Coupling LSTM with Technical Indicator as Trading Strategy

Rui Chen Yong1, a), Choo-Yee Ting1, 2, b), Goh Hui-Ngo1, 3, c) and Albert Quek1, 4, d)

*1Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, 63100, Cyberjaya, Selangor, Malaysia*

2Centre for Big Data and Blockchain Technologies, CoE for Advanced Cloud, Multimedia University, Persiaran Multimedia, 63100, Cyberjaya, Selangor, Malaysia.

3Centre for Natural Language Processing, CoE for Artificial Intelligence, Multimedia University, Persiaran Multimedia, 63100, Cyberjaya, Selangor, Malaysia.

4Centre for Image and Vision Computing, CoE for Artificial Intelligence, Multimedia University, Persiaran Multimedia, 63100, Cyberjaya, Selangor, Malaysia.

*b) Corresponding author:* [*cyting@mmu.edu.my*](mailto:cyting@mmu.edu.my)

*a) 1221303408@student.mmu.edu.my*

*c) hngoh@mmu.edu.my*

*d) quek.albert@mmu.edu.my*

**Abstract****.** Trading in financial markets has traditionally been performed through human analysis of market trends, news, and technical charts. While this approach leverages human intuition and experience, it is often constrained by cognitive biases, emotional influences, and the inability to process large volumes of data in real-time. These limitations can lead to inconsistent decision-making, missed opportunities, and suboptimal returns. Artificial intelligence (AI) used in stock trading is aimed to predict stock market movements and eliminate human’s weaknesses in terms of emotional influences and inability to analyze large data. This research proposes the development of an AI-driven trading bot that combines deep learning technique LSTM with technical indicators: MACD, ADX, CCI, BB and OBV, to optimize trading strategies. The primary contributions of this research include: (1) Developing a framework that will fit different technical indicators with A.I. models for real-time decision making, (2) Introducing an optimized backtesting methodology for evaluating AI-driven trading strategies, (3) Demonstrating the difference in performance of AI-driven trading bots against traditional human trading analysis. Based on the updated backtesting results, single indicator strategies averaged a 24.2% return under LSTM, compared to 21.4% with traditional methods, with LSTM notably reducing the worst trade losses (CCI’s worst trade improved from –$635.87 to –$40.82). Multi-indicator strategies showed even greater improvement with LSTM, averaging a 33.2% return versus 10.8% under traditional trading. The best LSTM performance came from the MACD + ADX + OBV combination, which delivered a 46.15% return and improved the worst trade from –$531.70 to $205.19. These results highlight the effectiveness of LSTM in enhancing both returns and risk management, especially when optimizing multi-indicator trading strategies.

# Introduction

Technical indicators are a tool used by traders which is calculated using historical stock market data, and is one of the ways traders analyze the stock market movements to help them gain trends and insights in the real life market [1]. Analysis of the stock market using technical indicator is a popular way but yet they have its cons [2], lagging is on main factor as historical stock data is required to obtain these insights. For example, MACD is one of the common indicators used by traders but it requires sufficient historical data only it would provide signals for trader to execute trades hence this would cause traders to miss the perfect opportunity to buy in or sell out [3], [4]. In recent years, researchers have came up with ways to counter the limitations of technical indicator by implementing Artificial Intelligence(AI) to predict the stock market’s movements [4]. The primary benefits of the implementation of AI with technical indicators are to reduce the lag and improves trader’s decision time [2], [4], [5]. Recent studies have introduced the integration of LSTM models with technical indicators. Piravechsakul et al.[4] used the LSTM model with MACD, Bollinger Bands, and RSI as its inputs [4]. Wiiava, Fatichah, and Saikhu [2] developed new LSTM features using golden cross and death cross signals [2]. Xue, Qin, and Fu [6] developed a multibranch LSTM for separate indicator processing [6]. Fahd et al. [7] showed an improvement on deep learning using optimized indicators [7]. Chatziloizos, Gunopulos, and Konstantinou [5] enhanced prediction by combining technical indicators with sentiment analysis [5]. Following these advancements, this study integrates MACD, ADX, CCI, Bollinger Bands (BB), and OBV into a trading bot, complemented by an LSTM model for price forecasting. The use of LSTM follows prior work demonstrating its ability to capture sequential market patterns [4], [5], [6]. Extending earlier research, this project not only combines multiple indicators but also optimizes their parameters individually through backtesting, testing ensemble strategies across indicator combinations, and applies these ensembles to LSTM predicted prices. The approach draws from Piravechsakul et al. [4] for multi-indicator integration [4], Xue, Qin, and Fu [6] for separated indicator processing [6], and Sukma and Namahoot [8] for enhancing profitability through optimization [8]. By combining feature engineering, parameter optimization, and LSTM time series forecasting, this project aims to better adapt to dynamic market conditions compared to traditional methods.

# Problem statement

Although integration of A.I in technical indicators has shown promising results, they present several challenges. Many technical indicators, such as Moving Averages and MACD, are inherently reactive rather than predictive [3], [4]. This lag leads to delayed trading signals, reducing the effectiveness of trading strategies in volatile markets [3], [4]. The volatile markets have made analyzing future prices of stock extremely hard for traders [1], [4]. Human Emotions is a factor that causes traders to make the wrong decision when they noticed the sudden changes in the stock market [1], [9]. Combining technical indicators is a great way of increasing the accuracy in trading however it is a problem for traders to use the suitable technical indicators [8], [10].

This project has three core objectives. First is to develop an LSTM framework with technical indicator by designing and implementing a framework that integrates LSTM with technical indicators to minimize lagging effects and improve signal accuracy in stock trading. Next, optimizing the multi-indicator strategies by combining multiple technical indicators effectively with the optimized parameters for technical indicators. Finally, conduct backtesting and performance analysis to assess the framework’s performance on real life market stocks using different technical indicators.

In this study, the primary stock that will be used for testing all the technical indicators are Apple Inc (AAPL).

# Literature Review

In recent years, the introduction of artificial intelligence (AI) in stock trading is being popularized as it serves as a new way to optimize traditional trading strategies [2], [4, [5]. The stock market is in a constant state of fluctuation and volatile which this causes traders problems to accurately find the trends and predict the stock market’s movements [2], [9]. To address this issues, traders are using technical indicators to better visualize and analyze the potential stock market movements so they are able to make more accurate trading decisions [1], [2], [6].

Technical indicators are a tool used by traders which requires historical stock market data to calculate the signals and insights [1]. There are four main groups of technical indicators which are trend, momentum, volatility, and volume [1]. Trend indicators like the Moving Average Convergence Divergence (MACD) indicates the potential buy and sell point of a stock by calculating the difference between short and long term EMAs [1], [4], [5]. Average Directional Index (ADX) is also a trend indicator that provides the trend strength of a stock to filter out the weaker signals [1], [7]. Relative Strength Index (RSI) is a momentum based indicator that identifies whether a stock is being overbought or oversold [4], [10], [11]. Commodity Channel Index (CCI) is also a momentum indicator that identifies the overbought or oversold conditions but the way it is calculated slightly varies from RSI [7], [9]. Volatility indicators like Bollinger Bands (BB) can be used to identify overbought and oversold condition as it detect price extreme helping traders filter out these weaker signals [4], [12]. Average True Range (ATR) focuses on the market’s volatility, it would capture if there’s a big shift in the stock market’s price [1], [5]. Finally, On-Balance Volume (OBV) is a volume-based indicator that identifies whether the price may closes higher or lower using the cumulative which would provide a confirmation for the trend direction [1], [8], [13].

Even though technical indicators are great tools for stock analysis, there are still many problems the researchers have faced when analyzing these technical indicators. The stock market’s high volatility, driven by external factors such as political events, economic changes, and global crises like pandemics, makes accurate price prediction extremely difficult [2], [4]. One example of global crises is that traders during the COVID-19 period are afraid to execute trades as the market is very volatile and there’s external factors constantly tempering the stock market’s price movement [1]. Even though technical indicators are an essential tool for analyzing the stock market, it’s often limited due to their lagging nature. For example, Moving Averages provides signal to trader after a stock experience a shift in price and these stock market prices might experience delayed updates causing traders to miss the optimal time to execute the trades [3], [4]. Researchers suggest enhancements like using regression techniques on moving averages to eliminate the lag [2], [3]. In addition, using multiple technical indicators may improve the reliability of the decision but selecting the right combination of technical indicators is still very challenging. Some studies used backtesting as a tool to improve the technical indicator’s performance to have a more optimized trading strategy [8], [10].

Long Short Term Memory (LSTM) is a type of enhanced deep learning neural network that can efficiently learn patterns in long sequences of data [2], [4], [5]. Unlike traditional RNNs, the LSTM model contains a memory cell, which is a container that can hold information for an extended period [6], [14]. The primary objective of LSTM is to eliminate the vanishing gradient problem which is common in traditional RNNs [2], [4], [7], [14]. LSTM architectures are capable of learning long term dependencies in sequential data [13]. Hyperparameter tuning and preprocessing could potentially improve a model’s performance [5], [15]. Hence, LSTM has been adopted by researchers to predict the future stock market price. According to Piravechsakul et al. [4], Xue, Qin, and Fu [6] and Fahd et al. [7], LSTM contains a memory cell controlled by three different gates, being Input gate, Forget gate and Output gate [4], [6], [7].

Input Gate: Decides what new information should be added to the memory. It checks the current input and the past result, and filters important values to store, which is shown in Equation (1).

(1)

Forget Gate: Equation (2) determines what old information is no longer useful and can be removed from memory.

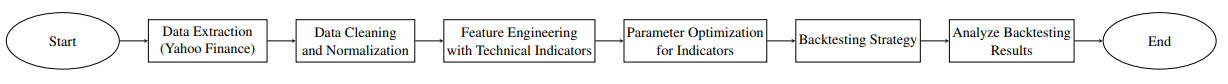
(2)

Output Gate: Controls what information from the current memory should be passed to the next step, which is shown in Equation (3).

(3)

# METHOD

This study develops a system that integrates LSTM model with a set of different combinations of technical indicators to analyze the stock market movements. The technical indicators selected are Moving Average Convergence Divergence (MACD), Average Directional Index (ADX), Commodity Channel Index (CCI), Bollinger Bands (BB), and On-Balance Volume (OBV) which each indicators have its own different abilities to capture different aspects of the market behavior. MACD identifies momentum shifts, while ADX measures the strength of a trend to filter out periods of low market directions. CCI highlights overbought and oversold conditions, Bollinger Bands identifies price volatility and potential breakout points, and OBV uses volume patterns to confirm the strength. By combining these indicators, it offers a balanced view of momentum, trend strength, volatility, and volume dynamics. To complement these technical indicators, an LSTM model is incorporated to forecast future prices, providing a predictive module that helps to better anticipate the market movements and improve trading decisions. Figure 1 explains the flow of this research.



**FIGURE 1.** Research framework

1. Data Extraction (Yahoo Finance): The historical market data for Apple Inc. (AAPL) is extracted from Yahoo Finance. The data consists of Datetime, Adjusted Close, Close, High, Low, Open and Volume.
2. Data Cleaning and Normalization: The price data is automatically adjusted for stock splits and dividends using Yahoo Finance’s auto\_adjust feature. The column names are normalized by flattening any multi-level columns and standardizing their formats. Forward filling and backward filling are applied to fill the existing gaps of prices. Rows that still have missing prices after filling are removed to maintain data integrity. Duplicate timestamps are dropped to ensure each timestamp appears only once. Additionally, the Datetime values are cleaned by removing any timezone information, making the timestamps consistent.
3. Feature Engineering with Technical Indicators: Once the data is cleaned, feature engineering is performed by calculating various technical indicators. The focused technical indicators, MACD, BB, CCI, ADX and OBV are derived from price and volume data. They serve to highlight market trends, momentum, volatility, and volume dynamics, primarily focusing on generating the buy and sell signals for informed trading decisions. The engineered features are then integrated into the dataset for subsequent analysis.
4. Parameter Optimization for Indicators: Each technical indicator has parameters (like the period of a moving average) that can significantly affect performance. Parameter optimization involves tuning these values to find the settings that yield the best results in backtesting.
5. Backtesting Strategy: After the indicators and parameters are set, the trading strategy is tested on historical data. Backtesting simulates how the strategy would have performed in the past to estimate its effectiveness and reliability. A multi-indicator strategy is also employed to observe how different combinations of indicators affect the results. When a buy or sell signal is indicated by the indicators, the LSTM model will be triggered to forecast the next hour stock price. The predicted stock price will be used to fulfill the conditions for the trading strategy. The logic behind the buy and sell decisions is based on two factors, the predicted price and the delta (∆). The delta (∆) is the difference of the current price and the predicted price. An adaptive threshold is implemented to calculate the market’s volatility. A buy is executed only if both of the following conditions are met: ∆ > adaptive\_thresh and the predicted price is greater than the current price. Similarly, a sell is executed only if ∆ < −adaptive\_thresh and the predicted price is lower than the current price.
6. Analyze Backtesting Results: The performance of the strategies are analyzed using metrics like Return, No. of Trades, Best Trade, and Worst Trade which are retrieved from back testing.

In this framework, the LSTM model is only used to predict the future prices. Rather than directly improving technical indicators, the LSTM provides price predictions that can complement indicator based strategies, offering a confirmation on the reliability of the trading strategy.

The delta (∆) is calculated as shown in Equation (4):

(4)

Equation 5 defines the adaptive threshold used to filter out insignificant price movements. It is calculated by scaling the 14-period Average True Range (ATR14) relative to the current price using a multiplier of 1.5. This ensures that the threshold dynamically adjusts to recent market volatility. A minimum threshold of 0.005 is enforced to prevent overly sensitive trading in low volatility conditions. The adaptive thresh is calculated in Equation (5).

(5)

The LSTM model will be triggered when a buy or sell signal is present. It uses 2 years historical data and takes in 48 time steps to learn historical trends and is trained on sequences of 72 steps, predicting one time step into the future. It consists of two LSTM layers, each with 32 hidden units, striking a balance between model complexity and efficiency. A dropout rate of 0.2 is applied to help prevent overfitting. Training is done with a batch size of 64 over 100 epochs, using the Adam optimizer with a learning rate of 0.001. The model incorporates a Gaussian likelihood to produce probabilistic forecasts, capturing prediction uncertainty. The LSTM model’s performance is assessed using MAE, RMSE, MAPE, SMAPE, and R². These metrics provide insight into both error magnitude and model reliability. Visual comparisons between predicted and actual prices are generated using Plotly.

# RESULTS AND DISCUSSION

The technical indicators are optimized using historical data of AAPL from the stock market using the date from 1st April 2024 to 1st April 2025 with one hour interval. The project also tested different combinations of technical indicators to analyze the effectiveness of multi-indicator strategy. The project starts with a base cash of 10000 USD and a commission of 0.2%.

Table 1 compares the performance of different trading strategies using traditional methods versus LSTM-based models, focusing on technical indicators such as MACD, Bollinger Bands (BB), CCI, ADX, and OBV. Most indicators show clear performance improvements under LSTM. For example, MACD’s return increased from 9.22% (traditional) to 25.57% (LSTM), with worst trade losses reduced from -$442.60 to -$263.09. ADX, which had a negative return of -0.81% under traditional trading, improved significantly to 31.42% under LSTM, and its worst trade dropped from -$340.84 to just -$0.62. Although CCI showed slightly lower returns under LSTM (19.83%) compared to traditional trading (24.44%), the worst trade loss improved drastically from -$635.87 to -$40.82. BB also saw a decrease in return from 52.62% to 19.92%, but again, with better downside protection, the worst trade losses dropped from -$63.55 to -$2.56.

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| **TABLE 1.** Performance metrics for different technical indicators | | | | | | | | |
| **Technical Indicators** | **Traditional Trading** | | | | **Trading with LSTM** | | | |
| **No. of Trades** | **Return (%)** | **Best Trade ($)** | **Worst Trade ($)** | **No. of Trades** | **Return (%)** | **Best Trade ($)** | **Worst Trade ($)** |
| MACD | 88 | 9.22 | 816.99 | -442.60 | 13 | 25.57 | 616.62 | -263.09 |
| BB | 11 | 52.62 | 1848.79 | -63.55 | 5 | 14.99 | 813.61 | 80.42 |
| CCI | 45 | 24.44 | 763.90 | -635.87 | 18 | 19.83 | 813.61 | -401.82 |
| ADX | 109 | -0.81 | 873.95 | -340.84 | 12 | 31.42 | 1095.88 | -0.62 |
| MACD + ADX | 15 | 9.38 | 1192.76 | -531.76 | 3 | 46.15 | 3324.77 | 205.19 |
| MACD + OBV | 66 | -10.52 | 816.99 | -1079.24 | 8 | 13.73 | 616.61 | -786.28 |
| BB + CCI | 11 | 52.62 | 1848.79 | -63.55 | 5 | 14.99 | 813.6083 | 80.42 |
| CCI + ADX | 4 | 34.03 | 2074.52 | -255.97 | 2 | 34.64 | 2074.52 | 1171.55 |
| CCI + OBV | 4 | 34.03 | 2074.52 | -255.97 | 11 | 35.15 | 773.30 | -32.23 |
| ADX + OBV | 109 | -0.81 | 873.95 | -340.85 | 5 | 31.42 | 1095.88 | -0.62 |
| MACD + ADX + OBV | 15 | 9.38 | 1192.76 | -531.7 | 3 | 46.15 | 3324.77 | 205.19 |
| CCI + ADX + OBV | 4 | 34.03 | 2074.52 | -255.97 | 2 | 34.64 | 2074.52 | 1171.55 |

LSTM had the most impact when indicators were combined. For instance, the combination of CCI + ADX + OBV yielded a 34.64% return and a best trade of $2074.52 under LSTM, compared to 34.03% and the same best trade under traditional methods, but the worst trade improved from -$255.97 to $1171.55. The top-performing multi- indicator LSTM strategy, MACD + ADX + OBV, achieved a 46.15% return, a best trade of $3324.77, and a greatly improved worst trade of $205.19 compared to -$531.70 in traditional trading. These results highlight that LSTM not only increases returns in most strategies but also significantly reduces downside risk, especially when integrating multiple indicators.

The technical indicators’ parameters are given a set parameter range to find the best pairing parameters which would yield the most return from 1st April 2024 to 1st April 2025. During this time frame, the best-performing MACD setup used a fast length of 20 and a slow length of 22, returning 9.22%. For Bollinger Bands, the top return of 52.62% came from a length of 13 and a standard deviation multiplier of 2.6. CCI worked best with a length of 10, yielding a 24.44% return. In contrast, ADX performed poorly across all top combinations, with the best return at -0.81% using a length of 25 and a threshold of 40. The selected parameters align with market conditions during the period. MACD (20, 22) reacts quickly to trends without excessive noise. Bollinger Bands (13, 2.6) effectively captured price extremes in a volatile range. CCI (10) focused on short-term momentum, suitable for quick shifts. ADX (25, 40) probably underperformed due to weak trend conditions, making it less effective despite tuning.

# CONCLUSION

Traditional trading using technical indicators is a crucial part of stock market analysis, but there are still many flaws. By integrating LSTM into stock market analysis, researchers have found ways to eliminate these problems as best as they could. However, volatility in the stock market will still create a lot of noise even though LSTM is incorporated into stock trading. This project aims to increase the effectiveness and efficiency of stock trading using optimized technical indicators with the help of the LSTM model to predict future stock prices, so that traders will suffer minimal losses even when the market suddenly becomes too volatile. In this project, the LSTM model was used to predict the next hour’s stock price, and trades were only executed when the predicted price movement was strong enough to indicate a meaningful change, helping to avoid reacting to minor fluctuations. The use of LSTM has been shown to improve returns and significantly reduce worst trade losses in most combination strategies. In particular, the combined indicator strategies under LSTM outperformed the single indicator approaches in both return and consistency, showing that integrating multiple signals through LSTM improves decision making and overall trading performance.

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