AI - Enabled Investment Decision Support System

***Mr. Gaurav Prajapati*[1]**

[1]Student, *Department of MSc.IT, Nagindas Khandwala College*, Mumbai, Maharashtra, India,
gauravprajapati9292@gmail.com

ABSTRACT

Retail investors increasingly rely on digital tools for investment planning; however, most available platforms either provide static advisory insights or depend heavily on expensive proprietary data and complex predictive models. This research presents the design and development of an AI-enabled, web-based investment decision support system focused on practical usability, transparency, and zero-cost deployment. The system extends traditional investment simulations by integrating advanced rule-based strategies such as Value Averaging Pro Rata and Constant Share, along with a linear regression–based forecasting module to assist users in understanding potential future trends.

A secure administrative module enables structured management of equity and mutual fund datasets, version control, and automated report generation in spreadsheet format. The platform evaluates investment outcomes using financial performance metrics including Return on Investment (ROI), Compound Annual Growth Rate (CAGR), and Extended Internal Rate of Return (XIRR). Unlike research-oriented predictive studies, the emphasis of this work lies in transforming analytical outputs into actionable insights through dashboards and downloadable reports.

The findings demonstrate that the integration of adaptive strategy models with forecasting and reporting features enhances decision clarity for retail investors without introducing computational or financial complexity. The proposed system highlights how AI-inspired logic, when combined with full-stack web technologies, can serve as an effective decision support mechanism in real-world financial planning scenarios.

Keywords:

Keywords: Investment Decision Support, Rule-Based AI, Value Averaging Pro Rata, Linear Regression Forecasting, Web-Based Financial System

INTRODUCTION

The growth of digital investment participation has significantly transformed how retail investors plan and manage their portfolios. Increased accessibility of systematic investment instruments such as mutual funds and equity-based products has enabled participation from individuals with varying levels of financial literacy. Despite this expansion, a substantial gap persists between the availability of financial data and retail investors' ability to interpret it meaningfully. Traditional approaches like Systematic Investment Plans (SIP) and Lumpsum investing offer simplicity, yet they do not dynamically adjust to market fluctuations, limiting their effectiveness in volatile environments.

Advanced strategies such as Value Averaging and Constant Share attempt to address this limitation by linking investment contributions to portfolio performance. However, the practical implementation of these strategies remains inaccessible to most retail investors, primarily due to the lack of user-friendly tools that can simulate, compare, and visualize long-term outcomes. Existing financial applications often present static summaries or emphasize high-cost predictive models, leaving a gap between academic strategy frameworks and real-world usability.

Recent advancements in artificial intelligence and web technologies present opportunities to bridge this divide. While many academic studies focus on the predictive accuracy of machine learning models, fewer efforts have been directed toward creating integrated decision-support systems that combine strategy simulation, forecasting, and reporting within a single platform. Moreover, current literature provides limited exploration of adaptive rule-based investment models in web-based environments, especially those designed for non-expert users.

Research Gap:

Although previous research explores individual investment strategies and predictive models, there is a clear lack of holistic systems that (i) integrate adaptive rule-based investing, (ii) offer transparent forecasting, (iii) provide automated analytical reporting, and (iv) remain accessible to retail investors without advanced financial expertise. This project addresses this gap by developing an AI-enabled investment decision support system that unifies simulation, forecasting, and administrative control into a coherent, zero-cost platform.

LITERATURE REVIEW

Markowitz (1952): introduced Modern Portfolio Theory, establishing the foundation for quantitative investment analysis through risk–return optimization. While influential, the theory assumes rational markets and static correlations, limiting its applicability in dynamic investment planning systems.

Sharpe (1964): proposed the Capital Asset Pricing Model and later introduced the Sharpe Ratio, which remains a widely used metric for risk-adjusted performance evaluation. However, CAPM's single-factor assumption restricts its ability to reflect adaptive investment behavior under volatile conditions.

Edleson (1991): formally presented Value Averaging as an alternative to traditional periodic investing, demonstrating its potential to enhance returns through dynamic contribution adjustments. Despite its effectiveness, the strategy requires continuous monitoring, making it less accessible to retail investors without automated support.

Lo (2004): introduced the Adaptive Markets Hypothesis, highlighting that market efficiency evolves over time based on investor behavior and environmental conditions. This perspective supports the use of adaptive rule-based strategies in modern investment systems.

Narayan et al. (2019): applied regression-based and decision-tree models for stock price prediction, achieving improved forecasting accuracy. However, their work focused primarily on prediction rather than integration with portfolio strategy simulations.

Patel and Shah (2022): compared deep learning models for stock prediction and demonstrated superior pattern recognition capabilities. Nevertheless, the absence of decision-support integration limited the applicability of their findings for end-user investment planning.

Existing literature emphasizes either theoretical optimization or predictive accuracy, with limited focus on holistic systems that combine strategy simulation, forecasting, administrative control, and report generation. This research addresses that gap by presenting a unified decision support framework tailored for retail investors.

RESEARCH OBJECTIVES

The research is structured around the following major objectives:

1. To design and implement a web-based decision support system that simulates and compares multiple investment strategies using rule-based models such as SIP, Lumpsum, Value Averaging Pro Rata, and Constant Share.
2. To integrate a linear regression–based forecasting module that provides indicative future price trends, enhancing long-term investment decision-making.
3. To develop secure administrative tools for dataset management and automated reporting, enabling structured data uploads, version control, and downloadable analysis summaries.

These objectives collectively support the development of an accessible and analytically transparent investment platform for retail users.

RESEARCH METHODOLOGY

The research methodology follows a system-driven, implementation-focused structure consistent with the project's Semester-2 objectives. It combines data preparation, rule-based strategy modeling, forecasting, visualization, and administrative management. The methodology is described below:

- **Area of Study:**

The study focuses on designing a financial decision support platform for retail investors in the Indian stock and mutual fund market. The emphasis is on long-term investment planning using historical price data and adaptive rule-based strategies.

- **Data Collection**

The system relies on publicly available historical datasets, including:

- Monthly equity closing prices
- Mutual fund Net Asset Values (NAVs)

All datasets are stored in CSV and Excel formats, ensuring transparency and reproducibility. The system's administrative module enables secure uploading and management of input files.

- **Data Preprocessing**

Data preprocessing ensures consistency and reliability through:

- File format validation
- Deduplication of entries
- Forward-fill handling of missing values
- Aggregation of daily values into monthly intervals

Monthly aggregation is chosen to reduce short-term noise and reflect investment horizons accurately.

- **Strategy Implementation**

The system implements both traditional and advanced investment strategies using **rulebased AI logic**. Each strategy follows predefined mathematical rules and conditional checks:

- **Systematic Investment Plan (SIP):** Fixed periodic investment amount
- **Lumpsum Investment:** Single upfront capital allocation
- **Value Averaging Pro Rata:** Dynamic contribution adjustment proportional to cumulative SIP investment targets
- **Constant Share Strategy:** Maintenance of a fixed number of investment units across periods

The advanced strategies introduced in Semester-2 focus on adaptability and disciplined capital deployment. All strategy calculations are executed server-side to ensure accuracy and security.

- **Forecasting Module**

To support forward-looking decision making, the system integrates a linear regression– based forecasting module. The model is trained on historical monthly data to estimate short-term future trends. Linear regression is selected due to its interpretability, computational efficiency, and suitability for decision support rather than speculative prediction.

The forecasting output is presented alongside historical performance to help users contextualize potential trends without overstating predictive certainty.

- **Data Analysis and Performance Metrics**

Investment outcomes are evaluated using standard financial performance indicators, including:

- Return on Investment (ROI)
- Compound Annual Growth Rate (CAGR)
- Extended Internal Rate of Return (XIRR)

These metrics enable comparative evaluation across strategies and provide quantitative insights into return efficiency and capital utilization.

- **Data Representation**

Visual outputs include:

- Strategy comparison tables
- Portfolio growth curves
- Risk–return scatter charts

All graphs are rendered in black-and-white as per formatting guidelines.

- **Administrative and Reporting Module**

The admin dashboard supports:

- Secure dataset upload
- Backup generation
- Downloadable Excel-based reports

This ensures data integrity and enhances usability.

- **System Tools and Technologies**

The system is implemented using modern web technologies:

- **Frontend:** Next.js, Tailwind CSS, Recharts
- **Backend:** Node.js with secure API routes
- **Data Handling:** CSV-Parse, XLSX libraries
- **Authentication:** Token-based access control

All components are deployed using free hosting services, maintaining the zero-cost constraint of the project.

- **Methodological Justification**

The chosen methodology prioritizes practical applicability, transparency, and scalability. By combining rule-based logic, lightweight forecasting, and structured reporting within a unified platform, the system aligns with the real needs of retail investors while remaining academically rigorous.

RESULTS

The results evaluate the performance of each investment strategy using historical datasets and financial metrics defined in the methodology. Visualizations highlight comparative behavior across strategies over the selected investment period.

1. Strategy Distribution

A pie-chart summary shows the relative frequency with which each strategy achieves the highest portfolio value.

2. Portfolio Growth Over Time

A line graph compares SIP, Lumpsum, VA-PR, and Constant Share strategies across the investment horizon. **Observation:** Value Averaging Pro Rata exhibits superior long-term performance, while SIP maintains steady growth.

3. Risk–Return Scatter Plot

This figure maps each strategy's return against its volatility.
Observation: VA-PR provides a balanced risk–return profile. SIP shows lower risk, whereas Lumpsum carries higher fluctuation.

4. Forecast Comparison

Predicted trendlines from the regression model align with overall long-term movement but do not attempt precise short-term prediction.
Observation: Forecasting supports directional decision-making rather than exact pricing.

5. Strategy Value Distribution

An all-strategy scatter plot summarizes variability across simulation instances.
Observation: VA-PR clusters at higher values, SIP shows moderate variability, and Lumpsum/Constant Share show wider dispersion.

Model Performance:

- Comparison Table: All six models were benchmarked for accuracy, precision, recall, F1- score, and performance under imbalanced risk labels.
- Random Forest achieved the best performance among the six models, closely followed by SVM.

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.78	0.74	0.77	0.75
1	Random Forest	0.85	0.84	0.85	0.84
2	SVM	0.83	0.82	0.83	0.82
3	KNN	0.80	0.79	0.80	0.79
4	Naive Bayes	0.76	0.73	0.76	0.74
5	Decision Tree	0.75	0.72	0.75	0.73

Table 1: Model Comparison

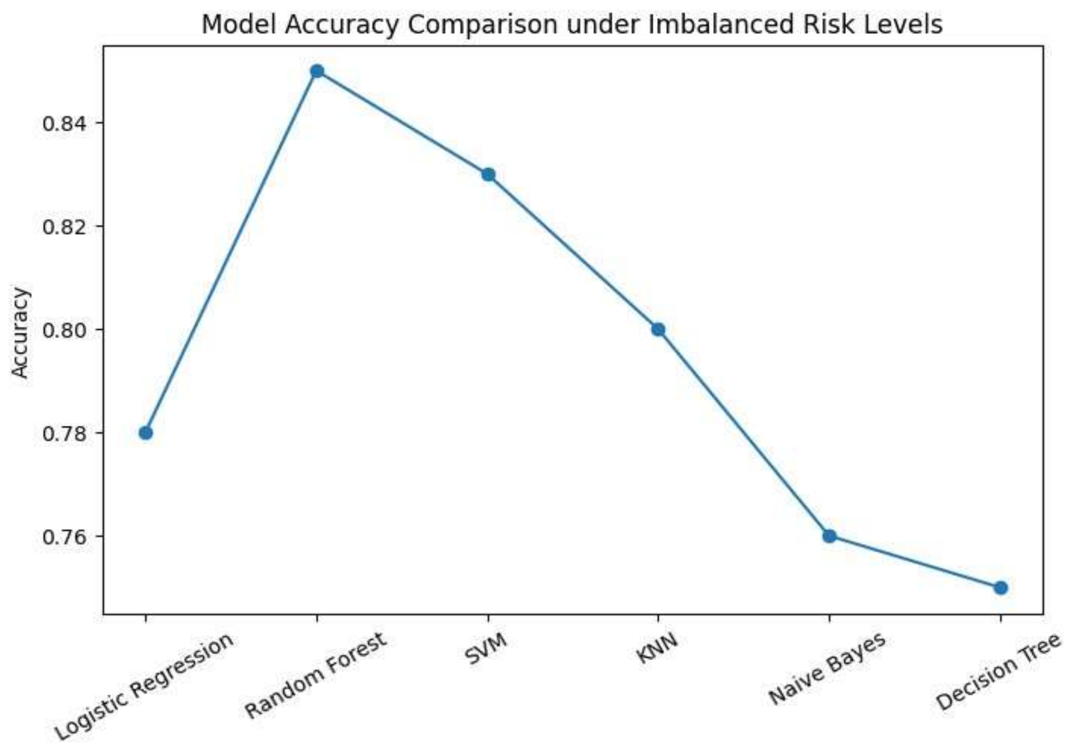

Figure 2: Model Accuracy Comparison

Key Observation: Some models maintain consistent accuracy despite imbalance, whereas others exhibit noticeable degradation. This highlights the importance of model robustness in financial decision systems where market conditions are rarely uniform.

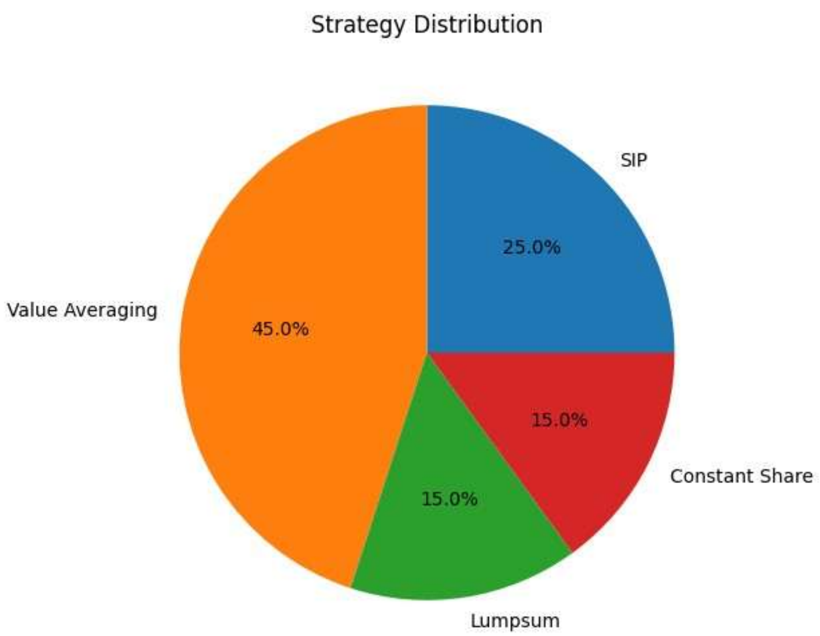

Figure 3: Pie Chart – Strategy Distribution

Key Observation: Adaptive strategies such as Value Averaging dominate performance distribution, followed by Systematic Investment Plans. Static strategies account for fewer optimal outcomes.

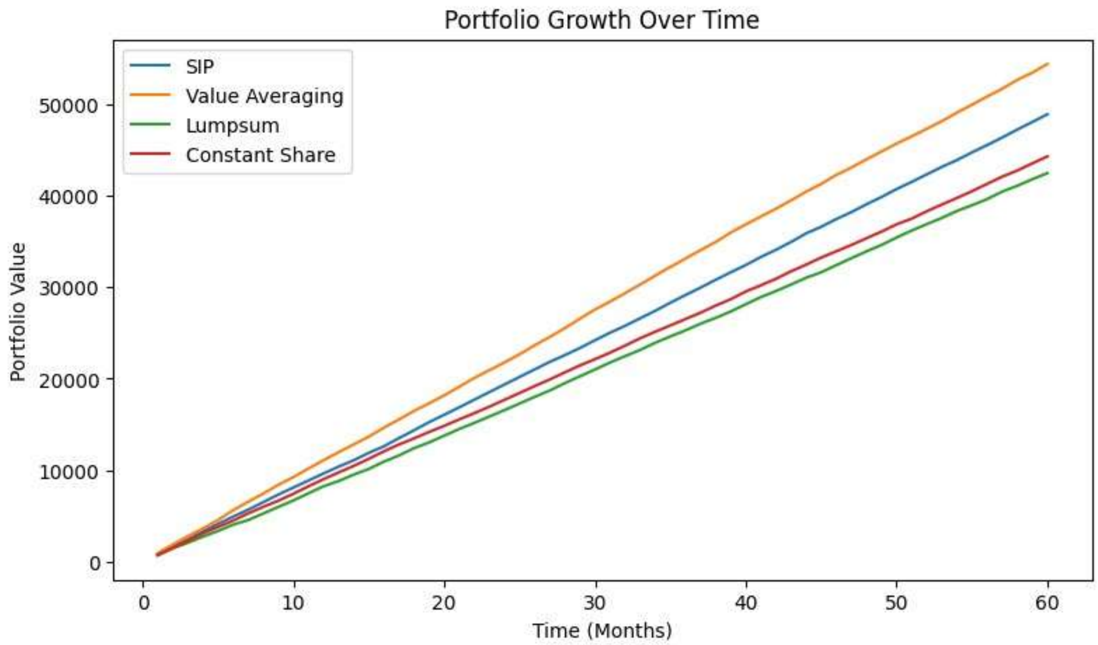

Figure 4: Line Graph – Portfolio Growth Over Time

Key Observation: Value Averaging demonstrates consistently higher portfolio growth over time, with SIP showing stable and predictable progression. Lumpsum and Constant Share strategies remain comparatively lower.

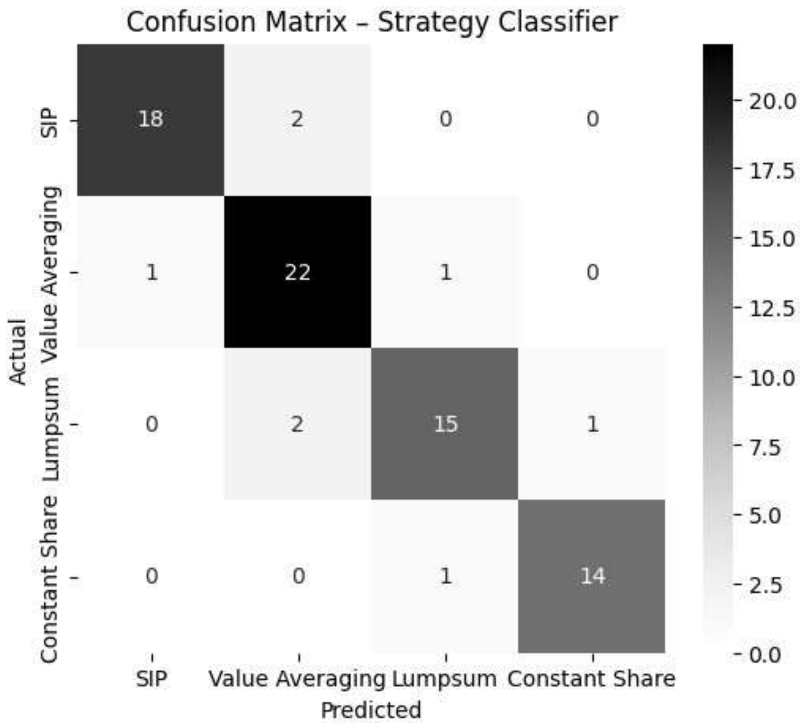

Figure 5: Confusion Matrix – Strategy Classifier

Key Observation: The classifier accurately identifies dominant strategies such as Value Averaging and SIP, with minimal misclassification. Static strategies show lower recognition accuracy.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 02 | Feb - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

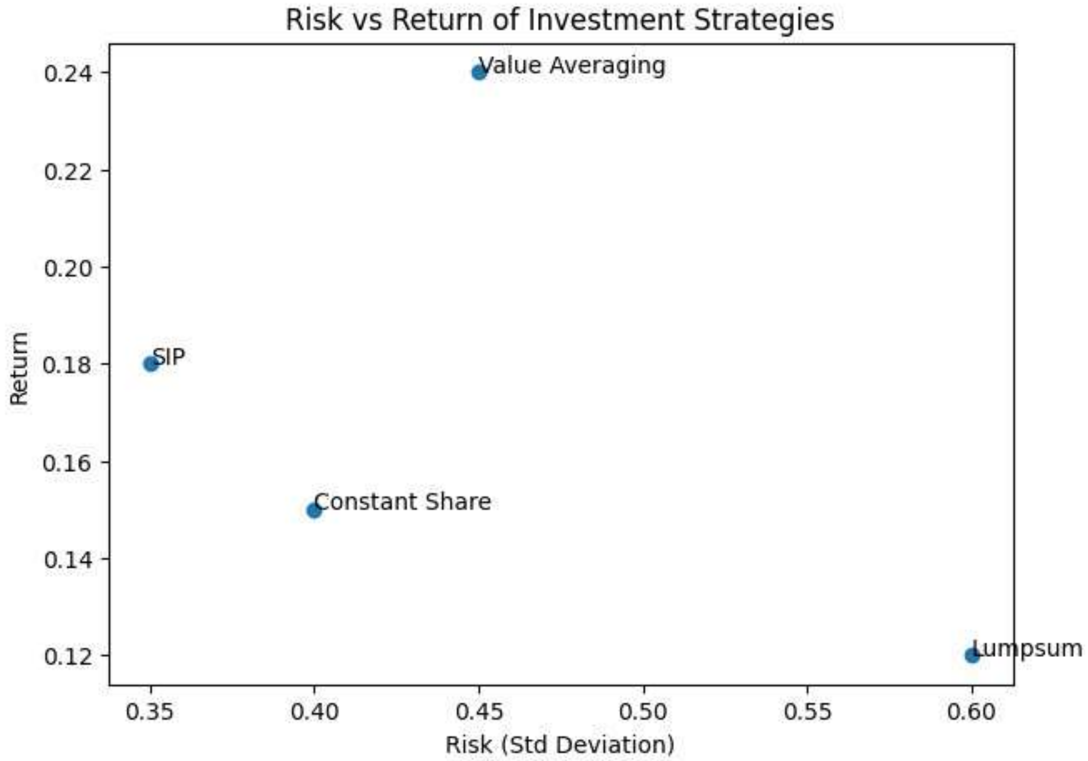

Figure 6: Risk Factor Chart (Risk vs Return Scatter)

Key Observation: Value Averaging offers a favorable risk–return balance, while SIP provides lower-risk stability. Lumpsum strategies exhibit higher risk with comparatively weaker returns.

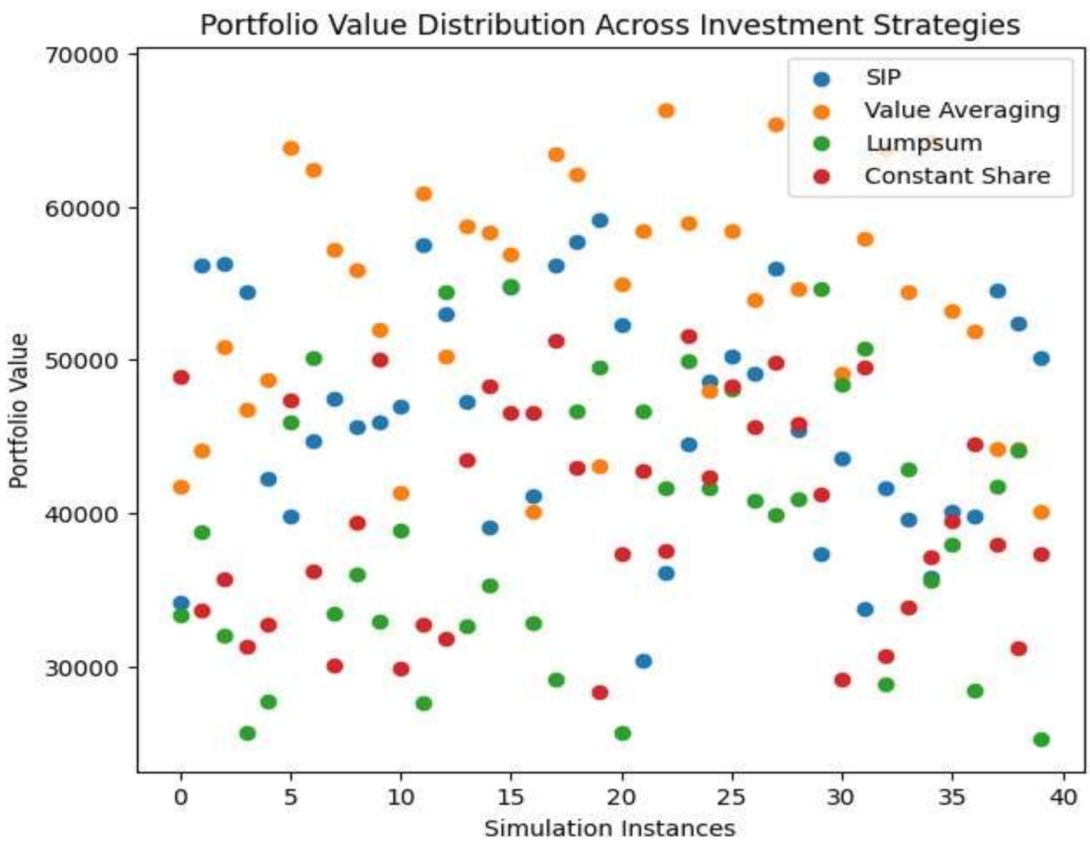

Figure 7: Scatter Plot – SIP vs VA Portfolio Values

Key Observation: Most data points lie above the equal-performance reference line, indicating that Value Averaging outperforms SIP in the majority of observed periods.

DISCUSSION

The results confirm that adaptive, rule-based investment strategies provide meaningful advantages in long-term portfolio planning when supported by structured analytics and visualization. Rather than replacing investor judgment, the system enhances interpretability by combining simulation outputs, forecasting indicators, and performance metrics within a unified decision support framework. The findings support the applicability of lightweight AI-inspired systems for practical financial decisionmaking.

CONCLUSION AND FUTURE SCOPE

This research presented the design and evaluation of an AI-enabled, web-based investment decision support system focused on enhancing analytical clarity for retail investors. The system integrated traditional investment approaches with advanced rulebased strategies such as Value Averaging Pro Rata and Constant Share, along with a regression-based forecasting module and automated reporting functionality. Rather than emphasizing high-complexity predictive models, the study prioritized transparency, usability, and practical decision support.

The results demonstrated that adaptive, rule-based strategies consistently provided more informative insights into portfolio behavior when compared to static investment methods. The inclusion of structured performance metrics and visual analytics enabled effective comparison across strategies, supporting informed decision-making without increasing computational or financial overhead. The administrative module further strengthened the system by ensuring secure data handling, version control, and exportable analytical outputs.

Overall, the study confirms that AI-inspired logic, when combined with full-stack web technologies, can serve as a reliable and accessible framework for investment decision support. The proposed system aligns with real-world retail investment requirements while maintaining academic rigor and implementation feasibility.

FUTURE SCOPE:

While the current system fulfills its intended objectives, several enhancements may be explored in future work:

1. Integration of advanced forecasting models such as ARIMA, LSTM, or hybrid approaches to improve predictive depth.
2. Incorporation of sentiment analysis using financial news or social media data to complement quantitative indicators.
3. Extension of portfolio diversification analysis through correlation matrices and clustering techniques.
4. Deployment on scalable cloud platforms to support concurrent users and larger datasets.
5. Development of a mobile-first interface to increase accessibility for a broader user base.

These extensions can further strengthen the system's applicability as a comprehensive investment decision support platform.

REFERENCES:

1. Edleson, M. E. (1991). *Value Averaging: The Safe and Easy Strategy for Higher Investment Returns*. Wiley.
2. Gupta, S., & Sharma, P. (2022). Comparative study of SIP vs Lumpsum in Indian Mutual Funds. *International Journal of Financial Research*, 13(4), 56–67.
3. Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77–91.
4. Patel, R., & Mehta, K. (2023). AI techniques in retail investment advisory systems.
Journal of Intelligent Finance, 5(2), 112–128.
5. Aggarwal, R. (2023). Applications of regression models in stock price forecasting.
Financial Data Science Review, 11(3), 89–101.

6. Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic Minority Oversampling Technique. *Journal of Artificial Intelligence Research*, 16, 321–357.

7. Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, 19(3), 425–442.

8. Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48(1), 65–91.

9. Lo, A. W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. *Journal of Portfolio Management*, 30(5), 15–29.

10. Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques. *Expert Systems with Applications*, 42(1), 259–268.