



Shri Vile Parle Kelavani Mandal's  
**DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING**  
(Autonomous College Affiliated to the University of Mumbai)  
NAAC Accredited with "A" Grade (CGPA : 3.18)



Department of Computer Engineering  
Academic Year 2024-2025

# ***An Integrated Approach to Multidimensional Portfolio Risk***

*Machine Learning Laboratory*

**Year 3, Sem VI Computer Engineering**

By

**Aditya Jaiswal C006      60004220073**

**Anay N C011                60004220189**

**Arham Shah C015        60004220110**

Guide:

**Prof. Khushali Deulkar**



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## Abstract

The **Multi-Dimensional Portfolio Risk and Performance Analyzer** is an interactive, feature-rich, and data-driven web application developed using Python and Streamlit, designed to equip retail investors, analysts, portfolio managers, and finance enthusiasts with robust tools to analyze, optimize, and manage equity portfolios. In today's complex financial landscape, understanding portfolio behavior under varying market conditions and optimizing asset allocations is crucial to achieving risk-adjusted returns. This application bridges the gap between institutional-grade analysis and retail accessibility by integrating statistical rigor with user-friendly design.

The tool enables users to input portfolios of up to 10 stocks with customized weight allocations and retrieve historical market data via **FinancialModelingPrep API** and **Yahoo Finance** (as fallback), ensuring data reliability and flexibility. Performance metrics such as **Compound Annual Growth Rate (CAGR)**, **Volatility**, **Sharpe Ratio**, and **Maximum Drawdown** are calculated for both individual assets and the portfolio as a whole, giving users a granular and holistic view of performance. Visualizations such as **correlation heatmaps**, **cumulative returns**, and **rolling Sharpe Ratios** enhance interpretability and support intuitive decision-making.

One of the key features of the tool is its **portfolio optimization engine**, which uses **Monte Carlo simulations** to generate the **Efficient Frontier** of 10,000 portfolios and helps users identify optimal allocations under different objectives—**maximum Sharpe ratio**, **minimum volatility**, or **maximum return**. This functionality aligns with Modern Portfolio Theory and provides a scientific basis for portfolio rebalancing.

The **Risk Analytics** module offers multi-layered insights into potential losses and downside risk. It calculates **Value at Risk (VaR)** using three techniques—Historical Simulation, Variance-Covariance, and Monte Carlo Simulation—and also supports **Conditional VaR (CVaR)** and **Expected Shortfall** to measure tail risk. Further enhancements include **beta analysis with benchmark selection**, **Calmar Ratio**, and **rolling volatility charts**, offering time-dependent risk insights.

Advanced users can dive deeper using **Extreme Value Theory (EVT)** to analyze rare loss events and **Factor Exposure Analysis** using the **Fama-French 3-Factor Model** to evaluate sensitivity to market, size, and value factors. The application also provides **risk attribution analysis**, which quantifies each asset's contribution to total portfolio risk.

This project demonstrates a convergence of data engineering, financial theory, and modern visualization, aiming to democratize advanced investment analytics. By making institutional-level portfolio intelligence accessible through an intuitive interface, this analyzer empowers users to make informed, data-backed investment decisions and better manage portfolio risks across market cycles.



## Introduction: Problem statement

In the evolving landscape of financial markets, effective portfolio management requires more than just diversification—it demands a deep understanding of asset behavior, risk exposure, and return optimization. While institutional investors often have access to sophisticated tools and data analytics platforms, retail investors and students face a lack of accessible, all-in-one systems that combine performance evaluation, risk analysis, and optimization in an interactive, user-friendly format.

Traditional investment platforms provide basic metrics but often fall short in offering dynamic simulations, comprehensive risk modeling (like Value at Risk or Conditional VaR), and advanced techniques such as factor-based analysis or Monte Carlo simulations. This creates a significant gap for individual investors and early-career analysts who need to make informed decisions in an increasingly volatile market.

This project addresses that gap by developing a **Streamlit-based web application** that integrates key financial performance metrics, portfolio optimization algorithms, and multi-dimensional risk analytics—all in one interactive platform. It aims to democratize access to professional-grade portfolio analysis and enable users to make data-backed, strategic investment decisions with confidence.

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## Literature Review

### The Challenge of Portfolio Risk and Performance Analysis

Managing portfolio risk while maximizing return remains a core concern in modern finance. Markowitz's foundational work (1952) introduced Modern Portfolio Theory (MPT), enabling investors to optimize portfolios based on expected return and risk (variance). However, in today's volatile and complex markets, traditional approaches fall short in capturing tail risks, dynamic correlations, and time-varying risk factors. Studies by Meucci (2005) and Fabozzi et al. (2002) emphasize the need for multi-dimensional risk measures that extend beyond variance, such as drawdown, Value at Risk (VaR), and Conditional VaR (CVaR), to provide a more comprehensive risk profile.

### Traditional Models and Metrics

Key financial metrics such as Sharpe Ratio (Sharpe, 1966), Calmar Ratio, Maximum Drawdown, and Beta have long been used to evaluate performance. CAPM and its extensions like the Fama-French 3-Factor Model (Fama & French, 1992) introduced systematic factor-based performance attribution. These metrics, though insightful, require precise data handling and dynamic visualization to support decision-making. Rockafellar and Uryasev (2000) proposed CVaR as a coherent risk measure, improving upon the limitations of traditional VaR by accounting for tail risk.



### **Portfolio Optimization Techniques**

Efficient Frontier simulation remains a central approach for identifying optimal portfolios. De Prado (2020) highlighted limitations of traditional mean-variance optimization in high-dimensional settings, recommending robust simulation and constraint-handling methods. Techniques like Monte Carlo simulation (Boyle, 1977) allow for probabilistic estimation of future returns, enhancing scenario planning and stress testing. Modern optimization strategies now include objectives such as maximizing the Sharpe Ratio, minimizing volatility, or maximizing return, depending on investor goals.

### **Time-Varying and Rolling Metrics**

Recent research has emphasized the importance of rolling statistics like Rolling Sharpe Ratio and Rolling Beta in understanding evolving portfolio dynamics. Andersen et al. (2003) demonstrated that financial volatility is not constant, and rolling analysis offers a window into the changing risk landscape. Similarly, dynamic correlation matrices and rolling volatility indicators provide real-time insights into diversification benefits.

### **Advanced Risk and Tail Event Modeling**

To assess extreme market conditions, Extreme Value Theory (EVT) has been applied for tail risk estimation (Embrechts et al., 1997). EVT, combined with simulation-based methods, allows for better forecasting of rare but impactful market events. These approaches have gained traction post-2008 financial crisis, where reliance on Gaussian assumptions proved inadequate.

### **Integration of APIs and Visualization Tools**

The rise of open financial data APIs such as yFinance and FinancialModelingPrep has enabled real-time portfolio analysis and model-driven dashboards. Tools like Streamlit, Plotly, and Pandas have transformed how financial models are deployed and consumed interactively (McKinney, 2010; Perez & Granger, 2007). The combination of back-end analytics with front-end visualization is crucial for democratizing access to sophisticated risk analytics for investors and analysts alike.

Our proposed system synthesizes these advancements by offering a unified, interactive platform that combines historical data fetching, optimization simulations, risk modeling, and dynamic visualization to empower users with actionable portfolio insights.

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## Proposed Solution/System Architecture

The proposed solution is a Streamlit-based web application that enables users to analyze, optimize, and manage investment portfolios using a comprehensive set of financial metrics and risk models. Users can input up to 10 stock tickers along with custom weight allocations and define a historical date range for analysis. The system retrieves price data from FinancialModelingPrep, with a fallback to yFinance, and processes it using Pandas and NumPy. Core performance metrics such as CAGR, volatility, Sharpe Ratio, and correlation matrices are computed and visualized through interactive Plotly charts.

For deeper insights, the application includes a risk analytics module that calculates Value at Risk (VaR) using historical, variance-covariance, and Monte Carlo methods, along with Conditional VaR, rolling volatility, maximum drawdown, and tail risk via Extreme Value Theory. A portfolio optimization engine simulates 10,000 possible portfolios to generate the Efficient Frontier and suggest optimal allocations based on objectives like maximizing Sharpe Ratio or minimizing volatility. Additionally, the Fama-French 3-Factor model is employed to analyze factor exposures. Together, these components form a powerful platform for data-driven portfolio management and decision-making.

## System Overview

The screenshot displays the user interface of the "Multi-Dimensional Portfolio Risk and Performance Analysis" web application. The interface is divided into two main sections: a left sidebar for "Portfolio Configuration" and a main content area for "Introduction" and "Step 1: Portfolio Configuration".

**Portfolio Configuration (Left Sidebar):**

- Quote:** "Risk is the price of opportunity; manage it wisely, and the rewards will follow."
- Portfolio Value (in USD):** A text input field set to 100000.00 with minus and plus buttons.
- Number of Stocks (up to 10):** A slider control set to 3, with a range from 1 to 10.
- Stock Ticker 1:** A dropdown menu showing AAPL.
- Weight (% 1):** A text input field set to 30.00 with minus and plus buttons.
- Stock Ticker 2:** A dropdown menu showing MSFT.
- Weight (% 2):** A text input field set to 20.00 with minus and plus buttons.
- Stock Ticker 3:** A dropdown menu showing TSLA.
- Weight (% 3):** A text input field set to 50.00 with minus and plus buttons.
- Total Weight:** 100.00%
- Start Date:** A date input field set to 2024/05/06.

**Main Content Area:**

- Header:** "Multi-Dimensional Portfolio Risk and Performance Analysis" with a subtitle "Project by Aditya Jaiswal C006, Arham Shah C015, Anay Narayanan C011".
- Section 1:** "Introduction: How to Use the Portfolio Risk and Performance Analysis Tool". It includes a welcome message and a step-by-step guide on how to use the tool effectively.
- Section 2:** "Step 1: Portfolio Configuration". It lists three steps:
  - Portfolio Value:** Enter the total value of your portfolio in USD. For example, you can start with \$100,000.
  - Number of Stocks:** Use the slider to select the number of stocks in your portfolio (up to 10). For example, select 2 for a two-stock portfolio.
  - Stock Tickers and Weights:**
    - Enter the stock tickers (e.g., AAPL for Apple, MSFT for Microsoft).
    - Assign weights to each stock as a percentage of the total portfolio. For example:
      - AAPL : 60%
      - MSFT : 40%
    - Ensure the total weight adds up to 100%. If not, the tool will prompt you to adjust the weights.



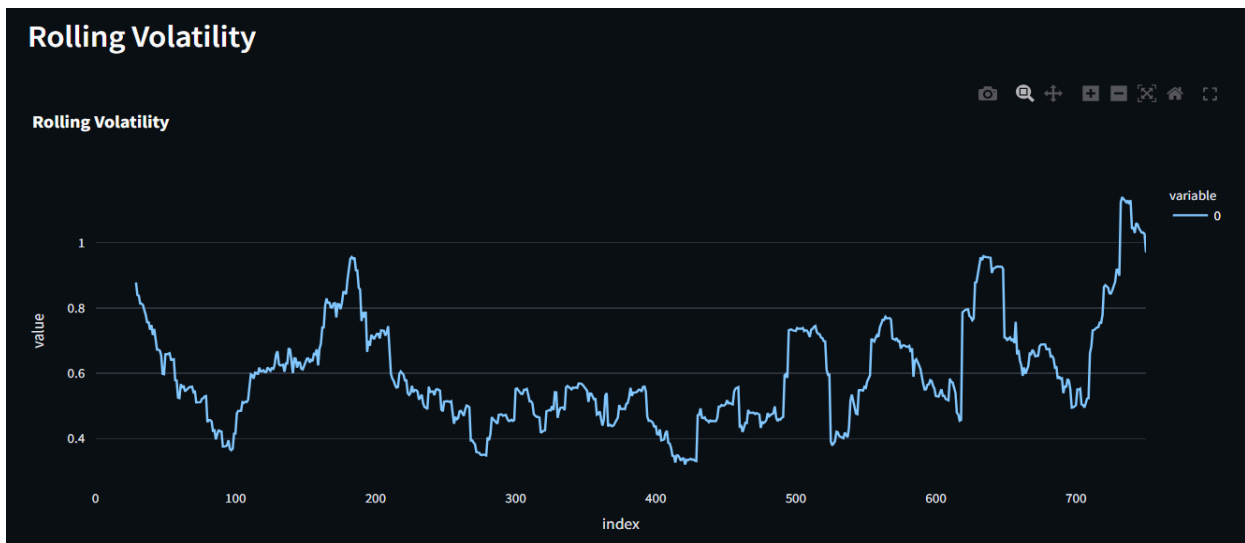
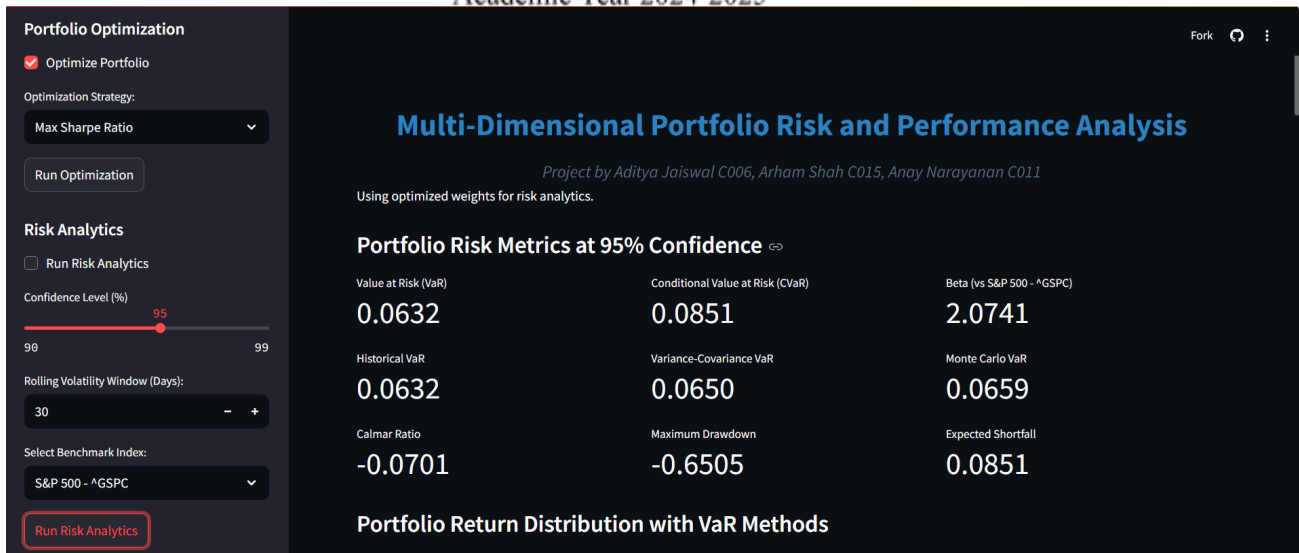
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Portfolio Metrics Comparison			
	Metric	Before Optimization	After Optimization
0	Return (%)	0.0659	0.0729
1	Volatility (%)	2.5259	3.9988



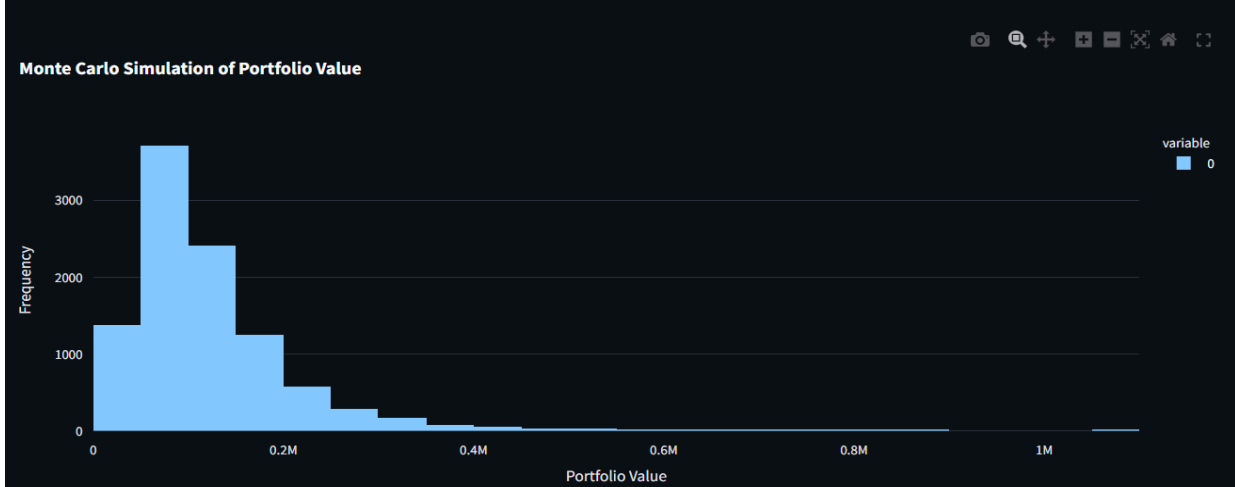
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## Monte Carlo Simulation of Future Portfolio Returns



## Stress Testing (Market Crash Scenario)





# Architecture Components

## 1. Frontend Interface (Streamlit UI)

- **Technology:** Streamlit
- **Function:** Provides an interactive web-based interface for user inputs, data visualizations, and outputs.
- **Key Features:**
  - Form fields for tickers, weights, dates
  - Buttons for fetching data, running optimization/analytics
  - Visual output: charts, metrics, tables

## 2. Data Ingestion Layer

- **Technology:**
  - `yFinance`
  - `FinancialModelingPrep API`
- **Function:** Retrieves historical stock price data and fallback handling.
- **Key Features:**
  - Custom date range support
  - API rate limit handling
  - Fallback logic to ensure data availability

## 3. Data Preprocessing & Management

- **Technology:** Pandas, NumPy
- **Function:** Cleans and aligns data, normalizes weights, handles missing values.
- **Key Features:**
  - Merges datasets across tickers
  - Prepares returns, log-returns, price series



- Manages custom portfolio weights

#### 4. Analytics Engine

- **Submodules:**

- A. Performance Metrics**

- **Functions:** CAGR, Sharpe Ratio, Volatility, Correlation
    - **Output:** Metric tables, heatmaps, time series plots

- **B. Risk Analytics**

- **Functions:**
    - VaR (Historical, VCV, Monte Carlo)
    - CVaR, Calmar Ratio, Drawdown
    - Beta, Rolling Volatility
    - EVT for tail risk
  - **Output:** Charts & summary tables

- **C. Optimization Engine**

- **Functions:**
    - Efficient Frontier simulation (10,000 portfolios)
    - Objective-based optimization (Sharpe, Return, Volatility)
  - **Technology:** SciPy (for optimization), NumPy

- **D. Factor Analysis Engine**

- **Function:** Fama-French 3-Factor regression
  - **Technology:** Statsmodels
  - **Output:** Factor loadings,  $R^2$  values



## 5. Visualization Layer

- **Technology:** Plotly
- **Function:** Converts raw metric outputs into interactive visualizations
- **Types:**
  - Line charts (Rolling metrics)
  - Pie charts (Weights)
  - Heatmaps (Correlation)
  - Scatter plots (Efficient Frontier)

## 6. Monte Carlo Simulation Module

- **Function:** Projects future returns using statistical distributions
- **Technology:** NumPy, SciPy
- **Features:**
  - Random walk simulation
  - Visual projection ranges
  - Tail risk integration

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## Technologies Used

### ◆ Frontend & UI

- **Streamlit** – Web interface for user interaction
- **Plotly** – Interactive charts and data visualizations

### ◆ Data & APIs

- **yFinance** – Fallback data source for historical stock data



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- **FinancialModelingPrep API** – Primary source for stock and financial data
- ◆ **Data Processing & Analysis**
  - **Pandas** – Data manipulation and time-series handling
  - **NumPy** – Numerical computations
  - **SciPy** – Optimization and statistical methods
- ◆ **Statistical & Financial Modeling**
  - **Statsmodels** – Regression analysis (e.g., Fama-French model)
  - **Monte Carlo Simulation** – Future return projections
  - **Extreme Value Theory (EVT)** – Tail risk modeling
- ◆ **Optimization**
  - **SciPy.optimize** – Portfolio optimization routines (e.g., Efficient Frontier)



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