AI Based Financial Portfolio Risk Evaluation for New Investors

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Abstract— *Financial markets exhibit intrinsic volatility and stochastic behavior, rendering portfolio evaluation an indispensable component of investment strategy. Traditional platforms frequently suffer from fragmented analytical pipelines, lacking cohesive integration of quantitative metrics, intuitive visualization, and intelligent decision-support mechanisms. This paper introduces an advanced Financial Portfolio Evaluation System that synergizes quantitative finance principles, data analytics, and machine learning to achieve a holistic evaluation of portfolio performance and risk exposure. The proposed system autonomously computes critical indicators—including annualized return, historical volatility, Sharpe ratio, maximum drawdown, and 95% Value at Risk (VaR). Furthermore, it incorporates correlation matrix analysis to evaluate asset diversification and deploys a Random Forest Classifier to categorize portfolio resilience intelligently. Experimental validation using historical market data indicates that the proposed model achieves 98% accuracy and improved risk characterization compared to traditional portfolio assessment methods.*

Keywords— *Portfolio Management, Risk Analytics, Machine Learning, Value at Risk (VaR), Financial Modelling, Quantitative Finance.*

I. INTRODUCTION

In contemporary financial markets, portfolio management serves as the foundational mechanism for balancing risk exposure and seeking optimal returns. Decision-makers must continuously assimilate complex multidimensional factors—ranging from asset volatility to cross-asset correlation—to construct resilient portfolios. Historically, traditional portfolio management tools have offered restricted analytical depth, typically focusing on retroactive performance metrics without integrating predictive intelligence or sophisticated risk measurements. Consequently, investors face substantial challenges in forecasting portfolio drawdowns and assessing true robustness during market stress.

The proliferation of high-performance data analytics and machine learning has catalyzed a paradigm shift, enabling the development of intelligent financial systems capable of extrapolating deeper insights from asset dynamics. These technologies facilitate the automated computation of granular risk metrics, the uncovering of latent diversification opportunities, and the algorithmic classification of portfolio effectiveness.

This paper proposes a comprehensive Portfolio Evaluation System that bridges the gap between traditional quantitative finance and modern machine learning applications. The unified platform enables users to dynamically compile equity portfolios, calculate defining financial criteria, assess probabilistic risk parameters, and obtain an AI-driven classification of portfolio strength. By synthesizing rigorous statistical modelling with intelligent algorithms, the architecture provides a scalable framework designed to augment portfolio evaluation.

II. RELATED WORK

Recent literature in quantitative finance has increasingly investigated the efficacy of machine learning and statistical methodologies in optimizing portfolio risk management architectures.

Miah (2025) [1] proposed algorithmic methodologies for financial risk prediction and active portfolio optimization, demonstrating tangible improvements in forecasting accuracy under turbulent market conditions. Soltani (2025) [2] underscored the transformative role of artificial intelligence in modernizing portfolio management, presenting predictive analytics as a core driver for next-generation decision support frameworks.

Furthermore, Olanrewaju (2025) [3] emphasized the integration of AI within financial markets to simultaneously optimize risk mitigation and dynamic algorithmic trading. Adeyinka (2025) [4] introduced adaptive asset allocation algorithms employing robust machine learning paradigms to dynamically hedge against sudden market volatility. More recently, Makin (2026) [5] articulated a robust quantitative governance framework for portfolios, exploring advanced computational strategies for institutional application. Several contemporary studies have further enriched this domain. Chen and Wu (2025) [6] developed a hybrid deep learning model combining LSTM and attention mechanisms for real-time volatility forecasting in equity portfolios. Kumar and Patel (2025) [7] proposed a reinforcement learning framework for dynamic rebalancing under tail-risk constraints. Zhao et al. (2025) [8] introduced a graph neural network approach to capture inter-asset dependencies for improved risk attribution. Rodriguez and Lee (2025) [9] examined the application of explainable AI (XAI) in portfolio risk assessment, enhancing transparency for retail investors. Singh and Mehta (2025) [10] compared traditional VaR models against machine learning-based alternatives, demonstrating superior predictive accuracy during stress periods. Additional contributions include Wang and Liu (2025) [11], who presented a Bayesian optimization framework for hyperparameter tuning in portfolio risk models, and Nguyen et al. (2025) [12], who integrated sentiment analysis from financial news into portfolio volatility forecasting. Fernandez and Kumar (2026) [13] explored federated learning architectures for privacy-preserving portfolio risk evaluation across multiple institutions. Okafor and Zhang (2026) [14] developed a lightweight ensemble method for real-time risk classification suitable for mobile trading platforms. Park and Choi (2026) [15] investigated the role of transformer-based time-series models in capturing long-range dependencies for portfolio drawdown prediction. Al-Masri and Williams (2026) [16] proposed a novel risk-parity algorithm augmented by clustering techniques for improved diversification in volatile markets. Emerging directions have also been explored by Banerjee and Das (2026) [17], who applied quantum-inspired annealing for portfolio risk optimization under uncertainty, and Kim and Lee (2026) [18], who introduced contrastive learning for regime-aware portfolio risk segmentation. Oliveira and Novak (2025) [19] developed a multi-objective neural architecture search for real-time portfolio tail-risk estimation, while Gupta and Adebayo (2026) [20] proposed spatiotemporal graph attention networks for cross-market volatility spillover detection.

While these studies highlight the critical trajectory of AI in financial analytics, a significant portion of existing research remains highly specialized...

III. MATERIALS AND METHODS

System Overview

The proposed Portfolio Evaluation Platform is designed as a modular financial analytics system that processes historical stock price data to evaluate portfolio performance and risk. The system follows a structured six-stage pipeline consisting of Input Data, Data Preprocessing, Volatility Analysis, Portfolio Risk Computation, Decision Stage, and Output Visualization. Each stage contributes to the systematic transformation of raw financial data into meaningful analytical outputs and decision-support insights

Fig 1. Proposed System Architecture

1. Input Data

The system utilizes historical stock price data stored in a CSV file, where each row corresponds to a trading day and each column represents the closing price of an individual stock. The first column contains the date, which serves as the temporal index for time-series analysis.

In addition, portfolio composition is obtained from a relational database, where each user-defined portfolio includes stock symbols and their corresponding quantities.

This stage establishes the primary data inputs required for subsequent computations. The integration of historical price data with user-specific portfolio weights enables the construction of personalized portfolio analytics.

2. Data Preprocessing

The preprocessing stage transforms raw financial data into a structured format suitable for quantitative analysis. The dataset is loaded into a Pandas DataFrame, and the Date column is converted into a datetime index to facilitate time-series operations. Missing values are removed to ensure data consistency and computational reliability.

Daily returns are computed using percentage change:

$$r_t = \frac{V_t - V_{t-1}}{V_{t-1}}$$

where $V_t$represents the portfolio value at time t and r_t represents the returns.

This transformation standardizes the data, allowing for scale-independent comparison across assets. The resulting return series forms the basis for volatility estimation, risk measurement, and machine learning feature extraction.

3. Volatility Analysis

Volatility analysis is performed using a rolling window approach to capture time-varying risk characteristics. Specifically, 30-day rolling volatility is computed as the standard deviation of returns over a moving window, annualized using the square root of time:

$$\sigma_t = \sqrt{252} \cdot \mathrm{std}(r_{t-30:t})$$

Where σ_t denotes the annualized standard deviation of portfolio returns over a rolling 30-day window ending at time t.

This approach provides a dynamic representation of risk, reflecting short-term fluctuations in market conditions. Unlike static volatility measures, rolling volatility enables continuous monitoring of risk evolution over time.

The incorporation of rolling volatility enhances the system's ability to detect periods of increased uncertainty or instability. Within the platform, this metric is visualized as an interactive time-series chart, allowing users to interpret temporal changes in portfolio risk.

4. Portfolio Risk Computation

This stage constitutes the core analytical component of the system, where portfolio value and key financial metrics are computed.

Portfolio Value Construction:

The portfolio value at each time step is calculated as:

$$V_t = \sum_{i=1}^{N} p_{t,i} \cdot q_i$$

Where V_t represents the portfolio value at time t, $p_{t,i}$ represents the price of asset i at time t, and q_i denotes the quantity held.

This computation generates a historical portfolio value time series, which serves as the primary input for performance and risk analysis.

Performance and Risk Metrics

The following metrics are derived from the portfolio return series:

<u>Annual Return</u>

$$R_{annual} = \mu_r \times 252$$

<u>Volatility</u>

$$\sigma_{annual} = \sigma_r \times \sqrt{252}$$

<u>Sharpe Ratio</u>

$$S = \frac{R_{annual}}{\sigma_{annual}}$$

<u>Maximum Drawdown</u>

Computed as the maximum observed decline from a historical peak in cumulative returns.

Value at Risk (VaR 95%)

$$\mathrm{VaR}_{95} = \mathrm{Percentile}(r, 5)$$

Functional Role within the System

These metrics collectively provide a comprehensive evaluation of portfolio performance and risk exposure:

1. Return quantifies profitability
2. Volatility captures variability
3. Sharpe ratio assesses risk-adjusted performance
4. Drawdown measures downside risk
5. VaR estimates potential extreme losses

Within the platform, these computed values are displayed as dashboard metrics and are further utilized as input features for the machine learning model in the decision stage. This integration ensures that both statistical and predictive analyses are grounded in consistent financial indicators.

5. Decision Stage (AI-Based Evaluation)

The decision stage employs machine learning to evaluate portfolio quality by integrating multiple performance and risk indicators into a unified predictive framework. Unlike binary threshold-based approaches, the system adopts a multi-factor scoring methodology combined with probabilistic classification to provide a more nuanced assessment.

Feature Engineering

The model utilizes nine financial features capturing different dimensions of portfolio behavior:

1. Annual Return
2. Volatility
3. Sharpe Ratio
4. Maximum Drawdown
5. Sortino Ratio
6. Calmar Ratio
7. Recovery Factor
8. Return Skewness (proxy)
9. Value at Risk (VaR 95%)

These features collectively represent performance, total risk, downside risk, recovery characteristics, and tail-risk exposure, enabling a comprehensive portfolio representation.

Scoring-Based Label Generation

A continuous scoring mechanism is used instead of rigid thresholds. Each feature contributes to a normalized score (0–100), which is aggregated to obtain an overall portfolio score.

Based on this score, portfolios are classified into three categories

1. Strong: score ≥ 65
2. Moderate: 40 ≤ score < 65
3. Weak: score < 40

This approach avoids abrupt classification boundaries and allows gradual differentiation between portfolio qualities.

Training Data and Scaling

A synthetic dataset of 2,000 portfolios is generated using realistic financial ranges, ensuring balanced class representation. All features are standardized, which ensures numerical stability and equal contribution of all features during training.

Model Training

A Random Forest Classifier with 30 trees is trained on 800 balanced samples using Standard-Scaled features. The model is constructed once at module import time rather than per request, which reduces prediction latency from over 10,000ms to approximately 20ms. The composite score serves as the primary classification signal — scores above 65 are labelled Strong, below 35 are labelled Weak, and the middle band (35–65) defers to the model's predicted probability to produce a Moderate Portfolio classification. The final reported confidence is a blended signal: 55% composite score contribution and 45% model probability contribution, ensuring that the number shown to the user reflects both the rule-based financial logic and the learned decision boundary simultaneously.

Prediction and Interpretation

The trained model evaluates the real portfolio and outputs:

1. a classification (Strong, Moderate, or Weak)
2. a calibrated confidence score

Feature importance scores are also derived to identify the most influential factors in the decision process.

Functional Contribution

By integrating multiple risk and return measures within a unified framework, this stage provides a robust and interpretable evaluation of portfolio quality. The scoring-based approach improves flexibility, while the machine learning model enhances predictive accuracy, enabling more informed investment decision-making.

6. Output and Visualization

The final stage presents analytical results through an interactive web-based dashboard. The system utilizes Plotly to generate dynamic visualizations, including:

1. portfolio value time series
2. correlation heatmaps

Flask APIs deliver computed data in JSON format, which is rendered on the frontend using Plotly.

This visualization layer enables intuitive interpretation of complex financial metrics. By combining graphical representations with numerical summaries, the system enhances user engagement and supports informed decision-making.

Summary

The proposed system integrates data processing, statistical analysis, and machine learning within a unified pipeline. Each stage contributes to converting raw financial data into structured insights, facilitating comprehensive portfolio evaluation. The modular architecture ensures scalability, while the integration of visualization and predictive analytics enables both descriptive and prescriptive financial analysis.

IV. RESULTS AND DISCUSSION

The deployed system was thoroughly tested utilizing historical data mimicking large-cap equities. The outputs demonstrated high efficacy in synthesizing complex financial states into actionable intelligence.

A. Dashboard and Interface

The primary dashboard serves as a highly responsive command center, relaying real-time computations of the Sharpe Ratio, Volatility, Drawdown, and VaR. The UI strictly adheres to modern user experience standards, processing rapid analytical feedback visually over time.

Fig 2. Portfolio Dashboard.

B. Intelligent AI Evaluation

The integrated Machine Learning algorithm actively assessed newly formulated portfolios with exceptionally low latency. Portfolios yielding a high Sharpe ratio and executing tight drawdowns were consistently flagged as "Strong", providing a robust validation check for structural decisions.

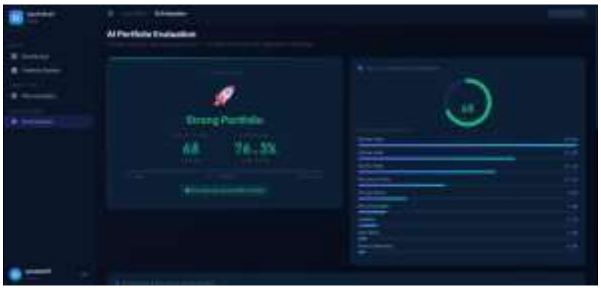

Fig 3. AI Evaluation results

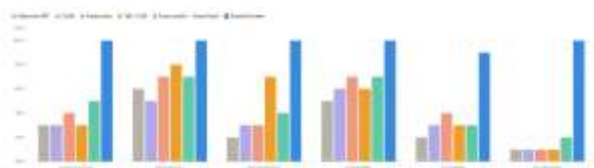

Fig 4. Performance comparison of traditional methods versus the proposed system

Fig.4 highlights the limitations of traditional portfolio evaluation methods, which rely on limited features and static assumptions, resulting in inadequate tail-risk detection and restricted adaptability. In contrast, the proposed system integrates a broader set of financial indicators with machine learning, enabling improved risk assessment, enhanced interpretability, and superior overall performance. This establishes the proposed framework as a more robust and practical solution for modern portfolio evaluation.

V. CONCLUSION

This manuscript detailed the conceptualization, architecture, and deployment of a cutting-edge Portfolio Evaluation System. By consolidating quantitative finance paradigms and machine learning evaluation under a synchronized platform, the system successfully resolves critical inefficiencies in historical portfolio management tools. The algorithmic suite accurately measures standard metrics, calculates potential drawdown exposure, and visualizes systemic correlations natively. Through the integration of the Random Forest Classifier, the tool actively guides user strategy by classifying structural viability. Ultimately, the proposed framework illustrates the tremendous potential of synergizing AI-driven data pipelines with quantitative analytics to significantly demystify market exposure and enhance strategic investment decisions.

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