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Subject review
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A Comprehensive Review of Artificial Intelligence Applications in Financial Market Predictions

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Abstract: This paper aims to provide a comparative summary of the possible applications of artificial intelligence (AI) in financial market movement forecasting. It also explores the historical development, key methodologies, and modern trends in AI-based market forecasting. Through the analysis of various studies and published research, this review aims to highlight the advantages, as well as the limitations of various AI techniques in the field. The findings provide actionable insight for researchers and practical users interested in using AI to analyse financial market trends.

Keywords: Artificial Intelligence (AI); financial markets; financial predictions; literature review; machine learning; neural networks

1 INTRODUCTION

The primary goal of this review is to provide a comprehensive overview of the various applications of artificial intelligence (AI) in financial market forecasting. By synthesizing existing research, the review aims to identify and compare key trends, methodologies and future directions in the field.

1.1 Background and Relevance

Forecasting financial market movements is a key challenge for all players in the field due to the inherent complexity and dynamic nature of markets. Traditional methods rely on economic theories and statistical models and are therefore limited [1] in their ability to capture non-linear relationships and complex patterns.

With the development of computational ability and the availability of extensive amounts of data, AI has come forward as a useful tool for analysing and predicting market movements. AI techniques such as machine learning and neural networks enable models to learn from large data sets, map extensive patterns, and make potentially more accurate predictions. Studies have shown that AI can outperform traditional methods in predicting stock price movements [2, 3], currency rates [4, 5] and other financial instruments [6].

The application of AI in finance is not limited to market forecasting. It is also used for risk management, fraud detection, and portfolio optimization. Understanding therefore the application of AI in financial markets has significant importance for researchers and practical users. For academic researchers, this review provides a comprehensive overview over the current trends, methodologies, challenges, and identifies areas for future research. For practical users in the field, it provides practical insight into successful AI applications, enabling them to make use of the latest techniques to improve analysis, and to make informed decisions.

Relevance is justified by the contribution to existing knowledge providing a comprehensive overview of the research up to date, and of the practical application in the financial sector. It also highlights key advantages as well as limitations of various AI techniques, essential for developing effective and reliable forecasting models.

1.2 Methodology

The methodology of this review is based on systematic research of relevant sources to collect and analyse studies related to the application of AI in the field. The search process involved several steps:

1) Selection of databases: the search was conducted through several academic databases, including IEEE Xplore, ScienceDirect, and Google Scholar. In addition, relevant field sources and reports were reviewed.
2) Keywords: Multiple combinations of keywords were used, including "AI", "financial market", "machine learning", "large language model", "LLM", "neural network", "forecasting", "pattern continuation", and "deep learning". The search was conducted exclusively in English.
3) Inclusion criteria: only studies published as of January 2015 were included to ensure that the data and conclusions were relevant. Studies had to be peer-reviewed and published in field-related journals or conferences. Also included are relevant field reports that provided conclusive insights.
4) Data analysis and synthesis: collected data was analysed and synthesized to identify repeating trends, methodologies, and results. The studies were further grouped according to topic, methodology, and the results of different studies are compared using a detailed descriptive method.
5) Validation and critical analysis: collected studies were critically analysed to assess their rigor, validity of result, and potential limitations. Special attention was paid to the identification of specific areas where further research is needed.

This methodology ensured a comprehensive and structured review of existing published work, so that the conclusions of this paper can be based on reliable and relevant sources.

2 OVERVIEW OF AI IN FINANCIAL MARKETS

The historical footprint of the application of AI in the field is traced from early statistical methods to modern machine and deep learning techniques:

- Early stages (1970s – 1990s): The first attempts are made in the application of computers in financial markets, which relied on statistical methods and existing econometric models [7]. These common forecasting methods were primarily regression analysis and time series; and the model used was primarily ARIMA [8]. In the 1980s first expert systems were developed, marking the beginning of proper AI application in the field. These systems [9] used rules which strictly followed expert knowledge to make objectively unbiased trading and portfolio management decisions.
- Development of neural networks (1990s – 2000s): Neural networks became popular in financial market applications due to their innate ability to learn from aggregated data and to recognize complex, extended-time-line patterns. Most notably, the use of multi-layer perceptrons (MLP) for stock price prediction. Such models had shown superiority [10] over traditional statistical methods in repeatable cases. In the early 2000s, further development of neural network training algorithms, most notably error backpropagation, measurably improved [11] the accuracy of the models applying them.
- The advent of machine learning (2000s - present): Algorithms such as support vector machines (SVM), random forests, and k-nearest neighbours (k-NN) came into utilization [12]. Simultaneously, an increase in the availability of financial data and the growth of computational power have enabled a more comprehensive utilization of these technologies. Today, deep learning and specific neural networks, most notably recurrent neural networks (RNN), and long-short-term memories (LSTM) have become the standard [13] in analysing large amounts of financial data, and therein predicting market movements.

2.1 Key AI Methodologies

Analysing the application of artificial intelligence in the field, different methodologies have been found [14, 15, 16, 17, 18] in use, each with its own measurable advantages and limitations. These included:

1) **Machine learning**
a) Supervised learning – uses labelled data to train models in predicting outcomes based on input data, so attempting to predict stock prices but also creditworthiness and the associated risk.
b) Unsupervised learning – analyses data without such predefined labels with the aim to discover hidden patterns and structures. Most notably it is used in customer segmentation, but in the field for the detection of trading anomalies.
c) Reinforcement learning – such models learn through making predetermined sequential decisions that aim to maximise long-term positive outcomes. It is mostly used in portfolio optimisation, as well as automated trading.

2) **Neural networks**
a) Multilayer perceptrons (MPL) – used for basic prediction and classification, through making used of one or more hidden layers in a simple neural network.
b) Recurrent neural networks (RNN) – aim to predict stock prices and financial indicators by working with time serious and sequential data.
c) Long-short-term memory (LSTM) – a type of RNN that is proven to be effective at capturing long-term dependencies in data, and therefore improving the accuracy of predictions.

3) **Deep learning**
a) Convolutional neural networks (CNN) – used to analyse and map patterns in a time series to a predetermined pattern.
b) Generative adversarial networks (GAN) – generate synthetic data to improve training and later testing of predefined trading strategies.

4) **Other noted techniques**
a) Genetic algorithms – utilised in the optimisation of trading strategies and portfolios, based on the natural selection principle.
b) Fuzzy logic – used to model uncertainty to define the conditions thereof, and later use these for decision-making.
c) Expert systems – these integrate existing expert knowledge and the resulting rules into automated trading decisions and supervise risk management.

These methodologies are a list of documented different approaches to using AI in the analysis and forecasting of financial market movements. By combining these, researchers and practical users can potentially develop robust models with ever more improved accuracy and efficiency of predictions and financial operations.

2.2 Current Trends and Applications

Applications of AI in the field continue to progress and become more prevalent with the advancement of technology itself and the ever-increasing availability of data. Current trends encompass several key areas and are transforming the way institutions as well as investors analyse their target market and make decisions.

The most prominently mentioned [14, 17, 18] trend is high frequency trading (HFT) which involves the execution of many transactions in very short time intervals (often milliseconds). AI algorithms are used to analyse real-time data and make near-instant trading decisions. Continually deep learning and machine learning algorithms analyse patterns and trends, enabling HFT systems to identify key events and anomalies in the market, to execute trades faster than a human trader. Consequently, this increases market liquidity and enables lower reaction times to market changes.

Sentiment analysis [19] is another prevalent application of AI in the field. It uses natural language processing (NLP) techniques to gauge the market sentiment, based on raw textual data retrieved from several sources, including news articles and social media. Institutions use sentiment analysis not only to predict market movements, but also to identify potential opportunities and risks, and to make better informed decisions. Uniquely, NLP covers the human input into the field, thereby increasing accuracy of forecasts and the quality of decision-making by providing a deeper insight into sentiments, trends, and moods.

AI also shows significant impact on portfolio management. Using combinations of machine learning algorithms, investors attempt to optimise their portfolios by analysing historical data. These algorithms specifically identify optimal asset combinations that minimise risk and maximise returns. Such optimization algorithms are used to automatically balance and adjust portfolios close to real-time, all the time considering market conditions but also the individual goals which are defined in advance.

Automated trading [17, 18] is found as another key innovation driven by the development of AI. These systems use AI algorithms to analyse market data, making decision and executing transactions without human intervention. They are used in a variety of strategies, notably arbitrage, market making, and trend following. Such algorithms adjust their strategies in real-time, in accordance with predefined parameters, based on changing market conditions, thus increasing the efficiency of all future trading operations, eliminating human error (but not in the setting of parameters), and enabling 24/7 trading.

Separate from the trading aspect of the financial market, AI also seems to play a key role in risk management and fraud detection [20], where it shows significant potential. AI algorithms recognize patterns and anomalies which may indicate potential risks or fraudulent activity, therein providing financial institutions with the ability to better monitor real-time transactions, assess credit risk, and prevent fraud. Fraud detection systems specifically use machine learning to continuously learn and adapt to new threats, increasing the security of transactions, reducing losses due to fraud, and improving risk management.

2.2.1 Examples of Successful Implementations

Among the numerous examples of successful implementations of AI in the financial sector, few are notable and verifiable. These illustrate how AI can transform business processes and improve decision-making:

1) Renaissance Technologies [21], the hedge fund known for its heavy reliance on advanced mathematical models and AI, manages one of the most successful funds of this type, the Medallion Fund. Using machine learning, deep learning, as well as other AI techniques, they analyse large amounts of market data to identify patterns and so attempt to predict market movements. Their in-house model continuously adapts to new data, enabling the fund to achieve exceptional returns and minimise risks.
2) Two Sigma Investments [22], another hedge fund relying on AI and machine learning to make trading decisions, uses large data sets, including but not limited to market data, economic indicators, and alternative data sources such as weather and social media, to develop models that aim to predict market data. Their AI systems analyse this data in real-time, allowing them to react and to adjust quickly.
3) Bridgewater Associates [23], another from the group of hedge funds, uses AI in its flagship fund, the Pure Alpha Fund. Their AI algorithms aim to analyse macroeconomic data, market trends and historical patterns to make informed decisions. Their models help them identify long-term and short-term investment opportunities, but also to adapt to changes in the global economy and markets more time-efficiently.
4) Citadel [24], one of the global financial institutions that manage hedge funds but also market making operations, uses AI in its quantitative trading strategies. Their machine learning algorithms analyse large amount of market data to identify potentially profitable trading opportunities and optimise the end-users' trading strategies. Their models also adapt to changes in the market in real-time, allowing their quantitative trading strategies to generate consistent returns.
5) Goldman Sachs [25] implements AI through their Marquee trading platform, which is used to analyse market data for the purpose of making informed trading decisions. Marquee aims to predict the prices of stocks as well as other financial instruments, thus enabling individual traders to identify potentially profitable trading opportunities. Notably they also use AI for risk management and portfolio optimisation.

These selected examples of successful implementation of AI in well-established financial institutions show how the subject technologies can improve operational efficiency, and mitigate or reduce risks, while still catering personalised services to clients.

3 COMPARATIVE ANALYSIS OF AI TECHNIQUES

Convolutional Neural Networks (CNN) have shown notable performance in forecasting specifically stock market prices. They perform well in error analysis, and are more effective when combined with other models, most often paired with LSTM as a hybrid model. In a relevant study [26], the use of CNN combined with a variational autoencoder (VAE) for the purpose of feature extraction, showed superior performance in stock market predictions when compared to other methods.

Long-Short-Term Memory (LSTM) networks are widely recognized for their stability as well as accuracy in forecasting stock market returns. These outperform [27] traditional models like ARIMA and are most often integrated into ensemble models with similar neural networks. In the same study, one LSTM model was shown to produce lower errors compared to RNN and CNN models in forecasting NIFTY50 stock prices.

Integrating different AI methods into hybrid models has shown to be effective in improving prediction accuracy. One noted example [28] includes a combination of CNN, GRU (Gated Recurrent Unit) and LSTM, and has shown significant improvement in stock market forecasting accuracy. Studied hybrid models in the study, such as the Random Forest + XG-Boost + LSTM ensemble, was particularly prominent for its effectiveness in predicting stock prices.

Explainable AI (XAI) methods like SHAP and LIME are currently being explored [29], with their purpose being providing transparency to the predictions of highly complex models such as LSTM and CNN. These seem to be the key to understanding the model's internal decision-making process, which is relevant for financial forecasting, as interpretability is as important as accuracy. [2]

Recurrent Neural Networks (RNN) are another noted time series forecasting model in the field. These have shown [30] to perform in various studies, very often with comparatively lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) value, when compared to models such as standalone LSTM.

Sentiment analysis, as a standalone technique, pulling current financial data from social media and news outlets, has proven [31] useful in improving the accuracy of forecasts. Market sentiment remains still a key driver of market movement. [5]

Ensemble models as their own category, models which combine multiple algorithms are noted for their robustness and superior performance in multiple financial forecasting variants. One such ensemble of neural networks has proven [32] to be superior to traditional models in predicting risk factors specifically in frontier markets.

Table 1 Comparative analysis of relevant findings

Technique	Accuracy	Stability	Interpretability	Notable indicators
CNN	High	High	Moderate	Superior feature extraction, effective in hybrid models
LSTM	Very high	Very high	Low	Lower errors when compared to RNN and CNN
Hybrid (CNN + LSTM)	Very high	Very high	Low to moderate	Significantly improved forecasting accuracy
XAI	High	N/A	High	Provides transparency in decision-making
RNN	High	High	Low	Lower RMSE and MAE values compared to others
Sentiment analysis integration	High	High	Low to moderate	Improved accuracy when combined with financial data
Ensemble models	Very high	Very high	Low	Outperforms traditional models in various scenarios

Labels "very high", "high", "moderate", and "low" used in the table were qualitative assessments based on the performed comparative analysis of the finding as reported in the reviewed studies. These were determined by examining key performance metrics, characteristics, and the overall conclusion presented in the research. These assessments were derived as follows:

1) **Accuracy**
a) Very high – consistently outperformed others regarding the forecast accuracy across multiple studies
b) High – showed strong performance in accuracy but were either less effective than "Very high" or had instances where the outperformance was not consistent
c) Moderate – performed adequately, with their accuracy less pronounced than in "Very high" or "High", and were generally outperformed by more advanced models
d) Low – had significantly higher error rates and lower accuracy compared to others

2) **Stability**
a) Very high – showed consistent performance across different datasets
b) High – performed reliably with most datasets but have shown slight variability
c) Moderate – had some degree of variability of performance across different datasets
d) Low – showed significant performance fluctuations, or were highly sensitive to changes in the input data

3) **Interpretability**
a) High – allowed clear insight into the decision-making process
b) Moderate – provided some level of interpretability
c) Low – had little to no ability to let users understand, or explain their decision-making process.

These qualitative labels are based on synthesizing information provided in the respective studies, where models were tested and compared. Performance indicators such as error rates, accuracy, and stability were the key factors in assigning these.

3.1 Advantages and Limitations

Among the main advantages of AI in the field, is the ability to parse large amounts of data in a short period of time, and to uncover complex patterns which may overwhelm traditional methods. CNNs excel at feature extraction, which allows for the recognition of complex patterns in large datasets. When combined with LSTMs most notably, they further improve on forecasting accuracy, as they successfully recognize spatial and temporal dependencies in the data.

LSTM networks are most effective at predicting a time series, which is the basis for all financial trend forecasting. Their reliability lies in the ability to retain tendencies over long sequences. On the other hand, the complexity of an LSTM can lead to overlearning [13], most commonly when small datasets are used.

When combined into a hybrid model, different AI techniques often achieve superior accuracy by combining the strengths of the different approaches. Consequently, the increased complexity and longer required training time can be a limitation. In hybrid models, alike LSTMs, their low interpretability introduces a further difficulty in working with them.

This problem of interpretability is met by XAI, created especially as its solution. However, in trying to bring insight into the decision-making process, to allow users to understand and justify the forecasts, it has the risk of oversimplifying the model.

Sentiment analysis aims to improve the predictive power of models, by enabling real-time insight into the market sentiment. In its application, it faces challenges such as messy and often unstructured data, difficulties in understanding nuances of natural language, and can ultimately fall victim to sarcasm or context-specific meaning, which result in misinterpretation.

Finally, ensemble models have shown a high degree of robustness and improved forecasting accuracy, in various financial scenarios. By averaging the predictions of several combined models, ensemble methods reduce risks and enhance the overall performance. This increased complexity however makes them more difficult to interpret and to implement, limiting their practical applicability.

4 CONCLUSION

The application of AI has fundamentally changed the approach to financial markets, offering tools that surpass traditional approaches in both accuracy and efficiency. Through the application of advanced techniques such as CNNs and LSTM networks, and ensemble models, financial institutions are now able to analyse extensive amounts of data with previously unattainable speed and measurably higher accuracy.

The comparative analysis presented here highlights significant leaps AI has made in the field, particularly in stock market predictions. CNNs have shown to be effective in feature extraction, making them valuable for identifying patterns within large datasets. LSTMs, which retain information over extensive data sequences, have become the staple for time series forecasting. Going even further, hybrid as well as ensemble models which integrate various AI techniques, combining the strengths of individual approaches, have an observable further enhanced predictive power.

Despite these advancements, the adoption of AI in the field remains challenging. The increasing complexity of models which is requires for greater accuracy brings the risk of overfitting and reduces the interpretability of the decision-making process ever more. These challenges require ongoing research and the refinement of AI techniques, which would ensure the provided predictions are not only accurate but also transparent and verifiable.

As AI continues to develop, its presence in the field is likely to expand further. Balancing this progress with the need for transparency will likely be crucial in realising its full benefits.

4.1 Advantages of AI in Financial Markets

Several key advantages were introduced into the field with the implementation of AI. Of the most significant benefits, is the ability to process and analyse large amount of data at unprecedented speeds. Models can efficiently parse large datasets, identify complex patterns and trends over long periods of time, which may be overlooked by a human analyst or a traditional statistical method.

In high-frequency trading (HFT) environments, where decisions are made in milliseconds, AI outperforms human traders by reacting to market movements at near instant times. This speed not only improved the efficiency of all trading operations, but at the same time also reduces the risk of missed opportunities due to delays in human cognitive decision making. The incorporation of real-time market sentiment analysis also provides a more comprehensive understanding of market dynamics.

In summary, the advantages are multifaceted, including enhanced data processing capabilities, forecasting accuracy, real-time decision-making, enhanced risk management, and the integration of sentiment analysis.

4.2 Limitations and Future Research

One of the primary challenges associated with AI is the required complexity of the models. Techniques such as LSTM and hybrid models often require extensive computational resources and time for training. At the same time, their complexity makes them difficult to interpret and manage. As models become more sophisticated, understanding how they arrive at specific decisions becomes vaguer. In the field, transparency and accountability are crucial, and the lack thereof hinders trust and adoption of AI driven decision-making.

Overfitting is a common problem with complex models (like LSTMs), where the models may perform exception on training data, but then fail to generalise to new, unseen data, particularly with smaller datasets. Mitigating overfitting required tuning and is very resource intensive. Sentiment analysis falls victim to unstructured and often ambiguous nature of textual data from social media and news outlets.

Future research for AI in the field should focus on several key areas: models need to become more interpretable. XAI addresses this issue but requires further advancement.

While hybrid and ensemble models show improved accuracy, their complexity and time required to train remain a hurdle. Research should aim to simplify these models without compromising on performance.

Improving sentiment analysis also seems to be essential. Its input into the decision-making process has a measurably positive effect but needs to be more reliable when it comes to interpreting the nuances of natural language.

Addressing the overfitting issue should be a priority. This could involve the introduction of new model validation techniques that ensure AI system generalise well to new data, particularly in the volatile financial markets.

By focusing on interpretability, simplification of complex models, refining sentiment analysis, and preventing overfitting, future research can help maximize the potential of AI in financial markets while minimizing its risks.

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