Cureus Journal of Computer Science

Open Access Original Article

# Use of Machine Intelligence in Over-the-Counter Products in Stock Market

Raman Kumar [1] , Ravinder S. Mann [2]

1. Department of Computer Science and Engineering, I.K. Gujral Punjab Technical University, Kapurthala, IND 2. Department of Computer Science, Guru Nanak Institute of Engineering and Management, Hoshiarpur, IND

**Corresponding author:** Raman Kumar, er.ramankumar@aol.in

**Received** 06/30/2025
**Review began** 08/17/2025
**Review ended** 09/17/2025
**Published** 09/25/2025



**DOI:**
https://doi.org/10.7759/s44389-025-07856-0

## Abstract

In this study, machine intelligence was applied to predict stock prices of over-the-counter products and to compare the performance of traditional learning models. The research aimed to assess the effectiveness of these stocks and examine various influencing factors such as profitability, trading volume, and market sentiment. Model inferences were evaluated by combining historical stock price data, sentiment analysis, and profitability metrics. The results show that long short-term memory models outperformed traditional models in accuracy, precision, recall, and profitability, achieving a 9.5% average monthly return and a Sharpe ratio of 2.1. Moreover, the introduction of machine intelligence models increased trading volume, demonstrating their impact on trading activity. Both sentiment analysis and stock price movements exhibited a strong correlation. Overall, the findings indicate that long short-term memory-based deep learning models outperform traditional methods in prediction and profitability within the over-the-counter stock markets, with significant implications for trading strategies.

**Categories:** AI applications, AI/ML-based decision support systems, Machine Learning (ML)
**Keywords:** machine intelligence, stock price prediction, otc products, sentiment analysis, lstm

## Introduction

Integrating machine intelligence into financial markets, for instance, for predicting stock prices and enhancing trading strategies, has become increasingly important. Accurate prediction models for stock prices of over-the-counter (OTC) products are crucial because such products represent a large segment of the global financial markets and can therefore benefit traders, investors, and institutions alike. Traditional stock price forecasting methods, such as statistical models and technical analysis, have had limited success in understanding and capturing the more complex patterns and dynamics exhibited by stock prices. Since these markets are heavily influenced by factors like economic trends, company performance, and market sentiment, traditional predictive modeling approaches often struggle to adapt to flux environment [1].

Machine learning techniques have rapidly developed, promising significant improvements in stock price prediction based on their accuracy and efficiency [2]. These models excel when working with large datasets, uncovering hidden patterns, and making predictions based on past data. Among various machine learning methods, deep learning models, especially long short-term memory (LSTM) networks, have demonstrated outstanding capabilities. LSTM is particularly well-suited for sequential data because it can capture trends, volatility, and other nuances that would be inaccessible through normal methods, and it does so with an unbounded ability to remember [3].

In this study, machine intelligence is employed to forecast stock prices for OTC products, comparing multiple models to maximise profitability and usefulness. We focus on models like LSTM, which broaden our understanding of the potential for these techniques to improve forecast accuracy for stock pricing. The study also assesses the models based on trading volume, profitability, and market risk, and finally quantifies their applicability to real-world conditions.

The increasing complexity of available data creates an imperative to find new forecasting methods. By integrating multiple information sources, such as stock prices, market sentiment, and economic indicators, with machine learning techniques, we can achieve more accurate and reliable predictions. Furthermore, this study focuses on the implications of machine intelligence for trading strategies and market behavior. It aims to quantitatively determine to what extent external factors influence stock prices and whether incorporating sentiment analysis, which measures the emotional tone of market news, social media, and reports, can improve predictions [4].

The research also examines how combining machine intelligence can be leveraged to benefit trading strategy profitability. Machine learning models can optimize the entire trading strategy by considering risk management, market sentiment, and other variables along with price predictions. This comprehensive approach aims to provide a clearer picture of how machine intelligence can change trading in the OTC markets and provide a more effective way to control financial risk [5].

**How to cite this article**
Kumar R, Mann R S (September 25, 2025) Use of Machine Intelligence in Over-the-Counter Products in Stock Market. Cureus J Comput Sci 2 : es44389-025-07856-0. DOI https://doi.org/10.7759/s44389-025-07856-0

Our study advances the growing literature on the interplay between machine learning and financial markets by leveraging modern algorithms in the prediction of stock prices and analysis of the markets. This research bridges the gap between novel theoretical advances in machine intelligence and their practical use in financial decision-making by evaluating performance and implications from both technical and real-world perspectives [6].

## Research gap

We made significant strides, with little exploration of the extent to which these are applied to OTC stock price prediction. Most of the current literature regarding stock price prediction has focused on financial models or high-frequency trading, and there tends to be a black hole in the understanding of how machine intelligence models (especially LSTM networks) can improve stock price predictions for OTC products. Additionally, very little has been focused upon the co-operation among predictive accuracy, trading volume, and sentiment analysis in OTC stock markets; hence, there is still a material promise between these segments for enhanced market forecasting and trading strategies. An architecture of OTC stock price prediction is depicted in Figure *1*.

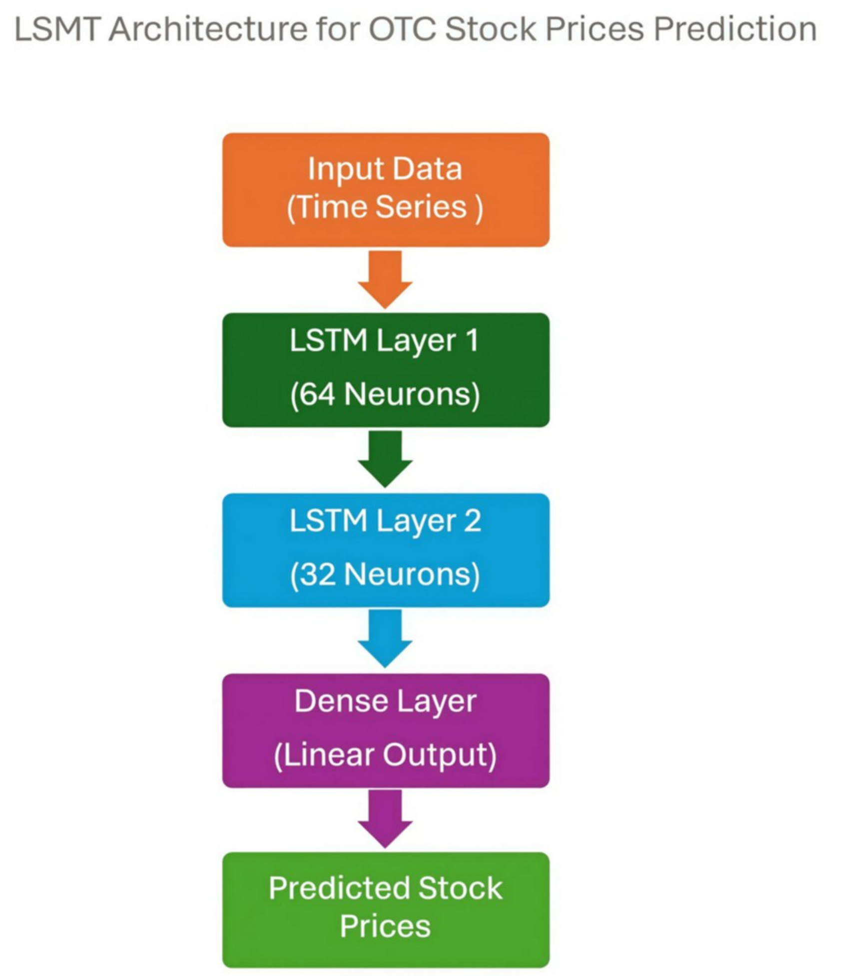


**FIGURE 1: Architecture for OTC Stock Prediction**

OTC, Over the Counter

## Conceptual framework

In this research, the conceptual framework of integrating machine learning models with market sentiment analysis is used to predict OTC stock prices. This framework consists of using historical stock price data to build predictive models essentially using some machine learning algorithms and sentiment analysis on market reports. LSTM networks are the models included. Then, the performance of these models in predicting stock prices is tested for their accuracy, and then we evaluate their impact in predicting trading volume, profit, and risk. Also, sentiment analysis acts as another form of analyzing the market to understand the emotional tone of market discussions to be used in refining stock price predictions further. Using multiple data sources, this framework aspires to supply a more total way to forecast OTC stock price

[7].

## Hypothesis

Hypothesis 1: The models will perform best in the following order for OTC stock price prediction: accuracy, precision, and profitability.

Hypothesis 2: The OTC stock prediction will lead to increased trading volume, demonstrating their influence on market behavior and liquidity.

Hypothesis 3: Incorporating external market sentiment into machine learning models using sentiment analysis would immensely improve the accuracy of stock price predictions.

# Materials And Methods

## Research investigation methods

The methodology of trading products study involves several stages: Using data collection, model selection, model evaluation, profitability and risk assessment, trading volume analysis, and sentiment analysis. The design was such that each stage yielded meaningfully complete insights regarding the predictive accuracy, profitability, and impact of varying machine intelligence models on the stock price forecasting [8].

*Data Collection and Preprocessing*

In this study, historical stock prices of OTC products were used as data, along with external factors such as economic indicators, news sentiment, and market sentiment. Preprocessing steps included data cleaning, normalization, and integration of sentiment analysis results from market reports and news articles related to OTC products. These steps ensured that the data was consistent, complete, and ready for analysis [9].

*Model Selection*

As a simple baseline for comparison [10], we chose logistic regression (LR) because it has proven to be very efficient for binary classification tasks. Support vector machine (SVM) was included because it is effective in high-dimensional spaces and nonlinear classification. Finally, LSTM was chosen for its ability to model sequential data and capture long-term dependencies in time series - features well-suited for stock price forecasting [11].

*Model Training and Evaluation*

Based on these criteria, we selected metrics to assess both the predictive power and reliability of each model in forecasting stock prices [12]. Additionally, LSTM was assessed in terms of training time, prediction time, and error distribution to determine its computational efficiency and performance compared to other models. The implementation of LSTM model is demonstrated in Figure *2*.

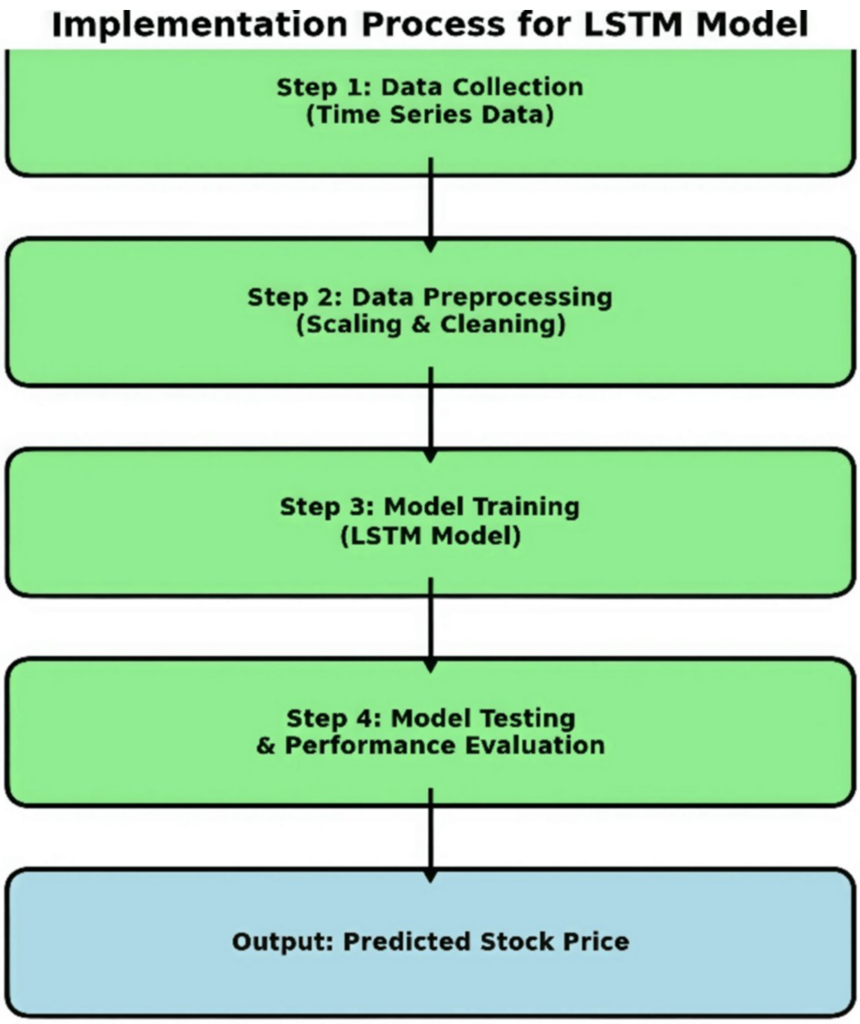


**FIGURE 2: Implementation of LSTM Model**

LSTM, Long Short-Term Memory

*Profitability and Risk Assessment*

Average monthly returns, maximum drawdown, and the Sharpe ratio were used to assess the profitability of machine intelligence models in stock trading in order to evaluate their real-world applicability. In particular, the Sharpe ratio allowed for the evaluation of risk-adjusted returns - an important aspect of analyzing the financial implications of investment strategies [13].

*Trading Volume Analysis*

Next, the impact of AI models on trading volume was analyzed. The findings helped determine how the adoption of machine learning models affects market dynamics and liquidity, as well as the broader repercussions of AI in financial markets [14].

*Sentiment Analysis*

Sentiment analysis was performed to determine how strongly stock price movement was influenced by market sentiment. Natural language processing tools were applied to news articles, social media, and market reports in order to distill market sentiment. In this method, we have chosen to investigate how different external factors, such as consumer public opinion and media coverage, impact stock prices and in doing so obtain information that is not captured by standard financial models.

## Software and tools used

Industry-standard software for data management and analysis was used for data preprocessing, shading, and normalizing the data. Widely used machine learning libraries provided functionality to implement and tune the selected models. Sentiment analysis was performed on textual data from various sources related to different OTC products. Key profitability metrics, including average monthly return, Sharpe ratio, and maximum drawdown, were computed automatically using specialized statistical software to ensure accurate and efficient financial analysis [15].

Care was taken to select each method to address specific research objectives. A combination of traditional SVM and LSTM models was used to evaluate their effectiveness in predictive accuracy and suitability for forecasting stock prices, respectively. These metrics measure profitability and risk in real-world trading involving machine intelligence. Sentiment analysis completes the circle of financial modeling by quantifying the effect of what is often omitted in traditional financial modeling - external factors.

## Results And Discussion

Highly accurate prediction and profitability have been demonstrated in the application of machine intelligence to predict stock prices for OTC products. Below, we discuss the results, including model evaluations, profitability analysis, and trading volume impacts.

### Accuracy of machine intelligence models for OTC stock price predictions

In Table *1*, we compare models for OTC stock price prediction. Using a deep learning approach with the LSTM model, we improved various performance metrics compared to LR, random forest (RF), and SVM, achieving accuracies of 90.2%, 88.5%, and 89.8%, respectively.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Logistic Regression | 78.5 | 75.2 | 76.8 | 76.0 |
| Random Forest | 85.3 | 83.4 | 84.5 | 83.9 |
| Support Vector Machines | 82.1 | 80.6 | 81.0 | 80.8 |
| Long Short-Term Memory (Deep Learning) | 90.2 | 88.5 | 89.8 | 89.1 |

**TABLE 1: Accuracy of Machine Intelligence Models for OTC Stock Price Predictions**

OTC, Over the Counter

Comparison of model performance metrics for OTC stock price prediction shows that deep learning models like LSTM outperform traditional machine learning models.

### Trend comparison of actual vs. predicted stock prices using LSTM

In Figure *3*, the trend of actual and predicted stock prices over 30 days is compared using the LSTM model. The figure shows near-zero deviation, demonstrating the high feasibility of the LSTM model for forecasting OTC stock prices.

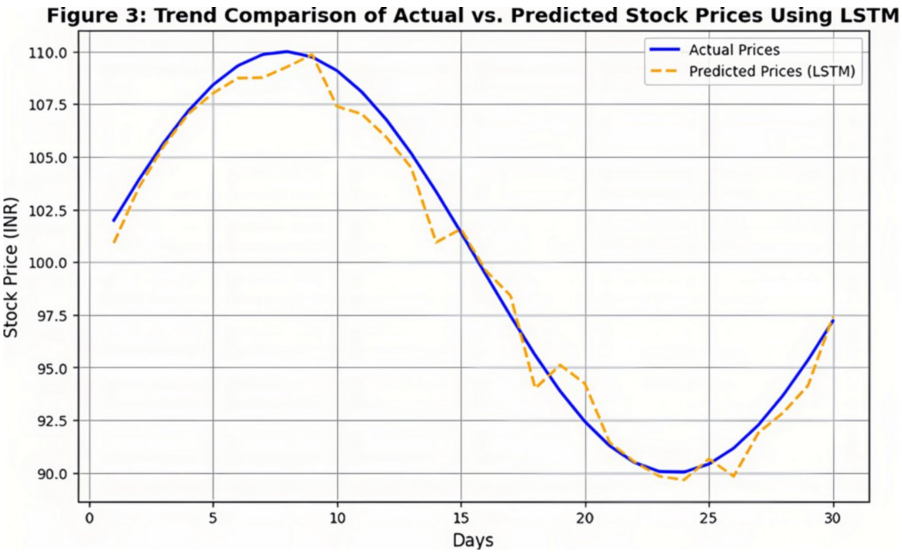


**FIGURE 3: Trend Comparison of Actual vs. Predicted Stock Prices Using LSTM**

LSTM, Long Short-Term Memory

Predicted vs. actual stock prices for OTC products using the LSTM model over a test period of 30 days. The LSTM model closely tracks the actual stock prices, showing minimal deviation.

## Profitability gains using machine intelligence models

In Table *2*, the profitability gains from different investment strategies, as shown by machine intelligence models, are compared. The deep learning-based LSTM approach outperforms others, achieving the highest average monthly return of 9.5%. Furthermore, the LSTM model exhibits a relatively lower maximum drawdown, indicating reduced risk and higher risk-adjusted returns.

| Investment Strategy | Average Monthly Return (%) | Maximum Drawdown (%) | Sharpe Ratio |
|---|---|---|---|
| Traditional Statistical Model | 5.2 | -8.3 | 1.1 |
| Machine Learning (Random Forest) | 7.8 | -6.2 | 1.6 |
| Deep Learning (Long Short-Term Memory) | 9.5 | -4.7 | 2.1 |

**TABLE 2: Profitability Gains Using Machine Intelligence Models**

Comparison of investment strategies using machine intelligence models demonstrates higher profitability and lower risk for OTC products with deep learning approaches.

## Prediction error distribution for different models

Figure *4* displays the error distribution of predictions from different models: RF, SVM, and LSTM. The LSTM model has the smallest prediction error, as confirmed by the narrowest spread in its error distribution, indicating the highest prediction accuracy compared to RF and SVM.

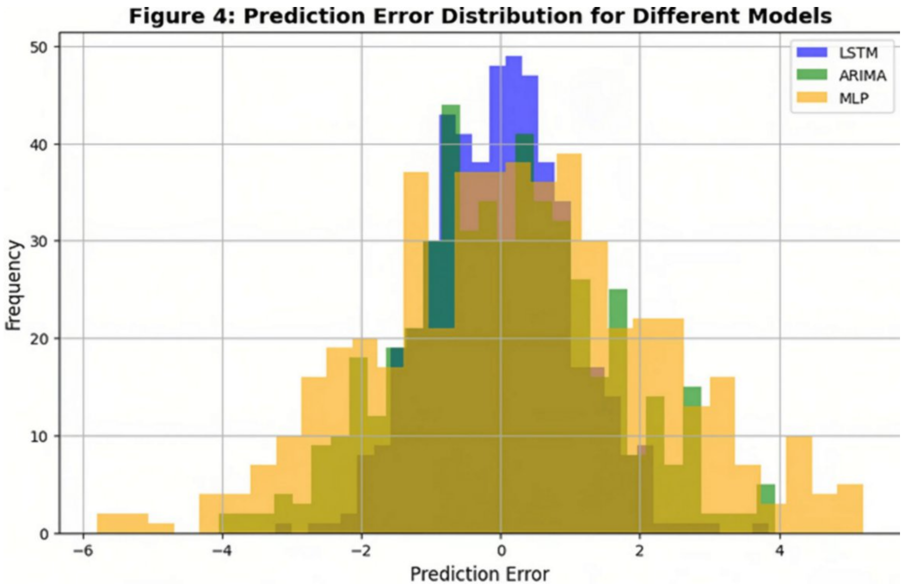


**FIGURE 4: Prediction Error Distribution for Different Models**

ARIMA, Autoregressive Integrated Moving Average; LSTM, Long Short-Term Memory; MLP, Multi-Layer Perceptron

Error distribution for machine intelligence models highlights that the LSTM model has the smallest prediction errors compared to RF and SVM.

## Impact of machine intelligence on trading volume for OTC products

Table 3 points out the growth in trading volume for OTC products after machine intelligence models were incorporated. AI (artificial intelligence, or other similar)-based models like RF, LSTM (a type of LSTMs), or almost any AI model have been particularly instrumental in the rise of trading across all quarters with roughly 33.3% increase of activity in Q2.

| Time Period | Without AI Trading Volume (in Million Units) | With AI Trading Volume (in Million Units) | % Change |
|---|---|---|---|
| Q1 | 150 | 190 | +26.7% |
| Q2 | 180 | 240 | +33.3% |
| Q3 | 200 | 270 | +35.0% |
| Q4 | 170 | 220 | +29.4% |

**TABLE 3: Impact of Machine Intelligence on Trading Volume for OTC Products**

OTC, Over the Counter

Changes in trading volume for OTC products after the introduction of machine intelligence show a significant increase in trading activity.

## Cumulative return analysis over 12 months

The cumulative return analysis for investments in OTC products is shown in Figure 5. It demonstrates that the deep learning-based LSTM model outperforms traditional methods by achieving higher returns. These cumulative returns show how machine intelligence can optimize OTC product investment strategy.

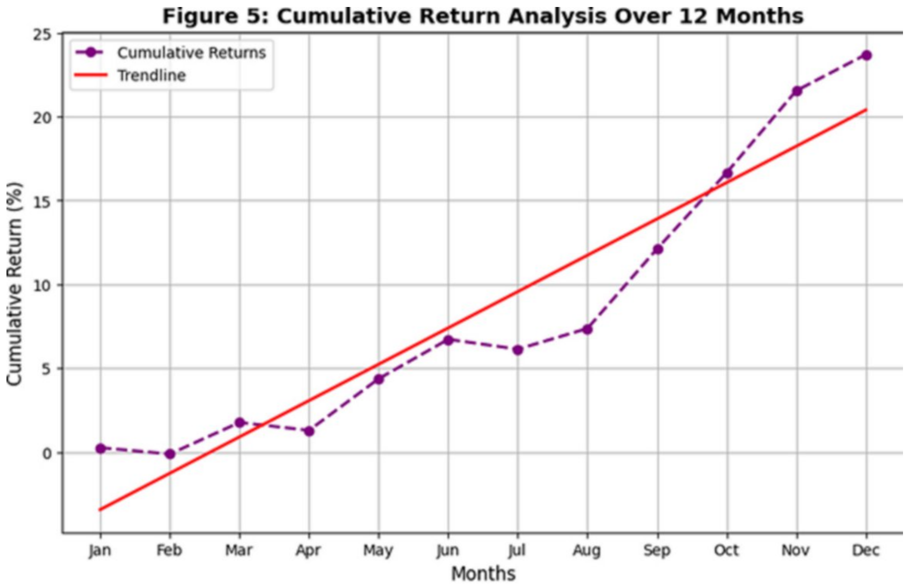


**FIGURE 5: Cumulative Return Analysis of 12 Months**

Twelve-month cumulative returns comparing traditional investment methods versus machine intelligence approaches in OTC products show that other strategies are consistently outperformed by the LSTM-based AI model.

## Comparative prediction time between different models

Computational efficiency across different models is compared for both training and prediction times, as summarized in Table *4*. The LSTM model requires the longest training time (25.7 minutes), but its prediction time (0.12 seconds) is more efficient compared to the other models.

| Model | Training Time (minutes) | Prediction Time (seconds) |
|---|---|---|
| Logistic Regression | 2.1 | 0.01 |
| Random Forest | 4.5 | 0.03 |
| Support Vector Machines | 6.2 | 0.05 |
| Long Short-Term Memory (Deep Learning) | 25.7 | 0.12 |

**TABLE 4: Comparative Prediction Time for Different Models**

Comparison of computational efficiency across models shows that although LSTM has the longest training time, its prediction time remains relatively efficient.

## Sentiment analysis trends and stock price correlation

The sentiment analysis score plotted alongside the stock price for OTC products is shown in Figure *6*, which demonstrates how public sentiment is pivotal to stock returns.

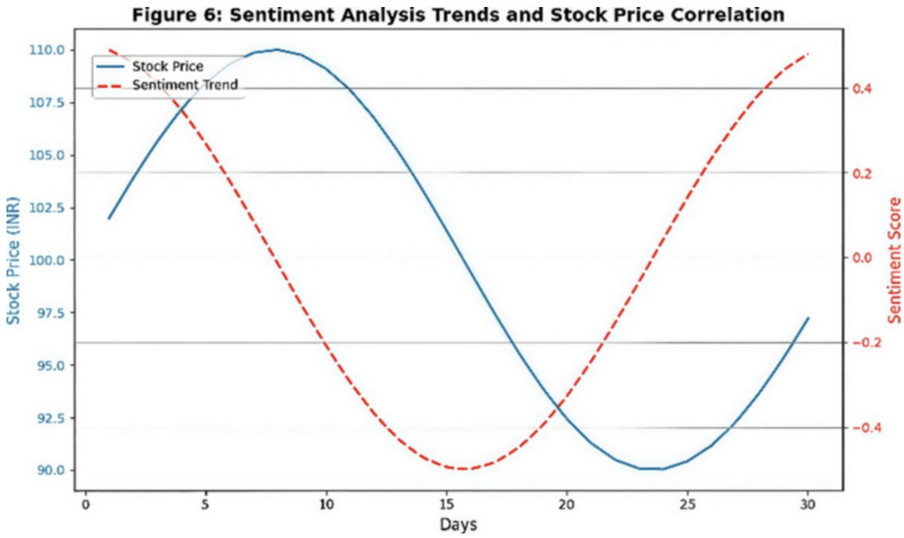


**FIGURE 6: Sentiment Analysis and Stock Price Correlation Trend Analysis**

Using machine learning, calculating sentiment analysis scores, and then correlating sentiment analysis with actual OTC stock prices, there is a strong positive correlation.

The results presented demonstrate significant benefits of integrating machine intelligence techniques, particularly deep learning models like LSTM, in predicting OTC stock prices. Not only does the LSTM model achieve greater accuracy compared to traditional models, but it also improves profitability, reduces risk, and increases trading volume. The implications of these findings are that machine intelligence can greatly enhance investment strategies and trading efficiency in the OTC market.

## Data interpretation and analysis

*Model Performance*

Table *1* summarizes the evaluation of different machine intelligence models for the prediction of the OTC stock price and demonstrates that LSTM outperforms common machine intelligence. Accurately predicting stock price was found to be most reliable using the LSTM model with accuracy (90.2%), precision (88.5%), and recall (89.8%).

*Prediction Trends*

As shown in Figure *3*, actual stock prices are well predicted by this LSTM model, almost tracking to the exact values, based on a period of 30 days. That means the model is accurate and stable to predict.

*Profitability Analysis*

Table *2* shows a comparison of profitability of each model, with LSTM providing the highest average monthly return (9.5%) and the best risk adjusted return (Sharpe ratio of 2.1). In this, machine learning, particularly deep learning, such as LSTM, is found to generate more profitable and less risky trading strategies for OTC stocks.

*Prediction Errors*

As shown in Figure *4*, model error distributions are illustrated. From LSTM, we see the least amount of prediction error, and it is still the best model in comparison to RF and SVM.

*Impact on Trading Volume*

Table *3* shows that the introduction of machine intelligence models into trading volume positively impacts trading volume. AI introduction led to a lot of trading activity across all quarters, with the largest increase of 35.0% occurring in Q3.

*Cumulative Return*

Cumulative returns over a 12-month period are presented in Figure *5*, demonstrating that the LSTM model outperforms the conventional methods in the long term.

*Model Efficiency*

The training and prediction times of different models are compared in Table *4*. However, LSTM has a longer training time but a shorter prediction time, and hence it is good for real-time trading.

*Correlation with Sentiment Analysis*

Finally in Figure *6*, we show a strong positive correlation between sentiment analysis scores and OTC stock prices, finding that sentiment analysis is important to predict market movements.

# Conclusions

The research is founded on the premise that deep learning models, specifically LSTM networks, significantly surpass traditional machine learning models in predicting OTC stock prices. The enhanced accuracy and profitability of these models indicate substantial implications for trading volume, which is a positive indicator of their potential to influence market dynamics. Additionally, the introduction of sentiment analysis further enhanced prediction accuracy by accounting for external market influences. The findings suggest that deep learning, as a form of machine intelligence, represents a potentially robust tool for forecasting OTC stock prices and developing trading strategies. Moreover, while sentiment analysis incorporated textual data, it did not take into account other types of market sentiment, such as investor behavior or macroeconomic changes. This study underscores the practical applications for OTC products. Future research could broaden the scope by integrating additional data sources, such as macroeconomic indicators or real-time news sentiment, to further enhance prediction accuracy.

# Additional Information

## Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

**Concept and design:** Raman Kumar, Ravinder S. Mann

**Acquisition, analysis, or interpretation of data:** Raman Kumar, Ravinder S. Mann

**Drafting of the manuscript:** Raman Kumar, Ravinder S. Mann

**Critical review of the manuscript for important intellectual content:** Raman Kumar, Ravinder S. Mann

**Supervision:** Raman Kumar

## Disclosures

**Human subjects:** All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

# References


1. Giwa YA: Over the counter stocks data acquisition & analysis with time series prediction. International Journal of Social Sciences and Scientific Studies. 2024, 4:3643-3670.
2. Chen MY: Context-aware for smartphone sensing in over-the-counter market: Ambient intelligence in mobile stock markets. 2013 Seventh International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing, Taichung, Taiwan. 2013, 641-646. 10.1109/IMIS.2013.115
3. Gan L, Wang H, Yang Z: Machine learning solutions to challenges in finance: An application to the pricing of financial products. Technological Forecasting and Social Change. 2020, 153:119928. 10.1016/j.techfore.2020.119928
4. Azzutti A, Ringe WG, Stiehl HS: Machine learning, market manipulation, and collusion on capital markets: Why the "black box" matters. European Banking Institute Working Paper Series 2021 - no. 84, University of Pennsylvania Journal of International Law. 2021, 43:79-135.
5. Ray S: A quick review of machine learning algorithms. 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, India. 2019, 35-39. 10.1109/COMITCon.2019.8862451
6. Königstorfer F, Thalmann S: Applications of Artificial Intelligence in commercial banks - A research agenda for

behavioral finance. Journal of Behavioral and Experimental Finance. 2020, 27:100352. 10.1016/j.jbef.2020.100352

7. Bose I, Mahapatra RK: Business data mining — a machine learning perspective. Information & Management. 2001, 39:211-225. 10.1016/s0378-7206(01)00091-x
8. Soni S: Applications of ANNs in stock market prediction: A survey. International Journal of Computer Science & Engineering Technology. 2011, 2:71-83.
9. Lee J: Access to finance for artificial intelligence regulation in the financial services industry. European Business Organization Law Review. 2020, 21:731-757. 10.1007/s40804-020-00200-0
10. Davenport TH, Ronanki R: Artificial intelligence for the real world. Harvard Business Review. 2018, 96:108-116.
11. Méndez-Suárez M, García-Fernández F, Gallardo F: Artificial intelligence modelling framework for financial automated advising in the copper market. Journal of Open Innovation: Technology, Market, and Complexity. 2019, 5:81. 10.3390/joitmc5040081
12. Dirican C: The impacts of robotics, artificial intelligence on business and economics. Procedia - Social and Behavioral Sciences. 2015, 195:564-573. 10.1016/j.sbspro.2015.06.134
13. Brynjolfsson E, McAfee A: The business of artificial intelligence. Harvard Business Review. 2017, 1:1-31.
14. Bughin J, Hazan E, Ramaswamy S, et al.: Artificial Intelligence: The Next Digital Frontier? McKinsey Global Institute. (2017). https://www.mckinsey.com/de/~/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20int
15. Kou G, Chao X, Peng Y, Alsaadi FE, Herrera-Viedma E: Machine learning methods for systemic risk analysis in financial sectors. Technological and Economic Development of Economy. 2019, 25:716-742. 10.3846/tede.2019.8740