# *Indonesia White Sugar Supply and Demand Forecast Using Machine Learning*

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***Abstract*— This paper aims to provide the best Machine Learning model to forecast Indonesia's white sugar supply and demand to provide potential supply chain efficiency and price stability.**

**The high price of white sugar in Indonesia is due to low productivity, imports, and high demand. In midyear 2018, domestic sugar reached almost three times higher than the international market price, reflecting the commodity scarcity in the country. Previous research has been carried out to forecast sugar prices in Thailand using machine learning and consumption data in 4 years.**

**The nonstationary data used in this research include 20 years of historical data in import and production as supply and demand data, research focused on this completeness and fulfilment of this data. Forecasting data using deep learning with LSTM is the best method model that produces the best performance compared with regressor models, which has not been done previously. The decrease in LSTM evaluation method compared to AdaboostRegressor was 37.33% for MSE and 14.12% for MAE. As a result, LSTM, as the best model, is confirmed by the most petite MAE and MSE values.**

***Keywords—neural networks, forecasting, sugar supply and demand, machine learning, deep learning.***

## I. Introduction

In the last ten years, on average, the sugar production indicator in Indonesia has shown slow growth [1]. Demand in 2022 of 3.187.000 tonnes, 2.405.907 tonnes met from domestic production, and the remaining 143.612 tonnes met from imports, and based on this data, there is still a shortage of national sugar demand after imports are made. Indonesians are consuming more white crystal sugar per person than ever before. Between 2009 and 2017, per capita consumption increased by more than 22%. This increase in demand, combined with low productivity and using imports as a solution, has led to high prices for white crystal sugar in Indonesia. Domestic sugar price in midyear 2018 was almost three times the international market price [21].

On the other hand, research has been carried out to forecast sugar prices in Thailand using machine learning; the experiment shows that Long Short-Term Memory (LSTM) provides effective results using consumption data in 4 years [22]. Supply and demand for white sugar are the main components that form prices. It is necessary to research optimizing the food ecosystem by forecasting the need for supply demand. The data used to predict the demand and supply for sugar consumption in Indonesia include domestic production, imports, and data on sugar demand circulating in the market for the past 20 years.

We can make forecasts using machine learning by determining whether Machine learning models can predict new outcomes, such as whether customers will leave, how much revenue a product will generate, or how to group customers into different segments. These models are created using known data, such as customer demographics, purchase history, and website behavior [2]. Machine learning is a computational algorithm for studying data, such as classifying and identifying data automatically. Algorithms are used to analyze, learn, and make decisions [3]. Machine learning is one of method in artificial intelligence, and deep learning algorithm is a part of machine learning, as shown in Fig. 1. The human brain inspires artificial neural networks, which can learn to make predictions and recognize patterns from data [4]. Deep learning can identify patterns in data without the need for human intervention. It does this by automatically extracting features from the data, which are then processed and used to make decisions.[5]

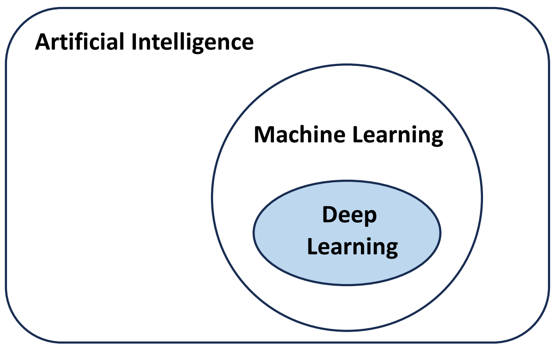



Fig. 1. Relationship between AI, Machine Learning, and Deep Learning [18].

Detecting patterns and developing classification-based decision support systems is machine learning. It is widely used to make it easier for humans to achieve various goals worldwide, such as making predictions and meeting various design and visual art needs. Deep learning models learn features from data in a hierarchical manner. The first layer will learn simple features, while the upper layers learn more complex features. This hierarchical learning allows deep learning models to deal with more extensive data and complexity [6]. This paper presents significant contributions as follows.

1) The machine learning algorithm models nonstationary data using 20 years of historical data on Indonesian sugar production, import, and demand data as input.

2) Compared to regressor algorithms for forecasting Indonesian sugar supply and demand, these algorithms have never been done before.

3) The error values formed in each algorithm model's MAE and MSE evaluation methods are new numbers in Indonesia Sugar Forecasting research and have never been done before.

This research is organized as follows: Section 2, related work; Section 3, the Background of the study; Section 4, the Proposed method, presents the proposed algorithm and experiments; Section 5, results and discussion; Section 6, the conclusion.

## II. Related Work

The nature of data representation is a critical factor that determines the performance of learning algorithms in classification problems [7]. In 2006, Geoff Hinton made a significant invention in feature extraction, which led to the proposal of deep learning [8]. Deep learning researchers have developed many new application areas in different fields [9].

Research publication platforms are used to collect information data, such as IEEE Explorer, Elsevier, and Springer, to learn how AI and ML are currently used in supply-demand forecasting. These platforms are reliable sources of information on the latest advances in AI and ML research. Fig. 2 shows the various publications in Supply Demand Forecast based on ML topics with keywords supply-demand forecast, supply forecast, demand forecast, and each keyword added with machine learning. The database platform has more research than shown, but only those related to our research topic.

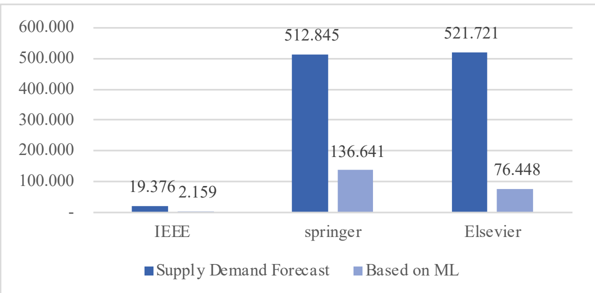



Fig. 2. Publication in Supply Demand Forecast.

## III. Background Study

### A. Machine learning

Machine Learning (ML) has two main subtypes on how the algorithm works and performs calculations: supervised and unsupervised learning, as shown in Fig. 3. Machine learning relies heavily on patterns and inferences [12]. The algorithm generates a mathematical model based on a sample called training data to get patterns and conclusions. ML can generate new knowledge from training data to produce new data in predictive patterns [13].

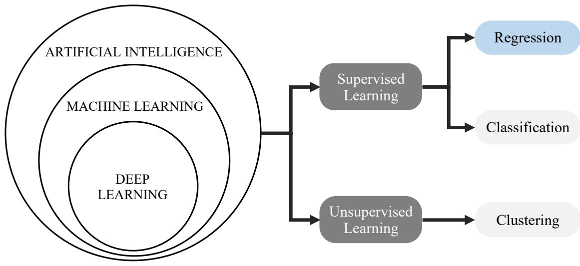



Fig. 3. Machine Learning Algorithm types and uses [12].

### B. Deep Learning

Deep learning is trained by feeding the network with large amounts of data. Networks learn to extract features from the data and combine them in complex ways to make predictions. The more layers a model has, the more complex features it can learn [6]. As we have access to more data and better algorithms to extract information from that data, this algorithm has become a promising alternative to traditional forecasting methods [10, 11].

### C. Dataset

Data processing is carried out by processing the data set into data ready to be used as predictive data, from which conclusions can later be drawn for the potential for optimizing the supply chain of the national sugar ecosystem [14]. The data processing starts from collecting raw data, data processing, cleansing, and analyzing the data needed to conduct research, and then creating data modeling. After the modeling data has been obtained for training and validation, modeling can be done using selected algorithms [15].

Data obtained is historical data from 20 years of sugar consumption data in Indonesia. This data consists of circulating the market's import, production, and stock data. Data in yearly and monthly terms can be used according to prediction needs.

This study analyzes the relationship between year, production, and import as supply data and demand in Table 1. The production data corresponds to the amount of sugar produced nationwide. Import data refers to sugar imported as white sugar and raw sugar, which is processed into white sugar at local factories. Supply data is the sum of domestic production data and white sugar imports. Demand data is Indonesia's annual sugar consumption demand.

The analysis in Table 2 shows no significant relationship between production, import, and demand. However, a robust negative relationship exists between production and import data and import and demand data. In addition, there is a strong positive relationship between production and supply. However, there is no significant relationship between imports and supply.

Research completeness and fulfilment of data sourcing are from Jurnal Gula between 2002 until 2022 [1] which supported by multi-stakeholder that are: (1) Indonesia's Ministry of Agriculture; (2) Indonesia's Ministry of Trade; (3) Dewan Gula Indonesia; (4) World trade price of Raw Sugar.

TABLE 1. INDONESIA WHITE SUGAR DATA SET (YEARLY) [1]

| a | b | c | d=b+c | e |
|---|---|---|---|---|
| **Year** | **Production** | **Import** | **Supply** | **Demand** |
| 2002 | 1.755.434 | - | 1.755.434 | - |
| 2003 | 1.631.919 | 647.908 | 2.279.827 | - |
| 2004 | 2.051.644 | 256.801 | 2.308.445 | - |
| 2005 | 2.241.744 | 419.860 | 2.661.604 | 2.538.830 |
| 2006 | 2.306.994 | 216.490 | 2.523.484 | 2.386.087 |
| 2007 | 2.448.151 | 448.679 | 2.896.830 | 2.017.000 |
| 2008 | 2.580.236 | 49.025 | 2.629.261 | 2.745.581 |
| 2009 | 2.299.505 | 13.000 | 2.312.505 | 3.112.032 |
| 2010 | 2.212.008 | 446.894 | 2.658.902 | 2.103.079 |
| 2011 | 2.228.258 | 143.479 | 2.371.737 | 2.768.831 |
| 2012 | 2.591.688 | 20.000 | 2.611.688 | 2.735.655 |
| 2013 | 2.551.025 | 21.600 | 2.572.625 | 2.684.000 |
| 2014 | 2.618.731 | - | 2.618.731 | 2.882.800 |
| 2015 | 2.498.087 | - | 2.498.087 | 2.927.610 |
| 2016 | 2.201.386 | 62.467 | 2.263.853 | 2.462.940 |
| 2017 | 2.117.902 | - | 2.117.902 | 2.125.130 |
| 2018 | 2.169.510 | - | 2.169.510 | 2.094.450 |
| 2019 | 2.227.042 | - | 2.227.042 | 2.628.730 |
| 2020 | 2.097.552 | 139.733 | 2.237.285 | 1.654.130 |
| 2021 | 2.350.000 | 152.162 | 2.502.162 | 3.358.770 |
| 2022 | 2.405.907 | 143.612 | 2.549.519 | 3.187.000 |
| **Grand Total** | **47.584.723** | **3.181.710** | **50.766.433** | **46.412.655** |

TABLE 2. PEARSON CORRELATION

| | Production | Import | Supply | Demand |
|---|---|---|---|---|
| **Production** | 1.000000 | -0.384901 | 0.981775 | 0.410588 |
| **Import** | -0.384901 | 1.000000 | 0.044426 | -0.348808 |
| **Supply** | 0.981775 | 0.044426 | 1.000000 | 0.391189 |
| **Demand** | 0.410588 | -0.348808 | 0.391189 | 1.000000 |

A 20-year analysis of sugar consumption supply and demand data in Fig. 4 shows that the supply of sugar has fluctuated more than the demand, which has been more stable. The demand for sugar tends to follow the same pattern every year, but the supply has yet to be able to keep up. The supply graph has become more stable in the last five years but still needs to meet the demand. It suggests that the sugar supply needs to be adequately planned to meet demand.

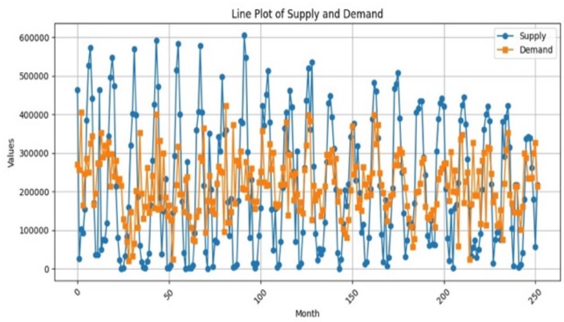



Fig. 4. Line Plot of supply and demand monthly series in 20 years.

A comparison of sugar demand and supply per year in Fig. 5 shows that demand fluctuates more than supply. In 2020, the national sugar demand and supply experienced a sharp decline, likely due to the COVID-19 pandemic. However, in 2021, demand and supply returned to previous levels and even increased.

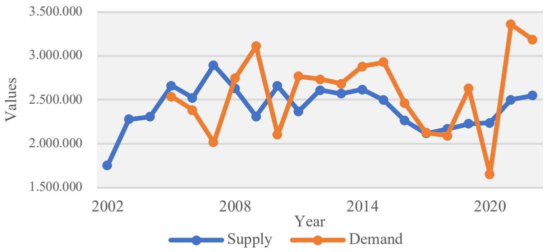



Fig. 5. Line Plot of supply and demand yearly in 20 years.

A year-on-year comparison of sugar production from January to December in Fig. 6 shows that the production graph tends to be the same yearly. Sugar production increases in mid-May, as the sugarcane milling season begins, and peaks in August. From October until November, the milling process has begun to end. However, in practice, there is often an error in the timing of imports that must match the needs, resulting in unstable sugar price fluctuations.

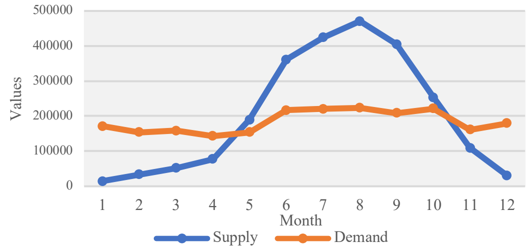



Fig. 6. Line Plot of supply and demand monthly YoY in 20 years.

Data separation is essential in data preprocessing, especially for creating data-based models. This technique will help ensure that the data models used in machine learning models are more accurate [16]. Used dataset:

1) Demand data for white sugar circulating on the market from 2002-2022 as demand dataset,
2) Supply data derived from import and production data from 2002 to 2022 as Supply dataset,

The experiment setup is as follows.

1) The dataset consists of production, import, supply, and demand data. The supply data is constructed by using production and import data. The previous five months' production and import are used to predict supply and demand for the next month. The dataset is split into three parts: 60% data training, 20% data validation, and the remaining for data testing.
2) LSTM architecture uses all dataset parts to learn sequence patterns and uses MSE as a loss function. The regressor model uses dataset training and testing, such as AdaBoostRegressor, RandomForestRegressor, BaggingRegressor, ExtraTreesRegressor, and GradientBoostingRegressor. Each model is measured performance using MAE and MSE evaluation.

## IV. PROPOSED METHOD

### *A. LSTM*

Because it has a specific type of memory cell that can store information from previous time steps, LSTM as a type of recurrent neural network (RNN) is designed to handle sequential data. This allows the network to learn long-term dependencies in the data, which is essential for many tasks, such as signature recognition and appliance translation [21]. It is shown in Fig. 7.

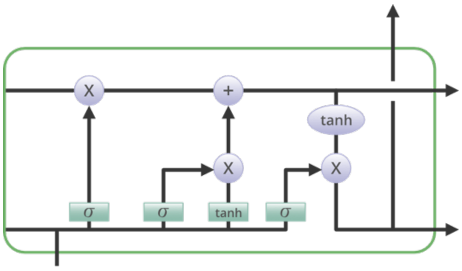


Fig. 7. Structure of LSTM [11].

There are three gates in an LSTM: (1) The forget gate controls how much of the Information from the previous step is forgotten, (2) the input gate controls new input is added to the hidden state, (3) the output gate controls numbers of the hidden state as its output.

1) Forget gate: The gate removes information from the previous step no longer used in the LSTM networks. Input value present with $x_t$ as current input, then $h_{t-1}$ as previous node output is fed to next gate, multiplied with weight and bias addition. The activation function will provide an output path for the leat and produce a binary output of the forget gate, which is either 0 or 1 and is retained for future computation. The equation is:

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

where:

- $W_f$ is the weight matrix in the forget gate.
- $[h_{t-1}, x_t]$ represents the current input value and the previously hidden value.
- and $b_f$ as biased forget gates.
- $\sigma$ sigmoid as activation function.

2) Input gate: At the input gate, information still in use will be added to the node. This information will be organized using the sigmoid function and sorting the values using $h_{t-1}$ and $x_t$. Next, values between -1 and +1 will be created using tanh, which contains the possible values $h_{t-1}$ and $x_t$. Then, the vector and set values are multiplied to get helpful information. The equation is:

$$i_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$C'_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

$$C'_t = f_t * C_{t-1} + i_t * C'_t \tag{4}$$

where:

- $*$ denotes elementwise product.
- $tanh$ is an activation function.

3) Output gate: filtering value presented at the output gate produces results. Applying tanh to cells will produce vectors. The sigmoid function will organize the Information and filter it to produce the value to be remembered using the input $h_{t-1}$ and $x_t$. Vector and set value are multiplied to get helpful information, which is shown in this equation:

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

### B. *ExtraTreesRegressor*

ExtraTreesRegressor is a learning algorithm based on decision trees. This type of random forest differs from random forests because it does not use bootstrapping. Instead, each tree in the Extra-Trees ensemble is trained on the entire dataset. The Extra-Trees algorithm works by training many decision trees on the data. Tree training uses a random subset of selected features and a random subset of data points. The final prediction from the algorithm is the average of the predictions.

### C. *Bagging*Regressor

This algorithm uses an ensemble meta-estimator to fit a random extraction base regressor from the original data set that selects or averages it to form a final prediction. Weak learners are combined to create strong learners [23].

This algorithm creates bootstrap samples from the previous data set. It produced a similar size as the previous data. However, there is a substitution where some data points may be included in the bootstrap sample multiple times while others may be excluded. The algorithm is a simple and effective way to reduce the variance of a base regressor. This is because the bootstrap sampling process helps to mitigate the effects of overfitting. The bagging regressor is also a robust method not sensitive to outliers.

### D. *RandomForestRegressor*

Collection of decision trees found in Random Forest that combine the predictions of several trees, which can increase accuracy. Each tree is trained using a random sample of data and a subset of features. This helps prevent overfitting [20].

The decision tree function is a recursive function that splits the data into two or more groups based on the values of the features. The decision tree parameters are the thresholds at which the data is split.

### E. *AdaBoostRegressor*

AdaBoostRegressor is a machine learning algorithm that combines weak learners to produce a strong learner. It is a type of ensemble learning algorithm. The algorithm's work sequence includes: (1) assigns a weight to the decision stump, which is inversely proportional to the error. The decision stump with the lowest error gets the highest weight. (2) The algorithm then repeats this process, training another decision stump and assigning it a weight. The weights of the decision stumps are adjusted so that the decision stumps that make the most mistakes are assigned lower weights. (3) Continue training until it reaches the maximum number of iterations. The weighted sum makes a final prediction of the decision stump predictions.

### F. *GradientBoostingRegressor*

Gradient boosting regression is a machine learning technique using a collection of decision trees. It works by adding trees sequentially to the ensemble; new trees are created to correct previous errors, and together, they work to make predictions [18].

Simple algorithms such as least squares regression form the first data tree. The remainder of the first tree is minimized in the second tree. The process repeats until the total number of targeted trees is fitted.

Gradient boosting in prediction models is created by combining the predictions of the entire tree. The weighted sum of the tree predictions becomes the final prediction, and the algorithm determines the weights.

These advanced machine learning techniques are used for a variety of tasks, including (1) Prediction of ongoing value, such as the price of a home or number of sales made, (2) Classification: grouping categorical values, such as whether a customer will churn or not, (3) Survival analysis: Predict the time until an event occurs, such as death or machine failure.

## G. *Evaluation Method*

Calculating error as the accuracy of forecast results will use the difference between actual and predicted values. Doing this by using existing data as measurement error [19].

1) MSE

The evaluation method uses MSE (mean squared error), which is a technique for minimizing the error between the predicted value of a model and the actual value. MSE is a quadratic loss function that penalizes significant errors more than small ones. Variety method in MSE: (1) Gradient descent, MSE is minimized by repeatedly updating model parameters; (2) Newton's Method, a more efficient method than gradient descent, but it can be more challenging to implement; (3) Bayesian optimization, a more sophisticated method using a probabilistic approach to find the optimal parameters. The method chosen will be specific to the resources available. The optimal model parameters are those that minimize MSE. New data predictions will use these optimal model parameters.

2) MAE

Error optimization using MAE (mean absolute error) minimizes the error between model predictions and actual values. MAE is a nonquadratic loss function that penalizes all errors equally, regardless of size. The optimal parameters of the model are the ones that minimize the MAE. The process flow of this experiment proceeds as in Fig. 8.

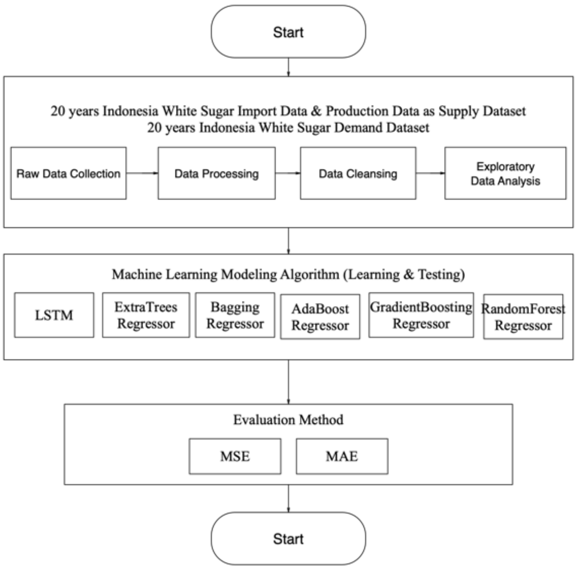



Fig. 8. Process Flowchart Data processing – Modeling Comparative – Evaluation Method.

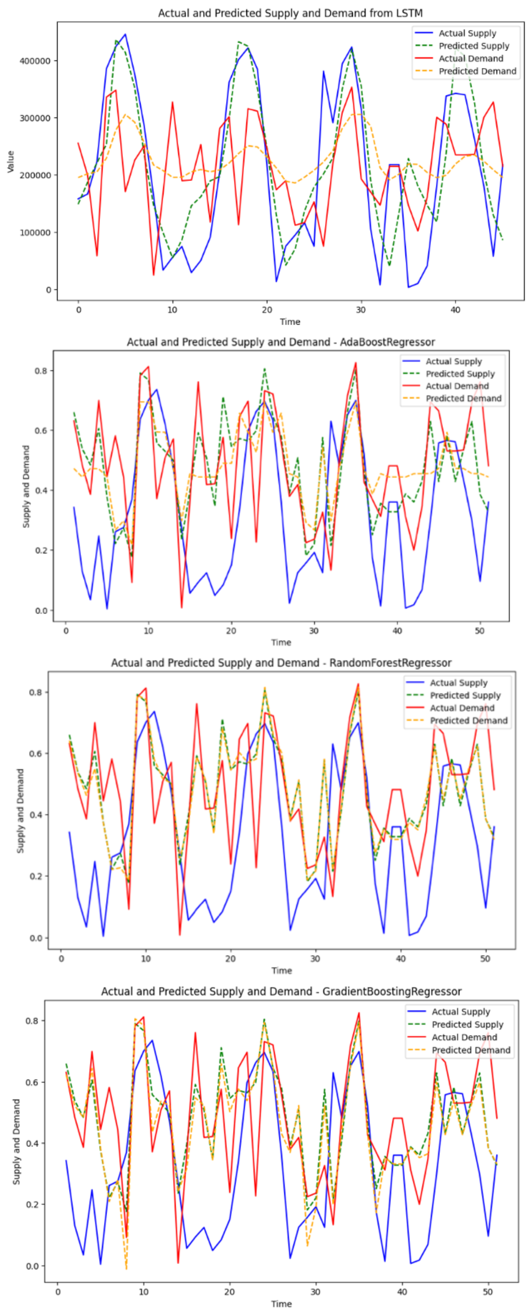
# V. RESULT & DISCUSSION

LSTM is the best method to produce data predictions with the best performance, as shown in Table 3, confirmed by the most petite MAE and MSE values. Meanwhile, AdaBoostRegressor is the second-best method model, after that followed by RandomForestRegressor, GradientBoostingRegressor, BaggingRegressor, and ExtraTreesRegressor. The decrease in LSTM evaluation method compared to AdaboostRegressor was 37.33% for MSE and 14.12% for MAE. This shows that LSTM can learn nonlinear patterns from 20 years Indonesia white sugar historical data using production, import, and demand data to predict supply and demand.

TABLE 3. PERFORMANCE COMPARISON

| Method Model | Evaluation Method | |
|---|---|---|
| | MSE | MAE |
| LSTM | 0,0300 | 0,1373 |
| AdaBoostRegressor | 0,0412 | 0,1567 |
| RandomForestRegressor | 0,0449 | 0,1575 |
| GradientBoostingRegressor | 0,0449 | 0,1582 |
| BaggingRegressor | 0,0462 | 0,1606 |
| ExtraTreesRegressor | 0,0517 | 0,1678 |

Plotline comparison between actual and predicted supply demand in Fig. 9 shows a pattern of LSTM as the best performance to predict value compared to the actual value. In LSTM, the actual supply pattern is close to the predicted supply pattern, while the actual demand is still not too close to the predicted demand. However, after all, LSTM is better than other modeling pattern algorithms.



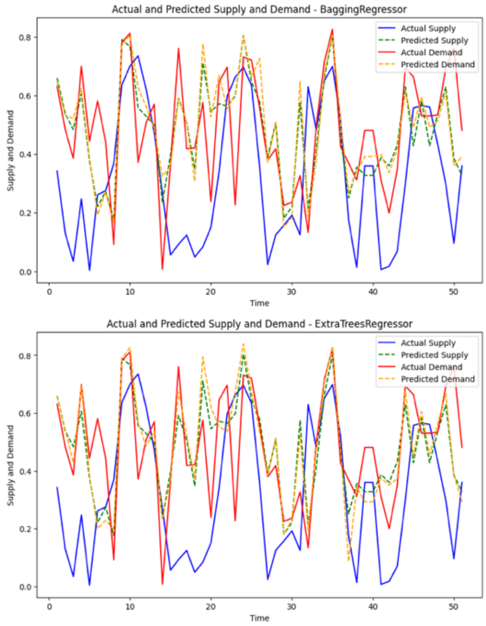


Fig. 9. Plotline forecasting comparison between actual supply–demand and predicted supply–demand.

## VI. Conclusion

This research aims to study the effectiveness of the dataset and forecasting methods to support the potential for optimizing the supply and demand of white sugar in Indonesia and maintaining the price. The results are essential to the parties in white sugar commodity who need to plan to fulfill domestic demand for sugar through domestic production and imports by assignments given by the government. Unlike research using only LSTM to deep dive modeling method in machine learning and uses four years of data, this research uses 20 years of supply data (import and production) and demand data to model with four different methods. The result is that LSTM is the best method model that produces the best performance in evaluation method compared to regressor models which have not been done previously, such as AdaBoostRegressor, the second-best method model, followed by GradientBoostingRegressor, BaggingRegressor, and ExtraTreesRegressor. The decrease in LSTM evaluation method compared to AdaboostRegressor was 37.33% for MSE and 14.12% for MAE. Meanwhile, RMSE has a root function that reduces the error value; for the result, LSTM is the best model confirmed by the most petite MAE and MSE values.

For further study, this research can be used to forecast white sugar prices that will form in the market, added with local and global price historical data, and also issued policy so they can influence the formation of sugar prices in the market.

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