Optimizing Investment: Combining Deep Learning for Price Prediction and Moving Average for Return-Risk Analysis

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Abstract— The ability to analyze predictions marks something going up or down, as well as the level of possible risk taken into account by much-needed stock investors. In a study, this analysis of risk and correlation between shares was calculated using the method of moving averages (MA). Besides that, a dataset of 4 stocks (Apple, Google, Microsoft, and Amazon) also performed prediction mark stock in period time next (future) with the use of the neural network method (deep learning) Long Short-Term Memory (LSTM) model. The result of programming in the Python language is several visualizations for easy graph-reading information. This article presents new research that aims to fill the gap in understanding investment analysis for beginners by visualizing risk and return analysis on shares. The results reveal that changes in stock sales volume did not occur significantly, although the short and long-term MA charts for the four stocks tended to fluctuate, offering new insights into investment analysis and providing a basis for future development. The best accuracy results were on MSFT shares, with an achievement of 0.9532 and a loss value of 0.0014. Thus, MSFT shares can be used as a priority for investment. Therefore, this research adds a new dimension to the literature and paves the way for further investigations in risk and return analysis and stock prediction using deep learning.

Keywords— correlation; LSTM; return; risk; prediction

I. Introduction

The stock investment business is a business that promises to get high returns in a short time and is most in demand by stock investors [1]. Of course, the higher the rate of return, the higher the level of risk. Institutional investors, namely foreign institutional investors (FIIs) and domestic institutional investors (DIIs), exhibit a preference for allocating their investments towards low-risk stocks. These stocks are characterized by a low beta, a low book-to-market ratio, and a high market capitalization [2]. Stocks are one of the keys to long-term wealth [3]. Daily movements are not easy to predict in total, and investors usually do research related to the financial statements of a stock in determining investment steps [4].

The number of variables that affect stock prices is one of the attractions and challenges [5] in being able to predict stock prices with high accuracy [6], [7]. Although many variables also have an impact on stock price movements, they become very random and complex [8]. Stock prices may not necessarily reflect a company's intrinsic value due to investor behavior and market sentiment, which also affect share value [9], [10].

The process of achieving success in the field of financial markets requires the complete ability to identify investments [11]. When is the stock in the lowest condition (undervalued) possible to buy and when is the stock in the highest value position possible to sell [12]?. The decision to take action (sell or buy) is still mostly made manually by financial experts [13]. The rapid development of today's technology makes it possible to process very large amounts of data at very high speeds (in real time) [14]. Processing historical data makes it possible to predict whether a stock's value will rise or fall with a predictable level of risk and return [15]. The ability of computer engines to carry out the learning process from historical data to produce trained models that can be used to predict stock values at a later time [16].

When predicting S&P 500 equities, research in [17] has shown that Long Short-Term Memory (LSTM) produces the best results when compared to Random Forest (RF), Deep Neural Network (DNN), and Logistic Regression (LR). In comparison to traditional machine learning approaches, research by [18] shows that deep neural networks (DNNs) are more effective at solving nonlinear issues. DNNs combine the advantages of deep learning (DL) with neural networks.

Reference [19] has performed stock prediction utilizing the complementary ensemble empirical mode decomposition (CEMD) and LSTM models. Stock predictions that have been carried out [20] using the Decision Tree (DT), Random Forest

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(RF), Adaptive Boosting (Adaboost), eXtreme Gradient Boosting (XGBoost), Support Vector Classifier (SVC), Naïve Bayes, K-Nearest Neighbours (KNN), Logistic Regression (LR) and Artificial Neural Network (ANN) and two powerful deep learning methods (Recurrent Neural Network (RNN) and LSTM [21] did research that used LSTM and regression models to make predictions. There have been a few research studies on the use of deep learning to predict the price of shares in recent years [22]–[25].

This research aims to predict stock price trends using the LSTM approach and measure the amount of risk and expected return value using the MA method. Combination of LSTM and MA to produce risk analysis and an expected return. This is used by investors to facilitate the risk and return analysis of a stock.

This particular study has certain limitations, in particular that the level of accuracy in predicting prices is highly dependent on the quality and quantity of the data used. If historical data is insufficient or unrepresentative, the model has the potential to produce less accurate predictions. The choice of parameter settings in deep learning models and moving average techniques must be done very carefully. Strong reliance on parameters can make models less common and more challenging to adapt to fluctuating market conditions. Deep learning has proven to be ineffective when faced with irrational or illogical behavior from market players. Emotional and psychological factors that influence prices cannot always be adequately accommodated by mathematical models.

II. Method

There are several stages carried out in this research, starting with the process of reading data directly from the Yahoo. Finance.com web by using a web reader library. The advantage is that there is no need to store data, which is generally large, in order to save on local storage [26]. Data on the four stocks 'AAPL', 'GOOG', 'MSFT', and 'AMZN' obtained 504 rows of data with 7 features ('Open', 'High', 'Low', 'Close', 'Adj.Close', 'Volume', and 'Company_name'). Dataset extraction using the Jupyter notebook editor.

This research aims to investigate and understand the share price behavior of AAPL, GOOG, MSFT, AMZN in recent years. The GAFAM stocks category includes these four stocks. GAFAM is an abbreviation for the five most popular technology stocks and major players in the United States [27]. As of March 31, 2020, the four GAFAM firms have a combined market capitalization of nearly $4.5 trillion and are all among the top ten companies in the United States by market capitalization [28]. Many investors assume that if these stocks do well, the entire industry will likely perform well as well. In certain ways, these equities function as a technology sector index. The flow of this research process can be seen in Figure 1.

A. Exploration Data Analysis (EDA)

EDA is the initial stage for further data analysis. Starting with the extraction of historical data on stock prices 'AAPL', 'GOOG', 'MSFT', and 'AMZN' over a period of two years, followed by the process of understanding data on opening prices, closing prices, highest prices, lowest prices, and trading volume.

Data cleaning needs to be done because stock data is incomplete due to holidays, and this can become anomaly data. Figure 2 represents the EDA process of dataset extraction for AAPL shares. Figure 3 is a representation of the EDA for the process of generating descriptive statistics about distribution and basic characteristics. When the mean value exceeds the quartile value (50%), there is an imbalance in the data (skew to the right), indicating an increasing trend (uptrend). The next stages of EDA can be carried out with distribution analysis, categorical variable analysis, correlation analysis in the form of a headmap matrix, time analysis, data visualization, and interpretation of results.

B. Moving Average (MA)

MA is an indicator commonly used by investors and traders to make decisions based on historical stock price data in the past (lag indicator) [29]. Dataset preparation uses a Pandas DataFrame with two columns, namely stock transaction date and daily closing price. The transaction date column set is used as the DataFrame index. The process of calculating MA uses the 'rolling' function, which functions to calculate moving statistics from the stock dataset from 2020 to 2022. We choose a specific time window, for example 10, 20, or 50 days, and calculate the average closing price over the period. This helps us identify short-term and long-term trends in stock prices. In this process, we use the 'window_size' function for further dataset analysis.

Figure 1. Research flow

'AAPL'

Date	Open	High	Low	Close	Adj Close	Volume
2020-05-22	78.942497	79.807503	78.837502	79.722504	78.739082	81803200
2020-05-26	80.875000	81.059998	79.125000	79.182503	78.205727	125522000
2020-05-27	79.035004	79.677498	78.272499	79.527496	78.546478	112945200
2020-05-28	79.192497	80.860001	78.907501	79.562500	78.581039	133560800
2020-05-29	79.812500	80.287498	79.117500	79.485001	78.504494	153532400
...	...	...	...	...	...	...
2022-05-16	145.550003	147.520004	144.179993	145.539993	145.539993	86643800
2022-05-17	148.860001	149.770004	146.679993	149.240005	149.240005	78336300
2022-05-18	146.850006	147.360001	139.899994	140.820007	140.820007	109742900
2022-05-19	139.880005	141.660004	136.600006	137.350006	137.350006	136095600
2022-05-20	139.089996	140.699997	132.610001	137.589996	137.589996	137194600

504 rows × 7 columns

Figure 2. Stock dataset extraction

	Open	High	Low	Close
count	2016.000000	2016.000000	2016.000000	2016.000000
mean	1456.662706	1473.017894	1438.833450	1455.684552
std	1338.498970	1353.129266	1321.830899	1337.094163
min	78.942497	79.677498	78.272499	79.182503
25%	181.024998	182.925003	178.972496	181.527504
50%	851.400024	872.634995	844.605011	851.505005
75%	2882.229980	2904.679993	2840.629944	2875.492493
max	3744.000000	3773.080078	3696.790039	3731.409912

Figure 3. Overall data statistics

The formula for MA with m time periods can be made as follows:

$$MA_m = \frac{C_{lag-1} + C_{lag-2} + \ \dots\ + C_{lag-(m-2)} + C_{lag-(m-1)} + C_{lag-m}}{m} \quad (1)$$

MA_m represents the moving average with a period of m. $Clag - 1$ in the context of the moving average formula is not used directly in the moving average calculation itself. Instead, historical data is used to calculate moving average values from the past. $Clag - m$ refers to the closing price of a particular asset or financial instrument over a previous time period of m days. In the context of financial analysis, this is historical data that includes the closing price of an asset in the previous days for m days. m is the number of time periods for which we want to calculate the moving average.

C. Daily Return

Return on investment obtained from selling and buying shares (difference in purchase price) The process of calculating the daily return uses the Pandas library; the stock transaction date column is used as the DataFrame index, which then initializes the daily return column. To count each row in the DataFrame starting from the second row. The first row is deleted; it has no return because there is no previous stock transaction data. Daily returns help us understand stock volatility and provide important information for risk analysis. Next, calculate the daily return value using the formula as follows:

$$R_t = (C_t - C_{t-1})/\ C_{t-1} \quad (2)$$

R_t is the daily return for the time period t. The daily return measures the daily change in an asset's value. C_t is the closing price on day t. The closing price is the last price at the end of the trading day on day t. C_{t-1} is the closing price on the previous day, namely day $t-1$. This is the closing price on the trading day before Day t. The R_t formula compares the closing price on day t with the closing price on the previous day $(t-1)$. This change is calculated as the difference between C_t and C_{t-1}, then divided by C_{t-1} to calculate the percentage change.

D. Expected Return and Risk

Next, we carry out an analysis of the expected return and investment risk. We use historical data to estimate the expected return, which is the expected rate of return from investing in AAPL, GOOG, MSFT, and AMZN company shares. We also measure investment risk by investigating stock price volatility and correlation with market indices or other relevant factors. The equation for expected return and risk is as follows:

$$Expected\ Return = \sum_{i=1}^{n} (P_i x\ R_i) \quad (3)$$

$$Risk = \sigma = \sqrt{\sum_{i=1}^{n} P_i\ x\ (R_i - \bar{R})^2} \quad (4)$$

Pi is the probability of the i-th state or investment scenario occurring. Ri is the expected rate of return for the i-th investment. n is the number of possible scenarios or circumstances. Risk is often measured by the standard deviation (σ) of the rate of return. $\bar{R}$ is the average rate of return. From the program made based on these calculations, a distribution visualization is generated that maps the two values in two dimensions.

E. Long Short-Term Memory (LSTM)

Starting from a simple neural network (NN), which can only be applied to linear regression and classification types [30]. Then it develops into a RNN by combining data input with previous data [31]. The increasing number of RNN layers creates a vanishing gradient problem, so that the RNN is only able to manage data with short dependencies [32]. Due to the problems in the RNN, the next development is in the form of a cell with a complex collection of gates known as LSTM (Long Short-Term Memory), which is capable of processing data with long dependencies [33].

The first step of implementation is using LSTM, namely, importing the required libraries such as Scikit-learn, Keras, Pandas, and Numpy. For this study, 2 layers of LSTM cells were arranged, each with 128 and 64 nodes, then 2 dense layers, each with 25 and 1 output node. Using the optimizer 'RMSprop' and measuring loss using 'Mean Squared Error' (MSE). Our model train process proposes batch sizes of 50 and epoch 100 [34]. The data is split for the training and testing process (approximately 20%), then fit to the model that has been formed before. Min-Max Scaling for the scale process, then we carry out the transformation process [35].

The following are the mathematical formulation and process steps of the LSTM method.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (5)$$

Forget gate f_t determines how much information the previous memory cell has C_{t-1} will be deleted. This is calculated using the sigmoid activation function (σ) which produces a value between 0 and 1.

$$i_t = \sigma(w_i.[h_{t-1}, x_t] + b_i \quad (6)$$

The input gate i_t governs the extent to which novel information is incorporated into the memory cells. Similarly, to the forget gate, this value is determined by the sigmoid activation function (σ).

$$\hat{C}_t = tanh\ (w_c.[h_{t-1}, x_t] + b_c) \quad (7)$$

Update candidate cell state, values for memory cell $\hat{C}_t$ updates are determined through the utilization of the hyperbolic tangent $tanh$ activation function, which yields output values that span the range from -1 to 1.

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (8)$$

Update the cell state in the memory cell. C_t is modified by considering the extent to which information from the preceding memory cell will be eliminated f_t and the extent to which new information will be incorporated into i_t and $\hat{C}_t$

$$o_t = \sigma(W_o\ .[h_{t-1}, x_t + b_o) \quad (9)$$

The output gate o_t is responsible for determining the extent to which the information stored in the memory cell will be conveyed as output. This determination is made by means of the sigmoid activation function σ.

$$h_t = o_t.\tanh(C_t) \quad (10)$$

The hidden state h_t represents the LSTM's ultimate output at time step t. It is calculated by multiplying the gate output o_t by the hyperbolic tangent activation function of the memory cell C_t.

The final result is a visualization for investment analysis; it is hoped that it can be used as a second opinion by investors and stock analysts to make better-informed decisions and detail complex information in an easy-to-understand format. It is important to use various relevant visualizations to gain a comprehensive understanding of the condition and prospects of a stock.

The dataset used comes from the Yahoo Finance website; the experiment uses datasets from four stocks from May 22, 2020, to May 20, 2022. The consideration is why choosing these four stocks (AAPL, GOOG, MSFT, and AMZN) are the Big 5 stock categories that contribute to achieving 23% on the S&P 500 stock index [36]. The calculation process that has been done is more likely to be analyzed from previously existing data. To be able to predict stock price trends (closed prices) in the next month, a deep learning method is used by creating a neural network layer model using LSTM cells.

III. Results and Discussion

A resume of statistical data can be obtained by adding the 'describe()' command after the data file name 'df' (Figure 3). From the statistical resume, the mean, min, max, and std (standard deviation) data are obtained, as well as the amount of data for each feature. The mean value is the center of mass, or center of gravity, of the data distribution.

The mean value is 1455.684, which means that the central measure provides a general idea of the "middle value" in the data set. The standard deviation value is 1337.094, which means that most of the values in the data set tend to be spread within a range of about 1337.094 units from the mean value (Figure 3). This means that the data distribution has significant variations. The higher the standard deviation, the greater the variation in the data in the set.

To find out the data type information for each feature, use the 'info()' command behind the data file name (Figure 4). From statistical data and feature information (Figure 4), it is known that the amount of data for each feature is the same, namely 2016 lines, which are divided into 4 stock data sets, each containing 504 lines.

```
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Open          2016 non-null   float64
 1   High          2016 non-null   float64
 2   Low           2016 non-null   float64
 3   Close         2016 non-null   float64
 4   Adj Close     2016 non-null   float64
 5   Volume        2016 non-null   int64
 6   company_name  2016 non-null   object
dtypes: float64(5), int64(1), object(1)
memory usage: 126.0+ KB
```

Figure 4. Information on each feature of the entire data

The data is fully loaded without empty data (null), and the data type of all features is float64 except for the 'Volume' and *'company_name'* features with types int64 and object. This data is very necessary so that the next process can run well and with the desired results. Because the data obtained already contains complete information (without null data) and the data type used is uniform using 64 bits (not 32 bits), the data does not require a complicated cleansing process.

A. Feature selection

Of the six stock price features ("Open", "High", "Low", "Close" and "AdjClose"), the "Close" feature is generally chosen to make predictions because this feature states the last stock price at closing. Furthermore, the "Close" feature is used to make predictions based on historical data on stock price values. The historical trace of the 'Close' feature data that has been obtained from Yahoo Finance can be seen in Figure 5 (stock of data AMZ). It can be seen that from January to May 2022, the four stocks (AAPL, GOOG, MSFT, and AMZN) experienced a decline with a slight increase in April and then dropped again until May. A very sharp decline occurred in AMZN (Amazon) shares compared to the other three stocks.

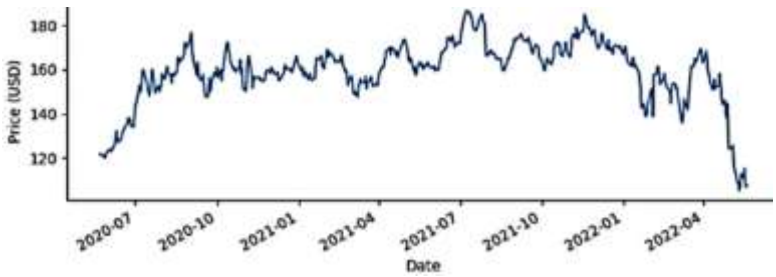


Figure 5. Track history of the 'Close' feature stock data AMZN

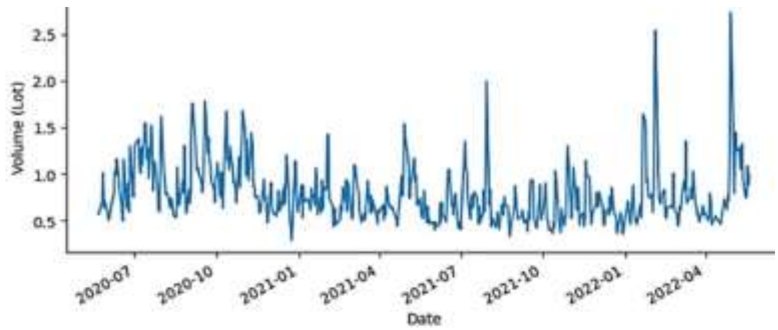


Figure 6. Track the history of the 'Volume' feature of sales for stock data AMZN

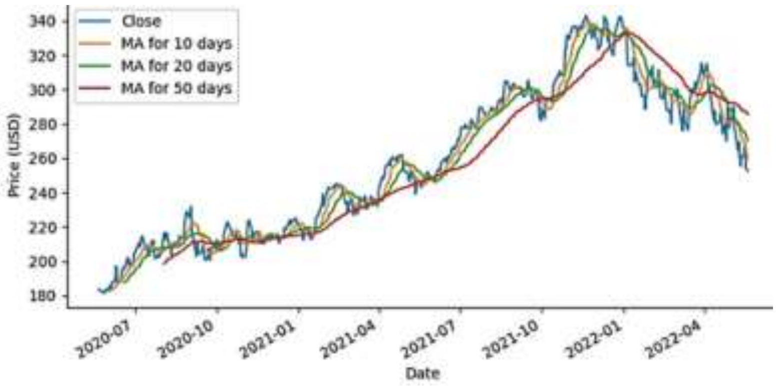


Figure 7. MA periods of 10-, 20- and 50-days MSFT stock

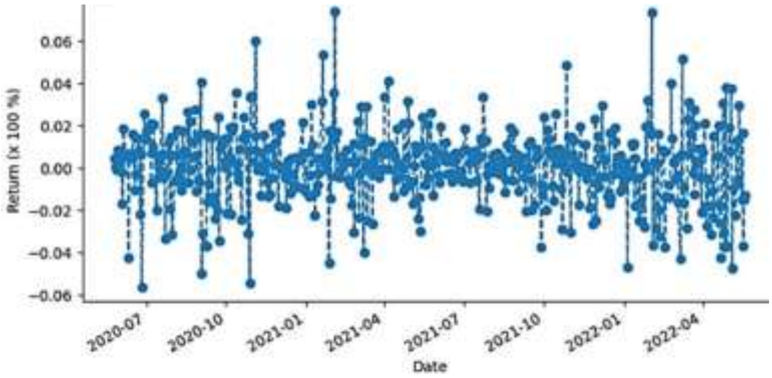


Figure 8. Daily returns GOOG stock

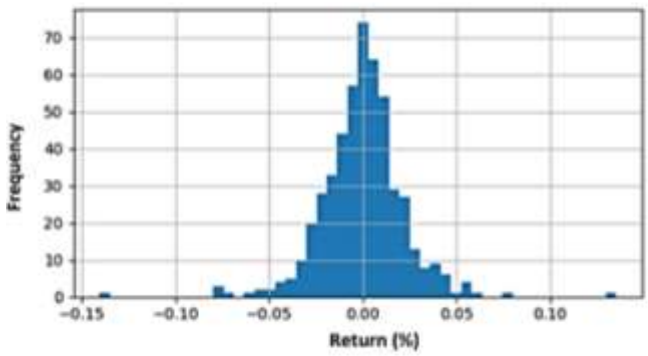


Figure 9. Distribution of daily returns AMZN stock

As a result of the drop in AMZN's share price, the number of sales of these shares reached twice the high volume in February and May. The highest sales volume for MSFT and GOOG shares occurred only once in February, while AAPL did not experience a significant increase in sales volume at all in 2022. To find out the trace of the sales volume of the stocks, see Figure 6. So here it can be seen that there is a connection between the existing data features ("close" and "volume"), which can provide insight into information on the condition of these stocks on a daily basis.

In this study, four stocks will be subject to MA with a period of 10 and 20 days for a short-term trend and a period of 50 days for a long-term trend. Figure 7 is an example of Microsoft's stock. The graphical programmed results show that after April 2022, the MA_{50} (green) is above the MA_{20} (yellow), and the MA_{20} (yellow) is above the MA_{10} (red). This indicates a strong downward trend, and a very sharp downward trend has occurred in Amazon stock. For Microsoft and Google, from around October 2020 to October 2021, it is clear that the position of MA_{10} (red) is above MA_{20} (yellow), and MA_{20} (yellow) is quite high above MA_{50} (red), indicating that there is an upward trend in stock prices. in that period. A turning point occurs if the MA values approach each other (coincide). An example is Microsoft's shares in October 2021, where it is seen that the stock price reversed suddenly with the MA_{50} acting as a barrier preventing the stock price from falling.

B. Daily Return

From the programmed that has been carried out by taking data starting 100 days before the last data point, it produces daily return charts for four stocks. From the graph, it can be seen that Google shares experienced the most negative returns, around -0.01 or 1% (the highest loss), as shown in Figure 8.

To see the distribution visually, which is useful for knowing the fluctuation rate of daily returns for each stock, a histogram A plot is performed from the existing data (daily return data). From the results of the plot, it can be seen that the distribution of daily returns for each stock averages at 0% because there are no large fluctuations every day. From the histogram, Amazon stock (Figure 9) looks slimmer with a distribution of ±5% indicating a higher risk than the other 3 stocks with a distribution of around ±10%.

C. Stock Correlation

In general, data will be easier to understand in visual form with clear color group differences, so the presentation of the correlation between the 4 stocks will be expressed in the form of visualization using the headmap tool, a data presentation by combining values in color levels (Figure 10).

From Figure 10, it can be seen that the level of similarity between stocks is that Google (GOOG) has the highest performance similarity rate of 75% with Microsoft (MSFT), Apple (AAPL) has 72% similarity with Microsoft, and Amazon (AMZN) has 68% similarity with Microsoft. With a correlation of 75%, it means there is a strong positive relationship between GOOG and MSFT price movements. When GOOG price rises or falls, there is about a 75% chance that MSFT will follow in the same direction.

This indicates a dependency between these two stocks in terms of their price movements. If two stocks are highly correlated, as in this example, then the portfolio may be under diversified. Diversification is a way to reduce risk by owning a large number of stocks that do not have a high correlation, so that when one stock experiences a decline, others may not be affected or may even rise. This level of performance similarity may be explained by both companies operating in similar technology industries and being affected by similar market factors.

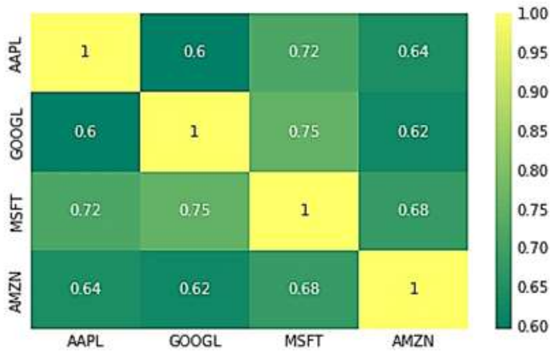


Figure 10. Headmap correlation of 4 stocks

D. Investment Risk and Expected Return

The expected return is calculated based on the average value of daily returns in a certain time period, while the risk is determined from the standard deviation (std) value of daily returns in a certain time period. From the programmed made based on these calculations, a distribution visualization is generated that maps the two values in two dimensions for the four stocks. From the results of the visualization, it can be easily seen that AMZN is the stock with the lowest expected return value and is classified as the stock with the highest risk compared to the other 3 stocks. The results of the risk and expected return are presented in Table I.

TABLE I. RISK AND EXPECTED RETURN

Stocks	Risk	Expected Return
AAPL	0.001283	0.019926
GOOG	0.001019	0.017828
MSFT	0.000784	0.017223
AMZN	-0.000003	0.022059

A negative risk value may indicate that "AMZN" stock currently has lower volatility than some specific reference point, such as a market index or similar stocks. This could be a signal that the stock is relatively stable in its price movements. The expected return value reflects the expected rate of return from investing in "AMZN" shares. In this case, the value is about 0.022059, which as a percentage is about 2.21%. This means that investors or analysts expect that “AMZN” stock will generate a rate of return of around 2.21% in a certain time period, for example, in one year.

The predicted return and risk for each stock are shown in Figure 11. It is intended that by using this visualization graph, investors will be able to quickly understand and make investment decisions. AMZN shares have the most risk when compared to other stocks, but the predicted return value is the lowest. The lowest risk is in MSFT shares, followed by GOOGL and AAPL. When compared to other stocks, AAPL shares have the highest projected return.

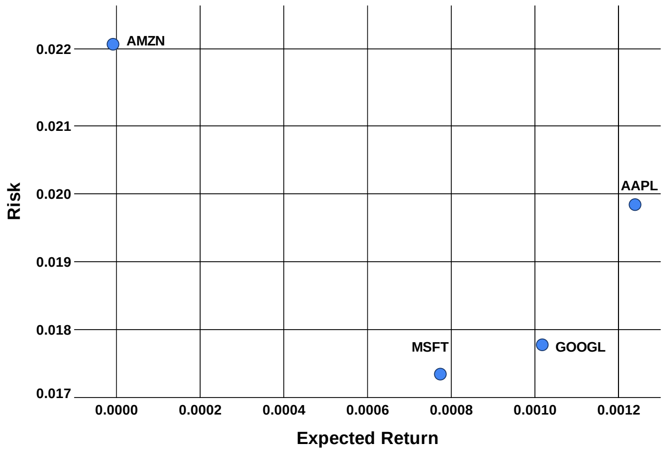


Figure 11. Distribution of risk and expected return of 4 stocks

E. LSTM Prediction

Testing was carried out using several epoch models, starting from 25, 50, 75, and epoch 100. This step is considered important in the process of developing a deep learning model. Convergence occurs when the model has reached a stable level of performance and does not change much with additional epochs. Model performance on the training dataset and validation set improves as the epoch increases; this can help identify signs of overfitting or underfitting. Overfitting occurs when a model overfits the training data and does not generalize well to new data. Underfitting occurs when the model has not learned enough from the training data.

The choice of learning rate value is an important factor in the RMSprop optimization method. It automatically adjusts the learning rate, but choosing a good starting value is still important. In this case, the learning rate value is 0.001, the momentum value is 0.9, and the decay is 1e-5. The model's performance is evaluated using MSE, and we also apply an “early stopping” technique to stop training if there is no significant improvement in performance on the validation set after a certain number of epochs.

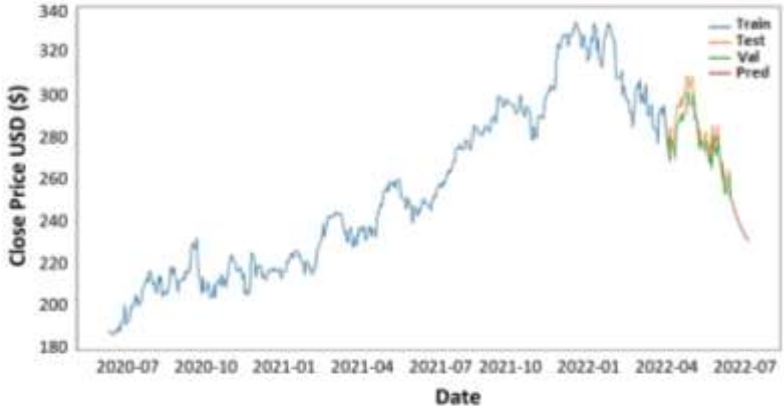
The results of the programmed for four stocks are shown in the form of a track chart against time (daily). From the graph results, it is known that predictions for the future are for Apple (AAPL), Google (GOOG), and AMAZON (AMZN) stocks to rise, while Microsoft (MSFT) will experience a decline in price (Figure 12).

Measuring error by comparing prediction results with target data (ground truth) is a process of evaluating model performance. Evaluating model performance by comparing prediction results with ground truth is important to measure the model's effectiveness in understanding and representing patterns in the data set from May 22, 2020, to May 20, 2022.

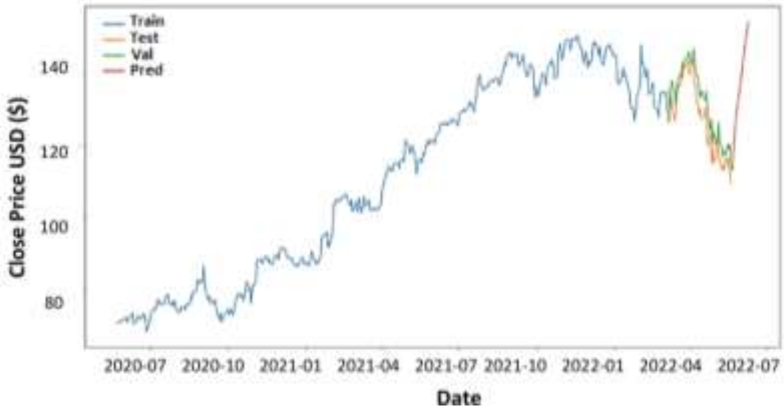
Table II summarizes the results of the history and training graphs. An accuracy of 0.9532 means that the model managed to classify approximately 95.32% of the total test data correctly. This indicates the model's ability to recognize desired patterns and characteristics in the data. A loss of 0.0014 reflects a small error rate in the model. In the context of model training, this loss indicates the degree to which the model approximates the correct representation of the training data. Thus, the accuracy and loss results provide an overall picture of the quality of the model in terms of its ability to classify and model data.

The references for utilizing deep learning models to forecast stocks are compiled in Table III. Deep learning architecture approaches for financial market predictions have been carried out in previous studies. LSTM method [37], RAF, DNN, and LOG [17], ARIMA [38], RF, XGBOOST, AdaBoost, Gradient

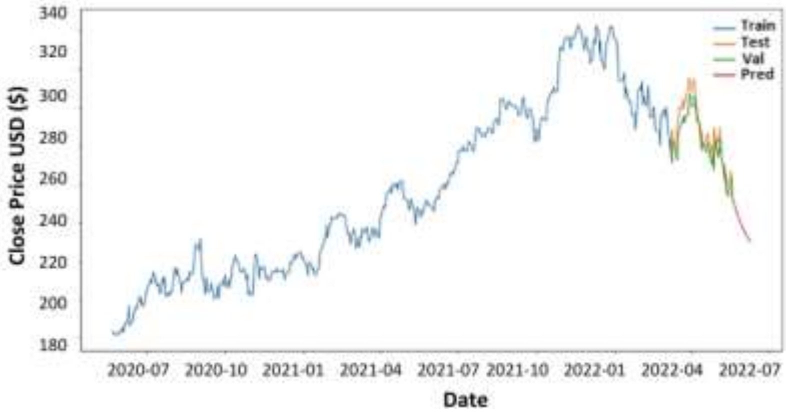
Boosting [39], and RNN [40]. These reference papers provide broad and in-depth insight into the various methods and techniques used to forecast financial market behaviour. Although this study provides a strong foundation for a deeper understanding of how technology can be optimized to support investment decision-making, it also has limitations and challenges related to the use of the DL method. The method proposed in this study deep learning for stock price prediction and moving averages for return-risk analysis. This study is expected to make a significant contribution to developing more sophisticated investment strategies.



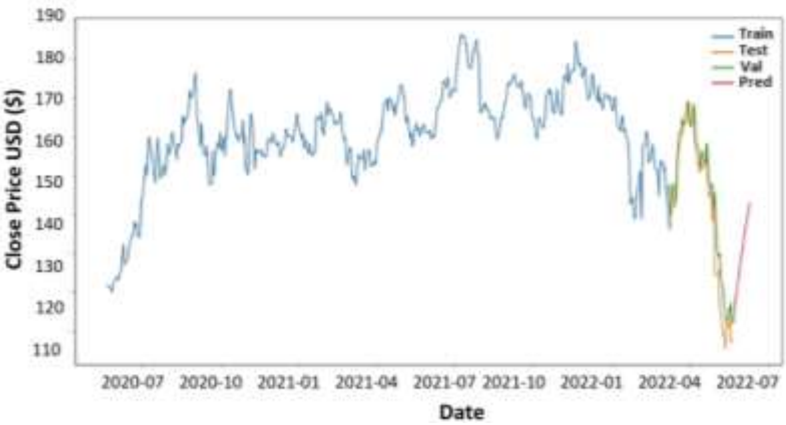
(a)



(b)



(c)



(d)

Figure 12. Predictions of stock (a) AAPL, (b) GOOG, (c) MSFT, and (d) AMZN

TABLE II. LSTM ARCHITECTURE TRAINING RESULTS

Epoch	AAPL		GOOG		MSFT		AMZN	
	Acc.	Loss	Acc.	Loss	Acc.	Loss	Acc.	Loss
25	0.8632	0.0052	0.8945	0.0028	0.9021	0.0050	0.8691	0.0027
50	0.8812	0.0033	0.9034	0.0019	0.8967	0.0032	0.9202	0.0037
75	0.8995	0.0022	0.9386	0.0020	0.9273	0.0016	0.9360	0.0023
100	0.9378	0.0017	0.9445	0.0015	**0.9532**	**0.0014**	0.9421	0.0018

TABLE III. PERFORMANCE STUDY OF PRESENT MODELS

Reference	Method	Dataset	Results
[17]	LSTM, RAF, DNN, LOG	S&P 500 from 1992 until 2015	daily return 0.46%, ratio sharp 5.83% and accuracy 54.3%
[37]	LSTM	S&P 500, trends for the last 120 days	MSE 0.004845
[38]	ARIMA and LSTM	Stock price Ford, GM, Toyota and TESLA	MSE ARIMA 0.025
[39]	RF, XGBOOST, AdaBoost, Gradient Boosting	NIFTY 500 for a holding period of 20 days	MSE XGBOOST 0.0030
[40]	RNN and LSTM	INFOSYS Ltd from NSE IT sector and NSE NIFTY 50	MSE LSTM 0.4761
Proposed models	LSTM for predicting stock price trends and MA for risk and return expectations.	Four stocks: AAPL, GOOG, MSFT, and AMZN, for a period of 2 years.	Predict risk 0.018% expected return 0.001283%, predict stock loss 0.0014

IV. CONCLUSION

Optimization achievement at epoch 100 on MSFT shares had an accuracy level of 0.9532 while the loss value was 0.0014. Because most optimizers get the highest accuracy with this batch size, 100 is the best batch size for all optimizers. Adaptive batch size improves model efficiency while increasing the convergence rate. To save computing time, we halted training at 100 epochs and confirmed that no overfitting occurred on the validation set. The smallest risk is on AMZN shares, with a value of -0.000003, while the expected return on MSFT shares is 0.017223. LSTM can identify complex patterns and non-linear relationships in historical data, allowing investors to make more informed decisions. However, although LSTM can provide promising results, the level of risk remains a key factor in investing, especially when using strategies that rely heavily on technology and models. It is hoped that these results can be used as a second opinion in investing in the Big 5 stock category. Future research can use methods from other DLs and apply them to stocks in Indonesia.

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