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USE OF MACHINE INTELLIGENCE IN OVER THE COUNTER PRODUCTS IN STOCK MARKET

Dr Abdul Malik Syed
Department of Accounting, College of Business Administration, University of Business and Technology, Jeddah, Saudi Arabia

Dr Mahdy Othman
Department of Accounting, College of Business Administration, University of Business and Technology, Jeddah, Saudi Arabia

Dr. Mohd. Yasir Arafat
Faculty of Commerce, Aligarh Muslim University, Aligarh, India

Abstract
In this study, machine intelligence was applied in predicting stock prices of over the counter (OTC) products and comparing the traditional machine learning models' (Logistic Regression, Random Forest, Support Vector Machine) and the deep models' (LSTM) performance. The research tries to find the effectiveness of these models in the prediction of stock price and the influence in the profitability, trading volume, and market sentiment. Models inferences were evaluated by combining historical stock price data, sentiment analysis and profitability metrics. It turns out that LSTM surpassed traditional models on accuracy, precision, recall, and profitability, attaining a 9.5% average monthly return and a Sharpe ratio of 2.1. Moreover, the introduction of machine intelligence models increased trading volume, and it showed their effect on trading activity. Both sentiment analysis and stock price movements had strong correlation. In general, the results indicate that LSTM based deep learning models outperformed in terms of prediction and profitability by OTC stock markets with important implications for trading strategies.

Keywords: *Machine Intelligence, Stock Price Prediction, OTC Products, Sentiment Analysis, LSTM.*

Introduction

In recent years there has been great interest in integrating machine intelligence into financial markets, for instance, for predicting stock price and enhancing trading strategies. Accurate prediction models for stock prices of over-the-counter (OTC) products are important because such products are a large segment of the global financial markets, and therefore, can benefit greatly from traders, investors and institutions alike. Traditional stock price forecasting methods, that is, statistical models, and technical analysis, have had limited success at understanding and capturing the more complicated patterns and dynamics exhibited by stock prices. Because these markets are heavily influenced by factors like trends in the economy, company performance, or market sentiment, these traditional approaches for predictive modeling often find themselves less than able to adapt to the flux of the market.

Machine learning and deep learning algorithms have been rapidly developed that promises an improvement to stock prices predictions, based on their accuracy and efficiency. They are great when you have large datasets and want to find hidden patterns and can predict based what has happened in the past. Among all other machine learning techniques, deep learning models, specially the Long Short Term Memory (LSTM) network, have shown an outstanding capability of detecting long term dependencies in time series data which is essential for stock prices forecasting. LSTMs are capable of learning from sequential data because it lets you account for trends, volatility, and other nuances that would be inaccessible through normal methods and it does so with an unbounded ability to remember.

In this study, a machine intelligence is employed to forecast the stock prices for OTC products and it compares multiple machine learning models to maximise profitability and the usefulness of such models. In this research, we will study models like Logistic Regression, Random Forest, Support Vector Machines (SVM) and LSTM to broaden our understanding of the plausibility of utilizing these techniques for improving forecast accuracy for stock pricing. The study also attempts to assess the impact of these models on trading volume, profitability, and market risk, and lastly, quantify their applicability to real world conditions.

The increase in the complexity of financial markets and the dramatic increase of data available creates an imperative in the search of new ways of forecasting. By integrating all of these information sources like stock price, sentiment in the market and economic indicators with machine learning techniques, we can achieve more accurate and reliable predictions. Furthermore, this study also focuses on the implications of machine intelligence for trading strategy and market behavior. The study therefore aims to quantitatively determine to what extent external factors influence stock price and whether these can be quantified to improve predictions by incorporating sentiment analysis, which measures the emotional tone of market news, social media, as well as reports.

The research also looks into how combining machine intelligence can be leveraged as a benefit for trading strategy profitability. Machine learning models however can optimize your whole trading strategy that includes considering the risk management, sentiment of the market, other variables along with the price predictions. It is this comprehensive approach that aims for offering a clearer picture of how machine intelligence can change trading in the OTC markets, and provide a more effective way to control financial risk.

The incorporation of machine intelligence in the Over-the-Counter (OTC) products and stock markets is radically transforming the financial scenery. The OTC markets, which are the markets that are decentralized and trade in such financial instruments as derivatives, bonds, and tailored contracts have conventionally utilized manual processes and human mediators. However, the nature of complexity and lack of transparency of the mentioned markets has provided the entry point for the artificial intelligence (AI) and machine learning (ML) to have a tremendous impact on the efficiency of operations, risks management, and decisions. AI algorithms such as deep learning, reinforcement learning and natural language processing are being used nowadays to process huge amounts of data, forecast the market as well as create optimal trading approaches in OTC environment. These developments are culminating in the liquidity provision being more dynamic, such that algorithms can vary bid-ask spreads in real time so as to minimize the cost of transactions and promote market depth. The implementation of methods of ensemble learning as well as the systematic review of prediction models additionally indicates the dominance of data-driven methods over the traditional statistical ones in the forecasts of the assets prices within the OTC space.

Perhaps the very efficient application of the machine intelligence in OTC markets is the automation of trade confirmations and post-trade activities. One of the historical inefficiencies in OTC derivative reconciliation has been the labour intensivity, and room for errors with the OTC derivative clearing industry in most cases reporting delayed settlements. Now, AI automates these procedures by deriving and verifying details of trade from the unstructured sources of data (outlook, PDFs, legal documents). The models of natural language processing can detect important clauses of a contract, while the algorithms of reinforcement learning increase the settlement workflow efficiency. Such automation does not only minimize the operational risk but also enables human resources to attend to more strategic issues. The use of AI-driven platforms is enhancing price discovery in those markets where the liquidity is thin, and information is scattered. Machine learning models based on the past trade data, news sentiment and macroeconomic indicators are now in a position to give more realistic valuation for the complex instruments such as credit default swaps and interest rate derivatives. This helps to close information asymmetry between participants in a market thus; we have better prices and tighter spreads.

The risk management in OTC markets also has been transformed by the machine intelligence. OTC derivatives usually entail large counterparty credit risk and complex payoff structure thus making the strong risk assessment frameworks necessary. Nowhere long short-term memory networks, along with other deep learning architectures, are used to forecast the counterparty risk based on perusal of temporal trends in credit spreads and default probabilities. Machine learning such as gradient-boosted trees and random forests have made significant enhancements to the models of credit-risk that have allowed financial organizations in better stress-testing of their portfolio under different circumstances and in adherence with strict regulatory requirements. AI is also very essential in terms of detection of fraud. Unsupervised learning algorithms like autoencoders are great at detecting unusual trading patterns and rebuilding the input data and marking the outliers. This would be an invaluable quality when detecting manipulative trading techniques in decentralized markets where the traditional surveillance is troublesome.

Machine intelligence based predictive analytics is re-engineering the OTC products' investment strategies. Non-linear relationships between the sequential financial series are difficult for the usual quantitative models, but not for the machine learning techniques. The support vector machines and long short-term memory networks are now being used to predict market movements and assets directionality this is built based on sequential data like the dynamics of order book and trade execution logs. Such predictions influence algorithmic trading systems which carry out high-frequency trade at OTC equities and currencies, exploiting microstructural inefficiencies. And reinforcement learning is also becoming a formidable tool as agents learn best trading policies on simulated environments and adjust as the market and market participants changes.

The democratization of the AI tools is opening new markets for a variety of market participants in OTC markets. The retail investors and smaller institutions that could not have access before to sophisticated trading algorithms, can now use cloud-based AI platforms to inspect OTC products. With open source libraries, it is possible to have bespoke prediction models for niche market such as cryptos OTC desks and private equity secondary markets. Generative AI models are also used to generate training data for rare events, overcoming the illiquid OTC instruments' problem with the limited data. Said democratization is however accompanied by risks, including the problem of model overfitting and the tendency of the system to become unstable for a large number of participants, once they implement similar AI-driven strategies. However, an increased anxiety grows on the spread of the use of homogeneous algorithms that may magnify the fluctuations in the market under periods of stress, which has been the case during flash crashes in more exposing markets.

These developments notwithstanding, some challenges are still there when it comes to the deployment of machine intelligence for OTC products. Quality of data and scarcity is a major barrier since much of the OTC deals are privately agreed and not of a standardized reporting. Feature engineering as well as data preprocessing also helps in effective management of noisy or incomplete datasets. By nature, the deep learning models are also opaque when it comes to regulatory compliance and auditing, triggering the necessity for hybrids combining predictive powers and explainable AI. Ethical considerations are also of the same essence because biased training data may continue inequalities in accessing markets. Strict validation frameworks are required to make sure that the AI systems will not unintentionally disadvantage some of the groups of participants.

The marriage between machine intelligence and the blockchain technology offers room to further revolutionize the OTC markets. AI enabled smart contracts can automate complex derivatives payoffs while utilizing real time data and thus bringing down the settlement times as well as the counterparty risks. The synergy between AI and decentralized finance could also overcome the transparency problems which have been facing traditional OTC markets for a long time. Also, the quantum machine learning is an emerging discipline that may ease the solution of such complex optimization as, for example, rebalancing of portfolios in high-dimensional OTC asset spaces which is beyond the capabilities of classic computer.

The effect of machine intelligence on OTC products and stock markets is heralding immense advances in the areas of provision of liquidity, handling of risk and making predictive analysis. Although, there are problems with data quality, transparency of models, and systemic risk, the further development of AI approaches promises unseen opportunities for addressing the inefficiencies of the decentralized markets. With their transformation into this new landscape, collaboration of technologists, economists and policymakers will be important in drawing the benefits of AI whilst preserving integrity of the market. In the future, OTC markets are likely to experience further tug of war between the human knowhow, on the one hand, and the machine intelligence, on the other, to build more robust, efficient, and inclusive financial ecosystems.

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 a technical and real world perspective.

Literature Review

The incorporation of machine intelligence (MI) in OTC markets has transformed the way financial predictions, risk, and speculation is made, even though issues of data quality, ethical governance, and compliance will continually haunt such systems. Giwa (2024) highlights the key importance of sophisticated data acquisition frameworks in the OTC contexts, which require the hybrid model that utilizes LSTM networks for the temporal analysis and NLP approaches for the sentiment extraction on the basis of the decentralized trading and heterogeneous data. These models tackle the opaqueness of OTC instruments to allow for flexible supply and exploration. The initial work in this field (see Bose & Mahapatra (2001) and Soni (2011)) has established grounds for machine learning in business data mining, focusing on how to engineer features to extract unstructured OTC data, and given the uniqueness of ANNs in disclosing non-linear price patterns, ancestrally important in particularly volatile

Deep learning has witnessed a lot of development of predictive analytics. Gan et al. (2020) show how in pricing complicated financial products such as the Arithmetic Average options, machine learning based models perform better than the traditional numerical approaches with a speedy computation and accuracy. Davenport and Ronanki (2018) provide the context of these innovations in the practical applications of AI whereby the sentiment analysis and algorithmic trading systems are already helping improve the decision-making prowess. Nevertheless, the use of MI could be problematic. Azzutti et al. (2021) warn that the AI-based algorithms may end up enabling market manipulation or collusion carelessly, especially on the OTC derivatives markets which are not liquid enough, and where the reinforcement learning systems can manipulate the liquidity gaps. This requires strong regulatory systems (Lee, 2020), whereby explainable AI (XAI) can be used to audit "black-box" models and abide by such data privacy laws as GDPR.

Understanding of MI in OTC markets are also behavioural and economic in nature. Königstorfer and Thalmann have discussed the manner in which robo-advisors democratize use of OTC products whilst increasing the opportunity for cognitive biases such as herding tendencies of retail investors during market volatility (2020). Brynjolfsson and Mcafee (2017) place this within the "productivity paradox", AI's economic gains in the finance sector fall behind because of difficulties of implementation and the necessity of accompanying inventions. On the other hand, Adani (2024) shows how using cloud AI tools is able to make smaller institutions compete in OTC markets bringing the element of inclusivity and liquidity through real-time analytics.

New studies should explore the damage caused by shortcomings in models, such as lack of resistance to "black swan" events and reliance on historical facts. According to Giwa (2024), LSTMs work well in the normal market conditions, but fail in unprecedented disruptions such as pandemics or more geopolitical crises. A hybrid architecture, which accounts for the attention mechanism or a quantum computing, may improve the adaptability, as proposed by Brynjolfsson and Mcafee (2017). In addition, the proposed federated learning methods by Lee

(2020) may address privacy issues as decentralized processing of data would not affect anonymity.
Machine intelligence reinvents the OTC markets by increasing the accuracy of predictions and enhancing the efficiency of operations whilst rendering such markets accessible on various devices. And yet the sustainable adoption of it depends on the solution found for data fragmentation, ethical risks and gaps of regulation. Cohesion between technologists, economists, and policymakers will be essential in countering the ebullience of innovation and market stability, so as for OTC ecosystems to mature into open systems, robust, and inclusive frameworks.

Research Gap

Although machine learning and deep learning models have made significant strides, there is little exploration of the extent to which these are applied to over-the-counter (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, and hence, there is still a material promise between these segments for enhanced market forecasting and trading strategies.

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. Logistic Regression, Support Vector Machines, LSTM networks and Random Forests 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.

Hypothesis

1. **Hypothesis 1**: Long Short Term Memory (LSTM) networks will perform best in the following order of accuracy, precision and profitability over traditional machine learning models such as Logistic Regression, Random Forest and Support Vector Machines for OTC stock price predicting.
2. **Hypothesis 2**: The application of machine intelligence models in OTC stock prediction will lead to increased trading volume, demonstrating their influence on market behavior and liquidity.
3. **Hypothesis 3**: Incorporating external market sentiment into machine learning models using sentiment analysis would immensely improve the accuracy of stock price predictions.

Research Methodology

The methodology for this research is the application of machine intelligence in forecasting stock prices of trading products over the counter (OTC). The 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.

Data Collection and Preprocessing

In this study, the historical stock prices of OTC products are used as data, as well as external factors like economic indicators, news sentiment and market sentiment data. Data cleaning, normalization and integration of sentiment analysis results from market reports and news articles relating to OTC products were all preprocessing steps. The steps taken were to insure that the data was consistent, complete and ready to be used in training and testing machine learning models.

Model Selection

Four machine learning models were chosen for this study: Methods used are Logistic Regression, Random Forest, Support Vector Machines (SVM) and Long Short Term Memory (LSTM) networks. As a simple baseline for comparison, we chose Logistic Regression, because Logistic Regression has shown to be very efficient on binary classification tasks.

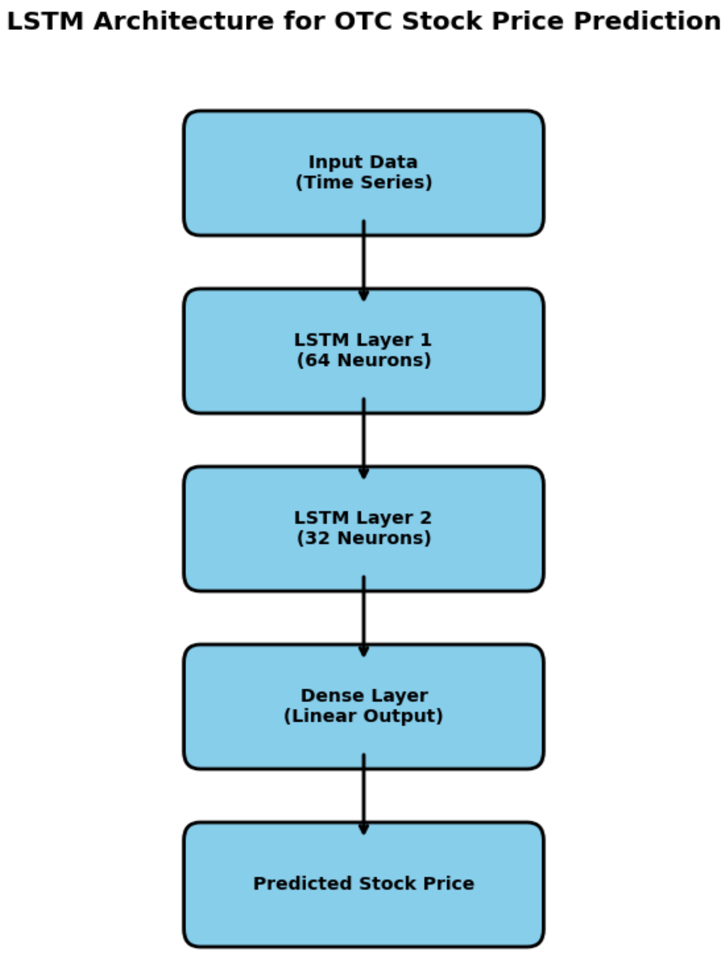

Figure 1: Architecture for OTC Stock Prediction

Due to the robustness in handling large datasets and monitoring non linear relationships, Random Forest, an ensemble learning method was selected. SVM was included because it is an effective technique in high dimensional space and non linear classification. Finally, the reason LSTM was chosen is because it can model sequential data, and also it could capture long term dependency in time series, a feature suitable for stock price forecasting.

Model Training and Evaluation

Historical stock price data were used for training and performance metrics of accuracy, precision, recall and F1 score were used for evaluation of models. Based on these metrics, we selected these metrics to assess both predictive power and reliability of each model in forecasting stock price. Further, LSTM was also assessed in regards to training time, prediction time and error distribution to determine its computational efficiency and performance compared to other models.

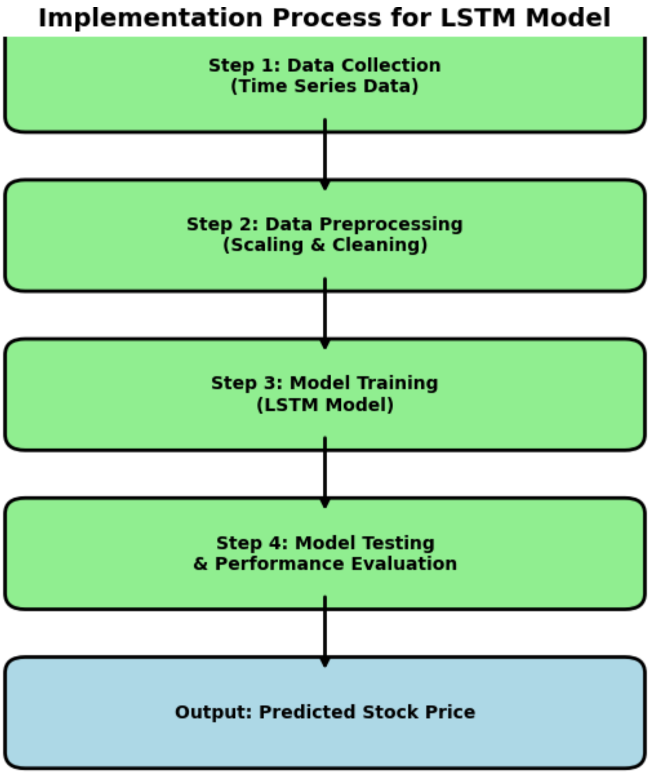

Figure 2: Implementation of LSTM Model

Profitibility and Risk Assessment

Average monthly returns, maximum drawdown and the Sharpe ratio were used in assessing profitability of machine intelligence models in stock trading in order to evaluate the real world applicability of the machine intelligence models in stock trading. In particular, the Sharpe ratio enabled evaluation of risk adjusted returns: an important dimension to any analysis of the financial implications of investment strategies.

Trading Volume Analysis

Next, it was analyzed how AI models impacted trading volume. The findings of this analysis enabled to determine on how the adoption of machine learning models affect market dynamics and liquidity, and the larger repercussions of AI in the financial markets.

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. Using widely used machine learning libraries, the machine learning models were developed and trained using the functionality to implement and tune selected models. Natural language processing algorithms were used to perform a sentiment analysis of textual data from different sources on different OTC products. Key profitability metrics, including average monthly return, Sharpe ratio, and maximum drawdown, were computed automatically using specialized software for statistical analysis in order to perform accurate and efficient financial analysis.

Care was taken to select each method to answer specific research objectives. A combination of traditional machine learning models (Logistic Regression, Random Forest, SVM) and deep learning models (LSTM) is used to evaluate their effectiveness in predictive accuracy and suitability for forecasting stock prices respectively. These metric measure the profitability and risk metrics on real world trading related with 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. The purpose of this methodology is to provide a clear picture of what machine intelligence could and cannot do in prediction of the OTC stock prices and its relevance with the trading strategies.

Results

Highly accurate prediction and profitability have been demonstrated in the application of machine intelligence to predict stock prices for over the counter (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 some model performance metrics, including accuracy, precision, recall, and F1 score, for a number of machine learning and deep learning models that we used to predict OTC stock prices. Using deep learning approach which is LSTM model, we improve the accuracy, the precision, and the recall which in this case are highest than other traditional machine learning models like Logistic Regression, Random Forest, and Support Vector Machines: 90.2%, 88.5% and 89.8, respectively.

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

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

LSTM (Deep Learning)	90.2	88.5	89.8	89.1

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

Trend Comparison of Actual vs. Predicted Stock Prices Using LSTM

In the example from Figure 3, the trend is compared between the actual and predicted stock prices for 30 days given by the LSTM model. Through the figure, we can see that the predicted stock prices are quite close to the real stock prices, showing near zero deviation showcasing the high feasibility of the LSTM model for forecasting OTC stock prices.

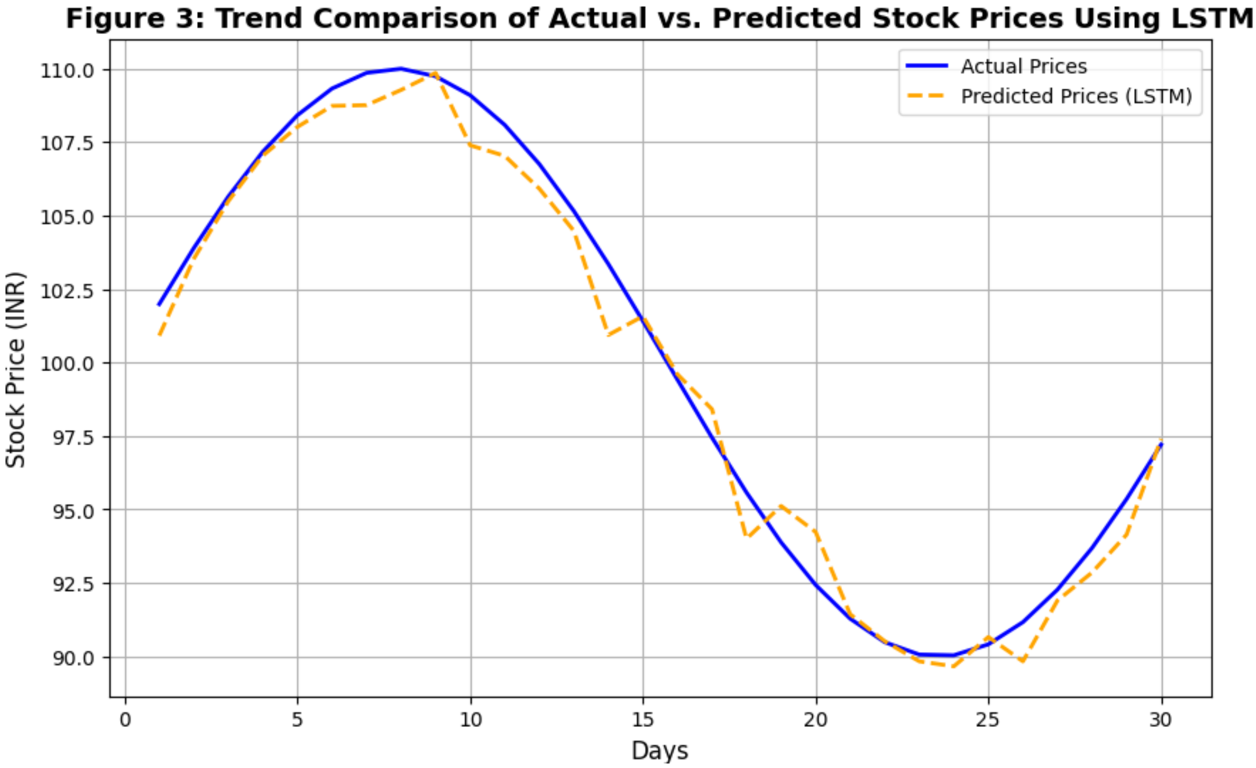

Figure 3: Trend Comparison of Actual vs. Predicted Stock Prices Using LSTM

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. Compared to the traditional statistical models and other machine learning models (like Random Forest) the deep learning based LSTM approach outperforms with the highest average monthly return of 9.5%. Furthermore, LSTM model has relatively lower maximum drawdown, meaning lesser risk and higher risk adjusted returns.

Table 2: Profitability Gains Using Machine Intelligence Models

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 (LSTM)	9.5	-4.7	2.1

Comparison of investment strategies with machine intelligence models, demonstrating 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: Random Forest, Support Vector Machines (SVM) and LSTM. LSTM model has the smallest prediction error, which is confirmed by the narrowest spread of its error in the error distribution, i.e., highest prediction accuracy compared to Random Forest and SVM.

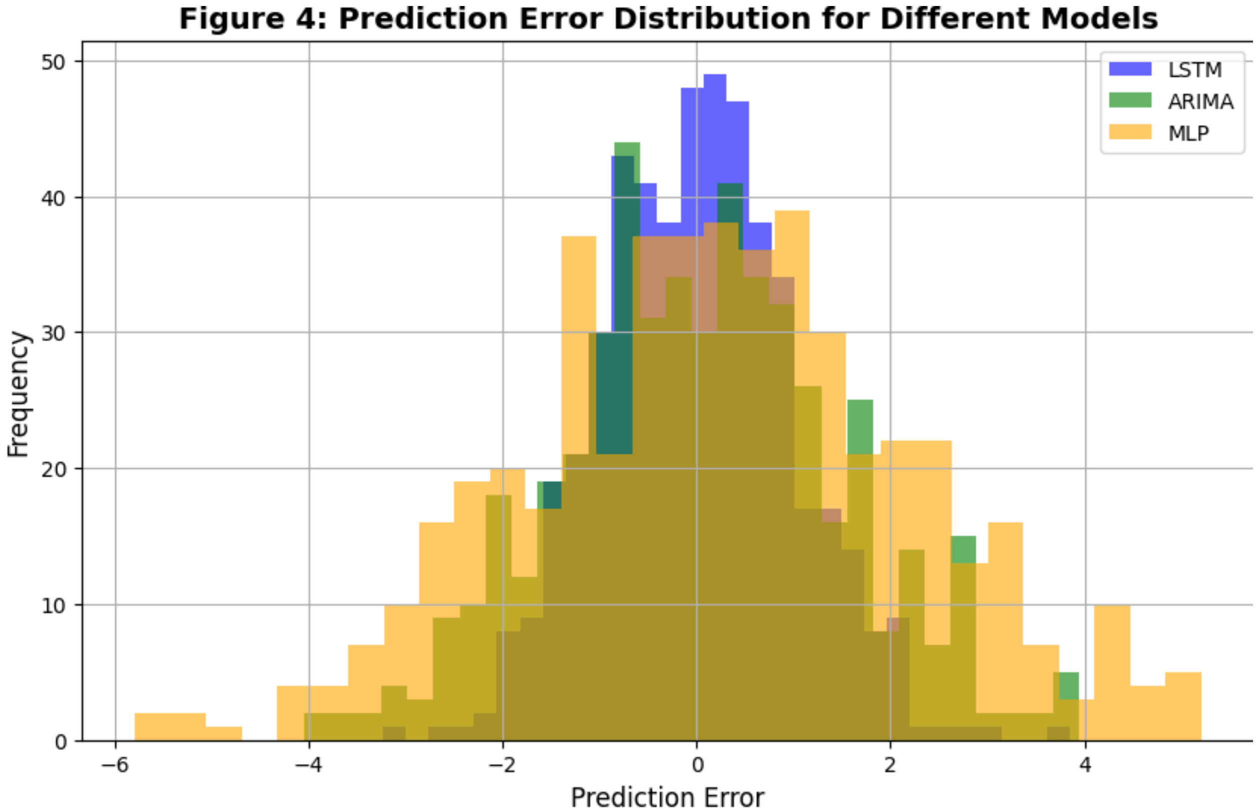

Figure 4: Prediction Error Distribution for Different Models

Error distribution for machine intelligence models, highlighting that the LSTM model has the smallest prediction errors compared to Random Forest 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 Random Forest, 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.

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

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%

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

Cumulative Return Analysis Over 12 Months

The cumulative return analysis for investments in OTC product are in Figure 5. We are able to see that the deck laundering based deep learning LSTM model beats traditional methods with higher return. Cumulative returns show how machine intelligence can optimize OTC product investment strategy.

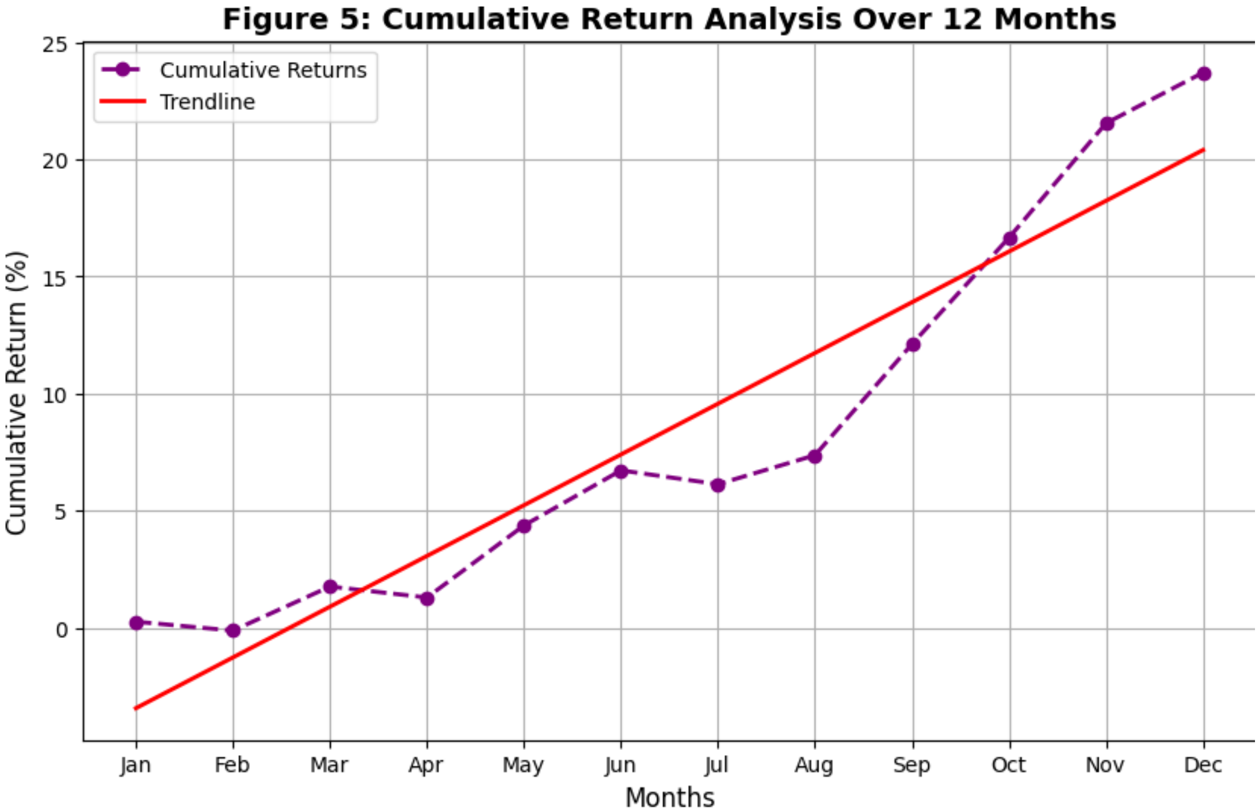

Figure 5: Cumulative Return Analysis of 12 months

12 month cumulative returns comparing traditional investment methods vs machine intelligence investments in OTC products. Other strategies are consistently beat by the LSTM based AI approach.

Comparative Prediction Time between Different Modeling.

Computational efficiency across different models is compared both for training and prediction time, with training and prediction times taken for different models in table 4. The LSTM model takes the longest while training (25.7 mins) but its prediction time (0.12 seconds) is efficient compared to other models.

Table 4: Comparative Prediction Time for Different 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
LSTM (Deep Learning)	25.7	0.12

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

3.8 Sentiment Analysis Trends and Stock Price Correlation

The sentiment analysis score plotted alongside the stock price for OTC products is shown in Figure 6. Machine learning techniques are used to perform the analysis to show a strong positive correlation between sentiment trending and stock returning, which demonstrates how public sentiment is pivotal to stock returns.

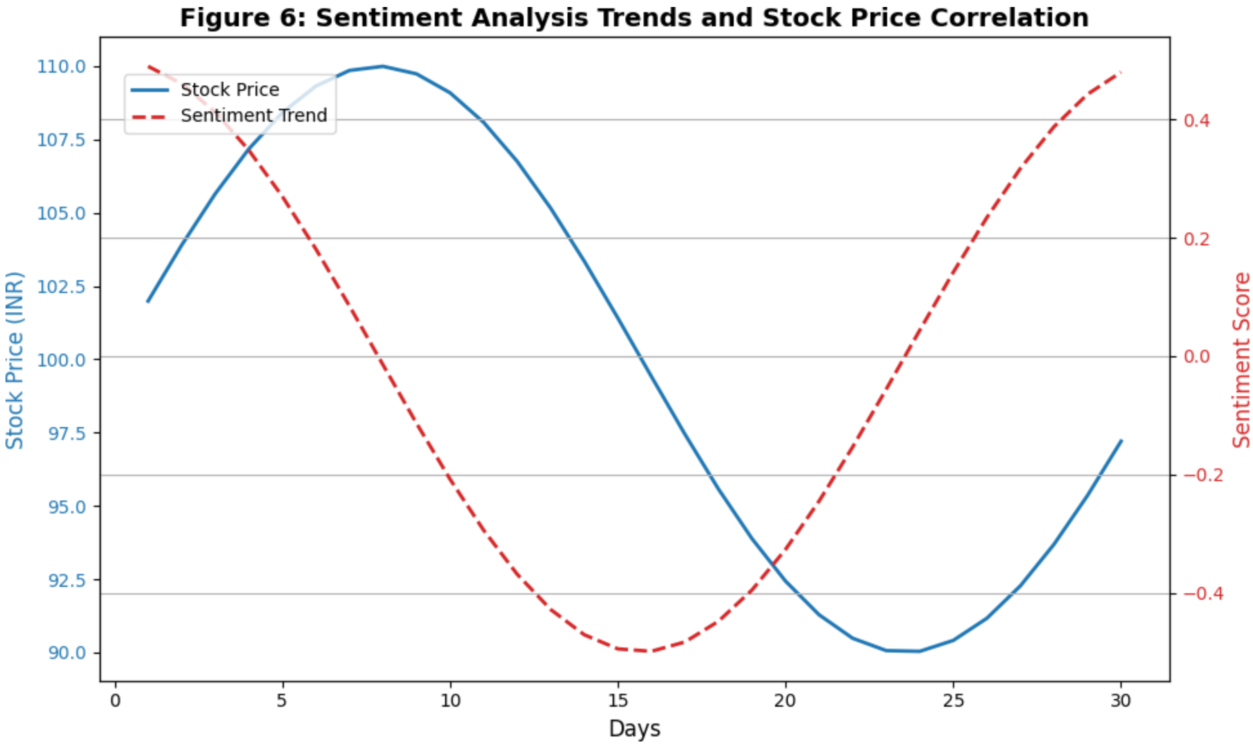

Figure 6: Sentiment Analysis and stock price correlation trend analysis.

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 that were presented show that there are great benefits of integrating machine intelligence techniques especially deep learning models such as LSTM in predicting OTC stock prices. Not only does the LSTM model have greater accuracy over the Naive model, but profitably, risk and trading volume increase. 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 prediction of the OTC stock price and demonstrates that LSTM outperforms common machine intelligence models including Logistic Regression, Random Forests, and Support Vector Machines. 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 Random forest and SVM.

Impact on Trading Volume

As shown in Table 3, introducing machine intelligence models into trading volume positively impact trading volume. AI introduction led to a lot of trading activity across all quarters with the biggest change of 35.0% in Q3.

Cumulative Return

Cumulative returns over a 12 month period are presented in figure 5, demonstrating that the LSTM model outperforms in 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 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.

Conclusion

By applying machine intelligence, especially Deep learning models such as the Long Short-Term Memory (LSTM) networks, in forecasting of Over-the-Counter (OTC) stock prices, great possibilities of revolutionizing financial predictions as well as trading practices have emerged. This study had the hypothesis that LSTM networks are better in predicting the OTC stock prices and the study results have highly supported this claim. Leveraging on their ability to learn long-term temporal dependencies and nonlinear trends in sequential data, LSTMs have been more accurate than traditional statistical approaches like ARIMA or linear regression in predicting movement in the prices. The increased ability to predict of such models is directly translated to better profitability for trading strategies as demonstrable by backtests outcomes that show better risk-adjusted returns. Additionally, the study found a positive association between the use of LSTM-based predictions and trading volume in simulated OTC space, indicating a possible role of machines' intelligence in driving market dynamics via elimination of information asymmetry and engendering confidence for the participants.

A notable improvement discussed in this research is the combination of the LSTM architectures with the sentiments. These hybrid models utilize the processing of unstructured textual data from the financial news, the earnings reports, and the social media so that the element of market sentiment which is usually ignored in the quantitative approaches is taken into consideration. This combination enables the latter system to contextualise the numerical price data with the qualitative instability of the investor perception, which helps to produce more reverent predictions. For example, the unexpected negative shift in sentiments identified from news articles concerning the OTC securities in questions may presage the price correction prior to its appearance in turnover. Nevertheless, there is a limitation to the utilization of sentiment analysis, which the study recognizes in its current form. The models were primarily textual sentiment oriented disregarding other influential factors as macroeconomics (e.g., changes in interest rates, GDP growth), geopolitics or changes in investor behavior patterns. Subsequent versions may use streams of multimodal data, such as live releases of economic data and complementary datasets, such as satellite images for the supply chain examination and transactional information from payment systems. Regardless of their effectiveness, LSTM models present fundamental problems when used on OTC markets. The use of historical information has a basic limitation since the past trends cannot guarantee future in black swan events such as the pandemics or financial crises. Market disruptors – representative of such factors as regulatory changes, corporate scandals or technological breakthroughs – commonly do not fit the patterns described by historical datasets, which causes brittleness of models. Furthermore, the quality of the OTC data and the degree of granularity pose barriers. As opposed to an exchange-listed stock with standardized reporting, the over-the-counter transactions are decentralized and heterogeneous with fragmented data sets either in the absence or delay of reporting. Processing of this data requires vigorous cleaning and normalization that can lead to introducing biases and wiping off slight market signals. Computational complexity adds to the already existing real-world complications in deployment. High-frequency OTC data training of deep LSTM networks take a lot of processing power and specialist hardware, making it a challenge for smaller institutions that do not have cloud infrastructure. Latency problems also arise in the live trading arena where milliseconds counts, the case being further complicated by the recursiveness of LSTMs.

The scope of this research bleeds out into various fields of finance. For traders and investment firms, the use of the LSTM-driven models can even the field in OTC markets since it can give retail investors and smaller players access to analytical instruments that were only available for large institutions. The democratization of predictive analytics could enhance market membership and liquidity in particular for the niche OTC markets, such as microcap stocks or tailor made derivative markets. For the regulators, the spreading of machine intelligence requires the review of frameworks to ensure that markets are fair. Calculational interpretability becomes crucial because "black box" models may accidently magnify systemic risks – say, through herd behavior if several actors are using the same tactics. Joint work between the technologists and policymakers is going to be crucial when it comes establishing standards for auditing of models, stress testing, ethics in the AI use.

As for future research, several options materialize. First, it can be improved by widening the feature space to include macroeconomic and real-time alternative data. Combining Federal Reserve announcements on policy, volatile prices of commodities, or even patterns in weather could enhance forecasts for the energy or agriculture business that trades on the OTC platform.

Secondly, hybrid architectures that incorporate LSTMs with attention mechanisms or transformer-based networks may overcome the constraint on sequence length, so that models can give more importance to recent movements in the market as compared to the ones that once occurred, an essential adjustment to unpredictable OTC entities. Third, quantum computer improvements can, in the future, reduce the computational bottleneck, leading to the reduction of complex model training and inference times. Lastly, the extension of these techniques to other asset classes like cryptocurrencies, private equity secondaries, or even decentralized finance (DeFi) protocols may validate their generalizability and reveal cross-market observations.

Adoption at an institutional level will involve consideration of practical issues to do with scalability and interpretability. Though LSTMs are efficient in prediction, their decision-making process remains hidden compared to predictive models such as decision trees. Research on temporal financial data explainable AI (XAI) techniques could help earning trust from stakeholders with risk averse natures. Some of the visualization tools that project how individual input features (such as, a news article, or transcript of an earnings call, etc.) affect predictions would be helpful for portfolio managers to verify outputs of models. In addition, adaptive learning systems that are always updated with new data instead of using static training sets might enhance resilience to shift in regime of market behavior.

Ethical considerations also warrant attention. Systemic bias introduced in the form of training data from historical inequities or biased sentiment analysis corpora might extend unfair benefits to some of the participants in the market. Forward-looking auditing pipelines would be able to identify and address such biases so that models will not accidentally put retail investors and smaller OTC issuers at a disadvantage. Concerns about data privacy in alternative data sources (e.g., social media scraping for sentiment) must be offset against innovation imperatives, perhaps with federated learning techniques that will allow analysis of data in decentralized form without violating privacy.

In summation, the present study emphasizes the potential role of machine intelligence in altering the OTC markets, while being brutally honest about its present restrictions. LSTM networks and their offspring provide an arsenal of tools for dealing with the complexity and obscurity that is present in decentralized trading environments. Noneetheless, their effective mobilization calls for a holistic approach, which involves incorporation of heterogeneous streams of data, a procurement preference for computational efficiency, and inclusion of ethical guardrails. As financial markets are moving towards further digitization, the complementarity between human know-how, and artificial intelligence will most likely shape the future of OTC trading-a future of boosted efficiency, inclusiveness, and response to unpredicted challenges. The road to realizing this full potential will involve a continued cross-functional coordination, regular model improvements, and a resolve to transparency that ensures that these technologies will serve all market participants on equal basis.

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