Research Project Report A&B <MCSN>

Comparison Methods of Stocks Prediction in Indonesia Stock Exchange - Industrial Classification (IDX-IC) Using LSTM & GRU

vorgelegt von

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Research Project Report

Title: Comparison Methods of Stocks Prediction in Indonesia Stock Exchange - Industrial Classification (IDX-IC) Using LSTM & GRU

Reviewers:

– Prof. Dr. Beate Rhein (TH Köln)

Abstract: Hier sollte eine Übersetzung des obigen Abstracts auf Englisch erfolgen (und kein komplett neuer Text). Auch hier bitte die Begrenzung auf maximal 10 Zeilen Text einhalten.

Keywords: LSTM, GRU

Restriction notice: (optional, falls Sperrvermerk oben ebenfalls existiert) The access to this thesis is restricted until <30 June 2022>.

Date: <13 June 2022>

Outline Contents

Einleitung

In diesem Dokument werden die wichtigsten formellen Punkte zur Erstellung einer Abschlussarbeit an der TH Köln zusammengefasst. Dieses Dokument kann als Leitfaden für die eigene Abschlussarbeit verwendet werden.

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Köln, 13.06.2022

1 Formale Hinweise

1.1 Introduction

Investing deals with managing your money (or financial wealth) today with the hope of receiving more money (or returns) in the future. This brings us to the next element of investing, the uncertainty of the future. In other words, the fact that you can only have hope for higher returns in the future means that you are exposed to risk (1). Stocks are generally one of the most popular among investors with their long-term investment horizons (2). Stock returns are excessively volatile & are difficult to predict in general (4), and there is no fixed factor responsible for the volatility trend, thus suggesting that investors should be aware of the factors causing volatility in the market (3). In addition to oil prices and the world crisis, it can be concluded that company performance, economic variables, financial liberalization, market integration, and economic events are determinants of stock market volatility (5).

Many studies have tried to study and predict stock price movements, which is considered an important step in developing investment strategies. ARIMA Model has been tried (website) with unsatisfactory results, and using conventional machine learning methods such as moving averages, Random Forest K-Nearest Neighbors and Support Vector Machines, and stochastic optimization methods, found accuracy results that are less than satisfactory compared to Multi-Layer Perceptron (7). Therefore, others turn to newer techniques and approaches, such as deep learning methods, for stock price prediction problems, where according to Yanlei Gu et al (19) deep neural network-based prediction method has better performance than the conventional methods.

One of the most widely used deep learning methods, especially for time series analysis, is the short-term long-term memory (LSTM) network. As an improved version of the iterative neural network (RNN), LSTM has been used in many fields. Especially in stock price prediction, LSTM has been proposed and applied by several researchers, such as Penglei Gao et al. [8], Adil Moghar et al. [11], Pramod et al. [10], Raghav Nandakumar et al (12), and Dr. Karunakar Pothuganti (13), with good results.

Another study (15), used Gated Recurrent Units (GRU) as an algorithm to predict future stock market prices, it worked with very good accuracy and they used mini-batch gradient descent which is a good trade-off between stochastic gradient descent and batch gradient descent.

Besides that, it is interesting for me to find a comparison between the two algorithms, namely LSTM and GRU, where some researchers who started with Yassine Touzani and Khadija Douzi (16) proposed two forecasting models (LSTM and GRU). Adjust, and Both deep learning models provide short and medium-term forecast accuracy. Tej Bahadur Shahi(17) using a hyperbolic tangent on the LSTM or GRU layer argues that the LSTM and GRU produce the same results. . Also, Jiayu Qiu (14) had recently published their paper on the stock closing prediction. In their study, they used 4 (four) different techniques, namely with LSTM, GRU, and 2 (two) modified methods namely WaveletLSTM (WLSTM) and WLSTM + Attention Mechanism. Arjun Singh Saud et al. [9] have even built a model using the LSTM network and compared it with the Gated Recurrent Unit (GRU). They found that GRU performs slightly better than LSTM. Akhil Sethia (18) in his research also wrote that GRU produced better results than LSTM with Open High Low Close (OHLC) data taken from yahoo finance. However, according to Sarit Maira (20), LSTM gives better results in making predictions than GRU if the order is large or the accuracy is very critical.

Many studies predict stock prices based on historical datasets such as Open High Low Close obtained from yahoo finance or other trusted websites. One of the effects of stock prices is also influenced by the Volatility Index (VIX Index). The CBOE Market Volatility Index is used as a very popular indicator to show market volatility. Prof. Menachem Brenner, et al (20) mention that the VIX Index and VIX Futures are perfectly correlated to the S&P 500 Stock Index and show that the VIX Index provides prices that are very close to market prices. Likewise, Alessio Bongiovanni (21) confirmed the better predictive power of the VIX Index. The VIX Index can be used as an input to deep learning, like Joerg Osterrieder (22) with a single layer LSTM with the VIX Index, giving an accuracy of 61.2%. Gaurav Dixit et al (23) tested the VIX Index using an Artificial Neural Network and also gave good results. Ali Hirsa et al (24) concluded that the multi-layer LSTM model performed better in predicting outcomes than the flat LSTM model in predicting VIX futures. Hemanth Kumar et al (25) and also James Hosker et al (26) gave the results that LSTM is a good technique for predicting the overall VIX Index.

In addition to the VIX Index, the economic conditions of a country (macroeconomy) are also very influential, such as currency exchange rates, Gross domestic product, inflation rates, unemployment rates, etc. Helmut Herwartz and Konstantin A. Kholodilin (27) recommend including a measure of macroeconomic uncertainty in the early warning system for the stock market. Bin Weng et al (28) test that macroeconomic indicators are the drivers for the monthly prices of stock indices and major sectors in the US, although M. Reza Palawan et al (29) conclude that the exchange rate alone does not have a significant impact on predicting stock prices in Indonesia even though stock prices and exchange rates have a positive correlation. In addition, Hazar Altinbas (30) with monthly values of macroeconomic factors (exchange rate, inflation rate, interest rates) produces a fairly small error (10%) on the stock market in Turkey.

In addition to macroeconomic factors that can affect stock prices, namely, microeconomic factors, namely factors related to the company's internal conditions. In calculating financial statements, the measure that is often used is the ratio, which shows the relationship between two financial data. In the study, the financial ratios studied were Return on Equity (ROE), Price to Book Value (PBV), and Price Earnings Ratio (PER). According to Asri Nurfathi Zahir (31) for future research, the models of stock price prediction may be improved by the use of microeconomic variables.

In this study, I will propose a comparison of the prediction method of stock prices on the Indonesia Stock Exchange by analyzing historical data from macroeconomics such as the Inflation Rate, Central Bank Indonesia Interest Rate, as well as the Indonesian Rupiah Exchange Rate against the United States Dollar, as well as historical data from microeconomics companies such as PER, PBV, and ROE. In addition, I will also analyze the movement of the VIX Index against stock price predictions. The time series analysis method that I will use in this paper is used LSTM and GRU as a comparison for each input.

2 Theoritical Foundation

2.1 Stocks

Stocks are sheets of proof of ownership of a company. Proof of ownership is in the form of share sheets, where currently the shares are electronic or digital unconventional. In Indonesia, in this case in the Indonesian capital market, the unit of ownership used is LOT, where 1 lot is 100 shares. Everyone or often called investors or traders can own by buying a minimum of 1 lot, while companies that make public offerings on the Exchange are called issuers. in this case the Indonesia Stock Exchange or the Indonesia Stock Exchange (abbreviated IDX). Every company that registers as a public company, generally requires external funds, for example, to be additional capital to pay company debts, or carry out company expansion, where the consequence of becoming a public company is to issue ownership that is owned into shares to the public for buying and selling transactions. . The public, in this case, everyone who buys shares, has several advantages from the company, such as the increase in the value of the shares due to the company's performance or capital gains, and also dividend gains, namely the company's income which is distributed to the owners of the shares. Many factors make up or down in value or commonly called stock prices. External factors that usually become a factor are the issuer's external conditions, for example, the economic conditions of a country or global conditions, which are commonly called macroeconomics factors. In addition to the macroeconomics, another condition that can influence is the microeconomy factor, namely the company's internal conditions such as profit factors, debt, and current stock prices. In addition to these two factors, in this study, the authors also found that the VIX Index or the volatility index can also affect stock prices

2.1.1 Composite Stock Price Index Composite (IHSG)

Stock price index or in Indonesian abbreviated JCI is the index value that describes the total number of shares listed on the Indonesian stock exchange, in other words, the JCI is a representation of all stock prices on the Indonesian stock exchange. In buying a share of an issuer, the public cannot buy directly from IDX, but through a securities company that has been registered with the Indonesian Financial Services Authority (abbreviated as OJK). The JCI functions in the IDX are :

- Market direction marker, describing the performance/portfolio of the Indonesian stock market, green or positive JCI means that the public is buying a lot, while the red or negative JCI means that the public has given up their share ownership.
- As an illustration of the investment portfolio. For example, the value of the JCI in 2008 was around 1800, while at the end of 2000 it was already at 6000, (an increase of about 600%), which means that more stocks have increased

2.1.2 Indonesia Stock Exchange - Industrial Classification (IDX-IC)

The IDX Industrial Classification is an Index created by the Indonesia Stock Exchange (IDX) to replace the Jakarta Stock Industrial Classification (JASICA) on January 25, 2021, which will provide more benefits to issuers and the public. This new grouping is considered to be an effective tool to benchmark each sector so that it is more relevant for making investment or trading decisions. IDX-IC responds to the development needs of new economic sectors and harmonizes with global practice. In addition, the IDX IC was also created to respond to economic developments in Indonesia, where a lot of new industries grew, in addition to aligning with other stock exchanges. The fundamental difference between IDX IC and JASICA is the principle of market exposure of the activities carried out.

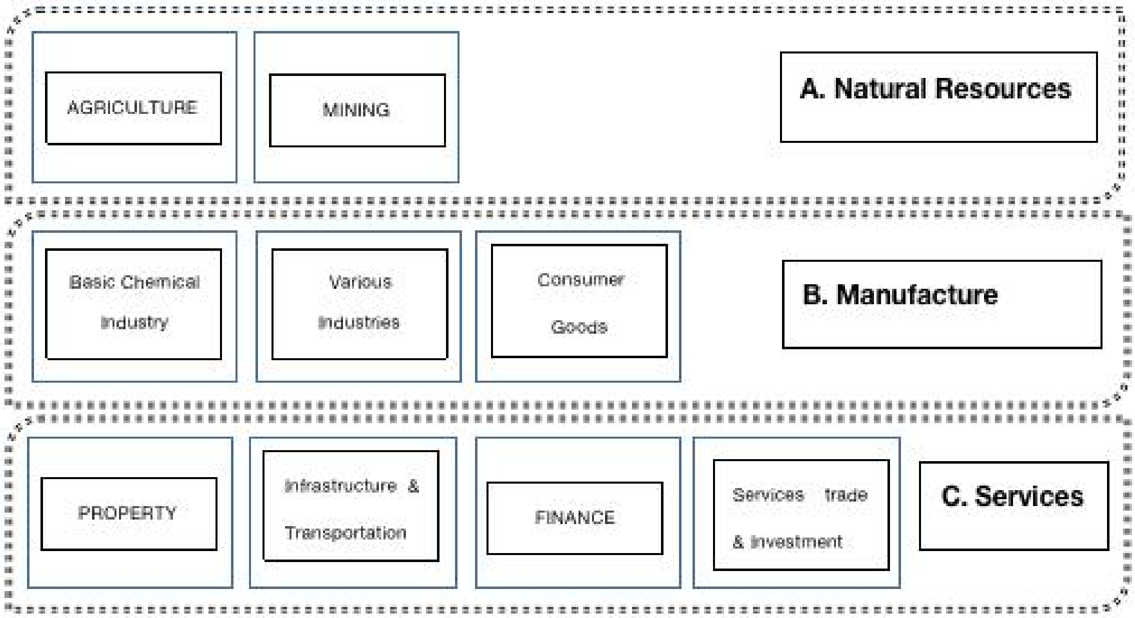

Fig 1. Industrial Sector Classifications IDX - IC

In this study, the authors took a sample of one company in each of 3 main categories, namely issuers in the Natural resources sector, manufacturing sector, and services sector.

2.2 Macroeconomy Factors

Macroeconomics is the science of the economy as a whole, explaining economic changes that affect many societies and markets. Economic factors for example are central bank interest rates, economic growth, inflation rates, unemployment rates, and the currency exchange rate against the US dollar.

According to Regina Eliza, 2018, stock prices are influenced by macroeconomic factors such as inflation, the Indonesian currency exchange rate against the US dollar, and Indonesian bank interest rates. In this study, the author will also take macroeconomic factors at the Central Bank Reverse Repo Rate - 7 days, as a substitute for interest rates, inflation rates, and also the Indonesian Rupiah (IDR - Indonesian state currency) exchange rate against the US Dollar.

2.2.1 Inflation

Inflation is an increase in the price of goods and services within a certain period of time, where when inflation or the inflation rate rises more money is needed to buy the same amount of goods and services, and this will result in a decrease in economic growth, and as a result of rising inflation, this usually forces banks to central, in this case, Central Bank of Indonesia (Bank Indonesia - BI) to increase central bank interest rates. In this study, the inflation value dataset was downloaded on the official website of the Central Bank of Indonesia https://www.bi.go.id/id/statistik/indikator/data-inflasi.aspx.

2.2.2 Central Bank of Indonesia Rate (BI Rate)

Bank Indonesia (BI) Rate is the interest rate that arises due to the cost of borrowing money either from individual companies or even the government. If people or companies borrow less from commercial banks, they have less money to spend or invest in, and vice versa. If interest rates rise, it will require more saving and less spending and reduce economic growth. The central bank meets every month to regulate interest rates in Indonesia. So it can be concluded that interest rates control inflation and control the money supply (Money supply).

2.2.3 Central Bank of Indonesia 7 Days Reverse Repo Rate (BI7DRR)

Often called the BI Repo rate, it is an interest rate that replaces the BI Rate, where if the BI rate waits for 1 year, while the BI repo rate only takes 7 days (and multiples thereof) commercial banks can withdraw money so that it is shorter and has a direct impact on accelerating the economic effect. In principle, the BI repo rate is the same as the BI rate, where if inflation rises, public consumption declines, and economic growth slows, the BI repo rate will decrease. In this study, the BI repo rate dataset was downloaded on the official website of Bank Indonesia https://www.bi.go.id/id/statistik/indikator/bi-7day-rr.aspx.

2.2.4 Currency Exchange Rate Indonesian Rupiah (IDR) - USDollar (USD)

The Currency exchange rate is a means of payment used in every Indonesian economic transaction, where the Indonesian currency used is Rupiah (IDR) against the US Dollar (USD). Basically, the currency exchange rate reflects the price of the domestic currency, so its value is influenced by the supply and demand of the currency itself through international transactions. If the level of domestic exports is lower than imports, there will be a deficit in the domestic trade balance which will result in a weakening of the exchange rate or a decline in the currency exchange rate because more people sell Indonesian rupiah (IDR) for payments in foreign currencies (dominated in US dollars). The impact of the weakening of the exchange rate is that the prices of consumer goods will rise and inflation will also increase. In this study, the currency exchange dataset was downloaded on the official website of Bank Indonesia https://www.bi.go.id/id/statistik/information-kurs/jisdor/default.aspx.

2.3 Micro Economy Factor

Microeconomics in the world of capital markets means seeing the good or bad performance of a company, which is reflected in the ratios obtained in financial reports which are regularly published either three months (quarterly) or annually (annually) by issuers. This financial report is mandatory for all issuers registered with IDX, either uploaded on their respective official websites or can also be downloaded on the official IDX website https://www.idx.co.id/usaha-tercatat/laporan-keuangan -and-annual/. According to Pungkas dika Saputra, 2021, there are 3 (three) ratios used to see the effect on stock prices, namely price Earnings ratio (PER), price to book value (PBV), and return to equity (ROE) which have a positive effect. In this study, the author will also use this ratio to see the effect of microeconomics and compare it with other factors (macroeconomics and volatility index). In looking at the three ratios, we pay attention to several values in the company's financial statements such as the company's net income, the company's book value, and the number of shares outstanding. One of the functions of looking at these ratios in addition to predictions in this study, is also usually used by investors or traders to assess the fairness of the price or assess the low price of the stock as the right time or not to buy the stock.

In this study according to Table 1, we take 3 companies that represent the three main categories of IDX-IC, namely in category A (natural resources), the authors take the company PT. Vale Indonesia, Tbk (INCO), in category B (manufacturing), the author takes the company PT. Charoend Pokphand Indonesia, Tbk (CPIN), and in category C (services), the author takes the company PT.Bank Rakyat Indonesia, Tbk (BBRI).

2.3.1 Price to Earning Ratio / PE Ratio (PER)

The price to Earning ratio (PER) is the value used to predict the price valuation of a stock. PER is also an indicator that compares stock prices with the company's ability to earn profits.

$$\text{Price to Earning Ratio (PER)} = \frac{\textit{Price Per Share}}{\textit{Earning Per Share}}$$

The PER value of a company will be useful when used by compared the PER value of similar companies. And it becomes ineffective when comparing with companies that are not similar or also not relatively the same in value. For example, comparing Bank Rakyat Indonesia (BBRI) with Bank Mandiri (BMRI), where a smaller PER ratio indicates a cheaper stock price when the time is right. Stocks with a relatively low PER ratio will be in great demand by investors and traders because they tend to be cheap, thereby increasing the possibility of capital gains

2.3.2 Price to Book Value (PBV)

Price to book value (PBV) is the ratio of the stock price to the book value of the company. PBV is used to see how much is a multiple of the market value of the company's stock price with its book value. The indicator used is to compare stock prices with the company's net worth (Assets-Debts).

$$\text{Price to Book Value (PBV)} = \frac{Stock\ prices}{Book\ value\ per\ share}$$

The PBV ratio is used by investors or traders by comparing companies in similar industrial sectors. If the PBV ratio is 1, then the stock price is sold according to the capital, if the PBV ratio is < 1, the stock price is cheaper (below) the company's capital

2.3.3 Return on Equity (ROE)

Return to Equity (ROE) is the company's net income to the company's net worth (total equity).

$$\text{Return to Equity (ROE)} = \frac{Net\ Profit}{Equity\ total\ (Assets - Debt)}$$

Stocks with a relatively high ROE ratio mean that the stock price return on capital is considered high or the company is getting better because the company can manage the company's capital so that it can generate large profits. The author considers a good ROE value if it is above the average value of deposits in Indonesia, in this case, the average value of deposits is around 8%, so the index ratio of 10% is a good value.

2.4 Volatility Index (VIX Index)

The VIX Index or volatility index (or VIX for short) is an index that measures the expected volatility of the stock market which is derived from the S&P 500 Index. The S&P 500 Index is an acronym for the Standard & Poor's 500, an index based on stock values. 500 companies with large market capitalization on the United States stock exchange. Sometimes stock players (investors or traders) call the VIX Index other names such as the 'fear index'. This is because volatility is closely related to risk, so the VIX Index is often used as a time benchmark to determine the level of the pessimism of market participants. The VIX index is formulated to provide information on the expected volatility of the stock market in the short term (less than 1 year). A high VIX (above 30) occurs when stock players anticipate that there will be a potential for large market movements, and conversely the VIX will be at a low level when market participants do not feel there is a significant downside risk or potential increase. There is a relationship that is commonly held by market participants, namely when the VIX is above level 30 it is associated with the potential for high volatility as an index of fear of market participants. When the VIX is below the 20 levels, this reflects that there is no significant pressure on the stock market that can cause high volatility. So that the VIX can simply read the expected volatility of the stock market by analyzing the value of the VIX.

2.5 Long-Short Term Memory (LSTM)

2.5.1 Forwarding Propagation LSTM / Forward Propagation LSTM

Long short term memory (LSTM) is designed to deal with problems that exist in the Recurrent Neural Network (RNN), namely long term dependency. The problem with forwarding propagation RNN, RNN can lose important information obtained if the sequence is long enough. Likewise for the backward propagation of RNN, where the RNN can also experience a vanishing gradient so that the gradient value is very small so that it does not contribute to the update of the weight. LSTM was introduced in 1997 by Hochreiter & Schmidhuber to deal with this problem, as an RNN unit development. LSTM is the same as RNN used for sequential data input.

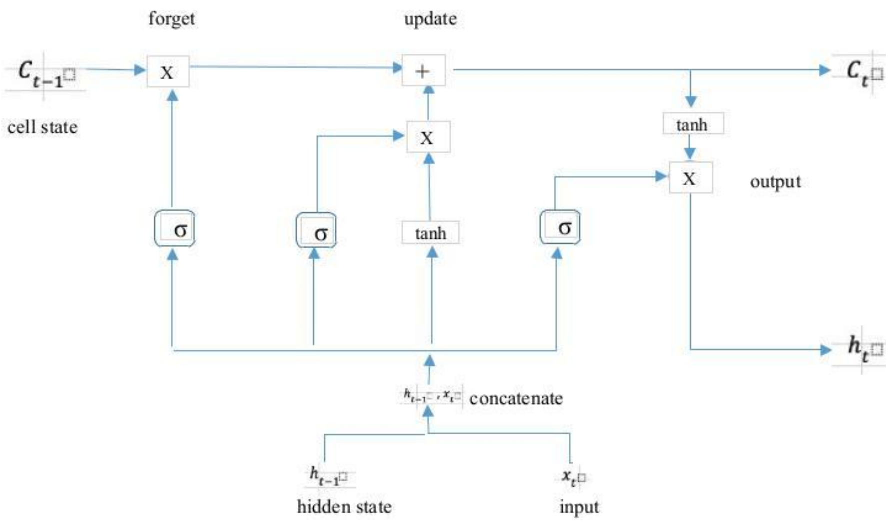

Figure 2. LSTM Architecture

Figure 2 above is the structure of the LSTM, which has a cell state and 3 gates, namely forget gate, input gate, and output gate.

- Cell state serves as 'additional memory' owned by the LSTM network unit. The cell state acts as a transport highway that transfers relevant information throughout the processing of the sequence.

$$C_t = (f_t x\ C_{t-1} + i_t x \subsetneq_t)$$

In the forward propagation of the LSTM cell state, there are f_t and i_t which are both generated by the sigmoid (values between 0 and 1), while C_t is generated by the tanh function (values between -1 and 1). f_t and i_t functions as weights that determine the old information to be stored or new information to be added.

- Forget gate to determine which information will be passed or used from the cell state because it is important and which information will be forgotten or discarded. In the forget gate this is due to the use of sigmoid activation where if the value is close to '1' it means to keep and the value is close to '0' means to forget.

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

In the LSTM forget gate forward propagation before entering the sigmoid activation function, the matrix U is multiplied by the input x_t, and the matrix W is multiplied by the previously hidden state h_{t-1} and added to the weight matrix b.

- Input gate decides what information is relevant to add from the current step and also updates the cell state by hidden state and current input.

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

$$\cancel{C}_t = tanh\ (U_c . x_t + W_c . h_{t-1} + \ b_c)$$

In forwarding propagation of the LSTM Input gate, it uses sigmoid activation, while $C^{\wedge t}$ uses tanh. The input gate is used to determine what new information will be stored in the cell state. This input gate has 2 main operations, namely to calculate the values of It and $C^{\wedge t}$, while still processing h_{t-1} and x_t using u, w, and b matrices for the input gate.

- Output gate decides what the next hidden state should be and the hidden state contains information on previous inputs. The hidden state is also used for predictions.

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

$$h_t = o_t x\ tanh(C_t)$$

In LSTM forward propagation, the forget gate already has a C_t value of the cell state, and we continue to use input (x_t) and h_{t-1} (previous hidden state). Where o_t still uses u, w, and b matrices that are different from the input gate

2.5.2 Backward Propagation LSTM

Backward means calculating the loss that will incorrect the output, and then will backpropagate the errors and this process whatever bias and weight are present in forwarding propagation will be tuned during the backpropagation process and they will be adapted to datasets. Calculating gradients with respect to weight (U and W) involve the calculation of gradients with respect to the gate and states in forwarding propagation.

$\omega_{new} = W_{old} - \frac{dL}{dW} \times \alpha$

with α = learning rate,

$\frac{dL}{dW}$ = derivative loss with respect to the weight

The new weight will be updated every time during the iteration process.

$L = \sum_{j=0}^{T} Lj$

Total loss corresponding to LSTM Unit for each time step

This equation calculates derivative loss with respect to the weight, and also with the respect to the bias.

2.6 Gated Recurrent Unit (GRU)

2.6.1 Forwarding Propagation GRU / Forward Propagation GRU

Gated Recurrent Unit (GRU) has more improvement than LSTM. One of the advantages compare to LSTM is GRU's simplified version of LSTM with two gates and one hidden state, which means GRU has smaller training time.

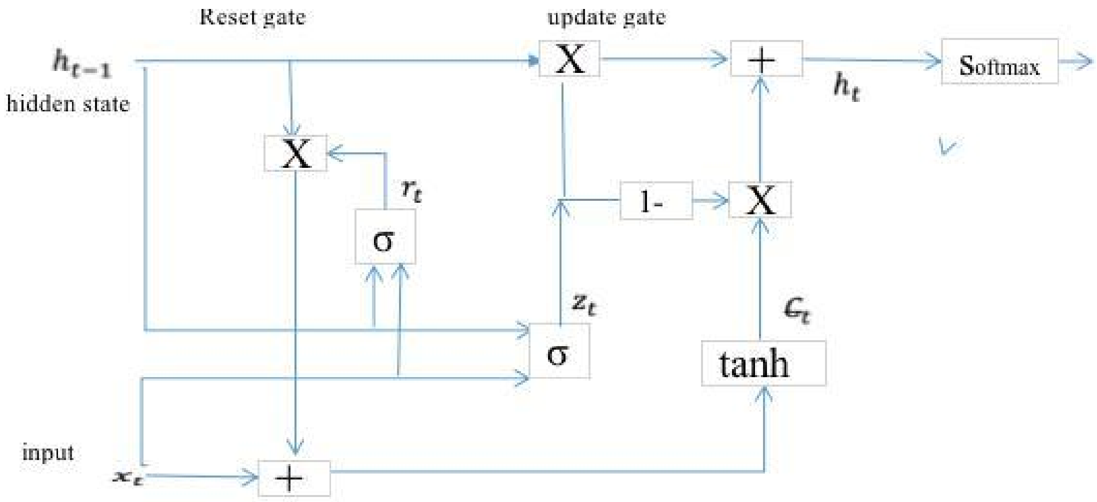

Figure 3. GRU Architecture

Figure 3 above is the structure of the GRU, which has 1 hidden state and 2 gates, namely the reset gate and the update gate.

- Reset gate to control how much information you want to pass from the previous hidden state (h_{t-1})to the next hidden state. It helps to decide how to add the new information to the memory (how much of the past information can forget).

$$r_t = \sigma\ (U_r.x_t + W_r.h_{t-1} + \ b_r)$$

The architecture of the reset gate is similar to forget gate of LSTM.

- Update gate to control how much information you want to add to the previous hidden state to the next hidden state. It helps to decide what information from the previous time step h_{t-1} can be taken forward to the next time step ht.

$$z_t = \sigma\ (U_z.x_t + W_z.h_{t-1} + \ b_z)$$

$$\cancel{C}_t = tanh\ (U_c.x_t\ + W_c.(h_{t-1} + b_c))$$

To update the hidden state, (add new information= we need a candidate state. A new candidate state (denote with ~~C~~t) is created for holding the information, which will be added to the previous hidden state (h_{t-1}) using the plus (adding) operator. Multiplying h_{t-1} with zt gives us relevant information from the previous step. Instead of having a new gate (compares to LSTM), we take the complement of z_t (1-zt) and multiply it with candidate state ~~C~~t. The hidden state is then updated as

$$h_t = (1 - z_t)\cancel{C}_t + z_t . h_{t-1}$$

2.6.2 Backward Propagation GRU

Backpropagation or backward propagation in GRU is also similar compares to the LSTM process (follow with the same orders).

$$L = \sum_{j=0}^{T} Lj$$

Total loss corresponding to GRU Unit for each time step

The total loss that we have is summing all the losses from time step 0 until time step T. Backprogation in GRU also calculates the derivative of loss with the respect to gate (reset gate and update gate) and the derivative of loss with the respect to weights (U and W)

2.7 Performance Metrics

To evaluate the performance of the model in this study, R squared and Mean Square Error (MSE) were used

2.7.1 R-Squared (R2 / R^2)

R squared tells us how a regression line predicts estimate actual values. R2 represents the proportion of variance (y) that has been explained by the independent variables in the model (x), and R2 provides an insight of the goodness of fit. It gives a measure of how well-unseen samples to be predicted by the model through the proportion of explained variance.

$$R\ squared\ (R^2) = \sum \frac{(\Upsilon - \gamma)^2}{(\Upsilon - \gamma)^2} = 1 - \sum i \frac{(\Upsilon_i - \gamma_i)^2}{(\Upsilon_i - \gamma_i)^2} = 1 - \frac{MSE}{Variance}$$

$R^2 \approx 1$, means perfect fit / close together
$R^2 \approx 0$, means no relationship at all / doesn't fit the data at all
$R^2 < 0$, means predictive medal worst than simple average over the original data

R squared is calculated by following these steps :

- Calculate actual values, and determine the mean of these values
- Draw the regression line and come up with estimated values and we take the distance from estimated values to the mean
- We compare this to the distance of actual values to the mean

2.7.2 Mean Squared Error (MSE)

MSE tells us the difference between observed values and the predicted values and after that take a square.

$$\text{MSE} = \frac{1}{n} \sum_{i-1}^{n} (\Upsilon_i - \gamma_i)^2$$

Υ_i = observed values
γ_i = predicted values

$$\text{RMSE} = \sqrt{MSE} = \sqrt{\frac{1}{n} \sum_{i-1}^{n} (\Upsilon_i - \gamma_i)^2}$$

MSE is calculated by following these steps :

- Calculate the errors for every data point
- Calculate the squared value of the errors
- Calculate the average of results from the squared value of errors

3 Methodology

This research focuses on a better comparison of deep learning algorithms by using a sample of three companies in the industrial classification index by comparing with 3 inputs that are considered to affect the value of the stock price. The following is the methodology of this research.

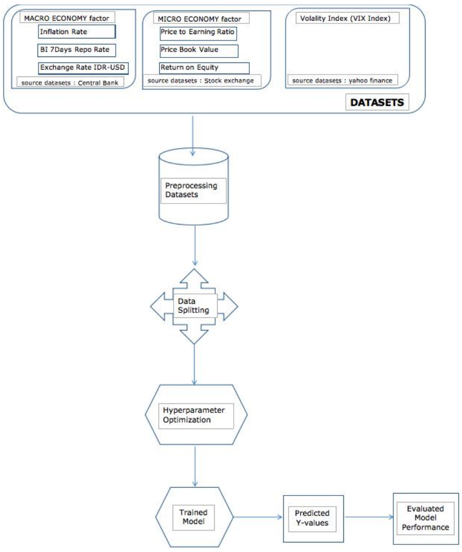

Fig 4. Research Methodology

3.1 Datasets

This research was conducted on the Indonesian Stock Exchange on the Industrial Classification Index (IDX-IC) by sampling companies on 3 companies in each category of main criteria according to Figure 1, namely in the natural resources sector, the manufacturing sector, and the services sector. For the company to be researched, it is by following with table 1.

No	Category	Company Name	Company Index
1	Natural Resources	Vale Indonesia Tbk. PT	INCO
2	Manufacturing	Charoen Pokphand Indonesia Tbk . PT	CPIN
3	Services	Bank Rakyat Indonesia (Persero) Tbk . PT	BBRI

Table 1. Sample of research companies

In this study, predictions will be made on the 'close' variable, which means the closing price of each working day of the Indonesian stock exchange. The datasets of the three companies were taken on the yahoo finance website, and also on the official website of the Indonesian Stock Exchange (IDX). For the dataset on yahoo finances there will be 7 different inputs, namely:

No	Variable	Company Name

1	Date	Date of the trading day
2	Open	Price of the stock when the market opened on this day
3	High	a stock's highest trading price for the day
4	Low	a stock's lowest trading price for the day
5	Close	Stock the priced close at for the preceding trading day
6	Adjusted Close	Closing price after adjustments for all applicable splits and dividend distributions
7	Volume	How many shares have traded hands today

Table 2. Yahoo finance historical data definitions

Yahoo finance provides historical data for every company on the Indonesian stock exchange, including the three companies that will be tested. The historical data retrieval process is carried out at the Max range (maximum) on the website, which means a stock's entire pricing history since the date it was offered for trading on a public exchange. For this reason, the LSTM and GRU Deep learning algorithms will be used separately and comparisons are made for each of the main categories of the company, as an algorithm for predicting this time series. In addition to measuring using these two algorithms, the author will also compare the three input parameters, namely Macroeconomy (Inflation, BI 7 Days Repo Rate, Indonesian currency exchange rate Rpiah - USD Dollar), microeconomy (PER, PBV, ROE), and also volatility index (VIX Index), so testing each algorithm, both LSTM and GRU, will require 9 results, with each dataset having a different date-time range.

No	Input Name	Dataset Source	Start Date	End Date	Freq	Size
1	INCO	www.finance.yahoo.com	29 September 2005	30 December 2020	Daily	3785 x 7
2	CPIN	www.finance.yahoo.com	29 September 2005	30 December 2020	Daily	3785 x 7
3	BBRI	www.finance.yahoo.com	10 November 2003	30 December 2020	Daily	4268 x 7
4	Macroeconomy - Inflation	https://www.bi.go.id/	October 2003	Desember 2020	Monthly	207 x 3
5	Macroeconomy - BI 7Days Repo Rate	https://www.bi.go.id/	21 April 2016	17 December 2020	Monthly	58 x 3
6	Macroeconomy - Exchange Rate	https://www.bi.go.id/	20 May 2013	30 December 2020	Daily	1850 x 3
7	Annual Report	https://www.idx.co.id	01 January 2015	30 December 2020	Yearly	24 x 5
8	Financial Report	https://www.idx.co.id	01 April 2015	30 December 2020	Kuartal	24 x 5
9	VIX Index	www.finance.yahoo.com	10 November 2003	30 December 2020	Daily	4315 x 7

Tabel 3. Datasets information

Microeconomy inputs are Price to Earnings Ratio (PER), Price to Book Value (PBV), and Debt to Equity Ratio (DER) got by performing calculations from the financial statements available in the annual report and financial report. So in this study, the author will divide each company with a dataset downloaded from the yahoo finance website, by comparing each input category.

3.2 Preprocessing

After collecting the datasets, it is seen that there are differences in the size of the datasets as well as the differences in time and frequency, both datasets of 3 companies, with the input that will be used as input to the deep learning algorithm. The initial stage of this preprocessing is to determine the input selection for the three existing company datasets, where for the datasets of the three companies we will discard the Adj Close and Volume Inputs because they show very small correlations and even tend to have no effect. So that the datasets for the three companies become 'Date', 'Open', 'High', 'Low', and 'Close' so that later we will shorten them to the OHLC dataset. And in the OHLC program, the dataset will be made into a variable dataframe1 or df1, where the author will separate each file from the three companies.

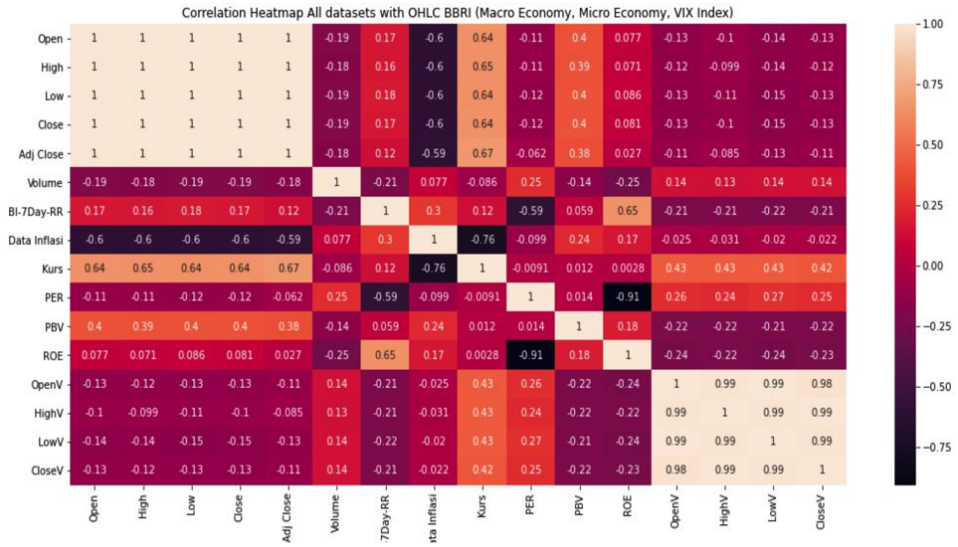

Figure 5. Correlation heatmap for Input selection

The microeconomy variable is also different for each file in the three companies because the calculation results are taken from the data of each company. Meanwhile, for macroeconomy inputs, namely inflation, BI 7 Daya repo rate and exchange rate as well as the Input VIX Index are used for each file of the three companies.

No	Input Name	Variables	Size
1	INCO	df1 - INCO files	3785 x 5
2	CPIN	df1 - CPIN files	3785 x 5
3	BBRI	df1 - BBRI files	4268 x 5

4	Inflation	df2	207 x 3
5	BI 7Days Repo Rate	df3	58 x 3
6	Exchange Rate	df4	1850 x 3
7	Micro economy	df5 - for each df1	24 x 5
8	VIX Index	df6	4315 x 7

Table 4. Variable dataset used

After determining the variables and Input selection from the correlation table from all existing datasets, the next step is to change the data types date all datasets become DateTime so that later it will be easier when doing the next process. In addition, we also change the data types of all object datasets to float, because for all datasets these are numeric. Before we group it into 3 main categories of inputs for each company (Macroeconomy, microeconomy, and the VIX Index), we can see the distribution of the dataset using a pair plot.

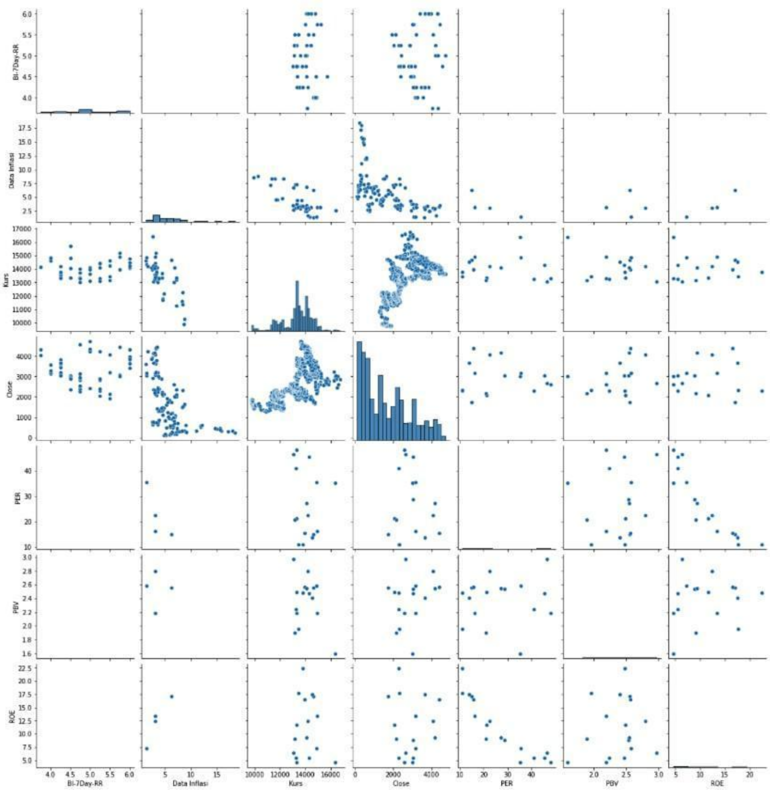

Figure 6. Distribution of datasets.

```
Date              0
Open              1
High              1
Low               1
Close             1
Adj Close         1
Volume            1
BI-7Day-RR     4210
Data Inflasi   4141
Kurs           2422
PER            4251
PBV            4251
ROE            4251
dtype: int64
```

Figure 7. Checking NaN Values from distribution datasets

From the BBRI pairplot image above, and checking NaN values with the isna( ).sum() method, it can be seen that several inputs have NaN values. To overcome this imputation, we use the interpolate method in the pandas libraries, with the parameters method time, because the existing datasets are time series sequences. After the imputation with interpolation is done, we can see the outliers in the existing input, and as an example in the BBRI below.

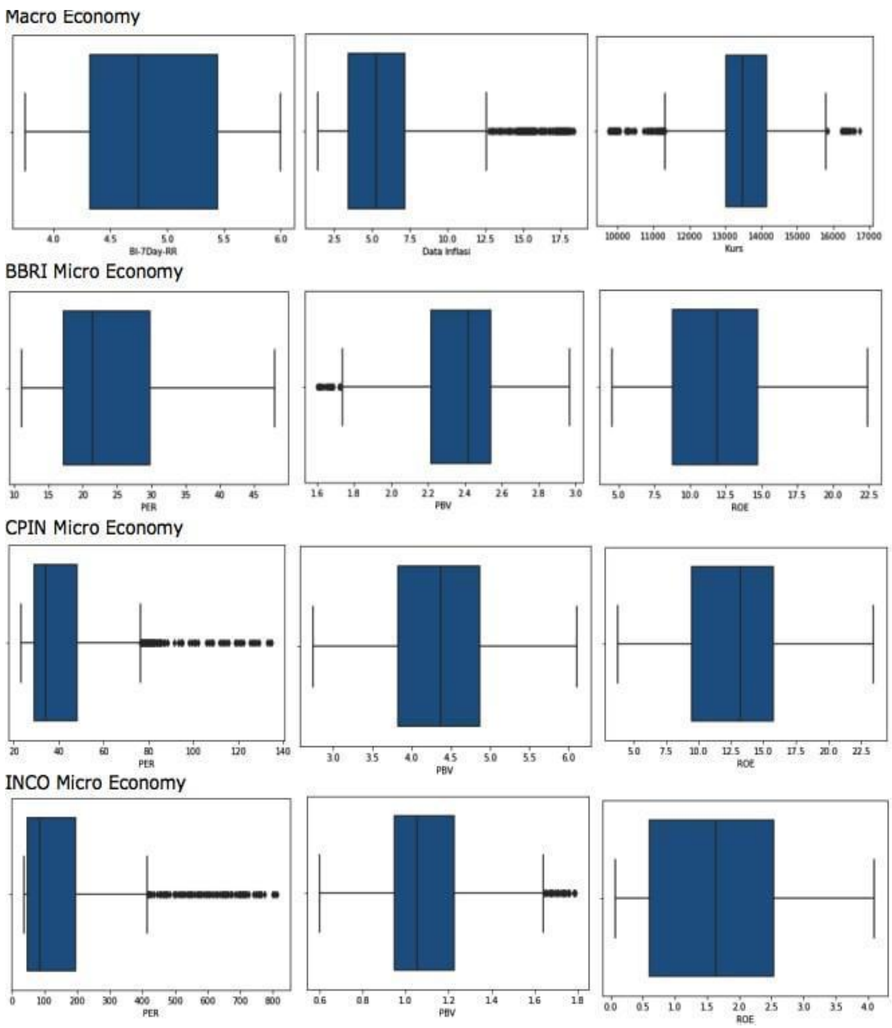

Figure 8. Outliers on Macroeconomy and microeconomy

Inputs From the boxplot image on the outliers data, several inputs that affect stock prices can be seen that there are values outside the quartile range. Because these datasets are primary data that are downloaded on the official website, the outliers values are ignored and forwarded to the next process. After this, we will merge all the Inputs into 3 main categories in each company that will be researched.

No	Input Name	Input Category	Start Date	End Date	Shape
1	Inflation	Macro Economy	October 2003	December 2020	207 x 3
2	BI 7Days Repo Rate	Macro Economy	21 April 2016	17 December 2020	58 x 3
3	Exchange Rate	Macro Economy	20 May 2013	30 December 2020	1850 x 3
4	PER (Price to Earnings Ratio)	Micro Economy	31 March 2015	30 December 2020	24 x 5
5	PBV (Price to Book Value)	Micro Economy	31 March 2015	30 December 2020	24 x 5
6	ROE (Return on Equity)	Micro Economy	31 March 2015	30 December 2020	24 x 5
7	VIX Index	VIX Index	10 November 2003	30 December 2020	4315 x 5
8	BBRI	OHLC	10 November 2003	30 December 2020	4315 x 7
9	CPIN	OHLC	29 September 2005	30 December 2020	3785 x 7
10	INCO	OHLC	29 September 2005	30 December 2020	3785 x 7

Table 5. Merged all datasets into category

After being grouped based on 3 input categories, the datasets will be cut based on the smallest datetime range, so that the final dataset after preprocessing will be as in table 6. And later 9 d These assets will be included in the Deep learning model.

No	Final Datasets	Smallest Input	Final Start Date	Final End Date	Final Shape
1	BBRI Macro Economy	BI-7Days Repo Rate	21 April 2016	30 December 2020	1186 x 7
2	BBRI Micro Economy	PER (Price to Earnings Ratio)	31 March 2015	30 December 2020	1445 x 7
3	BBRI VIX Index	BBRI	10 November 2003	30 December 2020	4268 x 5
4	CPIN Macro Economy	BI-7Days Repo Rate	21 April 2016	30 December 2020	1186 x 7
5	CPIN Micro Economy	PER (Price to Earnings Ratio)	31 March 2015	30 December 2020	1445 x 7
6	CPIN VIX Index	CPIN	29 September 2005	30 December 2020	3785 x 5
7	INCO Macro Economy	BI-7Days Repo Rate	21 April 2016	30 December 2020	1186 x 7
8	INCO Micro Economy	PER (Price to Earnings Ratio)	31 March 2015	30 December 2020	3785 x 5
9	INCO VIX Index	INCO	29 September 2005	30 December 2020	3785 x 5

Table 6. Final dataset after preprocessing

3.3 Model

After the category Input group is final in the preprocessing stage, the next step is data splitting. In this study, we split data based on the DateTime period because this is time-series data. And the composition of data splitting for Train: Validation: Test is 70:20:10. Before doing the data splitting, 'Close' in the OHLC dataset of each company as an independent variable or prediction target, is shifted to the end of the grouping (-1) of the final datasets to make it easier for the next modeling process. The table below shows data splitting before modeling

No	Final Datasets	Original Shape	Train Start Date	Train End Date	Train Shape	Validation Start Date	Train End Date	Train Shape	Test Start Date	Train End Date	Train Shape
1	BBRI Macro Economy	1185 x 7	21 April 2016	31 July 2019	837 x 7	01 August 2019	30 June 2020	227 x 7	01 July 2020	31 December 2020	121 x 7
2	BBRI Micro Economy	1444 x 7	31 March 2015	31 March 2019	1009 x 7	01 April 2019	23 May 2020	289 x 7	24 May 2020	31 December 2020	146 x 7
3	BBRI VIX Index	4268 x 4	10 November 2003	25 November 2015	2984 x 4	26 November 2015	31 March 2019	848 x 4	01 April 2019	31 December 2020	436 x 4
4	CPIN Macro Economy	1185 x 7	21 April 2016	31 July 2019	837 x 7	01 August 2019	30 June 2020	227 x 7	01 July 2020	31 December 2020	121 x 7
5	CPIN Micro Economy	1444 x 7	31 March 2015	31 March 2019	1009 x 7	01 April 2019	23 May 2020	289 x 7	24 May 2020	31 December 2020	146 x 7
6	CPIN VIX Index	3785 x 4	29 September 2005	30 July 2016	2664 x 4	01 August 2016	25 June 2019	747 x 4	26 June 2019	31 December 2020	374 x 4
7	INCO Macro Economy	1185 x 7	21 April 2016	31 July 2019	837 x 7	01 August 2019	30 June 2020	227 x 7	01 July 2020	31 December 2020	121 x 7
8	INCO Micro Economy	1444 x 7	31 March 2015	31 March 2019	1009 x 7	01 April 2019	23 May 2020	289 x 7	24 May 2020	31 December 2020	146 x 7
9	INCO VIX Index	3785 x 4	29 September 2005	30 July 2016	2664 x 4	01 August 2016	25 June 2019	747 x 4	26 June 2019	31 December 2020	374 x 4

. Table 7. Time series datasets after data splitting.

After data splitting, the next process is to normalize using MinMaxScaler in the scikit-learn library. Normalization is needed because the gap or difference in the range of datasets is quite large from units (such as inflation data) to tens of thousands (Currency rate), the details are shown in Figure 8 Outliers. The normalization is carried out on all data, both training data, validation data, and test data. Until the normalization stage, starting from the initial stage, the preprocessing is done the same for the Long short term memory (LSTM) and Gated recurrent unit (GRU) algorithms. After this normalization process, we enter the training stage, where at this training stage, we need training data and validation data. In addition, at this training stage we need several parameters as arguments in this process, which are called hyperparameters. Like parameters, hyperparameters are variables that affect the model's output, in this case, the prediction of the close price of a stock, or in other words, variables that affect how a model is trained. Before discussing hyperparameters, in this training process, we use a dropout of 0.2 from the Keras library. In this study, 5 hyperparameters are carried out by the tuning process or the optimal process, namely:

- Timesteps

  For a few timesteps, the backward propagation process has been explained in Chapter 2 previously. The LSTM and GRU algorithms as input to the training process require a three-dimensional array including samples, timesteps, and input. Where timesteps are the sequence of inputs. Referring to Figure 2-LSTM architecture, it can be seen that the forget gate as the initial gate of the LSTM process has a timestep data input vector at t=0 and the previously hidden state timestep vector at t=t-1. As an illustration, can be seen in the image below

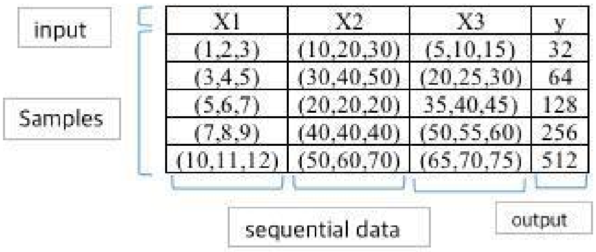

Figure 9 . illustration of timesteps

In the picture above is sequential data, dimension 3 (X1, X2, X3), with 3 timesteps. Where for LSTM and GRU requires 3 dimensions, namely samples, timesteps, and features, in the case of the picture above it is (5, 3, 3). To make predictions using LSTM/GRU, the timestep can also be used as a sliding window, where the sliding window sees sub-sequential data. In this case, the sliding windows that we use are a maximum of 7 days because the BI7DRR (Central Bank Rate 7 Days Repo Rate) input is 7 days.

- Hidden layer (hl)

The hidden layer is not the same as the hidden state or the number of inputs, basically, hidden layer is the number of layers in the LSTM or GRU, of course, it cannot be saved by copying the arguments to the Multi-layer perceptron or neural network, because LSTM and GRU are part from 'recurrent', you get over time. The hidden layer can also be interpreted as a layer between input and output. Because it is often referred to as the 'black box', there is no final number of how many layers should be used.

As an illustration in the previous image, the hidden layer and memory blocks or LSTM / GRU unit blocks can be seen in the image below

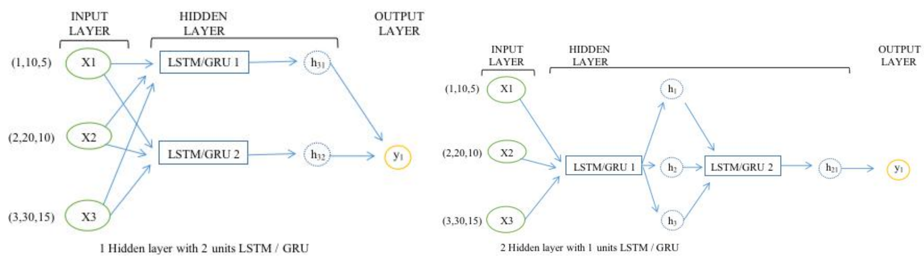

Figure 10. illustration of the hidden layer architecture with LSTM / GRU units

- Learnings rate (α)

For learning rate, we have explained a little about the backward process propagation in Chapter 2 earlier. The learning rate will control how quickly the LSTM and GRU algorithm models that we set can adapt to the existing problems. The challenge in training this algorithm is carefully selecting the learning rate, even in some studies writing that the most important hyperparameter for the model is the learning rate. In this study, the optimizer used is adam.

- Batch size

  This batch size specifies the number of samples that must be run before the internal model parameters are updated. In this study, the batch size ranges were 25 (32), 26 (64), and 27 (128), and also used Keras as the batch size for LSTM and GRU.

- Number of epochs

  This hyperparameter specifies how many complete iterations of the input dataset are to run. Just like other hyperparameters, there is no exact number in determining its value. Epoch itself is not the same as iteration. In this study, iteration ranges from 1 to 200, and uses early stopping to stop the training process to prevent overfitting in the model made.

  In addition to hyperparameters, in this modeling the author makes model functions consisting of:

  a) Dense layer with ReLu
  b) Dropout activation function between Dense layer and Dense output layer (dropout = 0.2)
  c) Dense output layer with 1 neuron
  d) Loss function used is the Mean Squared Error
  e) Optimizer used is Adam
  f) Early stopping is used so as not to overfit.

After the training process is run, the next step is to see the performance value. For this, the authors perform qualitative measurements using the MSE and R2 values as in chapter 2.7 on performance metrics. After all the models (of course by tuning the hyperparameters), the model is considered the best, both for the LSTM and GRU algorithms, the inverse normalization process is carried out before the visualization process is carried out.

4 Results

This research was conducted on an iMac Sierra OS computer with a 2.5 GHz Processor specification, using 12 GB 1333 DDR3 Memory, and an AMD Radeon HD 6750 512 MB Graphics card. Some of the libraries used can be seen in table 8.

No	Research Libraries	Version
1	Pandas	1.2.4
2	Numpy	1.19.5
3	Tensorflow	2.6.0
4	Scikit-learn	0.24.1
5	Seaborn	0.11.1

Table. 8. Research Libraries

Experimental research libraries that provide the highest performance value for each method are used as a model to find the best method by retesting the test data provided. Before testing this research method, it is necessary to use hyperparameters. Because analyzing the impact of hyperparameters will affect the accuracy of results. In addition, in this study, we will compare the LSTM and GRU algorithms with 3 main categories of input on 3 different stocks according to the latest index, namely industrial classification (IDX-IC).

From the tested hyperparameters and several main categories of input, scenarios can be made for several retests in this study. In Table 6 in chapter 3 we can see that there are 9 scenarios in each tested algorithm, based on the qualitative values of MSE and R squared, as well as subjective values, namely the view on the experimental prediction results

4.1 LSTM

In this study, build an LSTM prediction model based on a deep learning framework, Keras, which is a Python platform. The experiment was carried out several times based on the experimental hyperparameter tuning set out in Chapter 3.3. and the range of hyperparameters performed is according to table 9.

No	Hyperparameters	Hyperparamter range
1	timesteps	3, 5, 7
2	hidden layer	32, 64, 128
3	learning rate	0.001, 0.005, 0.0001
4	num_epochs	25, 50, 100
5	batch_size	32, 64

Table 9. Hyperparameters used in the experiment

For BBRI shares, we will look at some of the existing inputs, where the macroeconomy, microeconomy, and VIX Index inputs give good results in timesteps 3, with 32 hidden layers, with batch size 64, but slightly there is a difference in the learning rate range of 0.001, and 0.005 and epochs 25 and 100. The results can be seen in table 10.

BBRI LSTM Macro Economy		BBRI LSTM Micro Economy		BBRI LSTM VIX Index	
timesteps	3	timesteps	3	timesteps	3
hidden layer	32	hidden layer	32	hidden layer	32
learning rate	0.001	learning rate	0.001	learning rate	0.005
Epoch	25	Epoch	25	Epoch	100
Batch size	64	Batch size	64	Batch size	64
MSE	0.00261	MSE	0.00212	MSE	0.00877
R squared	0.91185	R squared	0.92236	R squared	0.92323

Table 10. Optimum of LSTM Hyperparameter on BBRI predictions

While the train results and prediction results can be seen in the image below :

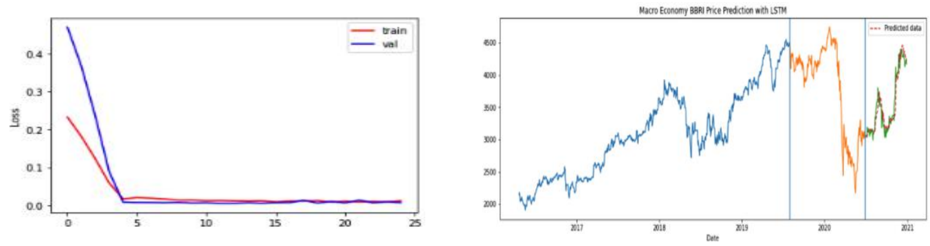

Fig 11. LSTM Train Results & Prediction for BBRI input Macro Economy

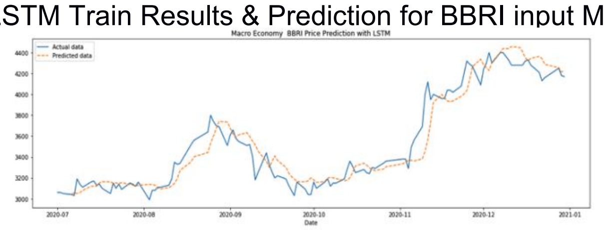

Fig 12. LSTM Price Prediction for BBRI input Macro Economy

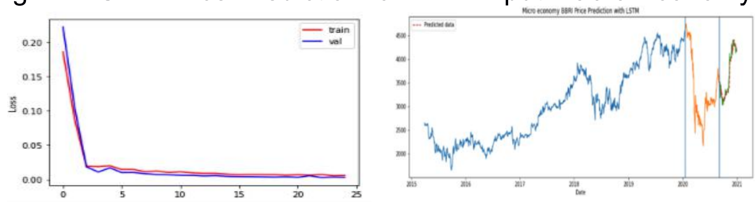

Fig 13. LSTM Train Results & Prediction for BBRI Micro Economy

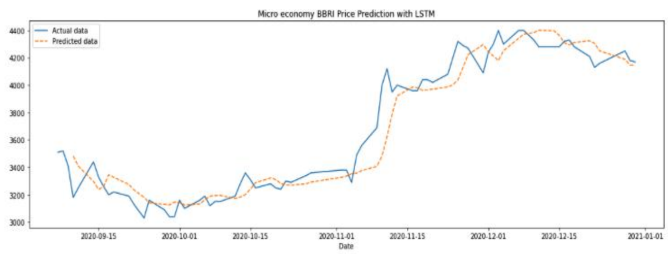

Fig 14. LSTM Price Prediction for BBRI input Micro Economy

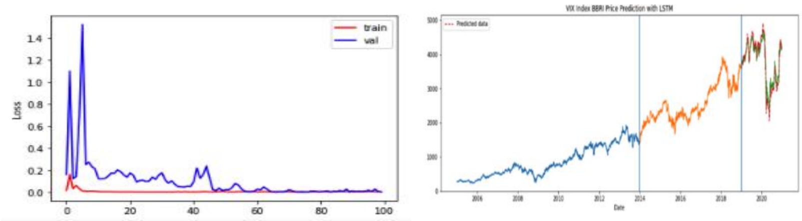

Fig 15. LSTM Train Results & Prediction for BBRI VIX Index

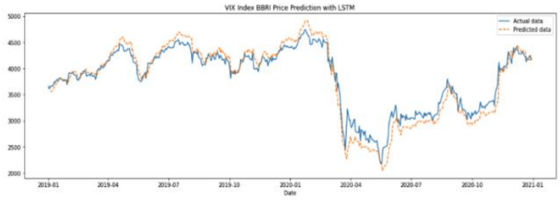

Fig 16. LSTM Price Prediction for BBRI input VIX Index

For CPIN stocks, we will look at some of the inputs used there is, where the input macroeconomy, microeconomy, and the VIX Index give good results at timesteps 3, with epoch 50, and a learning rate of 0.001, but there is a slight difference in the hidden layer and batch size. The results can be seen in table 11

CPIN LSTM Macro Economy		CPIN LSTM Micro Economy		CPIN LSTM VIX Index	
timesteps	3	timesteps	3	timesteps	3
hidden layer	128	hidden layer	128	hidden layer	64, 64, 64
learning rate	0.001	learning rate	0.001	learning rate	0.001
Epoch	50	Epoch	50	Epoch	50
Batch size	128	Batch size	64	Batch size	64
MSE	0.0029	MSE	0.00178	MSE	0.00348
R squared	0.22872	R squared	0.04223	R squared	0.85166

Table 11. Optimum of LSTM Hyperparameter for CPIN prediction

While the train results and CPIN prediction results can be seen in the image below :

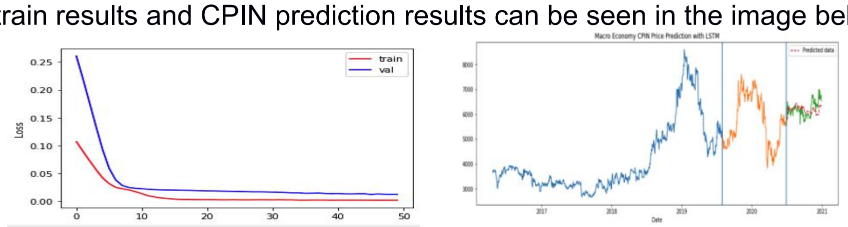

Fig 17. LSTM Train Results & Prediction for CPIN input Macro Economy

Fig 18. LSTM Price Prediction for CPIN input Macro Economy

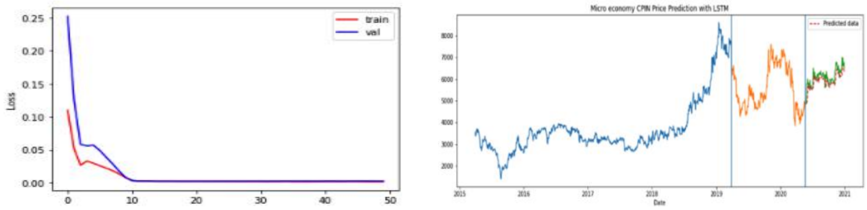

Fig 19. LSTM Train Results & Prediction for CPIN Micro Economy

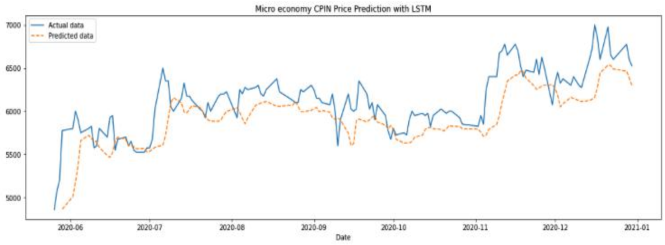

Fig 20. LSTM Price Prediction for CPIN input Micro Economy

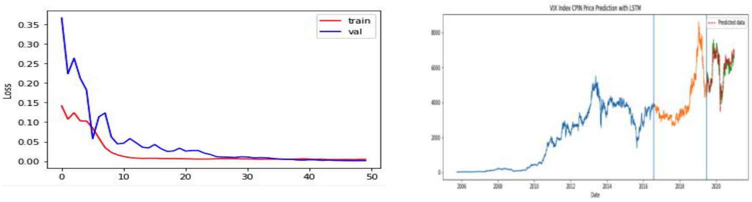

Fig 21. LSTM Train Results & Prediction for CPIN VIX Index

Fig 22. LSTM Price Prediction for CPIN input VIX Index

For INCO stock, we will look at some of the existing inputs, where in the input macroeconomy, microeconomy and VIX Index gave good results in timesteps 3, with hidden layer 32, with batch size 64, but there was a slight difference in the learning rate range of 0.001 and 0.005 and epochs 25 and 100. The results can be seen in table 12

INCO LSTM Macro Economy		INCO LSTM Micro Economy		INCO LSTM VIX Index	
timesteps	3	timesteps	3	timesteps	3
hidden layer	32	hidden layer	32	hidden layer	32,32
learning rate	0.005	learning rate	0.005	learning rate	0.001
Epoch	50	Epoch	50	Epoch	25
Batch size	64	Batch size	64	Batch size	64
MSE	0.005498	MSE	0.00159	MSE	0.000307
R squared	0.864074	R squared	0.96496	R squared	0.93954

Table 12. Optimum of LSTM Hyperparameters for INCO predictions

. Meanwhile, train results and prediction results can be seen in the image below :

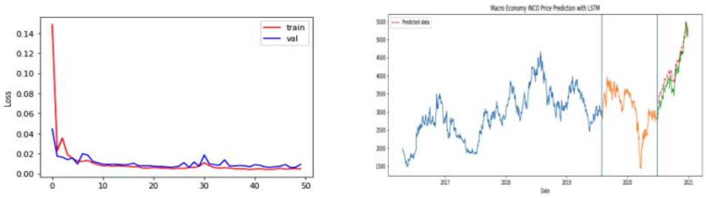

Fig 23. LSTM Train Results & Prediction for INCO input Macro Economy

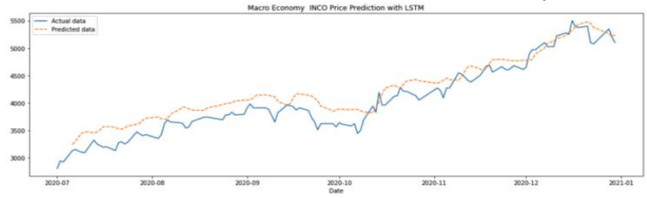

Fig 24. LSTM Price Prediction for INCO input Macro Economy

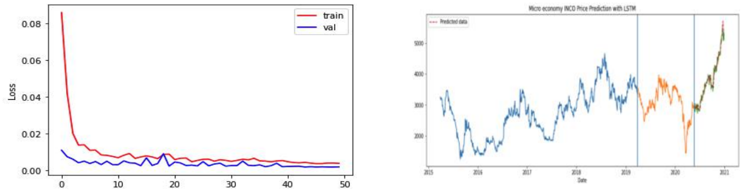

Fig 25. LSTM Train Results & Prediction for INCO Micro Economy

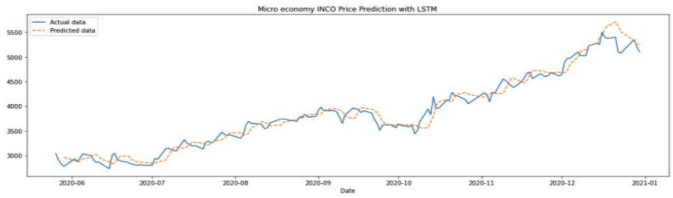

Fig 26. LSTM Price Prediction for INCO input Micro Economy

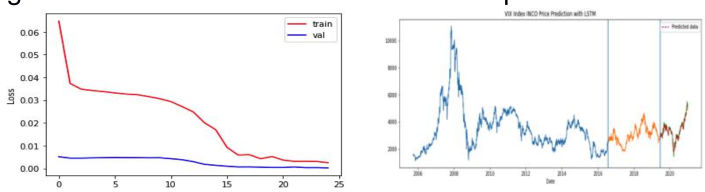

Fig 27. LSTM Train Results & Prediction for INCO VIX Index

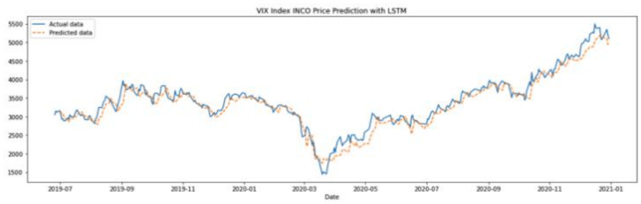

Fig 28. LSTM Price Prediction for INCO input VIX Index

Looking at the measurement results of the three stocks with three different inputs, we make an average value, then we look at the input VIX Index gives the best results, by giving an R squared of 0.9, and Micro economy gives the least good results with an R squared of 0.643.

LSTM Algorithm	Macro Economy	Micro Economy	VIX Index
MSE Average	0.0037	0.00183	0.0042
R squared Average	0.668	0.6432	0.9048

Tabel 13. Average results measurement of an LSTM algorithm

Besides we see the good results of measurements by performing hyperparameter tuning, in addition, the author also conducted several experiments by making the fifth change hyperparameter on the three stocks with the three inputs, the results obtained that the average input VIX Index also gives the best R2 value, but the highest MSE value.

Algorithm	Macro Economy		Micro Economy		VIX	
LSTM	MSE	R2	MSE	R2	MSE	R2
BBRI	0.032	-0.103	0.005	0.803	0.286	-1.618
CPIN	0.021	-7.644	0.036	-12.173	0.021	0.136
INCO	0.0337	0.156	0.0157	0.654	0.0006	0.875
AVERAGE	0.029	-2.531	0.0192	-3.572	0.102	-0.202

Tabel 14. Average results of all measurement LSTM hyperparameter

4.2 GRU

In addition to the LSTM algorithm, we will see the performance of the GRU algorithm by conducting the same experiment on three companies on IDX-IC with three different inputs.

For BBRI shares, we will look at some of the existing inputs, where the macroeconomy, microeconomy and VIX Index inputs give good results at timesteps 3, with a learning rate of 0.001, and batch size 64, but there is little difference in the hidden layer and epoch 25 and 100. The results can be seen in table 15

BBRI GRU Macro Economy		BBRI GRU Micro Economy		BBRI GRU VIX Index	
timesteps	3	timesteps	3	timesteps	3
hidden layer	32, 32, 32	hidden layer	32	hidden layer	32
learning rate	0.001	learning rate	0.001	learning rate	0.001
Epoch	25	Epoch	25	Epoch	50
Batch size	64	Batch size	64	Batch size	64
MSE	0.00241	MSE	0.05171	MSE	0.00744
R squared	0.91841	R squared	-6.79487	R squared	0.93488

Table 15. Optimum GRU Hyperparameter for BBRI predictions.

Meanwhile, train results and prediction results can be seen in the image below :

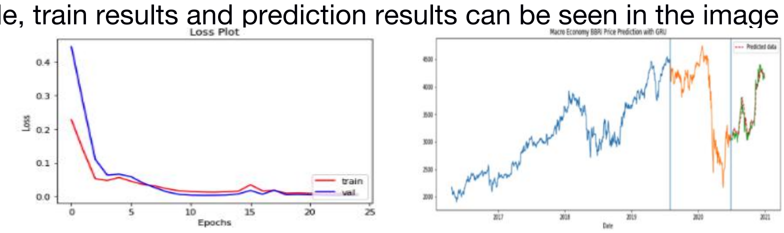

Fig 29. GRU Train Results & Prediction for BBRI input Macro Economy

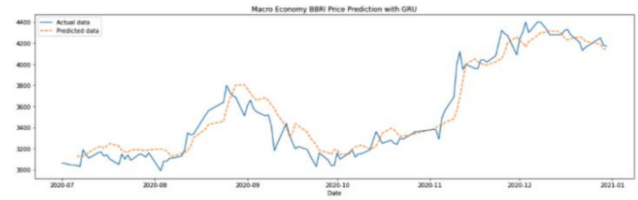

Fig 30. GRU Price Prediction for BBRI input Macro Economy

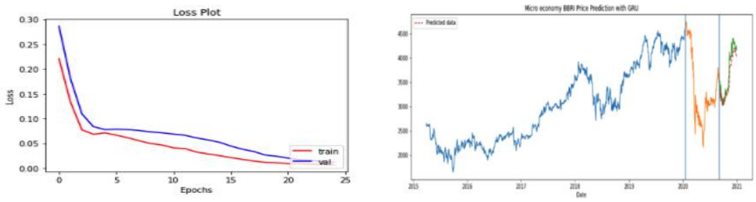

Fig 31. GRU Train Results & Prediction for BBRI Micro Economy

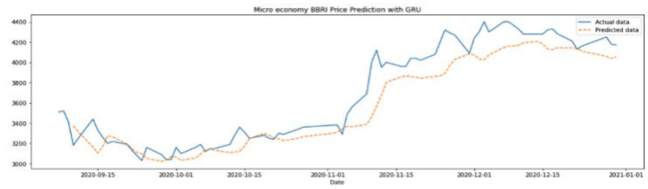

Fig 32. GRU Price Prediction for BBRI input Micro Economy

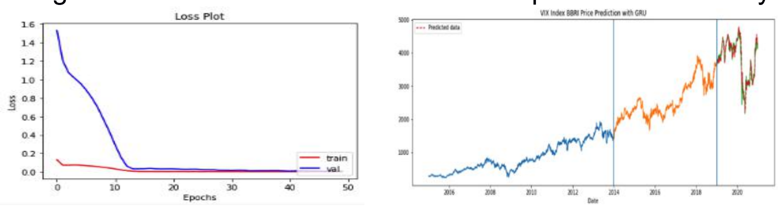

Fig 33. GRU Train Results & Prediction for BBRI VIX Index

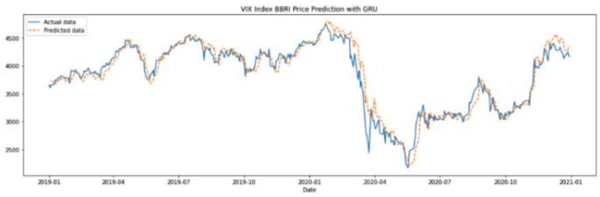

Fig 34. GRU Price Prediction for BBRI input VIX Index

For CPIN stocks, we will look at some of the existing inputs, where input macroeconomy, microeconomy, and the VIX Index gave good results at a learning rate of 0.001, and epoch 50, but there was a slight difference in the hidden layer, timesteps, and batch size. The results can be seen in table 16

CPIN GRU Macro Economy		CPIN GRU Micro Economy		CPIN GRU VIX Index	
timesteps	3	timesteps	3	timesteps	5
hidden layer	128	hidden layer	32, 32	hidden layer	32
learning rate	0.001	learning rate	0.001	learning rate	0.001
Epoch	50	Epoch	50	Epoch	50
Batch size	128	Batch size	64	Batch size	64
MSE	0.00114	MSE	0.0985	MSE	0.00336
R squared	0.51477	R squared	-7.37657	R squared	0.85638

Table 16. Optimum GRU Hyperparameter in CPIN prediction

Meanwhile, train results and prediction results can be seen in the image below :

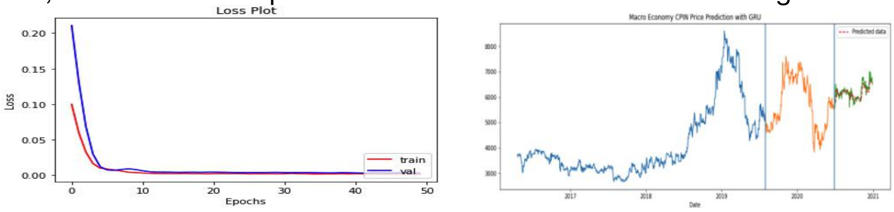

Fig 35. GRU Train Results & Prediction for CPIN input Macro Economy

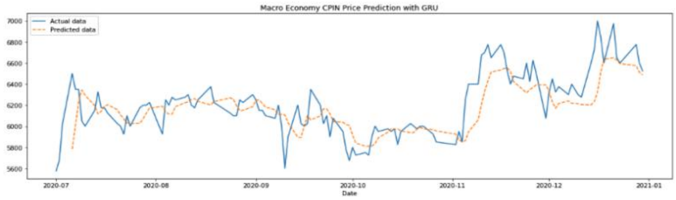

Fig 36. GRU Price Prediction for CPIN input Macro Economy

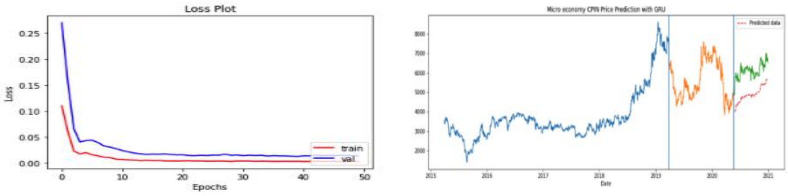

Fig 37. GRU Train Results & Prediction for CPIN Micro Economy

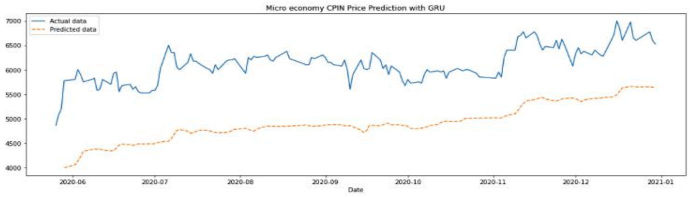

Fig 38. GRU Price Prediction for CPIN input Micro Economy

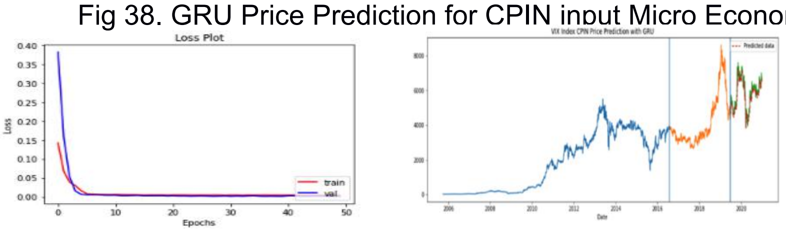

Fig 39. GRU Train Results & Prediction for CPIN VIX Index

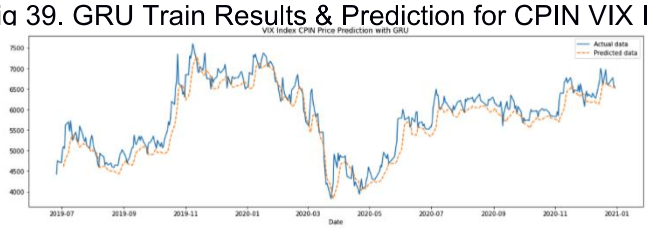

Fig 40. GRU Price Prediction for CPIN input VIX Index

For INCO stocks, we will look at some of the existing inputs, wherein the macroeconomy input, microeconomy and VIX Index give good results on hidden layer 64, with batch size 64, and epoch 100 but there is little difference in the learning rate range of 0.005 and timesteps. The results can be seen in table 17.

INCO GRU Macro Economy		INCO GRU Micro Economy		INCO GRU VIX Index	
timesteps	3	timesteps	3	timesteps	5

hidden layer	32	hidden layer	32	hidden layer	32
learning rate	0.005	learning rate	0.005	learning rate	0.0001
Epoch	100	Epoch	100	Epoch	100
Batch size	64	Batch size	64	Batch size	64
MSE	0.004595	MSE	0.00136	MSE	0.00031
R squared	0.88639	R squared	0.97009	R squared	0.93897

Table 17. GRU Optimum hyperparameters for INCO predictions

Meanwhile, train results and prediction results can be seen in the image below :

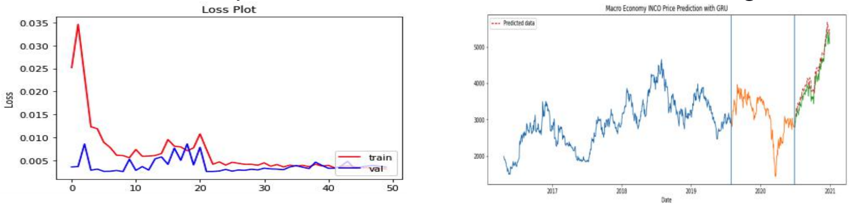

Fig 41. GRU Train Results & Prediction for INCO input Macro Economy

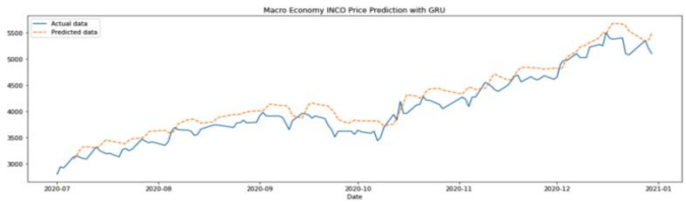

Fig 42. GRU Price Prediction for INCO input Macro Economy

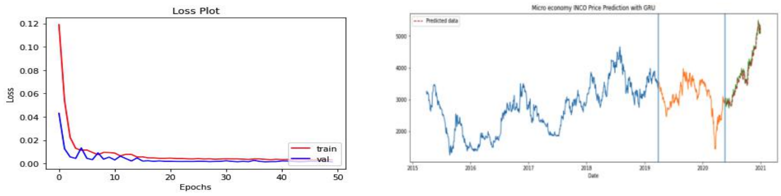

Fig 43. GRU Train Results & Prediction for INCO Micro Economy

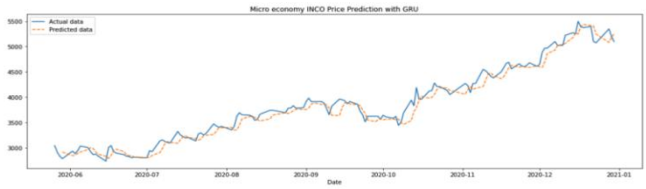

Fig 44. GRU Price Prediction for INCO input Micro Economy

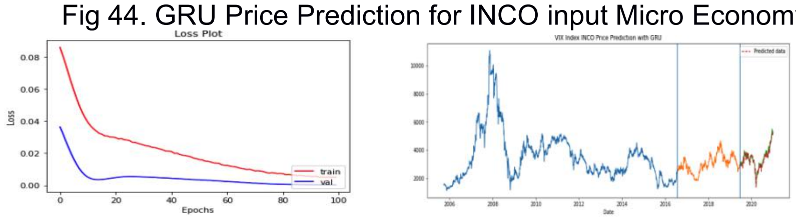

Fig 45. GRU Train Results & Prediction for INCO VIX Index

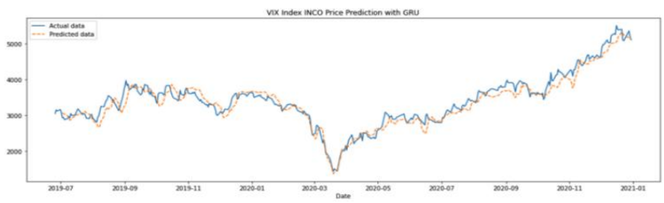

Fig 46. GRU Price Prediction for INCO input VIX Index

Looking at the measurement results of the three stocks with three different inputs, we make the average value, then we see input VIX Index gives the best result, giving R squared 0.91, and Micro economy gives the least bad result with R squared -4.4005.

GRUAlgorithm	Macro Economy	Micro Economy	VIX Index
MSE Average	0.003	0.0505	0.0037
R squared Average	0.773	-4.4005	0.9101

Table 18. Average measurement results of the GRU algorithm

Besides we see from the good results of measurements by performing hyperparameter tuning, in addition, the author also conducted several experiments by making the fifth change hyperparameter on the three stocks with the three inputs, the results obtained that the average input VIX Index also gives the best R2 value, and also with the best MSE value.

Algorithm	Macro Economy		Micro Economy		VIX	
GRU	MSE	R2	MSE	R2	MSE	R2
BBRI	0.021	0.278	0.054	-7.305	0.1336	-0.168
CPIN	0.011	-3.792	0.1286	-11.734	0.0173	0.263
INCO	0.031	0.2303	0.0048	0.894	0.0007	0.8705
AVERAGE	0.021	-1.0945	0.0626	-6.048	0.0505	0.3228

Table 19. Average results of all measurement GRU hyperparameters

5 Conclusions

Looking at the comparison results based on tests conducted on the Indonesia Stock Exchange - Industrial Exchange (IDX-IC), three samples of public companies were taken based on the three main categories given, by looking at the influence of three influential factors as input to the Deep learning algorithm. Long-Short term memory (LSTM) and Gated Recurrent Unit (GRU), namely Macroeconomy factors such as Inflation rate, Exchange Rate US Dollar-Indonesian Rupiah, and Central Bank 7 Days Repo Rate (BI7DRR), Microeconomy, or company fundamentals which are reflected in three ratios such as Price to Earnings Ratio (P/E Ratio), Price to Book Value (PBV), and Return on Equity (ROE), so And one more thing, namely the input Volatility index (VIX Index), the conclusions are drawn:

a) For the LSTM algorithm in table 13, based on the optimum value of the hyperparameter tuning results, the VIX index input is relatively very good for making predictions, this can be seen in the highest R-squared value 0.9048, although the MSE value is the largest, it is still in a good range of 0.0042, and it can be seen on the visual graph that the prediction is relatively good.

b) For the LSTM algorithm in table 13, based on the optimum value of the hyperparameter tuning results, the input microeconomy index is not good for making predictions, this can be seen in the MSE value which is the smallest 0.00183 but has the smallest R-squared value and is relatively not too good 0.6432 , and can also be seen in the visual prediction graph which does not coincide with the test value.

c) For the LSTM algorithm in table 14, based on the Average LSTM hyperparameter measurement results that are carried out manually for all existing hyperparameters, it can also be seen that the VIX Index input is relatively the best in making predictions, it can be seen in the largest R-squared average value of -0.202 although the smallest MSE value but still in a good range 0.102

d) For the GRU algorithm in table 18, based on the optimum value of the hyperparameter tuning results, the VIX index input is relatively very good for making predictions, this can be seen in the highest R-squared value of 0.9101, and has The minimum MSE value is 0.0037, and it can be seen on the visual graph that the prediction is relatively good.

e) For the GRU algorithm in table 18, based on the optimum value of the hyperparameter tuning results, it is found that the microeconomy index input provides the least good value for making predictions, this can be seen in the MSE value which is the largest 0.0505 and the largest R-squared value is -4.4005 and can It can also be seen in the visual prediction graph which does not coincide with the test scores.

f) For the GRU algorithm in table 19, based on the Average GRU hyperparameter measurement results that are carried out manually for all existing hyperparameters, it can also be seen that the VIX Index input is relatively the best in making predictions, it can be seen in the largest R-squared average value of 0.3228 and MSE is quite small but still in a very good range 0. 0505

g) Looking at the test results based on the optimum value of the hyperparameter tuning results, it is found in tables 13 & 18, that the GRU algorithm gives better results, except for the microeconomy input, where the R-squared value has a larger value and a smaller MSE value on the macroeconomy input. and VIX Index.

h) Looking at the test results based on the Average LSTM & GRU hyperparameter measurement results, it is found in tables 14 & 19, that the GRU algorithm gives better results, except for the micro economy input, where the R-squared value has a larger value and a smaller MSE value on the macro input. economy and the VIX Index.

i) Looking at the test results based on the LSTM hyperparameters obtained in tables 10, 11, and 12, it is found that deep learning testing is not necessary because most of the good optimum values only use 1 hidden layer unit.

j) Looking at the test results based on the GRU hyperparameters obtained in tables 15, 16, and 17, it is found that deep learning testing is not necessary because most of the good optimum values only use 1 hidden layer unit

6 Suggestions

Some suggestions for improvement are:

1. Since stock prices are investment instruments that are traded every day, it is advisable to look at the daily factors that can be seen and measured every day, so that monthly data such as the inflation rate or annual report are not suitable in seeing the factors that affect stocks.
2. There are many books or literature on value investment that emphasize buying long-term stocks that are influenced by company fundamentals or the microeconomy such as the P/E Ratio, but because the value in this study is quarterly data, using interpolation to fill in daily values and it is not suitable , then for further research it is better to make observations every day, because there is no dataset with daily intervals.
3. Combining the LSTM or GRU algorithm by using sentiment analysis or text mining/analytics as input, because news about whatever happens in the stock market is real time and has a direct impact on the movement of certain stock values.

Illustrations

Tables

Uploaded Documents

https://github.com/yhutagal/IDX-IC-Prediction-with-LSTM-GRU

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Ich erkläre an Eides statt, dass ich die vorgelegte Abschlussarbeit selbständig und ohne fremde Hilfe verfasst, andere als die angegebenen Quellen und Hilfsmittel nicht benutzt und die den benutzten Quellen wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.

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Unterschrift

(Yohanees Hutagalung)

Sperrvermerk

Dieser Teil ist optional – beachten Sie bitte die obigen Hinweise hierzu.

Die Einsicht in die vorgelegte Arbeit ist bis zum TT. Monat JJJJ gesperrt.

Köln, 15.06.2022

Unterschrift

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