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RESEARCH ARTICLE

Predicting Malaysian stock market with relative strength index and moving average convergence-divergence indicators using long short-term memory

S. Khairudin[1], N.A. Ramli[1,*] and L.J. Awalin[2]

[1]Centre for Mathematical Sciences, Universiti Malaysia Pahang Al-Sultan Abdullah, Lebuh Persiaran Tun Khalil Yaakob, 26300 Gambang,Kuantan, Pahang, Malaysia
[2]Department of Engineering, Faculty of Advanced Technology and Multidicipline, Universitas Airlangga, Jl. Mulyorejo, Surabaya 60115, Indonesia

ABSTRACT - Some Malaysians hold stocks or mutual funds, and majority of them are new investors. Bursa Malaysia's CEO stated that based on stock exchange data up to 2022, there are 80.8 million units of odd lot shares in Central Depository System (CDS) accounts, which has been expanding over the years. However, many people still need to learn how to use technical indicators for investing. Even though many researchers have used the Relative Strength Index (RSI) and Moving Average Convergence-Divergence (MACD) on other stock markets throughout the globe, there are limited studies that have been utilizing both indicators in the Malaysian stock market. This study mainly focuses on developing predictive modeling for individual investors, specifically RSI and MACD indicators on conventional Malaysian stock. Our research hypothesis is that the machine learning (ML) approach, the Long Short-Term Memory (LSTM) technique, can predict the Malaysian stock market. By combining the RSI and MACD indicators with LSTM, this study explores the possibilities of timing (buy and sell signals) in Malaysian stock market. This study used daily data gathered from the KLCI Index from 2011 until 2021. Performance metrics, including mean return, standard deviation risk ratio, and Sharpe ratio, were calculated, and hypothesis testing was conducted using t-tests on mean return and F-tests for risk comparison. The empirical data from the Malaysian market demonstrated that the RSI and MACD indicators combined with ML provide a considerable excess return. This strategy is applicable to Malaysia's conventional stock market since it generates an excess profit. The results show that MACD-LSTM provides more profitable trading than RSI-LSTM.

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1. INTRODUCTION

There is at least one way for people to make their money work for them. While there is legal guidance on personal finance, only a handful of individuals know how to put that advice into practice. There are dozens of investments from around the world from which to select. Money has always depreciated, so people prefer to invest it and earn high profits so that it can appreciate rather than retain its value. Smart et al. defined investment as the amount of funds or capital that can be put into a business venture, capital investment, or corporate development to double profits or raise capital [1]. Furthermore, Warren Buffett, a legendary investor, defined investing as setting money aside to earn extra in the future [2].

Nowadays, some Malaysians already hold stocks or mutual funds, most of whom are new investors. As of July 31, 2018, 1.9 million people were registered and making use of their CDS accounts, according to reports. Furthermore, it was stated that Bursa Malaysia opened more than 40% of CDS accounts for Gen Z members who were 25 years of age or younger in 2019 [3]. Furthermore, Bursa Malaysia's Chief Executive Officer stated that, based on stock exchange data up to October 30, 2022, there are 80.8 million units of odd lot shares in CDS accounts, which has been expanding over the years. Additionally, it was noted that the fastest-growing demographic in that year was millennials.

According to Koh and Fong, one of the primary benefits of investing in stocks is that investors have earned significantly better returns than fixed-income products [4]. Nonetheless, the investment is associated with greater year-to-year volatility in stock returns, and there is no assurance that investing in stocks will not lead to a capital loss. As a result, it is advised that investors give adequate understanding about investing in decision-making.

Retail investors may use fundamental and technical analyses to invest in the stock market. Analysts and investors currently rely on multiple approaches to know about the future of the markets to create accurate outcomes [5]. It is known that there are two different types of markets in Malaysia: conventional markets and shariah-compliant markets. In the conventional stock market, shares of a corporation are purchased, sold, or traded. In contrast, the Islamic Capital Market (ICM), a trading stock market that complies with Shariah, was created based on the Qur'an and Sunnah. Investment is screened to determine and validate their compliance with Sharia law.

*CORRESPONDING AUTHOR | N.A. Ramli| ✉ azuana@umpsa.edu.my

This research focuses on conventional stock market technical indicators, mainly using the Relative Strength Index (RSI) and Moving Average Convergence-Divergence (MACD). Analysis tools like RSI and MACD can assist investors in timing their stock purchases and sales for their portfolio. The primary goal of individual investors is to determine the best price point to buy or sell, which is what indicators are designed to measure. Several researchers have implemented RSI and MACD across various stock markets worldwide, however more significant studies need to be conducted using both indicators in the Malaysian stock market, mainly using the machine learning (ML) algorithm. Moreover, majority technical analysis research in Malaysia generally uses other indicators, such as momentum readings, moving averages, stochastic, candlestick patterns, and random indexes. Table 1 highlights the research gap in this study compared to previous studies that had been done.

Table 1. Comparisons between models

Decisive factor	Model in this research	Previous models
Methodology	- Using LSTM along with investment indicators, RSI and MACD. - The combination of RSI-LSTM and MACD-LSTM, the models can be more powerful, higher accuracy also minimize errors	- Lack of significant studies using RSI and MACD indicators in the Malaysian stock market. - Lack of studies of LSTM, machine-learning algorithm, with financial, investment, and technical indicators under one research.
Indicators	- Using the efficiency of two indicators, RSI and MACD with LSTM in the Malaysian stock market. - Evaluate the RSI-LSTM and MACD-LSTM to identify the profitability of the Malaysia's conventional stock market.	- Majority of the technical analysis research did in Malaysia normally use other indicators, such as moving average and stochastic. - Difficult to find the hybrid of technical indicators along with LSTM in the Malaysian stock market.
Sample Data	- The Financial Times Stock Exchange (FTSE) Bursa Malaysia Kuala Lumpur Composite Index (KLCI) from 1st January 2011 until 31st December 2021 (11 years) daily index prices.	- Different studies have different samples of countries and data. - Lack of research that uses the FTSE Bursa Malaysia KLCI Index as data.

Our research hypothesis is that the ML approach, the Long Short-Term Memory (LSTM) technique, can predict the Malaysian stock market. Both indicators are combined with LSTM as the objective of this study is to survey the possibilities of timing (buy and sell signals) using RSI and MACD indicators in Malaysian stock markets employing LSTM. This study employed a hybrid of LSTM techniques with RSI and MACD indicators due to its novelty in the financial industry in the Malaysian stock market. This strategy helps predict market moves or volatility that may increase returns. Nevertheless, only a few Malaysian investors are aware of these strategies.

Our approaches, as mentioned earlier, lead to the following main finding. Our results imply that even though the potential movement of the market is difficult to predict, the use of LSTM will provide a solution for investors regarding when to invest. It demonstrated that from predicted prices for both modeling using RSI and MACD indicators; investors tend to know when to gain an expected return, which this simple trading rule can determine. The analysis in this study also showed that the predicted price of the KLCI Index has a significant difference, which shows that this modelling can be used to predict the stock price.

Our study contributes to the literature that used ML applications in predicting the stock markets, such as the study by Moghar and Hamiche that used LSTM in predicting the New York Stock Exchange (NYSE), which are Alphabet Inc. (GOOGL) and NIKE, Inc. (NKE) [6]. Another similar study combined RSI-LSTM and MACD-LSTM to predict the Brazilian stock exchange (BOVESPA) by Nelson et al. in 2017 [7]. To our knowledge, a similar method has been applied to the Malaysian stock market. Therefore, our study is the first to apply such a method to the Malaysian stock market, and the results contribute to literature involving the Malaysian stock market.

Finally, we also conducted test statistics such as the F-test and t-test to evaluate and compare the risks and returns, reflecting RSI-LSTM and MACD-LSTM's performance. The following section will explain all the methods applied in this study. Then, all the results are presented and discussed in the subsequent section before the concluding remarks, and recommendations to improve this study are provided in the final section.

2. METHODOLOGY

In this section the details of research conducted are discussed. Partitioning on seven different sections, this process starts with sampling data and ended with the performance measurement.

2.1 Sample data

The data used for this study were collected through the FTSE Bursa Malaysia KLCI covered from 1st January 2011 until 31st December 2021. Furthermore, a three-month dataset from Kuala Lumpur Interbank Offered Bank (KLIBOR) will act as a risk proxy for the constant interval in this study. This study used a large dataset since it offers several benefits and addresses specific challenges in predictive modeling as a more extensive dataset leads to more statistically significant results, a model trained on a larger dataset is likely to be more robust and generalizable, and a large dataset helps mitigate sampling bias. It smooths out data volatility, resulting in more stable and reliable predictions.

2.2 Development of a predictive modelling using long-short term memory

The data of the KLCI Index for 11 years was used with the combination of RSI-LSTM and MACD-LSTM for predictive modeling. Following its extraction from investing.com, the data was normalized as a part of data pre-processing. The calculation of the RSI and MACD technical indicators was done next. The outcomes from the calculation were utilized to create a stock data trend chart, which was used to provide buy and sell signals for the KLCI Index. The new dataset of various RSI and MACD was divided into two datasets: a training dataset and a testing dataset for each technical indicator.

First, the LSTM model was developed and trained using the training data, while the test dataset will be used for model testing. In order to compare results on the same days, this study used a similar test and train dataset. The model was trained using ADAM optimizer, with a batch size equal to 32 and epochs set to 50. The model will produce a set of prediction datasets by using the test dataset. This dataset was combined with the training dataset to rebuild the model, and the process was repeated until the desired outcomes were obtained. Finally, the results were extracted and explained using charts. Figure 1 shows the flowchart on how the combination of technical analysis with LSTM was utilized in this study.

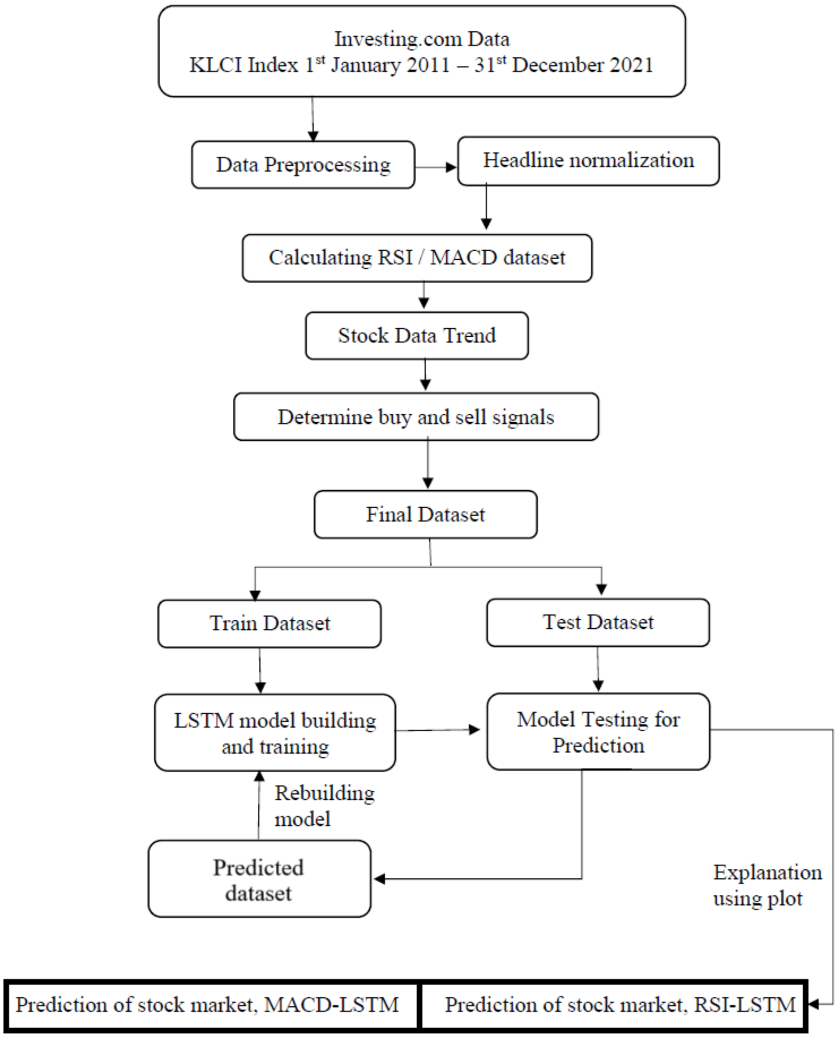

Figure 1. Machine Learning processes with the combination of technical indicators, RSI-LSTM and MACD-LSTM

2.3 Long-short term memory

The LSTM network has the ability to differentiate between recent and earlier examples and it is a form of recurrent network (RNN). Different weights are assigned to each example, and irrelevant memory is omitting to forecast the future output. In this regard, it outperforms other RNNs that can memorize short sequences.

The initial step in an LSTM network cell involves determining whether to retain or eliminate the data from the previous timestamp. The equation for the forget gate is as follows:

$$f_t = \sigma(X_t * U_f + H_{t-1} * W_f) \tag{1}$$

where f_t is the forget gate, X_t is the input to the current timestamp, U_f is the weight associated with the input, H_{t-1} is the hidden state of the previous timestamp, and W_f is the weight matric associated with hidden state.

Then, a sigmoid function is applied to the forget gate equation (1). If f_t is 0, the network will forget everything, and if f_t is 1, the network will retain all previous information.

$$\begin{aligned} C_{t-1} * f_t &= 0 \quad && \text{if } f_t = 0 \\ C_{t-1} * f_t &= C_{t-1} && \text{if } f_t = 1 \end{aligned} \tag{2}$$

where C_{t-1} is the cell state at the current timestamp. The input gate is then used to assess the importance of the new data brought in by the input as shown in the equation below:

$$i_t = \sigma(X_t * U_i + H_{t-1} * W_i) \tag{3}$$

where i_t is the input gate. The new data that must be supplied to the cell state is now a function of a hidden state at timestamp *t-1* and input *x* at timestamp *t*.

$$N_t = \tanh(X_t * U_c + H_{t-1} * W_c) \tag{4}$$

$$C_t = (f_t * C_{t-1} + i_t * N_t) \tag{5}$$

where N_t is called new information and C_t is the long-term memory. The next following equations are the equations of the output, where o_t is the output gate, H_t is the hidden state and $Output$ is the prediction.

$$o_t = \sigma(X_t * U_o + H_{t-1} * W_o) \tag{6}$$

$$H_t = o_t * \tanh\,(C_t) \tag{7}$$

$$Output = Softmax(H_t) \tag{8}$$

2.4 Relative strength index (RSI) indicator

RSI is an indicator that measures momentum (velocity of directional price movement) in the stock price movement. The RSI indicator oscillates between 0 and 100, as well as, between 70 and 30, indicating whether the asset is overbought or oversold. The 14-day RSI is a common length of time used by investors.

$$U_t = \begin{cases} P_t - P_{t-1}, & if, \quad P_t > P_{t-1} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

$$D_t = \begin{cases} P_{t-1} - P_t\,, & if, \quad P_{t-1} > P_t \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where U_t is up-closes*,* D_t is the down-closes*,* and P_t is the closing price, all in the period *t.* The next equation is to define as:

$$\overline{U}_t = \frac{\sum U_t}{N} \tag{11}$$

$$\overline{D}_t = \frac{\sum D_t}{N} \tag{12}$$

where $\overline{U}_t$ is the average gain, $\overline{D}_t$ is the average loss and N is the number of RSI periods. The divided averages give the Relative Strength (RS):

$$RS_t = \frac{\overline{U}_t}{|\overline{D}_t|} \tag{13}$$

The *RSI* over *N* periods at time *t* is then defined as:

$$RSI_t(N) = 100 - \frac{100}{1 + RS_t} \tag{14}$$

The combination of the above equations and the reordering will result in the following:

$$RSI_t(N) = \frac{\sum_{i=0}^{N-1}(P_{t-i} - P_{t-i-1})1\{P_{t-i} > P_{t-i-1}\}}{\sum_{i=0}^{N-1}|P_{t-i} - P_{t-i-1}|} \times 100 \tag{15}$$

$$\begin{gathered} 1\{P_{t-i} > P_{t-i-1}\} = 1, if\ true \\ 1\{P_{t-i} > P_{t-i-1}\} = 0, if\ false \end{gathered} \tag{16}$$

where $RSI_t(N)$ is Relative Strength Index at time *t*.

2.5 Moving average convergence-divergence (MACD) indicator

The MACD indicator consists of short-term and long-term Exponential Moving Averages (EMAs), which are lagging indicators used to predict whether a trend will continue or reverse. These lagging indicators are converted into momentum indicators by subtracting the short-term and long-term moving averages (Mas). In a standard design, the period for creating the first line is 12 and 26 days. The indicator was calculated using two lines, made of EMA, which is defined as:

$$EMA_t(N) = (\alpha \times P_t) + (1 - \alpha) \times EMA_{t-1}(N) \tag{17}$$

where the value of α is defined as:

$$\alpha = \frac{2}{(N + 1)} \tag{18}$$

The EMA over *N* periods at time *t* is then calculated as:

$$EMA_t(N) = \left[\frac{2}{N} \times (P_t - EMA_{t-1}(N))\right] + EMA_{t-1}(N) \tag{19}$$

where EMA_t is the Exponential Moving Average at time *t*, P_t is the price of the asset at time *t* and $N$is the number of days. The first indicator is MACD line, it can be calculated as:

$$MACD = \sum_{i=1}^{N} EMA_k - \sum_{i=1}^{N} EMA_d \tag{20}$$

where EMA_k is the current value of the first *EMA* (shorter period) and EMA_d is the current value of the second *EMA* (longer period). The second indicator is named signal line, and it is formed with the MA of nine data from the MACD line:

$$MACD_{signal} = EMA_d\ of\ MACD \tag{21}$$

2.6 Performance measurement

Measuring investment success is essential as it allows investors to assess the effectiveness of their decisions and identify if adjustments to their strategy are needed. In other words, performance measurement acts as a tool for investors to evaluate the potential of their portfolios. Currently, there are four methods for evaluating portfolio performance. The Treynor and Sharpe ratios both combine risk and return into a single metric, although each serves a distinct purpose.

2.6.1 Risk and return

Return is often referred to as capital gain and represents the money earned (profit) or lost from an investment over time. In financial terms, risk is defined as the possibility that the actual results or returns of an investment will differ from the expected outcomes. It also reflects the degree of uncertainty or potential financial loss associated with an investment decision. There is a positive correlation between return and risk; typically, higher returns are associated with higher risks, which is known as the return-risk trade-off. Investors must be willing to take on more risk to achieve higher expected returns. In terms of calculation, return can be expressed nominally as the change in an investment's price over time, while risk can be assessed using standard deviation.

The return of stock, *i,* on day, *t,* is given by:

$$r_{it} = \frac{P_1 - P_0}{P_0} \tag{22}$$

where r_{it} is the return of stock *i* on day *t*, P_0 is the price of stock on day *t* while P_1 is the price of stock on day *t*-1. The risk is measured using standard deviation.

2.6.2 Sharpe ratio

William F. Sharpe created the Sharpe ratio in 1996, which compared the portfolio's standard deviation of return to the risk premium [8]. The overall return of the portfolio less the free-rate risk is the portfolio risk premium. An investor's ability to distinguish profits linked to risk-taking behaviors will be improved by deducting the risk-free rate from the mean return. The risk-adjusted return is often more appealing as the Sharpe ratio increases. The following is the formula for the Sharpe ratio:

$$S_p = \frac{\bar{r}_p - \bar{r}_f}{\sigma} \tag{23}$$

where $\bar{r}_p$ is the rate of return of stock and $\bar{r}_p$ is the risk-free rate.

2.6.3 Treynor ratio

Treynor has established a portfolio performance metric similar to the Sharpe ratio. However, the Treynor ratio calculated price risk using portfolio beta and concentrated entirely on systematic risk. As a result, a greater ratio outcome is more positive, implying that a portfolio is more likely to be a profitable investment. The Treynor ratio is determined as below:

$$T_p = \frac{\bar{r}_p - \bar{r}_f}{\beta_p} \tag{24}$$

where β_p is beta index of the KLCI index.

2.7 Comparing risk and return

This research compared RSI and MACD indicators in the standard index. The comparison was reached by measuring both the risk and return. In addition, a two-sample hypothesis test was made to monitor the correlation between the two indexes.

2.7.1 Two samples of F-test for difference in variance

The F-test, based on the F-distribution, is used in relation to the null hypothesis. This test enables investors to statistically determine whether two population groups with normally distributed data have equal standard deviations. In this research, a one-tailed F-test was utilized to assess the equivalence of the two variances. The test was carried out under the following null and alternative hypotheses:

$$H_0: \sigma_1^2 = \sigma_2^2$$
$$H_1: \sigma_1^2 \neq \sigma_2^2$$

while test statistic (F-distribution):

$$F = \frac{{s_1}^2}{{s_2}^2}, {s_1}^2 \geq {s_2}^2 \tag{25}$$

and degrees of freedom:

$$df_1 = n_1 - 1, \quad df_2 = n_2 - 1 \tag{26}$$

where σ_1^2 is the variance of RSI return, σ_2^2 is the variance of MACD return, df_1 is the numerator degrees of freedom and df_2 is the numerator degrees of freedom.

2.7.2 Two samples of t-test for difference in means

In contrast to the F-test, the t-test was used to determine whether there is a significant difference between the averages of the two groups, which may be related to certain characteristics. Using the appropriate formulas, specific values were calculated and compared to standard values, leading to the acceptance or rejection of the expected null hypothesis. The t-test was conducted based on the following null and alternative hypotheses:

$$H_0: \mu_1 = \mu_2$$
$$H_1: \mu_1 \neq \mu_2$$

with t-test statistic value:

$$t = \frac{(\bar{r}_1 - \bar{r}_2) - (\bar{\mu}_1 - \bar{\mu}_2)}{\sqrt{\frac{S_p}{n_1} + \frac{S_p}{n_2}}} \tag{27}$$

and degrees of freedom:

$$df = n_1 + n_2 - 2 \tag{28}$$

where $\bar{r}_1$and $\bar{r}_2$ are the sample mean return of RSI and MACD return, $\bar{\mu}_1$and $\bar{\mu}_2$ are the population mean of RSI and MACD respectively, n_1 and n_2 are the sample size of RSI and MACD, and S_p is the pooled standard deviation.

3. RESULTS AND DISCUSSION

Based on the methodology explained in the previous section, LSTM was applied to develop predictive modeling for the Malaysian stock market based on two different indicators. Figure 2 shows the results obtained when LSTM was applied to the RSI indicator. It shows that the results can be used to foresee stock prices because the difference between the actual KLCI Index price and the predicted price using this method significantly differs. Additionally, these two datasets have substantially identical indications of falling and rising stock prices. Consequently, it can be roughly claimed that market price predictions can be made using RSI-LSTM predictive modeling.

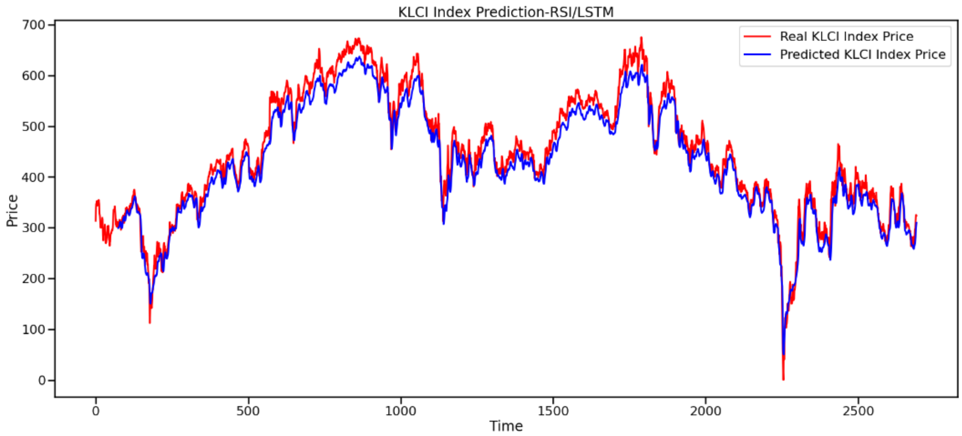

Figure 2. KLCI Index price prediction using RSI and LSTM

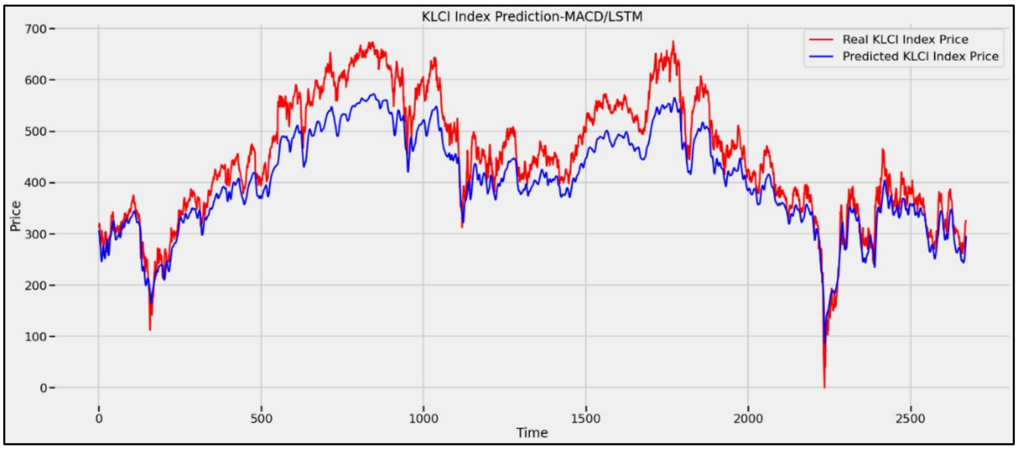

Figure 3. KLCI Index Prediction of MACD-LSTM

Figure 3 shows the results obtained using LSTM combined with the MACD indicator. It illustrates that LSTM can be employed to predict stock prices due to the difference between the actual KLCI Index price and the predicted price is significant. Even though there is a large spread between the actual and predicted prices, the MACD-LSTM model shows that the price fluctuation or downtrend is mostly the same as the actual price. This means that this predictive model can be used, as evidenced by the chart. Additionally, most of the falling and rising stock price indicators are nearly identical in these two datasets. However, based on the comparison from Figure 2 and Figure 3, it is clearly shown that the prediction obtained using RSI indicators is close to the actual KLCI Index price compared to the prediction obtained using the MACD indicator. Since it is not enough to see which model performs better just by looking at the graph, the model performance was measured using risk and return, Sharpe, and Treynor ratios.

Table 2 shows the risk and return of the predictive modeling of technical indicators: MACD, RSI with machine learning algorithm, LSTM. Based on Table 2, the total period of 2672 days for the KLCI index showed that the actual average mean is 0.1190%, for RSI-LSTM predictive price average mean is 0.1047%, and -0.1131% for MACD-LSTM. Predictive modeling and the actual market price indicate a return but slow down during the period.

Table 2. Risk and return

KLCI Index	Actual	RSI-LSTM	MACD-LSTM
Mean	0.1190%	0.1047%	0.1131%
Std Dev	5.2937%	4.5631%	5.0400%

Regarding risk, with 4.5631% and 5.0400%, RSI-LSTM has the lowest standard deviation compared to MACD-LSTM. Even though MACD-LSTM standard deviation is higher than RSI-LSTM, it is still lower than the actual standard deviation of the actual KLCI Index price. This result shows that the actual KLCI Index price has the highest return or profit with the highest risk, and RSI-LSTM has the lowest standard deviation/risk with the lowest mean/return. Generally, having a higher standard deviation would be dangerous because it is more unpredictable. In this research, the approach focuses more on the individual investor who wants to reduce the risk but stabilize the return instead of higher returns with higher risk.

The results in Table 3 are extracted from the collections of the daily return of predicted price from RSI-LSTM and MACD-LSTM. The analysis finds that the p-value of T-Statistic is 6.03248e^{-42}, which is less than the significant level (α=0.01). This means a significant difference exists between the return on the predicted price of RSI-LSTM and MACD-LSTM. It interprets that we have sufficient evidence to say that the mean return of RSI-LSTM and MACD-LSTM is not equal. Thus, the null hypothesis which is $H_0: \mu_1 = \mu_2$ is rejected. Hence, both predictive models significantly differ in average mean return.

Table 3. Two sample F and t-test for RSI-LSTM and MACD-LSTM strategies

t-Statistic	t-Statistic (p-value)	F-Statistic	F-Statistic (p-value)
13.69118	$6.03\text{x}10^{-42}$	1.30899	$3.25 \text{ x } 10^{-12}$

At the same time, the p-value of the F-Statistic is $3.25 \text{ x } 10^{-12}$, which is also less than α=0.01. The analysis shows that both predictive modeling has different variances since the outcome at either stage indicates significance at any level. This means that the data provides sufficient evidence to show that the variances of RSI-LSTM and MACD-LSTM are the same. Hence, it seems to reject the null hypothesis, which is $H_0: \sigma_1^2 = \sigma_2^2$. This indicates that RSI-LSTM and MACD-LSTM have different levels of risk. The results of both tests show that both predictive models significantly differ in risk and return. It also implies that MACD-LSTM has a higher return compared to RSI-LSTM. However, RSI-LSTM has a lower risk compared to it. It also concludes that both predictive modeling can be used to forecast stock prices, which will lead to higher returns and lower risk compared to the actual price of the KLCI Index.

Table 4 shows that the Sharpe ratio of the predicted price of RSI-LSTM is more profitable than that of MACD-LSTM. The RSI-LSTM predicted price offers the highest return per unit of price risk, with a total return of 0.02295 over 11 years, while the MACD-LSTM predicted price provides a return-to-risk ratio of 0.02245. This indicates that RSI-LSTM performs better in terms of risk-adjusted returns across all stocks invested compared to MACD-LSTM. Even though the return of MACD-LSTM is higher than RSI-LSTM, the value above shows that the MACD-LSTM predicted price is riskier than RSI-LSTM with 5.0400% and 4.5631%. In other words, the actual and MACD-LSTM Sharpe ratio gives a higher return than RSI-LSTM predicted price strategies; however, the standard deviations are higher, thus giving the lower Sharpe ratio. A lower mean return will not necessarily affect the lower Sharpe ratio.

However, both predicted prices show that both strategies can give an excess return with lower risk, especially the RSI-LSTM, with only a 0.0186% difference compared to the actual price of the KLCI Index. Even though the RSI-LSTM and MACD-LSTM predicted prices are lower than the actual price, they still give a higher Sharpe ratio than the actual price, 0.01966. It shows investors can still gain excess returns from investments using technical indicators and machine learning algorithm strategies, specifically RSI-LSTM and MACD-LSTM.

Table 4. Sharpe ratio

KLCI Index	Actual	RSI-LSTM	MACD-LSTM
Return	0.1190%	0.1047%	0.1131%
Std Dev	5.2937%	4.5631%	5.0400%
RF	0.0149%	0.0149%	0.0149%
Beta	1.0000	1.0000	1.0000
Sharpe Ratio	0.01966	0.02295	0.02245

Lastly, the Treynor ratio was applied to measure the model's performance. Table 5 shows that the Treynor ratio of MACD-LSTM prediction is more suitable for investment than RSI-LSTM. MACD-LSTM gives the highest return per portfolio beta, with a total of 0.1131% over 11 years, while RSI-LSTM prediction gives a ratio of -0.1047% of return over its portfolio risk. This means that MACD-LSTM is better at risk-adjusted to systematic risk than RSI-LSTM strategies.

Table 5. Treynor ratio

KLCI Index	Actual	RSI-LSTM	MACD-LSTM
Return	0.1190%	0.1047%	0.1131%
Std Dev	5.2937%	4.5631%	5.0400%
RF	0.0149%	0.0149%	0.0149%
Beta	1.0000	1.0000	1.0000
Treynor	0.1041%	0.1047%	0.1131%

These results show that technical indicators and machine learning strategies can give excess returns despite systematic risk. It is because the Treynor ratio for RSI-LSTM and MACD-LSTM is higher than the actual Treynor ratio, which is 0.1131% for MACD Treynor ratio and 0.1047% for RSI-LSTM's Treynor ratio. It shows investors can still gain an excess return from both strategies, even with systematic risk.

Individual investors can utilize the RSI (14, 30/70) rule from the study to time their market entries and exits as they see fit. The effectiveness of the RSI and MACD indicators, when applied through machine learning algorithms, was assessed based on the profitability of the predicted prices. The annualized risk and return results show many differences for both perspectives as an individual investor for both predictive modeling. As shown in Table 5, an individual investor's highest profit is 0.1131% for MACD-LSTM and 0.1047% for RSI-LSTM. It shows that both market portfolios are positive in mean return. It also shows that both predictive modeling returns will likely have the same amount as the actual KLCI Index price.

Based on the findings, even though the potential movement of the market is difficult to predict, using a machine learning algorithm, namely LSTM, will give the investor a solution as to when to invest. It demonstrated that predicted prices for both models using RSI and MACD indicators, investors tend to know when to gain an expected return, which this simple trading rule can determine. The analysis above also showed that the predicted price of the KLCI Index has a significant difference from the actual price, which shows that this modeling can be used to predict the stock price. RSI-LSTM and MACD-LSTM are powerful predictive models that retail investors can use to earn profitable trading for the KLCI Index. Based on the findings, both predictive models provided some profitable investment in which both will receive a positive return. This study used performance measurements, risk and return, Sharpe ratio, and Treynor ratio to analyze the efficiency of predicted prices of RSI-LSTM and MACD-LSTM. Both predictive models showed the bright side because both are outperforming the market. However, MACD-LSTM provides a higher means of earning money or is more profitable than RSI-LSTM.

This study also shows a significant difference between Malaysia's two predicted stock prices. Test statistics such as F-test and t-test were applied to evaluate and compare the risks and returns, reflecting RSI-LSTM and MACD-LSTM's performance. From an overall performance perspective, MACD-LSTM is more profitable than RSI-LSTM. However, the research shows that, despite the slowdown in the market, investment in the KLCI Index using this predictive modeling can produce a return and minimize the loss. This method can still give individual investors' confidence to invest in the KLCI Index as the performance remains higher and can still predict the stock price. Even though the returns are low, the research only focuses on capital gain instead of considering the dividend. The evidence from this study supports the profit potential of RSI-LSTM and MACD-LSTM predictive modeling in the KLCI Index. It is also capable of producing significant profits in the most recent sub-period.

4. CONCLUSIONS

This research represents the first attempt to provide stock market prediction using machine learning algorithms and technical indicators. This study investigated the use of RSI and MACD in machine learning, developed matching predictive techniques, and assessed the effectiveness of the strategies. The experimental findings demonstrated that RSI-LSTM and MACD-LSTM performance tend to have predictive potential in the KLCI stock market. By contrasting the

RSI-LSTM and MACD-LSTM outcomes, both findings demonstrated that the strategies might be utilized to forecast the stock market and that machine learning methods helped create more successful trading strategies. However, this study shows that MACD-LSTM predictive modeling is more potent than RSI-LSTM. Finally, many strategies can be used to predict the stock price. RSI and MACD indicators are two ways to do this, especially using the machine learning algorithm LSTM. This study shows that RSI-LSTM and MACD-LSTM can be the analytical and predictive tools that give confidence in the investors to enter and exit the market at the right time. Hence, this research will enhance RSI-LSTM and MACD-LSTM's profitability, specifically for Malaysia's conventional stock market. Thus, this study's results prove that the Malaysian stock market can be predicted using technical indicators and machine learning algorithms. In addition, the result shows that MACD-LSTM has better predictive modeling than RSI-LSTM.

However, this research still needs much more attention and investigation to strengthen the study's flaws. KLCI Index is the only topic of this study. For future study, it is advised to employ a variety of equities and other indices, such as the FTSE Bursa Malaysia Top 100 Index and the FTSE Bursa Malaysia Hijrah Shariah Index as a benchmark. Additionally, the data for this study was only available for 11 years; extended data collection would have allowed for more accurate results. Additionally, the study intends to assist investors in selecting stocks and timing the market through machine learning predictive modeling. Bonds are recommended as an alternative when no buy or sell signals are available, as they typically offer higher returns with lower risk compared to the stock market. Furthermore, future research should incorporate transaction costs to better reflect the actual returns for investors.

To test the robustness of the findings, more research may include realistic constraints such as trading fees and short-selling or short-selling prohibitions. Although RSI, MACD, and LSTM are mighty forecasting tools, combining them with fundamental analysis, other technical, analytical tools, and machine learning algorithms can yield more significant results.

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DECLARATION OF ORIGINALITY

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