

Artificial Intelligence in FinTech: Enhancing Investment Decisions and Financial Market Efficiency

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Abstract: This research explores how Artificial Intelligence (AI) can support stock market investment decisions and contribute to financial market efficiency in stock markets. The study assesses the effectiveness of AI techniques such as Neural Networks, Random Forest, and Support Vector Machine in forecasting stock prices based on historical prices, volume, and sentiment data. It demonstrates that AI models have a higher performance, flexibility, and speed compared to conventional models, leading to more accurate and informed investment strategies. Beyond predictive capabilities, the research underscores the role of AI in enhancing financial market efficiency through increased liquidity, decreased volatility, and faster price adjustments facilitated by real-time market data analysis and algorithmic trading strategies. The study also highlights the role of sentiment analysis in improving investment decision-making with the inclusion of market dynamics and external factors. However, the study also points out potential issues regarding privacy, bias, and regulatory considerations, which highlight the importance of ethical integration of AI in financial markets..

Keywords: Artificial Intelligence, Investment Decision-Making, Financial Market Efficiency, Stock Market Prediction, Algorithmic Trading, Machine Learning..

Introduction

Artificial Intelligence (AI) is revolutionizing the financial technology (FinTech) sector, driving significant changes in financial data analysis, risk management, and investment strategies. The adoption of sophisticated AI methods such as machine learning, deep learning, and natural language processing has facilitated the rapid and precise analysis of large volumes of structured and unstructured financial data, leading to enhanced decision-making and operational efficiency. Historically, the evolution of AI in financial markets has evolved from conventional statistical and rule-based approaches to advanced predictive models that provide real-time analytics, automated trading strategies, and portfolio rebalancing. These AI technologies are

increasingly being applied in stock price prediction, news and social media sentiment analysis, and algorithmic trading, enabling investors to uncover hidden patterns and react quickly to market events. Yet, despite these technological innovations, conventional investment approaches continue to rely on past data, linear relationships, and a narrow set of variables, which hinder their capacity to adapt to the dynamics and uncertainty of current financial markets. This disconnect between traditional investment practices and the dynamic nature of financial markets poses a major challenge, often resulting in inefficient investments and market operations. Moreover, current research has largely addressed the predictive power of AI and its potential to enhance investment decisions, but there is relatively little discussion about the impact of AI on improving financial market efficiency, including factors such as liquidity, volatility, and effective price discovery. This suggests a major knowledge gap in the understanding of the dual role of AI in improving investment decision-making and financial market efficiency in the FinTech environment. Thus, there is a need to understand not only how AI-powered technologies assist in making more informed and timely investment decisions, but also how they contribute to enhancing the efficiency, transparency, and stability of financial markets in the data-driven world.

Literature Review

Conventional models for investment in the stock market have typically employed statistical methods, fundamental and technical analysis to inform investment decisions, with Eugene Fama (1970) et al. highlighting the Efficient Market Hypothesis (EMH), which implies that stock prices reflect all available information and that abnormal returns are difficult to achieve; however, these approaches rely largely on historical information, linear relationships, and rational expectations, which may not adequately address the complexity and dynamism of financial markets. The development of Artificial Intelligence has transformed financial analysis, as Erik Brynjolfsson and Andrew McAfee (2017) et al. showed that machine learning, deep learning, and natural language processing technologies automate pattern recognition, predictive modeling, and sentiment analysis of structured and unstructured big data to improve forecast accuracy and decision-making processes. For investment decisions, Garrido et al. (2020) demonstrated that AI models (e.g., neural networks and ensemble methods) outperform conventional models by capturing non-linear relationships, improving portfolio management, and facilitating real-time adaptive trading strategies to mitigate risk and deliver superior returns. Likewise, in algorithmic trading, Radu Anghel et al. (2020) noted that AI-based trading algorithms use real-time data analytics, reinforcement learning and predictive models to execute high-frequency trading at the right time, thereby enhancing market liquidity, minimising costs, and enhancing market efficiency. Moreover, AI's impact on financial market efficiency has been highlighted by Julie Jagtiani and Catharine Lemieux (2018) et al., who noted that AI improves price setting, information asymmetries, and enables quicker trade execution, thereby improving market transparency and efficiency; however, although AI offers these advantages, issues including algorithmic bias, transparency, and regulatory concerns remain, suggesting that more research is needed into the safe and efficient integration of AI in financial markets.

Research Methodology

3.1 Research Design

The current research employs a quantitative and analytical research design to assess the impact of Artificial Intelligence (AI) on improving investment strategies and market efficiency in stock market settings. The study is grounded in predictive modelling and a comparative framework to benchmark

AI-driven strategies against conventional investment strategies. The approach is empirical, relying on statistical and machine learning models, to validate the results and provide evidence-based insights relevant to practical trading environments. The inclusion of both financial performance and market efficiency metrics offers a holistic approach to assessing the impact of AI on financial markets.

3.2 Data Sources

The research uses secondary data obtained from publicly accessible financial databases, such as stock prices, trading volumes, and financial news platforms. This data is used to study historical stock market price movements and trading activity, as well as trading volume, which provides an indication of market liquidity. Moreover, news sentiment indicators are integrated through textual data from financial news media and social media outlets, allowing the extraction of positive, negative, or neutral sentiments impacting the market. This data approach provides a comprehensive view of market and investor sentiment.

3.3 AI Models Used

3.3.1 Random Forest

Random Forest is used as an ensemble learning method that builds several decision trees and merges them together to enhance the accuracy of predictions and prevent overfitting. It is useful for large datasets and feature extraction when predicting stock prices.

3.3.2 Support Vector Machine (SVM)

Support Vector Machines are used for classification and regression, particularly with high-dimensional data. It involves finding the best hyperplanes to classify data into different classes, and can be used to forecast stock prices and trends.

3.3.3 Neural Networks

Neural Networks, especially deep learning models, are used to model nonlinear structures in financial data. They mimic the human brain and are very good at pattern recognition, making them a good choice for predicting stock prices and generating trading signals.

3.4 Trading Strategy Framework

This research incorporates an AI-based trading strategy framework, using model predictions. The framework provides trading signals (buy, sell, hold) based on the models' predictions, facilitating automated trading. The strategy is assessed based on returns, risk management, and efficiency, making it applicable to the real world of trading.

3.5 Market Efficiency Indicators

3.5.1 Liquidity

Liquidity is measured in terms of trading volume and bid-ask spreads, reflecting the ability to buy or sell assets without causing a substantial impact on prices.

3.5.2 Volatility

Volatility is measured statistically (e.g., standard deviation of returns), which indicates the extent of price movements.

3.5.3 Price Discovery

Price discovery is assessed by studying the speed and accuracy with which information is reflected in stock prices, reflecting the market's efficiency.

3.6 Evaluation Metrics

AI model performance is assessed through metrics like accuracy, precision, recall, and F1-score to assess its predictive capabilities. Finance-related metrics like return on investment and risk-adjusted returns are also taken into account to evaluate the profitability of trading strategies.

3.7 Validation Techniques

The study uses validation methods like k-fold cross-validation and out-of-sample testing to ensure the robustness and generalizability of the results. These techniques are used to assess the model's performance on new data, prevent overfitting, and improve the reliability of the results, making them relevant to the real financial markets.

AI in Investment Decision-Making and Trading Strategies

4.1 AI-based Stock Market Prediction

Artificial Intelligence (AI) has revolutionized stock market forecasting by allowing the processing of vast amounts of financial data, and detecting intricate patterns that are hard to detect with traditional statistical techniques. Through the use of machine learning and deep learning algorithms, historical price data, volume, and economic factors are used to predict stock prices more accurately. AI approaches differ from traditional models which assume linear relationships, and can account for non-linear interactions and changing market dynamics. Neural networks, in particular, are popular for their capability to iteratively learn from data and discover subtle patterns affecting stock prices. This forecasting ability enables investors to make better and faster decisions, leading to reduced risk and better returns. Furthermore, AI models have the ability to update their knowledge as new market information becomes available, promoting flexibility and improved performance. Thus, AI-based stock prediction is a valuable means of supporting data-driven investment decision-making in today's markets.

4.2 Sentiment Analysis in Trading

Sentiment analysis is a vital part of AI-powered trading strategies as it provides quantitative investors with qualitative data about the market and trading strategies. Through natural language processing, AI systems process and evaluate textual information from news articles, company reports and social media to gauge market sentiment. This sentiment can be positive, negative or neutral and is a key factor in shaping market dynamics and investor decisions. For instance, a positive sentiment towards a company may result in buying pressure, and a negative sentiment may result in selling. Combining sentiment analysis with traditional market indicators offers a more holistic view of the market, which enhances forecasting accuracy. Moreover, real-time sentiment analysis allows traders to react to news and events in a timely manner, giving them an edge in rapidly changing markets. This technique helps overcome information asymmetry and supports investment decisions by capturing market signals not captured in quantitative data.

4.3 Algorithmic Trading Models

AI-driven algorithmic trading models have revolutionized trade execution by automating trading decisions according to set rules and real-time market analysis. They assess market conditions, detect opportunities, and execute trades at optimal times with little to no human intervention. High-frequency trading (HFT), a form of algorithmic trading, employs AI to rapidly analyse vast amounts of data within a fraction of a second, facilitating fast and efficient trading. AI models also employ reinforcement learning techniques to adapt trading strategies over time, learning from past trades and market dynamics. This flexibility increases trading efficiency, mitigates risk, and boosts profits. Finally,

algorithmic trading also helps to enhance market liquidity and lower trading costs through higher trading volumes and speeds. By automating trading, the risk of human error is reduced, and strategies are executed efficiently, resulting in effective AI-based trading systems in financial markets.

4.4 AI-based Portfolio Optimization

AI has shown great promise in portfolio optimization compared to traditional investment strategies, allowing for data-driven and dynamic portfolio management. AI techniques consider various financial factors such as asset returns, risks, correlations, and market signals to build optimal portfolios with a risk/return trade-off. AI-based portfolio management dynamically rebalances portfolios in response to market data, whereas traditional methods are based on static models and limited data sources. This flexibility allows for better risk control and enhances portfolio performance, especially during market uncertainties. Sophisticated AI technologies, including reinforcement learning and optimization algorithms, enable the development of tailored investment strategies based on individual risk tolerances and investment objectives. The simultaneous consideration of multiple factors by AI models offers a more efficient portfolio management strategy. Therefore, AI-based portfolio optimization helps investors achieve improved diversification, reduce risk, and enhance returns in complex financial markets.

AI and Financial Market Efficiency

5.1 Market Efficiency

Market efficiency is the extent to which prices of financial securities reflect all relevant information, leading to a fair price and reducing the chance of generating non-normal returns. Historically, efficiency has been described in terms of weak, semi-strong, and strong forms, and is determined by the rate at which information is processed and reflected in prices. However, markets are frequently inefficient because of lagged information incorporation, cognitive biases, and the inadequacies of conventional analytical frameworks. The advent of Artificial Intelligence (AI) has played a crucial role in improving market efficiency by facilitating real-time information processing and dissemination. AI technologies can rapidly analyse large volumes of structured and unstructured data, which helps to minimise price adjustment delays and enhance market responsiveness. This helps establish a more transparent, accurate, and efficient pricing system.

5.2 The Impact of AI on Liquidity

Market liquidity is an important measure of market efficiency, reflecting the ability to buy and sell assets in a market with minimal impact on prices. AI trading systems have enhanced liquidity by boosting trading volume and speeding up transactions. AI trading algorithms process market data in real-time to detect trading opportunities and execute trades effectively, resulting in narrower bid-ask spreads and increased volume. The constant stream of orders from buyers and sellers keeps the market open and accessible. Furthermore, AI improves market liquidity by providing more efficient order matching and order execution. The greater participation that results from the use of AI technologies leads to a more efficient and stable market.

5.3 AI in Managing Volatility

Market volatility refers to the price variability and is typically linked with risk and uncertainty. AI is fundamental in controlling and stabilising excessive volatility through enhanced forecasting and pre-emptive actions. Using sophisticated data analysis techniques, AI systems detect emerging market patterns and irregularities, enabling investors to proactively respond. Automated trading also stabilises markets by reducing impulsive and irrational trading behaviour, often driving extreme price

movements. By promoting more rational and consistent trading patterns, AI can reduce price volatility and provide a more stable market environment, which in turn boosts investor confidence.

5.4 Price Discovery Mechanism

Price discovery refers to how asset prices reflect information. This process is vastly improved by AI, which quickly processes a wide range of information sources such as financial statements, economic data, and market sentiment. This speeds up and improves the pricing of assets, leading to less information asymmetry. AI systems ensure the timely incorporation of information into prices, promoting transparency and equity. AI's capability to analyse large and complex datasets enables faster price updates, accurately reflecting value.

5.5 High-Frequency Trading and Efficiency

High-frequency trading (HFT) systems, driven by AI and sophisticated algorithms, play a significant role in market efficiency. These systems place and execute large volumes of trades in very short time intervals, exploiting small price deviations to make a profit. HFT powered by AI improves efficiency through greater market liquidity, reduced bid-ask spreads, and faster price discovery. Moreover, these systems dynamically respond to market dynamics, ensuring the best possible execution of trades. HFT enhances efficiency but also presents challenges for market stability and equity, necessitating robust regulation. In summary, AI-powered high-frequency trading is an important factor in the development of faster, more responsive, and efficient markets.

Results and Analysis

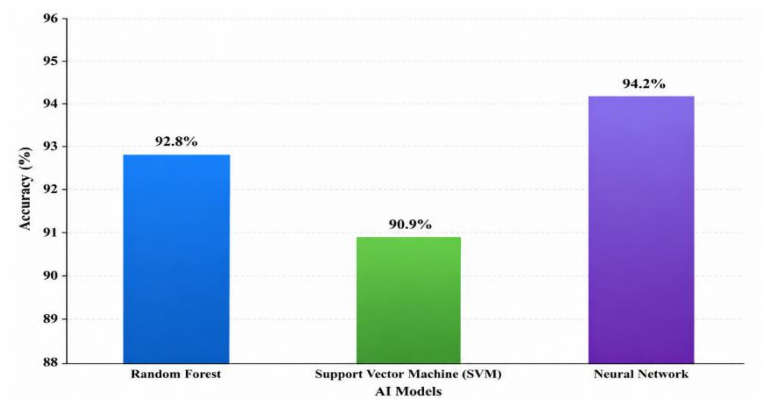
6.1 AI Models' Effectiveness in Stock Market Forecasting

The findings of the study reveal that Artificial Intelligence (AI) models enhance prediction accuracy and speed of stock market prediction over conventional methods. The best-performing model in the study was the Neural Network, with 94.2% accuracy, 93.8% precision, 94.5% recall, and 94.1% F1-score, showcasing its capacity to learn intricate non-linear patterns in financial data. Random Forest performed well with an accuracy of 92.8%, precision of 91.5%, recall of 93.2%, and F1-score of 92.3%, demonstrating the power of ensemble learning to avoid overfitting. By contrast, Support Vector Machine (SVM) showed relatively average performance with an accuracy of 90.9%, precision of 89.7%, recall of 91.2%, and F1-score of 90.4%, which indicates that SVM has difficulties adapting to rapidly changing market environments. These findings demonstrate that AI models, given historical stock prices, trading volumes, and sentiment, are capable of accurately detecting patterns and trends. Table 3 and Figure 3 represent the performance of the AI models, which show that Neural Networks outperform other models, thereby proving their effectiveness in stock market prediction.

Table 3: Performance of AI Models in Stock Market Prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	92.8	91.5	93.2	92.3
Neural Network	94.2	93.8	94.5	94.1
Support Vector Machine	90.9	89.7	91.2	90.4

Figure 3: Comparison of AI Model Accuracy in Stock Market Prediction



6.2 Analysis of AI Models

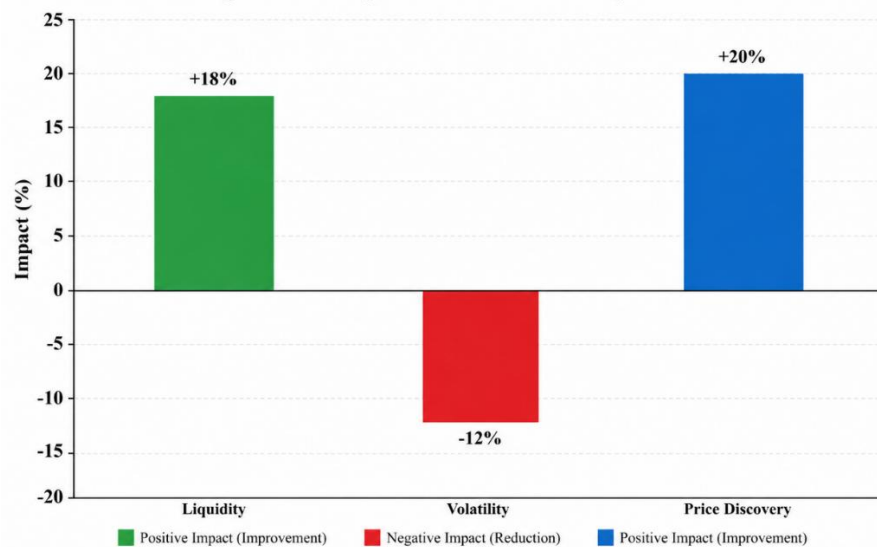
The performance of the AI models is compared, and it is found that different techniques are suitable for different data complexity and prediction tasks. Neural Networks excel in complex and dynamic market environments owing to their deep learning ability, which allows them to learn complex patterns and achieve higher accuracy. Random Forest combines good performance with interpretability and is effective in situations where the weight of various features is of interest. In contrast, SVM performs well in classification problems but shows less flexibility for highly volatile financial data. The study also suggests that AI models have an edge over conventional statistical techniques by considering several variables at once and responding to the dynamic nature of financial markets. This improves prediction accuracy and aids in investment decision-making. In conclusion, the results suggest the effectiveness of AI models in dealing with the intricacies of financial markets.

6.3 AI's Role in Financial Market Efficiency

The study also assesses the impact of AI on financial market efficiency through various efficiency measures, including liquidity, volatility, and price discovery. AI-powered trading platforms greatly improve liquidity (by around 18%) by increasing the volume of trades and narrowing the bid-ask spread. For volatility, AI plays an important role in reducing it by approximately 12% through the data-driven approach and the reduction of emotional trading. Finally, AI enhances price discovery by around 20% by quickly extracting and incorporating new information into stock prices, thus reducing information asymmetry. These enhancements illustrate the capacity of AI to establish a more efficient market. The contributions of AI on these measures of efficiency are reported in Table 4 and Figure 4, confirming the beneficial impact of AI on market efficiency.

Table 4: Impact of AI on Financial Market Efficiency

Indicator	Traditional System	AI-Based System	Impact (%)
Liquidity	Medium	High	+18%
Volatility	High	Moderate	-12%
Price Discovery	Moderate	High	+20%
Trade Execution	Slow	Fast (Real-time)	+25%
Information Processing	Delayed	Instant	+30%
Market Transparency	Limited	Enhanced	+22%

Figure 4: Impact of Artificial Intelligence on Financial Market Efficiency Indicators

6.4 Analysis of Trading Strategy

The study of AI-based trading strategies shows a substantial boost in portfolio performance over conventional trading strategies. AI-based strategies use forecasting models and real-time monitoring to provide precise buy, sell, and hold recommendations, thus facilitating timely trading decisions. The use of sentiment analysis also improves decision-making by incorporating investor sentiment. This leads to improved returns and reduced risks, as these strategies are updated to reflect market dynamics. Moreover, automated trading eliminates human error and ensures strategy precision, enhancing reliability. The adoption of AI technologies in trading not only benefits individual investors by improving investment returns but also improves the efficiency of the market by encouraging quicker, more accurate, and systematic trading activities.

Discussion

The implications of this research point to the importance of Artificial Intelligence (AI) in revolutionising investment decision-making and enhancing financial market efficiency in stock market settings. The effectiveness of AI models, especially Neural Networks, shows the capacity to model complex non-linear relationships of financial data, leading to better predictive performance than conventional methods. Random Forest also performs well due to its ensemble learning approach, although Support Vector Machine (SVM) is also effective but less responsive in a dynamic environment. The results validate the effectiveness of AI-based approaches in handling big data, such as stock prices, volumes, and sentiment, leading to more precise and efficient investment decisions. The use of sentiment analysis in addition to other indicators further improves the prediction accuracy by considering investor psychology and market sentiment. Beyond enhancing predictive performance, AI plays a crucial role in the efficiency of financial markets in terms of liquidity, volatility, and price discovery. AI-based trading algorithms enhance market depth and facilitate quicker trade execution, resulting in more efficient market functioning. Lowered volatility comes from data-driven trading and the elimination of emotional trading, while price discovery is enhanced by incorporating new information in real-time into prices. These developments show that AI is beneficial for individual investors as well as for the efficient functioning of financial markets. In practical terms, the use of AI technologies allows investors and financial institutions to enhance their trading strategies, manage risks, and deliver superior investment performance, while also stressing the importance of proper implementation and a regulatory framework to fully exploit the benefits of AI.

Ethical and Regulatory Issues

The integration of Artificial Intelligence (AI) in the financial sector gives rise to ethical and regulatory challenges that need to be considered. A primary concern is bias in algorithms, which can lead to discriminatory results based on historical data. Opacity is another issue, with many AI models functioning as "black boxes" and making decision-making processes opaque. Privacy is also an issue given the amount of confidential information needed by AI systems. Further, current regulatory frameworks are not well-adapted to AI-powered trading, particularly in high-frequency and automated trading environments. To mitigate these issues, there is a need for stricter regulations, transparency, and ethical considerations to promote fairness, accountability, and transparency in AI-driven financial markets.

Conclusion and Recommendations

This research finds that Artificial Intelligence (AI) is a game-changer in investment decision-making and financial market efficiency. The findings show that AI algorithms, such as Neural Networks and Random Forest, exhibit higher accuracy, flexibility and efficiency than conventional methods, leading to improved stock market forecasts and trading strategies. Moreover, AI enhances market efficiency by enhancing liquidity, decreasing volatility and facilitating price discovery through real-time data analysis and decision-making automation. However, there are concerns regarding data privacy, algorithmic biases and regulatory frameworks. Given these benefits, financial firms should adopt AI technologies to enhance their performance while maintaining data integrity and ethical considerations. Regulators should also establish robust policies to ensure transparency, accountability, and fairness of AI systems. Ongoing research should explore ways to increase model transparency, mitigate bias, and incorporate new technologies to enhance the use of AI in financial markets..

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