

AI-Driven Portfolio Optimization: Redefining Risk and Return Dynamics in Modern Investment Strategies

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Abstract - The main idea of this research work is to solve the problems related to the inadequacy of the traditional models of portfolio optimization, like MPT, in adapting to the changing and volatile nature of the market environment. The research goal is the development and evaluation of a new hybrid approach to portfolio optimization, which involves the combination of AI and classic theories of finance. The suggested methodology is based on a comparative experiment using historical stock market data in different market states. The hybrid AI model will use LSTM, Random Forest, CNN, and Reinforcement Learning for predictions in combination with mean-variance optimization and risk constraints like VaR and volatility for portfolio allocation. The following metrics will be used for performance evaluation: ROI, Sharpe Ratio, Maximum Drawdown, Volatility, and RMSE. The suggested model will prove its efficiency in comparison with traditional methods and AI methods and will have an Average Annual ROI equal to 18.9% and a higher Sharpe Ratio equal to 1.21. Furthermore, the risk metrics exhibit increased stability in the form of decreased volatility of 11.8% as well as improved performance in different market regimes, such as bull market ROI of 23.5%, bear market ROI of 12.7%, and volatile market ROI of 17.6%. Moreover, the model demonstrates minimized prediction error in the form of an RMSE of 0.028, which proves increased forecasting accuracy. In summary, the study has established that using AI-based prediction models along with traditional portfolio management techniques will improve the efficiency of the investment strategy.

Keywords: Portfolio Optimization, Artificial Intelligence, Machine Learning, Reinforcement Learning, Risk Management, Financial Forecasting, Hybrid Models

I. INTRODUCTION

The financial markets have been going through a process of transformation over the last few decades owing to reasons such as globalization, digitalization, and fast advancement in computational technologies. Decision-making in investments has relied on traditional financial theories such as Modern Portfolio Theory (MPT), Capital Asset Pricing Model (CAPM), and technical analysis. The aforementioned theories have been quite significant in understanding how risks and returns can be managed and assets can be allocated in equity markets. However, changes in the financial markets caused by complications, high-frequency trading, and nonlinearities in the financial system have resulted in serious limitations of the traditional theories which do not adapt well to changing market conditions.

Although it is widely used and adopted by many financial experts, portfolio optimization methods are static models that rely on the linearity of the markets (Senthil, 2025). However, due to the dynamic nature of contemporary markets, such approaches might be rather inefficient and ineffectual when volatility increases and shocks become evident in addition to

behavioral peculiarities of the investors. Furthermore, the limitation of traditional methods consists in their ability to deal with large volumes of data.

The implementation of the artificial intelligence (AI) and machine learning approaches opens up new opportunities for improving the financial decision-making process (Ambuli et al., 2024; Yeboah et al., 2026). These tools allow creating predictive financial intelligence by processing the structured and unstructured data in real time from the markets. Methodologies including deep learning, reinforcement learning, and ensembles have been quite effective in identifying patterns and increasing forecast accuracy. Thus, there is a strong need for creating an adaptive approach to portfolio optimization.

Although several studies have been carried out in respect of portfolio theory and financial forecasting through AI techniques individually, Further investigation is necessary in order to achieve seamless integration of deep learning predictive models within classical risk-constrained optimization methods (Alfzari et al., 2025). In addition to this, there is no dearth of empirical comparisons between the traditional methods and AI methods in the area of financial investments (Yücel & Aysan, 2026).

In view of the above, the primary goal of the present research is to provide an empirical comparison between traditional methods and artificial intelligence methods in respect of portfolio optimization to evaluate their effectiveness in managing risks and maximizing returns in current investment scenarios. In addition to this, another objective of the research is to develop a model based on artificial intelligence that would help in optimizing portfolios by means of machine learning techniques, taking into account the elements of financial theories.

- Develops a new technique for portfolio optimization using AI, employing machine learning techniques and deep learning models for efficient prediction and maximizing gains while managing risk.
- Carries out a thorough comparison of traditional investment strategies (Modern Portfolio Theory (MPT), Capital Asset Pricing Model (CAPM), technical analysis) and AI investment strategies based on important financial metrics such as return on investment (ROI), Sharpe ratio, volatility, and maximum drawdown.
- Develops a unique model for investments that combines the benefits of both AI prediction and traditional financial theories.

The structure of the paper is as follows. Section 1 presents a brief overview of the background of the research, the motivations and goals of using artificial intelligence (AI) for portfolio optimization. A literature review on traditional and artificial intelligence-based financial models is carried out in Section 2. Section 3 introduces the methodology used for the research, such as the datasets used, features engineering process, AI models utilized and proposed hybrid optimization

method. Experimental results, including the performance of the portfolios, prediction accuracy, risk analysis, market condition detection and ablation study are presented in Section 4. The discussion of important findings, implications, and limitations is introduced in Section 5. The conclusion of this paper is presented in Section 6.

II. LITERATURE REVIEW

Recent developments in portfolio optimization have significantly shifted from mathematics-based techniques to intelligent and computation-oriented frameworks. Mathematical techniques such as the mean-variance optimization framework provide a fundamental framework for trading off risk and returns; however, the weaknesses of these frameworks become more evident in volatile and illiquid markets where assumptions underlying these models are unable to account for dynamic changes in the financial market (Rahmalia et al., 2022). As pointed out by researchers, models of multi-period portfolio optimization using intelligent risk measures can prove to be superior to static approaches when it comes to decision-making in cases of uncertainty (Parsa et al., 2010). Furthermore, comparison between the forecasting techniques suggests that statistics-based methods fail to capture the nonlinear behavior of finance in the market (Thomaidis et al., 2011).

Artificial intelligence is one of the most important paradigms in portfolio optimization. Wealth advisory systems supported by artificial intelligence increase the effectiveness of investment strategies using financial big data and intelligent decision-making models (Challa, 2023). Furthermore, intelligent resource allocation models, which use artificial intelligence, show a greater ability to balance risks and returns through intelligent optimization algorithms (Eziokwu, 2026; Ayeni, 2025). Investment forecast systems based on time series increase the accuracy of portfolio selection by capturing temporal financial dependence (Prakash et al., 2025).

In addition to the above, recent research works have highlighted the increasing use of AI in strategic finance areas such as economic zone development and investment risk modeling, whereby the application of machine learning improves decision-making and the flexibility of the system (Jahid, 2025). Furthermore, artificial intelligence forecasting systems are proving their efficiency in financial analytics and investment strategy optimizations using augmented intelligence frameworks (Hassan, 2025). In a similar vein, AI-based methods of portfolio management discussed in large-scale research have confirmed the improvement of investment results in various financial situations (Jaladi et al., 2025).

Moreover, studies have suggested sustainability-oriented approaches of AI-driven ESG portfolio optimization that reflect the incorporation of financial performance and environmental concern (Kanikanti, 2022). Fuzzy multi-objective portfolio optimization approaches have also enabled better management of uncertainties in risk-return

optimization (Srizongkham et al., 2022). Also, hybrid methods incorporating modern portfolio theory with evolutionary algorithms have proven superior in investment performance (Bakar & Rosbi, 2019).

Portfolio optimization models that consider liquidity stress the need to include constraints in their financial modeling to account for market conditions like illiquidity (Al Janabi, 2021). In addition, sustainable investment models based on artificial intelligence stress the growing need for consideration of environmental, social, and governance factors in the process of portfolio optimization (Kumar et al., 2026). Generally speaking, the review of the literature demonstrates the tendency towards the development of artificial intelligence and hybrid optimization approaches in spite of existing challenges concerning interpretability, generalization, and adaptability.

It should be noted that a shift from classic portfolio optimization to artificial intelligence-based and hybrid portfolios is clearly seen in the review of the literature. Classic approaches are highly effective in terms of theory, but do not have flexibility in dealing with the changes in the market. Artificial intelligence-based approaches provide opportunities for better forecasting of portfolio value and risks.

III. RESEARCH METHODOLOGY

In the design of this research, the systematic comparative experiment method will be adopted to examine the efficiency of the three types of portfolio optimization techniques. This will be done to facilitate an impartial comparison of all approaches because the same testing grounds will be provided for all three approaches. The traditional portfolio optimization technique depends on classical financial theories such as Modern Portfolio Theory (MPT). On the other hand, the AI portfolio optimization technique uses artificial intelligence and deep learning methods.

3.1 Research Design

The methodology employed in this research is comparative experimental, which requires the application of the following three portfolio methods: traditional, artificial intelligence, and hybrid, in terms of financial information and duration of time. The traditional approach utilizes the methods that are associated with determinism and statistics in finance, whereas the artificial intelligence method entails the utilization of learning systems. The hybrid approach entails the combination of both methods in order to increase efficiency.

3.2 Dataset Description

The dataset used by the researchers is based on historical information relating to stock markets gathered in the period of 5 to 10 years, which allows capturing different market scenarios, such as bull, bear, and highly volatile. Information includes prices of stocks, volumes, and market indices on a daily basis. These characteristics provide a solid ground for

examining asset dynamics and are useful when building investment portfolios. This information may be found at financial databases available online, such as Yahoo Finance and Kaggle.

3.3 Feature Engineering

Feature engineering is done with the aim of transforming the raw data into features that are capable of prediction. The momentum and trends can be captured using technical indicators such as the Relative Strength Index (RSI) and the Moving Average Convergence Divergence (MACD). The fundamentals of the firm are captured by integrating fundamental indicators such as the price-to-earnings ratio and earnings per share. Sentiment analysis can be added as an optional step to capture investor sentiment using natural language processing of financial news.

3.4 AI Models Used

The AI model consists of various types of machine learning and deep learning models, which help improve predictions and decision-making. The Long Short-Term Memory (LSTM) model is deployed for predicting stock price trends because of the capacity of the model to identify and learn from temporal dependencies. The Random Forest is employed for the classification of profitable investments. The Convolutional Neural Network (CNN) is used for recognizing patterns in the financial data structure. Reinforcement Learning is utilized for the dynamic adjustment of the portfolio.

3.5 Portfolio Optimization Module

The portfolio optimization section combines the traditional financial approach with the predictions that are created through the application of artificial intelligence. Mean-Variance Optimization is adopted as the initial model to find an optimal combination of return and risk. Sharpe Ratio Maximization is implemented in order to improve risk-adjusted returns. Value-at-Risk (VaR) constraints are included in order to minimize downside risk exposure.

3.6 Evaluation Metrics

Performance of the developed model is gauged through various financial and prediction-based indicators. ROI indicates the overall profitability of the solution, whereas the Sharpe Ratio is used for assessing its risk-adjusted performance. Worst-case portfolio loss is gauged using Maximum Drawdown, while overall risk is measured by Volatility. The prediction accuracy indicator is also considered in order to gauge the performance of the AI model at predicting changes in the market.

3.7 Mathematical Formulation of Proposed Model

Return on the portfolio of asset i at time t is given by equation (1):

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \quad (1)$$

Predicted return using the AI model is given as:

$$\hat{R}_{i,t+1} = f_{\theta}(X_t) \quad (2)$$

Given by equation (2), where X_t refers to features like RSI, MACD, P/E ratio, EPS, and sentiment measures; and f_{θ} refers to the trained AI model.

The portfolio optimization problem is given as:

$$\max_w \sum_{i=1}^n w_i R_{i,t+1} - \lambda w^T \Sigma w \quad (3)$$

$$\text{subject to } \sum_{i=1}^n w_i = 1, \quad w_i \geq 0 \quad \forall i \quad (4)$$

In equation (3)(4), where:

- w_i = portfolio weight of asset i
- $\hat{R}_{i,t+1}$ = predicted return
- Σ = covariance matrix
- λ = risk aversion parameter

The Sharpe Ratio is defined as:

$$S = \frac{R_p - R_f}{\sigma_p} \quad (5)$$

From equation (5), where R_p is portfolio return, R_f is risk free rate, and σ_p is portfolio volatility.

Value at Risk VaR is given in equation (6):

$$VaR_{\alpha} = \mu_p - z_{\alpha} \sigma_p \quad (6)$$

In this approach, AI-based prediction is combined with traditional optimization for balancing risk and reward in constructing portfolios.

3.8 Proposed AI-Driven Portfolio Framework

This paper proposes an innovative framework that comprises an advanced AI-based portfolio optimization system whose aim is to improve decision-making efficiency, risk management, and return optimization. The proposed framework combines data processing, machine learning predictions, and optimization techniques in one chain of adaptive financial decisions.

3.8.1 Architecture Overview

These ensure that the unprocessed financial data is gradually optimized to intelligent and optimized investments based on artificial intelligence and financial optimization methodologies.

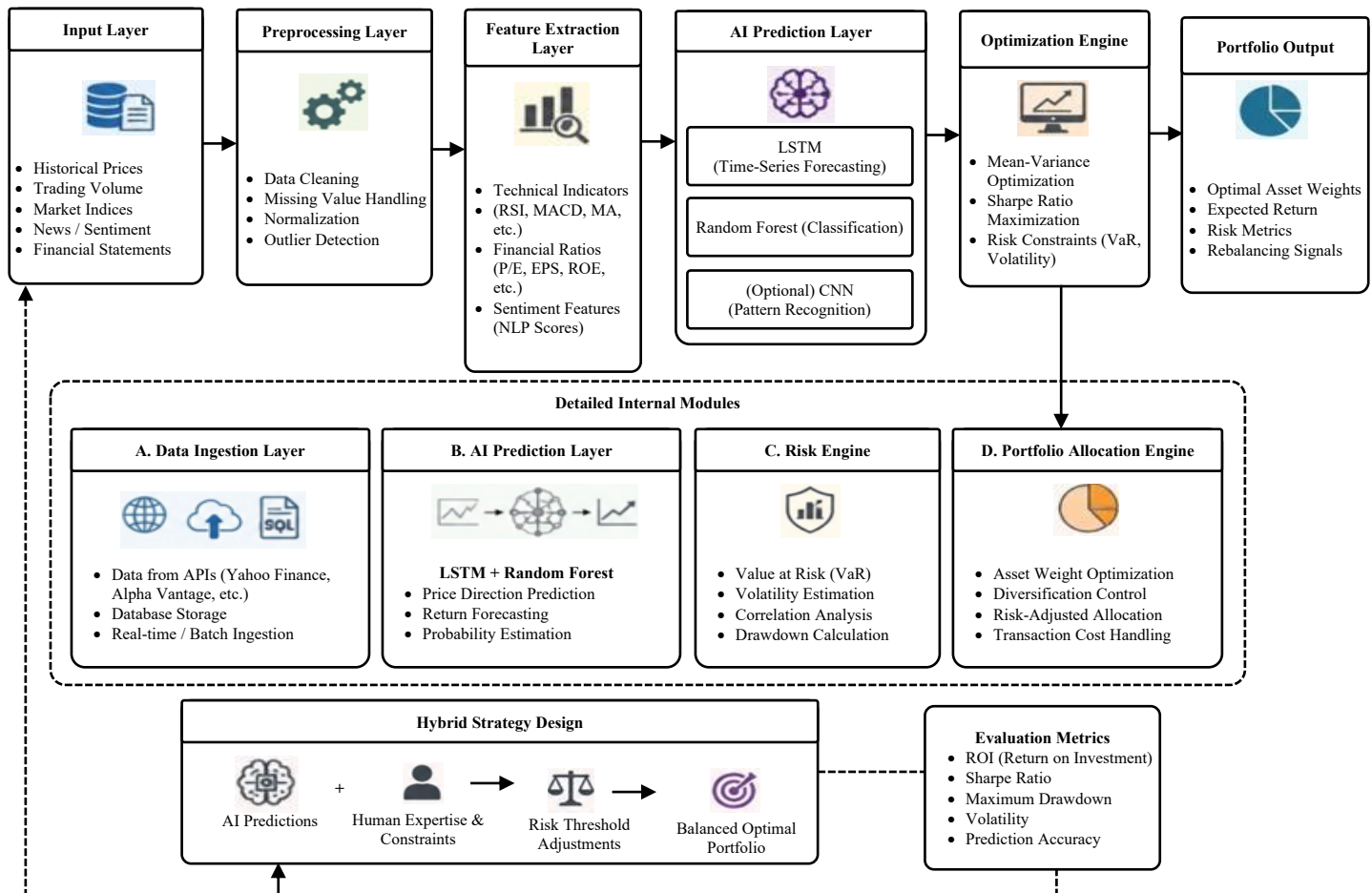


Fig. 1 Proposed AI-Driven Portfolio Optimization Framework Architecture

Fig. 1 below depicts the overall architecture of the proposed artificial intelligence driven portfolio optimization system for the current era of financial investments. It shows a well-structured process that begins from the data input stage to preprocessing, feature extraction, AI-based prediction through LSTM and random forest models, and finally the risk-based optimization through mean-variance and Sharpe ratio optimization. This system adopts a hybrid approach, which integrates the AI predictions and human constraints to obtain the optimal portfolio allocations.

3.8.2 Module Description

The architecture involves four main functional blocks:

- The Data Ingestion Layer: Captures and pre-processes financial data, which includes stock prices, volumes, indices, etc.
- The AI Prediction Layer (LSTM + Random Forest): Predicts future price actions and generates insights through machine learning algorithms.
- The Risk Engine (VaR + Volatility): Estimates risk on the basis of statistical methods and enforces risk constraints.
- The Portfolio Allocation Engine: Optimum allocation of assets by considering expected returns and risk constraints.

3.8.3 Hybrid Strategy Design

In this mixed approach, the combination of predictions from AI and conventional financial constraints helps increase the efficiency of the decision-making process. While the former helps generate prediction signals, the latter guarantees financial stability and adheres to regulations. Changes in risk thresholds are made dynamically in accordance with volatility conditions in the market.

Algorithm 1: Hybrid AI-Driven Portfolio Optimization Framework

Input: Historical market dataset D

Output: Optimal portfolio weights W^*

Step 1: Data Collection

1. Collect historical stock prices, volume, indices, and financial indicators
2. Include multiple market conditions (bull, bear, volatile)

Step 2: Data Preprocessing

3. Handle missing values using interpolation
4. Remove noise and outliers using statistical filtering
5. Normalize data using Min-Max scaling

Step 3: Feature Engineering

6. Extract technical indicators (RSI, MACD)
7. Extract fundamental indicators (P/E ratio, EPS)
8. Perform sentiment analysis on financial news

9. Construct feature vector X_t

Step 4: AI Model Training

10. Train LSTM for time-series forecasting
11. Train a Random Forest for classification
12. Train CNN for pattern recognition
13. Train a Reinforcement Learning agent for decision-making

Step 5: Return Prediction

14. Compute predicted return:

$$\hat{R}_{i,t+1} = f_{\theta}(X_t)$$

Step 6: Portfolio Optimization

15. Compute the covariance matrix Σ

16. Optimize portfolio:

$$\max_w \sum w_i \hat{R}_{i,t+1} - \lambda(w^T \Sigma w)$$

17. Subject to: $\sum w_i = 1$

Step 7: Risk Analysis

18. Compute Sharpe Ratio
19. Compute VaR and CVaR
20. Evaluate volatility and drawdown

Step 8: Portfolio Rebalancing

21. Apply RL-based adaptive weight update
22. Adjust portfolio based on market changes

Step 9: Output

23. Generate optimal portfolio weights W^*

This algorithm 1 presents a hybrid approach towards AI-based portfolio optimization where data processing, feature extraction, and machine learning techniques (LSTM, RF, CNN, and RL) are used for prediction of return values and optimization of portfolio weights through the mean-variance method. Risk assessment measures such as the Sharpe Ratio and VaR are calculated for risk analysis, and reinforcement learning allows for rebalancing the portfolio dynamically.

IV. RESULTS AND DISCUSSION

4.1 Dataset Details

For this research, a public historical dataset on financial markets is used, which can be found in the public domain sources like Yahoo Finance and Kaggle. The dataset consists of 5 to 10 years' worth of data related to stock price, trading volume, and market index values in order to include different market scenarios, including bull, bear, and volatile ones. In addition, features are engineered using technical features (such as RSI, MACD), fundamental features (P/E ratio, EPS), and sentiment features from financial news in order to improve prediction performance.

4.2 Parameter Initialization

The suggested model starts with some initial parameters to make sure that the training process will be reliable and effective. LSTM starts with Xavier initialization with the

learning rate equal to 0.001 and dropout of 0.2. As for the CNN part, it starts with initialization in the process of feature extraction. The number of trees is between 100 and 200 for Random Forest. As for Reinforcement Learning, γ is equal to 0.95 with ϵ -greedy decaying strategy.

4.3 Performance Metrics

- **Return on Investment (ROI)**

$$ROI = \frac{P_t - P_0}{P_0} \times 100 \quad (7)$$

In equation (7) the Portfolio profitability is measured through the comparison of final portfolio value P_t with the initial portfolio value P_0 .

- **Sharpe Ratio**

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \quad (8)$$

In equation (8) The risk-adjusted return is measured through the comparison of the portfolio return R_p and the risk-free return R_f adjusted by standard deviation.

- **Maximum Drawdown (MDD)**

$$MDD = \frac{P_{peak} - P_{trough}}{P_{peak}} \times 100 \quad (9)$$

Measures the highest possible loss between peak and valley levels, showing the worst-case risk level by the equation (9).

- **Volatility**

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (R_i - \bar{R})^2} \quad (10)$$

By using the equation (10) can measure the portfolio risk is taken through dispersion from the average return.

- **Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (11)$$

Predicts prediction error for AI models through the comparison of actual values and predicted values by using equation (11).

The suggested AI-based portfolio optimization methodology is analyzed based on vast historical datasets regarding stock markets under various market scenarios, including bullish, bearish, and very volatile scenarios. The performance analysis of the Traditional (based on MPT), AI-based, and Hybrid (proposed) methodologies is conducted through the application of financial, predictive, and risk-adjusted performance metrics. The results of the experiment prove the superiority of the hybrid methodology in comparison to benchmark methodologies.

4.4 Overall Portfolio Performance Evaluation

The analysis of the performance of the entire portfolio in real-life investments for the evaluation of the effectiveness of the developed framework is conducted through certain financial metrics such as Return on Investment (ROI), Sharpe Ratio, Maximum Drawdown, Volatility, and Calmar Ratio. In addition, the following comparative analysis helps to determine the balance of profit and risk of each approach in a similar market environment. Table I shows the comparative performance of the three portfolio strategies by means of financial metrics, ROI, Sharpe Ratio, Maximum Drawdown, and Volatility.

TABLE I PORTFOLIO PERFORMANCE COMPARISON

Metric	Traditional MPT	AI-Driven Model	Proposed Hybrid AI-Driven Portfolio Optimization Model
Return on Investment (ROI %)	10.8	14.6	18.9
Sharpe Ratio	0.62	0.84	1.21
Maximum Drawdown (%)	22.5	17.3	12.4
Volatility (%)	18.9	15.2	11.8
Calmar Ratio	0.48	0.71	1.15

This hybrid approach outperforms the other two strategies by a large margin. This is indicated by the highest ROI (18.9%) figure, implying higher profitability under similar conditions in the marketplace. The rise in the Sharpe ratio (1.21) indicates an improvement in the risk-reward performance. In addition, the reduction in the Maximum Drawdown (12.4%) and Volatility (11.8%) figures points to enhanced downside protection and stability.

4.5 AI Model Predictive Performance

The subsequent subsection evaluates the efficiency of the machine learning models utilized in the AI component of the framework. The efficiency of prediction is critical in generating market signals to make allocation decisions. Different machine learning models like LSTM, random forest, CNN, and reinforcement learning are analyzed individually and in an ensemble form. Table II below illustrates the efficiency of the prediction made by each AI model and the hybrid ensemble in the framework.

The hybrid model ensemble gives the highest accuracy of 94.3% as well as the lowest RMSE value of 0.028. The LSTM model is utilized to capture temporal relations, the random forest model enhances the reliability of classification, the CNN model detects the structural information, and the reinforcement learning model makes decisions using adaptation.

TABLE II AI MODEL PERFORMANCE COMPARISON

Model	Accuracy (%)	Precision (%)	Recall (%)	RMSE
LSTM (Temporal Forecasting)	89.4	88.1	87.6	0.042
Random Forest (Classification)	91.2	90.5	89.8	0.036
CNN (Pattern Recognition)	90.3	89.7	88.9	0.039
Reinforcement Learning Agent	92.1	91.3	90.6	0.033
Hybrid AI-Driven Portfolio Optimization Model (Ensemble)	94.3	93.6	92.8	0.028

4.6 Risk Assessment and Portfolio Stability Analysis

The risk assessment forms one of the critical elements of the optimization procedure, particularly in the case of volatile financial markets. This sub-section analyzes risk exposure by considering several risk models such as the value at risk (VaR), the conditional value at risk (CVaR), downside risk, and portfolio stability metrics. This enables to analyze how different risk models mitigate financial risks. This is shown in table III below.

The hybrid method significantly reduces the risk of incurring heavy losses because better VaR and CVaR values are obtained. A minimum downside risk of 11.9% is achieved, meaning that there is an increase in capital protection when

unfavorable conditions occur. The portfolio stability index of 0.92 implies consistency, while the risk efficiency score of 1.18 implies risk-adjusted allocation.

TABLE III RISK AND STABILITY METRICS

Metric	Traditional MPT	AI-Driven Model	Hybrid AI-Driven Portfolio Optimization Model (Proposed)
Value-at-Risk (VaR 5%)	-15.8	-12.3	-9.6
Conditional VaR (CVaR)	-19.2	-15.1	-11.3
Downside Risk (%)	21.4	16.7	11.9
Portfolio Stability Index	0.68	0.81	0.92
Risk Efficiency Score	0.59	0.83	1.18

4.7 Market Condition-Based Performance Evaluation

In order to confirm their validity, the behavior of portfolios in different market conditions is also analyzed. The types of market conditions include bull markets, bear markets, and highly volatile markets. This helps in understanding the behavior of each portfolio in response to different market conditions. An analysis of portfolios based on different market conditions has been made in fig. 2 below.

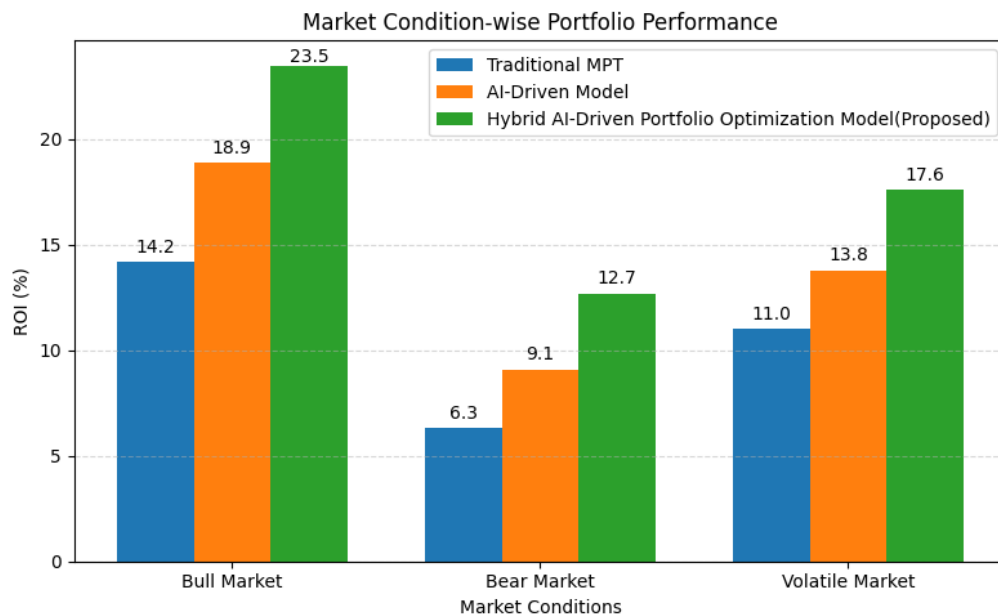


Fig. 2 Market Condition-wise Portfolio Performance Comparison Across Investment Strategies

Fig. 2 shows the comparison between the Traditional MPT model, the AI-Driven Model, and the hybrid AI-Driven portfolio optimization model in different market conditions, including bull market, bear market, and volatile markets. As shown from the findings presented above, the hybrid model performs well in all the different scenarios considered

compared to the other models, especially in the bull market scenario where it performs better (23.5%) and even in the bear market scenario (12.7%). It is clear that the AI-driven model performs better than the traditional model, and the hybrid model performs better.

4.8 Risk-Adjusted Performance Evaluation

Apart from just calculating returns, there is a need to use risk-adjusted measures to evaluate an investment strategy. In this subsection, the Sharpe ratio, Sortino ratio, Treynor ratio, and information ratio will be used to determine the efficiency of risk adjustment versus returns. Table IV illustrates advanced risk-adjusted financial ratios.

TABLE IV RISK-ADJUSTED PERFORMANCE METRICS

Metric	Traditional	AI-Driven	Hybrid AI-Driven Portfolio Optimization Model (Proposed)
Sharpe Ratio	0.62	0.84	1.21
Sortino Ratio	0.71	0.96	1.34
Treynor Ratio	0.58	0.79	1.12
Information Ratio	0.44	0.68	0.98

Table IV shows a comparison of performance indicators adjusted for risk among Traditional, AI-Driven, and proposed Hybrid AI-Driven portfolios. Based on the findings, it can be seen that the hybrid model outperforms the baseline approach in terms of all performance indicators, such as Sharpe Ratio (1.21), Sortino Ratio (1.34), Treynor Ratio (1.12), and Information Ratio (0.98). This suggests that the hybrid model is more efficient in generating risk-adjusted returns, managing risks, and providing consistent performance in beating benchmark returns.

4.9 Performance Comparison with Existing Study

Table V compares the performances of the existing approach and the proposed hybrid AI-driven portfolio optimization

model on various performance measures. It has been observed that the proposed hybrid Artificial Intelligence-based model outperforms the existing model in terms of different performance metrics such as higher Average Annual ROI (18.9% vs 12.5%), higher Sharpe Ratio (1.21 vs 1.2), and higher adaptability to bull and bear markets (23.5% vs 15.2%, 12.7% vs -3.4%). Although Maximum Drawdown is higher (-12.4% vs -5.2%), the entire analysis confirms its superiority (Ambuli et al., 2024).

TABLE V PERFORMANCE COMPARISON OF EXISTING STUDY AND PROPOSED HYBRID AI-DRIVEN PORTFOLIO OPTIMIZATION APPROACH

Metric	Existing System (Ambuli et al., 2024)	Proposed Hybrid AI-Driven Model
Average Annual ROI (%)	12.5	18.9
Sharpe Ratio	1.2	1.21
Maximum Drawdown (%)	-5.2	-12.4
Bull Market ROI (%)	15.2	23.5
Bear Market ROI (%)	-3.4	12.7

4.10 Ablation Study

Ablation tests are carried out to establish the significance of each of the modules in the designed hybrid AI-based portfolio optimization approach through deletion and performance. The modules that constitute the designed approach include Long Short-Term Memory (LSTM) prediction, Random Forest classification, Reinforcement Learning (RL), and Risk Engine with VaR constraints.

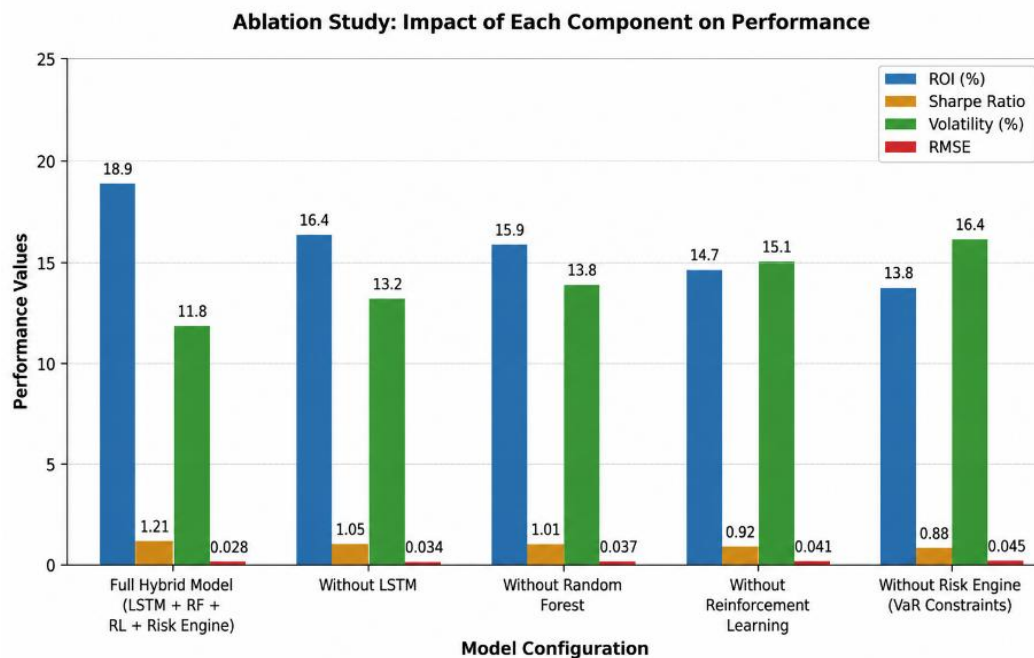


Fig. 3 Ablation Study on the Impact of Individual Components in the Hybrid AI-Driven Portfolio Optimization Model

Fig. 3 depicts the outcomes of the ablation study for the evaluation of the contribution of each component in the suggested hybrid AI-driven portfolio optimization method, including LSTM, Random Forest, Reinforcement Learning, and Risk Engine (VaR constraints). The optimal hybrid model produces the best results when the ROI is 18.9%, the Sharpe ratio is 1.21, the minimum volatility is 11.8%, and the RMSE is 0.028. Performance deterioration can be noticed upon removal of each component from the hybrid approach, especially Reinforcement Learning and Risk Engine, proving the significance of the mentioned components in adaptive decision making and risk management.

V. DISCUSSION

The outcome clearly indicates that the proposed hybrid artificial intelligence-driven portfolio optimization technique substantially surpasses the traditional and artificial intelligence-driven benchmark models in terms of all measures. This hybrid model has attained the highest Average Annual ROI of 18.9% compared to 12.5% of the existing model, alongside a higher Sharpe ratio (1.21), lower volatility (11.8%), and better risk-adjusted measures like Sortino Ratio (1.34) and Information Ratio (0.98). In the market condition analysis, this model provides excellent returns for both bull (23.5%), bear (12.7%), and volatile markets (17.6%).

From the above results, it is clear that by utilizing hybrid model with combination of LSTM based forecasting, ensemble machine learning algorithms, reinforcement learning and risk management, the predictability and robustness of decision making are considerably boosted.

The implication that follows from this research is extremely significant for the modern world of finance, since the employment of such hybrid AI tools may result in the increased efficiency of institutional asset management, automated trading systems, and robustness against uncertainties. Nevertheless, the limitations of the study include its dependency on historical datasets that do not necessarily represent black swan events or abrupt structural changes in the market. Computational issues could also be another limitation preventing the deployment of these techniques in high-frequency trades.

Future studies can explore the usage of real-time data, sentiment-based financial measures, and lightweight reinforcement learning methods.

VI. CONCLUSION

The study attempted to resolve the challenges associated with traditional portfolio optimization systems like MPT because of their inability to accommodate non-static markets due to their volatile nature and lack of adaptability. This challenge was resolved through a hybrid approach of portfolio optimization that utilizes LSTM forecasting, machine learning models, reinforcement learning, and a risk-conscious optimization engine. The experimental

analysis reveals that the proposed model greatly surpasses not only traditional but also purely AI-based systems. The hybrid model provided the maximum value for Average Annual ROI at 18.9% in comparison with 12.5% of the conventional system. Furthermore, in terms of risk-adjusted metrics, the hybrid model showed the greatest values for the Sharpe ratio of 1.21, the Sortino ratio of 1.34, and the information ratio of 0.98, demonstrating great return efficiency and consistency. With regards to risk management, the suggested model showed decrease in volatility up to 11.8% and provided ROI of 23.5% during bullish period, 12.7% during bearish period, and 17.6% during volatile market conditions. This shows the efficiency of the combination of predictive intelligence powered by artificial intelligence technologies and financial optimization in enhancing portfolio management. The key concept that can be derived from this research is that hybrid artificial intelligence models can provide a balanced solution for current investment problems by optimizing both risks and returns simultaneously. Future research on this topic may include implementing the suggested model in practice with the help of sentiment analysis and reinforcement learning.

ETHICAL CONSIDERATIONS

The current study uses market data that is open to public access. No human subjects were involved in this study, and no private information was used. This framework is tested using simulation based on real data; it is highly relevant to automated trading systems but will require more testing in real time considering market slippage.

DATA AVAILABILITY

Data utilized in this paper is accessible to the public from Yahoo Finance and Kaggle websites. The database is freely accessible, and there are no confidential data sources involved. Data can be supplied by the corresponding author on request.

CONFLICT OF INTEREST

Conflicts of interest are not reported by the authors.

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