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THE PREDICTION OF SHARIA STOCK PRICE BY USING SUPERVISED MACHINE LEARNING

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ABSTRACT

Investment in Islamic stock assets is currently increasingly in demand by the public. Similar to investing in stocks, this particular investment involves a substantial amount of risk because of the potential for rapid price fluctuations. Consequently, a forecasting tool is required to assist investors in thinking twice before acquiring Islamic stock. The data used is daily data from 2019 to 2022 with a total data of around 1200. The machine learning approaches we selected are variants of the Recurrent Neural Network model, namely Elman recurrent neural network (ERNN), long short-term memory (LSTM), and gated recurrent unit (GRU). The results of GRU models using mean absolute error (MAE) value is 0.0203. The root mean square error (RMSE)is 0.0325 in the GRU model with the best combination of hyperparameters. The model can make prediction values with small error values based on this combination of a proportion of 70% training data and 30% test data. This study recommends that the model is better to use more variations in hidden neurons, layers, activation functions, training algorithms, and parameters to get a better model architecture.

Keywords: *Supervised Machine Learning, Prediction, Sharia Stock*

1. INTRODUCTION

As the largest Muslim country globally, Islam teaching underlies Indonesian activities to fulfill their necessities of life and prepare for a better future, an investment. An investment is a commitment of some funds or other resources used for certain businesses at present, with the intention to obtain profits in the future [1], [2]. Profits gained from an investment can be cash receipts (dividends) or an increased investment value (capital gains) [3]. From the perspective of Islam, a good investment is an investment made based on Islamic law, and the activities carried out are not prohibited (haram). Investment based on Islamic law is known as Sharia investment [4]. In practice, there are two forms of Islamic investment that investors may choose: tangible assets (real assets) and financial assets. In recent years, Islamic investments in financial assets tend to be more attractive to investors in Indonesia than real investment because Sharia investment in financial assets offers many benefits that may be greater than investing in tangible assets without violating Islamic Sharia [5].

One type of Sharia investment in financial assets is sharia shares. Sharia shares are shares of a company with a line of business that does not conflict with Sharia principles [6]. In Indonesia, Islamic stock trading is centered on the Indonesia Stock Exchange (IDX) as the official capital market recognized by the Indonesian government with several advantages and the potential for greater profits than investing in tangible assets, Islamic stock investments are increasingly attracting investors in Indonesia [7]. The capitalization value of sharia shares on the Indonesia Stock Exchange increases every year. In 2015, the total market capitalization of sharia shares on the IDX was IDR 1737.23 trillion. Each year, the average increase was 3.955% until 2020, while the market capitalization of sharia shares was IDR 2058.77 trillion [8].The price movements of sharia shares traded on IDX Indonesia can be seen through the sharia share price index, namely the Jakarta Islamic Index (JKII). The value of the JKII, in particular, provides investors with the performance of Islamic stocks at a specific time, such as price movements and fluctuations, and profit levels. If the JKII is following a rising trend, the prices of Islamic shares on the IDX increase, and vice versa. In addition, JKII can also be used as a benchmark for stock portfolio performance.

A stock's performance can, to some extent, be analyzed based on financial indicators presented in the company's annual report. In which, the annual report provides a vast amount of information that can be use to produce various financial ratios. Many literatures told that financial ratios can be used for assessing future stock performance namely to project future stock price trends based on those previous values. Ratio analysis therefore becomes a key parameters used by stock analyst to determine the intrinsic value of stock shares. The study of financial ratios emerged after stock market crashes in the 1998s and 2009s in Indonesia. Today, ratios are also used in fundamental analysis to predict future company's performance. As the need in this type of analysis to grow, various new ratios, such as book value and price/cash earnings per share, have been included for share valuation. The level of importance given to these ratios differs from industry to industry and from one country to another. Thus, selecting appropriate ratios is very crucial in increasing the prediction success rate [9].

To analyze the stock price index, one of the quantitative models used to model and predict the stock price index value is supervised machine learning. For example, as Crude-Oil-Production forecasting, CO2 trapping estimation, and wind power prediction [10], [11], [12], [13]. They have also shown great potential in the field of financial time series forecasting. For example, using the method of support vector machine (SVM), implemented the prediction research on the daily exchange data of stock prices [14], [15]. Research predicting the direction of stock prices using the Artificial Neural Network (ANN) and Support Vector Machine (SVM) models and using ten technical indicators as variables, namely Simple 10-day moving average, Weight 10- day moving average, Momentum, Stochastic K%, Stochastic D%, RSI (Relative Strength Index), MACD (Moving Average Convergence Divergence) [16]. Support Vector Machines (SVM) is an AI representation for the order and this model is generally utilized for arrangement. These procedures are utilized to determine whether the cost of stock will be higher than its cost on a given day to make profitable trading strategies [17]. The results of SVM show good predictability because these results support the efficient market hypothesis [18]. Besides, compared with other most-used Machine learning (ML) methods, the generalization ability of SVM is relatively weak too [19].

Machine learning (ML) is an important approach to artificial intelligence in research. It aims to learn knowledge and laws from complex data to predict future behavior results and trends [20]. Based on different learning methods, machine learning can be divided into supervised machine learning and unsupervised machine learning [21]. The supervised machine learning is mainly used for completing regression and classification tasks. Its input and output are specified, and it attempts to learn from the input the pattern of the expected output [22]. The unsupervised machine learning is mainly used for completing clustering and dimension reduction tasks. Its output is not specified, and it aims to find connections between input data and discover potential patterns [23].

One of the Artificial Neural Network models which includes supervised machine learning can be used to process data in a short time is Recurrent Neural Network (RNN). RNN, or what is also called a feedback network, is a type of Neural Network where there are loops as feedback connections in the network [24]. Our focus is on recurrent neural networks (RNN)s, developed for sequence prediction that, nowadays, constitute a viable forecasting model. RNNs differ from other neural networks (NN) in that they contain a hidden layer that operates on an ordered sequence where each step includes a hidden state that is updated as a function of it's respective input features and the hidden state of the previous step [25], [26]. The process entails use of a window of data from a sequence and predicting the following sequence data points moving forward one data point at a time. Under this perspective, RNNs are self-supervised learning approaches [27]. Most popular RNN architectures comprise the Elman RNN (ERNN) [28], the long-short term memory (LSTM) [29], and the gated recurrent unit (GRU) [30]. The ERNN is among the simplest RNNs containing one hyperbolic tangent function as the activation function. Elman Recurrent Neural Network is an artificial neural network that is good for time series prediction problems such as predicting the US Dollar exchange rate against the Rupiah. The Elman Recurrent Neural Network can learn time dependencies from the training data set and predict future values that match the test data. At the same time, GRU does not use cell states but utilizes hidden states to store information. The reset gate in GRU determines whether new information should be forgotten, while the update gate is for remembering [31]. LSTM is a newer architecture explicitly designed to eliminate the long-term dependency problem where temporally distant data have a vanishing gradient, or are "forgotten" by the network. The GRUs are modifications of LSTM containing fewer parameters while improving performance on certain tasks [32]. Being RNNs contemporary forecasting models, global software libraries have added them since 2018 [33].

LSTM as a better version of recurrent neural networks (RNN), LSTM has been used in many fields. Particularly in stock price prediction, LSTM has been proposed and applied a some notable research, among others had built a model and predicted the stock returns of NIFTY 50 by using LSTM networks [34], [35]

Similarly, LSTM networks to predict the future trends of stock prices based on its historical data. This research is expected to build a system that can predict stock prices, especially Sharia shares, by utilizing the RNN Model Gated Recurrent Unit (GRU) and Elman as recommendations for Sharia stock investors [36]. The input variables used are data on the highest price, lowest price, open price, close price, average, volume, and change. The system is built from machine learning, which can predict using daily stock price data from mid-2018 to 2023 or around 1200 pieces of data.

2. METHOD

2.1. Time Series Forecasting

Time series forecasting uses the information in a time series to predict future values of that series. A univariate time series, as the name suggests, is a series with a single time-dependent variable. A multivariate time series, instead, has multiple time-dependent variables, each one depending not only on its past values but also on other variables. This dependency between variables is used for forecasting future values. A time series forecasting problem that requires a prediction of multiple time steps into the future can be referred to as multi-step time series forecasting. Shorter time horizons are often easier to predict with higher confidence. Many time series are characterized by trends and seasonal variations, which are relatively straightforward to identify. Serial correlation (also referred to as autocorrelation) measures the relationship between the current value of a variable and the values of the same variable from previous time periods. The study of serial correlations is commonly used in creating forecasting models.

2.2. Prediction Methods

A Prediction method is a predetermined sequence of steps that produces forecasts at future time periods [37]. Many forecasting methods have corresponding stochastic models that produce the same point forecasts and can also be used to generate prediction distributions and prediction intervals. A stochastic model makes assumptions about the process and the associated probability distributions. The selection of a forecasting method depends on many factors: the context of the forecast, the relevance and availability of historical data, the degree of accuracy desirable, the time period to be forecast, the cost/ benefit (or value) of the forecast, and the time available for making the analysis [38]. The system built in this research aims to predict sharia stock prices. This system is used for comparison methods with the forecasts generated by more sophisticated techniques. The system architecture begins with determining the network architecture carried out by Recurrent Neural Network (RNN) Elman and GRU models. After that, the network training process and sharia stock price predictions are carried out by Recurrent Neural Network (RNN) Elman, GRU, and LSTM models, as shown in figure 1.

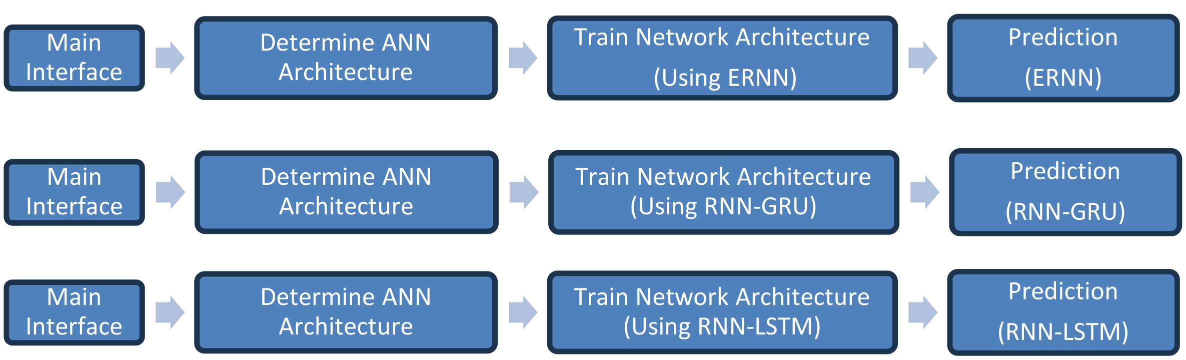

Figure 1. The Step Of System Prediction

2.3. Accuracy Measures

Before reviewing the most advanced forecasting methods, we present the accuracy measures that have been adopted in the M4 Competition [40]. The following notation is used. The actual value of the time series at point t is denoted as y^t . The estimated forecast is denoted as $\hat{y}^t$. The number of fitted points is n. The forecasting horizon is h. The seasonal period is m (e.g., 12 for monthly time series, 4 for quarterly, 24 for hourly). For non-seasonal time series (yearly, weekly and daily data)

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m = 1 [38]. The symmetric mean absolute percentage error (MAPE) is defined as

$$MAPE = \frac{2}{h}\sum_{t=n+1}^{n+h}\frac{|y^t-\hat{y}^t|}{|y^t|-|\hat{y}^t|} * 100\% \tag{1}$$

and the Root Mean Square Error (RMSE) is defined as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y^t-\hat{y}^t)^2} \tag{2}$$

Where n is the number of observations (amount of data), y^t is the true value of the ith observation, and $\hat{y}^t$ is the model prediction for the ith observation. Mean Absolute error (MAE) is the measure of difference between two consecutive variables, for example variable y and x denote the predicted and observed values, then MAE can be calculated as [39]:

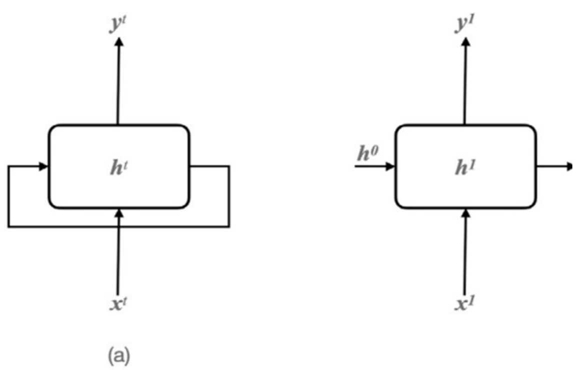

Figure 2. Single-Layer RNN: Folded (A) And Unfolded (B).

The input, output and hidden state at time step t are denoted as x^t, y^t and h^t , respectively.

$$h^t = \sigma\left(W_i h^{(t-1)} + V_i x^t + b_i\right)$$
$$y^t = tanh(W_o + b_o)$$

where $W_i \in R^{n\times n}$, $W_o \in R^{n\times n}$, $V_i \in R^{m\times m}$ are weight matrices, and b_i, b_o are bias vectors. The structure of the basic ERNN block is as shown in Figure 3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}^t - y^t)$$

2.4. Machine Learning Approaches

Recurrent Neural Networks (RNNs) are the most commonly used machine learning models for sequence prediction problems. Unlike standard feedforward neural networks, RNNs have feedback connections — which is biologically more realistic. Instead of neurons, RNNs have memory blocks, also denoted as cells, that may be connected into multiple layers. A block has components that make it smarter than a classical neuron and a memory for recent sequences. The idea (illustrated in Figure 2) is that, in each layer, the same RNN block repeats for every time step ($t = 1,..,T$), sharing the same weights and biases between each of them. The feedback loop of the block helps the network to propagate the hidden state to the future time steps. The input to the block at time step t is a vector $x^t \in R^n$,being *m* the number of features. The output of a block is a vector $y^t \in R^n$. It is worth nothing that *n* is a an externally tuned hyperparameter that may take on any appropriate value. To use RNNs for time series forecasting [40], it is necessary to project the output of the block to the expected forecasting horizon k by means of a dense layer that must be connected on top of the last recurrent block. The most popular RNN blocks are the Elman RNN (ERNN) block [41], Long Short-Term Memory (LSTM) block [42] and the Gated Recurrent Unit (GRU) [42]

2.4.1. ERNN

At each time step t, an ERNN block is characterized by an hidden state $h^t \in R^n$ that results from the application of an activation function (the sigmod, mostly) to the input vector $x^t \in R^m$ and to the hidden state of the previous time step $h^{(t-1)}$. Moreover, the ERNN block produces an output vector $y^t \in R^n$ that results from the application of another activation function (the hyperbolic tangent, usually) to the hidden state h^t . More precisely:

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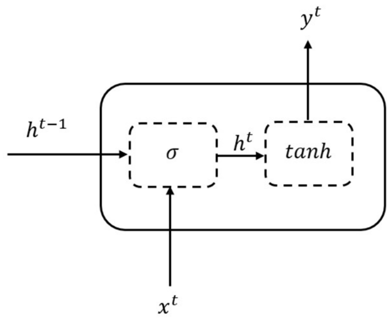

Figure 3. Scheme Of The Elman RNN Block

ERNNs have very complex dynamics and they are difficult to train. Going back with the gradients, the values may get either smaller exponentially (vanishing gradient problem) or larger exponentially (exploding gradient problem).

2.4.2. LSTM

An LSTM block features an input activation function, three gates (input, forget, output), an internal recurrence loop (the Constant Error Carousel), an output activation function and peephole connections (Figure 4). The LSTM block has an input x (with size m) and produces an output y (with size n). The output of the LSTM block is recurrently connected back to the block input.
The LSTM block is characterized by the following weights:

- Input weights: $W_z, W_i, W_f, W_o \in R^{n \times m}$
- Recurrent weights: $R_z, R_i, R_f, R_o \in R^{n \times n}$
- Peephole weights: $p_i, p_f, p_o \in R^n$
- Bias weights: $b_z, b_i, b_f, b_o \in R^n$

Let xt be the input vector at time t. Then the vector formulas for the LSTM block forward pass can be written as:
$z^t = g(W_z x^t + R_z y^{t-1} + b_z)$ input activation function
$i^t = \sigma(W_i x^t + R_i y^{t-1} + p_i \odot c^{t-1} + b_i)$ input gate
$f^t = \sigma(W_f x^t + R_f y^{t-1} + p_f \odot c^{t-1} + b_f)$ forget gate
$c^t = z^t \odot i^t + c^{t-1} \odot f^t$ internal recurrence loop
$o^t = \sigma(W_o x^t + R_o y^{t-1} + p_o \odot c^t + b_o)$ output gate
$y^t = h(c^t) \odot o^t$ output activation function

where $\odot$ denotes the point-wise multiplication of two vectors, $\sigma(x) = \frac{1}{1+e^{-x}}$ is the logistic sigmoid, $g(x)$ and $h(x)$ are usually the hyperbolic tangent $\tanh(x)$.

The way the LSTM block reduces the vanishing gradient problem is by creating an internal memory state which is simply added to the processed input. In this way, the multiplicative effect of small gradients is greatly reduced. The forget gate determines which states are remembered or forgotten.

Several variants of the LSTM architecture for RNNs have been proposed since its inception in 1995. A thorough survey and performance evaluation of LSTM variants considering three representative tasks: speech recognition, handwriting recognition, and polyphonic music modeling [43].

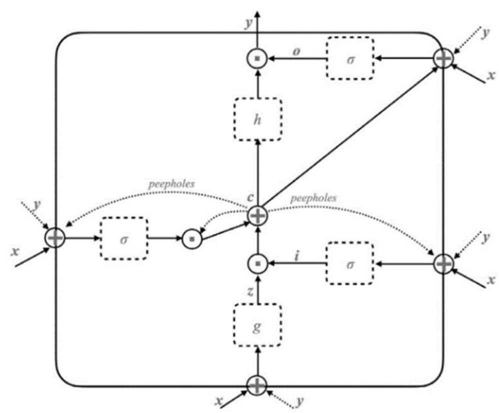

Figure 4. The most general scheme of an LSTM block. Continuous arrows refer to vectors at time t, dashed arrows refer to vectors at time $t - 1$.

LSTM models is built to perform one step ahead prediction, using multiple data streams as inputs, for predictive maintenance in the context of maritime industry [44].

2.4.3. GRU

The GRU block is a simplified variant of the LSTM block. Neither peephole connections nor output activation functions are used [30].The input and the forget gate are coupled into an update gate. Finally, the output gate (called reset gate) only gates the recurrent connections to the block input (W_z). A GRU-based deep learning approach is used to predict the remaining useful life (RUL) of lithium-ion batteries (LIBs), accurately [45].

2.5. Datasets

The data used in this study include total sharia stock price index which is composed of closing price, the high price and the low price of total price index [46]. Dataset of sharia stock price collected on hourly basis between 9th May 2018 to 29, September 2023. We divided the dataset into two

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sets: train and test. To calculate the accuracy of the network, we used a MAPE, RMSE and MAE.

3. RESULTS AND DISCUSSION

This research discusses the problem of predicting sharia stock prices in the next few months, namely after October 2023. This stock price prediction uses two types of neural network architecture in machine learning, namely recurrent neural network (RNN) with the Elman model, gated recurrent unit model (GRU), and long short-term memory (LSTM) models. This research uses the following steps: preprocessing data, architectural design, building and compiling models, training models, evaluating models, and comparing results. Each of these steps will be explained further in the sub-chapters below. It is calculated as the difference between the real and expected values. If the difference between observed and expected values is small and statistically unbiased, the model best matches the data [47].

3.1 Preprocessing data

In the first step, the researcher will select the columns that will be used for features (variables used as input to the model) and labels (columns used to test the accuracy of the model predictions). In the data that will be used for research, researchers will use the Close column as a temporary label for the Date, Open, High, and Low columns as features. Examples of data that will be used in research are presented in Table 1 as follows:

Table 1. Sample The First 10 Rows Of Data

Date	*Open*	*High*	*Low*	*Close*	*Adj Close*	*Volume*
09/05/2018	600	630	520	545	534.370728	275187300
11/05/2018	550	660	550	620	607.907898	285278000
14/05/2018	620	650	600	600	588.297974	124691400
15/05/2018	600	600	600	600	588.297974	0
16/05/2018	600	600	600	600	588.297974	0
17/05/2018	595	600	580	585	573.590515	26683900
18/05/2018	590	590	565	570	558.883057	10352200
21/05/2018	580	580	550	555	544.175598	21014600
22/05/2018	555	575	555	560	549.078125	25543200
23/05/2018	565	570	555	560	549.078125	12809900

Then for research needs the Close, Adj Close and Volume columns will not be used so these columns will be discarded. The results of the column selection are presented in table 2

Table 2. Sample The First 10 Rows Of Data After Selecting The Columns To Be Used

Date	*Open*	*High*	*Low*
09/05/2018	800	810	775
10/05/2018	805	805	805
11/05/2018	815	820	800
14/05/2018	805	825	785
15/05/2018	825	830	805
16/05/2018	815	825	805
17/05/2018	815	830	810
18/05/2018	835	865	825
21/05/2018	860	890	845
22/05/2018	880	885	845

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After selecting columns on the data, the researcher divided the data obtained into three schemes, each with a train and test data section. In the first scheme, the proportion of train and test data is 70% and 30%, then for the second and third schemes, it is 75% respectively; 25% and 80%; 20% with the first percentage being train data and the second percentage being test data. The data distribution is shown in Table 3. At this step of data separation, the researcher maintains to focus on the label and feature columns that were first separated. This is done for easier identification of train data and test data, using the words training data and test data accordingly, which will be utilized later.

Table 3. Division Of Train And Test Data For 3 Schemes

Scheme	Data	Total
70%; 30%	*Train* *Test*	934 401
75%; 25%	*Train* *Test*	1001 334
80%; 20%	*Train* *Test*	1068 267

The final step in data preprocessing is normalizing the feature data from the dataset to a standardized range. The data that needs to be normalized consists of both training data and test data, which will be normalized independently. The Min-Max scaling technique is employed to normalize each feature value in this study. To calculate the desired result, the MinMaxScaler normalized all data to the interval [0, 1] according to to Eq. (10) [48]:

$$X\_normalized = (X - X\_min) / (X\_max - X\_min) \quad (10)$$

The normalization process is applied to the entire dataset, with each value in the features column being normalized individually. The outcomes of this procedure will be displayed in Table 4. Subsequently, the outcomes of each characteristics column are shown to visually represent the results of data normalization, as depicted in Figure 5.

Table 4. Normalization Results For Data Samples

Date	*Open*	*High*	*Low*
09/05/2018	0.153117	0.144993	0.160544
10/05/2018	0.15481	0.143368	0.171565
11/05/2018	0.158198	0.148244	0.169728
14/05/2018	0.15481	0.14987	0.164217
15/05/2018	0.161585	0.151495	0.171565
16/05/2018	0.158198	0.14987	0.171565
17/05/2018	0.158198	0.151495	0.173402
18/05/2018	0.164973	0.162874	0.178913
21/05/2018	0.173442	0.171001	0.18626
22/05/2018	0.180217	0.169376	0.18626

Figure 5. Graph after data normalization

The normalization results graph clearly indicates that each column of characteristics has a value range spanning from 0 to 1. In addition, the graph indicates that there is minimal variation in the distance between variables, with all distances being equal. This will facilitate the machine learning process in analyzing existing data patterns.

3.2 Architecture Design

In this step, the researcher designs the architecture that he wants to use during the research, namely for the RNN model with Elman mode and RNN with GRU mode. For RNN with Elman mode itself, the simple RNN function from the hard module will be used, while for separate GRU mode it will use the GRU function on the hard module. What differentiates the three modes lies in the number of layers and the total number of parameters to be calculated. The first step in building this model will be divided into two, namely models for RNN Elman, RNN GRU, and RNN LSTM. For the RNN model, Elman use several parameters as in Table 5.

Table 5. Parameters For RNN Elman, RNN LSTM, And RNN GRU

Parameter	RNN Elman	RNN LSTM	RNN GRU
Number units	128	100	128
Activation function	"tanh"	"relu"	"tanh"
Optimizer function	"Adam"	"Adam"	"Adam"
Input shape	Mengikuti data uji	Mengikuti data uji	Mengikuti data uji
Batch size	128	1	128
Loss function	"mean_squared_error"	"mean_squared_error"	"mean_squared_error"
epochs	100	16	100

Based on these parameters, we can build a model that is presented in Table 6. Subsequently, the researcher constructed a model by incorporating hyperparameters for each individual model, aiming to identify the most suitable model.

Table 6. Model Creation for Three Models

RNN Elman		
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 14, 3)]	0
simple_rnn (SimpleRNN)	(None, 128)	16896
dense (Dense)	(None, 1)	129
RNN LSTM		
Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 100)	40800
dense_1 (Dense)	(None, 1)	101
RNN GRU		
Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 14, 3)]	0
gru (GRU)	(None, 128)	51072
dense (Dense)	(None, 1)	129

3.3 Practicing Model

In this step, researchers practice three models, each using 3 different schemes for dividing test data and training data. The result of training this model is a visualization of train loss and validation loss. The first step uses a scheme of 70% training data and 30% test data by paying attention to each hyperparameter of each model. Visualizations of

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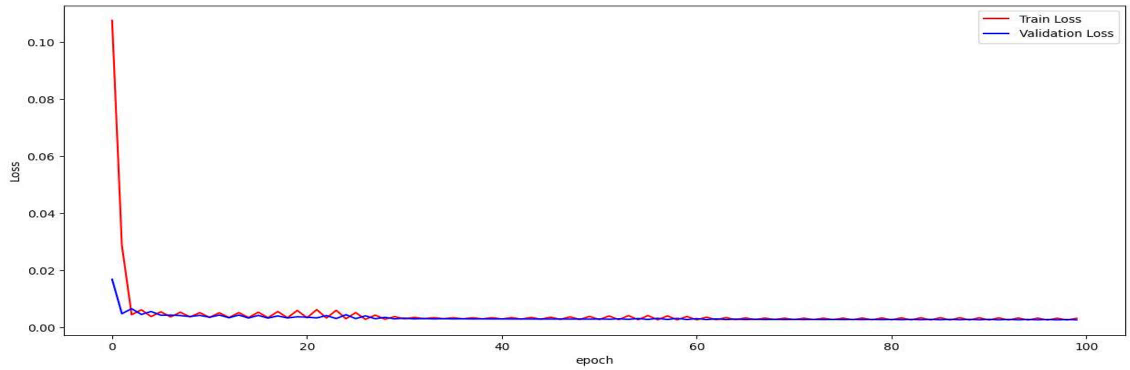
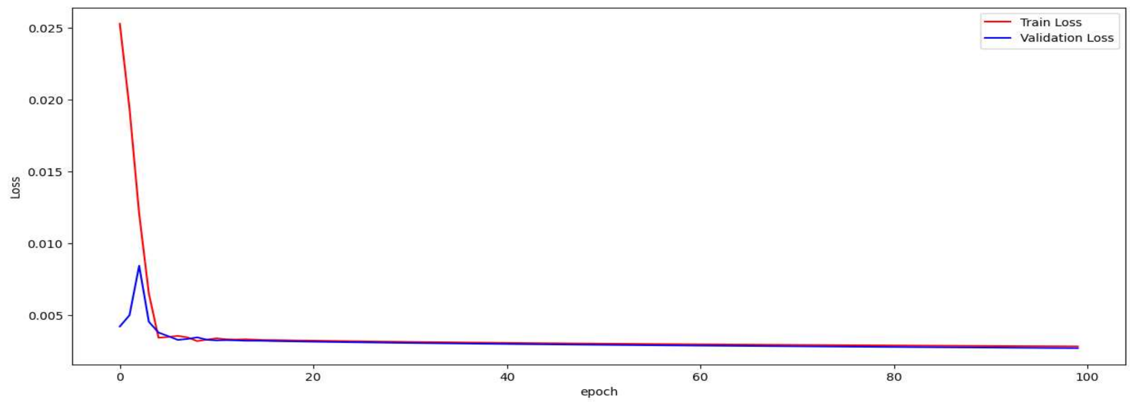
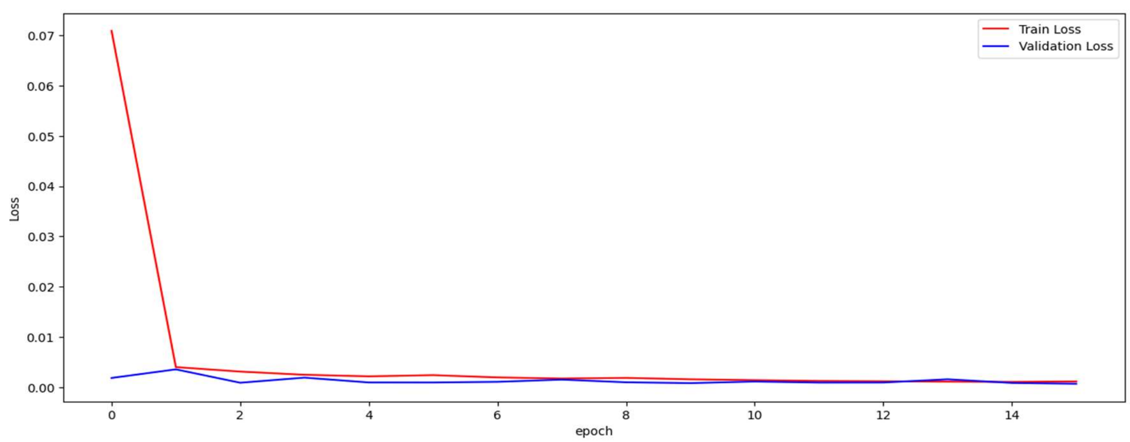
the Elman RNN, RNN GRU and RNN LSTM models are presented in Figure 6, Figure 7, and Figure 8, respectively.



a) RNN Elman



b) RNN GRU



c) RNN LSTM

Figure 6. Practicing Model With Scheme 70% Practiced Data And 30% RNN Model Data

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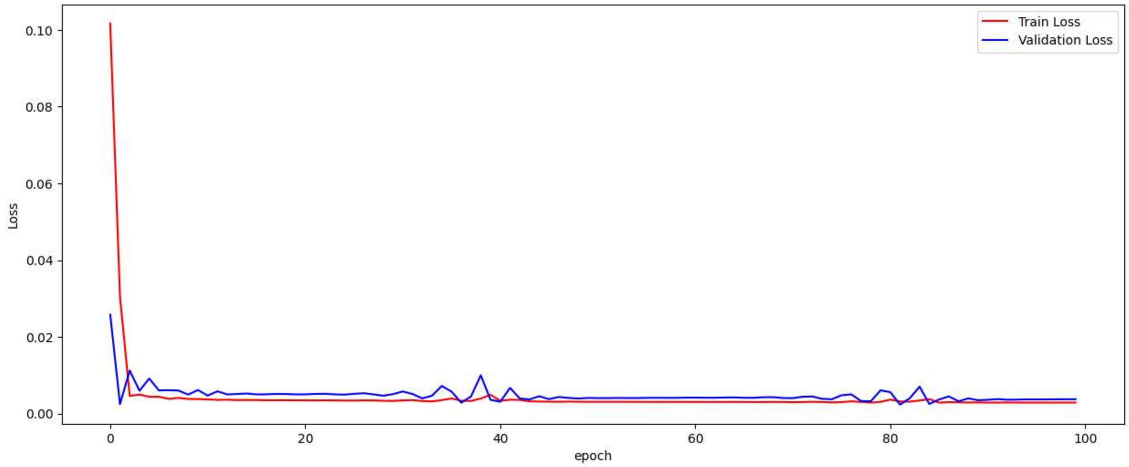
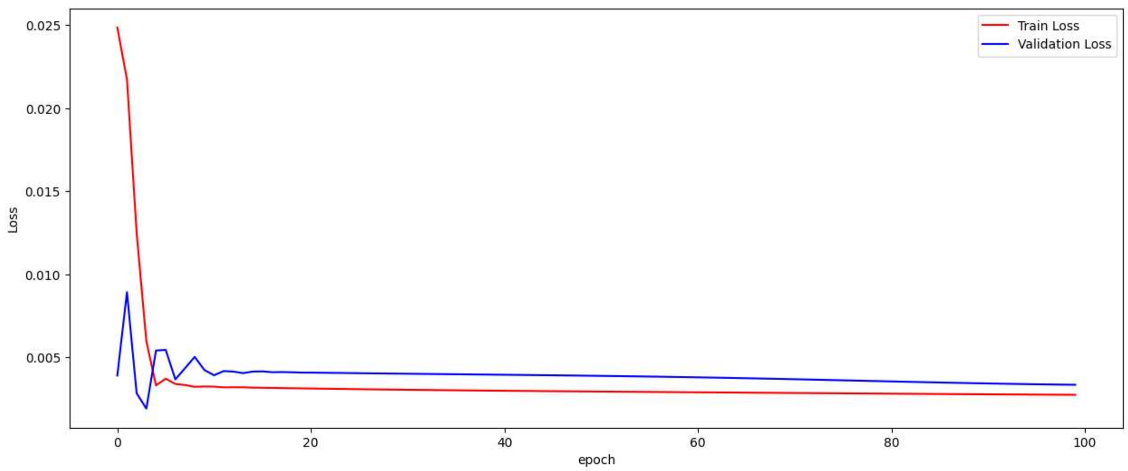
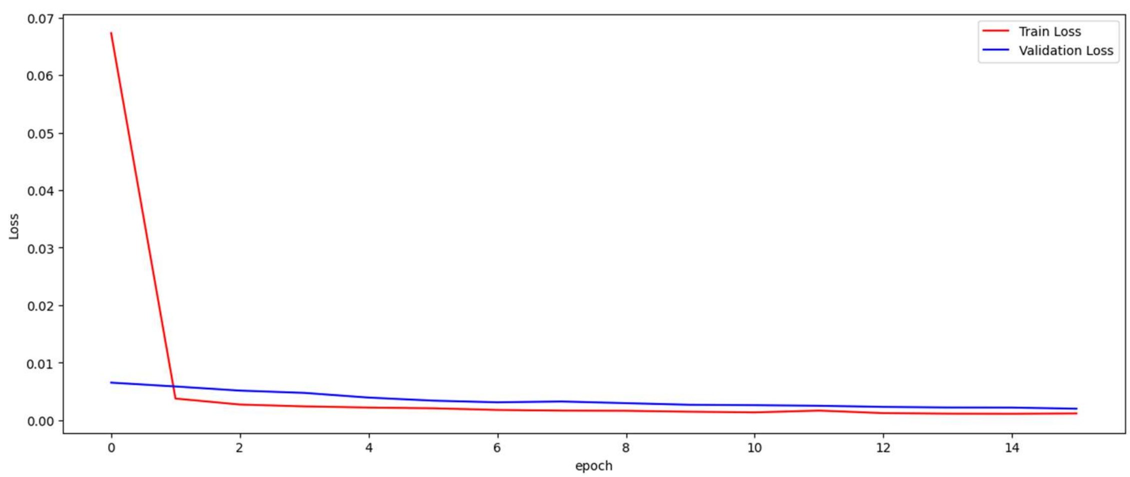


a) RNN Elman



b) RNN GRU



c) RNN LSTM

Figure 7. Practicing Model With Scheme 75% Practiced Data And 25% RNN Model Data

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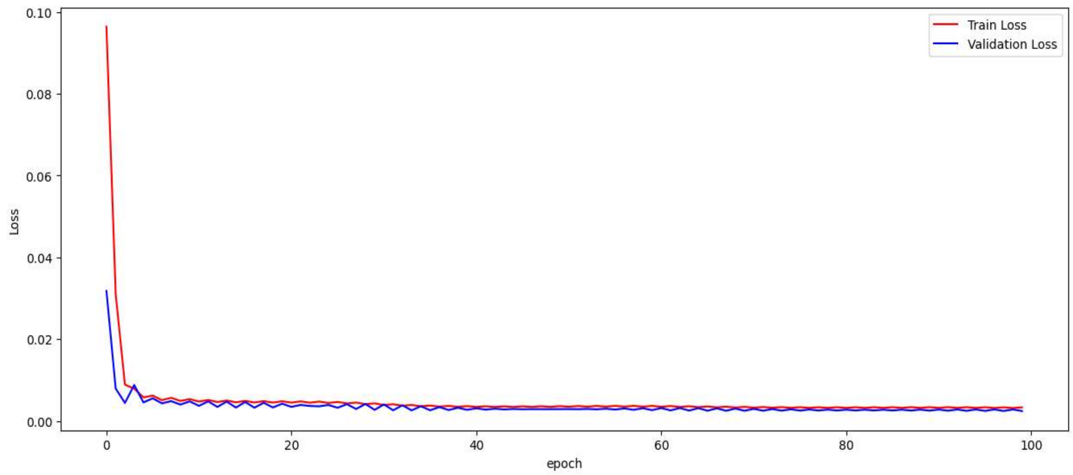
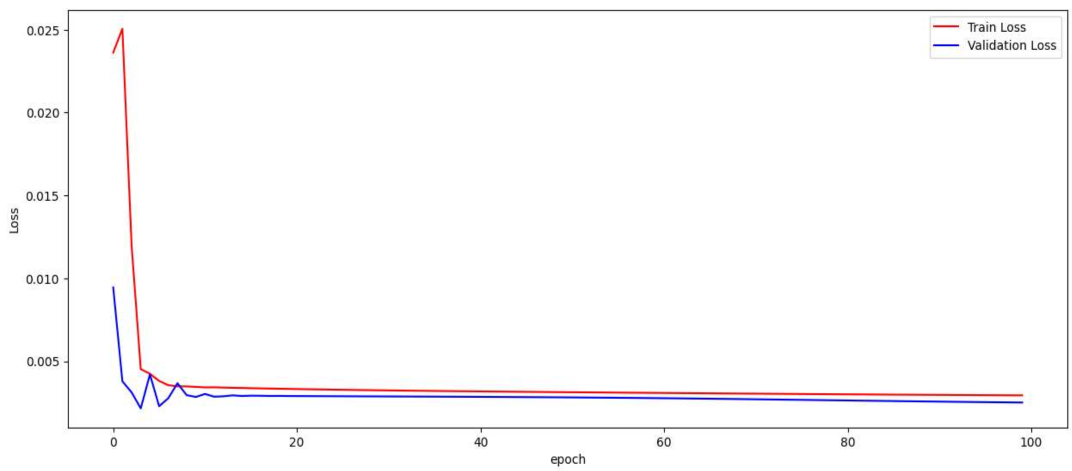
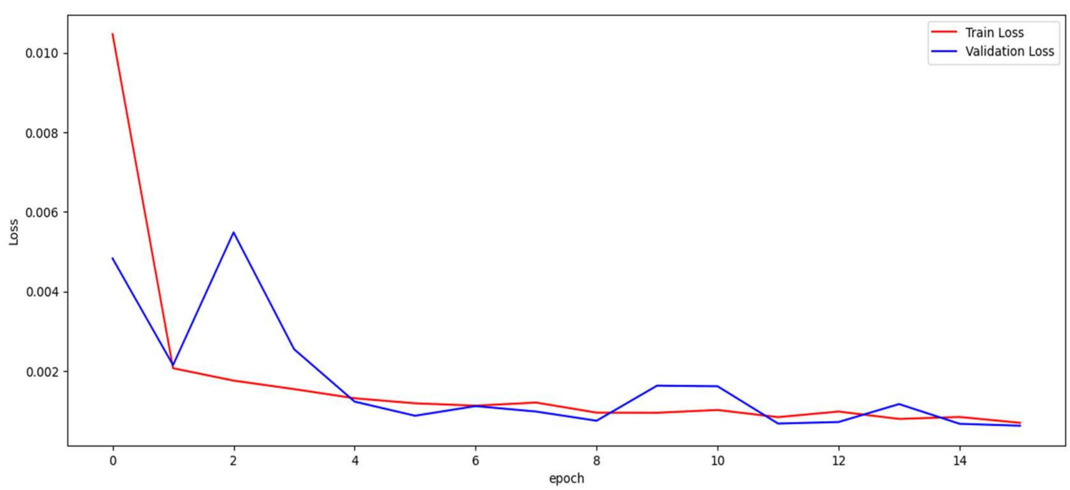


a) RNN Elman



b) RNN GRU



c) RNN LSTM

Figure 8. Practicing Model With Scheme 80% Practiced Data And 20% RNN Model Data

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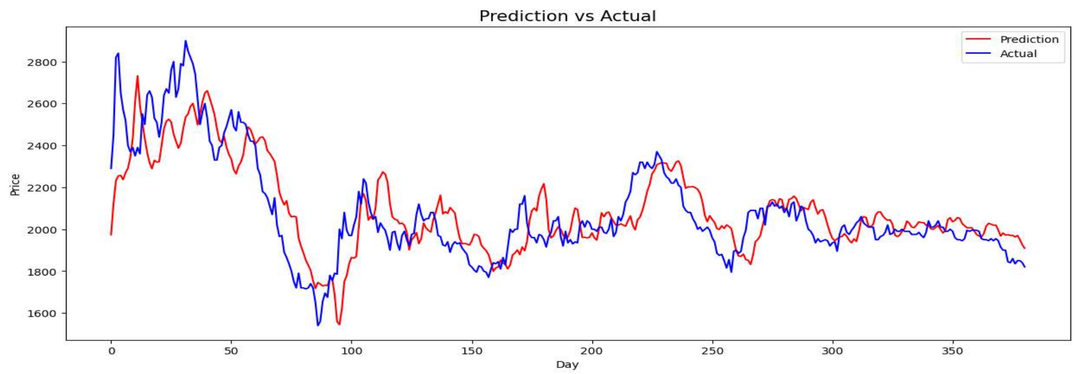
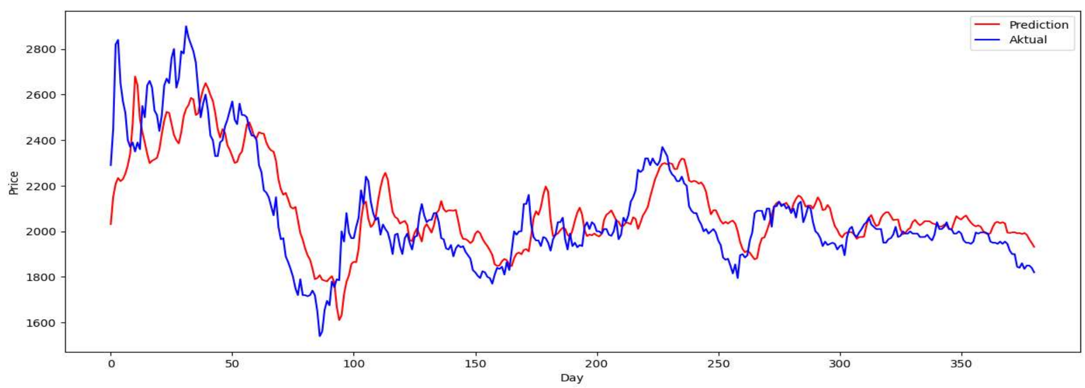
3.4. Evaluation Model

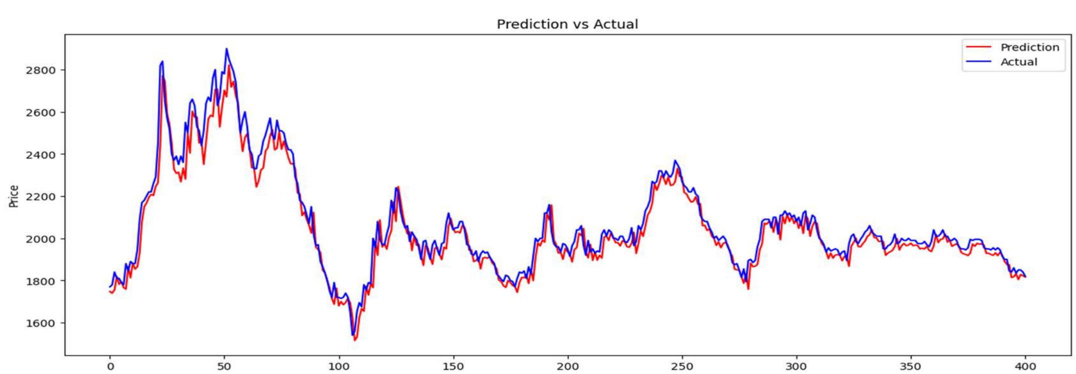
The step of evaluating the model, where this step is the result of the previous step, namely training the model. In this step the researcher will calculate the mean absolute percentage error, mean square error, mean absolute error and root mean square error to be able to compare with other models and obtain the optimal model for each model. The results obtained are presented in table form and the predicted and actual results are presented in graphical visualization form, showing in figure 9, figure 10, and figure 11, respectively. The blue line on each graph shows the actual stock value while the red line shows the predicted stock value. Each model evaluation with various schemes is shown in Table 7 (RMSE).



a) RNN Elman

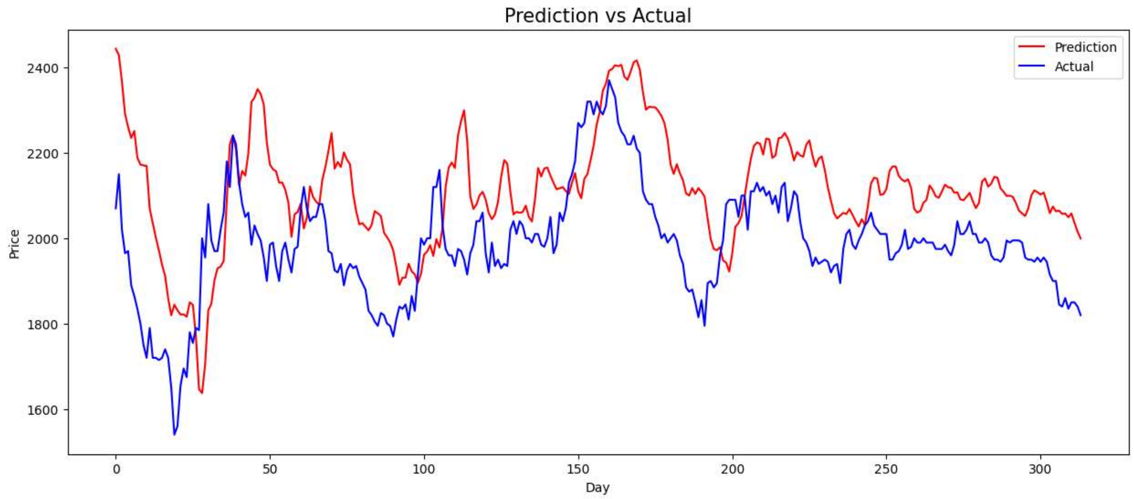


b) RNN GRU

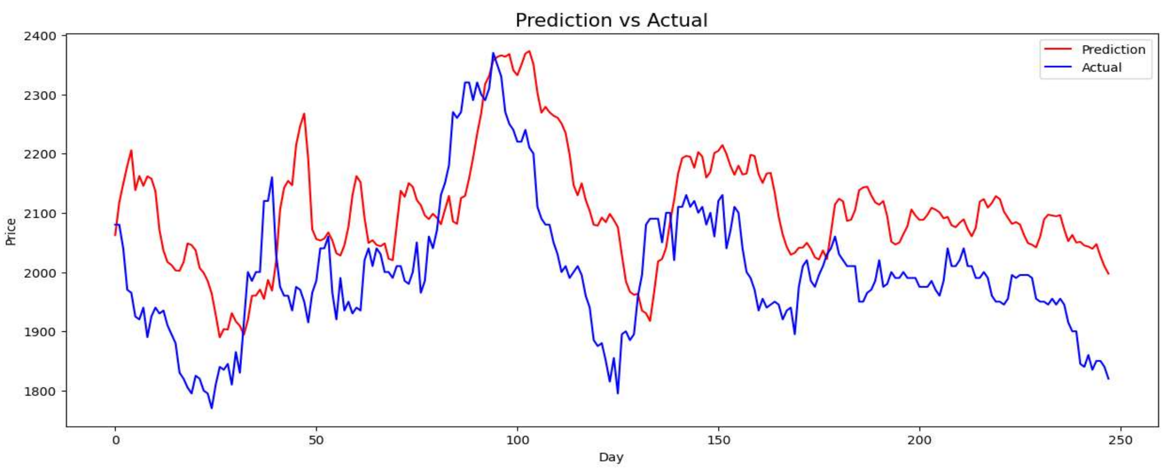


d) RNN LSTM

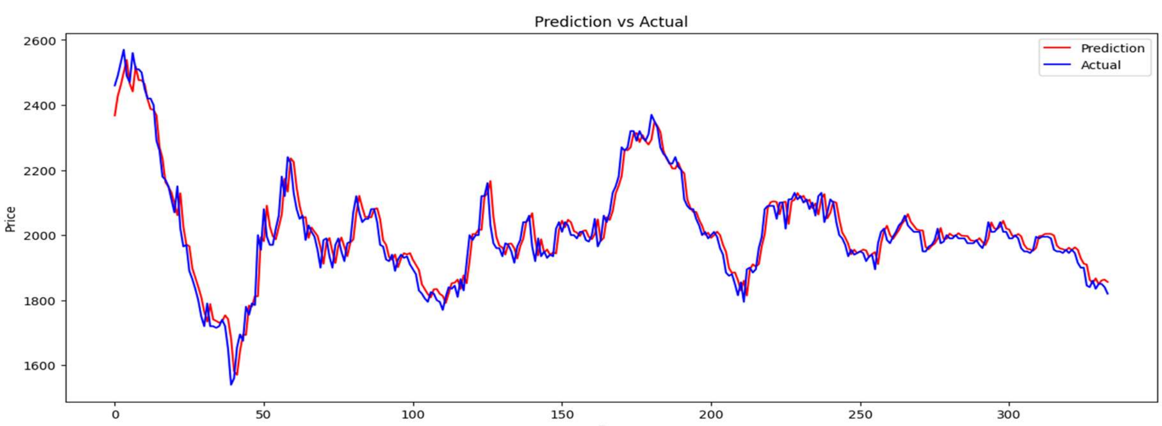
Figure 9. Visualization Of Predicted RNN Models Using Scheme 70%



a) RNN Elman



b) RNN GRU



c) RNN LSTM

Figure 10. Visualization Of Predicted RNN Models Using Scheme 75%

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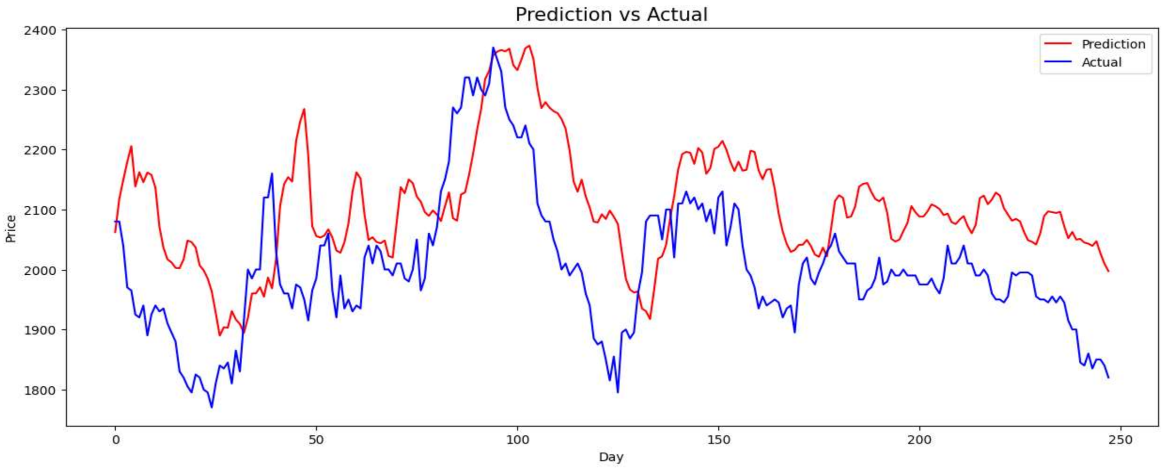
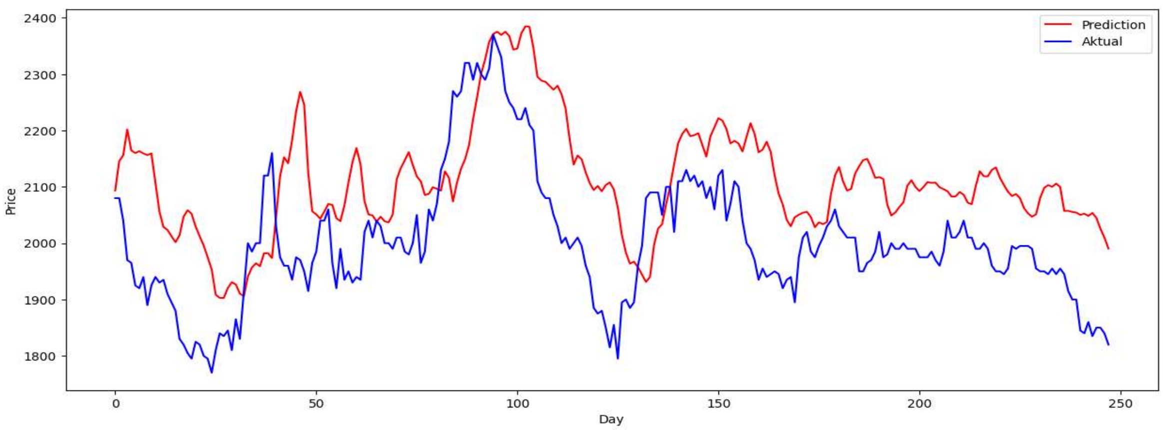
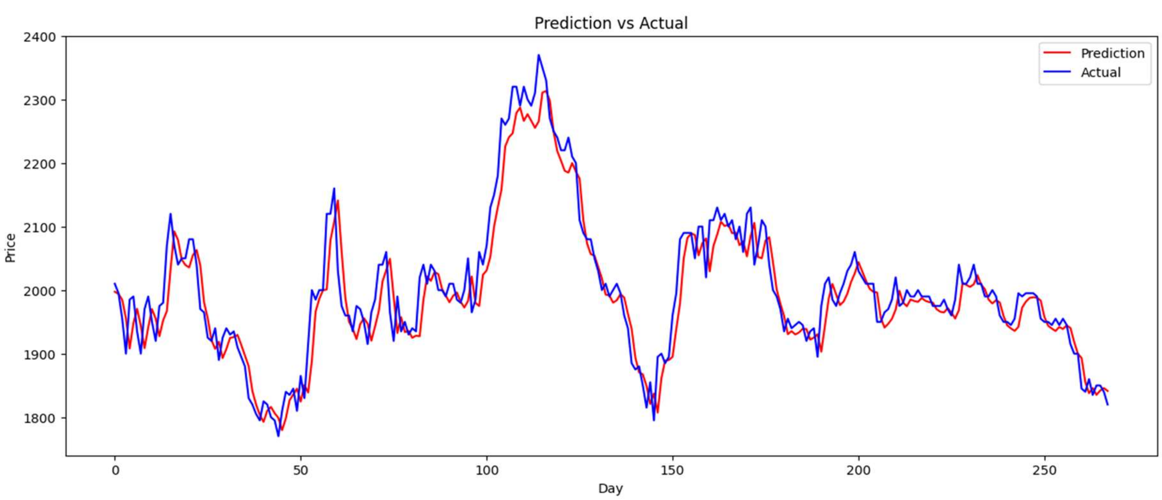


a) RNN Elman



b) RNN GRU



c) RNN LSTM

Figure 11. Visualization Of Predicted RNN Models Using Scheme 80%

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Table 7. RMSE And MAPE Results

Results	Scheme 70%			Scheme 75%			Scheme 80%		
	RNN Elman	RNN GRU	RNN LSTM	RNN Elman	RNN GRU	RNN LSTM	RNN Elman	RNN GRU	RNN LSTM
Mean Absolute Percentage Error	0.0644	0.0653	2.0774	0.0937	0.0884	1.5308	0.0752	0.0767	1.4141
Mean Square Error	0.0027	0.0027	4012.4682	0.0038	0.0034	1822.7342	0.0024	0.0025	1429.7170
Mean Absolute Error	0.0399	0.0401	44.4688	0.0527	0.0496	30.7270	0.0429	0.0437	28.5346
Root Mean Square Error	0.0522	0.0519	63.3440	0.0613	0.0579	42.6935	0.0493	0.0501	37.8116

Based on table 7, several different results can be displayed, then the researcher will take the best table for each model which will be taken as follows. For the Elman RNN model using a scheme of 70% training data and 30% test data as well as for the GRU RNN model using the same scheme, while the LSTM RNN uses a scheme of 80% training data and 20% test data. The final step is to compare the results from the Elman RNN model, GRU RNN model, and LSTM RNN model. The results obtained from these three tables indicate that the GRU RNN model is the best model among the three, followed by the Elman RNN model, then finally the LSTM RNN.

The studies related to Supervised Machine Learning for prediction have also been described that, given the growing application of artificial networks in materials design, the data-based protocol presented here expands the realm of science areas where supervised machine learning serves as a decision-making tool aiding the simulation practitioner to assess when long simulations are worth to be continued [49]. Another work depicting ERNN, LSTM, and GRU that, forecasting accuracy of the methods on series with different lengths, dimensions, and data frequency is an aspect we want to highlight is the outperforming of VARMA concerning the other methods in the majority of the time series considered; anyway, it is necessary to extend the analysis to a wider range of datasets before stating its major accuracy concerning RNN models. Among the statistical methods, the Theta method has been the worst one, concerning the considered dataset. However, it has always outperformed the machine learning models. Finally, our results do not allow us to decide the best RNN mode among ERNN, LSTM, and GRU [50].

We believe that this work can be a starting point for further investigation on the forecasting power of statistical and machine learning methods, with respect to multivariate multi-step time series forecasting, considering the high relevance they have in the field of predictive maintenance.

4. CONCLUSION

This study reveals the best performance from RNN models is GRU. The results of GRU by using MAE value is 0.0203. This model can make prediction values with small error values and recommends that the analysis of the model is better to use more variations in hidden neurons, layers, activation functions, training algorithms, and parameters to get a better model architecture. Therefore, hidden neurons well as their variations determine the number of Iterations. By several combinations, The RNN-GRU model is the current best model to predict Islamic stock values in Indonesia. However, the model needs to be advanced to provide the standard model for Islamic stock value prediction. Investors face the fluctuation of Islamic stock values to making investment decisions. Hence, the development of stock prediction is still important in further research.

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