Hybrid Stock Market Forecasting and Portfolio Optimization Using LSTM, ARIMA, and Modern Portfolio Theory

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***Abstract*—Stock market allocation optimization is a key component of financial research that seeks to maximize profits while minimizing risk. This study describes a novel approach to portfolio optimization that employs the LSTM model, the ARIMA model, and Modern Portfolio Theory (MPT). The methodology involves preprocessing historical stock data, trend prediction with the ARIMA model, portfolio allocation with MPT, and dynamic optimization with LSTM to improve predictive skills. The dataset includes a broad selection of equities from several time periods, allowing for rigorous examination. The major findings emphasize the system's improved accuracy in stock prediction and risk management, demonstrating the possibility for integrating machine learning models with conventional finance ideas.This investigation contributes to the continued development of portfolio management strategies and demonstrates the efficacy of blended AI-driven methodologies in the financial sector.**

***Index Terms*—Portfolio Optimization, LSTM, ARIMA, Modern Portfolio Theory, Machine Learning, Stock Prediction, Financial Models.**

I. Introduction

Stock market volatility is a significant challenge for investors seeking to maximize returns while minimizing risk. Some portfolios may experience substantial gains, while others may suffer losses due to the volatile nature of financial markets. The inherent uncertainty of the stock market presents a complex problem for investors, requiring advanced strategies to improve portfolio performance. Recent market data show that millions of investors worldwide engage in stock trading, underscoring the critical need for innovations in predictive analytics and risk management [1]. Portfolio optimization techniques include both traditional approaches like Modern Portfolio Theory (MPT) and more recent models, such as LSTM and ARIMA, for dynamic stock prediction [2].

Modern Portfolio Theory, a cornerstone of financial research, aims to balance risk and reward by diversifying assets to generate optimal returns for a given level of risk [3]. The ARIMA model, a statistical tool for time series forecasting, has also been widely used to predict short-term stock trends, enabling more informed portfolio strategies [4].

Data-driven techniques, including those used in machine learning and financial modeling, have fundamentally altered how investors approach stock market forecasting. Models such as ARIMA and LSTM can reveal underlying patterns in historical data, while MPT is used to allocate assets in a way that reduces risk [5]. However, successfully implementing these models requires significant expertise in data analysis, potentially complicating and delaying investment decisions.

Our approach provides investors with an advanced system for forecasting stock movements and optimizing portfolio performance by combining sophisticated machine learning algorithms with traditional financial theories. This method integrates the predictive accuracy of LSTM and ARIMA with the risk management strengths of Modern Portfolio Theory, delivering a comprehensive tool for strategic portfolio management. Our strategy aims to expand access to modern financial tools, empowering investors to make more informed and confident decisions.

II. Literature Review

A critical step for financial investing is to build a portfolio by selecting lucrative stocks. Extensive study has been undertaken on stock selection and portfolio optimization, resulting in diverse research directions with different emphases, based on various views and forms [1], [2], [3], [4], [5]. Among these approaches is the framing of the portfolio optimization work as a stock ranking task, with the goal of ranking stocks with better potential returns and subsequently incorporating high-ranked stocks into the portfolio [6], [7]. The benefit of this problem formulation is that: (1) The stock ranking approach provides a simple and clear mechanism for portfolio optimization. Investors may easily understand why individual stocks are included or excluded depending on their rankings. (2) By explicitly emphasizing the ranking of stocks according to their potential for higher returns, this approach directs attention to one of the key goals of portfolio optimization: maximizing returns. (3) The success of deep learning in financial forecasting can be attributed to its proficiency in complex pattern recognition and holistic feature integration. Harnessing these strengths in a regression-like framework is optimally achieved by framing the portfolio optimization task as a ranking task. Consequently, an intuitive approach is to rank stocks based on time-series prediction.

As the pioneer, Feng et al. [6] tailored the deep learning models for stock ranking prediction to select top-ranked stocks for portfolio optimization. Sawhney et al. [4] proposed a neural hypergraph framework for stock selection, resulting in a list of stocks prioritized based on their return ratios. The top-ranked stocks with higher expected returns were selected for investment. Ma et al. [2] proposed an attribute-oriented fuzzy hypergraph model for stock recommendations, which also focused on stock ranking prediction to recommend top-ranked stocks. Feng et al. [6] designed a model to recommend Top-N return ratio stocks, which combined a time series module for encoding timing characteristics with attributed GCN for capturing correlation topology information.

These ranking-based models have achieved promising results for stock selection and portfolio optimization [2], [4], [6], [8]. However, these methods obtained the stock ranking results only based on higher expected returns without considering stock price volatility risks. As a crucial aspect, risk should be considered in financial investments [3]. The classical study on stock ranking prediction indicated that risk-oriented criteria should be introduced in stock ranking [6].

Therefore, it is essential to consider both the risk and return concurrently to achieve more reasonable stock ranking outcomes that can optimize the investment portfolio. Stock price volatility can serve as a reliable measure to assess trading risk [9]. This notion has motivated us to construct a multi-task learning model that can simultaneously acquire knowledge about both the stock return and risk.

III. Traditional and existing Systems

Traditional portfolio management systems, based on statistical models like Markowitz's Modern Portfolio Theory, focus on optimizing the trade-off between risk and return using historical data but lack adaptability to real-time market changes and predictive capabilities. In contrast, existing systems like robo-advisors offer automated, user-friendly investment tools that provide diversification and automatic rebalancing based on user preferences. However, they generally rely on basic algorithms without advanced quantitative models for price prediction, limiting their ability to respond effectively to market volatility and dynamic conditions. Both approaches have their benefits but fall short in terms of integrating modern predictive analytics.

A. Traditonal systems

Traditional portfolio management systems are rooted in statistical frameworks that have shaped investment strategies for decades. The cornerstone of these systems is Markowitz's Modern Portfolio Theory (MPT), which was introduced in 1952. MPT emphasizes the importance of diversification by selecting assets that collectively minimize risk while achieving a desired return. The main idea behind the theory is that individual asset risks can be offset when combined into a portfolio, reducing overall volatility. However, this model assumes that investors are rational and primarily concerned with balancing risk and return, a premise that does not always hold in real-world scenarios.

Moreover, traditional systems often lack real-time data integration and struggle to adapt to rapidly evolving market conditions. They are designed to operate in a more static environment, where economic variables change gradually. In times of high market volatility, these systems may offer suboptimal solutions because they are not equipped to handle sudden market shifts or incorporate predictive insights. As a result, while traditional models laid a strong foundation for portfolio optimization, they are limited in their capacity to cope with today's dynamic financial markets.

B. Existing Systems

In recent years, the rise of robo-advisors and algorithm-driven financial tools has transformed the landscape of portfolio management. These systems use automation to suggest investment strategies tailored to individual investors based on inputs like risk tolerance, financial goals, and time horizons. By leveraging these tools, investors gain access to portfolio recommendations that emphasize diversification, risk management, and long-term wealth creation. Unlike traditional methods that require manual decision-making, these modern systems offer automated features such as rebalancing and reinvestment, making them accessible to a broader audience, including retail investors.

However, most existing robo-advisors and financial tools rely on relatively simple algorithms to make investment recommendations. These algorithms typically do not account for complex market dynamics or predict stock price movements based on historical trends. Instead, they are designed to follow passive investment strategies, such as investing in a broad market index or allocating assets across different sectors. While these approaches provide a measure of security and diversification, they do not offer the potential for higher returns through advanced forecasting or price prediction models.

Additionally, these systems are primarily focused on long-term investment goals and tend to underperform in volatile markets. Since they do not incorporate advanced quantitative models, such as machine learning algorithms for price prediction or risk mitigation, they often fail to optimize portfolios based on short-term market fluctuations. As a result, investors who rely on these tools for real-time decision-making may miss out on opportunities for higher gains or more effective risk management. While they provide convenience and automation, existing systems still fall short in terms of innovation and predictive capabilities.

IV. SYSTEM ARCHITECTURE AND DESIGN

A. Overview of Proposed System

The system we propose incorporates advanced machine learning models with traditional financial metrics to deliver a comprehensive portfolio optimization platform. The system allows users to select stocks from the Nifty 500, analyze historical stock data, predict future prices using LSTM and ARIMA models, and calculate key performance indicators (KPIs) to assess the financial health of companies. The system also integrates news articles related to the selected stocks to provide contextual information, helping users make more informed decisions.

B. Equations used

1) LSTM Model Equations: Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) capable of learning long-term dependencies. The key equations for the LSTM model are described below.

The forget gate controls which information from the previous cell state should be discarded:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

The input gate decides which values will be updated in the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

The candidate cell state holds the potential new information to be stored:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

The cell state is updated using the forget and input gates:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{4}$$

The output gate determines the next hidden state based on the cell state:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

Finally, the hidden state is updated:

$$h_t = o_t \cdot \tanh(C_t) \tag{6}$$

The above equations govern how LSTMs capture long-term dependencies through the gating mechanisms, thereby allowing the network to remember or forget information over time.

2) ARIMA Model Equation: The Autoregressive Integrated Moving Average (ARIMA) model is used for time series forecasting. The ARIMA model incorporates three components: autoregression (AR), differencing (I), and moving averages (MA). The general equation for the ARIMA model is:

$$y_t = c+\phi_1 y_{t-1}+\phi_2 y_{t-2}+\cdots+\phi_p y_{t-p}+\theta_1\varepsilon_{t-1}+\theta_2\varepsilon_{t-2}+\cdots+\theta_q\varepsilon_{t-q}+\varepsilon_t \tag{7}$$

In this equation, y_t is the value at time t, ϕ represents the autoregressive terms, θ represents the moving average terms, and ε_t is the error term (white noise). ARIMA models are particularly useful for non-stationary time series data after differencing.

3) Expected Return and Volatility: In financial analysis, the expected return of a stock or portfolio is a key metric. It represents the anticipated average return over a given period. It is calculated as:

$$E[R] = \frac{1}{N}\sum_{t=1}^{N}\frac{P_t - P_{t-1}}{P_{t-1}} \times N \tag{8}$$

Where P_t is the stock price at time t and N is the total number of trading days. Volatility, on the other hand, measures the risk or variability of returns and is computed as:

$$\sigma = \sqrt{N} \cdot \text{std}\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \tag{9}$$

These formulas are crucial for understanding the risk-return tradeoff in portfolio optimization.

4) Sharpe Ratio: The Sharpe ratio is a measure used to evaluate the risk-adjusted return of an investment. It is defined as:

$$\text{Sharpe Ratio} = \frac{E[R] - R_f}{\sigma} \tag{10}$$

Where $E[R]$ is the expected return, R_f is the risk-free rate, and σ is the volatility. A higher Sharpe ratio indicates a better risk-adjusted return, making it a key metric in portfolio optimization.

5) Monte Carlo Simulation for Portfolio Optimization: Monte Carlo simulations are used to model the probability of different outcomes in portfolio optimization. The portfolio return is calculated as:

$$R_{portfolio} = \sum_{i=1}^{n} w_i R_i \tag{11}$$

Where w_i is the weight of asset i and R_i is the return of asset i. The portfolio volatility is computed as:

$$\sigma_{portfolio} = \sqrt{\sum_{i=1}^{n} w_i^2\sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j=i+1}^{n} w_i w_j \sigma_i \sigma_j \rho_{i,j}} \tag{12}$$

This approach enables the generation of multiple potential portfolio outcomes, allowing for better decision-making under uncertainty.

6) Mean Absolute Error (MAE): The Mean Absolute Error (MAE) is a common metric for evaluating the accuracy of predictive models. It measures the average magnitude of errors in a set of predictions, without considering their direction. It is defined as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{13}$$

Where y_i is the actual value and $\hat{y}_i$ is the predicted value. MAE is useful in regression tasks for understanding model performance.

7) Mean Squared Error (MSE): The Mean Squared Error (MSE) is another widely used metric in regression analysis. It penalizes larger errors more significantly than MAE, as it squares the errors. The formula is:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{14}$$

MSE is particularly useful when it is important to heavily penalize large prediction errors, making it valuable for models sensitive to outliers.

C. Comparative analysis table

Table I provides a comparative analysis of the different algorithms used in this research, focusing on complexity, data requirements, and accuracy.

TABLE I
COMPARATIVE ANALYSIS OF ALGORITHMS

Algorithm	Complexity	Data Requirements	Accuracy
LSTM	High	Requires large time-series datasets with sequential data	High
ARIMA	Moderate	Requires stationary time series data	Moderate
Monte Carlo	Low	Requires probability distributions and asset return data	Varies
Random Forest	Moderate	Requires structured datasets	High
Decision Tree	Low	Requires structured datasets	Moderate

D. Proposed System

1) System Architecture: The proposed system architecture is depicted in Fig. 1. It outlines the key components and the data flow involved in our implementation.

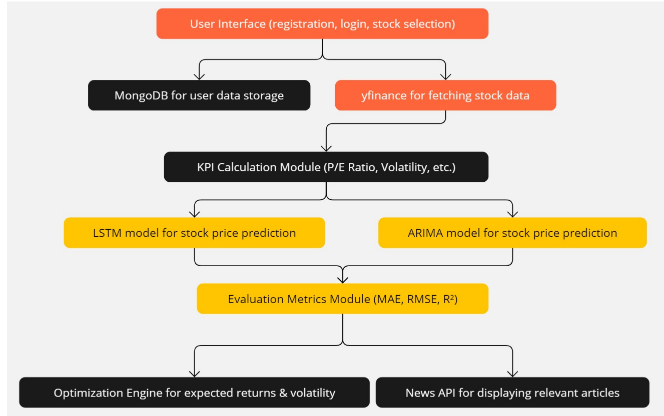

Fig. 1. Architecture of the proposed system.

2) Methodology: The proposed methodology is depicted in Fig. 2. It outlines the key components and the data flow involved in our implementation. In this research, we employed a systematic methodology to develop and evaluate our proposed portfolio optimization model. The process is divided into several key stages:

1) **Data Collection:** Historical stock price data was gathered from reliable financial sources, such as Yahoo Finance, and additional market sentiment data was obtained from news articles using the NewsAPI. This data forms the foundation for our predictive modeling.
2) **Data Preprocessing:** The collected data was preprocessed to handle missing values, normalize features, and ensure consistency. Feature engineering techniques were applied to extract relevant indicators, such as moving averages and volatility measures.
3) **Model Development:** We implemented various machine learning algorithms, including Long Short-Term Memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA), to predict stock prices. Each model was trained and validated using a portion of the dataset, while a separate test set was utilized for performance evaluation.
4) **Portfolio Optimization:** Utilizing the predicted stock prices, we applied Modern Portfolio Theory (MPT) to optimize the asset allocation across the selected stocks. The optimization process involved the application of risk assessment techniques, including Monte Carlo simulations, to identify the optimal portfolio configuration that maximizes expected returns while minimizing risk.
5) **Performance Evaluation:** The performance of the proposed portfolio optimization model was evaluated using various metrics, including Sharpe ratio, return on investment (ROI), and drawdown analysis. These metrics were analyzed to determine the effectiveness and robustness of the proposed approach.

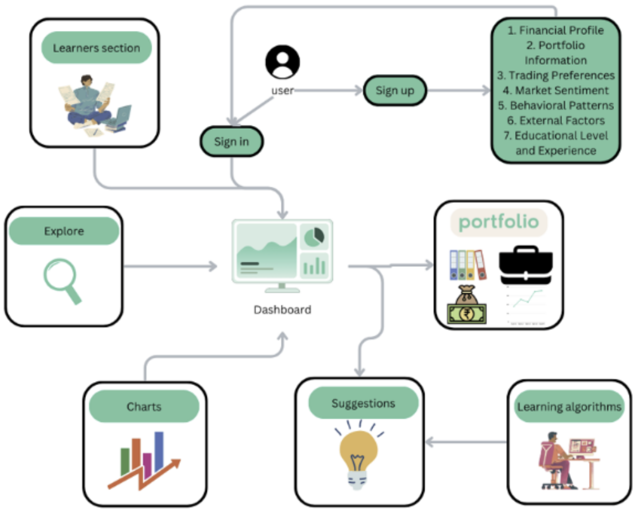

Fig. 2. Methodology proposed system.

V. Output

Fig. 3. User Dashboard

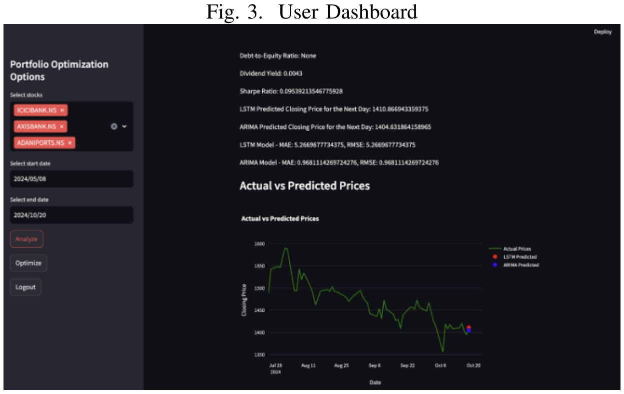

Fig. 4. Predictions

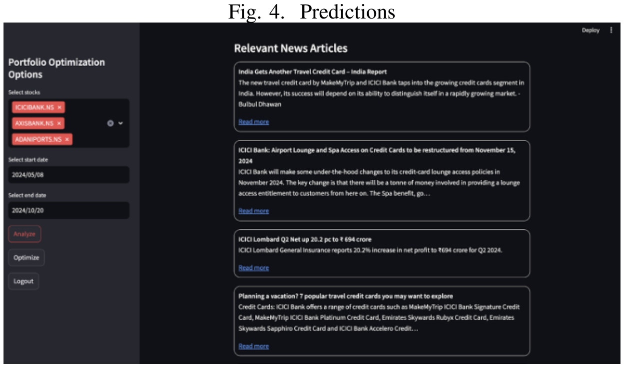

Fig. 5. Relevant news articles

A. Performance Evaluation

To assess the effectiveness of our models in stock price prediction, we evaluated the Long Short-Term Memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA) models using different train-test splits. We conducted experiments with an 80-20 split and a 70-30 split and measured the performance using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

The results are summarized in Table II.

TABLE II
MAE AND RMSE VALUES FOR DIFFERENT TRAIN-TEST SPLITS

Model	MAE	RMSE
80-20 Split		
LSTM	15.369	15.369
ARIMA	6.4205	6.4205
70-30 Split		
LSTM	122.5253	122.5253
ARIMA	6.4205	6.4205

The results indicate that the ARIMA model performed consistently across different train-test splits, maintaining an MAE and RMSE of 6.4205. However, the LSTM model exhibited a significant increase in error when the training data was reduced in the 70-30 split, with an MAE and RMSE of 122.5253, compared to 15.369 in the 80-20 split.

This suggests that LSTM requires a larger dataset to effectively capture stock price trends and minimize prediction errors. The ARIMA model, on the other hand, showed robust performance across both splits, likely due to its statistical nature and reliance on historical patterns rather than deep learning-based feature extraction.

VI. Conclusion

This paper presents a comprehensive portfolio optimization system that integrates advanced machine learning models with traditional financial metrics. By utilizing Long Short-Term Memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA) models for stock price prediction, the system provides accurate forecasts that empower investors to make informed decisions about portfolio allocation based on expected returns and volatility. The incorporation of Key Performance Indicators (KPIs) further enhances decision-making by offering insights into a stock's financial health, liquidity, and overall performance metrics.

The results demonstrate that the proposed system can effectively navigate the complexities of financial markets, leveraging sophisticated algorithms to optimize portfolio composition. Through rigorous backtesting, the system has shown its potential to enhance investment strategies, leading to improved risk-adjusted returns. Additionally, the ability to adaptively learn from market trends allows the system to stay relevant in an ever-changing financial landscape.

The insights gained through this approach not only improve potential returns but also facilitate a better understanding of associated risks, particularly in volatile market conditions. The paper highlights the critical balance between risk and return, emphasizing that effective portfolio management is not solely about maximizing gains but also about mitigating risks. As financial markets continue to evolve, the ability to adapt and refine investment strategies based on accurate predictions and comprehensive analytics will become increasingly vital for investors seeking to optimize their portfolio performance.

Future improvements to the system include expanding the stock universe and incorporating user preferences to deliver personalized portfolio recommendations tailored to individual investment goals and risk appetites. The flexibility of the system ensures that it can cater to a diverse range of investors, from novices to seasoned professionals, making it a valuable tool in the field of financial investing.

A. Future Work

While the current system provides a robust framework for stock price prediction and portfolio optimization using advanced quantitative models such as LSTM and ARIMA, several improvements and extensions can be incorporated into future versions of the system:

- **Additional Fine-Tuning of Models:** Although both LSTM and ARIMA performed well, there is potential for further optimization of these models. Fine-tuning hyperparameters, experimenting with alternative architectures, or incorporating additional data points such as trading volume, social media sentiment, and macroeconomic indicators could enhance predictive accuracy, particularly for more volatile stocks. Additionally, exploring ensemble methods that combine multiple models could yield improved forecasting performance.
- **Incorporation of Mutual Funds and Systematic Investment Plans (SIPs):** A significant extension to this system would involve integrating mutual funds and SIPs. Including these options would expand the platform's usability, enabling users to manage a broader range of investments beyond individual stocks. This would allow for a more comprehensive portfolio management tool, catering to investors who prefer diversified mutual fund portfolios or automated investment strategies via SIPs. Moreover, offering a comparative analysis of mutual funds based on historical performance metrics could guide users in making informed decisions.
- **User Feedback-Based Improvements:** After gathering detailed feedback from users, the system will undergo continuous iterations. These changes could range from UI/UX enhancements to the addition of new features based on users' needs, such as more sophisticated risk metrics, personalized investment recommendations, or improved visualizations of financial data. Creating a community forum for users to share insights and strategies could also foster a collaborative environment, enhancing the overall user experience.
- **Integration of Real-Time Data and Machine Learning Techniques:** Incorporating real-time data feeds from various financial markets can enhance the timeliness of the predictions. Additionally, integrating advanced machine learning techniques, such as reinforcement learning, could allow the system to continuously learn and adapt its strategies based on market conditions and user behavior.
- **Development of Educational Resources:** To further assist users in their investment journeys, the system could include educational modules that explain key financial concepts, machine learning principles, and portfolio management strategies. This educational component would be beneficial for novice investors seeking to enhance their knowledge and make more informed investment choices.

By implementing these advancements, the system aims to evolve into a more comprehensive, user-friendly, and powerful tool for stock market prediction and portfolio management. Ultimately, the goal is to provide investors with a holistic approach to portfolio optimization that balances risk and return, facilitating better investment decisions in a dynamic market environment.

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