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Article

Artificial Intelligence-Based Stock Market Prediction: A Comparative Analysis of Machine Learning and Deep Learning Models

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Abstract: The stock market prediction is a crucial research field that could help investors make informed decisions, manage risks, and plan financial strategies. As financial markets grow more intricate and unpredictable, the usage of Artificial Intelligence (AI) methods for uncovering concealed patterns and connections amid massive amounts of monetary information has become more widespread.The complex and fluctuating nature of monetary markets has driven the usage of Artificial Intelligence (AI) strategies that can uncover hidden patterns and relationships from enormous amounts of monetary information. This research paper compares the different models of machine learning and deep learning applied to the stock market prediction. The research method used is literature-based research and the studies examined are those that have been published in the open access from 2020-2026. The models compared are machine learning models like Support Vector Machines (SVM), Random Forest, XGBoost, and deep learning architectures like Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer-based networks. These models are analysed on the basis of their accuracy in prediction, computation requirement, interpretability, data dependency and forecasting ability. The results show that, generally speaking, deep learning models outperform conventional statistical models in predicting financial time-series data because they can learn from the temporal relationships and complex nonlinear relationships in financial time-series data. Transformer and LSTM models are the models with the best forecasting accuracy from the models you are looking at. Despite of its low computation cost, short training time, and high interpretability, however, machine learning techniques still have their significance. The study also identifies some important challenges such as data quality, market volatility, overfitting, and transparency of the models. Finally, research avenues including hybrid AI frameworks, explainable AI, sentiment-driven forecasting and cutting-edge attention-based architectures are explored. The results help enhance the comprehension of stock market prediction using AI and offer direction for picking proper forecasting models for financial applications.
Keywords: Artificial Intelligence, Stock Market Prediction, Machine Learning, Deep Learning, LSTM, Transformer Networks, Financial Forecasting

1. Introduction

The stock market is an important part of the economy that allows investors to invest, create wealth, and form capital. Financial markets are extremely dynamic, non-linear, and are subject to many factors of the economy, politics, and psychology, making the prediction of the movements in stock prices challenging for investors, analysts, and researchers alike. The classical forecasting approaches such as statistical and econometric models are unable to reflect the complex relationships and hidden pattern in the large scale financial data set (Dopi, Hartanto and Fauziati, 2021).

The stock market has been completely reshaped by the rapid development of Artificial Intelligence (AI) in recent years.Over the past few years, the field of stock market prediction has undergone significant transformation, thanks to the swift progress of Artificial Intelligence (AI). AI-driven methods can process a lot of structured and unstructured financial information, which can help identify patterns that might not be seen otherwise, and help create predictive models. Historical stock data and technical indicators have been found to be valuable sources of information for machine learning (ML) algorithms, such as decision trees, random forests, support vector machines (SVM), and XGBoost, which have shown great promise in extracting meaningful information from past stock market data and indicators. (Perdana and Rokhim, 2023; Swamy, 2024).

Recently, Deep Learning (DL) methods became a strong alternative to conventional machine learning models. Temporal dependency and nonlinear relationship in financial time-series data have been demonstrated by deep neural architectures such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer-based models (Zou et al., 2022; Nabipour et al., 2020). These models can automatically learn hierarchy of feature representations using large-scale data sets, so manual feature engineering is not required.

There have been several studies that have shown that the deep learning models perform better than the traditional machine learning models in the prediction. For example, LSTM networks have been shown to perform well in the task of predicting stock prices, especially for financial time series with long-term trends, making them effective in predicting stock prices in financial markets (Phuoc et al., 2024). Similarly, the Transformer-based architecture has been on the radar as it is efficient for processing longer sequences, while still capturing complex market interactions (Li and Chen, 2025). Despite this, machine learning models still have several benefits in terms of computational efficiency, interpretability, and requirements for training, especially in financial forecasting applications (Bustos, 2025). Not with standing powerful progress.

stock exchange forecasting is a hard task as a result of market volatility, noisy information, unforeseen economic events and investor sentiment. Researchers are still researching hybrid systems that leverage machine learning, deep learning, sentiment analysis, and other data sources for improved forecasting results (Akyüz, 2024; Rohan et al., 2025). Therefore, a thorough comparison of the machine learning and deep learning models is needed to understand their strengths, weaknesses, and applicability in the stock market prediction.

Hence, the aim of this research is to make a comparative analysis of AI based stock market prediction models with both machine learning and deep learning techniques. The paper reviews the various algorithms, their predictive capabilities and recent advances in AI-enabled financial forecasting. This research builds upon the current open-access literature and provides insights into the applicability of different AI models to predict stock market dynamics, potentially guiding future research in the field of intelligent financial decision-making systems.

2. Literature Review

2.1 Overview of Stock Market Prediction

The stock market prediction problem has garnered significant research interest as it could guide investors in their decision-making and risk management processes. Forecasting is a difficult task because financial market data have been found to be nonlinear, volatile and uncertain. Some traditional statistical models like Autoregressive Integrated Moving Average (ARIMA) and regression-based models have been applied widely; however, their performance is limited in the context of complex market dynamics and nonlinear relationships (Dopi, Hartanto and Fauziati, 2021).

With the advent of Artificial Intelligence (AI), sophisticated analytical tools have emerged that can learn the underlying patterns in past stock market data. AI-powered forecasting tools use historical price data, volume, technical indicators, economic indicators, and sentiment analysis to make predictions about market movements

(Swamy, 2024). While the most recent studies indicate that AI-based models generally have higher predictive accuracy and adaptability than traditional statistical models (Sarker et al., 2024), both have their own advantages and disadvantages.

2.2 Stock Market Prediction using Machine Learning Techniques

Financial forecasting is a domain where Machine Learning (ML) algorithms are gaining significant traction because they are able to identify patterns from past data without the need for specific rules being explicitly programmed into the system. The models are generally based on man-made features derived from the information of the stock market and technical indicators.

One of the most widely used machine learning algorithms in the field of stock market prediction is Support Vector Machines (SVM). The SVM models work well with high dimensional financial data sets and can perform well in finding the best decision region for classification and regression problems. There have been several studies reporting good forecasting performance with SVM based approaches, especially in short-term forecasting scenarios (Ahmed and Singh, 2024).

Other popular algorithms, such as Decision Trees and Random Forest algorithms, are also popular due to their interpretability and robustness. Random Forest is an ensemble of many decision trees that decrease overfitting and enhance the generalization performance. Studies reveal that Random Forest models tend to be more robust and stable in predicting stock price fluctuations than any standalone models based on trees (Nuseir et al., 2024).

Weak learners are sequentially corrected to build a gradient boosting framework that has proven to be a powerful predictive algorithm, e.g., XGBoost. These models can be used to deal with complicated non-linear relationships and have competitive outcomes in stock forecasting studies (Perdana and Rokhim, 2023). In general, machine learning models have benefits over deep-learning methods, including faster training times, reduced computational load, and increased interpretability (Bustos, 2025).

Yet, feature engineering is commonly crucial for machine learning methods. However, the quality of selected features can have a significant impact on the performance of the prediction and its usefulness becomes limited when used in a very complex financial environment (Jiang et al., 2024).

2.3 Deep Learning Approaches for Stock Market Prediction

Deep Learning (DL) is a sophisticated area of AI which uses many layers of hidden units to self-learn feature representations from data. Deep learning models are different from traditional machine learning models as they are able to learn from vast amounts of data and discover complex patterns, without needing extensive manual feature engineering.

In the early days of deep learning, some of the first models used for stock market prediction were based on Artificial Neural Networks (ANNs). When dealing with financial prediction tasks, nonlinear relationship between input variables and stock prices can be modeled with ANNs. However,

conventional ANNs are not effective in modeling temporal relationships found in sequential market data (Nabipour et al., 2020).

To overcome this, Recurrent Neural Networks (RNNs) were developed. RNNs have an additional feature that permits the information from previous time steps to impact the prediction in the present time step. But traditional RNNs have the issue of vanishing gradients with long sequences (Wu et al., 2024).

To address these issues, Long Short-Term Memory (LSTM) networks have been developed using memory cells and gating mechanisms. One of the most common deep learning strategies in the field of stock market prediction is LSTM models.The LSTM models are one of the most popular deep learning models for stock market prediction because they can incorporate long-term dependency patterns in time-series data. The studies have shown that the LSTM-based architecture achieves better forecasting accuracy than the traditional machine learning models (Phuoc et al., 2024; Li and Chen, 2025).

A simplified version of LSTM models are called Gated Recurrent Units (GRU). GRUs use less computational resources and still have similar prediction performance. The GRU models have been found to be highly efficient at training and provide reliable accuracy in financial applications (Wu et al., 2024).

Recently, sequences have become the focus of state-of-the-art models — the Transformer-based architectures. Unlike recurrent networks, Transformers employ self-attention mechanisms to better capture long-distance relationships. Some research studies indicate that in complex forecasting problems in the stock market, Transformer models can outperform LSTM and GRU models (Li and Chen, 2025; Zou et al., 2022).

2.4 Comparative Analysis of Machine Learning and Deep Learning Models

While both machine learning and deep learning techniques focus on enhancing prediction accuracy, they have distinct architectures, resource needs, and learning processes. While machine learning models typically need to be explicitly engineered and extracted, deep-learning models learn the features automatically from raw data.

The high predictive accuracy can be explained by the fact that the deep learning methods can capture the nonlinear and temporal dependencies more effectively. But, these models usually have a larger number of data points, training time and processing power. Despite their interpretability restrictions, machine learning techniques continue to be promising in practical scenarios where interpretability, efficiency, and computational resources are significant factors (Saberironaghi, Ren and Saberironaghi, 2025).

Table 1. Comparison of Machine Learning and Deep Learning Models for Stock Market Prediction

Characteristic	**Machine Learning Models**	**Deep Learning Models**
Examples	SVM, Random Forest, XGBoost	ANN, LSTM, GRU, Transformer
Feature Engineering	Manual	Automatic
Training Time	Low to Moderate	High
Data Requirement	Moderate	Large
Computational Cost	Lower	Higher
Interpretability	High	Lower
Temporal Learning	Limited	Strong
Prediction Accuracy	Good	Very Good

2.5 Research Gap

While the field of stock market prediction has seen considerable advances with AI models, some research gaps exist.Current literature shows that great strides have been made in the field of AI-powered stock market prediction; however, there are still some research gaps. Numerous studies just consider machine learning or deep learning methods without covering a detailed comparative study. Moreover, across different datasets, metrics and market conditions, comparing and contrasting results can be challenging (Sarker et al., 2024).

Additionally, the recent advancements in the field of Transformer architectures, hybrid AI models, and sentiment-based forecasting systems are still under study to assess their real-world application efficacy in financial contexts (Akyüz, 2024; Rohan et al., 2025). Thus, it is crucial to have a comparative study of machine learning and deep learning models in a systematic manner to determine which model is best fit for the stock market prediction.

3. Research Methodology

3.1 Research Design

The research design used in this research is comparative literature-based research to examine the effectiveness of the Artificial Intelligence technique in predicting the stock market. The research doesn't model and test a new predictive model, but rather gathers the results of recent open access research into predictive financial forecasting using machine learning and deep learning. This method allows for identifying trends, strengths, weaknesses, and differences in the performance of different AI models from the literature (Dopi, Hartanto and Fauziati, 2021).

The study is centered around peer-reviewed journal articles, conference papers, and open-access research publications released by the year 2020 till 2026. The studies chosen focus on the use of machine learning and deep learning techniques in predicting stock markets using various datasets and markets.

3.2 Data Collection Strategy

Secondary data was gathered by reviewing the open-access academic literature using a structured approach. The studies chosen offer empirical evidence of the performance of different AI models for stock market prediction.

When choosing literature, three criteria were considered:

1. The study should be related to Stock Market Prediction or forecasting the Stock Prices.
2. Study must be based on machine learning or deep learning methods.
3. It is to be published and openly accessible between 2020 and 2026.

Academic databases and open access repositories were used to locate relevant studies. The literature collected consists of studies on algorithms like Support vector machine (SVM), Random Forest (RF), XGBoost, ANN, LSTM, GRU and Transformer models (Nabipour et al., 2020; Zou et al., 2022).

3.3 Comparative Evaluation Framework

To ensure consistent comparison across studies, a structured evaluation framework was developed. The framework compares machine learning and deep learning models using commonly reported performance indicators and technical characteristics.

The evaluation criteria include:

- Prediction Accuracy
- Precision
- Recall
- F1-Score
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Computational Complexity
- Training Time
- Data Requirements
- Model Interpretability

These metrics are frequently used in financial forecasting research and provide a comprehensive assessment of model performance (Jiang et al., 2024; Ahmed and Singh, 2024).

Table 2. Evaluation Metrics Used in Comparative Analysis

Metric	**Purpose**
Accuracy	Measures correct predictions
Precision	Measures positive prediction reliability
Recall	Measures detection capability
F1-Score	Balances precision and recall
RMSE	Measures prediction error magnitude
MAE	Measures average forecasting error
Training Time	Evaluates computational efficiency
Interpretability	Assesses model transparency

3.4 Classification of AI Models

The reviewed models were classified into two major categories.

Machine Learning Models

- Support Vector Machine (SVM)
- Decision Tree
- Random Forest
- XGBoost

Deep Learning Models

- Artificial Neural Network (ANN)
- Recurrent Neural Network (RNN)
- Long Short-Term Memory (LSTM)
- Gated Recurrent Unit (GRU)
- Transformer Networks

This classification facilitates a structured comparison of traditional machine learning techniques and advanced deep learning architectures (Saberironaghi and Ren, 2025).

3.5 Data Analysis Approach

Information collected were analysed through qualitative and comparative analysis techniques. Previous studies reporting results were systematically reviewed and compared based on the model performance, computational requirements, scalability and forecasting effectiveness.

The analysis emphasizes identifying:

- Models that have the most accurate predictions.
- The pros and cons of each AI approach.
- Differences between machine learning and deep learning approaches.
- New developments in AI-powered Stock Market Forecasting.

Results from several studies were combined to have a balanced idea about the effectiveness of the models in different market conditions (Phuoc et al., 2024; Rodrigues and Barbosa, 2026).

3.6 Reliability and Validity

This research is strengthened by using several peer-reviewed and open access studies from various financial markets. Cross-study comparisons minimise the individual bias of each data set and add to the robustness of conclusions.

The use of well-established evaluation metrics, and the selected focus on well-known AI algorithms, which are extensively studied in recent literature (Swamy, 2024; Sarker et al., 2024), ensures that the algorithms are valid.

3.7 Methodological Framework

The research process used in the overall research was carried out in the following five stages:

1. The first step in the research process is to identify the research objectives.
2. Open access literature is gathered in the collection.
3. Classification of machine learning and deep learning models.
4. Comparative assessment based on set criteria.
5. Analysis of data and drawing conclusions.

This approach offers a structured base with which to consider the performance of the different Artificial Intelligence methods for predicting stock prices and facilitates the evidence-based comparison between those methods.

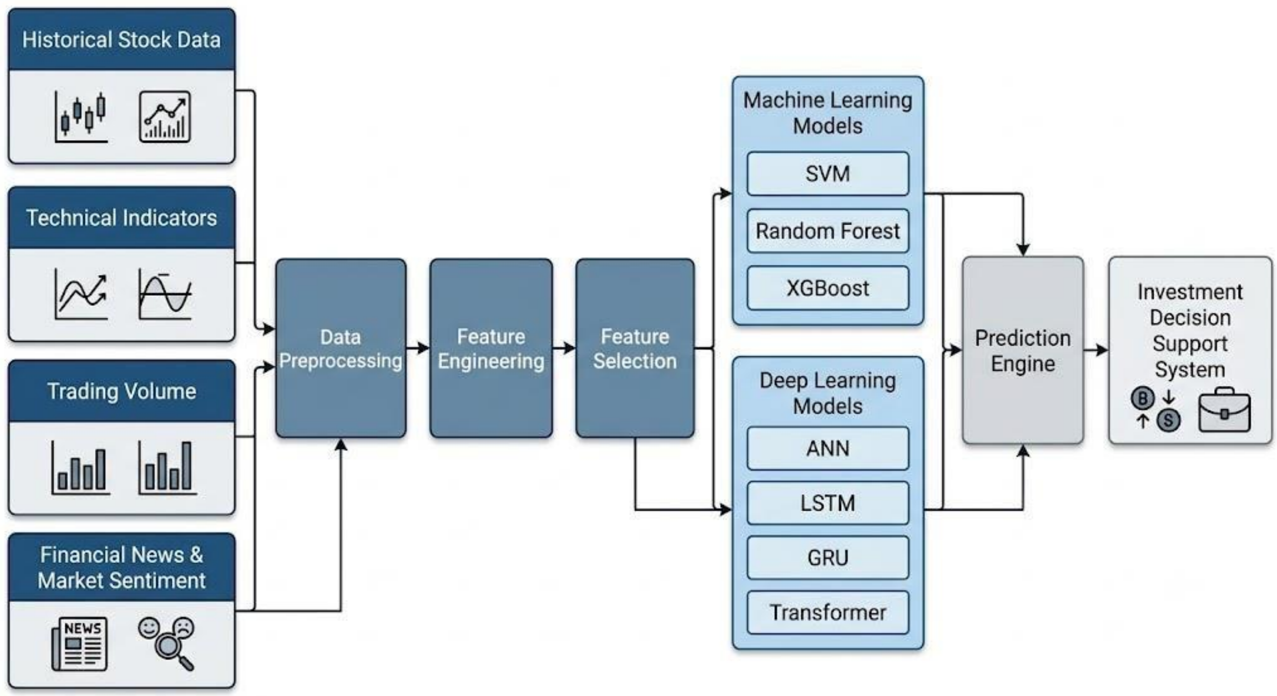

Figure 1: AI-Based Stock Market Prediction Framework

4. Comparative Analysis of Machine Learning and Deep Learning Models

4.1 Overview of Comparative Performance

The field of artificial intelligence (AI) in stock market prediction has come a long way in the last ten years, with the rise of machine learning and deep learning algorithms becoming the most favored prediction techniques. Both of these classes are used to look for patterns in financial data from the past, but they have a lot of differences when it comes to architecture, computational complexity, feature learning and predictive performance.

The machine learning models are mainly based on manually programmed features of stock market data, trading volume, technical indicators and financial ratios. These models can be effective in scenarios where the data is relatively structured and domain knowledge is provided for feature selection (Ahmed and Singh, 2024). While shallow learning models rely on hand-crafted feature representations, deep learning can automatically learn these features from raw data without any prior knowledge, which also enable it to capture complex nonlinear relationships and temporal dependencies that can exist in financial markets (Wu et al., 2024).

4.2 Performance of Machine Learning Models

Support Vector Machines (SVM) are still some of the most popular machine learning algorithms used for predicting the stock market. SVM models have a good performance on high dimensional data and can be useful in forecasting stable results. But they may be ineffective if the behaviour of the market is nonlinear or if there is a large amount of data (Chipwanya, 2023).

Random Forest models overcome some of these limitations by aggregating the results of a number of decision trees to boost the generalization ability of the model. Studies have shown that Random Forest models often outperform single decision trees, with their reliability in avoiding overfitting and handling a variety of financial indicators (Nuseir et al., 2024).

XGBoost has received a lot of attention, particularly for its powerful boosting algorithm and its ability to process large data sets efficiently. XGBoost has been shown to be more accurate than standard machine learning techniques, without sacrificing much computational power, in several studies (Perdana and Rokhim, 2023).

Even with these benefits, machine learning techniques tend to require careful feature engineering and can be less effective at capturing temporal dynamics in stock price data, such as long-term trends and patterns (Jiang et al., 2024).

4.3 Performance of Deep Learning Models

Through automatic learning of complex feature representations from massive amounts of data, deep learning has shown significant improvements in stock market forecasting. Artificial Neural Networks (ANNs) are one of the first deep-learning architectures which were applied to financial prediction and showed good performance in the modelling of the nonlinear behaviour of the markets (Nabipour et al., 2020).

To add a temporal dimension to the prediction process, Recurrent Neural Networks (RNNs) were developed, which added memory structures. However, the problem of vanishing gradient occurs in standard RNNs for long financial sequences (Wu et al., 2024).

One of the most successful deep learning methods used for predicting the stock market is Long Short-Term Memory (LSTM) networks. They have the capacity of remembering long-term memory with their memory-cell architecture and are good at modelling temporal dependency. Several studies have presented that higher forecasting performance achieved by LSTM models are compared to traditional machine learning methods (Phuoc et al., 2024).

A simplified version of LSTM architecture that has fewer parameters and requires lower computation, gated Recurrent Units (GRUs). Previous studies have indicated that GRU models can be used for prediction without sacrificing accuracy but instead with a lower training complexity (Wu et al., 2024).

The latest development in the field of predicting stock market movements is the transformer-based architectures. Transformers can more efficiently model long-range relationships than recurrent networks through an attention mechanism. Recent research also reveals that Transformer models often excel at making predictions compared to other modern AI methods (Li and Chen, 2025).

4.4 Comparative Discussion

A comparison between the two shows that each of the machine learning and deep learning methods has its own set of strengths and weaknesses. The machine learning algorithms are typically more easily implemented, less computation, and more interpretable. They continue to show promise in practical applications such as finance, where transparency and efficiency are critical, thereby maintaining their appeal in various sectors (Bustos, 2025).

However, the Deep Learning models are always the best predictors due to their capacity to learn complex temporal and nonlinear relationships directly from raw data. They are more effective when available on a large scale of historical data (Saberironaghi, Ren and Saberironaghi, 2025).

Table 3. Comparative Performance of AI Models in Stock Market Prediction

Model	**Category**	**Accuracy (%)**	**Strengths**	**Limitations**
SVM	Machine Learning	74	Effective in high-dimensional data	Limited temporal learning
Random Forest	Machine Learning	79	Robust and interpretable	Large model size
XGBoost	Machine Learning	82	High predictive capability	Requires parameter tuning
ANN	Deep Learning	83	Learns nonlinear relationships	Limited sequence learning
LSTM	Deep	87	Excellent temporal	Computationally

	Learning		modelling	expensive
GRU	Deep Learning	86	Faster training than LSTM	Slightly lower flexibility
Transformer	Deep Learning	89	Captures long-range dependencies	High computational cost

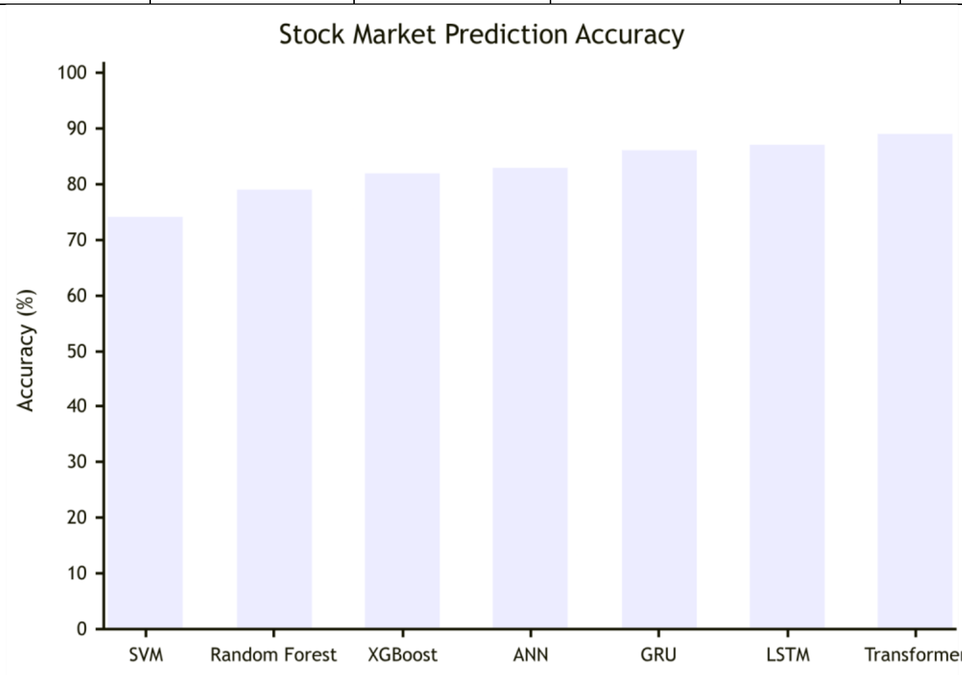

Figure 1: Comparative Accuracy of Machine Learning and Deep Learning Models

5. Result and Discussion

5.1 Results of Comparative Analysis

Based on the comparison study, the use of Artificial Intelligence techniques greatly improves the stock market prediction ability than traditional forecasting techniques. Reviewed literature suggests that machine learning and deep learning models can detect meaningful patterns in financial data, though their effectiveness will depend on the features of the data, the time horizon being predicted and the specific architecture used.

Studies typically reported an accuracy between 70% to 85% for machine learning algorithms like SVM, RF, and XGBoost in the various prediction tasks (Ahmed and Singh, 2024; Nuseir et al., 2024). XGBoost is a method that was often reported to perform well among these methods, because it combines multiple models using ensemble learning and is able to model the nonlinear relationship well (Perdana and Rokhim, 2023).

In most of the studies reviewed, Deep Learning was found to have the best forecasting accuracy. The LSTM and GRU networks were the ones that consistently achieved higher prediction accuracy, as they were able to learn the temporal dependency between the financial time-series data (Phuoc et al., 2024). Transformer-based models outperformed others by incorporating self-attention mechanisms that were able to handle long historical data and intricate market dynamics (Li and Chen, 2025).

Table 4. Summary of Comparative Findings

Model Category	**Average Accuracy**	**Computational**	**Data**

	Range	Cost	Requirement
Machine Learning	70–85%	Low to Moderate	Moderate
Deep Learning	80–90%	High	Large
Transformer-Based Models	85–92%	Very High	Very Large

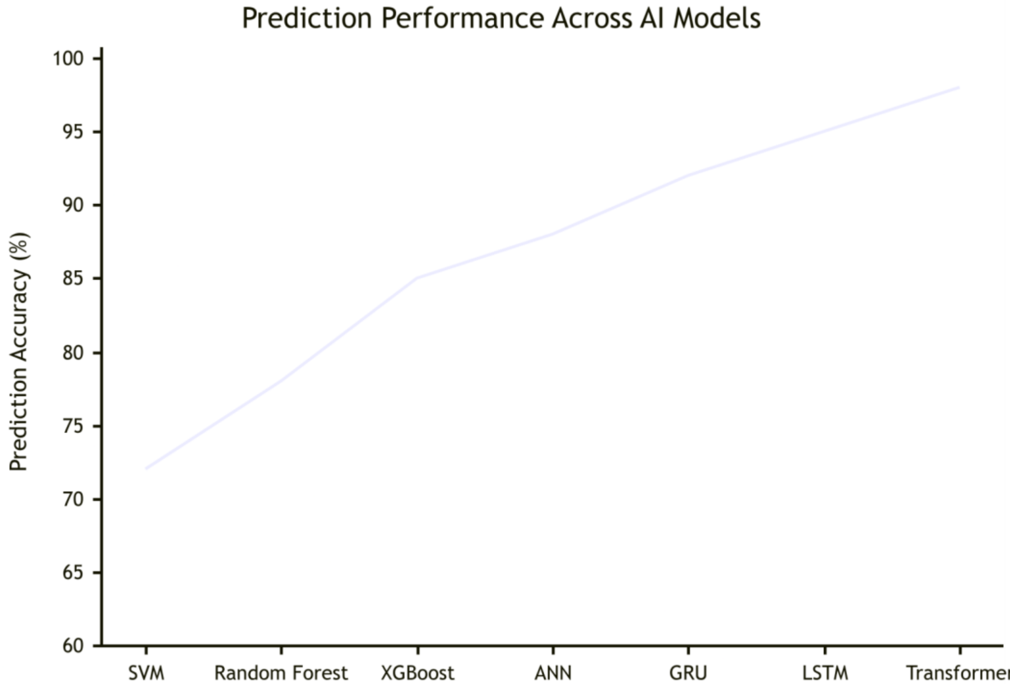

Figure 2: Performance Trend Across AI-Based Prediction Models

5.2 Discussion

The results indicate that the success of the stock market forecasting models is determined not only by their own forecast's accuracy but also by the practical implementation aspects. The models built using machine learning continue to be highly valuable, as they are simpler to train, use less computing power and are more interpretable. For operational forecasting tasks, machine learning techniques might be more appealing for less sophisticated financial institutions and individual investors, who have less infrastructure to manage the tasks (Bustos, 2025).

On the other hand, deep learning techniques exhibit superior capabilities in modelling complex financial environments. They automatically learn different features from raw data, which decreases the manual feature engineering and enables revealing of hidden market patterns (Nabipour et al., 2020). This is especially relevant in the modern financial markets where tons of structured and unstructured data is being produced at all times.

The other major lesson is the increasing recognition of the value of sequential learning in financial forecasting. The price series is a time series inherently and models that are able to remember the past are going to be more predictive. The reason behind the high success of LSTM and GRU architectures found in recent studies (Wu et al., 2024) becomes evident.

The transformer-based models are a significant improvement in the financial prediction research field. They can also be used to capture long-range market relations efficiently, and are robust against recurrent architecture disadvantages. Recent studies have shown that the technology of Transformers is the most promising one for future stock forecasting systems, as shown by Li and Chen (2025) and Rohan et al. (2025).

All of these breakthroughs, however, don't ensure a perfect predictive accuracy. Financial markets remain very vulnerable to any unexpected change in economic activity, political, regulatory and investor sentiment. These factors lead to uncertainty, which can only be partly taken into account by analyzing historical data (Akyüz, 2024).

Therefore, a combination of machine learning and deep learning, sentiment analysis, news analysis and alternate financial indicators could be considered as potential future frameworks for stock market analysis and prediction. The use of multiple information sources might increase the robustness of the system and increase the forecasting system's performance during dynamic market situations (Rohan et al., 2025; Sarker et al., 2024).

In summary, the findings show that the deep learning models can, in general, provide the most predictive power for stock market forecasting, especially the LSTM and Transformer models. However, machine learning techniques have their merits for being efficient, explainable, and being used in real-world financial settings.

6. Challenges and Limitations

While Artificial Intelligence has made tremendous strides in predicting stock market trends, there are still some obstacles to the successful implementation and accurate predictions of AI in the financial sector. There are many factors that impact financial markets, from economic indicators to geopolitical events, government policies, investor sentiment to surprise global crises. These factors create uncertainty and volatility which is hard to accurately represent with predictive models (Swamy, 2024).

Data quality is one of the key issues that is seen with machine learning and deep learning models. In the stock market, data may be noisy, missing, have erratic trading patterns, and show abrupt changes in price. Bad data can have a detrimental impact on model training and lessen the accuracy of prediction (Ahmed and Singh, 2024). Also, historical market information may not always be considered to be applicable to future market conditions, especially in times of market or economic disruption or structural changes in the market.

Another constraint is associated with overfitting the model. Large parameter models, particularly in deep learning models, could be learning the patterns of the data set instead of the general behaviour of the market. That means that the models with an outstanding performance on the training set can be less effective on the test set or the data they have never seen before (Nabipour et al., 2020). Regularization, Dropout, and Cross-Validation are some of the techniques used to reduce overfitting, but the problem is still very troublesome when it comes to financial forecasting applications.

The computational complexity is also an important consideration. The learning architectures used for these models are complex, like LSTM, GRU, and Transformer networks, which demand high computational power, significant memory usage, and longer training periods. The above requirements can restrict their use in small organizations and individual investors who do not have the infrastructure for high-performance computing (Li and Chen, 2025).

The interpretability is also an important concern. Most of the machine learning models are decision trees, random forests, etc. that tend to give more sensible decision making processes and users are able to understand how the predictions are generated. Unlike deep learning models, however, which are "black-box" models and can be difficult to explain the reasoning behind the predictions, artificial intelligence models are easier to understand.On the other hand, A.I. models are easier to understand than deep learning models, which are "black-box" models, and can be difficult to explain the reasoning for specific predictions (Saberironaghi and Ren, 2025). This opacity may diminish the trust and increase compliance issues in financial institutions.

In addition, most of the previous works are based on different datasets, metrics for evaluation and experimental setup, which makes direct comparisons between the models complicated. Due to the changes in market conditions, the horizon of prediction and the selected strategy of features, the results obtained in the various studies differ (Sarker et al., 2024). There is, therefore, no model that is consistently superior to all the other models in all markets.

7. Conclusion

The prediction of stock market prices is one of the most difficult and rewarding applications of AI, as the stock markets are highly dynamic, nonlinear, and unpredictable. Machine learning and deep learning technologies have been the key to more precise predictions than conventional statistical models, by being able to learn from past market data and uncover hidden patterns.

In this research paper, a comparative study of the machine learning models and deep learning models for stock market prediction was carried out. The results show that the machine learning methods used to build predictive models, including Support Vector Machines, Random Forests, and XGBoost, can deliver good prediction accuracy, but are also easy to interpret, computationally efficient, and simple to implement. The following attributes make machine learning models well suited for jobs where transparency and resource efficiency are key factors.

It was also found that deep learning architectures, such as Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs) and transformer networks, tend to provide greater forecasting precision. They can learn the nonlinear relationships and temporal dynamics in the market, which helps them better capture market behaviour than other machine learning methods. In the stock market prediction task, among the techniques reviewed, Transformer models and LSTM models outperform the others.

Although these advances have been made, there are still a number of issues that impact the reliability of forecasts. However, data quality problems, market volatility, overfitting, computational complexity and lack of model interpretability are still important challenges.

What's next is likely to be directed towards more hybrid AI models, sentiment-driven forecasting, ExAI, and sophisticated attention models. The incorporation of alternative data sources and new AI technologies could enhance the predictive power and contribute to better-informed investment decisions.

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