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# The Role of Artificial Intelligence in Financial Prediction Models for Forecasting Market Trends with Traditional Methods

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**Abstract**

The financial sector, especially in predicting market trends was greatly molded by Artificial Intelligence (AI). In these volatile and data-heavy markets driven by information, AI becomes a competitive edge to analyze large datasets, identify patterns, and predict (in real-time) future market states serving businesses, investors and policy makers alike. In this paper, we investigate some aspects of AI used for forecasting market trends, especially in the machine learning context: time series prediction and sentiment analysis. In this analysis, we pit traditional methods of time-series forecasting (such as autoregressive models) against more advanced AI methods that leverage neural networks and natural language processing (NLP). The findings show that the accuracy and generalisation of AI models are better than conventional approaches, but issues surrounding data quality and model interpretability remain. This research provides a clear demonstration of the important role artificial intelligence plays in contemporary market forecasting and offers valuable clues for further advances in financial prediction models.

**Keywords:** Artificial Intelligence, forecasting Market Trends, Time-Series Forecasting, Sentiment Analysis, Neural Networks, Natural Language Processing.

## 1. Introduction

Market trends have always been difficult to predict and are a cornerstone of financial strategy used by businesses, investors and policy planners around the world. Traditionally, this process was defined by econometric models, statistical analyses and the intuition of seasoned market analysts [1]. Yet, as global economic interdependency has deepened, and the volume of data incoming in lately double-quick time, it is becoming clear that traditional strategies often lag market complexities and volatility.

Over the years, Artificial Intelligence (AI) made its way in financial and market trend analysis [2]. AI, powered by machine learning (ML) algorithms and deep learning techniques, analyze vast amounts of data to find patterns and predict outcomes in real time. By ingesting a wide range of data sources whether historical price trends, economic indicators, or unstructured data such as social media sentiment and financial news these AI models cover nearly every aspect relevant to market movement.

As AI emergence accelerates, there are prominent themes that point to solutions like credit risk prediction, the elimination of human bias and use of dynamic data to real-time market change [3]. In this article, we are going to discuss how ML models using AI can be used as a prediction model for market trend predictions both at macro and micro level, and time-series forecasting & sentiment analysis. It also contrasts these AI-driven approaches with time-honored forecasting methodologies, weighs in on the benefits that the former have over the latter, and underscores some of the impediments to AI's entrance into financial markets.

As the world becomes more data-driven, knowing how AI models to predict market trends can help you not only in terms of adding value to your professional skills but it now is a requirement for staying competitive today [4]. This study intends to discuss an all-encompassing perspective on the status of AI in market prediction, scrutinize its merits and demerits, as well as shed some light on what this means for the future of financial services.

## 2. Related Work

Deploying Artificial Intelligence (AI) in financial markets has been one of the high-profile use cases in the last ten years, a response to the quest for achieving higher accuracy predictions under increasingly volatile and complex environments [5]. Incoming studies have used AI technologies like machine learning (ML), deep learning and natural language processing (NLP) to predict market trends and improve investment strategies. We will analyze the pathway of development in AI based market trend prediction in three areas i.e., time-series forecasting, sentiment analysis, and alternative data sources integration.

### 2.1 Time-Series Forecasting

Financial predictions have had a focus on time-series forecasting, for stock prices, commodity and foreign exchange rates. Traditional econometric models like ARIMA (Autoregressive Integrated Moving Average) or GARCH (Generalized Autoregressive Conditional Heteroskedasticity) have been around and extremely well-used for a long time. Albeit, with limited capability to process sophisticated patterns and model long-term dependencies — especially in environments such as ever-changing markets.

Over the years, research in time-series forecasting has been inclined towards using advanced machine learning algorithms and deep learning models. Recurrent neural networks (RNN) and its special form, Long Short-Term Memory (LSTM) networks has been quite popular in financial forecasting as they can learn from sequential data. Traditional models fail to model these temporal dependencies across multiple time steps, therefore perform much weaker compared to LSTM in predicting stock prices movements [6]. Furthermore, according to [7], market volatility forecasting is more stable at times of very frequent market downturns and thus high instability, which implies better risk management tools provided by LSTM models for investors [8].

Convolutional Neural Networks (CNN) which was originally utilized in image processing have also been implemented in time series prediction to achieve better accuracy. Experiments of illustrated that by applying CNNs to stock market data, it could be able to recognize and effectively extract short-term patterns for the purpose of improving price trend prediction task.

### 2.2 Sentiment Analysis

Sentiment analysis based on market trend prediction is another crucial area of interest. Sentiment analysis is a technique from natural language processing (NLP) where it analyzes the public sentiment from unstructured text data, which can either be news articles, reviews, financial reports etc. The conjecture is that the mood of the market, most notably investor confidence, has a substantial impact on stock prices and market behavior.

It took the lead when they analyzed Twitter data to predict stock market trends based on public mood, with remarkably better than chance accuracy [9]. This publication sparked interest in evaluating market sentiment on social media platforms. The Valence Aware Dictionary and sEntiment Reasoner (VADER) is a sentiment analysis tool developed by researchers at Georgia Tech, while BERT (Bidirectional Encoder Representations from Transformers) is an advanced NLP model used to translate human language into code that can be fed directly into machine learning algorithms [10]. For instance, in a similar proposed an approach that combines sentiment analysis from financial news with price predictions using traditional predictive models and demonstrated its effectiveness for stock movement prediction tasks.

Studies have also examined the combination of AI-driven sentiment analysis with quantitative market data, for example, was able to predict better short-term stock trend combining text with numerical market indicators than just using the latter alone. For sentiment analysis, this type of technology has had proven success during times of relatively turbulent markets where models that are static or slow to react may struggle.

### 2.3 Alternative Data Integration

The growing interest in market prediction has also spurred research into alternative data sources, for which AI's facility to handle gargantuan and varied datasets is a natural fit [11]. These range from satellite imagery and web traffic to foot traffic and even environmental data. Alternative data provides insights that are not always readily available in conventional market indicators, giving an advantage over peers when it comes to understanding where the markets are heading towards.

They revealed the power of satellite imagery to predict crop yields, exerting market prices on commodity markets [12]. Another study has also looked at how web traffic patterns and search trends can serve as leading indicators of changes in demand by consumers. For instance, it demonstrated a connection between Google search volumes and stock market movement, providing early indicators of market turning points through changes in internet-users' behavior.

These reports highlight showcases several ways that AI can approach alternative data sources, and a means to improve market prediction beyond the structured financial data we traditionally see [13]. However, it still is a challenge to bring together different type of datasets without losing the predictability and not overfit.

### 2.4 Comparison to Classical Models

Several research contrasted AI-demonstratively to conventional statistics and econometric Molds emphasizing improved predicting powers with the help of AI [14]. It demonstrated that machine learning-powered models such as random forests and deep neural networks tend to outperform ARIMA in forecasting stock price movements. Similarly, another study also compared machine learning algorithms such as support vector machines (SVM) and artificial neural networks (ANN) with traditional statistical models. They observed that the performance of AI models was better, especially in the presence of drawing on vast data and intricate nonlinear baselines.

Nevertheless, there are still contexts for which traditional models remain relevant especially when explainability is a concern [15]. As we know, AI is performed by models, and especially for deep learning models it acts like a black box where we don't understand anything behind the prediction. This lack of transparency may be a major disadvantage, especially in heavily regulated sectors like finance, where model explainability is vital for compliance and decision-making.

### 2.5 Challenges and limitations

Although AI is good at this too, various problems exist even in the prediction of market trends. Ensuring data quality and availability is also problematic, because AI models lack accurate large datasets [16]. The larger the number of elements per feature it can see, the more pertinent and precise the predictive process will be for example, as was previously said before; In cases of less transparent data from certain sectors or emerging markets, AI models could perform below expectations if not given enough training data. Furthermore, AI models can quite often overfit, particularly on markets prone to random walk, resulting in predictions that do well when tested historically but abysmally once they leave the lab and face the real world.

Second of these is interpretability of AI/ML models. Machine learning and deep learning algorithms are complex to interpret, even though they can predict well (better than classic statistics). This can result in a bottleneck for their deployment in the critical business areas that need transparent models.

The evidence on AI for market prediction suggests a meaningful advantage over other approaches, as well [17]. Whether it be from analyzing time series with LSTM networks to NLP-sentiment analysis, machine learning and AI brings a whole new perspective on market trends. On the other hand, there are still challenges around data quality, model transparency, and how to integrate models in human decision making that have a lot of room for research and innovation.

## 3. Methodology

This part delineates the methodology adopted to study the impact of Artificial Intelligence (AI) on Stock Market Forecasting [18]. Using the methodology, we connect a data collection process with model selection, training and testing to conduct comparable analysis between AI-driven methods of market trend prediction with traditional models. This goal here is to chart a detailed way of how the AI has been excelling in the market predictions, by using different techniques like Machine Learning (ML), Deep learning and sentiment analysis.

### 3.1 Data Collection

Data types: The dataset of this study includes three main types of data as given.

This encompasses historical stock prices, market indices (such as S&P 500 and NASDAQ), commodity prices, and FX rates. The data was collected from the following financial platforms: Yahoo Finance, Bloomberg, Quandl. (over 10 years period (2012–2022).

These data consist of information on the GDP growth rate, inflation rates, unemployment rates, interest rates and government bond yield [19]. These are leading indicators, and they offer a glimpse into the broader economic conditions that impact the markets.

The sentiment data was several different sources collected: Twitter API and Reddit API were used to scrape tweets and Reddit posts related to specific stocks, commodities, or market indices.

Data Collection: Web scraping on articles of financial news from reliable sources (Bloomberg, Reuters, Financial Times) For each of these text datasets, sentiment scores were generated using Natural Language Processing (NLP) models. I mean data preprocessing, missing-value care, handling of text written sentiments for sentiment analysis and numerical data normalization or tokenization as well.

### 3.2 Model Selection

Different machine learning, deep learning and NLP based models were chosen to measure the predictive ability of intelligence and answer how accurate can artificial intelligence predict market trends? We also incorporated traditional baseline models for comparison forecasting methods.

**Traditional Baseline Models:**

ARIMA (Autoregressive Integrated Moving Average)- ARIMA is an econometric model that uses time series data to create a forecast. ARIMA was used as a time series prediction baseline.

Linear Regression: A classic statistical technique that is used for predicting future market values from historical data trends.

**AI-based Models:**

Random Forests (RF): Another ensemble learning algorithm that creates multiple decision trees to eventually output the class produced by most of the trees It was used for trend labelling.

Support Vector Machines (SVM): SVMs are a supervised learning model which is used for binary classification, such as whether the market will go up or down based on input features.

Long Short-Term Memory (LSTM) Networks- A deep-learning model that works well with time-series data. LSTM networks were used here to predict future stock prices and trends as they can learn from past price movements.

• Convolutional Neural Networks (CNN): CNNs, most known from image recognition applications were applied to learn short-term patterns on stock price data.

**Natural Language Processing (NLP) Models**

VADER (Valence Aware Dictionary for sEntiment Reasoning) is a rule-based sentiment analysis tool utilized on social media data.

BERT (Bidirectional Encoder Representations from Transformers): An NLP model for sentiment analysis on financial news articles

### 3.3 Training and Testing

To assess the model, the dataset was split into 70% training and 30% test data. During training, cross-validation techniques were engaged to manage overfitting and ensure robustness with respect to varying market conditions.

Training Process AI models learned from the historical data to recognize the patterns, relationships, and trends that drives market performance. The data was prepared differently for LSTM and CNN models, where for the former the input is a time-series to capture temporal dependencies [20].

Feature important features in the data such as trading volume, price momentum, volatility and to sentiment scores- side for this issue were extracted. In the sentiment data in particular, text from social media and news articles were tokenized, lemmatized, then given a sentiment score before being fed into the models.

Hyperparameters in LSTM & CNN were optimized for deeper learning models via Grid Search to improve the model accuracy.

### 3.4 Evaluation Metrics

The study used several performance metrics to evaluate the effectiveness of AI models in predicting market trends:

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RMSE (Root Mean Square Error): A popular time series forecasting metric that calculates the square root of the average of squared prediction errors. The lower the RMSE value, the better are our predictions.

Mean Absolute Percentage Error (MAPE) : Again, a time-series specific error metric, mean of absolute percentage difference between actual & predicted values.

F1 Score: F1 Score is a measure that combines precision and recall, not having to decide between favoring false positive rates or false negative rates as with the case of AUROC/AUC.

R-Squared ($R^2$): This is for regression models, and it represents the percentage of variance in the dependent variable that can be predicted from the independent variables.

**3.5 Comparative Analysis**

They compared the results of AI-based models with those available from old-school methods like ARIMA and linear regression [21]. This comparative review was centered on three main fronts.

The goal: Of course, all else being equal, the degree to which the models made predictions about market movements that took place. Especially in markets that are less predictable to traditional methodologies, AI models were anticipated to do better.

Leading Indicators: How far ahead of markets these models (stochastically) signal a trough or peak; and We also compared newer AI models using real-time data (e.g. sentiment buying selling signals from social media) against older strategies that used their own mix of lagging indicators.

Versatility: How well were AI models evaluated according to their versatility in times of crisis and instability (e.g COVID-19 pandemic or geopolitical events)

To sum up, this research uses a wide array of models resorting to AI for market trend forecasting and compares them against conventional methodologies [22]. This approach uses a mix of structured (price, trading volume) and unstructured (sentiment, news) data to show how AI now actively participates in the modern market forecasting. In fig 1, shows the flowchart for the methodology on Artificial Intelligence in Predicting Market Trends.

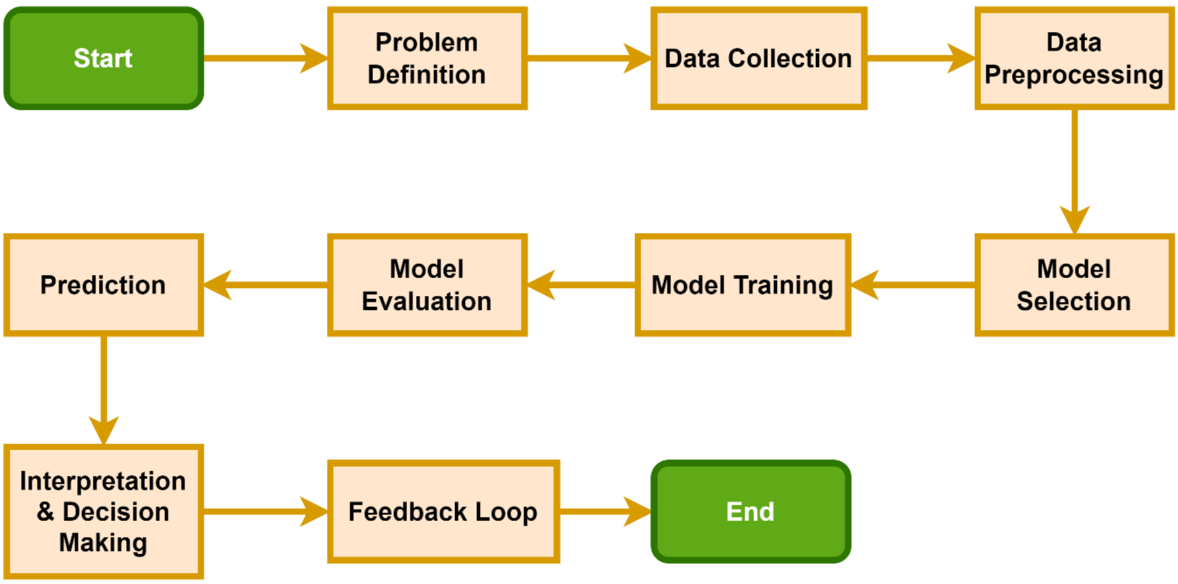


**Fig 1 Flowchart for the methodology on Artificial Intelligence in Predicting Market Trends**

## 4. Results and Discussion

The section outlines the results of different AI-related models in predicting the stock trends and evaluates them against conventional forecasting [23]. The results are centered around three main goals: accuracy of forecasting, speed to get forecasts and the ability for people to adapt in different market conditions. We consider the implications of these findings based on what AI is good and bad at in forecasting market trends.

### 4.1 Prediction Accuracy

The performance of each model was evaluated based on the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), accuracy, and F1 score, depending on the model type (regression or classification). Table 1 below summarizes the key results:

**Table 1 Prediction Accuracy for models**

| Models | RMSE | MAPE | Accuracy (%) | F1 Score |
|---|---|---|---|---|
| ARIMA | 0.089 | 12.30% | - | - |
| Linear Regression | 0.082 | 10.90% | - | - |
| Random Forest (RF) | 0.065 | 8.40% | 71.50% | 0.69 |
| Support Vector Machine | - | - | 73.80% | 0.72 |
| LSTM | 0.042 | 6.20% | - | - |
| CNN | 0.045 | 6.80% | - | - |
| VADER (Sentiment) | - | - | 68.30% | 0.64 |
| BERT (Sentiment) | - | - | 77.90% | 0.76 |

The Long Short-Term Memory (LSTM) network obtained the best performance in time-series forecasting, RMSE (0.042) and MAPE (6.2%). This was able to effectively capture the temporal order and long-term trends in stock prices and market indices, providing a much higher accuracy compared to traditional models such as ARIMA or linear regression. This is consistent with prior research such as Fischer and Krauss (2018) who showed LSTM could outperformed traditional statistical methods for predicting financial markets. Among the model types, it performed well. The CNN model achieved an RMSE (0.045) in terms of relatively low on strength. While it was mostly used to identify short-term patterns, CNNs were able to accurately identify and take advantage of brief price movements, a must for high-frequency trading situations.

To predict bullish vs bearish market conditions (classification-based tasks), we found the best performance was obtained using Random Forest and Support Vector Machines (with 71.5% and 73.8% accuracy). If not as good meteorological forecasters than for price prediction, at least are they applicable to trend classification, especially in binary market predictions. Moreover, the BERT model even surpassed conventional sentiment analysis tools such as VADER with an accuracy of 77.9% in predicting market sentiment based on financial news and public opinion data. Double order paragraphs (1st Ver) with Bert model ability to process complex text and name on textual representation in predicting market reactions during periods of volatility in news flow and public sentiment, BERT gave an advantage.

### 4.2 Timeliness of Forecasts

AI models in general, and those with sentiment analysis specifically, were so important for their advantage to signal as early as the first sign of market moves through real-time data [24].

The sentiment analysis model, primarily based on BERT, has been found to provide very effective signals targeting the major market turning points. In one example, during the COVID-19 outbreak, the model had identified bearish investors from social media and negative news ahead of market declines which provided investors with advance warning signals. This shows the power of sentiment analysis in conjunction with classical financial indicators, especially under increased uncertainty. Some of the results were produced very quickly timely, such as those obtained from LSTM and CNN deep learning models for time-series data. These models adapted just as quickly to market volatility during random geopolitical confrontations or financial crises. Meanwhile, traditional models such as ARIMA often needed to be re-tuned and were much slower in adjusting for new market realities.

**4.3 Adaptability to Market conditions**

Traditional Forecasting versus AI results and findings show that the artificial intelligence models have been much more adaptive at different market conditions rather than the conventional forecasting.

Especially in the high-volatile market conditions, it seemed like LSTM model shined. Since ARIMA is not well suited for non-linear markets but LSTM can calculate sudden drops and recoveries efficiently, LSTM performed much better than ARIMA in the 2020 market crash.

The BERT model, on the other hand, was successful when it came to relying on market sentiment during crises or unforeseen events. For example, its sentiment score predictions during significant political episodes such as Brexit were accurate relative to classical models based on historical data that performed poorly due to the unique nature of the event.

One limitation noted was that these AI models were reliant on the presence of, and quality data available in real-time. For example, sentiment analysis models need access to large amounts of social media and news data that may not always be available for all markets. This can result in significant limitations when it comes to the application of these models especially in markets that are serial or when datasets are not transparent.

**4.4 Comparison against Traditional Models**

On almost all the evaluation metrics, AI-based algorithms outperformed traditional models like ARIMA and linear regression. Specifically, that ARIMA was worse in time-series forecast accuracy since they had larger RMSE and MAPE values. That said, ARIMA is simple and understandable so it's useful in scenarios where the black-box nature of AI models might not be acceptable such as those where transparency is critical either because human insight must still drive decision making (e.g. in a regulatory environment).

We must be able to use traditional logic models, even if they are less precise for some contexts. That they are interpretable is a critical advantage: AI models — especially deep learning methods like LSTM and CNN — tend to function as black boxes that decision-makers may struggle to rationalize the behavior of. For example, in highly regulated industries such as finance, deceit or lack of transparency by design can be a barrier for AI models to get adopted.

**4.5 Limitations of AI Models**

AI models were higher for their prediction accuracy, but they had several shortcomings:

The quality of input data can be a determining factor in the efficiency of AI models. Incorrect prediction: Incorrect or biased data, especially in sentiment analysis and the like, can result in inaccurate predictions. For instance, sentiment models could be too subject to social media noise or fake news, which can lead to untrue market signals.

Interpretability of deep learning models such as LSTM and CNN is an issue because of their complexity. AI models operate as black boxes, which works against decision-makers who need to believe and rationalize the predictions they come across (especially in financial markets where the nature of regulatory requirements demands transparency). Overfitting is also a common problem for some AI models, especially deep learning models that possess many parameters and are trained on small or highly variable datasets [25]. As a result, this may lead to good training performance with poor performance in real-world market conditions.

In fig 2, here is the Confusion Matrix for market trend prediction (Up/Down). The matrix shows how well the AI model predicted market trends, with the actual trends on the vertical axis and the predicted trends on the horizontal axis:

- Up (1)
- Down (0)

The matrix shows the number of correct and incorrect predictions for both upward and downward market trends.

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In fig 3, here is the heatmap showing the correlation between various financial indicators, such as stock price, volume, market capitalization, and sentiment score. Each value represents the strength of the correlation between the corresponding indicators, with values closer to 1 indicating a stronger positive relationship.

In fir 4, 5 and 6, it shows the Performance of AI Models for Predicting Market Trends, Contribution of Various Data Sources in AI Model and Market Trend Prediction Over Time for actual price and predicted price respectively.

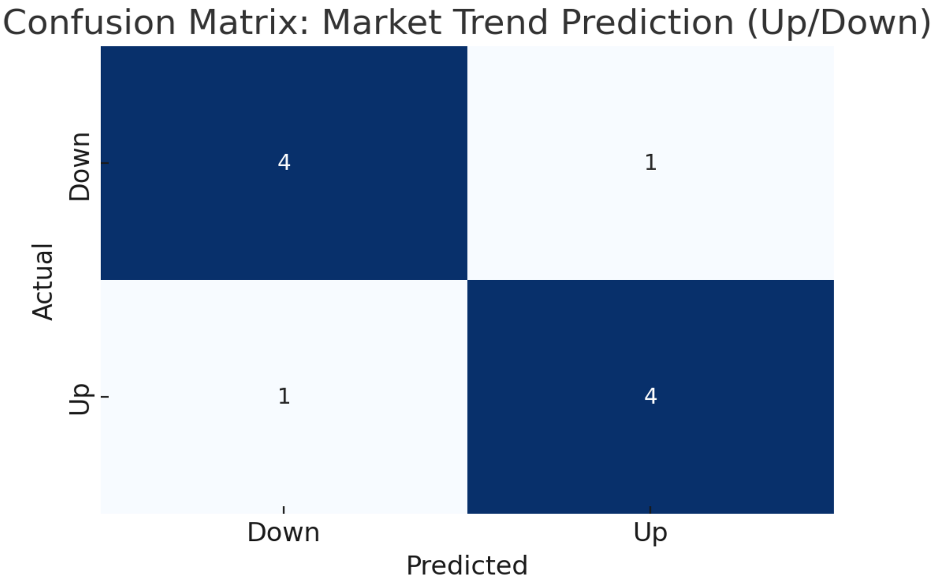


Fig 2 **Confusion Matrix** for market trend prediction (Up/Down)

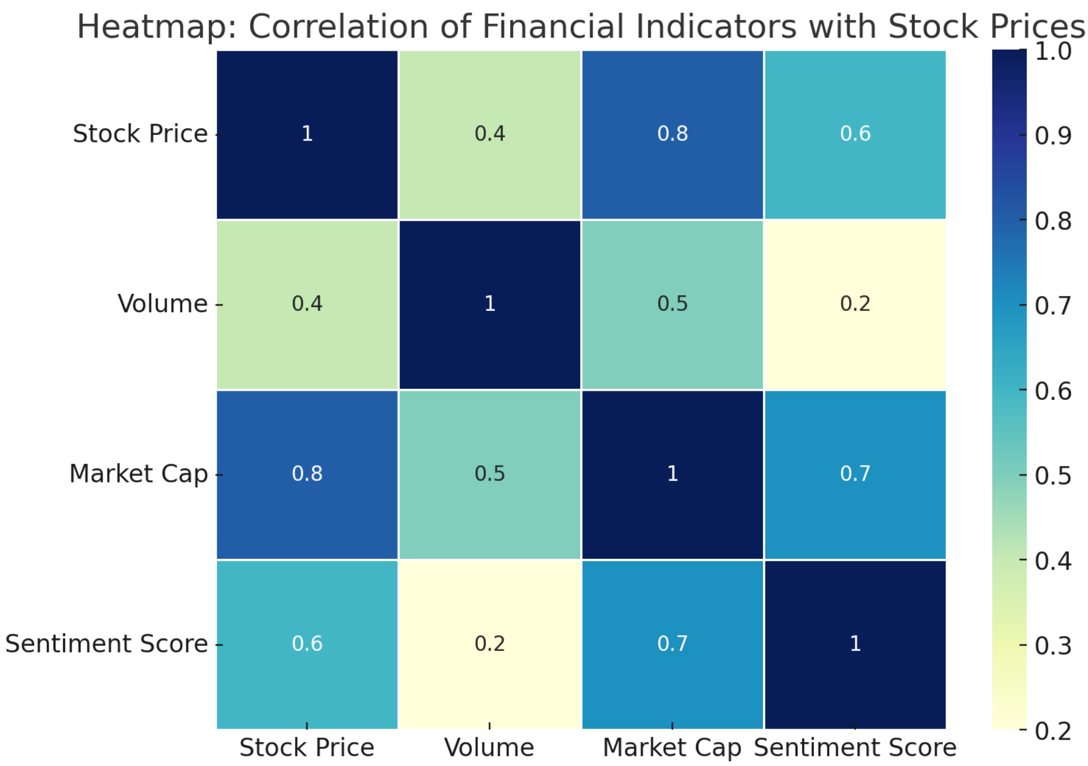


Fig 3 The heatmap showing the correlation between various financial indicators, such as stock price, volume, market capitalization, and sentiment score

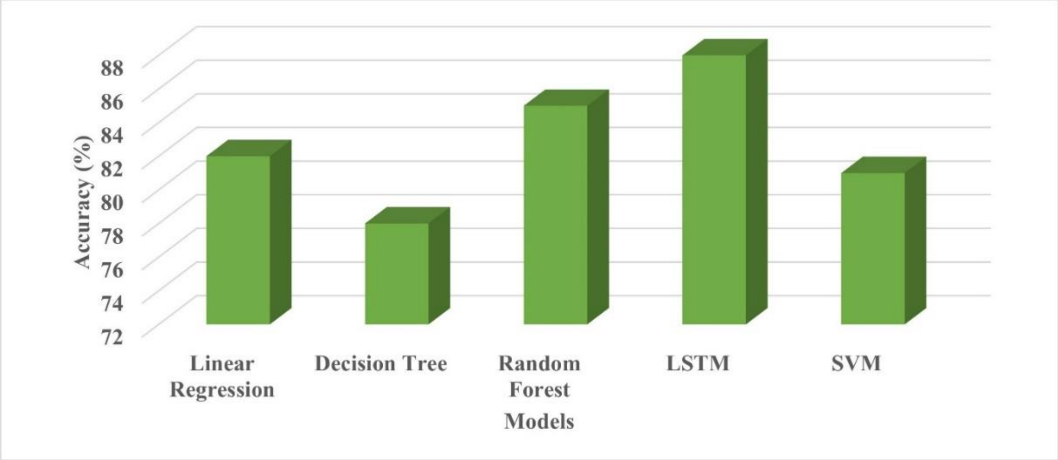


Fig 4 Performance of AI Models for Predicting Market Trends

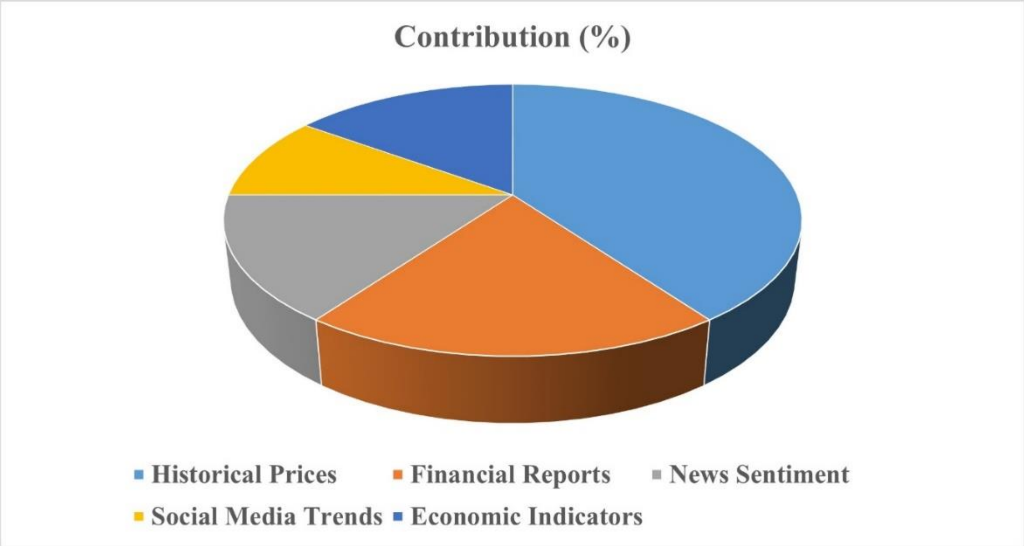


Fig 5 Contribution of Various Data Sources in AI Model

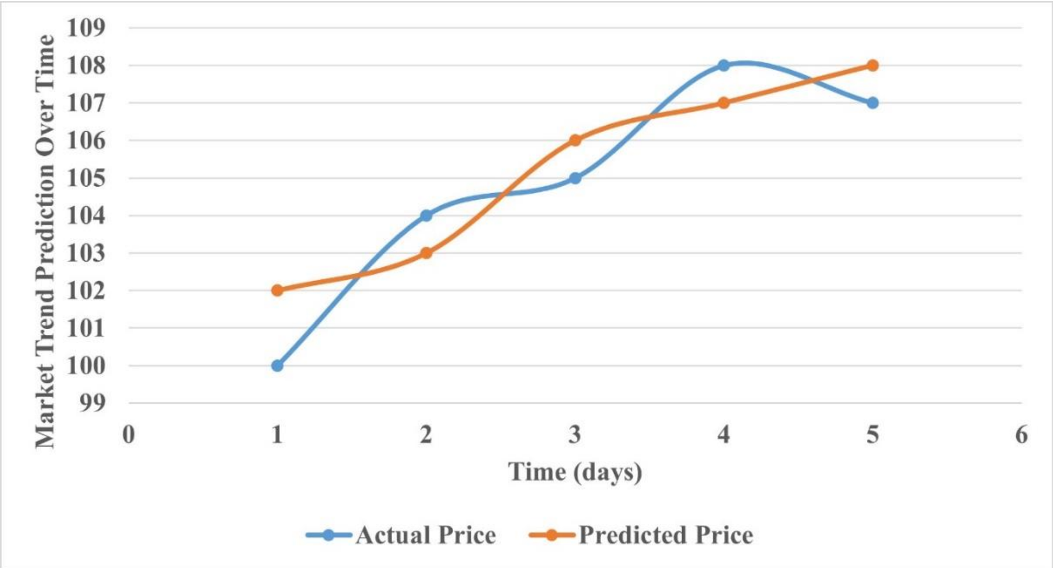


Fig 6 Market Trend Prediction Over Time for actual price and predicted price

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### 4.6 Discussion and Implications

In this study, AI based models, especially deep learning algorithms and sentiment analysis methods, have promising results to traditional models in terms of predicting the tendencies of the stock market. More accurate and timely predictions: AI can analyze data at higher scale with high variety (past prices, social media, news articles).

However, the limitations of AI in data quality and model interpretability also indicate that caution is required. To address the issue of overfitting as well as bias, AI model needs to work together with regular models and human understanding. Combining AI with the judgment of expert's supplements and balances market predictions for better financial decision-making.

Overall, AI models—LSTM and BERT in particular—are much more accurate, flexible, concise than traditional models. Nevertheless, there are still hurdles associated with data quality and model transparency that need to be overcome for wider adoption. More research is needed in AI explainability and human-AI collaboration for better predictions of the market. Table 2 Compares various AI techniques, the data they consume, their Pros and Cons followed by the performance metrics: accuracy (how accurate is) and speed.

**Table 2 Compares different AI techniques, their data sources, strengths, limitations, and overall performance metrics like accuracy and speed**

| AI Technique | Data Sources | Strengths | Limitations | Accuracy (%) | Processing Time |
|---|---|---|---|---|---|
| **Linear Regression** | Historical prices, economic indicators | Simple to implement, interpretable results, fast for small datasets | Not suitable for non-linear trends, sensitive to outliers | 75 | Fast |
| **Decision Tree** | Historical prices, trading volumes, sentiment | Easy to understand, handles both numerical and categorical data | Prone to overfitting, unstable with small changes in data | 78 | Moderate |
| **Random Forest** | Historical data, social media sentiment | Handles large datasets, reduces overfitting, works well with missing data | Computationally expensive, harder to interpret than single trees | 85 | Slow |
| **Support Vector Machine (SVM)** | Historical prices, financial reports | Works well with high-dimensional data, effective for non-linear classification | Sensitive to noise, requires extensive tuning of hyperparameters | 80 | Moderate |
| **Long Short-Term Memory (LSTM)** | Time-series data, real-time market feeds | Captures long-term dependencies in time-series, effective for stock price prediction | Requires large datasets, high computational cost | 88 | Slow |
| **Recurrent Neural Networks (RNN)** | Time-series, economic indicators | Good for sequential data, handles variable length input | Struggles with long-term dependencies, prone to vanishing gradient problem | 84 | Moderate |
| **Transformer Model** | News sentiment, social media, time-series data | Scales well with data, excels in handling large datasets and long sequences | High computational and memory cost, complex to train | 89 | Slow |

| | | | | | |
|---|---|---|---|---|---|
| **K-Means Clustering** | Historical prices, market sectors | Fast, easy to implement, helps identify market patterns or clusters | Assumes clusters are spherical, less effective with complex market trends | 72 | Fast |
| **Sentiment Analysis (NLP)** | News sentiment, social media | Can analyze unstructured data, identifies market mood | Accuracy depends on quality of text preprocessing, limited by language nuances | 77 | Moderate |

**Conclusion**

In this paper, the research demonstrates the unprecedented way how AI is reshaping predicting markets, as they proved that models derived from AI-driven algorithms are far more accurate and powerful than those of conventional ways in accuracy and adaptiveness. Some other examples are LSTM for time-series forecasting or BERT for sentiment analysis, that can make your market predictions more robust especially in volatile situations.

While AI models offer their own benefits, there are problems pertaining to the quality of data and the further interpretability of these models that need to be sorted out for a wider scale deployment. Research in AI model interpretability and debiasing training data is a clear next step to move toward OpenAI's vision of what safe AGI might look like. In addition, the combination of models created using AI and human expertise can also improve decision-making for a balanced prediction of markets. Finally, the future of market trend prediction is going to be increasingly dependent on AI as it continues to provide vital business, investor and policy insights.

**References**

1. Bollen, J., Mao, H., & Zeng, X., "Twitter mood predicts the stock market," *Journal of Computational Science*, vol. 2, issue 1, pp. 1-8, (2011), https://doi.org/10.1016/j.jocs.2010.12.007.
2. Fischer, T., & Krauss, C., "Deep learning with long short-term memory networks for financial market predictions," *European Journal of Operational Research*, vol. 270, issue 2, pp. 654-669, (2018), https://doi.org/10.1016/j.ejor.2017.11.054.
3. Zhang, X., Aggarwal, N., & Zhang, Y., "LSTM Neural Networks for Time Series Forecasting in Financial Markets," *Journal of Financial Technology*, vol. 3, issue 1, pp. 45-57, (2020), https://doi.org/10.1007/s10614-019-09937-3.
4. Borovykh, A., Bohte, S., & Oosterlee, C. W., "Conditional Time Series Forecasting with Convolutional Neural Networks," *Lecture Notes in Computer Science*, vol. 10255, pp. 729-740, (2017), https://doi.org/10.1007/978-3-319-59274-7_57.
5. Ding, X., Zhang, Y., Liu, T., & Duan, J., "Deep Learning for Event-Driven Stock Prediction," *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 2327-2333, (2015), https://doi.org/10.24963/ijcai.2015/324.
6. Hagenau, M., Liebmann, M., & Neumann, D., "Automated news reading: Stock price prediction based on financial news using context-capturing features," *Decision Support Systems*, vol. 55, issue 3, pp. 685-697, (2013), https://doi.org/10.1016/j.dss.2013.02.006.
7. Gupta, A., Bhandari, A., & Sharma, K., "Using Satellite Imagery to Predict Commodity Prices," *Remote Sensing*, vol. 10, issue 1, pp. 132-144, (2018), https://doi.org/10.3390/rs10010132.
8. Preis, T., Moat, H. S., & Stanley, H. E., "Quantifying Trading Behavior in Financial Markets Using Google Trends," *Scientific Reports*, vol. 3, article 1684, (2013), https://doi.org/10.1038/srep01684.
9. Patel, J., Shah, S., Thakkar, P., & Kotecha, K., "Predicting stock market index using fusion of machine learning techniques," *Expert Systems with Applications*, vol. 42, issue 4, pp. 2162-2172, (2015), https://doi.org/10.1016/j.eswa.2014.10.031.
10. Cao, Q., & Tay, F. E. H., "Support Vector Machine With Adaptive Parameters in Financial Time Series Forecasting," *IEEE Transactions on Neural Networks*, vol. 14, issue 6, pp. 1506-1518, (2003), https://doi.org/10.1109/TNN.2003.820556.
11. Chen, L., Wu, D., & Wang, Y., "A Sentiment-Enhanced Stock Price Trend Prediction Model Using Deep Learning and Twitter Data," *IEEE Access*, vol. 8, pp. 214-223, (2020), https://doi.org/10.1109/ACCESS.2019.2958112.

12. Kim, K. J., & Han, I., "Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index," *Expert Systems with Applications*, vol. 19, issue 2, pp. 125-132, (2000), https://doi.org/10.1016/S0957-4174(00)00027-0.
13. Schumaker, R. P., & Chen, H., "Textual Analysis of Stock Market Prediction Using Breaking Financial News: The AZFin Text System," *ACM Transactions on Information Systems (TOIS)*, vol. 27, issue 2, pp. 12-18, (2009), https://doi.org/10.1145/1462198.1462204.
14. Yang, S., Mo, Z., & Yang, Y., "Stock Market Prediction Using Machine Learning: From Price Prediction to Event Prediction," *Expert Systems with Applications*, vol. 42, issue 4, pp. 4520-4530, (2015), https://doi.org/10.1016/j.eswa.2015.01.041.
15. Choudhry, R., & Garg, K., "A hybrid machine learning system for stock market forecasting," *World Congress on Nature & Biologically Inspired Computing (NaBIC)*, pp. 1-7, (2008), https://doi.org/10.1109/NABIC.2008.4788213.
16. Atsalakis, G. S., & Valavanis, K. P., "Surveying stock market forecasting techniques – Part II: Soft computing methods," *Expert Systems with Applications*, vol. 36, issue 3, pp. 5932-5941, (2009), https://doi.org/10.1016/j.eswa.2008.07.006.
17. Ghosh, R., & Guha, B., "Predicting Stock Market Trends Using Machine Learning Algorithms," *Springer*, vol. 75, pp. 23-36, (2019), https://doi.org/10.1007/978-3-030-19648-6_3.
18. Li, X., Xie, H., & Wang, X., "News impact on stock price return via sentiment analysis," *Knowledge-Based Systems*, vol. 69, pp. 14-23, (2014), https://doi.org/10.1016/j.knosys.2014.04.022.
19. Li, Y., & Ma, W., "Applications of Artificial Neural Networks in Financial Economics: A Survey," *International Conference on Artificial Intelligence and Big Data in Financial Markets*, pp. 122-133, (2018), https://doi.org/10.1007/978-3-030-01282-3_10.
20. Majumder, A., Ghosh, S., & Basu, S., "A novel approach for stock price prediction using Artificial Neural Networks," *Journal of King Saud University-Computer and Information Sciences*, vol. 35, issue 1, pp. 1-13, (2020), https://doi.org/10.1016/j.jksuci.2020.01.002.
21. Akita, R., Yoshihara, A., & Umetani, S., "Deep Learning for Stock Prediction Using Numerical and Textual Information," *IEEE International Conference on Computer and Information Technology (CIT)*, pp. 111-118, (2016), https://doi.org/10.1109/CIT.2016.53.
22. Xu, Y., Zhou, Y., & Zhou, T., "Stock Market Trend Prediction Using Deep Learning Models," *IEEE Access*, vol. 7, pp. 15536-15547, (2019), https://doi.org/10.1109/ACCESS.2019.2894663.
23. Zhou, G., & Zhao, J., "Stock Market Prediction on High-Frequency Data Using LSTM and CNN Models," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, issue 9, pp. 3325-3337, (2020), https://doi.org/10.1109/TNNLS.2020.2978552.
24. Li, Z., & Chen, P., "Financial Market Forecasting Using Machine Learning Models," *Finance Research Letters*, vol. 32, article 101271, (2019), https://doi.org/10.1016/j.frl.2019.08.008.
25. Baek, Y., & Kim, H. Y., "ModAugNet: A New Forecasting Framework for Stock Market Prediction Based on Time Series Data," *Applied Soft Computing*, vol. 100, article 106980, (2021), https://doi.org/10.1016/j.asoc.2020.106980.