

Comparison Analysis of Activation and Optimizer on Long Short-Term Memory Algorithm for Artificial Intelligence in Transportation Stock Price Prediction

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ABSTRACT

Inflation growth in Indonesia and other countries impacts the currency value and investors' purchasing power, particularly in the transportation sector. This study aims to predict stock prices in Indonesia's transportation sector using data mining technique from Cross Industry Standard Process for Data Mining (CRISP-DM) framework such as business understanding, data understanding, data preparation, modeling, evaluation, and deployment, along with Long Short-Term Memory (LSTM) algorithm with comparison of activation functions like linear, relu, sigmoid, and tanh and optimizers like Adaptive Moment Estimation (ADAM), Adaptive Gradient (ADAGRAD), Nesterov-accelerated Adaptive Moment Estimation (NADAM), Root Mean Square Propagation (RMSPROP), Adaptive Delta (ADADELTA), Stochastic Gradient Descent (SGD), and Adaptive Moment Estimation with Maximum (ADAMAX). The results showed the best metric evaluation value of Mean Absolute Error (MAE) of 0.0092918, Mean Absolute Percentage Error (MAPE) of 0.06422, Mean Squared Error (MSE) of 0.00021230, R-Squared of 96%, Root Mean Squared Error (RMSE) of 0.01457 and shapiro-wilk test on T-Statistic of 0.7102 and P-Value of 4.716007 with elapsed time of 104.35 minutes on relu's activation and adam's optimizer. The prediction of each transportation stock shows that Temas (TMAS.JK) stock has increased significantly from April to October 2023 than other stocks. Besides that, web-based application for transportation stock price prediction using streamlit with 4 parameter input are Ticker, Activation-Optimizer, Start Date, and End Date.

1. Introduction

Growth of global capital markets has become one of the alternatives for investors to make short-term and long-term investments (Ritika et al., 2022). One of the forms or tangible evidence from investment in the capital market itself is stock (Rabinovich, 2023). Stock is a form of securities that represents an individual, institution, or organization's ownership in a company (Chen et al., 2021). When investors invest in stocks, they pay attention to the stock market to find out whether the stock price in a particular market is decreasing or increasing (Ballinari et al., 2022). Stock price is a value that represents the price of a stock during a certain period determined by market participants and the corresponding supply and demand in the stock market (Albahli et al., 2022). Decreasing or increasing stock prices are influenced by various factors, such as changes in interest rates, inflation, and others (Thampanya et al., 2020).

One of the right solutions for investors to make the right decision in understanding the stock market, especially in the transportation sector, is the role of data mining as a reference in predicting future stock prices, as has been shown in previous studies that successfully predict stocks using data mining methods (Kaur & Dharni, 2022). Data mining techniques have been used to predict the stock index of a Spanish company that engaged in infrastructure management sector is Acciona, Linear Regression (LR), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) algorithms. The lowest Root Mean Square Error (RMSE) metric evaluation was obtained with activation parameters linear and tanh, as well as adamax and adam optimisers of 0.0151 (Rana et al., 2019). National Stock Exchange (NSE) of India, LSTM and Multi-Layered Perceptron (MLP) algorithm model method was used with the lowest Mean Squared Error (MSE) metric evaluation of 0.58% at 60 timestamps, using the activation relu parameter

and the rmsprop's optimizer (Banyal* et al., 2020). Stock Exchange from Bangladesh, Hongkong, India, Indonesia, Japan, Malaysia, and Thailand used Long Short-Term Memory (LSTM) with several parameters of activation functions such as ELU, ReLU, and tanh along with number of epochs by 50-100. This study has found an accuracy from activation of tanh by 80% compared to another activation function of ELU and ReLU to predict stock price prediction from several stock exchanges (Sami et al., 2023). Financial industries at Pakistan, Long Short-Term Memory (LSTM) algorithm obtained best accuracy score of 92% from selu's activation and the adamax's optimizer with combining several parameters including 10 neurons, learning rate of 0.002, and 3000 epochs (Ali et al., 2019). Shanghai Composite Stock Index (CSI 300), Light Gradient Boosting Machine-Long Short-Term Memory (LightGBM-LSTM), Recurrent Neural Network (RNN), and Gated Recurrent Unit (GRU) algorithms along with activation and optimizer settings obtained lowest evaluation metric values for Root Mean Squared Error (RMSE) of 0.01108 and Mean Absolute Error (MAE) of 0.00770 from softsign's activation and rmsprop's optimizer in terms of training error. Besides that, testing error resulted in values of 0.01076 for RMSE and 0.00651 for MAE (Lv et al., 2021). Technology stock prediction is Apple Inc used Long Bilinear-Long Short-Term Memory (LBL-LSTM) to predict Apple Inc. This paper proposed the model has efficient performance compared to previous study. The comparative analysis reveals that LBL-LSTM performs better, achieving a 94% accuracy rate, even when taking into account changing external market conditions, such as fluctuations in quarterly lending rates of banks. Additionally, the reduced Root Mean Squared Relative Error (RMSRE) is only 0.00418, indicating a very low value (Gurav & Kotrappa, 2020). NIFTY 50 index stocks from financial, technology, energy, and consumer sectors used Recurrent

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Neural Network (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network along with activation functions such as ReLU, sigmoid, and softmax to predict several stocks from NIFTY 50 index. This study has performance of Mean Absolute Percentage Error (MAPE) from activation of ReLU by 0.4705 with Long Short-Term Memory (LSTM) algorithm compared to another activation functions such as sigmoid and softmax to predict stocks (Fathali et al., 2022). S&P500 stock index from United States of America, Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN) algorithms obtained lowest evaluation metric value of Mean Absolute Error (MAE) was 0.0178 for validation data and 0.0260 for test data, using the rmsprop's optimizer (Kamalov et al., 2020). Banking stock predictions from Bank Rakyat Indonesia (BRI), Bank Nasional Indonesia (BNI), Bank Tabungan Negara (BTN), and Mandiri using Long Short-Term Memory (LSTM) algorithm with several parameter from optimizers such as SGD, adam, and RMSProp along with number of epochs by 25, 50, 75, and 100. This study has lower performance of Root Mean Squared Error (RMSE) by 48.32 from optimizer of adam with accuracy score by 95% to predict Bank Rakyat Indonesia (BRI) stock price (Mutmainah et al., 2022).

Based on previous research, stock prediction using the LSTM algorithm model, as well as the comparison of activation and optimizer, has been carried out. However, the results of evaluation and activation metrics and optimisers are not fully utilised. Based on several studies that have been conducted, the Long Short-Term Memory (LSTM) algorithm modelling only uses several activation hyperparameters such as linear, relu, sigmoid, or tanh as well as the optimiser adam, adagrad, nadam, rmsprop, adadelata, sgd, or adamax optimisers only. In addition, the modelling only uses several metric evaluations such as Mean Absolute Error (MAE), Mean Squared Error (MSE), R2, Root Mean Squared Error (RMSE), or Mean Absolute Percentage Error (MAPE) and the use of streamlit also without based on modelling the LSTM algorithm with hyperparameter activation and optimizers. Therefore, this study aims using 6 transportation datasets in Indonesia. Data mining method or framework used is CRISP-DM for implementing conventional of Long Short-Term Memory (LSTM) algorithm modelling with the LSTM model from the comparison of hyperparameter comparisons of all activations namely linear, ReLU, sigmoid, and tanh, as well as all optimizers namely adam, adagrad, nadam, RMSProp, adadelata, SGD, and adamax. The evaluation elaboration uses metrics chosen are MAPE, MAE, RMSE, MSE, R2, and elapsed time in measuring the training model as well as the statistical test of the shapiro-wilk test. The contributions of this paper are as follows:

- To predict transportation stock prices using the Long Short-Term Memory (LSTM) algorithm model with various activation comparisons such as linear, ReLU (Rectified Linear Unit), tanh, and sigmoid, and optimizers such as adam, adagrad (Adaptive Gradient), nadam, RMSProp (Root Mean Squared Propagation), adadelata, SGD (Stochastic Gradient Descent), and adamax.
- To evaluate the success of the various activation comparisons and optimizers used to measure performance MAPE, MAE, RMSE, MSE, R-squared, elapsed time, and statistical tests.

- To design and develop a web application to predict transportation stocks price in Indonesia.

The structure of this paper is organised as follows. Section 2 presents of Materials and Method, starting with CRISP-DM framework implementation until LSTM model architecture using activation function and optimizer parameters. Section 3, the results and discussion of model performance from LSTM conventional model and LSTM using activation function and optimizer parameters along with the prediction of 6 transportation stocks with web-based information system from development of LSTM model based on activation function and optimizer parameters. Section 4, the paper concludes with model comparison limitations and some perspectives for future work.

2. Materials and Method

2.1. Proposed Research

The research workflow in Fig 2.1 shows an overview for transportation stock price predictions using data mining technique, namely CRISP-DM. First, business understanding explain inflation that happened from international and national countries. Data understanding was applied 6 transportation stock datasets from AKSI.JK, CMPP.JK, SAFE.JK, SMDR.JK, TMAS.JK, and WEHA.JK are collected and predicted from April until October 2023. Data preparation was applied including data pre-processing to replace missing values using mean imputation and splitting dataset randomly. From each datasets are used sequences for train the model using several activation function and optimizer combinations. The results were recorded based on metric performances in web-based system.

2.2. Business Understanding

Business understanding process shown in Fig 2.1, International inflation is the inflation that occurred in the top 10 countries in 2022, categorized by the percentage increase. The country that experienced the highest increase in inflation was Venezuela by 310% compared to other countries such as Zimbabwe by 244%, Argentina by 95%, Sudan by 87%, Turkey by 64%, Sri Lanka by 57%, Suriname by 55%, Ghana by 54%, Iran by 50%, and South Sudan experienced the lowest inflation by 41% (Jarne & Shveda, n.d.). In addition, year-on-year inflation in Indonesia inflation in Indonesia has increased from 2.18% in January 2022 to highest inflation in September 2022 of 5.95%, but the inflation trend decreased and constantly from September 2022 of 5.95% to 5.51% in December 2022 (Hadi, n.d.). Growth of inflation in some international countries, including Indonesia, may lead to a decline in the purchasing power of shares for investors (Chikwira, 2023).

2.3. Data Understanding

Initial data from data understanding process show in Fig 2.1 above, was collected from six transportation stocks namely Mineral Sumberdaya Mandiri (AKSI.JK), Air Asia Indonesia

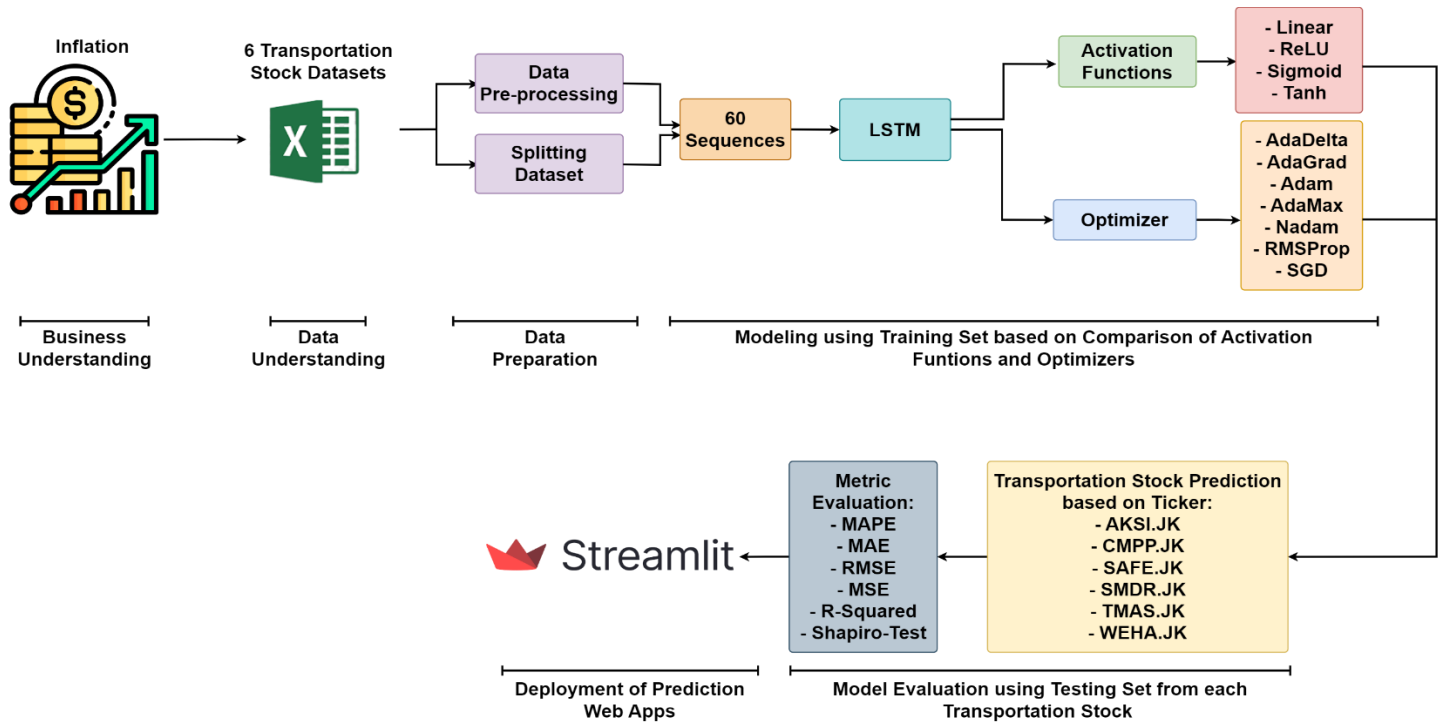


Fig 2.1 Research Workflow

(CMPP.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Temas (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK) from Yahoo Finance in 1st April to 2011 to 1st April to 2023 (Yahoo Finance, n.d.-b, n.d.-a, n.d.-d, n.d.-c, n.d.-e, n.d.-f). All transportation stock datasets have six attributes such as Open, High, Low, Close, Adj. Close, and Volume along with obtained have same number of datasets are 2.980 show in Table 2.1.

Table 2.1
Transportation Stock Dataset Info

Dataset	Total Attribute	Total Rows
AKSI.JK	6	2.980
CMPP.JK	6	2.980
SAFE.JK	6	2.980
SMDR.JK	6	2.980
TMAS.JK	6	2.980
WEHA.JK	6	2.980

2.3. Data Preparation

Data understanding is process to prepare all transportation stock datasets such as Mineral Sumberdaya Mandiri, Air Asia Indonesia, Steady Safe, Samudera Indonesia, Temas, and WEHA Transportasi Indonesia from Yahoo Finance website to several sheet in excel file. Storage of all transportation stock datasets from periods April 1, 2011 until April 1, 2023 will be prepared into 2 processes area data pre-processing and splitting dataset. The following are several stages of data preparation, among others:

2.3.1. Data Pre-processing

Data Preparation stage shown in Fig 2.1 above is the process of preparing data by adjusting the dataset to suit the

modelling needs. Data Pre-processing is the process of preparing raw data for modelling purposes. In the process of data pre-processing, there are several stages starting from checking for missing values for NULL values shown in Table 2.2.

Table 2.2
Total Missing Values from Datasets

Dataset	Total Missing Values	Total Rows
AKSI.JK	1	2.979
CMPP.JK	1	2.979
SAFE.JK	8	2.972
SMDR.JK	0	2.980
TMAS.JK	0	2.980
WEHA.JK	1	2.979

Total missing values for each attribute from Table 2.2 above across from 6 transportation stock datasets. SAFE.JK have 8 more than missing values from another transportation stock datasets such as AKSI.JK, CMPP.JK, WEHA.JK, SMDR.JK, and TMAS.JK. AKSI.JK, WEHA.JK, and CMPP.JK only has 1 missing value from each dataset, while SMDR.JK and TMAS.JK don't have missing values from each dataset.

Four datasets of SAFE.JK, AKSI.JK, CMPP.JK, and WEHA.JK that have missing values, requires further data processing from mean imputation. Mean Imputation is one of the most commonly used single imputation methods to replace missing data with the sample mean or median, mode, or distribution of the data (Jadhav et al., 2019). The process of replacing missing data ignores the correlation between each data point as its value is considered independent of any predictor value, leading to a bias in variance (Kabir et al., 2020). This method can also ignore the computation time required to replace missing data and significantly reduce the predictive performance of the model (Fletcher Mercado &

Blume, 2020). This method will be implemented to handle missing values for each transportation stock datasets are AKSI.JK, CMPP.JK, SAFE.JK, and WEHA.JK.

2.3.2. Splitting Dataset

Splitting dataset from Fig 2.1 above, training datasets plays a role in building the algorithm model, while testing datasets plays a role in measuring or evaluating the performance of the algorithm model used from each six transportation stock datasets such as AKSI.JK, CMPP.JK, SAFE.JK, SMDR.JK, TMAS.JK, and WEHA.JK. Target attribute from each transportation stock datasets is "close" attribute, that used to build a prediction algorithm model with a training data ratio of 90% and a test data ratio of 10% (Rana et al., 2019). Example from comparison of training and testing datasets obtained 2.682 samples from training set and 298 from testing set of each transportation stock datasets are AKSI.JK, CMPP.JK, SAFE.JK, SMDR.JK, TMAS.JK, WEHA.JK show in Table 2.3 that have been data cleaned using mean imputation.

Table 2.3
Example of Training and Testing Set from AKSI.JK Dataset

	Ratio	No. Samples
Training	90%	2.682
Testing	10%	298

Data distributions from training and testing set in transportation stock datasets are CMPP.JK, SAFE.JK, SMDR.JK, TMAS.JK, and WEHA.JK will be processed with the same distribution of AKSI.JK dataset show in Table 2.3 above. Next process, all transportation stock datasets will be normalized using MinMaxScaler. MinMaxScaler is data preprocessing technique used to normalize data and ensure that all data has the same range of values (Deepa & Ramesh, 2022). It adjusts and shifts each feature independently based on the range specified in the training set (Pires et al., 2020). The normalization process can be expressed to implemented from each stock datasets are AKSI.JK, CMPP.JK, SAFE.JK, SMDR.JK, TMAS.JK and WEHA.JK before modeling process, where X_i represents the value of an observation in the feature, and X_{min} and X_{max} denote the minimum and maximum values of the feature, respectively (Mohd Faizal et al., 2023).

$$Z = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

2.4. Modeling

Modeling process shown in Fig 2.1 above, specific methods and algorithms to construct models as solutions to fulfill the business understanding. Modeling process will utilize Visual Studio Code, employing the Python programming language and other frameworks such as Keras and Tensorflow. Python programming language is chosen because there have been numerous previous studies (Banyal* et al., 2020; Rana et al., 2019; Sami et al., 2023). have used Python, and it has been proven that Python is a more efficient programming language. Stages of modeling in deep learning algorithmic modeling with

60 sequences with activation function comparison and optimization of 240 sequences, including (Kamalov et al., 2020):

2.4.1. Long Short-Term Memory

LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) that focuses on long-term memory (Nan, 2023). It is a suitable option for analyzing, handling, and making forecasts using time series data due to the potential presence of an uncertain lack of time intervals between significant events (Kristiyanti & Hardani, 2023). Additionally, LSTM utilizes a specialized hidden state and three controlling gates to regulate and manage both of long-term and short-term memory (Huang et al., 2023). LSTM network, being a distinct type of RNN, consists of an input layer, a hidden layer, and an output layer, with the structure of the LSTM cell depicted in Fig 2.2 (Filho et al., 2020).

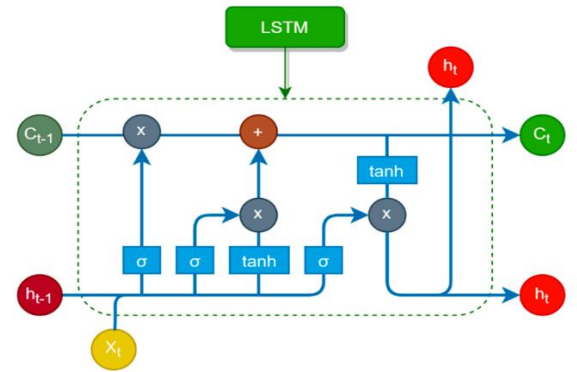


Fig 2.2 LSTM Architecture

The process of sending the information initially starts from the forget gate layer, as shown in Fig 2.2 above. The function of the forget gate is to retain significant data in the cell state while discarding irrelevant information (Zaheer et al., 2023). It can be proven by the calculation following below (Kratzert et al., 2018).

$$f_t = \sigma(Wf[ht - 1, xt] + bf) \quad (2)$$

f_t is the resultant vector containing values between 0 and 1, $\sigma(\cdot)$ denotes the logistic sigmoid function, and Wf , Uf , and bf consists of a set of adjustable parameters that determine the weight matrix and bias vector for forgetting gates. Hidden states, referred to as ht are initialized in the first step using a vector of zeros with a length specified by the user. Next, the potential update vector for the cell state is calculated in the next step using the current input xt and the previous hidden state $ht - 1$ like the following below (Zaheer et al., 2023).

$$\hat{C}t = \tanh(Wc \cdot [ht - 1, xt] + bc) \quad (3)$$

Wc represents the weights, $ht - 1$ indicates the previous state value, xt represents the input at the current time step, bc represents the bias, and $\hat{C}t$ represents the cell state function value at a given time step. The result of cell function and output of the input gate are combined by multiplying and adding them

to the cell state like the following below (Sen & Raghunathan, 2018).

$$Ct = ft \odot Ct - 1 + it \odot \hat{C}t \quad (4)$$

The input vector and the candidate memory cell vector are combined together to modify the previous memory cell $Ct - 1$ and \odot represents element-wise multiplication. The output gate layer holds the results of computation or processing of information from the early stage layers, including forget gate and update gate. In this layer, the overall calculation result is obtained through two computational stages to get the final result like following below (Sen & Raghunathan, 2018).

$$Ot = \sigma(Wo.[ht - 1, xt] + bo) \quad (5)$$

Ot represents the output gate, known as the final gate, organize transfer of information from all current memory cell to the current hidden state. This hidden state is also the output of the LSTM at the current time step. An LSTM architecture involves several calculation procedures within its layers to produce results, and these procedures are detailed in Table 2.4, an outline of the calculation process for each layer in the LSTM.

Table 2.4
Pseudocode LSTM Algorithm

Algorithm 1 Pseudocode LSTM Algorithm

```

1: Input:  $x = [x_1, \dots, x_n], x_t \in \mathbb{R}^m$ 
2: Given parameters:  $W_f, U_f, b_f, W_c, U_c, b_c, W_o, U_o, b_o, W_g, U_g, b_g$ 
3: Initialize  $h_0, c_0 = \vec{0}$  of length  $p$ 
4: for  $t=1, \dots, n$  do
5:   Calculate  $f_t, \hat{c}_t, i_t$ 
6:   Update cell state  $c_t$ 
7:   Calculate  $o_t$ 
8: end for
9: Output:  $h = [h_1, \dots, h_n], h_t \in \mathbb{R}^p$ 

```

2.4.2. Activation Techniques

Activation is a function used to determine whether a node will be activated or not in artificial neural network modelling (Brito da Silva et al., 2019). It can also be applied to the neuron's output to obtain more specific results in the form of a nonlinear transformation of the input signal (Zhao et al., 2021). Activation that were used in the experiments are Linear, ReLU (Rectified Linear Unit), Tanh, and Sigmoid.

Linear's activation is a function that has a gradient that is directly proportional to the input entered in neural network modelling (Sharma et al., 2020). ReLU's activation is a simple function that acts as an identity function for positive input values and returns 0 for negative input values (Dubey et al., 2022). Tanh's activation is a simple computational function, the derivative of one used in the backpropagation process of Recurrent Neural Network (RNN) modelling (Poornima & Pushpalatha, 2019). Sigmoid's activation is a function designed using a non-linear resistive load that takes current as an input value and provides voltage as an output value to the neurons (Venugopal & Vigneswaran, 2019). The formula for Linear, ReLU (Rectified Linear Unit), Tanh, and Sigmoid activation's are given in Eqs. (6)-(9).

$$f(x_i) = kx_i \quad (6)$$

$$ReLU(x) = \max(x, 0) \quad (7)$$

$$\tanh(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (8)$$

$$f(x) = \frac{1}{1 + e^{-x}} \quad (9)$$

2.4.3. Optimization Techniques

An optimizer is a mechanism that aims to improve processing or learning efficiency in a prediction algorithm model based on improving accuracy scores in a prediction task (Hamdia et al., 2021). In other words, optimizer by the optimiser can shape and improve the accuracy score by utilising the weights to achieve the most accurate prediction possible (Lee & Kim, 2023). Optimizer that were used in the experiments are Adam, AdaGrad (Adaptive Gradients), Nadam (RMSProp (Root Mean Square Propagation), AdaDelta, SGD (Stochastic Gradient Descent), and AdaMax.

Adam's Optimizer is an algorithm optimization method based on stochastic gradients that is well suited for direct implementation in any model, in particular for large data sets and parameters (Iboudo et al., 2022). AdaGrad's Optimizer is a variant of the Stochastic Gradient Descent optimisation algorithm that adjusts the learning rate dynamically for different parameter (Tokgoz et al., 2023). Nadam's optimizer is an extension of Adam's algorithm that combines Nesterov momentum with gradient descent (Fofana et al., 2021). RMSProp's optimizer stands for Root Mean Square Propagation, and has been developed to achieve better results and prevent convergence by not reducing the learning rate (Olanipekun et al., 2022). AdaDelta's optimizer is an extended optimization algorithm of AdaGrad that solves the problem of decreasing learning rate but not accumulating squared gradient values (Yaqub et al., 2020). SGD's optimizer stands for Stochastic Gradient Descent, a popular choice of optimization algorithm for many recent advances in deep learning across domains (Abdulkadirov et al., 2023). AdaMax's optimizer is a variant of Adam's optimization algorithm that simplifies the learning rate range and has been used to train Convolutional Neural Network (CNN) models (Weiss et al., 2022). The formula for Adam, AdaGrad (Adaptive Gradients), Nadam, RMSProp (Root Mean Square Propagation), AdaDelta, SGD (Stochastic Gradient Descent), and AdaMax optimizer's are given in Eqs. (10)-(16).

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t \quad (10)$$

$$W_t = W_{t-1} - \lambda'_t \frac{\partial \nabla}{\partial W_{t-1}} \quad (11)$$

$$w_t^i = w_{t-1}^i - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \cdot \tilde{m}_t \quad (12)$$

$$G = \nabla_W C(w_t) \quad (13)$$

$$g'_t = \frac{\sqrt{u_{t-1} + \epsilon}}{\sqrt{s_t}} g_t \quad (14)$$

$$W_{i+1} = W_i - \eta \frac{\partial L}{\partial W_i} \quad (15)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) |g_t|^2 \quad (16)$$

2.5. Evaluation Metrics

Evaluation process show in Fig 2.1 above, processes or stages carried out to assess the performance of the applied modeling. This evaluation process serves to determine how well the predictions made using the model built to answer the business understanding stage of each transportation stock prediction from Mineral Sumberdaya Mandiri, Air Asia Indonesia, Steady Safe, Samudera Indonesia, Teras, and WEHA Transportasi Indonesia. Evaluation metrics that were used in the experiments are Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), r-squared, elapsed time, and shapiro-wilk test.

Mean Absolute Percentage Error (MAPE) calculates the prediction error by dividing the absolute error of each period by the actual observed value for that period (Hayder et al., 2023). Mean Absolute Error (MAE) is one of the evaluation metrics that can be used when outliers on each attribute resubmit dirty data (Chicco et al., 2021). Root Mean Squared Error (RMSE) is a metric that measures the distribution of residuals, indicating the extent to that data is spread around the optimal line of fit (Murugesan & Jung, 2021). Mean Squared Error (MSE) is a widely used approach in neural network models to determine error and precision (Lyu et al., 2022). R-squared proves useful when comparing different models and evaluating their ability to capture fundamental patterns in the data (Khan et al., 2020). Elapsed Time refers to the average time taken from when a data point is generated by SenSE until the performance result is received (Kamiński et al., 2019). Shapiro-Wilk test is the most widely used statistical hypothesis testing method to test the normality of data (Mishra et al., 2019). The formula for Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), r-squared, elapsed time, and shapiro-wilk test are given in Eqs. (17)-(23).

$$MAPE = \frac{100}{n} \sum_{i=1}^n \frac{|y_l - y_i|}{y_i} \quad (17)$$

$$MAE = \frac{\sum_{n=1}^N |r_n - r_n|}{N} \quad (18)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (19)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (20)$$

$$R - Squared = 1 - \frac{\sum_{i=1}^n (X_i - y_i)^2}{\sum_{i=1}^n (\bar{Y} - y_i)^2} \quad (21)$$

$$T = t_n - t_1 \quad (22)$$

$$W_X = \frac{(\sum_{i=1}^n a_i X_{(i)})^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (23)$$

2.6. Deployment

Deployment process shown in Fig 2.1 above, the process of developing algorithmic models with various activation comparisons namely linear, ReLU, tanh, and sigmoid, as well as optimizations namely adam, adagrad, nadam, RMSProp, adadelta, SGD, and adamax into a web-based application using streamlit with input parameters will be carried out. The deployment stage begins with saving all models that have been trained based on linear, ReLU, tanh, and sigmoid activation comparisons, as well as optimization of adam, adagrad, nadam, RMSProp, adadelta, SGD, and adamax into .h5 format. The stored models will be implemented in a web-based application to display transportation stock predictions as well as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R-squared evaluation metrics.

3. Result & Discussion

This section are the results and discussion of performance from Long Short-Term Memory (LSTM) conventional model and comparison LSTM model using activation functions and optimizers to predict transportation stocks in Indonesia namely Mineral Sumberdaya Mandiri, Air Asia Indonesia, Steady Safe, Samudera Indonesia, Teras, and WEHA Transportasi Indonesia.

3.1. Comparison Algorithm and Evaluation Metrics

In this section, Long Short-Term Memory (LSTM) algorithm will compared based on conventional model and LSTM with hyperparameter from activation functions and optimizers. Evaluation metrics that used to evaluate the model from each transportation stock datasets are MAE, MAPE, MSE, R-Squared, and RMSE along with elapsed time from training time model in LSTM conventional.

3.1.1. LSTM

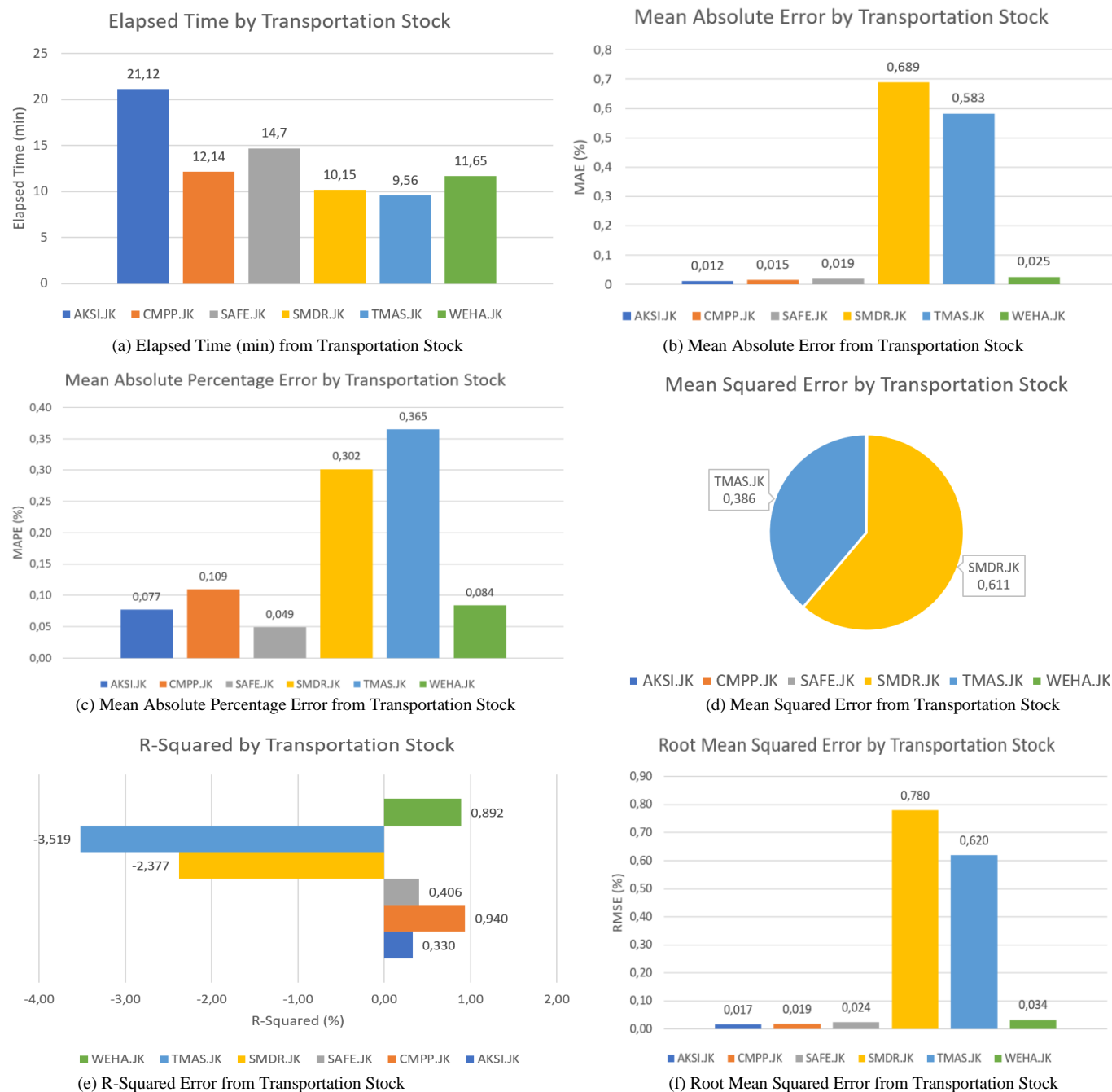
This section presents the performance results of the conventional LSTM model in predicting the transportation stock dataset, specifically Mineral Sumberdaya Mandiri (AKSI.JK), Air Asia Indonesia (CMPP.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Teras (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK). Table 3.1 and Fig 3.1 show the performance of the conventional LSTM model for the transportation stock dataset. The time taken analysis shows that the TMAS.JK, SMDR.JK, and WEHA.JK stock datasets exhibit slower training speed for the LSTM algorithm compared to the CMPP.JK, SAFE.JK, and AKSI.JK stock datasets. Among the three datasets, TMAS.JK has the shortest training time of 9.56 minutes, followed by SMDR.JK and WEHA.JK. On the other hand, the CMPP.JK, SAFE.JK, and AKSI.JK datasets require longer time compared to the TMAS.JK, SMDR.JK, and WEHA.JK datasets. In particular, the AKSI.JK stock dataset has the longest time of 21.12 minutes, exceeding the time taken by the SAFE.JK and CMPP.JK datasets.

MAE analysis shows that the AKSI.JK, CMPP.JK, and SA-

Table 3.1

Model Performances of LSTM Conventional Model from Transportation Stocks

Dataset	Elapsed Time (min)	MAE (%)	MAPE (%)	MSE (%)	R-Squared (%)	RMSE (%)
AKSI.JK	21.12	0.0116605	0.07697	0.0002741	0.329813	0.01656
CMPP.JK	12.14	0.0146438	0.10927	0.0003563	0.939591	0.01888
SAFE.JK	14.7	0.0191644	0.04884	0.000599	0.40595	0.02447
SMDR.JK	10.15	0.6891372	0.30152	0.607971	-2.377048	0.77972
TMAS.JK	9.56	0.5825399	0.36527	0.3841733	-3.518707	0.61982
WEHA.JK	11.65	0.0253701	0.08396	0.00114	0.891818	0.03376

**Fig 3.1** Model Performances of LSTM Conventional Model from Transportation Stocks

FE.JK stock datasets have lower performance errors compared to the SMDR.JK, TMAS.JK, and WEHA.JK stock datasets. In particular, the AKSI.JK stock dataset has a smaller Mean Absolute Error (MAE) of 0.0116605 compared to the stock

datasets. On the other hand, the SMDR.JK, TMAS.JK, and WEHA.JK stock datasets have higher MAE values than the SAFE.JK, CMPP.JK, and AKSI.JK. SAFE.JK, AKSI.JK, and WEHA.JK stock datasets based on MAPE analysis, have lower

performance errors compared to the TMAS.JK, SMDR.JK, and CMPP.JK stock datasets. In particular, the SAFE.JK stock dataset has a smaller Mean Absolute Error (MAE) of 0.04884 compared to AKSI.JK and WEHA.JK. On the other hand, the TMAS.JK, SMDR.JK, and CMPP.JK stock datasets have higher MAE values compared to the SAFE.JK, AKSI.JK, and WEHA.JK stock datasets. In particular, the CMPP.JK stock dataset has a smaller Mean Absolute Error of 0.10927 compared to the SMDR.JK and TMAS.JK stock datasets.

Specifically, the performance from LSTM conventional model from each transportation stock datasets, Air Asia Indonesia (CMPP.JK) has best performance from MAE of 0.0146438, MAPE of 0.10927, MSE of 0.0003563, R-Squared of 93%, RMSE of 0.01888. Although this stock has a longer LSTM model training of 12.14 minutes and higher error performance compared to the SAFE.JK, WEHA.JK, TMAS.JK, and SMDR.JK stock datasets, there is something interesting about this dataset, it has a coefficient of determination value that reaches 93% greater than the other stock datasets. This result indicates that the predicted value results have a greater chance of explaining the dependent variable or a very accurate prediction value and the prediction error performance of MAE, MAPE, MSE, and RMSE is smaller than the AKSI.JK, SAFE.JK, WEHA.JK, TMAS.JK, and SMDR.JK stock datasets.

3.1.2. LSTM with Activation Functions & Optimizers

This section presents the performance of LSTM models based on different hyperparameters, including activation functions and optimizers. The activation functions evaluated for the LSTM model are linear, ReLU, tanh, and sigmoid. The optimizers used are Adam, Adagrad, Nadam, RMSProp, Adadelta, SGD, and Adamax. The performance of these activation functions and optimizers is demonstrated on a dataset of transportation stocks, which include Mineral Sumberdaya Mandiri (AKSI.JK), Air Asia Indonesia (CMPP.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Teras (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK).

Table 3.2 below presents the model performance of the activation function and optimizer of the LSTM model from the AKSI.JK and CMPP.JK stock datasets. The AKSI.JK dataset has 5 best performances based on activation function and optimizer, namely ReLU, linear, and tanh activation with adam, nadam, RMSProp, and adamax optimizers. Based on the performance of the top 5 models, there is something interesting about this dataset. ReLU activation with nadam optimizer has a lower performance in terms of MSE of 0.0002039, RMSE of 0.01428, and a higher coefficient of determination from R-Squared of 50% when compared to other activations, namely linear and tanh with adam, RMSProp, and adamax. The CMPP.JK dataset has 5 best performances based on activation function and optimization such as ReLU, tanh, and linear activation with adam, nadam, and adamax optimization. Based on the top 5 model performance, there is something interesting about this dataset. ReLU activation with adam optimizer has a lower performance in terms of MSE of 0.0002123, RMSE of 0.01457, and a higher coefficient of determination from R-Squared of 96% compared to other activations, namely linear and tanh with adam, nadam, and adamax optimizers. The

performance of LSTM model is further shown in Table 3.3 below which displays the SAFE.JK and SMDR.JK stock datasets. The SAFE.JK dataset has 5 best performances based on activation functions and optimizations such as tanh, sigmoid, and ReLU activations with nadam and adam optimizations. Based on the top 5 best performing models, there is something interesting about this dataset. Tanh activation with nadam optimizer has a lower performance in terms of MSE of 0.0004659, RMSE of 0.02158, and a higher coefficient of determination from R-Squared of 53% compared to sigmoid and ReLU activation. The SMDR.JK dataset has 5 best performances based on activation function and optimization such as linear, tanh, and ReLU activation with SGD, adamax, and adam optimization. Based on the top 5 model performance, there is something interesting about this dataset. The tanh activation with adamax optimizer has a lower performance in terms of MSE of 0.0880576, RMSE of 0.29675, and a higher coefficient of determination from R-Squared of 51% compared to other activations, namely linear and tanh with SGD and adam optimizers.

Table 3.4 below presents the model performance of the activation function and optimizer of the LSTM model from the TMAS.JK and WEHA.JK stock datasets. The TMAS.JK dataset has 5 best performances based on activation function and optimizer, namely ReLU, linear, and tanh activation with adamax and nadam optimizers. Based on the top 5 model performance, there is something interesting about this dataset. ReLU activation with adamax optimizer has a lower performance in terms of MSE of 0.0404941, RMSE of 0.20123, and a higher coefficient of determination from R-Squared of 52% compared to other activations, namely linear and tanh with adam optimizer. The WEHA.JK dataset has 5 best performances based on activation functions and optimizers such as linear activation and tanh with adam, nadam, and adamax optimizers. Based on the top 5 model performance, there is something interesting about this dataset. Linear activation with adam optimizer has a lower performance in terms of MSE of 0.0010775, RMSE of 0.03283, and a higher coefficient of determination from R-Squared of 89% compared to other activations, namely tanh with nadam and adamax optimizers.

Based on Fig 3.2, the prediction of transportation stocks using different activation functions and optimizers, along with performance evaluation metrics. The stocks analyzed for the period between April and October 2023 include Mineral Sumberdaya Mandiri (AKSI.JK), Air Asia Indonesia (CMPP.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Te-mas (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK). The evaluation metrics used are MAE, MAPE, MSE, R-Squared, and RMSE. Starting with Mineral Sumberdaya Mandiri stock, the first stock, there was no significant increase between April and May 2023, with prices ranging from 1.4 billion to 1.6 billion. However, in June to August, there was a significant increase in price, ranging from 1.4 billion to 2 billion, followed by a decrease from September to October to 1.2 billion. Predictions for this stock used the ReLU activation function and the Nadam optimizer. Furthermore, Air Asia Indonesia, the second stock, followed a similar pattern to Mineral Sumberdaya Mandiri. This stock experienced a significant decline from May to October, dropping from 1.6 billion to 600 million, after experiencing a price inc-

Table 3.2

Model Performances of LSTM Model by Activation Functions and Optimizers from AKSI.JK and CMPP.JK Stock Datasets

Dataset	Activation	Optimizer	Elapsed Time (min)	MAE (%)	MAPE (%)	MSE (%)	R-Squared (%)	RMSE (%)
AKSI.JK	Linear	AdaDelta	114.08	0.1411001	0.93828	0.0203102	-48.658497	0.14251
		AdaGrad	120.22	0.0407017	0.26025	0.0020034	-3.898347	0.04476
		Adam	125.25	0.013728	0.08885	0.0003509	0.141948	0.01873
		AdaMax	128.11	0.0147873	0.09769	0.0004355	-0.064861	0.02087
		Nadam	124.63	0.0093744	0.06011	0.0002329	0.43057	0.01526
		RMSProp	122.99	0.0108179	0.06903	0.0002787	0.318511	0.01669
	ReLU	SGD	115.98	0.032883	0.20994	0.001365	-2.337351	0.03695
		AdaDelta	113.75	0.1463257	0.97308	0.0218322	-52.379844	0.14776
		AdaGrad	118.91	0.0564243	0.36556	0.003572	-7.733444	0.05977
		Adam	119.66	0.0083481	0.05275	0.0002139	0.476992	0.01463
		AdaMax	111.45	0.0166904	0.11066	0.0005104	-0.247851	0.02259
		Nadam	127.26	0.0088794	0.05601	0.0002039	0.501388	0.01428
	Sigmoid	RMSProp	120.75	0.0102312	0.06505	0.0003208	0.21568	0.01791
		SGD	117.2	0.0358757	0.22994	0.00157	-2.838739	0.03962
		AdaDelta	107.27	0.115355	0.79716	0.0137251	-32.557885	0.11715
		AdaGrad	122.5	0.1210827	0.83573	0.0150717	-35.850371	0.12277
		Adam	101.21	0.0110326	0.0704	0.0003012	0.263464	0.01736
		AdaMax	109.99	0.0133187	0.08828	0.0005293	-0.294086	0.02301
	Tanh	Nadam	121.19	0.0109521	0.07034	0.0003428	0.161754	0.01851
		RMSProp	126.1	0.0279379	0.18246	0.0010325	-1.524418	0.03213
		SGD	108.9	0.0444058	0.28396	0.0023744	-4.80547	0.04873
		AdaDelta	117.94	0.146567	0.97489	0.0219018	-52.550061	0.14799
		AdaGrad	110.03	0.0443995	0.28459	0.0023436	-4.73006	0.04841
		Adam	108.86	0.0192328	0.12722	0.0005197	-0.270645	0.0228
CMPP.JK	Linear	AdaMax	117.74	0.009806	0.06264	0.0002964	0.275403	0.01722
		Nadam	116.83	0.014555	0.09527	0.0003581	0.124507	0.01892
		RMSProp	117.03	0.0213475	0.14184	0.0006638	-0.622879	0.02576
		SGD	115.3	0.0366961	0.23549	0.0016294	-2.983821	0.04037
	ReLU	AdaDelta	141.16	0.1189503	0.84968	0.0192562	-2.265067	0.13877
		AdaGrad	117.75	0.0457831	0.2762	0.00065805	-0.115791	0.08112
		Adam	116.18	0.0121662	0.09417	0.0002672	0.954698	0.01635
		AdaMax	118.2	0.0168838	0.13477	0.0004791	0.918757	0.02189
		Nadam	135.91	0.0119413	0.08811	0.000268	0.954561	0.01637
		RMSProp	146.07	0.0181908	0.14688	0.0004841	0.91791	0.022
	Sigmoid	SGD	147.05	0.0364132	0.22087	0.004005	0.320908	0.06329
		AdaDelta	112.97	0.1294893	0.93195	0.0224197	-2.801469	0.14973
		AdaGrad	121.72	0.0530037	0.29859	0.0078665	-0.333831	0.08869
		Adam	104.35	0.0092918	0.06422	0.0002123	0.963999	0.01457
		AdaMax	120.25	0.0122212	0.09055	0.0003171	0.946239	0.01781
		Nadam	111.58	0.0093115	0.06567	0.000216	0.963374	0.0147
	Tanh	RMSProp	121.12	0.0184314	0.15146	0.0004958	0.915934	0.02227
		SGD	98.96	0.0372071	0.22589	0.0042278	0.283142	0.06502
		AdaDelta	115.49	0.2384949	2.26155	0.0605894	-9.273472	0.24615
		AdaGrad	106.56	0.0472191	0.2799	0.0069161	0.172683	0.08316
		Adam	126.7	0.0113837	0.08164	0.0002794	0.952617	0.01672
		AdaMax	82.5	0.0172547	0.12295	0.0005945	0.899198	0.02438
	ReLU	Nadam	110.99	0.0262671	0.1897	0.0013371	0.773279	0.03657
		RMSProp	119.66	0.0332332	0.27776	0.001394	0.763629	0.03734
		SGD	121.86	0.0471479	0.27893	0.0068557	-0.162437	0.0828
		AdaDelta	91.82	0.1373486	0.98181	0.0256706	0.6484	0.16022
		AdaGrad	89.88	0.0369543	0.22637	0.0041433	0.297473	0.06437
		Adam	77.37	0.0143202	0.0922	0.000507	0.914033	0.02252
	Sigmoid	AdaMax	86.5	0.0098673	0.06988	0.0002425	0.958882	0.01557
		Nadam	87.29	0.0120772	0.09287	0.0002585	0.956175	0.01608
		RMSProp	96.59	0.0130281	0.0974	0.0003032	0.948582	0.01741
		SGD	84.86	0.0327754	0.20161	0.0032411	0.450447	0.05693

Table 3.3

Model Performances of LSTM Model by Activation Functions and Optimizers from SAFE.JK and SMDR.JK Stock Datasets

Dataset	Activation	Optimizer	Elapsed Time (min)	MAE (%)	MAPE (%)	MSE (%)	R-Squared (%)	RMSE (%)
SAFE.JK	Linear	AdaDelta	71.65	0.3891133	0.96892	0.1524513	-150.19068	0.39045
		AdaGrad	69.15	0.0948563	0.23246	0.0097508	-8.670196	0.09875
		Adam	59.36	0.0199288	0.05077	0.0006262	0.378951	0.02502
		AdaMax	73.79	0.0183383	0.0456	0.0006443	0.361067	0.02538
		Nadam	72.88	0.0211785	0.05391	0.0006727	0.332891	0.02594
		RMSProp	73.28	0.0225846	0.05784	0.0007769	0.229568	0.02787
	ReLU	SGD	76.14	0.0329282	0.07959	0.0015712	-0.558246	0.03964
		AdaDelta	70.21	0.3496615	0.87044	0.1231789	-121.160323	0.35097
		AdaGrad	72.3	0.1523978	0.37608	0.0241184	-22.919016	0.1553
		Adam	65.61	0.0184185	0.04551	0.0006138	0.391229	0.02477
		AdaMax	78.57	0.0187016	0.04709	0.0006586	0.346848	0.02566
		Nadam	74.36	0.016943	0.04197	0.000543	0.461457	0.0233
	Sigmoid	RMSProp	77.64	0.0296531	0.07295	0.0012285	-0.218327	0.03505
		SGD	72.31	0.0458683	0.11119	0.0026298	-1.608041	0.05128
		AdaDelta	69.85	0.4281985	1.06717	0.1843068	-181.782786	0.42931
		AdaGrad	76.42	0.1581624	0.39018	0.0260116	-24.796492	0.16128
		Adam	79.59	0.0211831	0.05229	0.0008193	0.187497	0.02862
		AdaMax	85.06	0.0346803	0.08257	0.0018996	-0.883877	0.04358
	Tanh	Nadam	82.98	0.0163909	0.04056	0.0005087	0.495545	0.02255
		RMSProp	74.82	0.0264128	0.06493	0.0010606	-0.051861	0.03257
		SGD	67.68	0.157868	0.38957	0.0258794	-24.66537	0.16087
		AdaDelta	76.08	0.3340162	0.83136	0.1124454	-110.515619	0.33533
		AdaGrad	107.67	0.0945184	0.23162	0.0096887	-8.608627	0.09843
		Adam	100.28	0.0160239	0.03985	0.0005089	0.495301	0.02256
		AdaMax	75.47	0.0183708	0.0464	0.0006471	0.358257	0.02544
		Nadam	87.06	0.0158117	0.03984	0.0004659	0.537937	0.02158
		RMSProp	76.88	0.0395254	0.09723	0.0019361	-0.920052	0.044
		SGD	87.56	0.0406081	0.09852	0.0021445	-1.12678	0.04631
SMDR.JK	Linear	AdaDelta	114.54	1.9216183	0.8891	3.8524586	-20.398944	1.96277
		AdaGrad	91.07	1.8465863	0.8513	3.5877094	-18.928362	1.89412
		Adam	89.82	0.2800096	0.12416	0.1098653	0.38974	0.33146
		AdaMax	125.05	0.3157966	0.13806	0.1429296	0.20608	0.37806
		Nadam	136.34	0.3781864	0.16957	0.1800447	-8e-05	0.42432
		RMSProp	111.17	0.3444461	0.14917	0.175245	0.02658	0.41862
	ReLU	SGD	76.14	0.0329282	0.07959	0.0015712	-0.558246	0.03964
		AdaDelta	173.14	1.9350504	0.89484	3.9116207	-20.727567	1.97778
		AdaGrad	119.61	2.0320714	0.93917	4.3175704	-22.982463	2.07788
		Adam	127.87	0.3489477	0.15544	0.1585388	0.119377	0.39817
		AdaMax	177.01	0.5362993	0.23549	0.3676068	-1.041916	0.60631
		Nadam	110.22	0.4412922	0.19799	0.2385993	-0.325328	0.48847
	Sigmoid	RMSProp	72.56	0.4054026	0.17519	0.2361109	-0.311507	0.48591
		SGD	193.23	1.783136	0.82222	3.3430151	-17.569179	1.82839
		AdaDelta	178.63	0.6316804	0.2673	0.5868883	-2.259942	0.76609
		AdaGrad	138.71	2.061405	0.95381	4.4313475	-23.614451	2.10508
		Adam	176.3	1.1191406	0.50405	1.4135866	-6.851936	1.18894
		AdaMax	175.23	1.4587871	0.6665	2.2933001	-11.73841	1.51436
	Tanh	Nadam	174.26	0.8827884	0.39446	0.9128652	-4.07062	0.95544
		RMSProp	175.78	1.0499303	0.47232	1.2513875	-5.950982	1.11865
		SGD	178.08	1.9433511	0.89779	3.9528967	-20.956839	1.98819
		AdaDelta	172.61	2.093085	0.96907	4.5629419	-24.345408	2.1361
		AdaGrad	173.93	1.7444241	0.80444	3.2005391	-16.77778	1.78901
		Adam	183.67	0.3569744	0.15756	0.1681515	0.065982	0.41006
		AdaMax	173.18	0.2101362	0.08806	0.0880576	0.510873	0.29675
		Nadam	190.53	0.4370276	0.19432	0.2381563	-0.322868	0.48801
		RMSProp	176.31	0.5245328	0.22956	0.360404	-1.001907	0.60034
		SGD	172.5	1.4444561	0.66291	2.2245312	-11.356426	1.49149

Table 3.4

Model Performances of LSTM Model by Activation Functions and Optimizers from TMAS.JK and WEHA.JK Stock Datasets

Dataset	Activation	Optimizer	Elapsed Time (min)	MAE (%)	MAPE (%)	MSE (%)	R-Squared (%)	RMSE (%)
TMAS.JK	Linear	AdaDelta	105.35	1.6988036	1.10194	2.9811393	-34.064634	1.7266
		AdaGrad	144.38	1.3594205	0.87749	1.9276772	-21.673645	1.38841
		Adam	72.91	0.1648907	0.10099	0.0413225	0.513958	0.20328
		AdaMax	129.16	0.1727892	0.10533	0.0471447	0.445476	0.21713
		Nadam	112.58	0.2766955	0.17442	0.0931482	-0.095623	0.3052
		RMSProp	135.32	0.377653	0.23375	0.1736341	-1.042312	0.41669
	ReLU	SGD	138.87	1.3045373	0.8415	1.7777032	-19.909627	1.33331
		AdaDelta	87.76	1.588086	1.02825	2.6142226	-29.7489	1.61686
		AdaGrad	153.03	1.2031804	0.77573	1.5141695	-16.809902	1.23052
		Adam	135.15	0.2298114	0.14208	0.0704677	0.171148	0.26546
		AdaMax	69.0	0.1484958	0.09002	0.0404941	0.523703	0.20123
		Nadam	133.87	0.2580699	0.16288	0.0830604	0.023031	0.2882
	Sigmoid	RMSProp	87.05	0.2983446	0.18196	0.1174824	-0.381847	0.34276
		SGD	72.64	1.4147432	0.91228	2.091806	-23.604154	1.44631
		AdaDelta	81.14	1.9527325	1.27434	3.8990916	-44.861733	1.97461
		AdaGrad	70.78	1.5624308	1.01335	2.5225199	-28.670279	1.58824
		Adam	63.9	1.0371461	0.6617	1.1529433	-12.561101	1.07375
		AdaMax	83.94	1.2344657	0.7924	1.6088571	-17.923633	1.26841
	Tanh	Nadam	86.97	1.244571	0.79951	1.6324352	-18.200962	1.27767
		RMSProp	84.29	0.9123407	0.57994	0.9013942	-9.602341	0.94942
		SGD	85.25	1.4164581	0.91503	2.0891936	-23.573427	1.4454
		AdaDelta	61.05	1.399788	0.90569	2.0341072	22.925492	1.42622
		AdaGrad	68.79	1.3858043	0.89492	2.0012696	-22.539251	1.41466
		Adam	84.72	0.2635969	0.16299	0.088622	-0.042387	0.29769
WEHA.JK	Linear	AdaMax	60.99	0.2017587	0.12199	0.0610237	0.282229	0.24703
		Nadam	63.25	0.267067	0.16604	0.089608	-0.053984	0.29935
		RMSProp	65.1	0.3675875	0.22508	0.170889	-1.010024	0.41339
		SGD	63.0	1.2461414	0.803	1.6258883	-18.123956	1.2751
	ReLU	AdaDelta	64.08	0.2749349	0.88865	0.0845976	-7.028241	0.29086
		AdaGrad	70.43	0.0996529	0.39217	0.0117979	-0.119607	0.10862
		Adam	62.05	0.0247843	0.08116	0.0010775	0.897742	0.03283
		AdaMax	151.92	0.0269593	0.08949	0.001224	0.883845	0.03499
		Nadam	77.96	0.0254886	0.08243	0.0011212	0.893601	0.03348
		RMSProp	62.99	0.0376284	0.12874	0.0021684	0.794225	0.04657
	Sigmoid	SGD	151.44	0.0479684	0.17974	0.0030352	0.711965	0.05509
		AdaDelta	67.45	0.2712285	0.87701	0.0822644	-6.806816	0.28682
		AdaGrad	72.65	0.1044148	0.42142	0.0137194	-0.301959	0.11713
		Adam	139.2	0.0270935	0.08845	0.0012668	0.879783	0.03559
		AdaMax	70.0	0.0273615	0.09051	0.001263	0.880142	0.03554
		Nadam	71.62	0.0292362	0.09586	0.0015118	0.856534	0.03888
	Tanh	RMSProp	70.42	0.0294683	0.10088	0.0014157	0.865647	0.03763
		SGD	73.97	0.0933411	0.36469	0.0102868	0.023787	0.10142
		AdaDelta	62.75	0.4872805	1.64241	0.2470682	-22.446559	0.49706
		AdaGrad	71.42	0.0954021	0.34475	0.0103983	0.013213	0.10197
		Adam	73.09	0.0271899	0.08793	0.0012765	0.878858	0.03573
		AdaMax	70.2	0.0310937	0.10239	0.0017582	0.83315	0.04193
		Nadam	72.24	0.0558406	0.19467	0.0054107	0.486529	0.07356
		RMSProp	68.78	0.0561839	0.1949	0.06764	0.565823	0.06764
		SGD	69.89	0.1710757	0.6951	0.037233	-2.533382	0.19296
		AdaDelta	65.84	0.2811222	0.90771	0.0886422	-7.412066	0.29773
		AdaGrad	71.78	0.1212396	0.48275	0.0176672	-0.676603	0.13292
		Adam	77.36	0.0256809	0.08505	0.0011522	0.890653	0.03394
		AdaMax	72.91	0.0269378	0.089	0.0012465	0.881711	0.03531
		Nadam	71.77	0.0255236	0.08348	0.0011487	0.890993	0.03389
		RMSProp	68.89	0.0345188	0.11929	0.001821	0.827186	0.04267
		SGD	71.24	0.0397785	0.13997	0.0024724	0.765371	0.04972

increase in April from 1 billion to 1.6 billion. The forecast for this stock also used the ReLU activation function and the Adam optimizer. Turning to Steady Safe, the third stock, there was a significant decline from April to June, dropping from 4.2 billion

to 3.4 billion, and then maintaining a constant price range of 3.4 billion to 4.2 billion from July to October. The prediction for this stock uses the Tanh activation function and the Nadam optimizer. For Samudera Indonesia, the fourth stock, there was

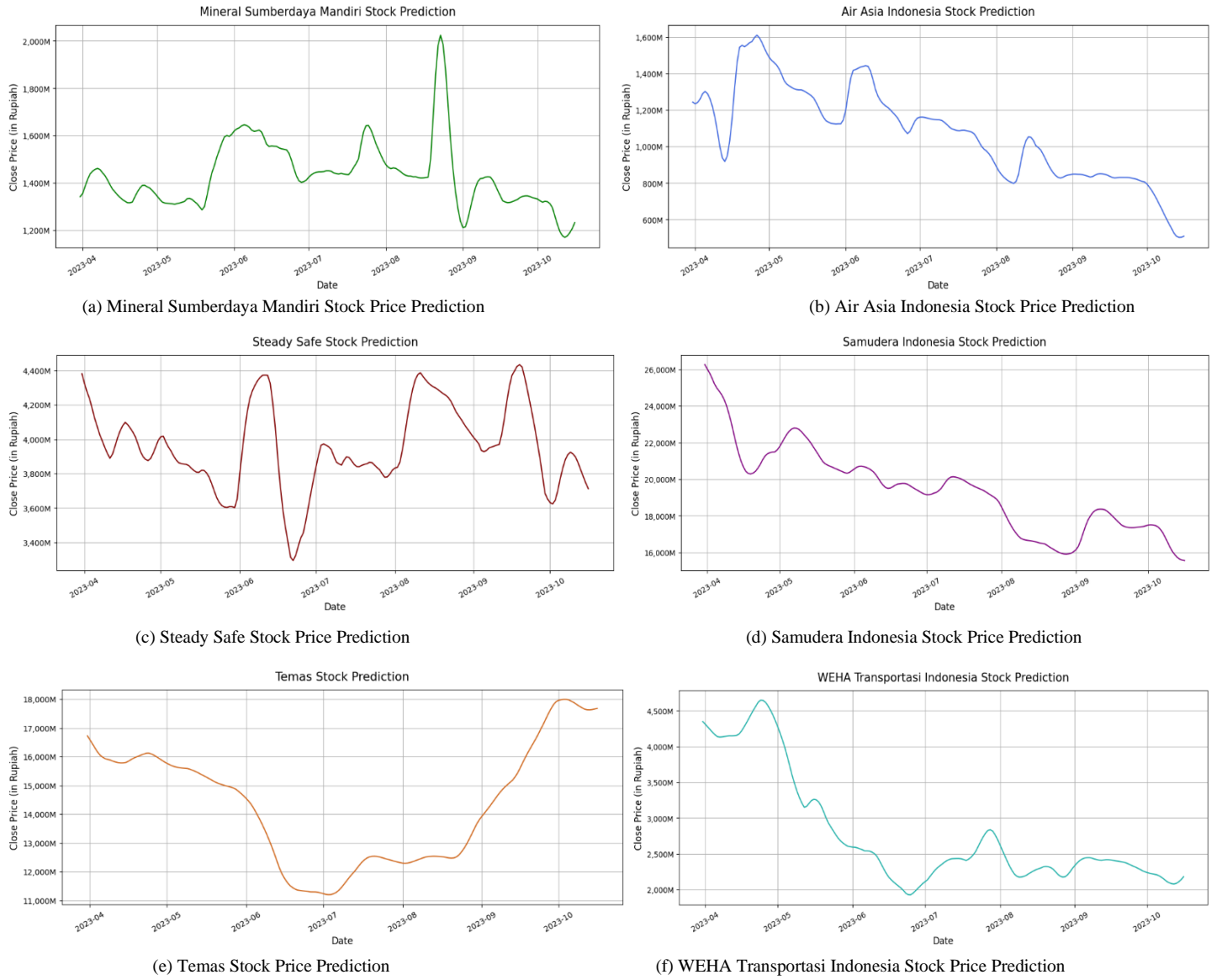


Fig 3.2 Transportation Stock Predictions based on Activations Functions and Optimizer

a significant drop from 24 billion to 14 billion. Predictions for this stock used the Tanh activation function and the AdaMax optimizer. As for Temas, the fifth stock, there was a decline from April to June, down from 16 billion to 11 billion, followed by a significant increase from July to October, up from 11 billion to 17 billion. Predictions for this stock used the ReLU activation function and the AdaMax optimizer. Finally, the last stock is WEHA Transportasi Indonesia, experiencing a significant decline from April to July, dropping from 4.5 billion to 2 billion, and then maintaining a constant price in the range of 2 billion to 3 billion from July to October. The prediction for this stock uses Linear activation function and Adam's optimizer.

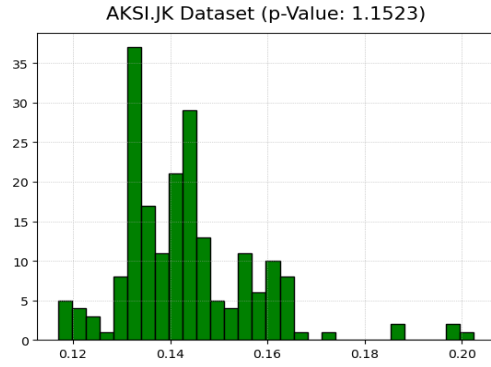
3.1.3. Statistical Test to Support the Evaluation Metrics Results

This section presents statistical tests using the shapiro-wilk test to support the results of evaluation metrics based on activation functions and optimizers from transportation stock datasets such as Mineral Sumberdaya Mandiri (AKSI.JK), Asia

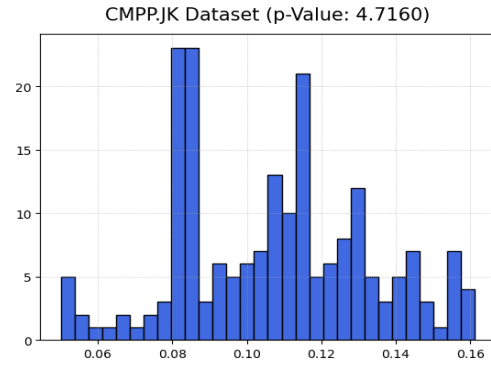
Indonesia (CMPP.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Temas (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK). Based on Table 3.5 and Fig 3.3, the transportation stock dataset has several normality distributions from the shapiro-wilk test. The CMPP.JK and SAFE.JK transportation stock datasets have a normally distributed population compared to other transportation stock datasets such as the AKSI.JK, SMDR.JK, TMAS.JK, and WEHA.JK stock datasets. The normality distribution of the CMPP.JK stock dataset has a higher shapiro-wilk test with a p-value of 4.7160 compared to the SAFE.JK stock dataset in the shapiro-wilk test with a p-value of 0.0004. AKSI.JK, SMDR.JK, TMAS.JK, and WEHA.JK stock datasets have a skewed population distribution. The WEHA.JK stock dataset has a population with a higher skew distribution compared to other transportation stock datasets such as the AKSI.JK, SMDR.JK, and TMAS.JK transportation stock datasets. The WEHA.JK stock dataset has a skew distributed population with a p-value of 1.5495, while AKSI.JK has a p-value of 1.1523, SMDR.JK has a p-value of 1.0190, and TMAS.JK has a p-value

Table 3.5
Shapiro-Wilk Test Statistics of Transportation Stock Dataset

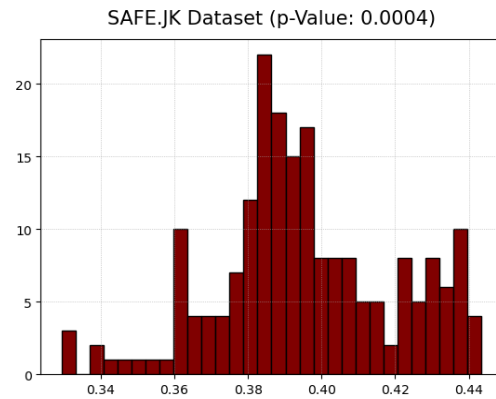
Dataset	Activation	Optimizer	MAE (%)	MAPE (%)	MSE (%)	R-Squared (%)	RMSE (%)	T-Statistic	P-Value
AKSI.JK	ReLU	Nadam	0.0088794	0.05601	0.0002039	0.501388	0.01428	0.8974	1.1523
CMPP.JK	ReLU	Adam	0.0092918	0.06422	0.0002123	0.963999	0.01457	0.7102	4.7160
SAFE.JK	Tanh	Nadam	0.0158117	0.03984	0.0004659	0.537937	0.02158	0.9761	0.0004
SMDR.JK	Tanh	AdaMax	0.2101362	0.08806	0.0880576	0.510873	0.29675	0.946	1.0190
TMAS.JK	ReLU	AdaMax	0.1484958	0.09002	0.0404941	0.523703	0.20123	0.9372	1.4691
WEHA.JK	Linear	Adam	0.0247843	0.08116	0.0010775	0.897742	0.03283	0.8278	1.5495



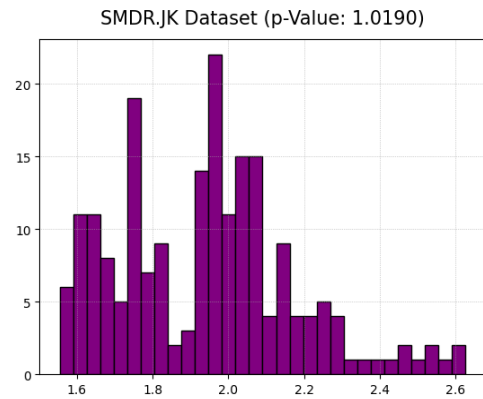
a) Mineral Sumberdaya Mandiri Stock Price Prediction Distribution



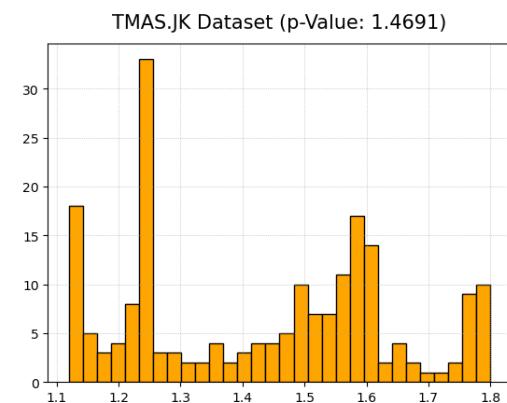
(b) Air Asia Indonesia Stock Price Prediction Distribution



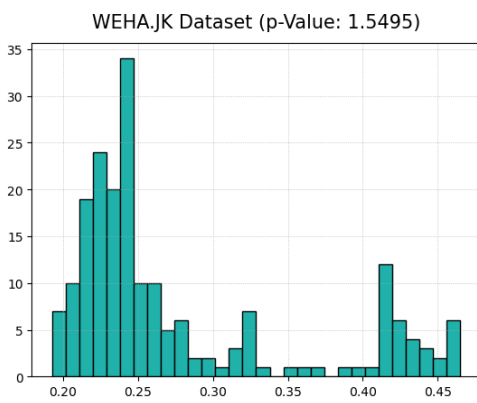
(c) Steady Safe Stock Price Prediction Distribution



(d) Samudera Indonesia Stock Price Prediction Distribution



(e) Temas Stock Price Prediction Distribution

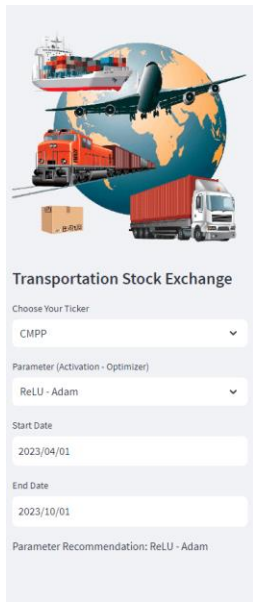


(f) WEHA Transportasi Indonesia Stock Price Prediction Distribution

Fig 3.3 Shapiro-Wilk Test Statistics of Transportation Stock Datasets

of 1.0190, and TMAS.JK has a p-value of 1.4691 from the shapiro-wilk test statistics. There is something interesting about the CMPP.JK transportation stock dataset. This dataset has a higher shapiro-wilk test statistic compared to other

transportation stock datasets with a p-value of 4.7160. This dataset supports evaluating the LSTM model algorithm based on the comparison of activation functions and optimizing hyperparameters, as well as the evaluation metrics of MAE,



Air Asia

Dataset

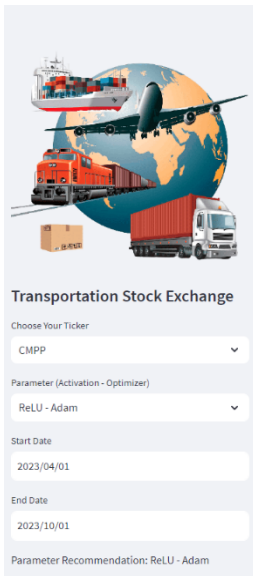
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	Date	Open	High	Low	Close	Adj Close	Volume
17	2011-04-27	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
18	2011-04-28	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
19	2011-04-29	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
20	2011-05-02	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
21	2011-05-03	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
22	2011-05-04	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
23	2011-05-05	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
24	2011-05-06	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
25	2011-05-09	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586
26	2011-05-10	115,297,188	115,297,188	115,297,188	115,297,188	115,297,188	437,586

Stock Prices History



Fig 3.4 Home screen of the web-based application for Transportation Stock



Future Stock Price Prediction



Evaluation Metrics :

Mean Absolute Percentage Error (MAPE) : 0.06422

Mean Absolute Error (MAE) : 0.00929

Mean Squared Error (MSE) : 0.00021

Root Mean Squared Error (RMSE) : 0.01449

R-Squared (R2) : 0.96

Fig 3.5 Example result of web-based application for Transportation Stock

MAPE, MSE, RMSE, and R-Squared. Specifically, the CMPP.JK transportation stock dataset has statistics from the shapiro-wilk test that support MAE of 0.0092918, MAPE of 0.06422, MSE of 0.0002123, R-Squared of 96%, and RMSE of 0.01457.

3.1.4. Model Implementation in Web-Based Application

This section presents the implementation of the Long Short-Term Memory (LSTM) algorithm model into a web-based application for the prediction of transportation stock prices such as Mineral Sumberdaya Mandiri (AKSI.JK), Air Asia Indonesia (CMPP.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Teras (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK) show in Fig 3.4 and Fig 3.5. This prediction uses activation functions such as linear, ReLU, tanh, and sigmoid, and optimizers such as adam, adagrad, nadam, RMSProp, adadelta, SGD, and adamax. The web-based application to generate prediction results based on

4 inputted parameters namely ticker, activation and optimizer, start date, and end date. The ticker parameter is a dataset of transportation stocks such as AKSI.JK, CMPP.JK, SAFE.JK, SMDR.JK, TMAS.JK, and WEHA.JK, while the start date and end date are the prediction start period to the selected prediction end period.

Fig 3.4 above shows the initial view of the web-based application for transportation stocks. Here, each transportation stock is displayed with several sections. There is the transportation stock dataset, the stock price history from April 1, 2011 to April 1, 2023, the current stock price prediction which is the actual price and stock price prediction from the closing price, and the future stock price prediction from April 2023 to August 2023 based on the MAPE, MAE, MSE, RMSE, and R-Squared evaluation metrics. An example of the results from transportation stocks shown in Fig 3.5 above, Air Asia Indonesia (CMPP.JK) transportation stocks have the best performance from MAE of 0.0092918, MAPE of 0.06422, MSE of 0.0002123, R-Squared of 96%, and RMSE of 0.01457

compared to other transportation stock datasets such as Mineral Sumberdaya Mandiri (AKSI.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Temas (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK). The purpose of implementing the model in a web-based application is to provide information about stock price trends to investors to evaluate several transportation stocks that have decreased or increased in price due to inflation. The web-based application for transportation stock price predictions can be assessed at streamlit web apps (bayunova28-transportation-stock-analysis-app-u94np4.streamlit.app/).

3.2. Discussion

This section presented the results of study aims to predict the performance of six transportation stocks, specifically Mineral Sumberdaya Mandiri (AKSI.JK), Air Asia Indonesia (CMPP.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Temas (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK). Performance evaluation using Long Short-Term Memory (LSTM) algorithm with comparison of activation functions such as linear, ReLU, tanh, and sigmoid, as well as optimizers such as adam, adagrad, nadam, RMSProp, adadelta, SGD, and adamax. Besides that, statistical test from shapiro-wilk test is very important to support evaluation metrics based on MAE, MAPE, MSE, RMSE, and R-Squared. Based on several of transportation stock datasets, CMPP.JK stock dataset has best performance from MAE of 0.0092918, MAPE of 0.06422, MSE of 0.0002123, R-Squared of 96%, and RMSE of 0.01457, as well as training speed LSTM model from elapsed time of 104.35 minute compared to other transportation stock datasets such as Mineral Sumberdaya Mandiri (AKSI.JK), Steady Safe (SAFE.JK), Samudera Indonesia (SMDR.JK), Temas (TMAS.JK), and WEHA Transportasi Indonesia (WEHA.JK). Besides that, there is something interesting about the CMPP.JK transportation stock dataset. This dataset has a higher shapiro-wilk test statistic compared to other transportation stock datasets with a p-value of 4.7160. This dataset supports evaluating the LSTM model algorithm based on the comparison of activation functions and optimizing hyperparameters, as well as the evaluation metrics of MAE, MAPE, MSE, RMSE, and R-Squared.

Compared to the previous study conducted by (Rana et al., 2019), which used Linear Regression (LR), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) algorithms to predict Acciona stock, our study achieved superior results. The performance evaluation of the previous study showed an RMSE of 0.0151 using Linear and Tanh activations, along with the AdaMax optimizer, showing a higher error rate than this study with an RMSE value of 0.01457. It is important to note that both studies used the same dataset divided into a training set of 90% and a testing set of 10%, with batch size of 32, dropout of 0.2, and 10 epochs.

Furthermore, another study aims to predict the National Stock Exchange (NSE) stock index using the Long Short-Term Memory (LSTM) and MultiLayered Perceptron (MLP) algorithms. However, the Mean Squared Error (MSE) evaluation metric obtained in that study, MSE of 0.58, shows a relatively higher error performance compared to this study with an MSE value of 0.0002123 in ReLU's activation function and

adam's optimizer with timestamp length used in their research is 60 (Banyal* et al., 2020).

Similarly, a study focused on predicting the stock exchange from Bangladesh, Hongkong, India, Indonesia, Japan, Malaysia, and Thailand used Long Short-Term Memory (LSTM) with several parameters of activation functions such as ELU, ReLU, and tanh along with number of epochs by 50-100. This study has found an accuracy from activation of tanh by 80% compared to another activation function of ELU and ReLU to predict stock price prediction from several stock exchanges (Sami et al., 2023). These performance results exhibited lower performance of accuracy compared to this study, achieved R-squared value of 96% with number of epochs by 10 on ReLU activation and adam optimizer.

Lastly, a separate study conducted by (Kamalov et al., 2020), predicted banking stock from Bank Rakyat Indonesia (BRI), Bank Nasional Indonesia (BNI), Bank Tabungan Negara (BTN), and Mandiri using Long Short-Term Memory (LSTM) algorithm with several parameter from optimizers such as SGD, adam, and RMSProp along with number of epochs by 25, 50, 75, and 100. This research has a lower Root Mean Squared Error (RMSE) performance of 48.32 from adam optimizer with an accuracy value of 95% to predict the stock price of Bank Rakyat Indonesia (BRI). The RMSE error performance is still higher than this research which has an RMSE of 0.01457 with ReLU activation and adam optimizer and gets an accuracy value of 96%.

4. Conclusion

In this study, the prediction of transportation stock prices using the Long Short-Term Memory (LSTM) algorithm model by comparing several activations such as linear, ReLU, tanh, and sigmoid, as well as optimizers such as adam, adagrad, nadam, RMSProp, adadelta, SGD, and adamax. This study shows a decrease in the stock prices of Air Asia Indonesia (CMPP.JK), Samudera Indonesia (SMDR.JK), and WEHA Transportation Indonesia (WEHA.JK). However, the stock prices of Mineral Sumberdaya Mandiri (AKSI.JK) and Steady Safe (SAFE.JK) showed stable movements. In addition, there was a significant increase in the stock price of Temas (TMAS.JK) from April to October 2023. Besides that, ReLU activation with Adam optimizer is best performance to predict Air Asia Indonesia (CMPP.JK) transportation stock dataset from MAE of 0.0092918, MAPE of 0.06422, MSE of 0.00021230, R-Squared of 96%, RMSE of 0.01457 and shapiro-wilk test on t-statistic of 0.7102 and p-value of 4.716007 with elapsed time of 104.35 minutes. This performance compared to another activation functions and optimizers from each transportation stock datasets such as AKSI.JK, SAFE.JK, SMDR.JK, TMAS.JK, and WEHA.JK.

However, it is important to note several limitations in this study. The data used consists of transportation stocks from April 1, 2011, to April 1, 2023. The transportation stocks included in the study are Mineral Sumberdaya Mandiri, Air Asia Indonesia, Steady Safe, Samudera Indonesia, Temas, and WEHA Transportasi Indonesia. The study utilized the Long Short-Term Memory (LSTM) algorithm with various activations such as linear, ReLU, tanh, and sigmoid, as well as optimizers such as Adam, AdaGrad, Nadam, RMSProp,

AdaDelta, SGD, and AdaMax. In addition, the elapsed time process is very long when training the Long Short-Term Memory (LSTM) algorithm because the Graphics Processing Unit (GPU) is not used to speed up the training time of the Long Short-Term Memory (LSTM) algorithm.

For future research, we encourage researchers to explore modeling approaches with time series algorithms or other deep learning techniques such as Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Convolutional Neural Network (CNN) along with metaheuristic optimization algorithms to speed up the training process and determine the best model for each model. In addition, they can compare different types of LSTM algorithms such as Vanilla, Stacked, and Bidirectional LSTM. Expanding the dataset to include stocks from sectors such as banking, technology, food and beverages, or other sectors, with longer time periods and more extensive data, will help avoid overfitting during the modeling process. Additionally, comparing the number of epochs and batch size to evaluate metrics such as Mean Forecast Error (MFE) and Mean Absolute Scaled Error (MASE), among other relevant metrics, can be included in the modeling process. In addition, researchers can explore the distribution of training and testing samples ranging from 70:30, 80:20, 90:10, or all of them as 70:30 and 80:20 performed poorly in this study.

CRedit authorship contribution statement

Willibrordus Bayu Nova Pramudya: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing - Original & Draft. **Dinar Ajeng Kristiyanti:** Conceptualization, Funding Acquisition, Supervision, Writing – Review & Editing.

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