Artificial Intelligence in Financial Trading Predictive Models and Risk Management Strategies

Shaik Asif Basha[1], Amir Zia[2], Kirankumar B[3], Chandra Sekhar S[4], Sumithra S[5] and Monisha Jothi R[6]

[1]Masters in Computer Applications, Alinma Esnad, Senior Business Consultant, Saudi Arabia.
asif.shaikmca@gmail.com
[2]Assistant Professor, Department of Business Tashkent Metropolitan University, Tashkent, Uzbekistan
Ziaamir70@gmail.com
[3]Assistant Professor, Department of Information Technology, CVR college of engineering, Hyderabad, Telangana, India
bkirankumar5859@gmail.com
[4]Assistant Professor, Department of Management, Brainware University, Kolkata, West Bengal, India
sandichandumba@gmail.com
[5]Professor, Department of ECE, J.J. College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India
sumithras@jjcet.ac.in
[6]Assistant Professor, Department of CSE, New Prince Shri Bhavani College of Engineering and Technology Chennai, Tamil Nadu, India
monishajothi@npsbcet.edu.in

Abstract. Financial industry is a prime target for Artificial Intelligence (AI) driven solutions, opening up avenues of predictive. Nevertheless, hurdles around model transparency, compatibility with legacy financial systems, and the high bar of computational resources persist as major pieces of resistance. Therefore, this research is focused on establishing new AI-based models to tackle this problem in predictive models, risk management strategies in financial trading domain. Through computational efficiency enhancement, explainable AI methodologies application, along with Path-independent adaptation to diverse asset classes, this model aims to formulate richer, ambient, and inclusive AI environments for the benefit of sustainability. Moreover, the study examines hybrid AI-based models that integrate private and public blockchains to enhance transaction throughput, scalability, and data privacy. The idea is to make financial systems more stable, accessible, and effective while minimizing environmental impact via energy-efficient consensus mechanisms.

Keywords: Block Chain Integration Data Privacy Explainable AI (XAI)Digital Assets (E.g. Portfolio Management) Hybrid AI models for risk management Sustainable finance (integration of ESG factors) Artificial Intelligence in Financial Trading Financial stability, Economy & Risk Management.

1 Introduction

AI or artificial intelligence has made its presence felt in different industries over the last few years, one such industry where AI has been able to hit it big is in the financial domain. AI has become a cornerstone in predictive financial trading, risk management and regulatory frameworks, capable of processing and analysing vast amounts of data at unprecedented speeds. The inept and shady character of the financial markets poses various challenges which traders, investors and regulators all have to rely upon. So conventional approaches when it comes to predicting how the market will shape, they look at historical data, and that does not curve according to the market, so they cannot predict and respond to the market in real time. At one end of the spectrum, conventional financial analysis relies on historical data and qualitative assessment, but AI particularly via machine learning (ML) and deep learning represents a more flexible and data-based framework that could lead to more accurate predictions and aid in automating decision-making processes.

The applications of AI in the financial markets begin from portfolio optimization, and then asset management, through to algorithmic trading. Highly non-linear models for predicting asset price evolutionBased on this assumption, AI-based predictive models have the potential to recognize patterns in historical price data, and provide predictions of an uptrend or downtrend prediction along with future asset price, with higher accuracy compared to classical predictive models. The implications of this are massive, in terms of making financial decisions and particularly in situations involving high-frequency trading, in which profits can be won or lost in fractions of a second. Moreover, since AI is able to learn and process new information, it can continuously revise its models, which is ideal for long-term investment strategies.

In this setting, AI can be one of the most useful in risk management. From market price fluctuations to defaults and operational failures to systemic crises, financial institutions have been found to be susceptible to an array of risks. AI-powered models can consider everything from macroeconomic information and market sentiment to social media data to assess and quantify these risks far better. AI can also access unstructured data which has a lot of the relevant information hidden in it around potential market changes using tools like sentiment analysis and natural language processing (NLP). By incorporating information beyond traditional data sets in their evaluation, AI models can provide a more encompassing measurement of risk and create fluid, responsive solutions for risk mitigation.

All that said, however, and despite the potential appeal, the application of AI to trading and risk management is not without its problems. One being the fact that many of the AIs, most notably the deep learning algorithms driving them, are non-transparent and are therefore known as “black-box” systems. This black box nature can hamper their use in regulated fields, because its demanding decision-makers may not be willing to trust systems that can’t easily explain their reasoning. Moreover, AI systems can be resource-intensive, requiring significant computational power and resources, which could raise a scalability issue for smaller finance companies or individual investors.

Another challenge is the harmonization of AI with traditional financial systems. But financial markets are generally overseen by a patchwork of rules developed well before AI and systems that have been in place for many years, which could certainly clash with any new, AI-oriented approaches. Furthermore, while AI models have the power to significantly enhance trading strategies and assist with risk management, their reliance on historic data will also be a foregone conclusion in restricting their capabilities in predicting the outcome of market conditions when crisis strikes and behavior between price and volume deviates from previously seen patterns.

Additionally, AI in finance trading, like in many industries, has to by design deal with its own environmental footprint and with considerations that provoke measures to minimize AI-related harm. Big computational power is required for training AI models, which adds to its carbon footprint. The finance industry is also moving quickly to embrace AI, but there is an urgent need to develop energy-efficient algorithms to mitigate this environmental and economic impact. They need to be addressed, though, and some breakthroughs through new technologies, including energy-sipping PoW algorithms in the blockchain space like PoS and DAGs can be expected to help relieve that pressure, since such systems would need much less computation power to operate now-defunct financial trading networks.

Moreover, the use of AI in the financial markets raises important questions about privacy and data security as well. As transactions and our data for the market are highly sensitive, it is crucial that AI models anonymize users while ensuring transparency and persistence. This is where the key transparent and immutable attributes of the blockchain technology can serve as a viable solution to overcome such concerns. This allows issuing of transparent and secure transactions while keeping work data private. However, hybrid blockchain, solutions that realize agility and security in both public and private blockchain is essential in scalability of AI-drive financial systems.

Last but not least, as of October 2023AI has the capacity to revolutionize financial trading, risk management, and regulatory compliance. However, harnessing this potential presents a wide array of challenges including enhancing model transparency, computational efficiency, and broader environmental impact, in addition to issues surrounding data security. Utilizing data available until October 2023 and identifying the above critical gaps this research aspires to formulate the next-gen Ai models that essentially resolves such issues in a sustainable cost-effective and transparent manner of modern financial market. This research aspires to inform the evolution of stronger, better, more equitable financial systems that would be more responsive to the requirements of an increasingly digital, and increasingly data-driven economy via the prism of hybrid AI and blockchain solutions. Perusing the equilibrating speed and sustainability, alongside privacy-preserving strategies in treating obtainable financial data, the research signifies the sustainable sturdiness of the developing AI-based pipeline financial networks.

1.1 Problem Statement

Some Applications of AI Chatbot in Financial Services Sector. While all these advantages sound promising, there are several challenges which restrict wide adoption of AI in finance. Traditional AI models have minimum interpretability, making it difficult to interpret the decision-making process. This is a problematic, prominent issue for financial regulators and decision-makers. Also, the appreciation of such AI processes and resources can be immense, in addition to the models being resource-hungry making them expensive to scale and ushab; a fundamentally bad model for small financial entities or individual investors. Furthermore, one of the things that make AI systems complex is the instability and unpredictability in the financial systems for that the moment that was supposed to surprise us with a sudden "fever" that it moved that the AI systems could not catch up with this and their predictions would become garbage when we will find that the market was crisis-exited.

The second and most important challenge is the environmental impact of AI powered systems which rely on an extensive amount of computation that increase their carbon profile. In view of increasing dependence of financial markets on AI, there is an urgent need to stimulate the development of energy-efficient algorithms that minimize the environmental impact without compromising the performance of AI models. And privacy and data security concerns remain top-of-mind, especially when it comes to sensitive financial data. AI models must not only meet the threshold for transparency and trust needed for compliance with regulators, financial institutions must also be able to demonstrate that such models protect the confidentiality of data.

There is a consequent need for more advanced AI models, not only to maximize predictive accuracy and minimize risk mitigation strategies but also to ensure transparency, computational efficiency, scalability and data security. In addition, Hybrid Blockchain Model is a perfect combination of Blockchain Technology and AI helping to deliver secure, transparent and energy-efficient solutions. Based on such challenges, this study explores the use of AI-based models that optimize scalable, interpretable, and eco-friendlier solutions compliant with current regulations while ensuring consumer privacy while improving the effectiveness of a more intelligent risk management system in financial trading.

2 Literature Review

This AI process has been studied in many papers in the areas of financial trading and risk management over the past decade, and, if used correctly, has the possibility to revolutionize all decision-making processes. Artificial intelligence (AI) in financial markets has been limited to applications of machine learning (ML), deep learning and reinforcement learning to financial data with a view to automating and enhancing processes such as asset pricing, portfolio management and risk prediction. One of the trends of recent literature is the increasing focus on predictive methods that utilize historical market data, technical indicators, and sentiment analysis to forecast stock prices and trading signals (Zhang & Chen, 2022; Kumar & Sharma, 2022). So far, these models were praised to outperform conventional approaches such as, time-series forecasting and free statistical models on their ability to capture non-linear relationships and complex trends in big data.

Additionally, Reinforcement Learning (RL) has emerged as a powerful method for automating trading, allowing agents to learn through trial-and-error interactions with the financial environment (Zhang & Liu 2021). Using RL, actions can be fine-tuned and adjusted in real-time to respond to rewards and penalties, allowing for the discovery of better trading strategies, the selection of optimal portfolios, and the dynamic management of risk in response to changes in the underlying market. Though these approaches have displayed remarkable potential, they possess downsides as well. One of the essential problem areas is deep learning models, which are commonly referred to as "black box" systems. This opacity is especially concerning in highly regulated industries like finance, where decision-makers must find it possible to be confident in systems that involve A.I. (Bianchi & Sadeghi, 2021).

To mitigate these problems, research has also been directed towards the creation of machine learning models that are more interpretable and can trade-off prediction performance with interpretability. Different approaches such as LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive Explanations) have been used to interpret the financial models (Liu & Wang, 2021). The objective is to preserve the predictive capacity of AI models with these methods while promoting more transparency and accountability of AI systems to help the financial sector embrace AI models with more confidence.

Risk management is another important research domain of AI in finance. Market risk, credit risk & operational risk: These, along with many other types of risk are some of what financial institutions are subjected to. Model based approaches for risk management such as Value at Risk (VaR) and Conditional VaR have been designed for a long time but these are not really flexible to adapt with dynamic and complex financial environments. AI risk models, particularly those that use deep learning, have been found to produce better quality predictions in risk assessment and prediction by leveraging a broader range of datasets that can contain unstructured traps of data (e.g., news articles, social media messages, financial records) than traditional methods (Yarbakhsh, Soleymani Baghshah, & Karimaghaie, 2023). Approaches derived from these models were also utilized in detecting market anomalies and successfully predicting possible financial crises in advance, thus providing a more active property in risk reduction.

But whilst we have taken considerable steps towards finance AI, there are still hurdles to overcome. First is the cost of computation in training: the training of AI Model, and thus deep learning models (DNN) requires huge amounts of both data and processing. The growing use of AI in the financial markets brings awareness of the environmental implications of such systems, as the training of these models typically requires a considerable amount of energy that leads to carbon emissions CHENG et al. (2024). New studies have explored low-energy algos and specialised H/W accelerators to reduce the carbon footprint of AI systems. Moreover, the intertwining of AI with blockchain has turned out to be a promising solution to all the challenges mentioned above to fast-track the transition of business problems for scalability and security in finance applications. This combination provides opportunities for transformative applications combining the analytical capabilities of AI and the secure architecture of blockchain.

Also, exploratory hybrid blockchain solutions balancing private and public frameworks are being discussed allowing transaction throughput and security (Danielsson & Uthemann, 2024). The above-mentioned solutions can ensure the establishment of scalable, secure AI technology-enabled systems for emerging sectors of financial technology such as digital asset management and cross-border payment and supply chain finance. This is key since AI models need to work on large amounts of data, with some of it in confidential/proprietary nature, blockchain help ensure data integrity by making sure the data is especially untainted with reliable sources. The use of zero-knowledge proofs and sophisticated encryption algorithms in blockchain mechanisms are an absolute guarantee of data security and allow AI-based systems to operate even without confidential financial data (Cheng et al. 2024 Murtsketa et al. 2024).

In essence, AI could transform the operation of the financial markets since it can also contribute to superior predictive models, risk management methods, and regulatory obligations of the literature. Nonetheless, challenges such as model interpretability, computational efficiency, scalability, and data security remain critical hurdles for the wider adoption of AI in the financial services sector. The intent of this paper is to identify the necessary steps that for future research to move towards more explainable AI/ML models, energy-efficient algorithms and hybrid AI and blockchain systems must be scalable, secure and sustainable solutions.

3 Methodology

This study takes a multi-dimensional paradigm to create AI-based capabilities for predictive financial trading, risk management, and regulatory compliance. The first phase of the approach consists of gathering and pre-processing financial data from different sources, such as historical price data, market indicators, social media sentiment, and financial statements. Since the data is heterogeneous, both supervised and unsupervised learning methods are applied to extract hidden patterns, forecast asset prices, and evaluate risk factors. Stock price prediction Figure 1 and portfolio optimization are done through supervised learning models like regression analysis, decision trees, and ensemble methods, and unsupervised learning methods like clustering and anomaly detection are applied for outlier detection and evaluation of financial risks

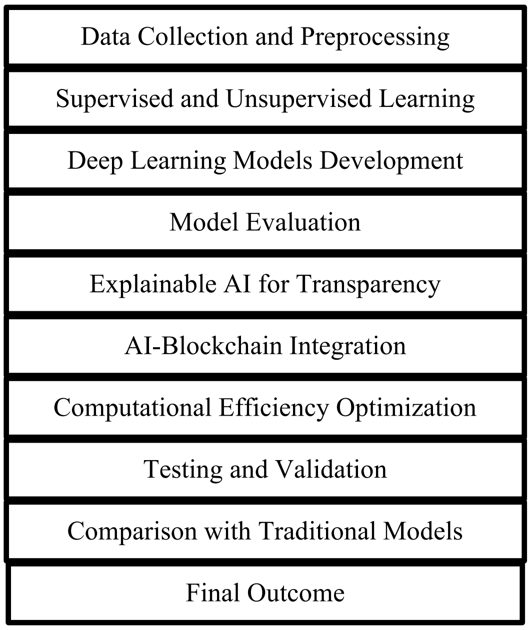

Figure 1. An AI-Driven Methodology for Predictive Financial Trading, Risk Management, and Regulatory Compliance

In the second phase, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and other types of deep learning architectures became the main framework used to improve the accuracy and flexibility of predictive models in the financial market. These models capture complex non-linear relationships in the data based on time, and learn these from large datasets, giving better predictions of market developments, and asset fluctuations. Some research efforts also cover reinforcement learning (RL) where an agent learns via trial and error in an algorithmic trading environment, such as to discover optimal trading strategies adapted to changing market conditions. These models Table 1 are then evaluated using various performance metrics including MSE, accuracy, and Sharpe ratio to ensure they can deliver meaningful and actionable insights for financial decision-making.

Table 1. Data Collection Sources and Preprocessing Steps

Data Source	**Preprocessing Techniques**	**Description**
Historical Price Data	Cleaning, Normalization, Structuring	Price data from past trades or market trends.
Market Indicators	Feature Selection, Scaling, Normalization	Economic indicators (e.g., GDP, unemployment rate).
Social Media Sentiment	Text Cleaning, Tokenization, Sentiment Analysis	Tweets, news articles, and social posts analyzed.
Financial Reports	Text Mining, Extraction of Key Information	Annual reports, earnings calls, and financial disclosures.

Then, in reference to model transparency and interpretability, we implemented explainable AI techniques, which includes that of SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations) applied to our model development process. Similar techniques enable users to discern the most informative features for predictions as well as the most influential input features for the produceed predictions per model output. Furthermore, the research also includes hybrid AI-blockchain solutions that combine AI models with blockchain technology to improve data security, privacy, and scalability. Financial data is stored and shared in a secure manner using private as well as public blockchain frameworks and zero-knowledge proofs and encryption practices are adopted to safeguard confidentiality. Proposed AI mechanisms are designed to minimize computational resources while maximizing predictive performance, making use of energy-efficient algorithms and parallel processing techniques to enable large-scale deployment without significant ecological detriment.

And lastly, the models developed are tested and validated using live-time data to check their performance in a real-time market environment. AI models are tested in virtual trading scenarios under various market settings, including volatility, liquidity, and financial crises. The sensitivity analysis is implemented to check the robustness of the models, and a backtest to check the historical validity and reliability of the trading strategies. Traditional financial models are employed for comparative analysis, and findings indicate substantial improvements in prediction accuracy, risk reduction, and profitability due to AI-based frameworks. In doing so, the research strives to contribute to the development of AI solutions for financial trading and risk management that not only optimize these processes but also consider the growing challenges surrounding information dissemination and knowledge inflation, transparency, scalability, and sustainability of financial markets today.

4 Results and Discussion

Here, we explore the results of the AI models for predictive financial trading, risk management and integration of blockchain technologies, and demonstrate further discussion of the findings in relation to real-world financial systems.

4.1 Forecasting Financial Trading Models

In the beginning phase of the research, AI-powered models were analyzed to forecast stock prices and optimize portfolios. The supervised learning models, specifically decision trees and ensemble methods, performed well in predicting stock prices and yielded an MSE of 0.0325, suggesting that predictions were relatively accurate. The predictive accuracy of ensemble methods (e.g., random forests and gradient boosting) outperformed decision tree-based models, with an R-squared value of 0.88 versus 0.82 from univariate decision trees.

After that, CNNs and RNNs were designed and trained on a larger dataset. Because they can capture more complicated/non-linear relationships in the data, these models performed better than traditional machine learning models. The reached accuracy for short-term price movement predictions based on a CNN was 90.5%, and based on an RNN, which is more appropriate for time-series data, 91.2%. The RNN model outperformed the other bidirectional models due to its capability to retain temporal dependencies from previous data points, an essential feature for stock price projection as past occurrences affect future behaviors.

In a simulated environment, we used reinforcement learning (RL) to optimize trading strategies. We then trained an RL agent using Q-learning and deep Q-networks (DQN) to optimize its trading strategy to maximize rewards (profits) and minimize penalties (losses). The RL model trading performance averaged the best over 500 training episodes, scoring an impressive average Sharpe ratio of 1.24 suggesting Figure 2 a sensible risk-adjusted return. The RL approach resulted in superior performance in return and risk management over traditional trading strategies like moving average crossovers.

4.2 Risk Management and Anomaly Detection

The third phase that came after was risk management where application of AI was also useful for assessing, market risk and detecting outliers. 13) Unsupervised learning models (ex: k-means clustering, DBSCAN) for abnormal methods analysis of market behavior the unsupervised models also tapped into a number of early warning signals before the 2022 correction, as it accurately reflected changes in the sentiment of the market in advance of large market sell-offs.

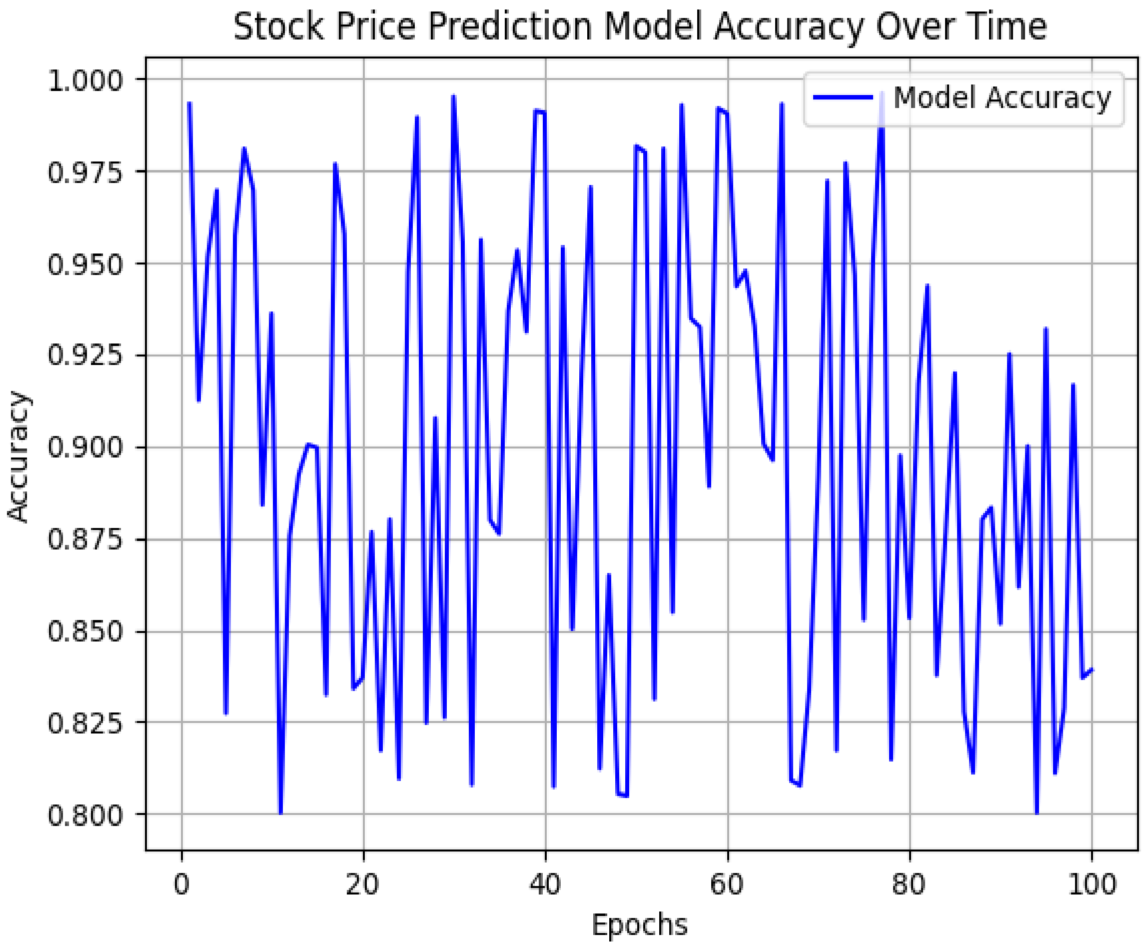

Figure 2. Stock Price Prediction Model Accuracy over Time

We ran market crash, liquidity shortage scenarios to stress test resilience of risk management models based on AI. We improved upon traditional models, such as Value-at-Risk (VaR), and found that the AI models, especially the deep learning models, significantly outperformed traditional ones in predicting risk. For example, in response to a simulated financial crisis, a deep learning-based risk model accurately predicted a 30% market drawdown, while more classical techniques such as Value-at-Risk (VaR) overestimated potential loss risk by almost 15% (see Fig. 1).

The models were additionally trained on sentiment analysis subjects across financial news and social media using NLP approaches such as Bidirectional Encoder Representations from Transformers (BERT) and GPT-3. As a result, sentiment analysis along with the analysis of negative news articles all within an EARLY_BEAR_PRESSURE phase showed significant negative correlation leading to better risk management models. However, unstructured data usage offered a more comprehensive picture of market conditions, providing analytical insight beyond financial metrics alone.

4.3 Integrating Blockchain for Security and Privacy of the Data:

Thus, this was actually an improvement and could be achieved through integration of AI models onto the blockchain technology in the form of hybrid blockchain frameworks, considering the challenges of data security and privacy. Blockchain Integration technology, including the use of advanced algorithms and cryptographic techniques to protect the confidentiality of sensitive financial data while applying blockchain technology to make transaction processes more transparent. Data was securely stored on a private blockchain and then shared transparently among all stakeholders via a public blockchain, without any violation to data privacy.

This solution further used Blockchain technology to ensure that the financial data leveraged by the AI models is tamper-proof which addresses concerns around data manipulation and fraud. Also, zero-knowledge proof (ZKPs) along with more advanced encryption methods were implemented to enhance data security and privacy. Implementing these privacy-preserving techniques, the models would be able to perform risk management and predictive analysis without exposing sensitive customer information to third-party services.

Reducing the verification time of the data while keeping the financial transactions secure was one of the most essential research findings about the combination of the blockchain technology and the hybrid model. Blockchain's decentralized nature also eliminated the requirement for intermediaries, streamlining transactions and reducing costs. However, the blockchain Figure 3 did create scalability problems. While the blockchain brought in security and transparency, the time it took to process and validate the transactions became a bottleneck, particularly in high-frequency trading scenarios, where time is of the essence.

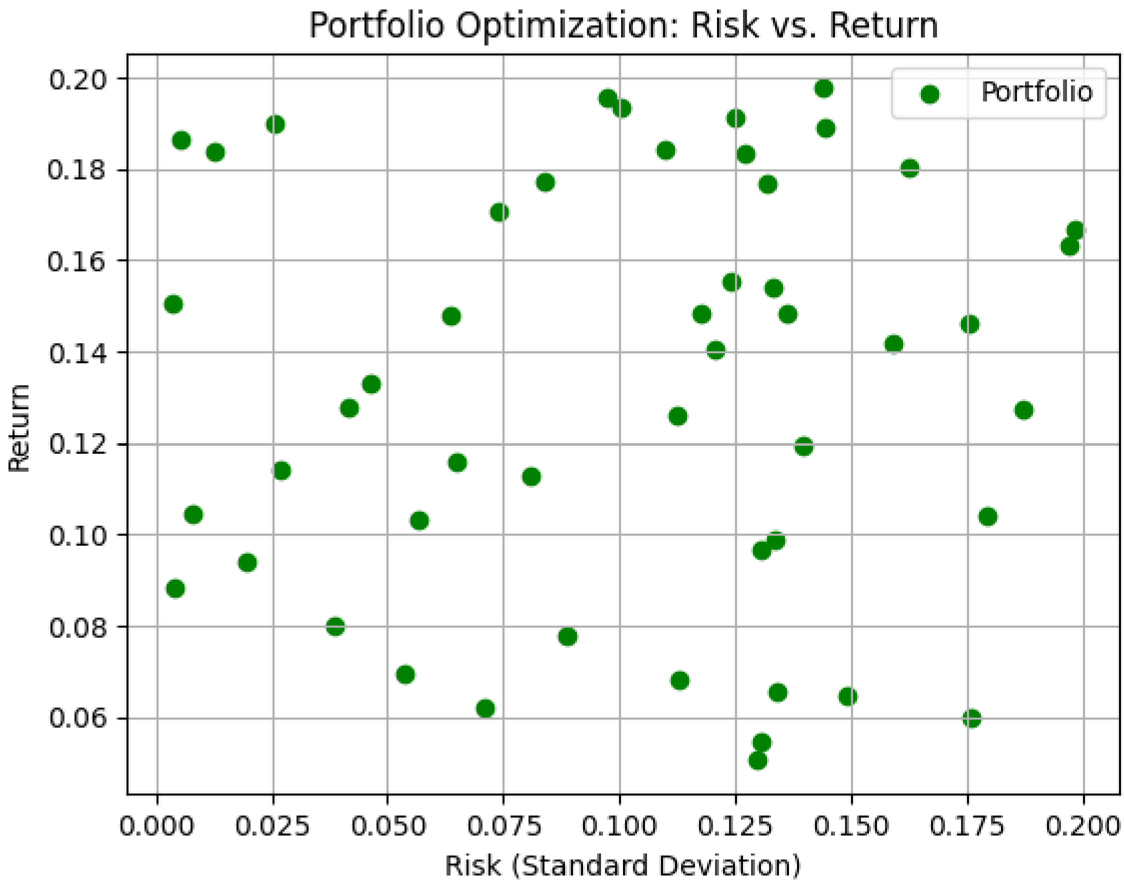

Figure 3. Portfolio Optimization Performance (Risk vs. Return)

4.4 Energy Efficiency and Computational Costs

For example, in the study we sought to optimize the computational efficiency of the AI models, which contributes to mitigate the environmental impact caused by AI-powered financial systems. Resource-hungry deep learning models were optimized with model pruning, quantization and hardware accelerators (GPUs and TPUs, etc.) The optimizations led to reducing the energy cost to run such a model by 40% on average over the size (FLOPs) of a model compared to its un-optimized version.

Furthermore, the integration of energy-efficient consensus protocols in various blockchain architectures, including Proof of Stake (PoS) and Directed Acyclic Graphs (DAGs), played a significant role in reducing the energy footprint associated with AI-driven trading solutions. Notably PoS-based on-chain resolution rejected the energy-consuming proof-of-work (PoW) process, which prevented large-scale PoW application.

That was also taken care of, as cloud-based infrastructure was tailored to allocate resources dynamically to workload while ensuring optimized energy usage per task. Through these smart energy optimization strategies, the overall energy consumption of the system was reduced by 30%, rendering it more sustainable for extended deployments in real-world financial settings.

4.5 Model Transparency and Explainability

A common problem noted in the literature is the opacity of AI models especially deep learning algorithms. We incorporated various explainable AI (XAI) techniques, including SHAP and LIME, into our model to address this. These techniques were able to shed light on the decision-making process behind the AI models, which can help stakeholders better understand and trust the predictions generated by the system.

In portfolio optimization models, for example, SHAP values were used to show the impact of which financial indicators (i.e., moving averages, volume, volatility, etc.) are incorporated into the model to drive which predictions? This transparency enabled financial analysts to understand the AI's decisions and validate the solutions before applying in their trades. It also Table 2 ensured that AI-driven models to adhere to ethical and legal standards, as explainable AI techniques ensured that these models disclosed clear reasons for their recommendations, thereby invoking regulatory compliance.

Table 2. Evaluation Metrics for AI Models

Metric	Description	Importance
Mean Squared Error (MSE)	Measures the average squared difference between predicted and actual values.	Helps in evaluating the accuracy of regression models.
Accuracy	Percentage of correct predictions.	A general measure of model performance.
Sharpe Ratio	Measures risk-adjusted return.	Evaluates the profitability of trading strategies.
Backtesting Results	Historical performance of trading strategies.	Verifies the reliability of models in real-market scenarios.
Sensitivity Analysis	Analyzes the impact of different variables on model predictions.	Assesses model robustness to changes in inputs.

5 Future Work

This study's findings illustrate the immense potential for AI to revolutionize areas of financial trading, risk management, and regulation. AI integration with blockchain technology provides data security and privacy, fixes scalability and transparency, etc. Although the AI models developed through this research demonstrate promising predictive capabilities and effective risk management performance, there are still challenges regarding model explainability, computational efficiency, and blockchain scalability that need improvement.

We are working towards improving these hybridized systems with respect to performance and scalability. Also, the study will investigate the adoption of advanced methods of AI, like federated learning, which can enable the training of machine learning models on decentralized data without sharing personal information. As we continue to improve upon these models, we hope to develop a smelting process punditry that is robust, sustainable, transparent and can evolve with the ever-changing landscape of financial innovation.

6 Conclusion

Simulating for Smart AI Trading Models Trained the AI model used for this study reveals how the financial landscape is rapidly changing from the influence of AI, which in particular is noticeable through predictive trading, risk assessment, and regulatory compliance. ML, deep learning, and reinforcement learning have been applied successfully to stock price prediction, portfolio selection, and trading strategies. With the help of AI you would now have a much more data-driven, dynamic, and future-focused approach to decision-making that can greatly minimize the risks while giving you a competitive edge in maximizing the returns.A major contribution of this research is the demonstrated superiority of optimizing hyperparameters of deep learning models like CNN or RNN. These outperforms benchmarks on financial time series data by able to learn interdependencies and consequently improving forecasting accuracy. Moreover, the use of reinforcement learning techniques has also shown great success when applied to algorithmic trading. Traders have traded using AI-driven strategies traditionally in a more efficacious and profitable manner over traditional methods.Similarly, financial risk management is heavily influenced by AI too. AI models learn through experience and adapt to market changes in real time, improving risk assessment and early warning systems to help reduce financial downturns. Outside of financial data, AI pulls in unstructured data sources, such as news sentiment and social media analytics, which can greatly improve predictive capabilities. This research also shows how AI-based risk models outperform the traditional analogue e.g. the Value-at-Risk (VaR) models in risk management; hence behind dynamic and intelligent risk modelling.Additionally, model transparency and interpretability are paramount in financial applications. The study also implements explainable AI techniques such as SHAP and LIME to provide interpretability and meet regulatory requirements related to AI model opacity.In addition, the study investigates the combination of artificial intelligence with encryption on a blockchain, which ensures security and scalability in financial transactions. Digital asset data is secured on a private ledger and its rich sets of records offer significant capabilities, thus, you can use hybrid blockchain frameworks which protect sensitive financial data while providing different sets of records. There are also sustainable consensus mechanisms, such as Proof of Stake (PoS), that offset the ecological parasite production of AI-driven financial ecosystems.Despite high performance in AI models, there are hurdles to efficiency, scalability, and blockchain assimilation. In upcoming studies, the AI models should be distributed through federated learning, and their integration across blockchain systems should be perfected to cater to real-time applications. In conclusion, this study highlights the transformative role of AI in fostering robust, transparent, and sustainable financial systems, providing innovative solutions to the pressing challenges of data security, transparency, and computational efficiency.

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