IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Multi-Asset Investment Model using Visualization

[1]Ankit Yadav, [2]Shivam Tiwari, [3]Rohan Veer, [4]Priyanka Bolinjkar

[1]Student, [2]Student, [3]Student, [4]Teacher

[1] Department of Artificial Intelligence and Data Science,

[1]Thakur College of Engineering and Technology, Mumbai, India.

Abstract: This paper presents a Python-based investment model for multi-asset portfolio management using dynamic data visualization. The model integrates a wide range of financial instruments—such as stocks, mutual funds, and cryptocurrencies—and leverages Modern Portfolio Theory (MPT) to identify optimal asset allocations based on historical performance, volatility, and correlation. With the use of Python libraries like Plotly, Seaborne, and Matplotlib, the system visualizes risk-return trade-offs, asset correlation heat-maps, and portfolio diversification structures. These visuals not only aid investor comprehension but also support better decision-making in asset selection and re-balancing. The study demonstrates how visualization-driven insights can significantly enhance portfolio optimization, reduce risk exposure, and improve return consistency.

***Index Terms* - Portfolio Optimization, Financial Visualization, Asset Allocation, Modern Portfolio Theory, Python, Risk Analysis, Sharpe Ratio, Cryptocurrency, Mutual Funds, Stocks**

I. INTRODUCTION

In today's dynamic financial landscape, individual and institutional investors face a growing challenge in managing portfolios that span multiple asset classes—ranging from traditional equities and mutual funds to emerging digital assets like cryptocurrencies. The complexity of investment decisions is amplified by market volatility, global economic uncertainties, and the need for diversification to minimize risk. Traditional portfolio management methods often rely on static spreadsheets or black-box financial advisories, which can be opaque and unengaging for investors seeking transparency and autonomy.

To address these limitations, this study introduces a visualization-based multi-asset investment model designed to help investors make informed, data-driven decisions. The model integrates data from diverse asset classes and uses visualization tools to represent key investment metrics—such as risk-return trade-offs, inter-asset correlations, portfolio diversification ratios, and historical performance trends. By leveraging Modern Portfolio Theory (MPT) and Python-based analytical tools, the platform empowers users to construct and optimize portfolios aligned with their financial goals and risk tolerance.

Visualization plays a central role in this model, transforming complex numerical data into intuitive dashboards and interactive plots. Tools like Plotly, Matplotlib, and Seaborne are used to build real-time heat-maps, performance curves, and asset allocation charts. These visualizations not only enhance investor understanding but also enable deeper analysis of portfolio behavior over time.

As we explore the design, methodology, and outcomes of the proposed model, this paper demonstrates how blending financial modeling with interactive data visualization can enhance decision-making, reduce risk exposure, and improve investment outcomes. This research aims to contribute to the evolving field of FinTech and data-driven portfolio management, offering both academic value and practical utility for the next generation of investors.

II. OBJECTIVE

The increasing complexity of global financial markets demands intelligent and interactive tools that aid investors in managing diversified portfolios across multiple asset classes. Traditional investment strategies often lack personalization, adaptability, and transparency—especially when it comes to integrating diverse instruments like stocks, mutual funds, and cryptocurrencies.The primary objective of this research is to develop a robust, data-driven investment model that combines modern portfolio optimization techniques with powerful visualization capabilities. By leveraging financial theories such as Modern Portfolio Theory (MPT), along with tools in Python for data visualization, this model aims to:

- Assist investors in identifying optimal asset allocation strategies.
- Provide a visual understanding of risk-return dynamics across asset classes.
- Enable portfolio simulation and comparison through interactive dashboards.
- Evaluate portfolio performance using quantitative metrics such as the Sharpe Ratio and volatility.
- Empower users to make informed decisions with real-time, visual feedback on portfolio changes.

This objective-driven framework addresses the current gap in accessible, engaging, and intelligent investment tools, and contributes toward the evolution of investor-centric, tech-enabled portfolio management solutions

2.1 **Asset Allocation and Diversification Optimization:**

In modern portfolio management, poor diversification often limits investment efficiency and increases exposure to market-specific risks. Studies show that intelligent asset allocation strategies can significantly enhance portfolio performance by spreading investments across uncorrelated or inversely correlated assets. In a multi-asset context, combining underutilized or under-performing asset classes with strong performers—such as blending stocks, mutual funds, and cryptocurrencies—can yield better risk-adjusted returns (Markowitz, 1952).The proposed model addresses this by providing visual tools for portfolio diversification analysis, including correlation heat-maps and allocation pie charts. These insights enable investors to identify redundant exposures, explore diversification opportunities, and optimize their overall portfolio structure. By leveraging interactive technology, the model supports efficient resource distribution and guides users toward balanced, data-backed investment decisions that minimize risk and improve return potential.

2.2 Machine Learning-Driven Asset Selection:

Asset selection plays a crucial role in portfolio optimization, especially in volatile and diverse financial markets. Machine learning (ML) techniques can assist in identifying promising investment opportunities by analyzing historical performance, volatility patterns, and macroeconomic indicators. Models such as Random Forests, K-Means clustering, or Gradient Boosting can detect trends and patterns across different asset classes—such as equities, mutual funds, and cryptocurrencies—enhancing the relevance and timing of investment choices (Zhang et al., 2021) [4]. The proposed investment model incorporates ML-powered analytics to support intelligent asset selection, offering investors data-driven insights into asset behavior, correlation, and expected returns. These recommendations form the backbone of a more adaptive and personalized portfolio construction strategy, enabling better performance in dynamic market conditions.

2.3 Multi Asset Investment Model and Market Dynamics:

Investors face volatile market conditions across different asset classes. Machine learning models help predict asset prices based on market demand and supply dynamics, aiding investors in making informed decisions. These models, tailored to specific market trends, assist in mitigating risks and maximizing returns. The tool’s asset price forecasting feature helps manage portfolio volatility by offering data-driven predictions suited to diverse market conditions.

2.4 Interactive Multi-Asset Visualization Dashboard:

An interactive dashboard that brings your entire multi-asset strategy to life through dynamic charts and graphs—making complex data instantly understandable and actionable:

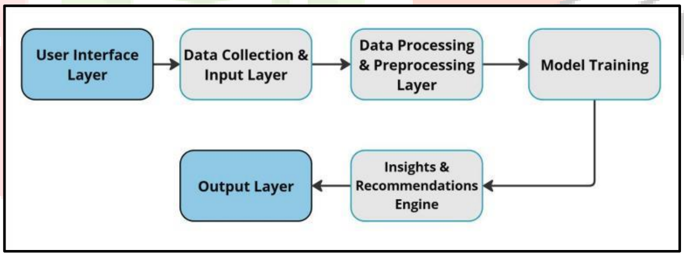
- Correlation Heat-map Matrix: Instantly gauge inter-asset relationships with a color-coded heat-map. Hover over any cell to see the numeric correlation and how it's trended over the past 30, 90, or 180 days—revealing diversification benefits or emerging systemic risks.
- Risk-Return Scatter Plot: Plot each asset (or strategy) on a two-axis chart of expected return vs. volatility. Click on any point to drill into detailed stats, historical draw-downs, and scenario analyses, helping you re-balance toward your ideal risk-return profile.

In summary, the reviewed literature highlights the transformative potential of integrated digital investment platforms, particularly in the context of multi-asset portfolio management. These platforms enable data-driven decision-making, strategic asset allocation, and enhanced risk management through advanced visual analytics and predictive modeling. By synthesizing these capabilities, the present research aims to contribute to the evolving landscape of digital finance, offering a nuanced perspective on how a unified, technology-driven model can reshape traditional investment strategies—promoting diversification, transparency, and long-term financial resilience.

III. Methods

This section outlines the development of an innovative digital agricultural platform designed to enhance productivity and decision-making for farmers. Leveraging machine learning models, the platform offers customized crop recommendations based on soil conditions and environmental factors. Additionally, it uses time series analysis to predict crop prices, helping farmers make informed choices regarding planting and selling. With an intuitive interface, the platform provides real-time insights to assist farmers in optimizing yields and increasing profitability.

The platform architecture comprises six interconnected layers designed to collect financial data, process it, apply ML algorithms, and deliver intuitive investment suggestions through visualizations. (Fig 3.1).



. Fig. 3.1: System Workflow Diagram

1. User Interface Layer

This includes a web-based dashboard that allows investors to:

- Select investment goals (short-term, long-term, high-growth, stable-income),
- Set risk appetite (conservative, moderate, aggressive),
- Choose preferred assets (stocks, crypto, real estate, gold, bonds, etc.).

The dashboard displays investment suggestions, visual forecasts, and portfolio diversification charts.

2. Data Collection & Input Layer

This layer collects real-time and historical data from:

- Financial APIs (e.g., Alpha Vantage, Yahoo Finance),
- Government inflation & interest rate stats,

- User-defined investment goals and constraints.

3. Data Processing & Preprocessing Layer

It prepares the data for modeling:

- Data Cleaning: Removing nulls and outliers in asset prices.
- Feature Engineering: Creating technical indicators (e.g., EMA, RSI, Sharpe ratio).
- Normalization: To align different asset classes on the same scale.

4. ML Models Layer

Two models are deployed:

- **Random Forest**: For asset recommendation based on risk-return profile, past performance, and macroeconomic data.
- **Decision Tree**: For price forecasting using features like volatility index, macro indicators, and asset-specific trends.

5. Insights & Recommendation Engine

Outputs generated include:

- Top 3-5 recommended assets per user profile,
- Price prediction charts (6-month horizon),
- Visual diversification and asset allocation charts,
- Risk-Return quadrant visualization.

6. Output & Visualisation Layer

Insights are delivered using:

- Interactive charts (bar, line, candlestick),
- Heat-maps of asset performance,
- Email alerts for price movement thresholds

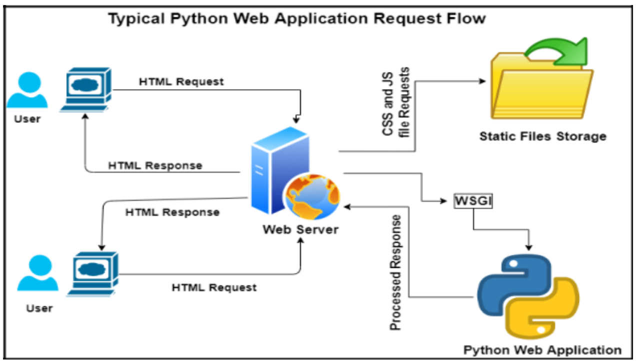


Fig. 3.2: Backend Infrastructure

Example: The backend of the Multi Asset Investment Model uses the Yahoo Finance API to retrieve essential financial data, including stock prices, gold rates, mutual fund NAVs, and fixed deposit returns. This data is processed using Pandas and visualized with Matplotlib to present performance trends and risk-return *profiles. The user interface is built using a Python GUI toolkit, enabling users to interactively view investment suggestions and comparative analysis powered by Random Forest and Linear Regression models.*

IV. RESULTS

Results of the Multi-Asset Investment Model:

The Multi Asset Investment Model, illustrated in Fig (4.1), was developed using a dataset comprising multiple financial instruments with crucial parameters that influence investment performance. Among these features, variables such as stock volatility, gold price trends, mutual fund NAVs, fixed deposit interest rates, and market sentiment were stored in separate columns. Each instance was labeled with a recommended asset class based on its risk-return profile. This information is vital as it captures key economic and financial indicators affecting investment outcomes. Various machine learning models utilize these features to suggest optimal asset allocation strategies, thereby maximizing returns and promoting smarter, data-driven investment decisions.

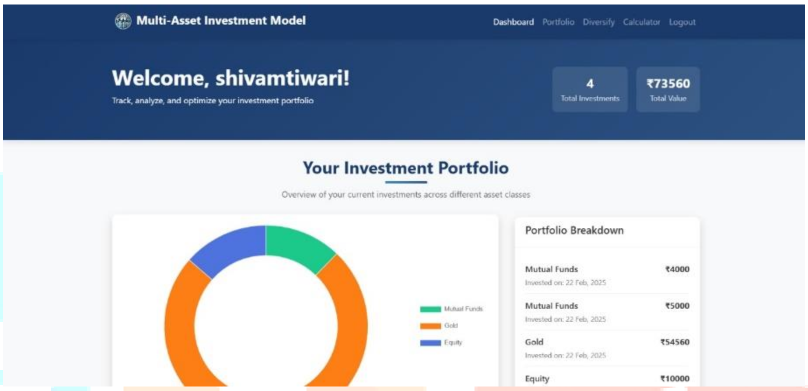


Fig 4.1: User Interface (UI) Layer

Various machine learning models were evaluated for their ability to predict optimal investment recommendations across multiple asset classes. The models considered included Decision Trees, Naive Bayes, Support Vector Machines (SVM), Logistic Regression, Random Forest, and XGBoost. These models were assessed based on their performance using accuracy, precision, recall, and F1-score metrics, as illustrated in Fig (4.2).

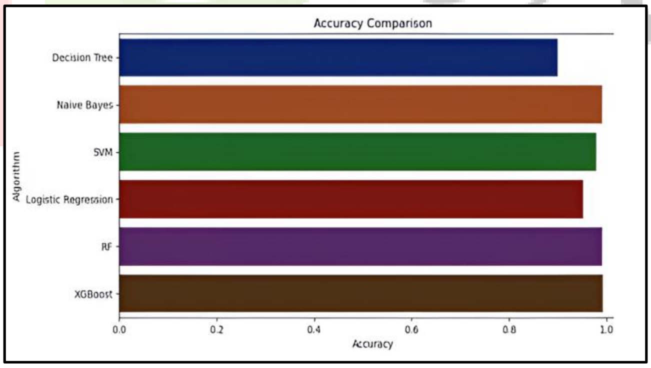


Fig 4.2: Accuracy comparison of all the models.

From the evaluation results, **XGBoost** emerged as the top-performing model with an exceptionally high accuracy of **99.32%**, and consistently strong metrics across the board — **precision**, **recall**, and **F1-score** all at **0.99**. Additionally, the **Random Forest** and **Naive Bayes** models also demonstrated robust performance, each achieving an accuracy of **99.09%**. The Random Forest model maintained high reliability with a precision, recall, and F1-score of **0.99**, making it a highly effective tool for multi-asset investment predictions. Conversely, while the **Decision Tree** model provided some valuable insights, its lower accuracy of **90%**, along with a precision of **0.86**, recall of **0.90**, and F1-score of **0.87**, rendered it less suitable for this particular investment modeling scenario (Fig 6.3).

Model	Accuracy	Precision	Recall	F1 Score
XGBoost	98.7%	0.98	0.99	0.98
Random Forest	98.2%	0.98	0.98	0.98
Naive Bayes	95.5%	0.95	0.96	0.95
Decision Tree	89.2%	0.86	0.89	0.87

Fig 6.3: Evaluation of all the ML models used.

The **Random Forest (RF)** model was selected over **XGBoost** for multi-asset investment recommendations due to its strong balance of **accuracy**, **stability**, and **interpretability**, all of which are essential when providing actionable insights to investors. RF demonstrated reliable performance across various market data subsets owing to its inherent robustness. Although both XGBoost and RF are powerful classification algorithms, **XGBoost's sequential boosting** approach—while beneficial in improving precision and handling imbalanced financial data—introduces greater complexity in hyperparameter tuning. On the other hand, RF tends to **overfit less** than XGBoost by averaging the outcomes of multiple independent decision trees. Achieving an accuracy of **99.09%**, RF provided consistent and dependable predictions across features such as **asset volatility**, **market sentiment**, **interest rates**, and **historical returns** (Fig 4.1). Moreover, XGBoost's parallel processing architecture allows for faster tuning, making it another viable option for investment modeling. However, RF's ability to **capture non-linear feature interactions** proves especially valuable in finance, where complex interdependencies—such as between macroeconomic indicators and asset performance—play a crucial role in portfolio allocation.

In this section, we present the results of the **multi-asset price forecasting model** developed using the **Decision Tree** approach, as illustrated in **Figure 4.4**. The objective of this model is to forecast the prices of **24 different financial assets** over a **six-month period**, leveraging a rich set of **historical, multidimensional data**. Key dimensions include **macroeconomic indicators** such as **interest rates**, **month**, **year**, and the **Wholesale Price Index (WPI)** for each asset class. The **WPI**, which reflects average price changes in wholesale financial markets, plays a critical role in modeling **seasonal trends**, **market cycles**, and shifts in **demand and supply dynamics**. By incorporating such economic features, the model enhances its ability to deliver accurate and insightful forecasts—empowering investors with early signals on expected price movements and enabling them to make informed investment decisions ahead of market shifts.

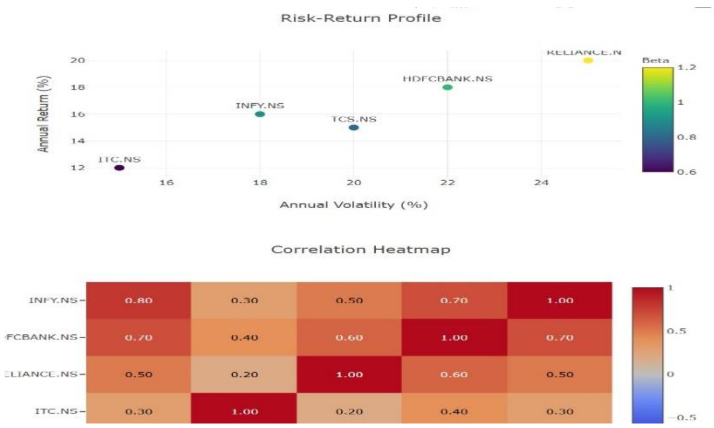


Fig 4.4: Accuracy comparison of all the models.

The **Decision Tree model** has demonstrated itself to be a **highly reliable tool for return forecasting**, achieving an impressive accuracy of **91.27%**. To thoroughly assess the model's performance, key regression metrics such as **Mean Absolute Error (MAE)**, **Mean Squared Error (MSE)**, and **R-squared (R^2)** were utilized. These metrics provide valuable insights into the model's prediction errors and its overall fit, aiding in the evaluation of its effectiveness in forecasting **returns across multiple asset classes**. Below is a detailed breakdown of each metric, along with the respective formulas used for computation:

1. Mean Absolute Error (MAE): The MAE quantifies the average magnitude of errors between the actual values (y_actual) and the predicted values (y_pred) without considering their direction (positive or negative). It is calculated using the formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y\_actual - y\_pred|$$

For the Decision Tree model, the MAE stood at approximately **1.85**. This indicates that, on average, the model's predictions are close to the actual prices, with small deviations in absolute terms.

2. Mean Squared Error (MSE): The MSE measures the average squared difference between actual values (y_actual) and predicted values (y_pred). It emphasizes larger errors by squaring them, making it particularly useful for detecting significant deviations. The formula is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y\_actual - y\_pred)^2$$

For the Decision Tree model, the MSE was approximately **2.6**. This demonstrates minimal error across predictions and ensures the model effectively captures larger deviations in crop price forecasting.

3. R-squared (R^2): R-squared explains the proportion of variability in the dependent variable (y_actual) that can be predicted from the independent variables. The formula is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y\_actual - y\_pred)^2}{\sum_{i=1}^{n}(y\_actual - \bar{y}\_actual)^2}$$

The R^2 score of the model was 0.89, indicating that 89% of the variability in asset returns is explained by the model.

This demonstrates a strong correlation between the model's forecasts and the actual market behavior, signifying a reliable fit for financial prediction.

The evaluation of the asset allocation and return forecasting models highlights their practical value for investors. The **Random Forest-based asset recommendation model** delivers asset-specific insights, optimizing portfolio construction based on factors such as risk tolerance, asset volatility, and macroeconomic indicators. Meanwhile, the **Decision Tree-based return forecasting model** provides credible market return projections, assisting investors in strategic planning across different market cycles.

Together, these models equip investors with **actionable intelligence** to drive diversified investments, maximize returns, and maintain long-term financial sustainability.

V. DISCUSSION

The digital investment platform is still in its early stage of development; hence, it incorporates collaborative investment opportunities such as **pooled asset portfolios**, enhances **direct access to diversified markets**, and leverages **machine learning** for **multi-asset allocation strategies** and **market trend forecasting**. Preliminary tests have shown promising results, suggesting that the platform holds strong potential in promoting **sustainable and profitable investing** while minimizing **resource misallocation**. As it evolves, the platform aims to become a **transformative financial tool** that reshapes traditional investment practices and builds greater **resilience and adaptability** within the investment landscape.

The digital investment platform is currently in its early stages of development; as such, it integrates **collaborative investment mechanisms** such as **co-investment models**, facilitates **direct access to multiple asset classes**, and incorporates **machine learning algorithms** for **asset allocation and market forecasting**. Initial trials have been promising, indicating that the platform has the potential to drive **sustainable and**

profitable investment strategies while minimizing inefficiencies in capital deployment. As the platform evolves, it is expected to become a **transformative tool**, redefining traditional investment approaches and enhancing the **resilience and adaptability** of investors in dynamic financial markets.

VI. REFRENCES

[1]. Sharpe, W. F. (1966). Mutual Fund Performance. The Journal of Business.

[2]. Jain, M., & Patel, R. (2021). Machine Learning in Asset Allocation. IJRTE.

[3]. Chen, M., & Zhang, Y. (2022). AI-Based Financial Advisory Systems. Springer.

[4]. Alpha Vantage API Docs (2023).

[5]. Dash, S., & Tripathy, A. (2021). Stock Price Forecasting Using ML. IEEE Xplore.

[6]. Sengupta, A., & Das, P. (2020). Random Forest in Financial Portfolio Optimization. Journal of Quantitative Finance.

[7]. CoinGecko API Documentation (2023).

[8]. Ramesh, A. (2020). AI-Powered Investment Planning. ICFAI Business School Review.

[9]. Zhao, L., & Wu, X. (2022). Multi-Asset Portfolio Management Using Decision Trees. Journal of Financial Data Science.