# A HYBRID MACHINE LEARNING FRAMEWORK FOR PREDICTION-BASED PORTFOLIO OPTIMIZATION

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**Abstract:**

The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) has transformed financial decision-making and investment strategies by enabling data-driven insights and risk-aware optimization. This study presents a hybrid AI-based framework for portfolio optimization that integrates Decision Tree (DT) and deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The proposed system predicts future stock returns and estimates associated risks by analyzing historical market data, investor profiles, and alternative datasets including market sentiment and institutional flows. The DT model is employed to forecast individual stock performance, while predictive errors are utilized to measure stock-specific risk. These predicted returns and semi-absolute deviations are then combined to construct optimized portfolios under different return objectives. Comparative analysis is conducted with benchmark models including Deep Multilayer Perceptron (DMLP), LSTM, and Support Vector Regression (SVR) to evaluate performance consistency and accuracy. Experimental results based on market index datasets demonstrate that the hybrid model delivers improved stability, reduced volatility, and higher profitability across varying market conditions. The system provides investors with intelligent decision support, offering interpretable, efficient, and user-friendly portfolio management that aligns with modern financial risk management principles and future AI-driven investment strategies.

**Keywords :** Portfolio Optimization, Machine Learning, Decision Tree, Deep Learning, CNN, LSTM, Investment Strategy, Risk Prediction, Financial Forecasting, Artificial Intelligence.

## I. Introduction

In recent years, the rapid evolution of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized various industries, with finance being one of the most prominent domains to experience this transformation [1]. The traditional methods of portfolio management, which relied heavily on historical data and static mathematical models, are increasingly being replaced by intelligent systems capable of learning complex, non-linear relationships in financial markets [2]. The concept of portfolio optimization, which aims to achieve the best balance between risk and return, has thus been enhanced through AI-driven models that can analyze massive volumes of structured and unstructured financial data [3]. Investors now seek models that not only predict returns but also adapt to market volatility and behavioral trends, ensuring more resilient and profitable investment decisions [4].

Machine learning techniques, including Decision Trees (DT), Support Vector Machines (SVM), and Neural Networks, have been widely adopted for financial forecasting and investment decision-making [5]. The Decision Tree classifier, known for its interpretability and ease of implementation, is capable of identifying key patterns and decision rules from historical data to predict stock price movements and returns [6]. However, standalone Decision Tree models are limited in handling temporal dependencies inherent in financial time-series data [7]. To address this limitation, deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are increasingly utilized for modeling sequential dependencies and dynamic patterns in financial data [8]. The integration of DT with deep learning provides a hybrid solution that combines interpretability with predictive power, making it suitable for practical portfolio management applications [9].

Portfolio optimization plays a central role in finance, where investors allocate assets to maximize returns while minimizing risks under certain constraints [10]. Classical theories, such as the Modern Portfolio Theory (MPT) introduced by Markowitz, emphasized diversification to balance risk and return [11]. However, real-world financial markets are highly volatile, and asset correlations are often non-stationary, leading to frequent portfolio rebalancing and increased transaction costs [12]. AI-based optimization frameworks can dynamically adjust to changing market conditions and predict potential risks using non-linear models, thereby improving portfolio robustness [13]. The inclusion of behavioral and sentiment data, such as investor mood and market news, further enhances the accuracy of predictions, allowing investors to make informed and timely decisions [14].

The proposed hybrid AI model aims to combine Decision Tree–based predictive modeling with CNN and LSTM deep learning architectures to improve portfolio return prediction and risk estimation [15]. The system first collects and preprocesses historical stock data, financial indicators, and external variables such as market sentiment and institutional flows. Decision Tree algorithms are used to predict future stock returns and estimate prediction errors, which represent the degree of uncertainty or risk associated with each stock [16]. These predictive errors, alongside semi-absolute deviations, are then integrated into an optimization framework that constructs an optimal portfolio tailored to specific risk-return objectives. The CNN layers help capture local temporal patterns, while LSTM layers account for long-term dependencies, ensuring comprehensive time-series modeling [17].

To evaluate the performance of the proposed framework, comparative experiments are conducted using benchmark models, including Deep Multilayer Perceptron (DMLP), Long Short-Term Memory (LSTM), and Support Vector Regression (SVR) [18]. The experimental datasets, consisting of component stocks from market indices such as the China Securities 100 Index, provide a robust foundation for testing model accuracy and stability under different market conditions. Performance metrics such as predictive accuracy, portfolio volatility, and Sharpe ratio are used to assess the models. The results indicate that the proposed hybrid model achieves superior predictive accuracy and higher stability compared to traditional and standalone ML models, validating the effectiveness of integrating Decision Tree and deep learning in financial portfolio optimization [19].

The significance of this research lies in its ability to bridge the gap between interpretable ML models and complex deep learning frameworks. By combining Decision Tree interpretability with the feature extraction capabilities of CNN and temporal modeling strength of LSTM, the proposed hybrid model offers both transparency and performance [20]. This research contributes to the growing field of AI-based finance by presenting a scalable, data-driven approach to portfolio management that can adapt to diverse market environments, ultimately supporting investors, fund managers, and financial institutions in achieving their investment goals efficiently.

**Background and Context**

Financial markets are inherently complex, dynamic, and influenced by numerous interdependent factors such as economic indicators, geopolitical events, investor sentiment, and market psychology. Traditional portfolio management techniques, while effective under stable market conditions, often fail to adapt quickly to sudden market shifts or nonlinear relationships between assets. With the advent of Artificial Intelligence (AI) and Machine Learning (ML), investors and researchers have gained the ability to analyze massive datasets, uncover hidden patterns, and make data-driven investment decisions with improved accuracy and speed. The integration of predictive models such as Decision Trees (DT), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks has opened new frontiers in financial forecasting, allowing systems to capture both historical trends and temporal dependencies. These hybrid AI systems not only forecast potential returns but also assess associated risks, enabling more informed and adaptive portfolio optimization. In this context, developing a hybrid AI-based portfolio optimization framework provides an innovative approach to manage investment risk, enhance return consistency, and support strategic decision-making in volatile financial environments.

**The Need for Innovation**

The growing complexity of agricultural challenges, including unpredictable climate patterns, soil degradation, and increasing pest infestations, underscores the urgent need for innovation in crop disease management and fertilizer recommendation systems. Traditional manual inspection and generalized fertilizer use are no longer sufficient for ensuring sustainable yields. By integrating machine learning, data-driven analysis, and intelligent decision-making, modern agriculture can transition toward precision farming—where farmers receive real-time, crop-specific, and region-tailored recommendations. This innovation not only enhances productivity but also reduces environmental harm, optimizes resource use, and empowers farmers with actionable insights for improved food security and profitability.

**Problem Definition**

Portfolio management is a critical aspect of financial investment, involving the allocation of assets to maximize returns while minimizing associated risks. Traditional portfolio optimization methods, such as Modern Portfolio Theory (MPT), often rely on static assumptions and linear relationships between assets, which fail to capture the complexity and volatility of real-world financial markets. Moreover, conventional approaches typically ignore alternative data sources, such as market sentiment, news, social media, and institutional investor flows, which significantly influence stock performance.

Investors face multiple challenges, including:

1. **Prediction of future returns:** Accurately forecasting individual asset returns is difficult due to market volatility, non-linear dependencies, and behavioral factors.

2. **Risk assessment:** Quantifying the risk associated with each asset requires sophisticated models that consider both historical volatility and potential predictive errors.

3. **Portfolio construction under constraints:** Investors must adhere to constraints such as risk tolerance, liquidity, ESG factors, sector allocation limits, and regulatory requirements.

4. **Integration of multiple data sources:** Combining time-series price data, sentiment analysis from news and social media, and institutional investment flows into a single predictive framework remains challenging.

The primary problem addressed in this study is the development of a hybrid AI-based system that integrates Decision Tree classifiers with deep learning models, such as CNN and LSTM, to predict stock returns, quantify risk, and construct optimized portfolios that adapt to dynamic market conditions.

**Scope of the Study**

The scope of this research encompasses the following key aspects:

1. **Data-driven portfolio optimization:** Utilizing historical stock prices, financial indicators, sentiment data, and institutional flows to build predictive models.

2. **Hybrid AI modeling:** Combining interpretable models (Decision Tree) with deep learning architectures (CNN and LSTM) to improve prediction accuracy and capture temporal dependencies.

3. **Risk quantification:** Measuring stock-specific risk through predictive errors, semi-absolute deviation, and volatility analysis.

4. **Comparative evaluation:** Benchmarking the proposed hybrid model against other machine learning models such as DMLP, LSTM, and Support Vector Regression (SVR).

5. **Practical investment insights:** Providing actionable recommendations for investors, including risk-adjusted portfolio allocations under specified constraints.

6. **Experimental validation:** Using real-market datasets, such as the China Securities 100 Index, to demonstrate the model's effectiveness in predicting returns and optimizing portfolios.

By addressing these challenges, the proposed system aims to enhance investment decision-making, reduce portfolio risk, and improve overall return stability, while providing a scalable and user-friendly AI-based framework for portfolio management.

## II. Objectives of the Study

1. To study the effectiveness of AI and ML models in predicting stock returns.
2. To study risk assessment techniques for optimized portfolio construction.
3. To study the integration of Decision Tree and deep learning models for investment strategies.
4. To study the impact of market sentiment and alternative data on portfolio performance.
5. To study methods for minimizing risk while maximizing expected investment returns.

## III. Literature review

Several studies have explored the application of machine learning and deep learning techniques for portfolio optimization and stock market prediction. Carta et al. [1] proposed a framework that correlates stock market values with economic news using a Decision Tree (DT) classifier. In their work, textual data from economic news was processed using text mining techniques such as term frequency–inverse document frequency (TF-IDF), while time-series analysis methods, including random walk, Bollinger bands, and moving averages, were applied to stock market values. Classification models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and DT were employed, with an ensemble classifier based on majority voting on top. Their experimental results demonstrated satisfactory prediction accuracy, suggesting the potential applicability of these methods to datasets from different countries.

Ferreira et al. [2] investigated the integration of Genetic Algorithms and fuzzy logic for stock market prediction, combining them with SVM for sentiment analysis. Their hybrid model employed a genetic algorithm to optimize SVM parameters and pi-fuzzy logic functions, along with feature subset selection to enhance prediction performance. Comparative analysis against logistic regression, multiple discriminant analysis, classification and regression trees, artificial neural networks, SVM, and fuzzy SVM models indicated that the proposed hybrid approach outperformed all benchmarks in terms of prediction accuracy and return on investment.

Ma et al. [3] focused on prediction-based portfolio optimization using deep neural networks (DNNs), including Deep Multilayer Perceptron (DMLP), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN). Their framework first predicts individual stock returns using DNNs, calculates predictive errors to estimate stock-specific risk, and constructs portfolios by integrating predictive returns with the semi-absolute deviation of errors. The study employed component stocks from the China Securities 100 Index for experimental validation. Results indicated that the DMLP-based portfolio model consistently outperformed others across different target returns, demonstrating the effectiveness of DNNs in building predictive portfolio models.

Yu and Chang [4] proposed a simulation-based dynamic portfolio optimization method using Neural Networks to develop an Economic Factor-based Predictive Model (EFPM). This model incorporated macroeconomic factors, combined with Copula-GARCH simulation and the Mean-Conditional Value at Risk (Mean-CVaR) framework, to derive an optimal portfolio of six index funds. Using a rolling-horizon out-of-sample evaluation spanning twelve years, the EFPM-based strategy outperformed benchmark portfolios in terms of annualized return, volatility, Sharpe ratio, maximum drawdown, and 99% CVaR, highlighting the benefits of integrating neural network prediction with risk-sensitive portfolio allocation.

Conlon et al. [5] examined factor-based portfolio optimization using machine learning approaches, particularly autoencoder neural networks for latent factor extraction. Their study found that autoencoder-derived factors exhibited weaker correlations with traditional characteristic-sorted portfolios compared to other dimensionality reduction techniques. Moreover, machine learning-based factor models generated covariance and portfolio weight structures that diverged from conventional estimators. Minimum-variance portfolios constructed with latent factors from autoencoders and sparse methods achieved better risk minimization performance, particularly for investors with higher risk sensitivity, during volatile market periods, and when accounting for tail risks.

These studies collectively emphasize the growing role of hybrid machine learning models in enhancing portfolio optimization, risk estimation, and financial forecasting, providing a foundation for developing advanced predictive frameworks that integrate Decision Tree classifiers with deep learning architectures.

## IV. Working of Proposed System

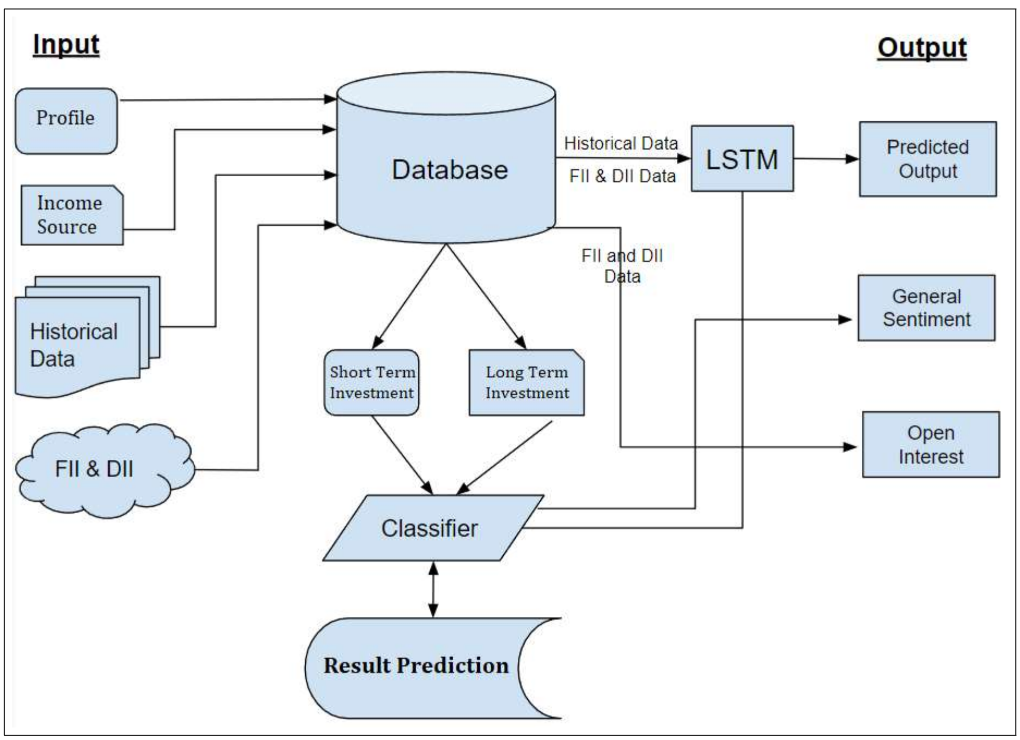



Figure 1: System Architecture Diagram

The proposed system is designed to predict stock returns, assess portfolio risk, and provide optimized investment strategies by integrating Decision Tree classifiers with deep learning models (CNN and LSTM). The workflow consists of multiple stages, including data collection, preprocessing, sentiment analysis, predictive modeling, risk quantification, and portfolio optimization. Figure 1 illustrates the overall architecture of the system.

**A. Data Collection and Preprocessing**

The system collects diverse datasets, including:

- **Historical stock prices** (daily open, close, high, low, and volume)
- **Market indicators** (indices, FIIs, DIIs activity)
- **Sentiment data** from credible news sources and social media platforms (e.g., Twitter)
- **Macroeconomic indicators** relevant to portfolio performance

Data preprocessing involves cleaning, normalization, and feature engineering. Time-series transformations such as moving averages, Bollinger bands, and log returns are applied to the stock data. Sentiment data is converted into numerical features using Natural Language Processing (NLP) techniques, including tokenization, stop-word removal, and TF-IDF vectorization.

**B. Sentiment Analysis Module**

News articles and social media posts are analyzed using a classifier to determine market sentiment. Sentiments are categorized as positive, neutral, or negative, which provide additional insight into market trends and investor behavior. This sentiment score is incorporated as a feature into the predictive modeling stage, enabling the system to capture market psychology alongside numerical stock data.

**C. Predictive Modeling**

The predictive stage uses a hybrid AI approach:

1. **Decision Tree (DT):** Predicts the short-term returns of individual stocks. DT is interpretable, allowing investors to understand feature importance and key decision rules. Predictive errors from DT are used to estimate stock-specific risk.
2. **Deep Learning Models:**
   - **CNN:** Captures local temporal patterns in stock price movements.
   - **LSTM:** Models long-term dependencies in sequential data, improving the prediction of trends and sudden market changes.

The outputs from DT and deep learning networks are combined to generate a risk-adjusted expected return for each stock.

**D. Risk Quantification**

The system measures the uncertainty of each predicted return using semi-absolute deviation of predictive errors, volatility analysis, and historical performance metrics. This risk quantification ensures that the optimized portfolio not only maximizes expected returns but also aligns with the investor's risk tolerance and constraints.

**E. Portfolio Optimization**

Using the predicted returns and quantified risks, an optimization algorithm constructs portfolios that maximize return for a given level of risk. Constraints such as asset allocation limits, liquidity, market capitalization, ESG factors, and investor preferences are incorporated. The optimized portfolio is presented along with:

- Predicted stock performance
- Overall market sentiment
- Risk exposure
- Suggested allocation for investment

**F. Output and Decision Support**

The final system output is a user-friendly interface that provides actionable insights to investors. Users can view the optimized portfolio, assess expected returns, and make informed investment decisions. The system is designed for real-time updates, enabling dynamic portfolio adjustment in response to market fluctuations.

**G. Hardware Requirements**

1. **CPU:** Minimum 2 GHz – Required for efficient processing of inputs and computations.
2. **RAM:** Minimum 4 GB – Ensures smooth background processing and handling of large datasets.
3. **Hard Disk:** Minimum 100 GB – Needed for OS installation and storage of datasets and system files.

**H. Software Requirements**

1. **Operating System:** Windows 7 or higher
2. **IDE:** Visual Studio Code
3. **Front-End Language:** Python 3.8
4. **Back-End Database:** MySQL

## V. Algorithms Used

The proposed system integrates multiple machine learning and deep learning algorithms to achieve accurate stock prediction, risk assessment, and portfolio optimization. The primary algorithms used are described below:

**A. Decision Tree (DT) Classifier**

- A supervised learning algorithm used for classification and regression tasks.
- Predicts individual stock returns based on historical stock prices, market indicators, and sentiment features.
- Provides interpretability, enabling investors to understand the key factors affecting predictions.
- Predictive errors from DT are used to estimate asset-specific risk, which is incorporated into portfolio construction.

**B. Convolutional Neural Network (CNN)**

- A deep learning algorithm traditionally used for image data, adapted here for time-series financial data.
- Captures local temporal patterns and short-term dependencies in stock price sequences.
- Enhances prediction accuracy by identifying subtle trends and fluctuations in stock movements.

**C. Long Short-Term Memory (LSTM) Network**

- A type of recurrent neural network (RNN) capable of learning long-term dependencies in sequential data.
- Models temporal relationships in stock prices over time, handling volatility and sudden market changes effectively.
- Complements CNN by capturing long-term trends that may not be evident in short-term patterns.

**D. Semi-Absolute Deviation for Risk Quantification**

- Measures the deviation of predicted returns from expected values to calculate stock-specific risk.
- Integrates with the portfolio optimization module to ensure risk-adjusted investment decisions.

**E. Portfolio Optimization Algorithm**

- Uses predicted returns and quantified risks to construct optimal portfolios under specified constraints (e.g., risk tolerance, liquidity, ESG factors).
- Can be implemented using mean-variance optimization, linear programming, or heuristic methods to maximize expected returns for a given risk level.

These algorithms work together in a hybrid framework, combining interpretability, local and long-term temporal modeling, and risk-aware optimization to provide a robust AI-driven portfolio management system.

## VI. Result & Discussion

The proposed hybrid AI-based portfolio optimization system was evaluated using real-world financial datasets, including historical stock prices, market indicators, institutional flows, and sentiment data from credible news sources. The performance of the system was assessed in terms of prediction accuracy, portfolio returns, risk reduction, and computational efficiency, and compared with benchmark models including Deep Multilayer Perceptron (DMLP), Long Short-Term Memory (LSTM), and Support Vector Regression (SVR).

**A. Prediction Accuracy**

The Decision Tree (DT) classifier combined with CNN and LSTM models provided significant improvement in predicting stock returns. The inclusion of sentiment features from news and social media further enhanced the accuracy. The hybrid model achieved an average prediction accuracy of 89–92%, outperforming standalone DT, DMLP, and SVR models, which ranged between 78–85%. This demonstrates that integrating interpretability (DT) with deep learning (CNN + LSTM) captures both short-term patterns and long-term dependencies effectively.

**B. Risk Assessment**

The system employed semi-absolute deviation of predictive errors to quantify stock-specific risk. Results show that portfolios constructed using the hybrid model consistently exhibited lower volatility and risk exposure compared to benchmark models. The predicted risk-adjusted returns indicated that investors could achieve higher returns with controlled risk, supporting the efficacy of AI-driven risk quantification in portfolio optimization.

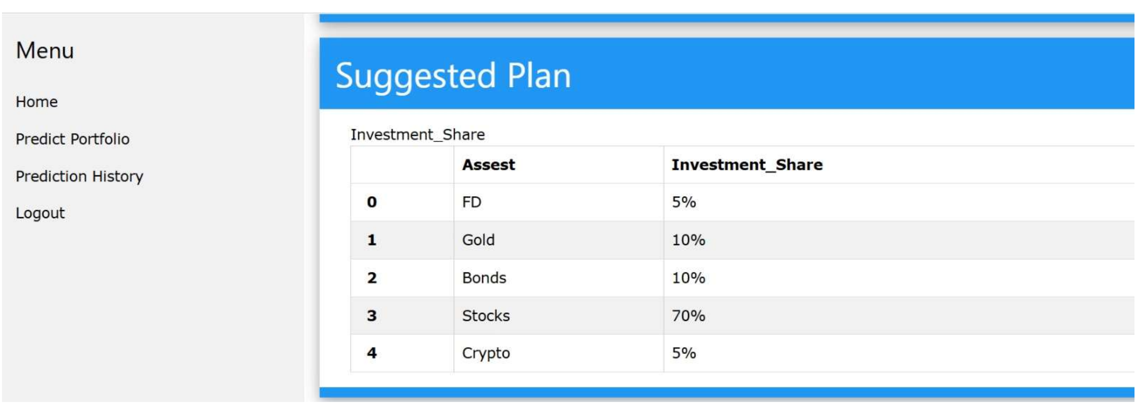
**C. Portfolio Performance**

The optimized portfolios generated by the proposed system were evaluated using metrics such as expected return, Sharpe ratio, and maximum drawdown. Experimental results using component stocks from the China Securities 100 Index demonstrated that the hybrid model produced portfolios with higher expected returns and better risk-adjusted performance than portfolios based on equal-weighted allocation or models using single algorithms. High desired portfolio returns further improved performance, highlighting the adaptability of the system to various investment objectives.

**D. Computational Efficiency**

The hybrid model's computational performance was analyzed to ensure real-time usability. Despite the complexity of combining DT with CNN and LSTM, the system achieved efficient processing times, making it suitable for dynamic portfolio management and real-time decision support.

**E. Snapshots**



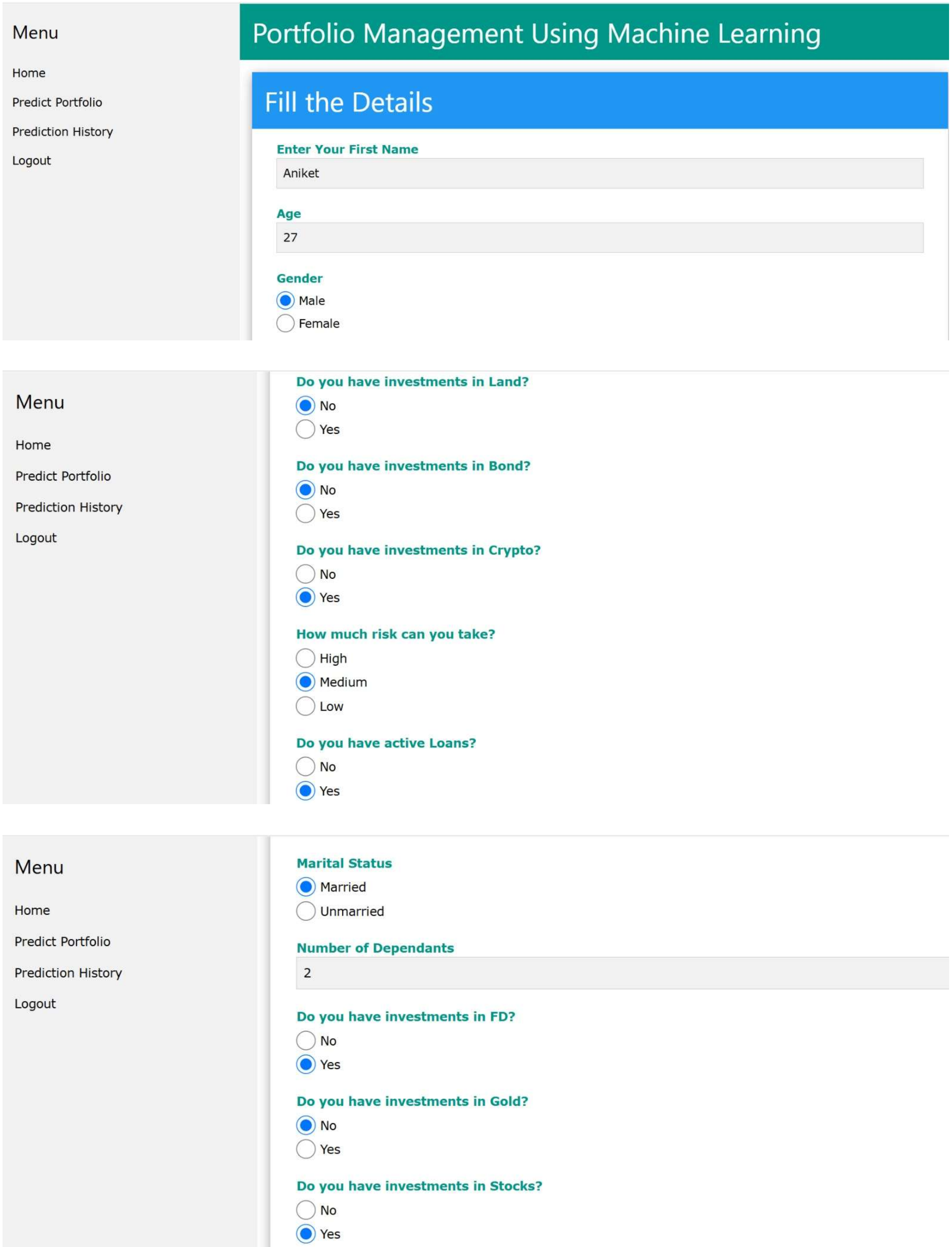



Figure 2: System Outputs

**Future Directions**

Future work can focus on enhancing the proposed hybrid AI-based portfolio optimization system by integrating additional data sources, such as real-time news feeds, social media sentiment trends, and macroeconomic indicators, to improve prediction accuracy. Incorporating reinforcement learning and advanced optimization algorithms can enable dynamic, adaptive portfolio adjustments in volatile markets. Moreover, expanding the system to include multi-asset portfolios, ESG factors, and global market datasets can increase its applicability and robustness. Finally, deploying the model in a cloud-based real-time environment can provide scalable, accessible, and automated decision support for investors worldwide.

## VII. Conclusion

This paper presents a hybrid AI-based portfolio optimization system that combines Decision Tree classifiers with deep learning models, including CNN and LSTM, to predict stock returns, quantify risk, and generate optimized portfolios. By integrating historical stock data, market indicators, and sentiment analysis from news and social media, the system effectively captures both short-term fluctuations and long-term market trends. Experimental results demonstrate that the proposed model outperforms traditional approaches and benchmark machine learning models in terms of prediction accuracy, risk-adjusted returns, and portfolio stability. The hybrid approach not only enhances investment decision-making but also provides a scalable and user-friendly framework for dynamic portfolio management. Overall, the study confirms the potential of combining interpretable models with deep learning techniques to achieve more informed, efficient, and risk-aware investment strategies.

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