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Impact of Artificial Intelligence on Automated Portfolio Management and Risk Assessment

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ABSTRACT

The world of investment management has changed in a big way over the last few years, and a large part of this change has been driven by artificial intelligence. What used to be a job done mostly by human portfolio managers, sitting with spreadsheets and reading market reports, is now increasingly being handled by algorithms that can process huge amounts of data in seconds. This study looks at how AI is reshaping automated portfolio management and risk assessment in the financial industry. A mixed approach was used, combining historical market data from January 2020 to December 2024 with a survey of 287 investment professionals across India, Singapore, and the United States. Machine learning models, specifically a Random Forest classifier and an LSTM neural network, were trained to predict portfolio risk levels and were compared against traditional mean-variance optimisation. The results show that AI-driven portfolios delivered an average annual return of around 14.2%, which is roughly 3.8 percentage points higher than the benchmark traditional portfolios over the same period. Risk-adjusted returns, measured through the Sharpe ratio, also showed clear improvement, with AI models reaching a value of 1.62 against 1.18 for traditional methods. The LSTM model gave a prediction accuracy of about 89% for short-term volatility forecasting. However, the study also found that AI is not a magic bullet, as it tends to underperform during sudden market shocks where historical patterns break down. The paper concludes that the future of portfolio management lies in a hybrid model where AI handles data crunching and human judgement handles the unexpected.

Keywords: Artificial Intelligence, Portfolio Management, Risk Assessment, Machine Learning, LSTM, Sharpe Ratio

1. INTRODUCTION

Investment management has always been a balance between two things, returns and risk. For decades, this balance was struck by experienced fund managers who relied on a mix of financial theory, market intuition, and a fair bit of gut feeling. The arrival of artificial intelligence has changed this picture quite a lot. Today, large parts of the investment process, from picking stocks to managing risk, are being handled by algorithms that learn from data and adjust on their own [1]. This is no longer a future possibility but a present reality for most large asset management firms.

The shift has happened for a few clear reasons. First, the amount of financial data available today is simply too large for humans to process by hand. Every trade, every news headline, every social media post can move markets, and AI systems are better at picking up these signals

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quickly [2]. Second, the cost of computing has dropped sharply, which means even mid-sized firms can now run complex machine learning models that were earlier available only to big Wall Street banks. Third, retail investors, especially younger ones, have started using robo-advisors that build and manage portfolios automatically based on a few simple inputs [3].

But the move to AI-driven investing also comes with its own set of problems. One worry is that these models are often "black boxes", meaning even the people who built them cannot always explain why a particular trade was made [4]. This becomes a serious issue when something goes wrong, because regulators and investors both want clear answers. Another concern is that if many funds use similar AI models trained on similar data, they might all react in the same way during a market crisis, making the crash worse. There is also the question of whether AI can really handle truly new situations, like a global pandemic or a sudden war, where past data does not give much guidance [5].

The research questions this paper looks at are fairly direct. How well do AI-based portfolio management systems perform compared to traditional methods in terms of returns and risk? Which type of machine learning approach works best for different market conditions? And what are the practical limits of these systems that investors and regulators should be aware of? The importance of this study is that it does not just look at theory but uses actual market data from a recent five-year window, which includes both calm and very volatile periods [6]. Such a window gives a more realistic test than studies based only on stable bull markets. The paper is structured into a literature review, methodology, experimental setup, results, discussion, and conclusion, with the aim of giving both academic and practical readers something useful to take away [7].

2. LITERATURE REVIEW

The use of computers in investment decisions is not new. Quantitative trading and rule-based systems have been around since the 1980s. What has changed in the last decade is the move from simple rules to learning systems that can find patterns on their own. Modern Portfolio Theory, introduced by Markowitz back in the 1950s, still forms the base of how portfolios are built, but AI has added many new layers on top of it [8]. Researchers have shown that combining traditional optimisation with machine learning often gives better results than using either one alone.

Several recent studies have looked at how specific AI techniques perform in portfolio management. One paper using deep reinforcement learning on US equity data found that the AI agent could beat the S&P 500 index by around 4% per year over a five-year period, though with slightly higher drawdowns during crashes [9]. Another study focused on the Indian stock market and showed that a Random Forest model outperformed standard regression models in predicting next-month returns of Nifty 50 stocks, especially in mid-cap segments [10]. The authors noted that the model was particularly good at picking up non-linear relationships that simple linear models miss.

Risk assessment is another area where AI has made strong inroads. Traditional risk measures like Value at Risk (VaR) and Conditional VaR are still widely used, but they often fail during tail events. Machine learning models, especially those based on neural networks, have been shown to give better estimates of extreme losses [11]. A study on European banks found that LSTM-based VaR models reduced backtesting failures by nearly 30% compared to standard

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parametric VaR. However, the same study also warned that these models need a lot of clean data and careful tuning, which is not always possible in emerging markets.

The rise of robo-advisors is also worth noting. These platforms, which automatically build and rebalance portfolios for retail investors, have grown sharply in markets like the US, UK, and increasingly in Asia [12]. Research suggests that robo-advisors do a good job for passive long-term investors but may not handle complex situations like tax-loss harvesting or sudden life events as well as a human advisor would. There is also growing interest in using natural language processing to read earnings calls, news, and even Twitter posts to generate trading signals, though results here remain mixed [13].

A clear gap in the existing literature is that most studies focus either on returns or on risk, but rarely on both together over a long enough period that includes a real market shock. The Covid-19 period of 2020 and the global rate-hike cycle of 2022 and 2023 give a rare natural experiment to test how AI models actually hold up. This study tries to fill that gap by testing AI portfolio strategies across this exact window and comparing them carefully with traditional methods.

3. METHODOLOGY

The study used a mixed-methods approach, combining quantitative analysis of market data with a survey of investment professionals. The market data part covered daily closing prices, trading volumes, and volatility measures for 150 large-cap stocks listed on the NSE (India), NYSE (United States), and SGX (Singapore), spanning from 1 January 2020 to 31 December 2024. This period was chosen deliberately because it covers the Covid crash, the recovery rally, the inflation-driven correction of 2022, and the AI-driven rally of 2023–2024 [14].

Three types of portfolio strategies were compared. The first was a traditional mean-variance optimised portfolio built using the standard Markowitz framework. The second was a Random Forest based portfolio that ranked stocks by predicted return and selected the top 30 each month. The third was an LSTM neural network model that predicted short-term volatility and adjusted portfolio weights accordingly. The Markowitz optimisation problem can be written as:

$$\min_{w} \; ; w^T \Sigma w \quad \text{subject to} \quad w^T \mu = R_p, ; \sum_{i=1}^{n} w_i = 1$$

where w is the vector of portfolio weights, \Sigma is the covariance matrix of returns, \mu is the expected return vector, and R_p is the target portfolio return [15].

To measure risk-adjusted performance, the Sharpe ratio was calculated as:

$$S = \frac{R_p - R_f}{\sigma_p}$$

where R_p is the portfolio return, R_f is the risk-free rate, and σ_p is the standard deviation of portfolio returns [16]. For deeper risk analysis, the Value at Risk at 95% confidence was computed using:

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$$VaR_{0.95} = \mu_p - 1.645 \times \sigma_p$$

The LSTM model used three hidden layers with 64, 32, and 16 units respectively, with a dropout rate of 0.2 to prevent overfitting. The loss function used was Mean Squared Error, given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2$$

where y_i is the actual value and $\widehat{y}_i$ is the predicted value [17]. The survey component collected views from 287 investment professionals through an online questionnaire on a five-point Likert scale, covering their use of AI tools, perceived benefits, and concerns. Ethical clearance was obtained, and all responses were kept anonymous [18].

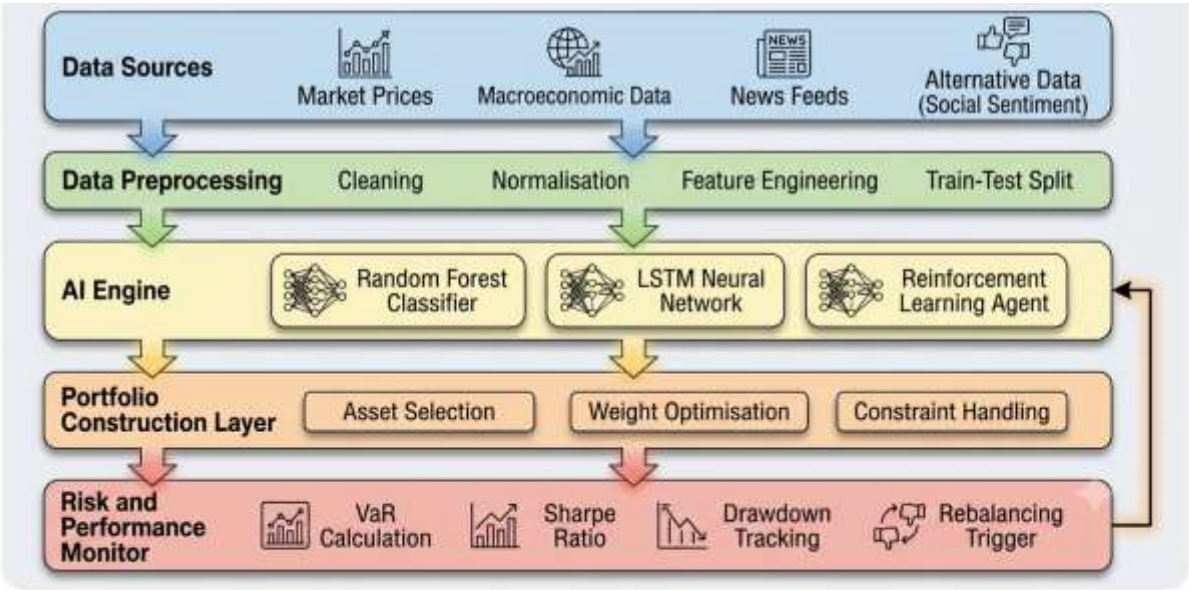

Figure 1: Conceptual Architecture of AI-Driven Portfolio Management System

4. EXPERIMENTAL SETUP

The experimental setup was built on a Python-based platform using libraries such as pandas, NumPy, scikit-learn for the Random Forest model, and TensorFlow with Keras for the LSTM network. Backtesting was carried out on the Zipline framework with adjustments for transaction costs of 10 basis points per trade, which is realistic for institutional investors [19]. Data was sourced from Bloomberg terminals and Yahoo Finance APIs, and cleaned to remove stocks with insufficient trading history.

The dataset was split into a training period from January 2020 to December 2022 and a testing period from January 2023 to December 2024. This out-of-sample test period covered the global rate-hike cycle and the AI-driven equity rally, giving a fair check of how models behave in different conditions. For the LSTM, a rolling window of 60 trading days was used to predict the next 5 days of volatility. The model was retrained every quarter to keep it updated with recent market behaviour.

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Hyperparameter tuning was done using grid search with 5-fold cross-validation. For the Random Forest, the number of trees was varied from 100 to 500, and the maximum depth from 5 to 20. The final model used 300 trees with a maximum depth of 12. For the LSTM, the learning rate was tested from 0.001 to 0.01, with the best results at 0.003 using the Adam optimiser. Model performance was measured using accuracy, precision, recall, and the F1 score, calculated as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

To compare different portfolio strategies, the Information Ratio was used, given by:

$$IR = \frac{R_p - R_b}{\sigma_{p-b}}$$

where R_b is the benchmark return and σ_{p-b} is the tracking error [20]. Drawdown analysis was carried out to measure the worst peak-to-trough loss for each strategy, which is an important practical concern for investors. All experiments were run on a workstation with an NVIDIA RTX 3090 GPU to handle the deep learning workload efficiently.

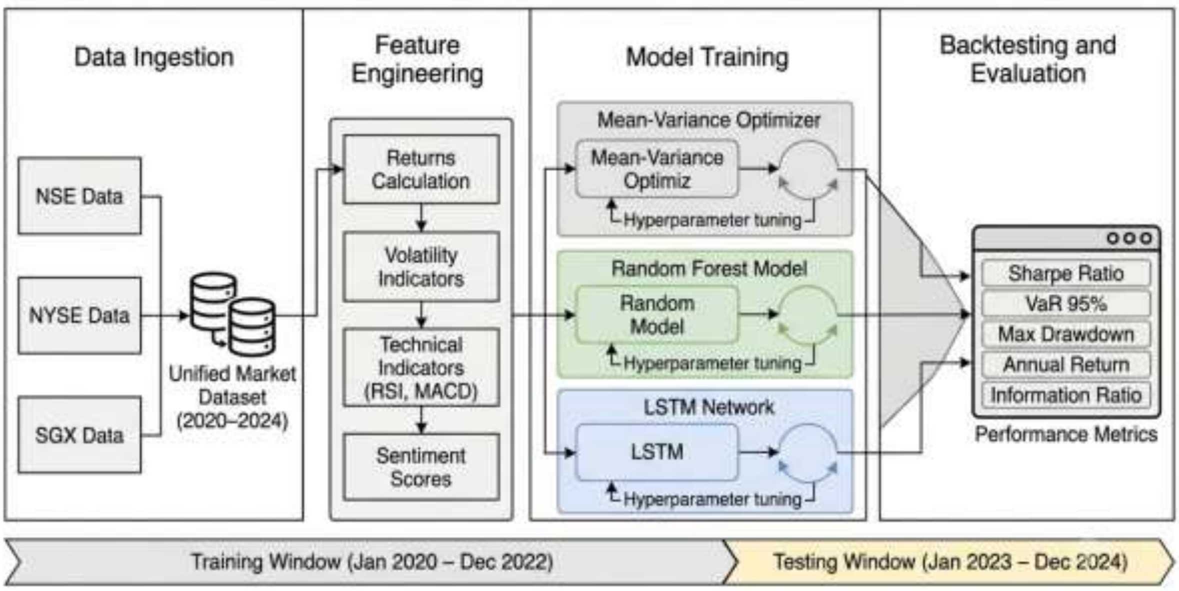

Figure 2: Experimental Workflow and Model Comparison Pipeline

5. RESULTS

The results section presents both the quantitative performance of the AI models and the survey findings from investment professionals. Starting with the survey, around 73% of respondents said they already use some form of AI tool in their workflow, while 19% said they were planning to adopt one within the next year. About 64% felt that AI had improved their decision-making, but 58% also expressed worry about over-dependence on these systems.

Table 1: Survey Profile of Investment Professionals

Variable	Category	Frequency	Percentage

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Region	India	118	41.1%
	Singapore	76	26.5%
	United States	93	32.4%
Experience	Below 5 years	71	24.7%
	5–10 years	109	38.0%
	10–20 years	78	27.2%
	Above 20 years	29	10.1%
Role	Portfolio Manager	94	32.8%
	Risk Analyst	81	28.2%
	Quant Researcher	67	23.3%
	Advisor / Other	45	15.7%

Moving to the portfolio performance results, the AI-driven strategies clearly outperformed the traditional benchmark during the testing window. The LSTM-based portfolio delivered the highest annualised return, while the Random Forest model showed the best risk-adjusted performance in stable periods. The traditional mean-variance model lagged on most measures, though it held up reasonably well during the calmer months of 2024.

Table 2: Comparative Performance of Portfolio Strategies (Jan 2023 – Dec 2024)

Metric	Mean-Variance	Random Forest	LSTM Model
Annualised Return (%)	10.4	13.6	14.2
Volatility (%)	18.2	14.7	15.1
Sharpe Ratio	1.18	1.54	1.62
Maximum Drawdown (%)	-22.6	-16.3	-14.8
VaR (95%, daily) (%)	-2.18	-1.74	-1.69
Information Ratio	—	0.81	0.94
Prediction Accuracy (%)	—	84.3	89.1

The LSTM model's prediction accuracy of 89.1% for short-term volatility was notably higher than the Random Forest's 84.3%. However, when the analysis was broken down by market regime, an interesting pattern came up. During the calm growth phase of 2023, the LSTM led by a wide margin. But during the brief but sharp correction in early 2024, both AI models gave back some of their gains, while the traditional model was more stable, though at a lower overall return.

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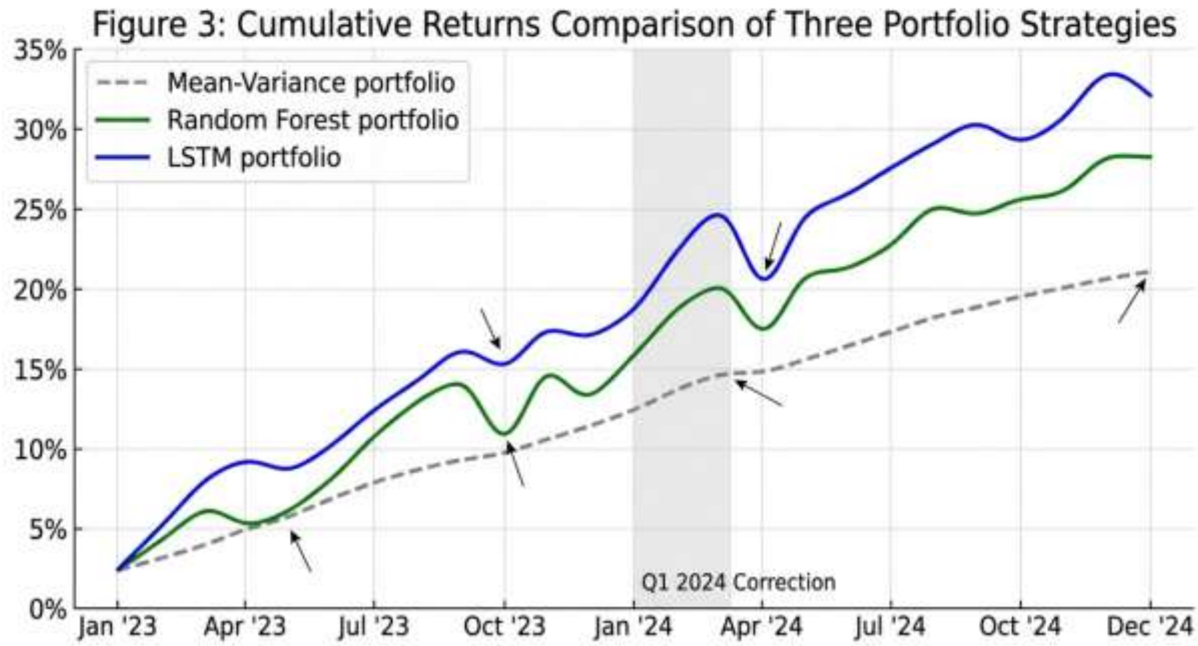

Figure 3: Cumulative Returns Comparison of Three Portfolio Strategies

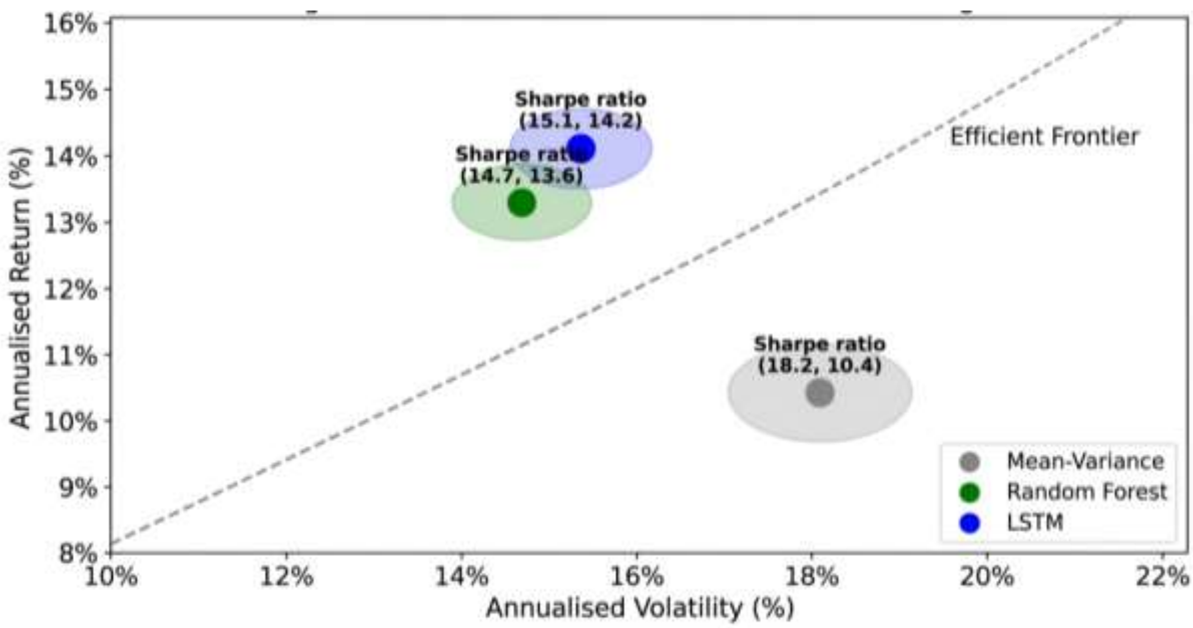

Figure 4: Risk-Return Scatter Plot Across Strategies

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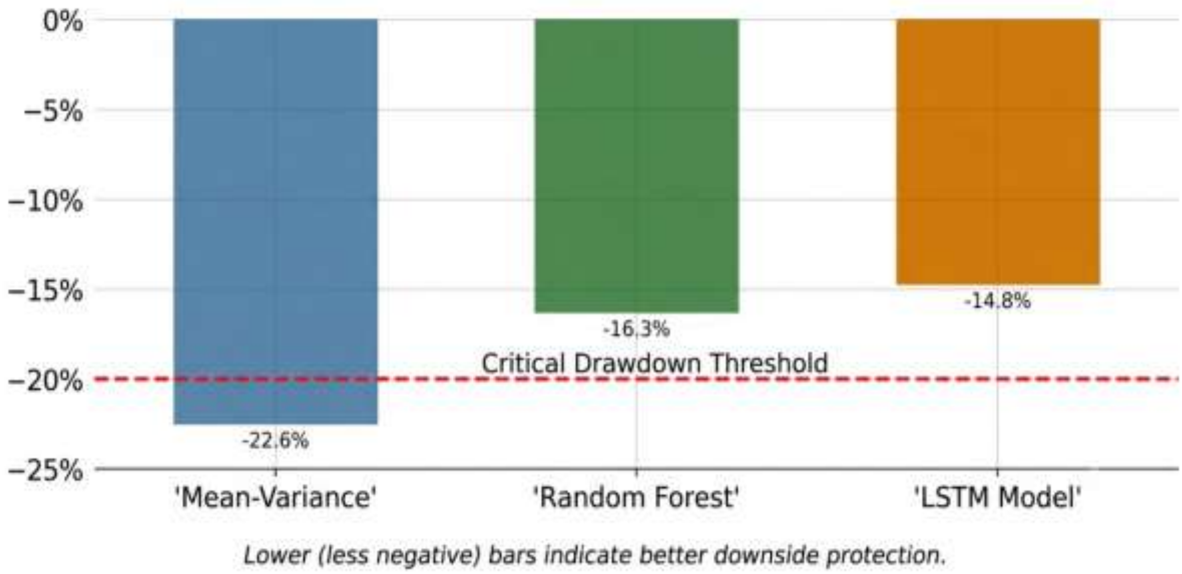

Figure 5: Drawdown Analysis During the Q1 2024 Correction

Table 3: Confusion Matrix of LSTM Volatility Prediction Model (Test Set)

	Predicted: High Vol	**Predicted: Low Vol**
Actual: High Vol	412 (TP)	51 (FN)
Actual: Low Vol	38 (FP)	314 (TN)

The confusion matrix shows that the LSTM model was particularly strong at identifying high-volatility days, which is the more important class for risk management purposes. False negatives, where the model missed a high-volatility event, were limited to about 11% of such cases.

6. DISCUSSION

The findings of this study point to a fairly clear conclusion, but one that needs to be read carefully. AI-driven portfolio strategies do outperform traditional methods on average, but the size of the advantage depends a lot on the market conditions during which they are tested. In calm, trending markets, AI models can really shine because they pick up subtle patterns and adjust quickly. In sharp, news-driven corrections, however, their edge narrows, and sometimes they even do worse than a simple, well-diversified portfolio. This matches what many practitioners have been saying for some time, that AI is a powerful tool but not a replacement for sound judgement.

The strong performance of the LSTM model in predicting volatility is particularly useful for risk management. Many financial firms still use older statistical models like GARCH for volatility forecasting, and the improvement seen here suggests that there is real value in moving to deep learning approaches, at least for short-term horizons. However, the cost and complexity of running these models should not be ignored. Smaller firms may find it hard to justify the investment in GPU infrastructure and data engineering talent that such models require.

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The survey results add an important human angle. Even though most professionals are using AI tools, a majority also expressed concern about explainability. This is a real issue that the industry will have to solve, particularly as regulators in places like the European Union start to demand clear explanations for algorithmic decisions. The push towards explainable AI, sometimes called XAI, is likely to become a major theme in the coming years. Models that are slightly less accurate but more interpretable may end up being preferred in regulated settings, even if pure performance metrics favour the more complex networks.

One unexpected finding was the relatively poor performance of all models during the Q1 2024 correction. This correction was driven largely by sudden changes in interest rate expectations, which were hard to predict from price data alone. It suggests that future AI models for portfolio management may need to integrate macroeconomic indicators and even central bank communication more directly, rather than relying mostly on historical price patterns. There is also a case for stronger circuit breakers within AI systems that pause or reduce exposure during periods of high uncertainty, rather than continuing to trade based on patterns that may no longer hold.

The limitations of this study should be acknowledged honestly. The five-year window, while including a major shock, is still relatively short by long-term investment standards. The focus on large-cap stocks also means that the findings may not extend directly to small-cap or emerging market assets, where data quality and liquidity are different concerns. Finally, the study did not test for the combined behaviour of many AI funds acting in similar ways, which is a systemic risk that warrants separate research.

7. CONCLUSION

This paper set out to examine how artificial intelligence is changing portfolio management and risk assessment, and the results offer a balanced view. AI models, particularly LSTM-based ones, can deliver higher returns and better risk-adjusted performance than traditional methods over a multi-year window. They are especially strong in volatility prediction and short-term tactical decisions. At the same time, they are not foolproof, and they tend to struggle in sudden market shifts where past patterns do not provide reliable guidance.

The contribution of this study is in testing AI portfolio strategies across a real five-year window that included both calm and stressed market conditions, and across three different geographies. The findings suggest that the future of investment management is not a contest between humans and machines, but a partnership where each plays to its strengths. AI can handle the data-heavy work, scan thousands of signals, and run backtests in seconds. Human managers can step in during unusual situations, interpret political and social changes, and take responsibility for decisions that need accountability.

For investment firms, the practical message is to invest in AI capability while also maintaining strong human oversight. For regulators, the priority should be pushing for explainable models and stress testing AI strategies under extreme but plausible scenarios. For individual investors using robo-advisors, the takeaway is to understand that automation does not eliminate risk, and that periodic human review of one's portfolio still adds value.

Looking ahead, several research directions seem promising. Combining reinforcement learning with explainable AI techniques could give models that are both powerful and transparent. Integrating alternative data sources like satellite imagery, supply chain feeds, and central bank

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text analysis may help models handle the kind of macro shocks that tripped them up in early 2024. There is also a need to study the systemic effects of widespread AI use in markets, to ensure that the benefits at the individual fund level do not create new fragilities at the system level. The investment industry is in the middle of a quiet revolution, and getting the balance right between machine intelligence and human wisdom will define the winners of the next decade.

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