Coupling LSTM with Technical Indicator as Trading Strategy

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 sub-optimal returns. Artificial intelligence (A.I.) 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 worst trade losses (e.g., CCI 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 pattern-based tools derived from historical stock data, widely used to analyze price movements and inform trading decisions [1]. Although effective in conventional trading [2], they suffer from lag, as they depend on past data. For example, the MACD, based on short- and long-term EMA differences, often signals trades after significant price movements, causing missed opportunities [3, 4]. The rise of Artificial Intelligence (A.I.) addresses this limitation, with AI models processing large datasets rapidly and forecasting future trends [4]. When combined with technical indicators, AI enhances trading strategies by reducing lag and improving decision timing [2, 4, 5]. Recent studies have explored integrating LSTM models with technical indicators: Piravechsakul *et al.*[4] incorporated MACD, Bollinger Bands, and RSI as LSTM inputs [4]; Wiiava, Fatichah, and Saikhu[2] refined LSTM features using golden cross and death cross signals [2] ; Xue, Qin, and Fu[6] developed a multi-branch LSTM for separate indicator processing [6] ; Fahd *et al.*[7] showed that optimized indicators improve deep learning performance [7]; and 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 predicting 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

The integration of artificial intelligence (A.I.) in stock trading has gained substantial attention due to its potential to improve decision-making and optimize trading outcomes [2, 4, 5]. Stock prices are uncertain, nonlinear, and non-stationary, making accurate prediction challenging but potentially profitable [2, 9]. Central to this field is the use of technical indicators, which are mathematical calculations derived from historical price and volume data used by traders to identify trading opportunities [1, 2, 6].

Technical indicators are mathematical tools used by traders to analyze past market data—such as price, volume, and open/close levels—to forecast future price movements [1]. These indicators are categorized into four main types: trend, momentum, volatility, and volume [1]. Trend indicators like the Moving Average Convergence Divergence (MACD) identify directional movement using differences between short- and long-term EMAs to generate buy or sell signals [1, 4, 5]. The Average Directional Index (ADX) measures trend strength without indicating direction, making it useful for filtering out weak signals [1, 7]. Momentum indicators such as the Relative Strength Index (RSI) help identify overbought or oversold conditions, with RSI values above 70 or below 30 suggesting potential reversals [4, 10, 11]. Similarly, the Commodity Channel Index (CCI) measures price deviation from its moving average to highlight overbought or oversold market conditions [7, 9]. Volatility indicators like Bollinger Bands (BB) use standard deviations around a moving average to detect breakout opportunities and price extremes [4, 12], while the Average True Range (ATR) assesses overall market volatility and is often used to set stop-loss levels [1, 5]. Finally, On-Balance Volume (OBV), a volume-based indicator, tracks the cumulative volume based on whether prices close higher or lower, providing confirmation for trend direction and potential reversals [1, 8, 13].

$$MACD_t = EMA_{12}(P_t) - EMA_{26}(P_t), \quad \text{Signal Line}_t = EMA_9(MACD_t) \tag{1}$$

$MACD_t$ is the Moving Average Convergence Divergence value at time t, Signal Line_t is the 9-period Exponential Moving Average of the MACD, $EMA_n(P_t)$ represents the n-period EMA of the closing price P_t, and $EMA_n(MACD_t)$ is the n-period EMA of the MACD.

$$UpperBand_t = SMA_t + k \cdot \sigma_t, \quad LowerBand_t = SMA_t - k \cdot \sigma_t \tag{2}$$

Bollinger Bands consists of the Upper ($UpperBand_t$) and Lower ($LowerBand_t$) Bollinger Bands at time t, SMA_t is the Simple Moving Average of closing prices over N periods, σ_t is the standard deviation of closing prices over N periods, and k is the band width multiplier, typically set to 2.

$$ADX_t = \frac{100}{N} \sum_{i=t-N+1}^{t} \frac{|+DM_{s,i} - -DM_{s,i}|}{+DM_{s,i} + -DM_{s,i}} \tag{3}$$

ADX_t is the Average Directional Index at time t, $+DM_{s,i}$ and $-DM_{s,i}$ are the smoothed Positive and Negative Directional Movements at time i, and N is the smoothing period, typically 14.

$$CCI_t = \frac{TP_t - \left(\frac{1}{N}\sum_{i=t-N+1}^{t} TP_i\right)}{0.015 \times \left(\frac{1}{N}\sum_{i=t-N+1}^{t} \left|TP_i - \left(\frac{1}{N}\sum_{i=t-N+1}^{t} TP_i\right)\right|\right)} \tag{4}$$

CCI_t is the Commodity Channel Index at time t, TP_t is the Typical Price at time t calculated as $\frac{H_t+L_t+C_t}{3}$, N is the number of periods used for smoothing, and H_t, L_t, and C_t are the High, Low, and Closing prices at time t.

$$OBV_t = \begin{cases} OBV_{t-1} + V_t & \text{if } C_t > C_{t-1} \\ OBV_{t-1} - V_t & \text{if } C_t < C_{t-1} \\ OBV_{t-1} & \text{if } C_t = C_{t-1} \end{cases}$$

OBV_t is the On-Balance Volume at time t, OBV_{t-1} is the previous On-Balance Volume, V_t is the trading volume at time t, and C_t and C_{t-1} are the closing prices at time t and $t-1$ respectively.

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]. Emotional decision-making further complicates trading outcomes, especially in uncertain markets like during COVID-19 [1]. Although widely used, technical indicators often fall short due to their lagging nature and limited predictive power. For example, Moving Averages react after significant price shifts, potentially missing optimal trade opportunities [3, 4]. Researchers suggest enhancements, such as transforming indicator signals or using techniques like regression on moving averages to improve responsiveness [2, 3]. Moreover, selecting the right combination of indicators remains challenging due to inconsistencies across signals and context-dependent effectiveness. Studies emphasize the importance of individualized indicator evaluation and backtesting as essential tools to optimize trading strategies [8, 10].

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to effectively learn and retain patterns over long sequences of data [2, 4, 5]. Unlike traditional RNNs, LSTMs model address this problem by introducing a memory cell, which is a container that can hold information for an extended period [6, 14]. LSTM is also designed to overcome the limitations of traditional RNNs, such as the vanishing gradient problem [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.

$$i_t = \sigma(W_i \cdot x_t + U_i \cdot h_{t-1} + b_i) \tag{5}$$

Forget Gate: Determines what old information is no longer useful and can be removed from memory.

$$f_t = \sigma(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f) \tag{6}$$

Output Gate: Controls what information from the current memory should be passed to the next step.

$$o_t = \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \tag{7}$$

METHOD

This study develops an AI-driven trading bot that integrates Long Short-Term Memory (LSTM) models with the selected technical indicators to analyze the stock market trading. 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) due to their ability to capture different aspects of market behavior. MACD identifies momentum shifts and trend reversals, while ADX measures the strength of a trend, helping to filter out periods of low market direction. CCI highlights overbought and oversold conditions relative to historical averages, Bollinger Bands visualize price volatility and potential breakout points, and OBV uses volume patterns to confirm the strength behind price movements. Together, these indicators offer 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 in better anticipation of the market movements and improve trading decisions.

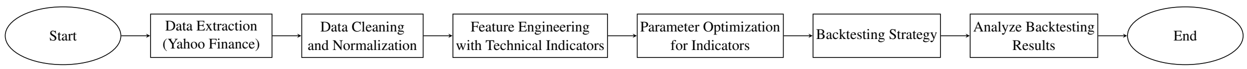

FIGURE 1. Research Framework

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 next hour stock price will be used to fulfill one of the condition for the trading strategy. The logic behind the buy and sell decisions is based on two factors, the predicted price and the delta (Δ). A calculated value called *delta* (Δ), which represents the relative difference between the predicted price and the current price. An adaptive threshold is introduced to account for changing market volatility. A buy is executed only if both of the following conditions are met: $\Delta > \texttt{adaptive\_thresh}$ and the predicted price is greater than the current price. Similarly, a sell is executed only if $\Delta < -\texttt{adaptive\_thresh}$ 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 backetesting.

In this framework, the LSTM (Long Short-Term Memory) model is used specifically to forecast future prices based on historical data. Rather than directly analyzing or enhancing the technical indicators, the LSTM provides price predictions that can complement the indicator-based strategies, offering an additional signal to guide trading decisions.

The delta (Δ) is calculated as followed:

$$Delta(\Delta) = \frac{\text{Predicted Price} - \text{Current Price}}{\text{Current Price}} \tag{8}$$

The adaptive thresh is calculated as followed:

$$Adaptive\_Thresh = \max\left(0.005, \frac{\text{ATR}_{14}}{\text{Current Price}} \times 1.5\right) \tag{9}$$

Equation 9 defines the adaptive threshold used to filter out insignificant price movements. It is calculated by scaling the 14-period Average True Range (ATR_{14}) 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 LSTM model's performance is assessed using MAE, RMSE, MAPE, SMAPE, and R^2. These metrics provide insight into both error magnitude and model reliability. Visual comparisons between predicted and actual prices are generated using Plotly.

FINDINGS

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 commision of 0.2%.

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

The table 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% traditionally, 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—worst trade losses dropped from -$63.55 to -$2.56.

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 across 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, suiting quick shifts. ADX (25, 40) underperformed likely 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 in it. By integrating LSTM into stock market analysis, researchers have found ways to eliminate these problems as best as they could. However, the volatility of 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 traders will suffer minimal loss 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 shown to improve returns and significantly reduce worst trade losses across most strategy combinations. Notably, combined indicator strategies under LSTM outperformed single-indicator approaches in both return and consistency, showing that integrating multiple signals through LSTM enhances decision-making and overall trading performance.

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