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# TIME SERIES MODEL WITH LONG SHORT-TERM MEMORY EFFECT FOR GREENHOUSE GAS ESTIMATION IN INDONESIA

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ABSTRACT

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*Climate change is one of the major challenges in the world today, characterized by changes in meteorological values, such as rainfall and temperature, caused by the concentration of greenhouse gases in the atmosphere, such as $CO_2$, $N_2O$, and $CH_4$. These accumulated greenhouse gases form a layer that prevents heat radiation from escaping, causing the greenhouse effect and global warming. Addressing the effects of greenhouse gas emissions requires appropriate strategies, one of which is to predict future greenhouse gas emissions for planning appropriate actions. Time series models such as the Autoregressive Integrated Moving Average (ARIMA) model are often used but have drawbacks due to their assumption of linear relationships. On the other hand, the Long Short-Term Memory (LSTM) model, introduced by Hochreiter and Schmidhuber in 1997, can learn complex and nonlinear relationships in data. This study uses LSTM to estimate greenhouse gas emissions in Indonesia based on emitting sectors, hoping to anticipate negative impacts and reduce greenhouse gas emissions. The results show that the LSTM model has good performance with an error below 20%, and it is predicted that greenhouse gas emissions will continue to increase.*



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# 1. INTRODUCTION

Climate change is one of the significant challenges for the world today. Climate change is in the form of changes in values in meteorological aspects such as rainfall and temperature [1], [2]. One of the causes of these changes in value is the concentration of greenhouse gases in the atmosphere [3]. This greenhouse gas contains several gases that are harmful to the environment, such as carbon dioxide (CO2), Nitrogen Oxide (N2O), methane gas (CH4), and various other harmful gases [4]. Greenhouse gases accumulated in the atmosphere result in the formation of a layer covering the earth and not allowing heat energy to radiate out, thus causing the greenhouse effect, which leads to global warming [5], [6].

To mitigate the adverse effects of greenhouse gas emissions, accurate forecasting of greenhouse gas emissions is crucial for developing effective strategies and policies. Estimating future emissions allows policymakers to anticipate trends and take timely action [7]. Various time series models have been used to estimate emissions, such as the Autoregressive Integrated Moving Average (ARIMA) model [8], [9]. However, ARIMA assumes a linear relationship in the data, which may not adequately capture the complex, non-linear nature of emission patterns [10], [11].

To address this limitation, Long Short-Term Memory (LSTM), a deep learning-based model introduced by Hochreiter and Schmidhuber in 1997, offers an advanced alternative [12]. LSTM has demonstrated a superior ability to learn complex temporal dependencies and capture nonlinear relationships in sequential data [13], [14]. Moreover, LSTM can handle both short and long-term predictions, making it a promising tool for estimating greenhouse gas emissions [15], [16].

This study aims to develop an LSTM-based time series model for forecasting greenhouse gas emissions in Indonesia over the period 1970 to 2022, focusing on major emission-contributing sectors. Unlike traditional forecasting approaches, this research not only provides emission projections but also examines sectoral trends to support targeted mitigation policies. By leveraging LSTM's predictive power, the study seeks to contribute to data-based decision-making for emission reduction strategies in Indonesia. The results are expected to assist policymakers and environmental agencies in designing more effective interventions to curb emissions and combat climate change.

# 2. RESEARCH METHODS

## 2.1 Data Source

The data used in this research is data on greenhouse gas emissions in Indonesia from 1970 to 2022, which can be obtained from https://edgar.jrc.ec.europa.eu/. The data obtained is annual data on several greenhouse gas-producing sectors with the following information:

**Table 1. Research Variable**

| Sector | Description |
|---|---|
| Agriculture | Includes agriculture livestock, agriculture soils, and field burning of agricultural residues. |
| Buildings | Includes small-scale non-industrial stationary combustion |
| Fuel exploitation | Includes solid waste disposed on land, solid waste composted, hazardous solid waste processing/storage, waste water handling, and waste incineration. |
| Industrial combustion | Includes combustion for industrial manufacturing |
| Power industry | Includes power and heat generation plants |
| Processes | Includes industrial process emissions |
| Transport | Includes road transport, rail transport, domestic aviation, domestic shipping, and inland waterway transport |
| Waste | Includes solid waste disposed on land, solid waste composted and hazardous solid waste processing/storage, waste water handling, and waste incineration. |

Table 2 below presents the historical GHG emissions data for the first five-year period that was used in this research, covering the eight sectors identified as research variables in Table 1. The data in Table 2 are expressed in metric tons of $CO_{2eq}$, derived from the data source obtained.

**Table 2** The First 5 Data Points of The Data Used

| Year | Agriculture | Buildings | Fuel Exploitation | Industrial Combustion | Power Industry | Processes | Transport | Waste |
|---|---|---|---|---|---|---|---|---|
| 1970 | 132159670 | 16612168 | 31908488 | 4938001 | 3653496 | 1914473 | 8253790 | 18447532 |
| 1971 | 133982675 | 16612168 | 32250537 | 4938001 | 3653226 | 1928243 | 8256379 | 19057394 |
| 1972 | 129240735 | 17930973 | 39990990 | 5324691 | 3952725 | 2038089 | 8903075 | 19654530 |
| 1973 | 132788547 | 18916604 | 48693559 | 5722832 | 4194392 | 2263751 | 9438943 | 20370806 |
| 1974 | 133553122 | 20391057 | 50885341 | 6141811 | 3877281 | 2540359 | 10845549 | 21007323 |

## 2.2 Preprocessing Data

The data that has been obtained previously goes through a data preprocessing process before being used in the model. Data preprocessing is carried out as follows:

**Data normalization**. Data normalization is done to change the value interval to [0,1] because the value in the data is tremendous so as not to interfere with the model-building process **[17]**. The data normalization used in this paper is a min-max scaler with the following equation:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Description:
$x$ : Data before normalization
$x_{min}$ : The minimum data from the dataset
$x_{max}$ : The maximum data from the dataset
$x_{scaled}$ : Data after normalization

**Data Sequencing**. Data sequencing is a key step in creating models that work with data based on sequences like RNN (Recurrent Neural Networks) or LSTM (Long Short-Term Memory). The main goal of data sequencing is to help the model understand the order or sequence of data points. This allows the model to predict the next data point based on patterns it has learned from previous sequences. This process involves creating multiple data sequences that match the model's input, where each sequence has a specific length called $k$. The length of the sequence determines how many data points will be fed into the model in one process. For example, if $k = 5$, each sequence will consist of 5 data points. This process is illustrated in **Figure 1**

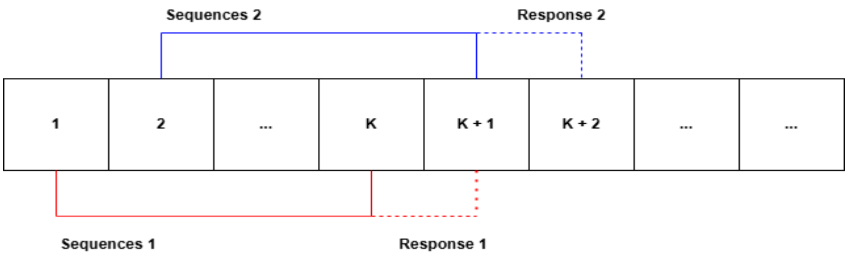


**Figure 1** Data Sequencing Process

**Split of training and testing data**. It is an essential step in the modeling process to ensure the model can handle new data. The dataset is split into two parts: 70% for training and 30% for testing. The training data, which covers the period from 1970 to 2006, is used to train the model so it can learn patterns and relationships within the data. The testing data from 2007 to 2022 is used to see how well the model works with data it hasn't seen before. This ensures that the model doesn't just memorize the training data but also makes accurate predictions based on new data. This process helps show how well the model can be used in the real world.

### 2.3 Long Short-Term Memory

LSTM is a specialized model of RNN [14]. It uses a memory unit that can update the previous hidden state and provide feedback to each neuron [10]. Therefore, it not only relies on the current neuron's input and weight but also relies on the previous neuron's input, which allows the model to understand temporal relationships in the long term [18]. The internal memory unit and gate mechanism can overcome the problem of exploding and missing gradients that often occur in conventional RNN models [19]. The LSTM model includes four critical units: the input gate, output gate, forget gate, and cell state. The process is as in Figure 2 and can be given in the following equation:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{2}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{3}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{4}$$

$$\tilde{c}_t = \tanh\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{5}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \tag{6}$$

$$h_t = o_t \cdot \tanh c_t \tag{7}$$

Description:
$f_t$ : Forget gate
$i_t$ : Input gate
$o_t$ : Output gate
$c_t$ : Cell state
$x_t$ : Input vector
$h_t$ : Hidden state
$W$ : Weight matrix
$b$ : Bias vector
$\sigma$ : Activation function sigmoid
tanh : Activation function hyperbolic tangent

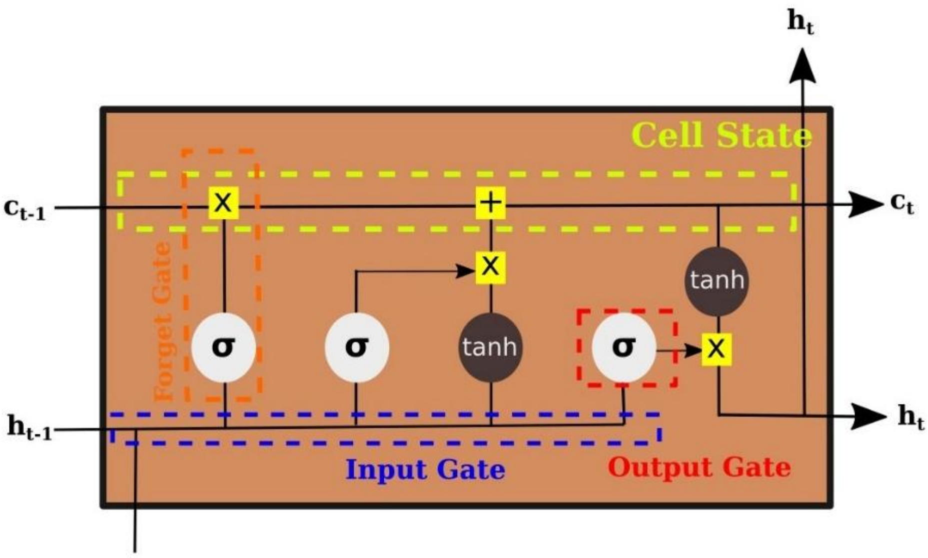


Figure 2 LSTM Architecture

### 2.4 Model Accuracy

The measurement error is calculated to determine the accuracy of the model. The best model is the model with the smallest error obtained by comparing the variation of the difference between the actual value $y_i$ and the predicted value $\hat{y}_i$. The error measures used in this study are Mean Squared Error (MSE), which calculates the squared difference between the actual value and the predicted value [20], and Mean Absolute

Percentage Error (MAPE), which calculates the percentage ratio of the error between the predicted value and the actual value [19]. The MSE and MAPE equations are as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{8}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{9}$$

The assessment criteria of mape are as follows [21]:

a) If the MAPE rate is < 10%, then the criteria for the model are very good.
b) If the MAPE rate is 10% to 20%, then the model criteria are good.
c) If the MAPE rate is 20% to 50%, then the model criteria are pretty good.
d) If the MAPE rate is >50%, then the model criteria are not good.

## 3. RESULTS AND DISCUSSION

### 3.1 Descriptive Statistic

The plot of annual data of greenhouse gas emissions in each sector from 1970 to 2022 is visualized in the following graph:

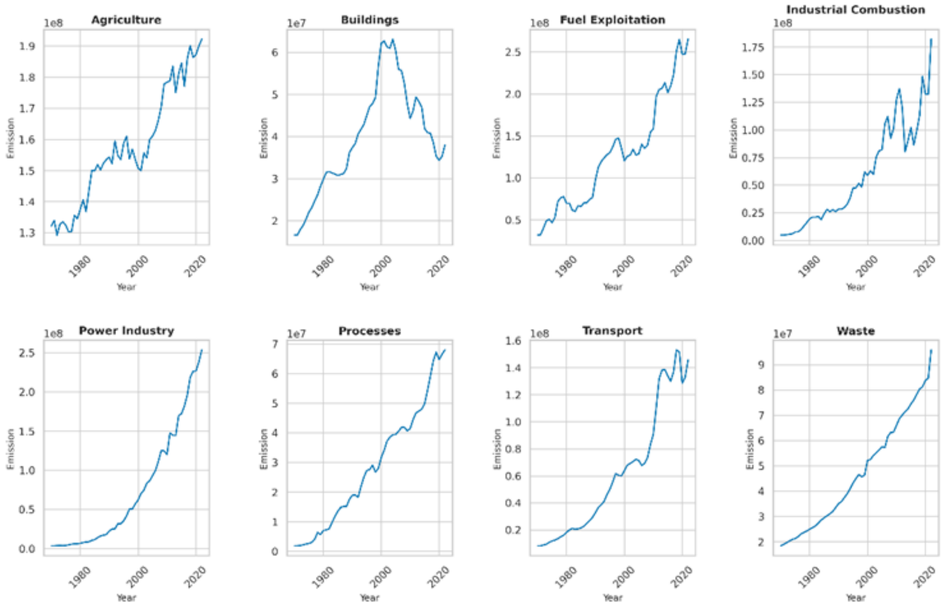


**Figure 3 Greenhouse Gas Data for 1970-2022 for Various Greenhouse Gas Emitting Sectors**
Source of application: python

As illustrated by the graph in Figure 3, there have been fluctuations in greenhouse gas emissions in Indonesia from 1970 to 2022, with varying increases across different sectors. The Agriculture sector has seen a significant rise since the 1980s, with continuous growth up to 2022. The Buildings sector experienced a sharp increase until around 2000, followed by a substantial decline, but emissions have started rising again in the past two years. The Fuel Exploitation sector exhibited fluctuations, with notable surges after 2000, although some periods showed temporary declines. The Industrial Combustion sector displayed a steady upward trend since 1970, with a more pronounced acceleration after 2000. The Power Industry sector emerged as a major contributor to emissions, consistently increasing, especially post-2000, indicating significant growth. The Industrial Processes sector has experienced a sharp increase since the 1980s, with an ongoing upward trend until 2022. The Transportation sector exhibited a stable increase from 1970 to 2022, with no significant declines, while the Waste sector demonstrated a gradual and sustained growth in emissions since 1970, reflecting contributions from the management of both solid and liquid waste. The comprehensive analysis of data reveals a consistent upward trend in emissions across various sectors, accompanied by distinct growth patterns.

### 3.2 Model Used

The model architecture used in this study was chosen after trying out various possible model architectures. After trying the possible model architectures, the model architecture was selected as follows:

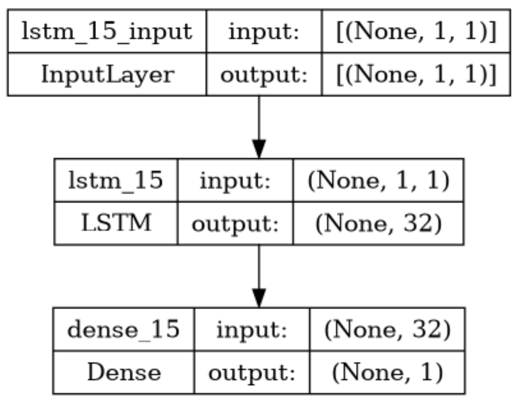


**Figure 4 Model Architecture**
Source of application: python (tensorflow)

As illustrated in **Figure 4**, the model architecture employed in this study comprises three primary layers designed to efficiently process time series data. The initial layer is designated as the input layer, which receives input data in the form of a tensor with dimensions (None, 1, 1). The second layer is the Long Short-Term Memory (LSTM) layer with 32 neurons, which plays a crucial role in capturing both short-term and long-term dependencies within time series data. By utilizing memory cells and gating mechanisms, LSTM retains relevant information while mitigating the vanishing gradient problem, making it more effective than traditional neural networks for sequential data processing. The third layer is the dense layer, which serves as the output layer. This layer transforms the LSTM output, which has dimensions of (None, 32), into a final output with a single neuron (None, 1). The dense layer generates the predicted value based on the patterns learned by the model. The model is then trained using the Adaptive Moment Estimation (ADAM) optimization algorithm, which dynamically adjusts the learning rate to improve convergence speed and stability. The loss function employed is Mean Squared Error (MSE), which seeks to minimize the discrepancy between the predicted and actual values, thereby enhancing the model's precision.

### 3.3 Model Training Result

The model in **Figure 4** will then be trained for 1000 epochs by paying attention to the loss value on the training data (loss) and the loss value on the testing data (val_loss) during the training process. The results of the model training process are as follows: The model in **Figure 3** will then be trained for 1000 iterations by paying attention to the loss value on the training data (loss) and the loss value on the testing data (val_loss) during the training process. The results of the model training process are as follows:

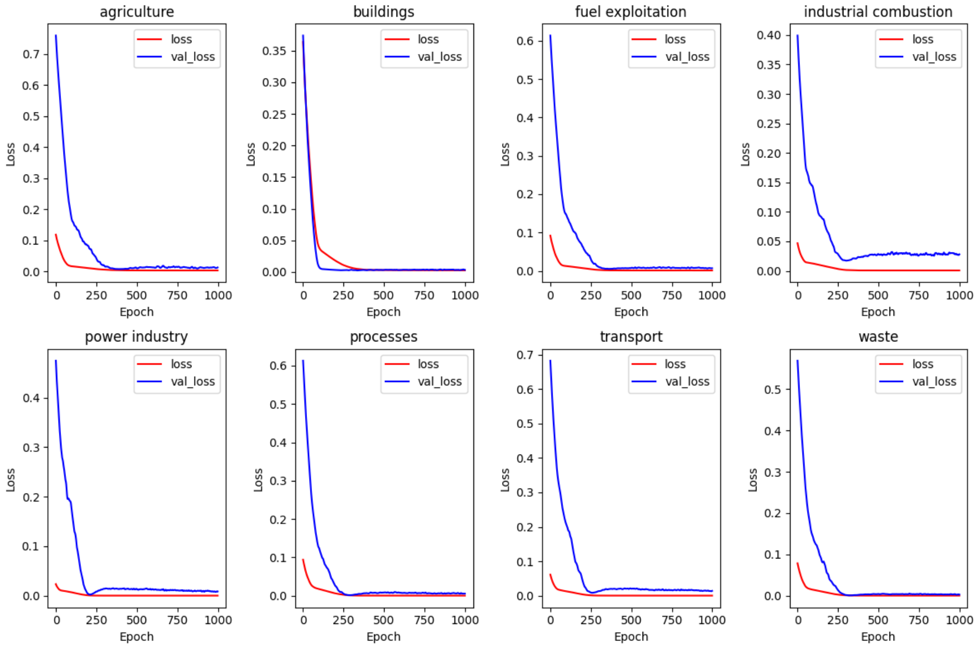


**Figure 5** **Model Training Results**
Source of application: python

As illustrated in **Figure 5**, the model's training outcomes exhibit robust performance across all sectors examined. The graph illustrates a substantial decrease in the loss (training data loss) and val_loss (validation data loss) values during the training process, attaining convergence after approximately 1,000 epochs. A close examination of the loss and val_loss values across various sectors reveals similar patterns, with a pronounced decline in the initial phases of training, followed by a gradual deceleration and stabilization at low values. This observation suggests that the model can effectively learn patterns from the data without experiencing overfitting or underfitting.

The sectors of buildings and fuel extraction demonstrate a more precipitous decline in loss values compared to other sectors, suggesting that the model exhibits a higher degree of proficiency in recognizing patterns within these data sets. In contrast, the power industry and waste sectors initially exhibit higher loss values compared to other sectors but still achieve good convergence. Furthermore, the disparity between loss and val_loss in each sector is minimal, suggesting that the model demonstrates effective generalization capabilities when confronted with novel data. The absence of a significant disparity between these two metrics further validates the model's resilience to overfitting, a phenomenon where the model becomes overly reliant on the training data yet struggles to effectively predict new data. In summary, these findings indicate that the model employed is capable of producing reliable and precise predictions for both training and validation data.

### 3.4 Model Training Result

After the model is trained, it is evaluated to see how it performs by looking at the MSE and MAPE values of the model for each greenhouse gas-producing sector. The evaluation results of the model are as follows

**Table 3** **Model Error Results**

| | Agriculture | Buildings | Fuel | Industrial | Power | Processes | Transport | Waste |
|---|---|---|---|---|---|---|---|---|
| MSE | 0.0033 | 0.0027 | 0.0011 | 0.0079 | 0.0001 | 0.0005 | 0.0003 | 0.0003 |
| MAPE (%) | 1.9863 | 4.8156 | 6.9406 | 10.4804 | 10.7469 | 15.4851 | 6.6913 | 2.4128 |
| Val_MSE | 0.0131 | 0.0033 | 0.0075 | 0.0254 | 0.0083 | 0.0057 | 0.0145 | 0.0028 |
| Val_MAPE (%) | 3.1524 | 5.1584 | 6.6425 | 19.8025 | 11.0317 | 6.5946 | 10.3429 | 4.6894 |

As illustrated in **Table 3**, the model's performance is evaluated through the analysis of key performance indicators, including Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE), for various greenhouse gas-producing sectors. MSE quantifies the mean squared deviation between the model's predictions and the observed data, with lower values denoting higher precision. As evident in **Table 3**, the MSE values on the training data are comparatively minimal for all sectors, with the lowest value recorded in the Power sector (0.0001) and the highest in the Industrial Combustion sector (0.0079). This observation signifies the model's adept capacity to predict the training data accurately. When evaluated on the validation set, an increase in the MSE values was observed, which is to be expected as the model is subjected to testing on new data. However, this increase was not significant, with the lowest value recorded in the Power sector (0.0083) and the highest in the Industrial Combustion sector (0.0254), indicating the model's overall effectiveness.

Conversely, the MAPE metric calculates the percentage of absolute error between the model's predictions and the actual data. A lower percentage, in this case, indicates more accurate predictions. On the training data, the Agriculture sector demonstrated the lowest MAPE (1.9863%), indicating high accuracy, while the Processes sector exhibited the highest MAPE (15.4851%), potentially attributable to elevated data complexity or variability. A similar trend is observed in the validation data, where the MAPE values, though higher, remain within acceptable limits. The agriculture sector maintains its position as the sector with the lowest MAPE (3.1524%), while the industrial combustion sector has the highest MAPE at 19.8025%. Despite the observed increase, the overall MAPE values remain within acceptable limits, thereby indicating the model's satisfactory generalization capability. The model's performance in predicting both training and validation data for all sectors is promising, as evidenced by the low MSE and MAPE values on the training data. These findings suggest that the model possesses the capacity to effectively learn data patterns. The slightly higher values observed on the validation data demonstrate the model's capability to predict new data with a satisfactory degree of accuracy. The observed variation in error values across sectors, such as Industrial Combustion and Processes, might be attributed to the complexity and variability of the data in these specific sectors. In summary, this model demonstrates effectiveness in predicting greenhouse gas emissions across various sectors.

### 3.5 Model Prediction

After evaluating the model, the pre-trained model was used to predict greenhouse gas emissions in each sector. The results of the model prediction are as follows:

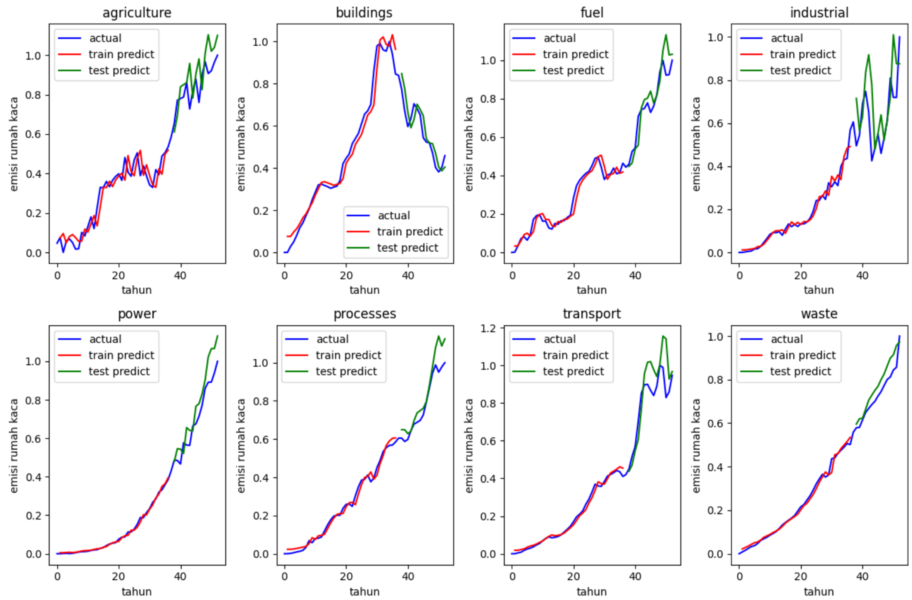


**Figure 6** **Actual Data vs Model Predicted Data**
Source of application: python

**Figure 6** shows how well the model can predict greenhouse gas emissions data. The model was trained to predict emissions in each sector. The results show that the model can predict the actual values. The predicted values are close to the actual values. This shows that the model can find patterns and trends in the data. This allows the model to make accurate estimates of greenhouse gas emissions in different sectors. This means that the model can learn complex relationships between variables that influence emissions and generalize to new data.

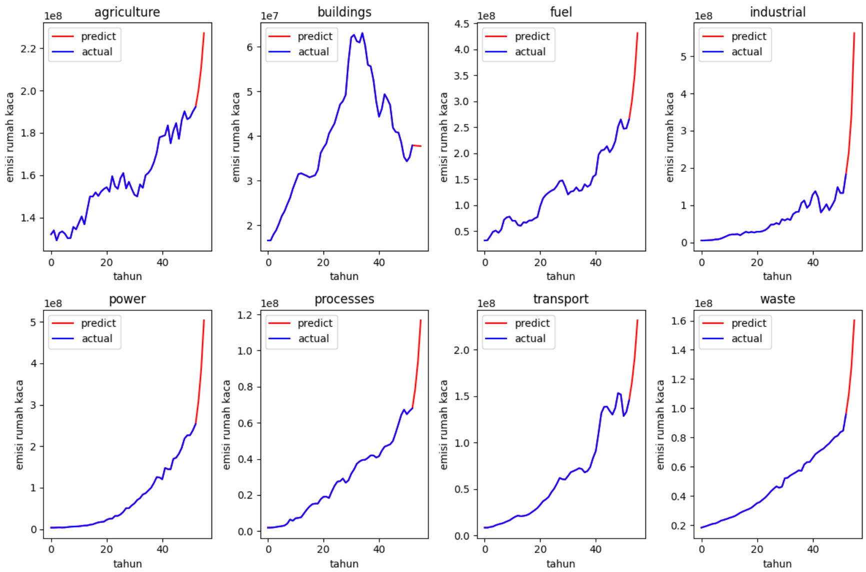


**Figure 7 Predicted Greenhouse Gas Emissions for the Next 3 Years**
Source of application: python

**Figure 7** shows how much greenhouse gas emissions will increase or decrease in the next three years. This is based on a pre-trained model. In the agriculture sector, predictions show that emissions will likely increase because of livestock farming, how land is used for farming, and burning crop waste on fields. The buildings sector will likely not increase as much as other sectors. It will have small changes instead of a consistent increase. This suggests that emissions from small, non-industrial, stationary combustion may not grow as much as in other sectors. The fuel extraction sector is increasing its emissions because of waste management, hazardous waste processing and storage, and waste burning and wastewater treatment. The industrial combustion sector is also increasing its emissions, according to the model. The power industry is increasing its emissions from power and heat generation plants, suggesting a continued reliance on fossil fuels. The industrial processes sector also shows an upward trend due to various industrial activities that generate greenhouse gases. The transport sector records an increase in emissions from road transport, rail transport, domestic aviation, and inland waterway shipping. This suggests that without significant changes in transportation policies, emissions from this sector will likely continue to rise.

Finally, the waste sector also shows an increase in emissions. These emissions come from disposing of solid waste on land, processing and storing hazardous solid waste, handling wastewater, and burning waste. This rise can be linked to population growth and increasing waste production. Overall, the model predicts that greenhouse gas emissions will continue to increase in almost all sectors. However, the buildings sector is relatively stable compared to the other sectors. This shows that we need stricter policies to reduce greenhouse gas emissions. These policies should include switching to cleaner energy sources, improving industry and transportation efficiency, and using more sustainable waste management practices.

## 4. CONCLUSIONS

After conducting research using the LSTM model, the model as a whole produces good predictions with an average error below 20%, which means that the LSTM model created is good in the prediction process based on the previous criteria. This also suggests that the LSTM model is effective in capturing patterns of greenhouse gas emissions based on historical data. In addition, the model predicts that, except for the building sector (which is expected to remain stable), other sectors will experience a significant increase in emissions over the next three years. These emphasize the urgent need for stricter policies and sustainable practices to mitigate greenhouse gas emissions. Without proper intervention, Indonesia's emissions will continue to rise at an accelerated rate, potentially exacerbating environmental and climate-related challenges. Policymakers must consider implementing measures such as transitioning to renewable energy, improving energy efficiency in industries, promoting sustainable transportation, and enhancing waste management strategies. Strengthening regulations and encouraging low-carbon technologies will be crucial in ensuring a more sustainable future while minimizing the environmental impact of these increasing emissions.

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