Portfolio Construction Based on LSTM RNN and Black-Litterman Model: Evidence from Yahoo Finance

Junzhe Wang
Department of Bigdata, Beijing Institute of Technology, Beijing, China

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Abstract: Portfolio optimization is always a tough issue in fiance field. This study explores the integration of Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNN) with the Black-Litterman model (BL model) to improve portfolio optimization. The BL model, which combines the views from the investors with market equilibrium to modify the revenues that are expected, is commonly used for asset allocation. Yet the model has a few limitations, including subjectivity, data sensitivity, and complexity. In order to deal with these issues, the paper proposes incorporating LSTM RNN predictions into the BL model to mitigate bias and enhance decision-making. The study utilizes historical data from Yahoo Finance for four major corporations(Apple;Intel;Google;NVIDIA) from January 2023 to August 2024. The LSTM RNN is trained on this data to generate machine predictions, which are then treated as investor views in the BL model. The Omega matrix, representing the uncertainty or confidence in these predictions, is adjusted to combine machine and investor perspectives. Results indicate that while LSTM RNN predictions can improve price forecasting, they also introduce biases that require careful calibration. The modified BL model, incorporating machine-generated views, provides a more personalized and potentially more accurate portfolio allocation. This approach offers a novel way to balance human and machine insights in financial decision-making, though it requires significant computational resources and expertise to implement effectively. Future research might focus on refining the Omega matrix estimation and exploring alternative machine learning models to further enhance the model's robustness.

1 INTRODUCTION

The concept of portfolio was first proposed by Medici family in the 15th century during the renaissance in Italy. It was used to describe the collections of the artists' works. The famous architect Michelangelo Buonarroti (1475-1564) once presented his portfolio of works for an hospital for confirmation (Christensen, 2012). However, nowadays portfolios are mostly described as a combination of different assets like derivatives, bonds and real estate. For each asset, there exists its return and risk. Therefore, for the investors, the objective is to either minimize risk or maximize total return when ceteris paribus. Especially in 1952, Harry Markowitz first transferred the concept into a mathematical problem and proposed the portfolio theory in Markowitz model (Markowitz, 2019). In the early theory, returns were represented as $r=\sum_{i=1}^{n} w_i r_i$ where w represents for the weight of each asset in the portfolio and the risk as $R=E\left(\left(r-E(r)\right)^2\right)$. In Markowitz model, returns and risks are shown as the following formulae (w and r are in vector forms, and Σ is a variance covariance matrix):

$$\text{Return} = w^T r \tag{1}$$

$$Risk = w^T \Sigma w \tag{2}$$

Harry Markowitz converts the portfolio management as an optimization problem as an equation like this.

$$\max_{w} w^T r - \frac{\delta}{2} w^T \sum w \tag{3}$$

The model aims to seek the balance between return and risk, which of the relationship can also be described as the Sharpe Ratio. Despite this, inefficiency still existed in the model. The non negligible fact is that those investors aren't always risk-averse as well as their expected return won't always be the highest (Ban et al, 2016; Best, 2010; Fabozzi et al, 2007).

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The portfolio theory was developed ever since. And in 1992, Fisher Black and Robert Litterman put forward the Black-Litterman Model (BL model) (Black & Litterman, 1992a; Black & Litterman, 1992b; Jorion, 1992). The BL model is an asset allocation model that combines investors' views on the market with the equilibrium portfolio implied by the market's risk and return characteristics (Gunjan & Bhattacharyya, 2023). It adjusts the market equilibrium using the investor's views to create a new expected return for each asset, which is then used to optimize the portfolio allocation. This enables investors to factor their personal opinions about how the market will behave in the future into their investment choices. Matrix P represents for the map of investors' views to assets (He & Litterman, 2002). Vector Q represents for actual views. Matrix Ω is an uncertainty matrix. Nevertheless, BL model yet is not perfect nor complete, that it is defective in several aspects as follows (Walters, 2014):

- Subjectivity. The model requires subjective inputs from the user, such as views on expected returns and the choice of risk aversion parameters. This subjectivity can lead to bias and errors in the results.
- Data sensitivity. The covariance matrix and expected returns are two examples of the input data that the model is extremely sensitive to, and even slight changes in these inputs can have a big impact on the allocation outcomes.
- Complexity. The model is complex and requires a deep understanding of financial markets and investment theory in order to use it effectively. This complexity can make it difficult for less experienced users to implement the model correctly.
- Lack of historical validation. The model is based on forward-looking views and expectations, which may not be accurately reflected in historical data. This can lead to the model producing unrealistic or unreliable allocations.
- Limited application. The model is best suited for institutional investors with access to extensive resources and data, making it less practical for individual or retail investors.

Due to the inefficiency and the improvement based on previous research to BL model, the paper aims to research on the construction of portfolios under Markowitz model and BL model, using LSTM model to eliminate the bias from the investors and trying to add machine views against human views. Hopefully, it will generate a more humanized result according to the proportion of how the investors trust the prediction from machines. Additionally, the influence from the machines could be artificially adjusted as a parameter within a specific scope (Selvin et al, 2018).

2 DATA AND METHOD

The paper choose the history data for four corporations from https://finance.yahoo.com: NVDA, Apple, Intel, Google from 2023.01.01 - 2024.8.1 and put them into the LSTM RNN for former prediction as the machine view, and combine it with investor's view to verify and predict the future value of each stock. This study mainly based on an improved BL model, associated with LSTM model. To be specific, it will be dealing with the Omega Matrix in the BL model, in which interfered with the machine view to combine with the investors' view.

The modified model addresses the issue of having to make a return assumption for an asset when no historical data is available. The model initially specifies the mean together with covariance matrix of expected returns based on the market equilibrium. The formulas for the mean-variance optimization are as minimize $w'\Sigma w$and subject to $w'\mu = R$. Here, w is the weight of the assets in vector form; μ represents for the expected returns in vector form; Σ is the covariance matrix; R is the targeted return. The modified model then incorporates the investor's subjective views through a Bayesian adjustment process. The equation to calculate the adjusted expected returns is:

$$E^* = \Sigma((\Sigma^{-1} + P'Q^{-1}P)^{-1})(\Sigma^{-1}E + P'Q^{-1}Q) \quad (4)$$

Where E* is the adjusted expected return; Σ is the covariance matrix; P is the matrix mapping the expected returns to the views; Ω is the covariance matrix of the errors in the views and Q is the vector of views. Finally, the model suggests the computation of the new optimized portfolio weights using the adjusted expected returns and the covariance matrix.

Recurrent neural network (RNN) architectures such as Long Short-Term Memory (LSTM) are specifically created to solve the vanishing gradient issue that can arise with conventional RNN. RNN' capacity to identify long-range dependencies in sequential data may be constrained by the vanishing gradient problem.

LSTM networks consist of memory cells that are connected through special gates. By controlling the information entering and leaving the memory cells, these gates enable the network to store and recall data as needed. The input gate, forget gate, and output gate are the three primary gates in an LSTM network.

The forget gate regulates the amount of data that is eliminated from the cell state, whereas the input gate regulates the amount of new information that is added to the cell state. The quantity of data transferred to the network's subsequent layer is then controlled by the output gate.

For experiment steps, one first trains the LSTM model on historical asset prices to predict future returns and extracts the predicted returns for the relevant assets. Then, this study will treat the LSTM predictions as views on expected returns for the assets. Construct the Omega matrix based on the confidence in the LSTM predictions. For example, Omega could be a diagonal matrix where each element corresponds to the inverse of the variance of the LSTM prediction errors. Subsequently, this research will Combine the equilibrium returns (from a market capitalization-weighted portfolio) with the LSTM-based views, weighted by the Omega matrix, to derive the posterior expected returns. Finally, this paper will use the posterior expected returns to optimize the portfolio, typically using mean-variance optimization.

To assess the performance of the BL model and the LSTM RNN in portfolio optimization and forecasting, one evaluated both models using historical market data from 2023.01.01 to 2024.08.27. The primary metric for evaluation include the comparison and combination of Omega Matrix which represent the uncertainty and confidence of an investor and the machine view generated by the model. While the BL model excels in portfolio optimization with a robust risk-adjusted return, the LSTM RNN outperforms in price prediction accuracy. However, the LSTM RNN's performance may vary significantly due to the choice of hyper-parameters and the volume of training data. The omega matrix is a key parameter in the BL model, which is used to incorporate the investor's confidence in the equilibrium market returns. It represents the uncertainty or in another way, the confidence in the market equilibrium returns and is typically derived from the investor's views or historical data. The omega matrix helps to adjust the variance of the equilibrium returns and influences the overall portfolio weights. A higher value in the omega matrix indicates higher uncertainty or lower confidence in the equilibrium returns, which can lead to a higher adjustment in the portfolio weights.

3 RESULTS AND DISCUSSION

This section presents the performance of the BL model and LSTM RNN on the chosen data set from four corporations in four different parameters in omega matrix of investor’s view which represents how the investors believe in machine prediction. The metrics used for evaluation include the Omega matrix, which is constructed as a diagonal matrix, with elements derived from the variance of the LSTM prediction errors. The results are shown in Figure. 1, Figure. 2, Figure. 3 and Figure. 4 for Microsoft, Intel, Apple and NVIDA, respectively.

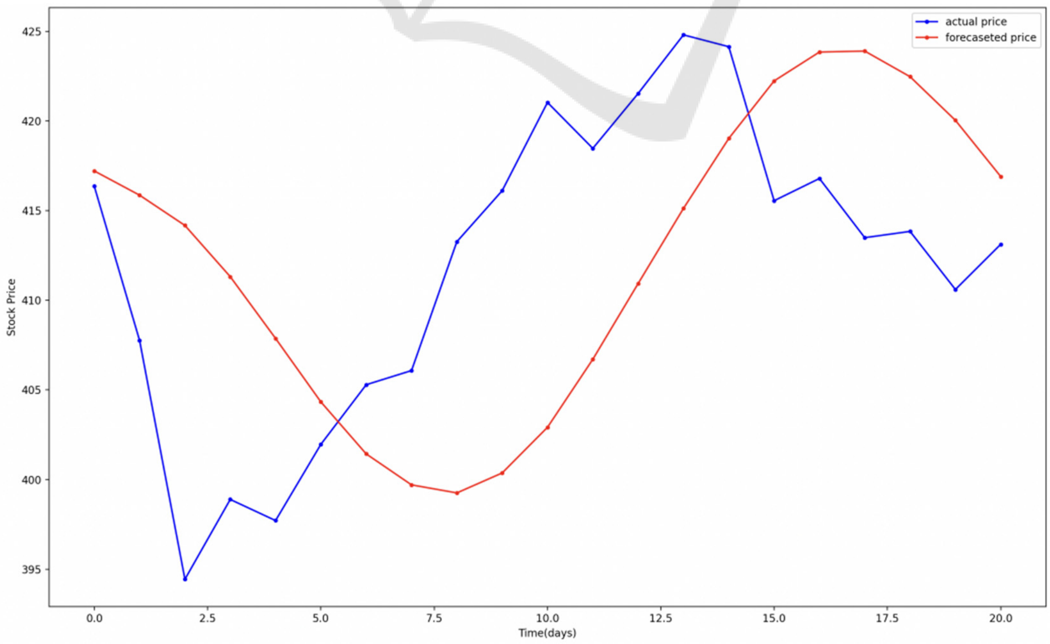

Figure 1: Results for Microsoft (Photo/Picture credit: Original).

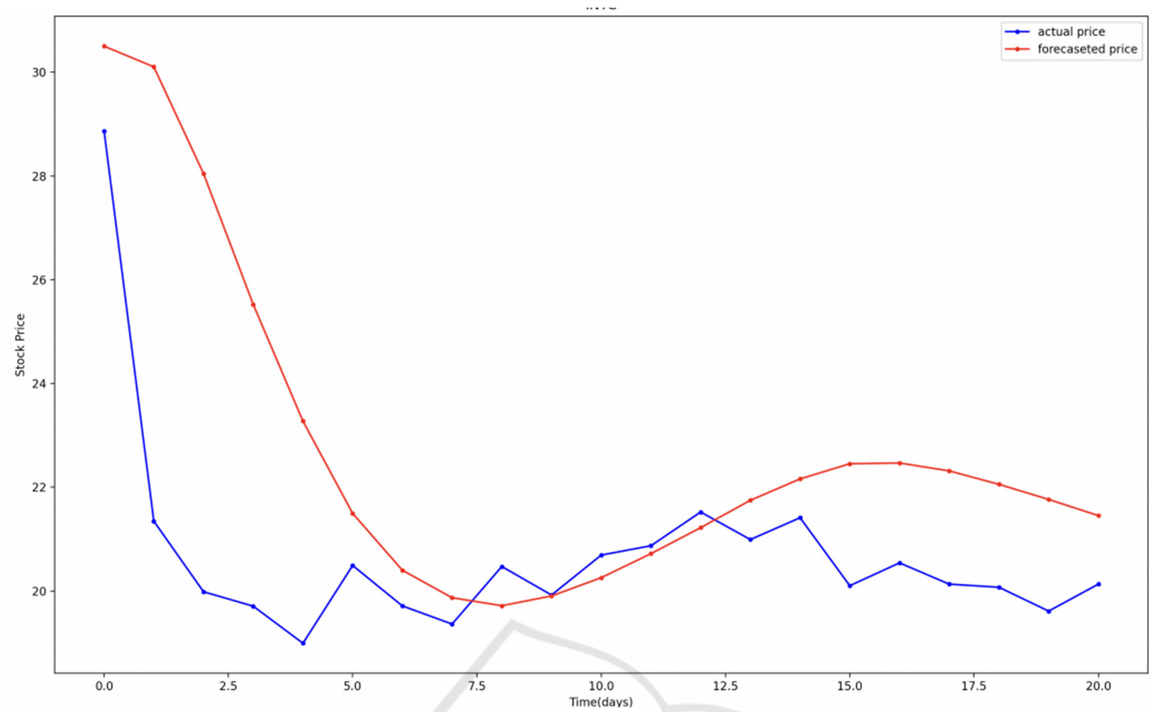

Figure 2: Results for Intel (Photo/Picture credit: Original).

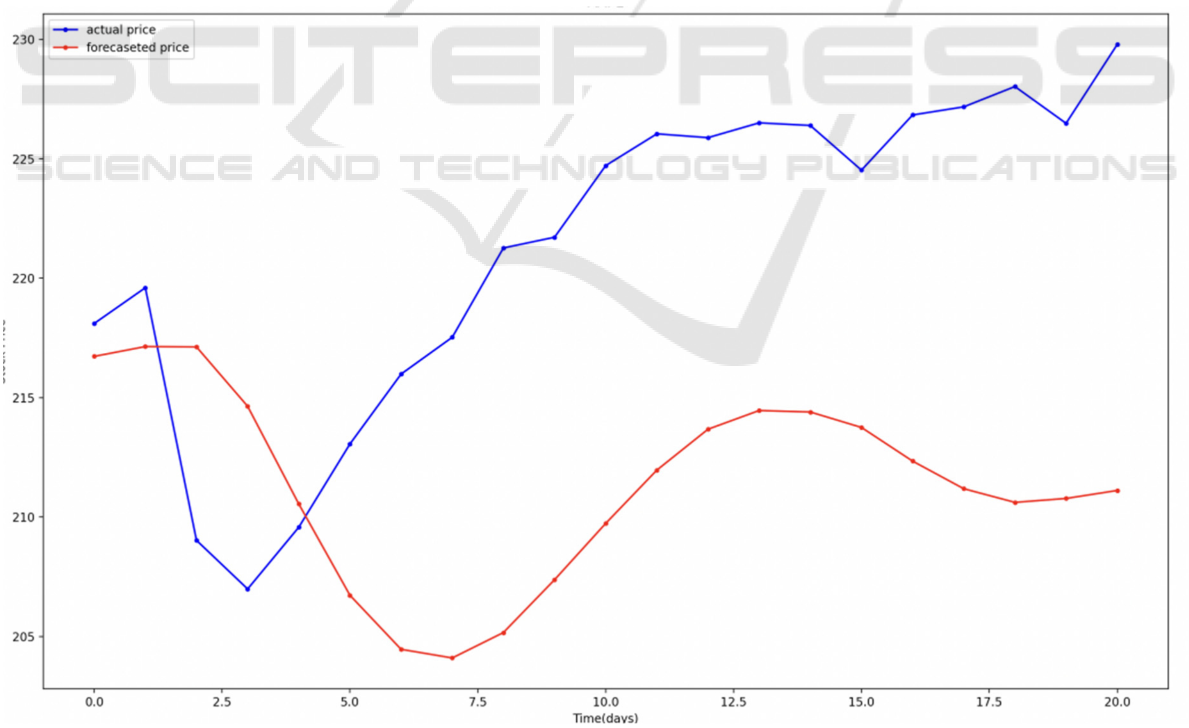

Figure 3: Results for Apple (Photo/Picture credit: Original).

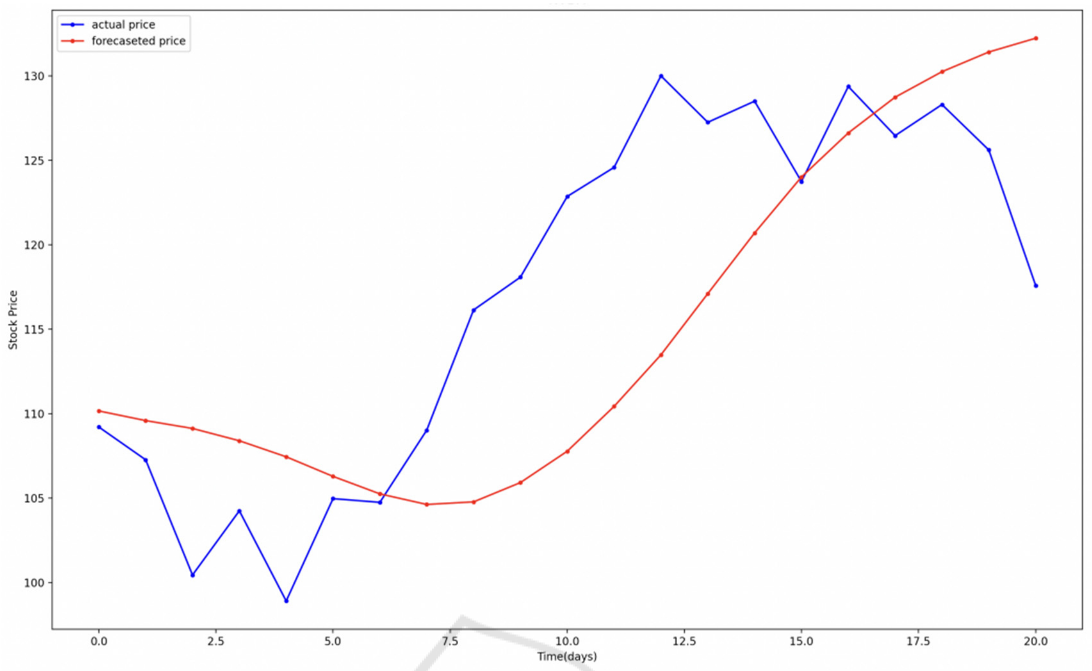

Figure 4: Results for NVIDIA (Photo/Picture credit: Original).

First of all, the results shown in Figures represents for the LSTM RNN training results based on the historical data from four corporations(Apple, Microsoft, Intel, NVIDIA) from 2023.1.1 to 2024.8.1 and the prediction period is 30 days in August. The blue fold line is the real time market trend while the red one shows the forecast prices. Despite exhibiting varying degrees of deviation and offset, the LSTM model was well learned from the past market situation and performed approximately similar trend lines as it could be seen from the chart. Further correction and modification against these deviations and bias ought to be taken into consideration. Next, one views and the Omega matrix are constructed as the confidence and the uncertainty. The prediction from the LSTM RNN would be treated as views on expected returns, machine views in another word. The formats are as follows:

$$Q_1 = \text{Prediction Returns} = \begin{pmatrix} r_{Intel}^{LSTM} \\ r_{Microsoft}^{LSTM} \\ r_{Apple}^{LSTM} \\ r_{NVIDIA}^{LSTM} \end{pmatrix} \quad (5)$$

$$Q_2 = \text{Investor View} = \begin{pmatrix} r_{Intel}^{Investor} \\ r_{Microsoft}^{Investor} \\ r_{Apple}^{Investor} \\ r_{NVIDIA}^{Investor} \end{pmatrix} \quad (6)$$

This study adds the investors' views as Q2 to the machine prediction and modify the proportion of each views to combine and forms a integrated view as the views Matrix Q. Together with the Omega matrix constructed from the variance of each historical error, one would apply it to the BL model to combine with the LSTM predicted returns, weighted by the Omega matrix. Finally, it Optimize Portfolio Using the posterior expected returns, mean-variance optimization are performed to build an optimized portfolio. The analysis revealed that the LSTM model exhibited a certain degree of bias and deviation in its stock price predictions. The model consistently overestimated or underestimated the actual stock prices, leading to relatively high MAE and RMSE values. Furthermore, the model's predictions showed a tendency to deviate from the actual stock price trends, particularly in the presence of sudden market fluctuations or anomalies. These findings indicate that the presence of bias and deviation can significantly affect the accuracy and reliability of the LSTM RNN for stock prediction.

The presence of bias and deviation in the LSTM model's stock predictions has important implications for its practical utility in financial markets. Inaccurate predictions can lead to substantial financial losses for investors and traders, and undermine the trust and credibility of the model as well. Therefore, it is crucial to mitigate bias and deviation in the model's predictions through the use of advanced regularization techniques, feature engineering, and data preprocessing methods. Additionally, transparency and interpretability in the model's decision-making process are essential for building confidence in its predictions and insights.

The BL model provides a more realistic and robust allocation of the portfolio by accounting for both the market equilibrium and the subjective opinions of the investor. The model enables a more specialized and customized portfolio that is in line with the investor's objectives and risk tolerance by taking into account the investor's opinions. The implication is that the portfolio generated using BL model has a higher chance of fulfilling the demands and expectations of the investor. After implementing the BL model and generating the portfolio, we could conducted a back test analysis to evaluate its performance. The portfolio was compared to a standard market benchmark to assess its risk-adjusted returns and volatility. Additionally, this research examined the portfolio's reaction to shifts in the market as well as the effect of investor opinions on portfolio allocation.

Combining the LSTM RNN predictions with the Omega matrix from the BL model offers a novel approach to portfolio optimization, but it is not without limitations. One key limitation lies in the estimation of the Omega matrix. The Omega matrix, which represents the uncertainty in the LSTM predictions, is often constructed using the variance of prediction errors. However, accurately estimating these variances can be demanding, especially in volatile markets or when working with limited historical data. Misestimation of the Omega matrix could lead to overconfidence in the LSTM predictions, resulting in sub-optimal portfolio allocations. Another limitation is the inherent complexity of the combined model. Integrating LSTM RNN predictions into the Black-Litterman framework requires careful calibration and understanding of both models' mechanics. The complexity may make it difficult for practitioners without advanced technical expertise to implement and interpret the results correctly. Moreover, the LSTM model, being a data-driven approach, is highly dependent on the quality and quantity of the input data. Inaccurate forecasts resulting from inadequate or poor quality data can impact views and ultimately the performance of the portfolio. The computational demands of training LSTM models and running the Black-Litterman optimization are also non-trivial. These models require significant computational resources, particularly when working with sizable datasets or asset-rich portfolios. This can be a barrier for smaller institutions or individual investors with limited access to high-performance computing resources.

Despite these limitations, the combination of LSTM RNN predictions and the Omega matrix from the Black-Litterman model holds significant potential for future development. One promising area is the refinement of the Omega matrix estimation. Advanced methods could be explored to better capture the uncertainty in the LSTM predictions (e.g., Bayesian approaches or machine learning techniques), leading to more robust portfolio allocations. Another prospect lies in enhancing the interpretability of the combined model. A wider range of users may find the model more approachable if more natural ways to see and understand the relationships between the BL model outputs and the LSTM predictions were developed. Additionally, integrating alternative machine learning models with the Black-Litterman framework could be explored. Models like Transformers or reinforcement learning-based approaches might offer improvements in prediction accuracy and decision-making under uncertainty. Finally, as computational resources continue to advance, the practical barriers to implementing complex models like this one will diminish, making it more feasible for a wider range of practitioners. This could lead to broader adoption and further refinement of the model in real-world portfolio management scenarios, ultimately improving investment outcomes in a dynamic and uncertain financial environment.

4 CONCLUSIONS

To sum up, this study explores the integration of LSTM RNN predictions with the BL model to enhance portfolio optimization. Results demonstrate that incorporating LSTM RNN predictions into the BL model framework can mitigate biases and offer a more refined approach to asset allocation. While the LSTM model improves forecasting accuracy, it introduces biases that require careful calibration. The modified Black-Litterman model, combining machine and investor views, provides a more tailored portfolio allocation but demands significant computational resources and expertise. Future research could focus on refining the Omega matrix estimation and exploring alternative machine learning models to further improve robustness. This research advances the understanding of combining machine learning with traditional financial models, offering a novel approach to enhance portfolio management and decision-making in a dynamic market environment.

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