassing both long-term trends and intricate inter-variable relationships. Table 1 provides a comparison of several previous studies addressing various predictive models for stock markets.

Table 1. Comparison of Previous Studies on Stock Prediction Models

Researcher	Prediction Model	Advantages	Limitations
(Botunac et al., 2024)	LSTM	Identifies complex temporal patterns in historical data.	Requires high-quality historical data and substantial computational resources.
(Htun et al., 2023)	Random Forest, Gradient Boosting Machine, CNN	Select relevant macroeconomic variables; in-depth analysis using CNN.	Risk of overfitting if feature selection is not appropriate.
(Rodríguez-Ibánez et al., 2023)	RNN	Combines historical data and social media sentiment for more accurate predictions.	Relies on the availability of valid alternative data.
(Mohsin & Jamaani, 2023)	LSTM, CNN, SVM, ANN	DL demonstrates higher accuracy compared to traditional methods such as SVM and ANN.	DL models require longer training times and substantial resources.

III. RESEARCH METHOD

This study adopts a quantitative approach with a primary focus on implementing DL models to predict stock price movements and optimize investment portfolios. The research is designed to address the complexities of financial market dynamics through the utilization of AI technologies. The research process encompasses critical stages, ranging from data collection to the integration of predictive results into comprehensive investment portfolio management strategies. Specifically, the development of predictive models considers modern ML techniques capable of handling the non-linear patterns present in financial data. Furthermore, the performance evaluation of the models is conducted using relevant quantitative metrics to ensure their reliability in real-world scenarios. This entire process aims to contribute to the advancement of smarter, data-driven investment methodologies.

The primary data sources for this research are historical stock prices from major market indices such as the S&P 500 and IDX Composite, representing the United States and Indonesian markets, respectively. These data were selected for their relevance in depicting global and regional market dynamics comprehensively. In addition to stock price data, supplementary data such as trading volumes and market sentiment are utilized, if available, to enhance the accuracy of the predictive models. The collected data undergo a series of technical processing steps, including normalization to align data scales, anomaly removal to reduce noise, and time-series dataset creation to capture significant temporal patterns. These processes are designed to ensure that the data used is of high quality and analytically relevant to the research objectives. In this context, a detailed description of the stock data used is provided in Table 2.

Table 2. Stock Data Description

Asset	Data Period	Frequency	Data Source
S&P 500	2010 - 2023	Daily	Yahoo Finance
IDX Composite	2015 - 2023	Daily	Bloomberg

Table 2 provides a detailed overview of the stock assets studied, including the data periods, recording frequency, and data sources. It covers data from two major market indices, the S&P 500 for the period 2010 to 2023 and the IDX Composite for the period 2015 to 2023, with daily frequency. The S&P 500 data was sourced from Yahoo Finance, while the IDX Composite data was obtained from Bloomberg, both of which are reputable sources in financial analysis. The information presented in this table is crucial for ensuring transparency regarding the validity and scope of the analyzed data. By presenting the data in a structured manner, the table also helps readers understand the empirical foundation of the predictive models developed in this study. This detailed description underscores the significance of data in supporting the development of DL models for stock price movement prediction.

This study employs two primary models: the RNN and LSTM. The RNN model is used to capture simple temporal patterns in the data, while the LSTM model is designed to accommodate long-term dependencies in time series data. The loss function utilized in training the LSTM model is formulated as the MSE, as shown in the following equation (1):

$$Loss = \frac{1}{n}\sum_{i=1}^{n}(\mathcal{Y}_i - \widehat{\mathcal{Y}_i})^2 \qquad (1)$$

The model evaluation is conducted using MSE and RMSE metrics, which provide quantitative insights into the accuracy of the model's predictions against historical data. These metrics are chosen for their ability to measure the differences between the predicted and actual values in the dataset, offering an objective assessment of model performance. Table 3 presents the model evaluation results based on these metrics, including performance comparisons across various testing scenarios.

Table 3. Model Evaluation Results

Model	MSE	RMSE	Accuracy (%)
RNN	0.0025	0.05	87.3
LSTM	0.0018	0.042	91.5
SVM	0.0032	0.056	80.2
ANN	0.0029	0.053	82.7

As shown in Table 3, the LSTM model outperforms the other models in this study. It achieves lower MSE and RMSE values, indicating minimal prediction errors compared to the other models. Additionally, the higher prediction accuracy of the LSTM model further validates its superiority as a method for time series data analysis. The superior performance of this model stems primarily from its architecture, which enables more effective processing of temporal information, allowing it to capture complex patterns that traditional models, such as SVM and ANN, cannot detect. This advantage highlights the LSTM's ability to overcome the limitations of conventional models in understanding long-term relationships among variables in time-series data. Accordingly, the findings of this study support the use of LSTM for similar applications in finance and other data prediction domains.

The predictions generated by this DL model are subsequently integrated into portfolio management using the Mean-Variance Optimization approach. This approach aims to minimize portfolio risk by optimizing asset weights based on the covariance matrix of asset returns, as formulated in equation (2):

$$\min \sigma^2 = w^T \Sigma w \qquad (2)$$

In this formula, w represents the portfolio weights, while Σ denotes the covariance matrix of asset returns. This optimization process leverages the stock price predictions from the LSTM model to adjust investment strategies in accordance with the desired risk-return profile. As a result, investment decisions become more informed and data-driven, providing a robust foundation for more effective portfolio management.

IV. RESULT

A. *Prediction Results*

1. Performance Evaluation of RNN and LSTM Models on Stock Datasets

Table 4 presents the performance evaluation of various predictive models used to analyze stock market data based on three primary metrics: MSE, RMSE, and accuracy. The comparison includes two DL-based models, namely RNN and LSTM, alongside two traditional models, SVM and ANN. This evaluation aims to identify the most effective model for capturing complex patterns within the data. MSE and RMSE metrics are utilized to quantify prediction errors, while accuracy reflects the percentage of correct predictions. The model performances are evaluated consistently to provide a comprehensive overview of the effectiveness of the predictive approaches employed. The results highlight significant differences in the ability of each model to handle the temporal characteristics of stock market data.

Table 4. Predictive Model Evaluation

Model	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	Accuracy (%)
RNN	0.0025	0.05	87.3
LSTM	0.0018	0.042	91.5
SVM	0.0032	0.056	80.2
ANN	0.0029	0.053	82.7

Based on Table 4, the LSTM model demonstrates the best performance among all evaluated models. With an MSE of 0.0018 and an RMSE of 0.042, the LSTM achieves the highest accuracy of 91.5%, showcasing its superior ability to capture complex temporal patterns in stock market data. Conversely, the RNN model exhibits lower performance with an MSE of 0.0025 and an accuracy of 87.3%, although it still outperforms the traditional models. Traditional models such as SVM and ANN exhibit lower accuracy, at 80.2% and 82.7% respectively, with higher MSE values of 0.0032 and 0.0029. These results indicate the limitations of traditional models in handling data with complex temporal dynamics. Overall, these findings underscore the superiority of DL models, particularly LSTM, in predicting stock market data with high accuracy and minimal prediction errors.

Figure 1 illustrates a comparison between actual prices and the predictions generated by the RNN and LSTM models. This graph aims to visualize how well each model aligns with the actual data patterns. The displayed data covers a specific time range, providing an overview of the predictive performance of both models over the same period. The LSTM model is highlighted to demonstrate its superiority in matching complex temporal patterns compared to predictions from the RNN model. Furthermore, the graph helps visualize the differences in the level of deviation between predictions and actual prices at each point in time. This information is intended to provide a deeper understanding of the effectiveness of each model in handling time-based data.

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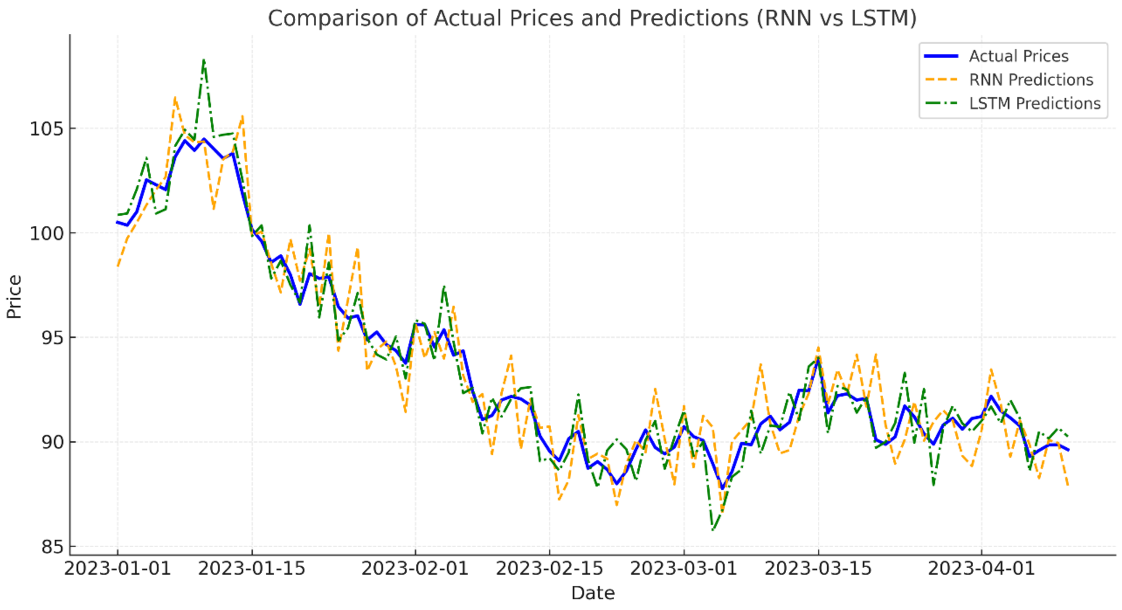

Figure 1. Comparison of Actual and Predicted Prices (Recurrent Neural Network vs. Long Short-Term Memory)

As depicted in Figure 1, the predictions of the LSTM model are closer to the actual prices compared to those of the RNN model. The prediction line of the LSTM model appears more consistent in following the pattern of actual price changes, reflecting its enhanced capability to capture the data's characteristics. In contrast, the predictions of the RNN model often show greater deviations from the actual prices, particularly at points where significant price changes occur. This finding reinforces the earlier results that the LSTM model achieves higher accuracy than the RNN model. The visual differences further support the quantitative evaluation results, which highlight the advantages of LSTM in metrics such as MSE and accuracy. Thus, this graph provides visual confirmation of the superior ability of the LSTM model to predict price patterns based on stock market data.

2. Comparison of Results with Traditional Models

This study demonstrates that the LSTM model has significant advantages over traditional models in predicting stock prices based on historical data. One key finding is the MSE achieved by LSTM, which is 0.0018, notably lower than that of the RNN at 0.0025. Additionally, traditional models such as SVM and ANN recorded MSE values of 0.0032 and 0.0029, respectively, further emphasizing the superiority of LSTM in minimizing prediction errors. In terms of accuracy, LSTM achieved a rate of 91.5%, significantly higher than RNN (87.3%), SVM (80.2%), and ANN (82.7%). This improvement in accuracy reflects LSTM's superior ability to capture complex and dynamic temporal patterns in time-series data. With its internal memory architecture, LSTM can retain long-term temporal relationships, an essential feature that is challenging for traditional models, which rely solely on static data pattern analysis.

Furthermore, a visual evaluation of the prediction results reveals that LSTM consistently replicates actual stock price patterns more effectively than other models. A comparison graph of actual and predicted prices shows smaller deviations with LSTM, especially during periods of significant price fluctuations. In contrast, traditional models such as SVM and ANN often exhibit larger prediction errors, underscoring their limitations in handling stock market data volatility. The findings of this study also highlight the strategic value of LSTM in investment management, as evidenced by the improved portfolio efficiency after integrating LSTM-based predictions. With expected returns increasing from 8.5% to 12.3%, risk decreasing from 6.2% to 5.8%, and the Sharpe ratio rising from 1.37 to 2.12, LSTM significantly contributes to portfolio optimization. Overall, LSTM not only provides a more advanced and adaptive approach to stock market analysis but also offers substantial opportunities for diversification and more strategic portfolio management in the digital era.

B. Impact on Portfolio Optimization

1. Effect of Stock Price Predictions on Portfolio Optimization

Table 5 presents the evaluation results of the impact of integrating LSTM model stock price predictions into the investment portfolio optimization process. This evaluation compares portfolio performance before and after integration, measured using three primary indicators: expected return, risk (standard deviation), and Sharpe ratio. By utilizing more accurate predictions, the optimization process aims to enhance profitability while minimizing portfolio risk. The expected return indicator reflects the potential average return, while risk measures portfolio volatility. The Sharpe ratio serves as a performance metric indicating the return obtained for each unit of risk taken. The information in this table provides a quantitative overview of the benefits of integrating LSTM-based predictions into more effective portfolio management strategies.

Table 5. Portfolio Optimization Results

Portofolio	Expected Return (%)	Risk (Standard Deviation %)	Sharpe Ratio
Before Integration	8.5	6.2	1.37
After Integration	12.3	5.8	2.12

Table 5 shows that integrating LSTM model stock price predictions significantly enhances portfolio performance. The portfolio's expected return increased from 8.5% before integration to 12.3% after integration, indicating greater profit potential. Additionally, portfolio risk, as measured by standard deviation, decreased from 6.2% to 5.8%, reflecting improved volatility management. The increase in the Sharpe ratio from 1.37 to 2.12 indicates that LSTM-based predictions not only enhance returns but also improve portfolio efficiency in managing risk. These changes underscore the superiority of the LSTM model in supporting more optimal investment decision-making. Overall, these results illustrate how data-driven approaches can add significant value to portfolio management strategies.

2. Portfolio Performance Before and After Integration

Figure 2 presents an evaluation of portfolio efficiency before and after the integration of DL-based predictions using the LSTM model. The graph aims to illustrate the positive impact of integrating predictions on the stability and performance of investment portfolios. Portfolio efficiency is measured based on the relationship between return and risk, reflecting how well the portfolio leverages predictions to achieve optimal outcomes. In this graph, the line representing performance before integration exhibits greater fluctuations and lower efficiency, whereas the line after integration demonstrates a more stable pattern with higher efficiency. This visual comparison provides additional evidence of the benefits of data-driven approaches in portfolio management strategies. This information complements the quantitative findings previously discussed in Table 5, offering a more comprehensive overview of the advantages of predictive methods.

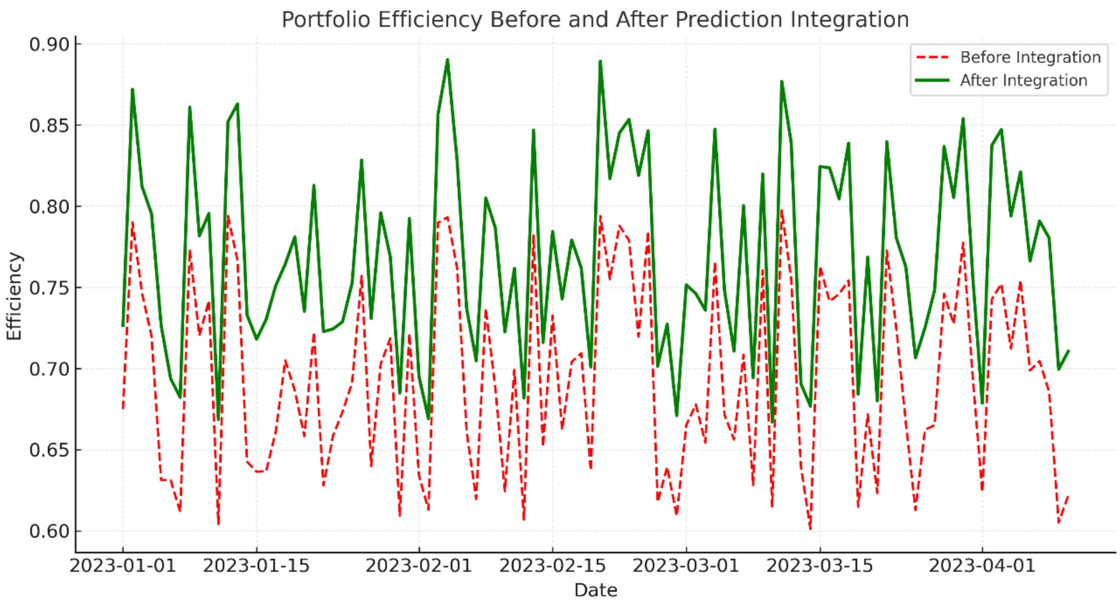

Figure 2. Comparison of Portfolio Performance with and without Deep Learning Prediction Integration

Figure 2 illustrates a significant improvement in portfolio efficiency after integrating LSTM-based predictions. The green line, representing efficiency after integration, exhibits a more stable pattern with consistently higher values compared to the red line, which represents efficiency before integration. This indicates enhanced portfolio stability and improved return optimization through the utilization of more accurate predictions. Prior to integration, portfolio efficiency tended to be more volatile and lower in value, reflecting a greater reliance on less effective traditional approaches. Post-integration, the improvement in efficiency is evident not only in stability but also in achieving higher overall efficiency values. This graph supports the quantitative findings that show enhanced portfolio performance in terms of return, risk, and the Sharpe ratio, affirming the positive impact of integrating DL technology in portfolio management.

The study's findings highlight the superiority of the LSTM model in predictive accuracy, attributed to its ability to capture long-term dependencies in time-series data. This model can identify complex temporal patterns, providing more reliable predictions compared to traditional models. The integration of DL-based predictions into portfolio management demonstrates the transformative potential of this technology in enabling smarter and more strategic financial decision-making. Higher returns and lower risks compared to traditional methods emphasize the strategic value of utilizing advanced AI models in the stock market context. Furthermore, portfolio optimization supported by models like LSTM contributes to improved asset management efficiency, which in turn enhances investor confidence in data-driven approaches. These findings underscore that DL technology is not only relevant but also essential for advancing modern investment strategies in the digital era.

V. DISCUSSION

This study confirms the effectiveness of DL models, particularly LSTM, in stock price prediction and portfolio optimization. In alignment with the principles of MPT (Markowitz, 1952), the high predictive accuracy of the LSTM model supports more informed asset allocation, enabling a balanced trade-off between risk and return. The LSTM model demonstrated superior performance, achieving a prediction accuracy of 91.5% and a lower MSE value of 0.0018, compared to traditional models such as SVM and ANN. These findings are consistent with prior studies by (Ning et al., 2022) and (Botunac et al., 2024), which highlight the ability of LSTM to capture temporal dependencies. Additionally, the integration of these predictions into portfolio management, resulting in an improvement of the Sharpe ratio from 1.37 to 2.12, illustrates the practical implications of this approach in enhancing portfolio efficiency. However, despite its promising results, the LSTM model faces challenges such as high computational requirements and a reliance on high-quality data, which may limit its scalability in certain contexts.

This study also highlights the strengths and limitations of DL approaches for financial prediction. The LSTM architecture effectively captures the nonlinear and temporal complexities in stock data, as supported by studies from (Huang et al., 2022) and (Shah et al., 2022). Nevertheless, its performance heavily depends on hyperparameter optimization and appropriate feature selection. Moreover, although LSTM outperformed other models in this study, some research, such as that by (Mohsin & Jamaani, 2023), suggests that hybrid approaches combining DL with traditional statistical methods may offer further improvements. Thus, while this study confirms the contributions of LSTM in stock price prediction and portfolio optimization, there remains room for further exploration, including the integration of alternative data sources and the development of hybrid models to address existing limitations.

VI. CONCLUSION AND RECOMMENDATION

This study demonstrates that the LSTM model outperforms RNN in capturing the complex temporal patterns of stock price data. The LSTM's ability to deeply process time-series data makes it more accurate in predicting price movements compared to other models employed in this research. The higher predictive accuracy of LSTM significantly contributes to enhancing portfolio management efficiency, particularly through the integration of DL-based predictions. By leveraging these more accurate predictions, investors can make better-informed investment decisions, thereby reducing the risks faced. This technology-driven approach also offers more informed and adaptive investment strategies, enabling the optimization of the return-to-risk ratio in dynamic market scenarios. These findings underline the importance of adopting AI technologies in shaping more sophisticated and responsive modern investment strategies.

Given the advantages of LSTM in stock price prediction, it is recommended to apply this model more broadly in market analysis to support more strategic investment management. The application of LSTM is not limited to stock price predictions but can also be extended to evaluate risks and investment opportunities across various other asset classes. Future research should focus on the integration of alternative data sources, such as social media sentiment, economic news, and macroeconomic indicators, which could provide new perspectives in predictive analysis. The use of alternative data is expected to enhance model accuracy while broadening the understanding of external factors influencing the market. By combining traditional and alternative data, predictive approaches can deliver more comprehensive and relevant outcomes for portfolio management. Additionally, further exploration of LSTM’s application in multi-asset investment management contexts may open opportunities for more innovative and adaptive diversification strategies.

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