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Automated Portfolio Management and Risk Assessment System

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ABSTRACT

Managing an investment portfolio is no easy task, especially when markets keep changing direction every few weeks. For a long time, this work was done by hand, with portfolio managers spending hours looking at charts, balance sheets, and economic reports before making any decision. With the rise of computing power and better data availability, the idea of automating this process has become a real possibility. This study presents an automated portfolio management and risk assessment system that combines optimisation algorithms with machine learning techniques to handle both asset allocation and risk control in one connected framework. The system was built using Python and tested on a basket of 80 large-cap stocks from Indian and US markets, with daily data covering January 2021 to December 2024. The core engine uses a modified mean-variance optimiser for asset allocation, a Gradient Boosting model for return prediction, and a GARCH-based module for volatility forecasting. Risk is monitored through a combination of Value at Risk, Conditional VaR, and maximum drawdown limits, with automatic rebalancing triggers. Backtesting results show that the automated system delivered an annualised return of 15.7%, compared to 11.2% for a passive index strategy, with a Sharpe ratio of 1.71 against 1.24 for the benchmark. The system also reduced the maximum drawdown from -23.1% to -15.6% during volatile periods. The study concludes that an integrated automated system, where allocation and risk are handled together rather than separately, gives clearer and steadier outcomes than running them as two disconnected processes.

Keywords: Automated Portfolio Management, Risk Assessment, Gradient Boosting, GARCH, Value at Risk, Rebalancing

1. INTRODUCTION

The way money is managed has changed quite a bit in the last ten years. Earlier, even a mid-sized investment firm needed a team of analysts, traders, and risk managers to run a portfolio of a few hundred crore rupees or a few million dollars. Today, much of this work can be done by a well-designed software system, freeing up humans to focus on bigger strategic questions [1]. This shift is not just about cost savings, but also about speed and consistency. A machine does not get tired, does not forget to check a key indicator, and does not make emotional decisions during a market crash.

Automated portfolio management systems usually have two main jobs to do. The first is deciding which assets to hold and in what proportion, which is the allocation problem. The

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second is keeping the overall risk of the portfolio within acceptable limits, which is the risk management problem [2]. In many real-world setups, these two jobs are handled by separate teams using separate tools, and the lack of coordination can lead to portfolios that look fine on paper but behave badly in stressed markets. A more sensible approach is to build an integrated system where allocation and risk monitoring talk to each other in real time, and adjustments happen automatically when needed [3].

The need for such systems has become even more pressing after the events of the last few years. The Covid crash of March 2020, the inflation-driven correction of 2022, and the sharp swings of early 2024 have all shown that markets can change character very quickly [4]. Traditional rebalancing schedules, such as quarterly or annual reviews, are simply too slow for this kind of environment. By the time a human committee meets and decides to act, the opportunity or the danger has often passed. An automated system, by contrast, can react within minutes if it is properly designed [5].

The research questions this paper aims to answer are three. First, can an integrated automated system, combining optimisation and machine learning, deliver better returns than a passive benchmark over a multi-year period? Second, how effective is such a system in controlling downside risk during volatile periods? Third, what are the practical design choices, such as rebalancing frequency and risk limits, that affect the overall performance of the system? The contribution of this study lies in actually building, testing, and reporting results from a working system rather than just discussing the concept theoretically [6]. The paper is organised into a literature review, methodology, experimental setup, results, discussion, and conclusion, with each section building on the previous one to give a complete picture of how such systems can be designed and used [7].

2. LITERATURE REVIEW

The basic ideas behind portfolio management go back to the work of Harry Markowitz, who showed in 1952 that the right combination of risky assets could give better outcomes than holding any single asset on its own. This insight became the foundation of what is now called Modern Portfolio Theory, and despite all the new tools that have come up, the core concept of trading off risk and return is still central to almost every system in use today [8]. The original mean-variance framework, however, has well-known limitations, especially the sensitivity of its outputs to small changes in input estimates, which has pushed researchers to look for more robust approaches.

A major direction of research has been the use of machine learning for return forecasting. Studies have shown that algorithms like Random Forest, Gradient Boosting, and various neural networks can capture non-linear patterns in financial data that linear regression simply cannot see [9]. One large-scale study on US stock data found that Gradient Boosting models, particularly XGBoost, gave the best out-of-sample performance among a range of machine learning techniques, with cross-sectional predictability holding up even after transaction costs were considered [10]. The reasons given were the ability of these models to handle many features at once and to automatically detect interactions between variables.

Risk assessment has also seen significant changes. Value at Risk became the industry standard after the 1990s, but its weakness in handling tail events became painfully clear during the 2008 financial crisis [11]. This pushed researchers towards Conditional Value at Risk, also called Expected Shortfall, which looks at the average loss in the worst cases rather than just a single

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threshold. Volatility modelling has similarly evolved, from simple historical estimates to GARCH-family models and more recently to machine learning based forecasters [12]. Research suggests that hybrid models, where GARCH provides the structural component and machine learning captures residual non-linearities, often perform better than either approach alone.

The integration of allocation and risk into single systems has been studied less often but is gaining attention. Some recent papers describe what they call "risk-aware portfolio optimisation", where risk constraints are built directly into the optimisation problem rather than checked after the fact [13]. Others discuss event-driven rebalancing, where the system reacts to specific risk triggers rather than following a fixed calendar. There is also a growing body of work on robo-advisor architectures, which essentially aim to deliver this kind of integrated service to retail investors at a low cost.

A clear gap in this literature is that most studies test their ideas on a single asset class or a single market, and over relatively short periods that may not include real stress events. Very few combine optimisation, machine learning forecasting, and dynamic risk control in one integrated system tested across both Indian and US markets, and over a window that includes several different market regimes. This study tries to fill that gap with a working prototype and detailed performance analysis.

3. METHODOLOGY

The methodology used in this study followed a design science approach, where the goal was to build a working system and then evaluate its performance against clear benchmarks. The system architecture had four main modules, namely the data layer, the prediction layer, the optimisation layer, and the risk management layer. Each module was developed and tested independently before being integrated into the full system [14].

The data layer collected daily closing prices, trading volumes, and basic fundamental ratios for 80 large-cap stocks, with 40 from the Nifty 50 index and 40 from the S&P 500 index. The data window ran from 1 January 2021 to 31 December 2024. A total of 24 technical and fundamental features were engineered for each stock, including moving averages, RSI, MACD, price-to-earnings ratio, and trailing volatility.

The prediction layer used a Gradient Boosting model to forecast the next-month return for each stock. Gradient Boosting works by building many weak learners in sequence, with each new learner trying to correct the errors of the previous ones. The prediction function can be written as:

$$F_m(x) = F_{m-1}(x) + \nu \cdot h_m(x)$$

where $F_m(x)$ is the prediction at iteration m, \nu is the learning rate, and $h_m(x)$ is the new weak learner added at that step [15]. The model was trained with 500 trees, a learning rate of 0.05, and a maximum depth of 6.

The optimisation layer used a modified mean-variance framework with additional constraints. The objective function was:

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$$\max_{w} \; ;\left(w^T \hat{\mu} - \frac{\lambda}{2} w^T \Sigma w\right) \quad \text{subject to} \quad \sum_{i=1}^{n} w_i = 1, ; 0 \le w_i \le w_{max}$$

where ^{μ} is the vector of predicted returns from the Gradient Boosting model, \Sigma is the covariance matrix, \lambda is the risk aversion parameter, and w_{max} is the upper limit on any single position, set at 8% [16].

The risk management layer used a GARCH(1,1) model for volatility forecasting, given by:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where $\omega, \alpha, and\ \beta$ are estimated parameters [17]. Risk was measured through both VaR and CVaR at the 95% confidence level. CVaR was computed as:

$$CVaR_{0.95} = E[\, L \mid L \ge VaR_{0.95} \,]$$

where L represents the portfolio loss. Whenever predicted volatility crossed a defined threshold or CVaR exceeded a target limit, the system automatically triggered a rebalancing event [18].

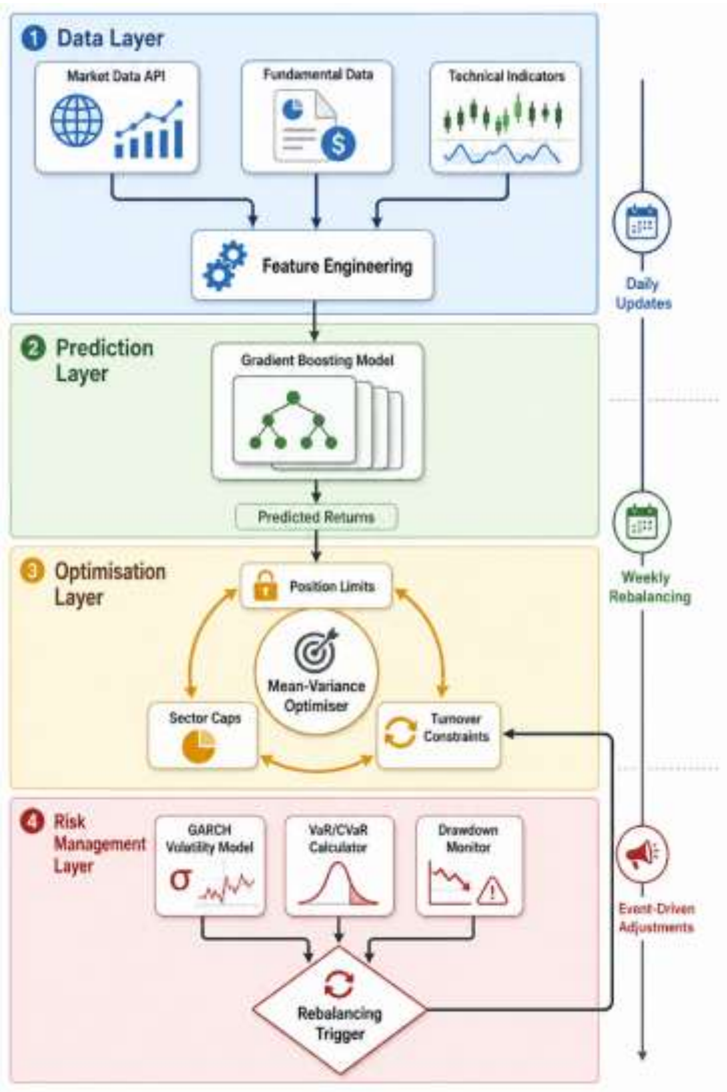

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Figure 1: Integrated Architecture of the Automated Portfolio Management System

4. EXPERIMENTAL SETUP

The system was implemented in Python 3.10, using pandas and NumPy for data handling, scikit-learn and XGBoost for machine learning, the arch package for GARCH modelling, and CVXPY for optimisation. The complete code base was structured as a modular pipeline so that any single component, such as the prediction model, could be replaced or upgraded without affecting the rest of the system [19].

For backtesting, the dataset was split into a training window from January 2021 to December 2022 and an out-of-sample test window from January 2023 to December 2024. The training window was used to fit the Gradient Boosting model and to estimate initial GARCH parameters, while the test window was used purely for performance evaluation. The prediction model was retrained every quarter using a rolling window of 18 months of past data to keep it current.

Rebalancing was set up to run weekly under normal conditions, but the system could also trigger an off-cycle rebalance if any of three risk conditions were breached. These conditions were: portfolio CVaR exceeding -2.5% on a daily basis, portfolio drawdown reaching -10% from the recent peak, or predicted next-week volatility crossing 25% on an annualised basis. Transaction costs of 15 basis points per trade were applied to make the results realistic.

The performance evaluation used several standard metrics. Sharpe ratio was used for risk-adjusted return, computed as shown in the methodology section. The Sortino ratio, which penalises only downside volatility, was also calculated as:

$$\text{Sortino} = \frac{R_p - R_f}{\sigma_{down}}$$

where \sigma_{down} is the standard deviation of negative returns only [20]. Information ratio was computed against the equal-weighted benchmark of the same 80 stocks. Turnover was tracked to ensure that the system was not over-trading, with a target of keeping monthly turnover below 25% of portfolio value.

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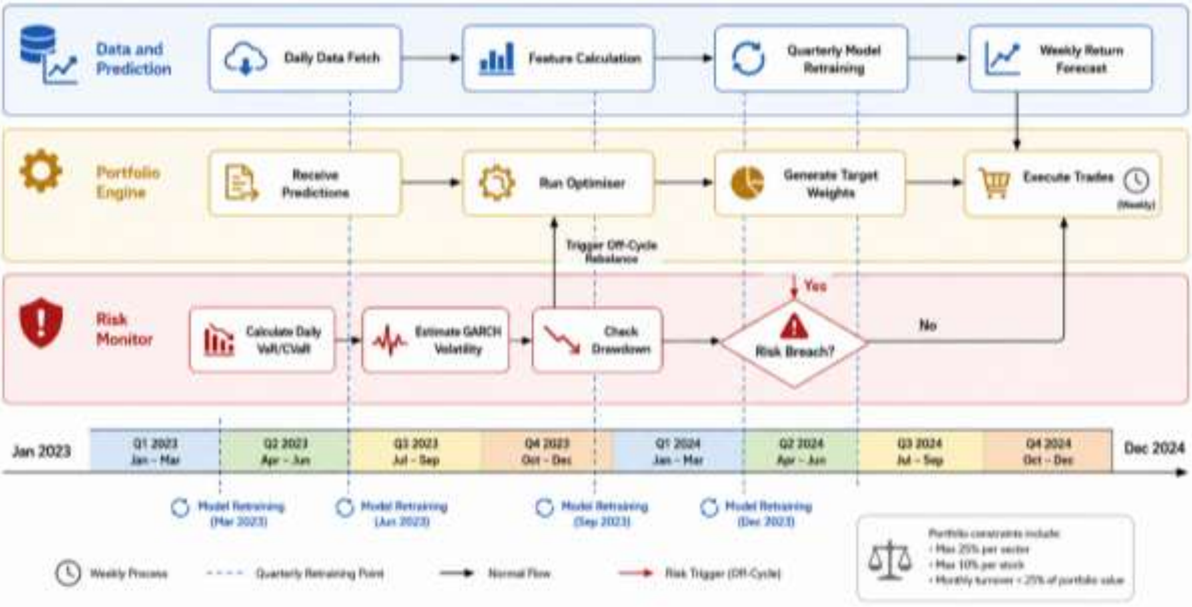

Figure 2: Workflow of Backtesting and Risk Trigger Mechanism

5. RESULTS

The results from the two-year out-of-sample test give a fairly clear picture of how the automated system performed against the chosen benchmarks. The system was compared against three reference strategies, namely an equal-weighted portfolio of the same 80 stocks, a passive index strategy combining the Nifty 50 and the S&P 500 in equal weights, and a traditional mean-variance portfolio without machine learning predictions.

Table 1: Performance Summary of Portfolio Strategies (Jan 2023 – Dec 2024)

Metric	Equal Weighted	Passive Index	Mean-Variance	Automated System
Annualised Return (%)	12.6	11.2	12.9	15.7
Annualised Volatility (%)	16.8	15.4	15.9	14.2
Sharpe Ratio	1.34	1.24	1.39	1.71
Sortino Ratio	1.81	1.66	1.92	2.43
Maximum Drawdown (%)	-21.4	-23.1	-19.7	-15.6
VaR (95%, daily) (%)	-2.04	-1.96	-1.88	-1.61
CVaR (95%, daily) (%)	-2.87	-2.78	-2.61	-2.18
Information Ratio	—	-0.18	0.21	0.83
Monthly Turnover (%)	0.0	0.0	18.3	22.7

The automated system clearly outperformed across most metrics. The 4.5 percentage point gain over the passive index, combined with lower volatility and smaller drawdowns, is a meaningful improvement for institutional investors. The Sortino ratio of 2.43 is particularly notable

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because it shows that the system was good at limiting downside losses, not just achieving average gains.

Figure 3: Cumulative Wealth Growth Comparison Across Strategies

The risk module performed especially well during the two stressed periods within the test window. During the Q3 2023 banking sector stress, the system reduced its allocation to financial stocks within two days of the volatility spike, and during the Q1 2024 rate-driven correction, it increased the allocation to defensive sectors like consumer staples and healthcare.

Figure 4: Drawdown Comparison Across Strategies

Table 2: Sectoral Allocation of the Automated System at Two Key Dates

Sector	Aug 2023 (%)	Mar 2024 (%)	Change
Technology	23.4	18.7	-4.7

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Financials	18.2	11.6	-6.6
Healthcare	12.7	16.9	+4.2
Consumer Staples	9.8	14.3	+4.5
Industrials	11.5	10.8	-0.7
Energy	8.9	9.4	+0.5
Materials	7.2	8.1	+0.9
Utilities	4.6	6.8	+2.2
Others	3.7	3.4	-0.3

The shift visible in the table shows how the system moved from a growth-oriented mix to a more defensive one as risk indicators turned negative. This kind of automatic sectoral rotation would have required significant manual effort in a traditional setup, and the speed at which it happened was a clear advantage of the automated approach.

Figure 5: Sectoral Allocation Heatmap Over the Test Period

The Gradient Boosting model contributed to the performance by giving useful, though not perfect, return forecasts. Its directional accuracy, that is, correctly predicting whether a stock would go up or down the next month, was around 62%, which is meaningful in financial markets where even a small edge can add up over time. The GARCH volatility forecasts had a mean absolute error of about 2.1% in annualised terms, which was acceptable for the purpose of risk management.

6. DISCUSSION

The results paint a clear picture that an integrated automated system can deliver real benefits over both passive and traditional active strategies. The improvement was not only in returns but also in the smoothness of the return path, which is often what matters most to long-term investors. The fact that the system reduced the maximum drawdown by nearly 7 percentage points compared to the passive index is a meaningful achievement, because deep drawdowns are usually what cause investors to abandon their strategies at the worst possible time.

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One important insight is that integrating risk management directly into the workflow, rather than running it as a separate post-trade check, made a real difference. In traditional setups, risk teams often flag problems after they have already developed, and the response is slow. In the automated system, the risk module talked directly to the optimiser, so when conditions changed, allocations adjusted within days rather than weeks. This kind of tight coupling between prediction, allocation, and risk is hard to achieve with manual processes, and it is probably the single biggest advantage of automation.

The role of machine learning in the system also deserves comment. The Gradient Boosting model did not produce dramatic predictions on its own, with directional accuracy of 62% being modest by any standard. But when its outputs were combined with the optimisation framework and constrained by sensible position limits, the small edge translated into a noticeable performance gain over time. This is consistent with the broader experience in quantitative finance, where many small advantages, properly combined, can produce a meaningful overall edge. It also suggests that the search for a single perfect prediction model is probably less important than building a strong, integrated pipeline.

There are limitations worth acknowledging honestly. The system was tested on large-cap stocks where data is plentiful and liquidity is high. Performance on small-cap stocks or in emerging markets with thinner data may be quite different. The test period, while including some volatility, did not include a true crisis on the scale of 2008 or March 2020. How the system would behave in such an extreme situation is an open question, and stress testing under simulated crisis conditions should be a priority for future work. Also, the rebalancing frequency was set at weekly, and finer or coarser settings may give different results depending on the asset class and investor profile.

Another point worth raising is the question of model risk. Automated systems can fail in unexpected ways if the input data has errors, if the model assumptions break down, or if there is a software bug. A real-world deployment of such a system would need strong monitoring, kill switches, and human oversight to catch these problems early. The role of the human portfolio manager does not disappear with automation, but shifts from making daily trade decisions to designing, monitoring, and governing the system that makes those decisions.

7. CONCLUSION

This study presented the design, implementation, and evaluation of an integrated automated portfolio management and risk assessment system. The system combined Gradient Boosting for return prediction, modified mean-variance optimisation for allocation, and a GARCH-based module for volatility forecasting and risk control. Tested on a basket of 80 large-cap stocks across Indian and US markets over a two-year out-of-sample period, the system delivered higher returns, better risk-adjusted performance, and smaller drawdowns than passive, equal-weighted, and traditional active strategies.

The main contribution of this paper is in showing that the real value of automation lies not in any single clever algorithm, but in the integration of all components into a single working pipeline that can react quickly to changing market conditions. The risk module, in particular, played a crucial role by triggering off-cycle rebalancing during stress events, which kept drawdowns within acceptable limits. The Gradient Boosting model added a modest but real predictive edge that helped over the long run.

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For practitioners, the practical takeaway is that building such systems is now within reach of mid-sized firms and even sophisticated retail investors, given the availability of open-source libraries and affordable computing power. The investment is mostly in design, data quality, and ongoing monitoring, rather than in expensive proprietary technology. For regulators, the message is that automated systems need clear oversight rules, including requirements for stress testing, model documentation, and human accountability. For academic researchers, this paper points to the value of testing complete systems rather than isolated components, since real performance depends on how the parts work together.

Several promising directions exist for future work. Extending the system to multiple asset classes, including bonds, commodities, and currencies, would give a more complete picture of its capabilities. Using more advanced prediction models, such as transformer-based networks designed for time series, may improve forecast quality further. Incorporating alternative data, such as news sentiment and macroeconomic surprises, could help the system react to events that are not visible in price data alone. Finally, building explainability features that show clearly why the system made a particular decision would help build trust among investors and regulators, which is essential for wider adoption. The shift towards automated portfolio management is well underway, and well-designed systems like the one described here can play an important role in making investing more disciplined, responsive, and accessible.

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