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The Capital Asset Pricing Model Forecast Using Artificial Intelligence

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Abstract

The application of Artificial Intelligence (AI) with the Recurrent Neural Network (RNN) Long Short-Term Memory (LSTM) algorithm which has excellent accuracy in predicting stock prices, but still needs to be developed optimally in the accounting and finance fields. In many cases it was found that the value of the results of the traditional Capital Asset Pricing Model (CAPM) calculations was consistently below the estimated return. Therefore, it is necessary to calculate the CAPM that can optimize the estimated returns more accurately, by combining it using AI technology with the LSTM method RNN algorithm. The purpose of this study is to prove the accuracy of the CAPM calculation results generated by AI compared to the traditional CAPM calculation method in providing an estimate of the return on the best blue-chip group in the LQ45 index during the 2015-2019 observation period. The sample of this study uses data on closing prices adjusted for companies with the lowest Debt to Equity Ratio (DER). The results of the adjusted closing price prediction using AI with the LSTM method have high accuracy. From the analysis of the different paired sample t-test, it was found that there was a significant difference in the mean Absolute Percentage Error (MAPE), where the AI-optimized CAPM model had a lower MAPE value than the traditional CAPM model. This study concludes that the AI-optimized CAPM calculation method has proven to be able to provide more accurate return estimates than traditional CAPM calculation methods.

Keywords
artificial intelligence; long short-term memory; prediction; capital asset pricing model; investment

I. Introduction

The rapid advancement of Artificial Intelligence (AI) in finance and time series analysis enables investors to make technical investment decisions in the capital market, particularly in stock price forecasting. One of the technical methods that can be used in conjunction with AI to assist investors in forecasting stock prices is the Recurrent Neural Network (RNN) algorithm using the Long Short-Term Memory method (LSTM) (Manurung et al., 2018). The application of AI technology using the LSTM method and the RNN algorithm, which is extremely accurate at forecasting stock values but still needs to be improved in the accounting and finance industries. The majority of studies that employ this algorithm stop at the level of stock price prediction, as the majority of researchers come from the field of information technology and have inadequate expertise of accounting and finance. According to the CFA Institute (Chartered Financial Analyst), future successful securities firms are those that strategically plan to incorporate AI into their investment processes (CFA

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Institute, 2019). Successful investment managers are those who can best understand and take advantage of the opportunities generated by AI technology (CFA Institute, 2019). In the study of S. Siami-Namini, et al. (2019) which compares the accuracy of the model of Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM), as a representative technique when forecasting data time series. These two techniques were applied and applied to a set of financial data and the results showed that LSTM was superior to ARIMA. More specifically, the LSTM-based algorithm improves predictions by an average of 85% compared to ARIMA. Several previous studies that support this result were carried out by Manurung, et al. (2018), F. Qian and X. Chen (2019), Eliasy and Przychodzen (2020), and Ta, et al. (Ta et al., 2020) which states that the LSTM method is superior to other methods in predicting stock data of time series and has a smaller forecasting error rate (Supriyanto & Hendri, 2021).

Relationship between return with the risk of an investment can be described by the CAPM method. In Yunita et al. (2020) the research which aims to determine the accuracy of the model Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) to forecast return company shares that listing in the LQ45 index by using Mean Absolute Deviation (MAD), where a small MAD value will indicate a higher level of accuracy for predicting stock returns. The MAD results on the CAPM show an average difference of 0.015, while the MAD results on the APT have an average difference of 0.017. Based on these differences, it can be seen that return of CAPM is closer return of each share during the period. Other studies that discuss the reliability of the CAPM model compared to the estimation other return model are include Zhang (2017), Agarwal, et al. (2018), Indra (2018), Suroso et al. (2018), Lubis, et al (2019), Hou, et al. (2019), and Afzal and Haiying (2020). The study stated that the CAPM method showed superiority when compared to other methods in predicting return of the share. However, in this study using MAD as a value analysis tool of average absolute error in the period of observation, where MAD has a drawback, namely, the small level of accuracy of the predictions made, because it cannot show the position of the prediction whether it is larger or smaller when compared to real conditions. The sample in this study also only used certain company sectors and companies that listing on the index, where the selection of the company sample in the study did not use specific financial ratios to see the company's financial health in more depth.

In contrast to the research of Eliasy and Przychodzen (2020) which states that in most cases it is found that the result value of the CAPM calculation is consistently below the estimate return. Therefore, a CAPM calculation method is needed that can optimize the results of stock return estimates more accurately, by combining it using AI technology with the LSTM method RNN algorithm. This research is aimed at proving the accuracy of the analysis using the AI-optimized CAPM method compared to the traditional CAPM calculation method in providing estimated return for the best company's stock group of blue chip in the LQ45 index during the 2015-2019 observation period (Hakim & Naelufar, 2020).

Based on researcher's knowledge, studies that combine estimating models return such as CAPM with AI technology as a tool for optimizing stock return estimation results has never been done before, because most researchers only predict stock prices with AI, and compare the CAPM model with APT and other traditional estimating models return. This study tries to combine the best AI algorithm in predicting stock prices, namely LSTM with the best method in estimating returns, namely CAPM to optimize the estimated share return results. Followed by testing the accuracy of the results of CAPM calculations generated with AI compared to traditional CAPM calculation methods in providing estimated returns.

AI technology or also known as artificial intelligence, so that this intelligence is able to process external data very well, then analyze and learn from mistakes repeatedly, so that the technology can perform the given task correctly flexibly (Kaplan & Haenlein, 2019). The Recurrent Neural Network (RNN) algorithm is the most sophisticated and powerful Artificial Intelligence (AI) that can process sequential data that is used to predict stock prices. Stock returns can be measured by the current stock price minus the previous stock price and then divided by the previous stock price (Helia, 2020). Stock option is one of the derivative products used as a financial risk management Tool (Solihin, 2021). Most of the big tech companies, including Google and Apple, use this algorithm for a variety of reasons including translation, speech recognition, adding subtitles, and even stock price prediction (Eliasy & Przychodzen, 2020). Long Short-Term Memory (LSTM) is a technological extension of the Recurrent Neural Network (RNN) proposed by Sepp Hochreiter and Jurgen Schmidhuber (Hochreiter & Schmidhuber, 1996). Long Short-Term Memory (LSTM) analyzes the pattern of information held, then sorts out which information is needed that can be used and which ones should be deleted, this is because the core (neurons) of Long Short-Term Memory (LSTM) have their own gates that can cause neurons to organize the information they have. Long Short-Term Memory (LSTM) has three main components called forget gate (1), input gate (2), and output gate (3).

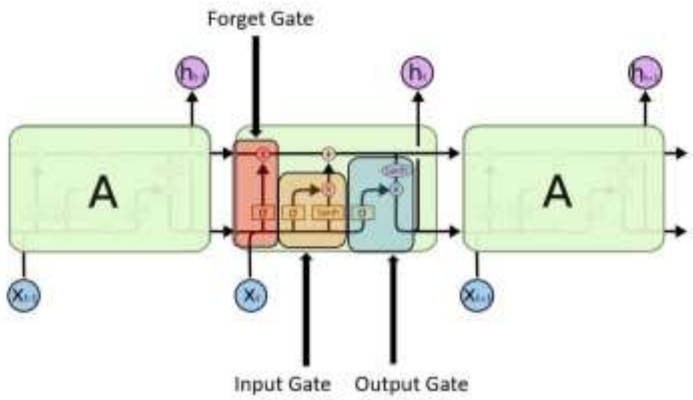

Figure 1. *LSTM Unit Model Looping Architecture*

Research by S. Siami-Namini, et al. (2019) shows that AI with the RNN algorithm using the LSTM method is superior to other methods in predicting stock prices. This condition is supported by the statement put forward in the research by Manurung, et al. (2018), Bhowmick, et al. (2019), F. Qian and X. Chen ((2019)), Ta, et al. (2020), and Eliasy and Przychodzen (2020). However, this research still requires more knowledge, especially in accounting and finance, because in this study it only discusses the comparison of stock price forecasting models and does not reach more in-depth aspects such as estimating the return of stock price forecasting results.

Capital market theory is a positive theory that hypothesizes how investors behave rather than how investors should behave, as in the case of modern portfolio theory. This theory is based on the existence of Markowitz's portfolio theory where this theory explains that investors will diversify their portfolios according to the Markowitz model (Jones & O'Reilly, 2012). The Capital Asset Pricing Model (CAPM) is also a theory put forward with reference to the Markowitz theory where an investor will sort out the investment posts he makes according to the most profitable or optimal portfolio. While according to Jogiyanto (2017) Capital Asset Pricing Model (CAPM) is a method used to assess the price of an asset. The CAPM analyzes the relationship of an asset's potential risk to its own risk under ideal market conditions. According to the CAPM, a good and decent asset will have a positive relationship of risk with return that shares granted. The magnitude of risk in an investment indicates the value or size of the indicator of the stock in CAPM is projected through variable β (beta). The greater the β (beta) owned by a stock instrument, it shows the greater the risk faced in investing. So that this method can be used to predict expected returns and investment risks (Indra, 2018).

Furthermore, Indra (2018) suggests that the CAPM model shows better accuracy than the APT model as an analyzer of share return. These findings are in line with Zhang (2017), Agarwal et al. (2018), Suroso et al. (2018), Lubis, et al. (2019), Hou, et al. (2019), Yunita, et al. (2020), and Afzal and Haiying (Afzal & Haiying, 2020). In contrast to the research of Eliasy and Przychodzen (2020) which states that in most cases when the CAPM calculation is compared with the realized return, it is found that the result value of the CAPM calculation is consistently below the estimated return. Where the CAPM calculation needs to be optimized in order to get a better estimated return, one of which is by combining it using AI technology.

Referring to the description presented above, it can be formulated a hypothesis in this study, namely:

Ha: There is a difference in the average of Mean Absolute Percentage Error (MAPE) between the results of CAPM calculations optimized by AI and traditional CAPM in providing return estimates.

II. Research Methods

The technique or method for analyzing data in this research is a quantitative method with a comparative study approach. The location of this research is done on the Indonesia Stock Exchange through access to www.idx.co.id and accessing the official website of companies listed on the LQ45 Index for the period 2015 to 2019. The data analyzed in this research are annual financial reports that have been audited for see the balance sheet used for calculations of Debt to Equity Ratio (DER) in the sample selection criteria and historical closing stock prices adjusted for the Composite Stock Price Index (CSPI) and companies listed on the LQ45 index for the 2015-2019 period, which were obtained through the IDX official website and the official website of listed companies as well as the official website Yahoo Finance. The population of this research is all companies that have never left the LQ45 Stock Index for 10 research periods from 2015 to 2019, with a total population of 28 companies. The sample of this study uses adjusted closing stock price data on 17 companies with DER below 1 in the LQ45 index for the 2015-2019 observation period.

Table 1. Research Sample Data

No	Company	Code	Average DER
1	Indocement Tunggal Prakarsa Tbk.	INTP	0.166
2	Vale Indonesia Tbk	INCO	0.194
3	Kalbe Farma Tbk	KLBF	0.218
4	Surya Citra Media Tbk	SCMA	0.258
5	Media Nusantara Citra Tbk	MNCN	0.518
6	Perusahaan Gas Negara Tbk	PGAS	0.544
7	Indofood CBP Sukses Makmur Tbk	ICBP	0.562
8	Gudang Garam Tbk	GGRM	0.574
9	Bukit Asam Tbk	PTBA	0.620
10	Bumi Serpong Damai Tbk	BSDE	0.624
11	Adaro Energy Tbk	ADRO	0.684
12	Semen Indonesia (Persero) Tbk	SMGR	0.684

13	United Tractors Tbk	UNTR	0.776
14	Telekomunikasi Indonesia (Persero) Tbk	TLKM	0.800
15	Astra International Tbk	ASII	0.932
16	Indofood Sukses Makmur Tbk	INDF	0.942
17	AKR Corporindo Tbk	AKRA	0.970

Source: www.idx.co.id

This research examines two variables in CAPM technology, namely traditional CAPM and AI CAPM. CAPM is used to calculate the return desired or expected [E(Ri)] is determined by return that given by the market (Rm), and also the rate of return that free from risk (Rf), and systematic risk (β).

$$R_i = R_f + \beta_i \left(R_m - R_f\right)$$

Description:
R_i : Return share to i
R_f : Return risk free assets
R_m : Return market portfolio
β_i : Beta of security to i

The data analysis technique was carried out using AI with the LSTM method to predict stock prices, then hypothesis testing using the normality test and the paired sample t-test difference test to find out the difference in the average MAPE between the traditional CAPM method and the AI-optimized CAPM which was processed using a program with Python programming language that is typed on the Google Colab website.

The initial stage in analyzing the data in this study is to predict the closing stock price adjusted using AI with the LSTM algorithm. Starting from data collection, data preprocessing, data splitting, model training, prediction, to model evaluation. The percentage distribution of the composition of testing data and training data that will be processed to predict stock prices analyzed through this research can be seen in Table 2.

Table 2. Dataset Composition

Training Data	**Testing Data**
80%	20%
Adjusted closing share price data for 2015 to 2018.	Adjusted closing share price data for 2019.

MAPE was utilized in this study to assess the model accuracy's performance. MAPE indicates the percentage of forecast error that corresponds to the actual set of variables.

$$MAPE = \frac{\sum_{t=1}^{n} \frac{\left|Y_t - \hat{Y}_t\right|}{Y_t}}{n} \times 100$$

Description:
Yt : Return realization period of t
Ŷt : Forecast value for period of t
t : Period of — t (1, 2, 3, ..., n)
n : Number of periods compared

Table 3 is the criteria for MAPE analysis (Chang et al., 2007).

Table 3. MAPE Criteria

MAPE Value	Description
< 10%	Excellent forecast results
10% - 20%	Good forecast result
20% - 50%	Sufficient forecast results
>50%	Bad forecast result

The second stage is to calculate CAPM using traditional methods, AI-optimized CAPM, and realized returns. The formula for calculating the realized return is described in equation 3.

$$Rit = \frac{P_{it} - P_{it-1}}{P_{it-1}}$$

Description:
Rit : Return stock i in period of t
Pit : closing share price of company i in period of t
Pit-1 : closing share price of company i in period of t-1

In the following stage, the MAPE value of the CAPM is calculated using both traditional methods and an artificial intelligence-optimized CAPM. Aside from that, hypothesis testing is carried out through the use of normality tests as well as paired sample t-tests to determine whether or not there are differences in the average MAPE between the standard method CAPM and AI optimized CAPM.

III. Discussion

3.1 Stock Price Prediction

The results of the adjusted closing stock price predictions from the 17 best blue-chip companies in the 2019 LQ45 index obtained and then evaluated using MAPE to determine the percentage error of the stock price prediction model using the LSTM method. It can be seen in figure 2 that the results of stock price predictions using the LSTM method are close to the original stock prices.

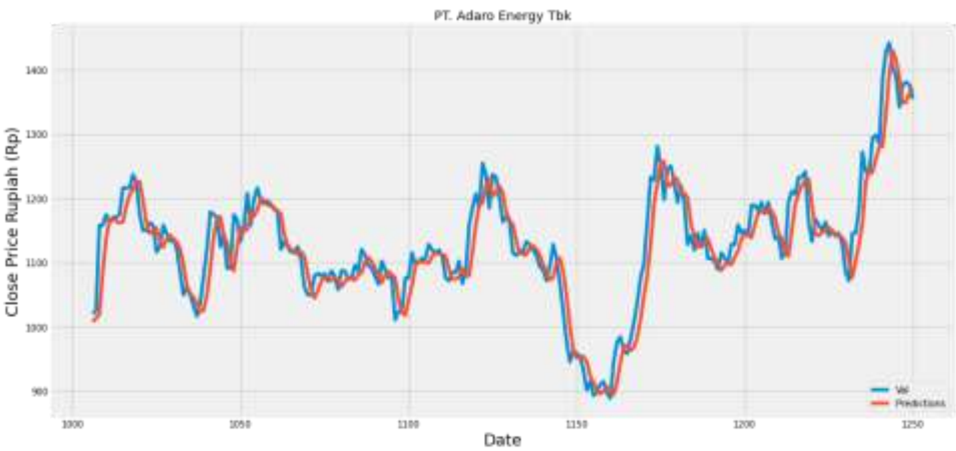

Figure 2. *Closing Stock Price Prediction of PT. Adaro Energy Tbk in 2019*

Based on the data from the evaluation of the stock price prediction model, the average MAPE value is 2,6%. This shows that the AI model with the LSTM algorithm can predict stock prices very well, because the average MAPE value generated by AI with the LSTM method is below 10%.

Table 4. Evaluation of Stock Price Prediction Model

No	Company name	Stock code	MAPE
1	PT. Adaro Energy Tbk	ADRO	3.5%
2	PT. AKR Corporindo Tbk	AKRA	2.9%
3	PT. Astra International Tbk	ASII	2.5%
4	PT. Bumi Serpong Damai Tbk	BSDE	1.9%
5	PT. Gudang Garam Tbk	GGRM	4.0%
6	PT. Indofood CBP Sukses Makmur Tbk	ICBP	1.2%
7	PT. Vale Indonesia Tbk	INCO	2.3%
8	PT. Indofood Sukses Makmur Tbk	INDF	2.2%
9	PT. Indocement Tunggal Prakarsa Tbk	INTP	4.3%
10	PT. Kalbe Farma Tbk	KLBF	1.2%
11	PT. Media Nusantara Citra Tbk	MNCN	5.8%
12	PT. Perusahaan Gas Negara Tbk	PGAS	2.3%
13	PT. Bukit Asam Tbk	PTBA	2.0%
14	PT. Surya Citra Media Tbk	SCMA	2.6%
15	PT. Semen Indonesia (Persero) Tbk	SMGR	1.9%
16	PT. Telekomunikasi Indonesia (Persero) Tbk	TLKM	1.2%
17	PT. United Tractors Tbk	UNTR	1.8%
Mean of MAPE			**2.6%**

3.2 Calculation of Realized Return and CAPM

The results of the calculation of Realized Return, Traditional CAPM, and AI-optimized CAPM from the 17 best blue-chip companies in the 2019 LQ45 index are presented in Table 5. While the results of the MAPE calculation of Traditional CAPM and AI-optimized CAPM are presented in Table 6.

Table 5. Calculation Results of Realized Return, Traditional CAPM, and AI CAPM

No	Stock code	Return Realization	Traditional CAPM	CAPM AI
1	ADRO	0.373	0.105	0.174
2	AKRA	0.039	0.091	0.005
3	ASII	-0.106	0.105	0.062
4	BSDE	0.068	0.106	0.048
5	GGRM	-0.359	0.106	-0.021
6	ICBP	0.109	0.067	0.068
7	INCO	0.230	0.106	0.139
8	INDF	0.147	0.098	0.115
9	INTP	0.141	0.105	0.112
10	KLBF	0.113	0.102	0.104

11	MNCN	1.031	0.101	0.324
12	PGAS	0.087	0.103	0.077
13	PTBA	-0.321	0.097	0.062
14	SCMA	-0.157	0.102	0.046
15	SMGR	0.137	0.110	0.118
16	TLKM	0.103	0.102	0.102
17	UNTR	-0.134	0.105	0.065

Table 6. Calculation Results of Traditional CAPM MAPE and AI CAPM

No	**Stock code**	**MAPE Traditional CAPM**	**MAPE CAPM AI**
1	ADRO	71.8%	53.4%
2	AKRA	133.3%	87.9%
3	ASII	199.1%	158.9%
4	BSDE	55.9%	28.9%
5	GGRM	129.5%	94.2%
6	ICBP	38.5%	37.6%
7	INCO	53.9%	39.7%
8	INDF	33.3%	21.8%
9	INTP	25.5%	20.6%
10	KLBF	9.7%	7.8%
11	MNCN	90.2%	68.6%
12	PGAS	18.4%	11.5%
13	PTBA	130.2%	119.2%
14	SCMA	165%	129%
15	SMGR	19.7%	13.9%
16	TLKM	1.0%	1.3%
17	UNTR	178.4%	148.6%

3.3 Hypothesis Testing

Tests for the normality of the data show the value of Sig. on the Kolmogorov-Smirnov test, the MAPE value data of the Traditional CAPM model and the CAPM optimized with AI were 0.184 and 0.102, respectively. Value of Sig. in the Shapiro-Wilk test, the MAPE value data for the Traditional CAPM model and the CAPM optimized with AI were 0.092 and 0.054 respectively. Based on the results of the Kolmogorov-Smirnov test and the Shapiro-Wilk test, the Sig. <0.05, so it can be said that the MAPE values of the Traditional CAPM model and the CAPM optimized with AI are normally distributed and meet the requirements for paired sample t-test.

Table 7. Normality Test

CAPM	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistics	df	Sig.	Statistics	df	Sig.
Traditional CAPM	0.174	17	0.184	0.908	17	0.092
AI CAPM	0.19	17	0.102	0.894	17	0.054

Based on the results of the paired sample analysis in Table 8, the average MAPE value for the Traditional CAPM model is 79.612% and the CAPM model optimized with AI is 61.347%. The results of the calculation of the Traditional CAPM model and the AI-optimized CAPM have an estimated return value that is still relatively bad because the average MAPE value generated with this model is still above 50%.

Table 8. Paired Sample Statistics

CAPM	Mean	n	Std. Deviation
Traditional CAPM	79.612	17	64.1392
AI CAPM	61.347	17	52.1250

Based on the results of the paired sample correlations in Table 9, there is a correlation between the Traditional CAPM and AI-optimized CAPM variables, which is 0.989 with a Sig value. < 0.05. This shows that there is a significant effect of AI optimization in minimizing the MAPE value in the CAPM model.

Table 9. Paired Samples Correlations

n	Correlation	Sig.
17	0.989	0.000

In Table 10, the results of the paired samples test show that there is an average significant difference in MAPE between the Traditional CAPM and AI-optimized CAPM models of 18.2647% with a Sig value. (2-tailed) of 0.00. The results of this analysis explain that the AI-optimized CAPM can minimize the MAPE value of 18.2647%, which means that the AI-optimized CAPM model can predict returns better than the Traditional CAPM model. Value of Sig. (2-tailed) < 0.05, these results can then be interpreted that H_0 is rejected and H_a is accepted, where H_a states that there is a difference in the average MAPE between the CAPM calculation results generated by AI and traditional CAPM in providing return estimates.

Table 10. Paired Samples Test

Mean	18.2647
Std. Deviation	14.8638
t Stat	5.066
df	16
Sig. (2-tailed)	0.000

This study tries to combine the best AI algorithm in predicting stock prices, namely LSTM with the best method in estimating returns, namely CAPM to optimize stock return estimation results. Followed by testing the accuracy of the CAPM calculation results generated by AI compared to traditional CAPM calculation methods in providing return estimates. This study uses the MAPE analysis tool to analyze the comparison of the percentage error values from the CAPM calculation results and the paired sample t-test difference test in explaining the average difference for the MAPE value between the CAPM calculation results generated by AI and traditional CAPM.

Based on the results of the evaluation of the adjusted closing stock price prediction model of the 17 best blue-chip companies in the LQ45 index for 2019, it shows that the AI model with the LSTM algorithm is proven to be able to predict stock prices very well and is close to its original value. Based on this, the results of this research can support the results of previous research conducted by S. Siami-Namini, et al. (2019), Manurung, et al. (2018), Bhowmick, et al. (2019), F. Qian and X. Chen. (2019), Ta, et al. (2020), and Eliasy and Przychodzen (2020) who stated that AI with the RNN algorithm using the LSTM method was proven to be accurate in predicting stock prices. The results of research findings on the paired sample t-test, The Traditional CAPM and AI-optimized CAPM models have a low estimated return value. This shows that the estimated return value generated by the CAPM model based on the capital market theory is still far different from the realized return value.

In this study, a significant correlation was found between the Traditional CAPM and AI-optimized CAPM variables. There is a significant difference in the mean MAPE value between the Traditional CAPM model and the AI-optimized CAPM. Where the AI-optimized CAPM has a lower MAPE value than the Traditional CAPM, this proves that optimization using AI technology plays a role in minimizing the MAPE Mean value in the CAPM model. Through these findings, it can be said that H_0 is rejected and H_a is accepted, where H_a states that there is a difference in the mean MAPE between the CAPM calculation results generated by AI and traditional CAPM in providing return estimates. The findings of this research are the answer to the formulation of the problem and also the purpose of this research, where the AI-optimized CAPM calculation method is proven to be able to provide more accurate return estimates than the traditional CAPM calculation method for the best blue-chip company stocks in the LQ45 index during the 2015-2019 observation period. Based on this, the results of the research carried out show support for the results of research conducted by Eliasy and Przychodzen (2020) which show that in most cases when the CAPM calculation is compared with the realized return, it is found that the result value of the CAPM calculation is consistently below the estimated return. However, the findings of this research did not provide results that are in line with those carried out by Zhang. (2017), Agarwal, et al. (2018), Indra. (2018), Suroso et al. (2018), Lubis, et al. (2019), Hou, et al. (2019), Yunita, et al. (2020), and Afzal and Haiying (2020) which states that the CAPM model is superior to other methods of estimating return.

IV. Conclusion

Based on the results of the evaluation of the adjusted closing stock price prediction model of the 17 best blue-chip companies in the LQ45 index for 2019 it shows that the AI model with the LSTM algorithm is proven to be able to predict stock prices very well and is close to its original value. Based on the findings of the different paired sample t-test research findings, the Traditional CAPM and AI-optimized CAPM models were found to have poor return estimates. This shows that the estimated return value generated by the CAPM model based on the capital market theory is still far different from the realized return value. In this study, a significant correlation was found between the Traditional CAPM and AI-optimized CAPM variables. While a significant difference in mean MAPE was found between the Traditional CAPM and AI-optimized CAPM models. Where the AI-optimized CAPM has a lower MAPE value than the Traditional CAPM, this proves that optimization using AI technology plays a role in minimizing the MAPE Mean value in the CAPM model. Thus, it can be concluded that H0 is rejected and Ha is accepted, where Ha states that there is a difference in the mean MAPE between the CAPM calculation results generated by AI and traditional CAPM in providing return estimation. This condition explains that the findings have been able to answer the formulation of the problem and the objectives of this research, where the AI-optimized CAPM calculation method is proven to be able to provide more accurate return estimates than the traditional CAPM calculation method for the best blue-chip company stocks in the LQ45 index during the 2015-2019 observation period.

The researchers hope that the findings of this research will assist investors and investment managers in educating themselves, as well as developing knowledge in accounting and finance, regarding the use of AI technology to optimize stock return estimation results to aid in investment decision making.

There are a number of limitations in this study. The AI method chosen for this study only relied on the literature and the results of previous studies without making direct comparisons between different AI algorithms using statistical calculations. In this study, the calculation results of the Traditional CAPM model and the CAPM optimized with AI have an estimated return value that is still relatively poor due the average MAPE value generated with this model is above 50%. Based on this condition, it is recommended for future research to use other methods of estimating returns such as Arbitrage Pricing Theory (APT) which can be optimized with other AI algorithms such as Adaptive Neuro Fuzzy Interference System (ANFIS), Backpropagation, Autoregressive, and others to obtain better return estimation results.

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