Machine Learning Methods for Predicting Manure Management Emissions

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***Abstract*—Indonesia is committed to reducing greenhouse gas (GHG) emissions through a nationally determined contribution (NDC) scheme. The target to reduce GHG emissions is 29% through the business as usual (BAU) scheme or 41% with international aid. These ambitious targets require transformations in energy, food, and land-use systems, which need to cope with the potential trade-offs among many targets, such as food security, energy security, avoided deforestation, biodiversity conservation, land use competition, and freshwater use. Mitigation and adaptation have complementary roles in responding to climate change at both temporal and spatial scales. This paper aims to perform simulations and predictions on manure management emissions producing CO_2eq using machine learning methods of long short-term memory (LSTM) and gated recurrent unit (GRU). The hidden layer architecture used was six combinations, while the dataset was obtained from the *fao.org* repository. The optimizer used in this paper was RMSprop, with a graphical user interface using the Streamlit dashboard. The results of this study are (a) cattle with fifteen epochs using hidden layer four combinations (LSTM, GRU, LSTM, GRU) yielded RMSE 450,601; (b) non-dairy cattle with fifteen epochs and one hidden layer (GRU, GRU, GRU, GRU) yielding RMSE 361.421; (c) poultry birds with twelve epoch values and three hidden layers (GRU, GRU, LSTM, LSTM) resulted in an RMSE value of 341.429. The challenges faced were the determination of epochs, the combination of hidden layers, and the characteristics of the relatively small number of datasets. The results of this study are expected to provide added value for developing better decision support tools and models to assess emission trends in the livestock sector and develop CO_2eq emission mitigation strategies that lead to sustainable fertilizer management practices.**

***Keywords*—Machine Learning, Manure Management, GRK, LSTM, GRU.**

I. Introduction

Anthropogenic greenhouse gas (GHG) emissions have increased significantly along with the increasing use of fossil fuels, deforestation, and land-use change. The Intergovernmental Panel on Climate Change (IPCC) has highlighted the impact of GHG emissions, particularly carbon dioxide (CO_2), nitrous oxide (N_2O), troposphere ozone (O_3), methane (CH_4), and chlorofluorocarbons (CFC), on climate change [1]. The average increase in global GHG concentrations has been higher over the last half-century than in previous years [2]. Anthropogenic activities in agriculture and forestry are mainly caused by intensification and changes in land use that result in GHG emissions, thereby causing ecosystem imbalances [3].

Direct emissions from livestock refer to emissions produced directly from livestock through enteric fermentation and excreta (dung and urine) excretion [4]. In particular, livestock CH_4 is a direct by-product of digestion through enteric fermentation [4]. CH_4 is produced in herbivores as a by-product of enteric fermentation. Enteric fermentation is a digestive process that uses microorganisms to break down carbohydrates into simple molecules that can be absorbed into the bloodstream. The amount of CH_4 released depends on the type of digestive tract, age, the animal’s weight, and the quality and quantity of feed consumed. Ruminant livestock (e.g., cattle and sheep) are the primary source of CH_4 with moderate production. Examples of non-ruminant livestock are pigs and horses [5].

Manure management is a source of N_2O and CH_4 emissions. N_2O is produced as part of the nitrification and denitrification cycle of organic nitrogen substances contained in animal waste. N_2O emissions are related to handling the manure before its application to the soil. CH_4 from manure management is produced during the anaerobic decomposition of dung and is usually much less than enteric fermentation emissions. In principle, CH_4 emissions are associated with limited animal management facilities, namely handling animal waste in liquid form [5].

The livestock sector is the largest emitter of GHG emissions from the world’s agricultural industry. Enteric fermentation and manure management account for 35-40% of total anthropogenic CH_4 emissions [6]. CH_4 emissions from enteric fermentation and manure management account for 78.3% of total agricultural CH_4 emissions [7]. Livestock activities account for 65% of total anthropogenic N_2O emissions, representing 75%–80% of total farm emissions [6]. N_2O emissions from manure management accounted for 6.3% of total agricultural N_2O emissions [7].

The Indonesian Government is committed to reducing GHG emissions by 41% with international aid and 26% with its own efforts. It follows Presidential Regulation No. 61 of 2011 regarding GHG reduction [8]. The government provides education to farmers to participate in reducing CH_4 by substituting animal feed with leaves that are low in CH_4 emissions, such as Calliandra, Gliricidia, and Leucaena. Animal feed containing tannins and saponins can also be given to reduce CH_4 gas [9].

In recent decades, the use of machine learning algorithms for a predictive manure management decision-making model has

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attracted the interest of researchers. Several studies that have been carried out are the use of machine learning algorithms of gradient boosted trees (GBT), bagged tree ensembles (BTE), random forest ensembles (RFE), and feedforward neural networks (FNN) to predict liquid dairy manure [10]; research on the use of waste from dairy farming for fields and crops using the boosted regression (BR) algorithm [11]; a study used machine learning models of multiple linear regression (MLR), artificial neural network (ANN), gradient boosting machine (GBM), dan random forests (RF) to predict CO_2 and N_2 produced by cattle manure [12]. In addition, research has also been carried out using machine learning methods ANN and least squares support vector machine (LS-SVM) to predict pyrolysis of cattle manure [13] and research on the prediction of agricultural emissions using the autoregressive integrated moving average (ARIMA) algorithm, long short-term memory (LSTM), as well as simple linear regression models [14].

A literature review has been carried out using ANN, support vector machine (SVM), genetic algorithm (GA), decision tree (DT), RF methods, which have great potential for various fields of waste management decision making, reduction of waste treatment cycles, improvement of resource utilization, and mitigating the risk of waste pollution [15]. Research using machine learning Bayesian network (BN) and boosted regression trees (BRT) has also been carried out to predict nitrogen in dairy cattle [16]. Research related to GHG emission mitigation for CH4 projection using machine learning methods, namely Gaussian processes, ordinary multilinear regression, and least robust neural networks in naturally ventilated livestock buildings, have also been carried out [11]. In addition, the implementation of deep learning LSTM has also been carried out to predict GHG emissions in the agriculture sector [17]; and research using the ANN method to predict GHG emissions in the agriculture sector [18]. Machine learning methods, linear regression, decision tree regressors, and random forest regressors are also proposed to analyze and predict GHG emissions in the agricultural sector [19].

The research in this paper intends to take advantage of two machine learning methods LSTM and gated recurrent unit (GRU), to predict manure management in influencing GHG emissions in Indonesia by using six combinations of hidden layers. The stacking of hidden layers of deep neural networks (DNN) makes the model deeper and more accurate for a description as a deep learning technique. It also has the potential to allow hidden states at each level to operate on different timescales [20]. In addition, it also increases the depth of the network and provides an alternative solution that requires fewer neurons and performs training faster [21]. Ultimately, this depth addition is representative optimization [22].

II. METHODOLOGY

This experiment used the manure management dataset obtained from the *fao.org* repository page [7]. The dataset has value and time attributes. It is included in the category of time-series data that can be used as input to machine learning methods. LSTM-GRU regression is used to predict emission trends from manure management to provide alternative solutions for GHG mitigation in Indonesia.

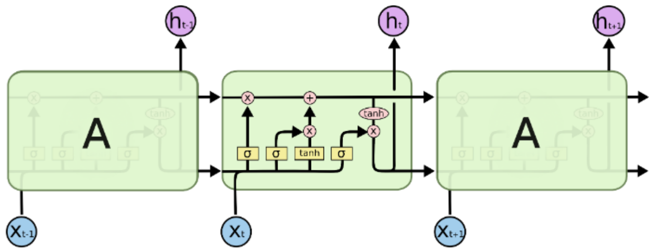

Fig. 1 Four layers of activation functions in LSTM cells.

A. *Long Short-Term Memory (LSTM) Algorithm*

LSTM is a type of recurrent neural network (RNN) that allows the network to maintain long-term dependencies between data at a given time from many previous time steps [23]. The LSTM is the form of an iterative chain of modules from an ANN, in which each module encompasses three control gates, namely forget gate, input gate, and output gate. Each gate consists of a sigmoid neural net layer and a pointwise multiplication operation. The result of the output in the sigmoid layer is a number in the interval of [0, 1], representing a portion of the input information that must be passed. As the use of RNN for time series data, the LSTM reads a sequence of input vectors $x = \{x_1, x_2, \ldots, x_t, \ldots\}$, where $X_t \in R^m$ represents the m-dimensional reading vector for m variables at time t. Fig. 1 illustrates the four layers of activation function in LSTM.

Given the new information x_t in t condition, the LSTM module works as follows. First, the LSTM module determines which old information should be forgotten by displaying it as a number [0, 1].

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

where h_{t-1} is the output in the $t-1$ state, W_f is the weight matrix, and b_f is the bias of the forget gate. Then, x_t is processed before being stored in the cell state. The i_t value is determined at the input gate along with the candidate vector Ct value generated by the tanh layer simultaneously to be updated in the new cell state Ct, with

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

$$C_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * C_{t.} \tag{4}$$

where (W_i, b_i) and (W_c, b_c) are the weight and bias matrices of the input gate and cell state memory, respectively. Finally, the output gate is defined by (5), where W_o and b_o are the matrix weights and the output gate bias, determining the portion of the cell state output.

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

$$h_t = O_t + tanh(C_t). \tag{6}$$

The output gate controls the number of activations for each unit that can be sustained. It allows the LSTM cell to store irrelevant information to the current output yet may be applicable in the future. The ability of LSTMs to control how the data is stored in each unit has proven to be of general use.

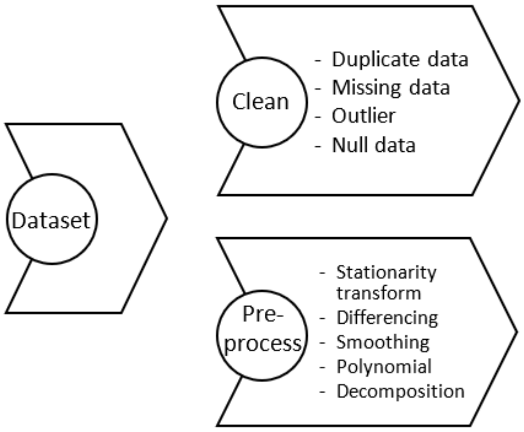

Fig. 2 Experiment flow.

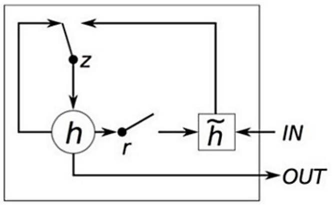

Fig. 3 GRU graphic illustration.

The initial step of this experiment begins with dataset input. The next stage is data cleansing, which cleans data from duplicate, missing, outliers, and null data. Following that is preprocessing, namely the stationary transformation, differencing, smoothing, polynomial, and decomposition processes. Then the next stage is the autoregressive process, moving averages, charts, and RMSE. The following process is data analysis, consisting of data training and testing. The result is a graphical visualization and the RMSE value. The experimental flow is shown in Fig. 2.

B. *Gated Recurrent Unit (GRU) Algorithm*

The GRU was first proposed in 2014 [24]. GRUs are similar to LSTMs but are simpler to compute and implement. The GRU cell structure is shown in Fig. 3. The GRU cell generally consists of two gates: the reset gate, *r*, and the update gate, *z*. Like the LSTM cell, the hidden state output at time *t* is calculated using the hidden state at time *t*-1 and entering the time series value at time *t*, as presented in (7). The reset gate function is similar to the LSTM forget gate since the GRU has some similarities to the LSTM.

$$h_t = f(h_{t-1}, x_i). \tag{7}$$

C. *Combination of LSTM and GRU Hidden Layers*

There are three layers in machine learning: input, hidden, and output layers. In this paper, four hidden layers were used, using a combination of LSTM and GRU for each layer [25], [26]. This layered design forms six models for each dataset, as shown in Table I.

The success of DNNs is generally attributed to the hierarchies introduced due to multiple layers. Each layer processes some part of the task to be completed and passes it on to the next section. In this sense, DNN can be seen as a processing pipeline, i.e., each layer completes a part of the task before passing it on to the next part until, finally, the last layer provides output [27]. Fig. 4 is an illustration of the hidden layer combination for model 5.

TABLE I
HIDDEN LAYER DESIGN FOR SIX MODELS

Hidden Layer	1	2	3	4
Model 0	LSTM	LSTM	LSTM	LSTM
Model 1	GRU	GRU	GRU	GRU
Model 2	LSTM	LSTM	GRU	GRU
Model 3	GRU	GRU	LSTM	LSTM
Model 4	LSTM	GRU	LSTM	GRU
Model 5	GRU	LSTM	GRU	LSTM

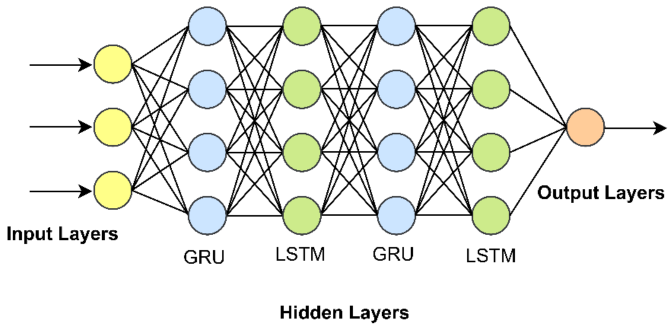

Fig. 4 Hidden layer design (model 5).

D. *Root Mean Squared Error (RMSE) and Mean Square Error (MSE)*

RMSE is the square root of the value obtained from the mean square error (MSE) function. Using RMSE, it is easy to plot the difference between the estimated value and the actual value of a model parameter. The formulas for RMSE and MSE are shown in (8) and (9).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_1 - \widehat{y_1})^2}{n}} \tag{8}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_1 - \widehat{y_1})^2 \tag{9}$$

where

$\widehat{y_1}, \widehat{y_2}, \dots \dots, \widehat{y_n}$ = predicted values

INDONESIA

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df_v1=df.loc[df['Area']=='Indonesia'][['Item','Element','Year','Unit','Value']]
df_v1
```

	Item	Element	Year	Unit	Value
1095162	Buffaloes	Stocks	1961	Head	2.893281e+06
1095163	Buffaloes	Stocks	1962	Head	2.803000e+06
1095164	Buffaloes	Stocks	1963	Head	2.836000e+06
1095165	Buffaloes	Stocks	1964	Head	2.836000e+06
1095166	Buffaloes	Stocks	1965	Head	2.951000e+06
...	...	...	...	...	...
1107637	Swine	Emissions (CO2eq) (Manure management)	2016	gigagrams	1.226370e+03
1107638	Swine	Emissions (CO2eq) (Manure management)	2017	gigagrams	1.262807e+03
1107639	Swine	Emissions (CO2eq) (Manure management)	2018	gigagrams	1.325453e+03
1107640	Swine	Emissions (CO2eq) (Manure management)	2030	gigagrams	1.188199e+03
1107641	Swine	Emissions (CO2eq) (Manure management)	2050	gigagrams	1.276329e+03

12480 rows × 5 columns

Fig. 5 Raw data of manure management (source: *fao.org*).

$y_1, y_2, \dots \dots \dots \dots, y_n$ = observed values
n = the number of data observed

E. RMSProp Optimizer

The root means squared propagation (RMSProp) optimizer is similar to the gradient descent with momentum algorithm. RMSProp limits the oscillation to the vertical direction. It can increase learning speed and algorithms and take more significant steps in the horizontal direction that quickly converge. The difference between RMSprop and gradient descent is in how the gradient is calculated.

Parameter determination is needed for the compilation process and handling and training network. RMSprop is used to train the loss function and network in evaluating the network minimized by the algorithm. The next step is determining the metrics to be collected while adjusting the model in addition to the loss function.

F. Streamlit

This paper used the Streamlit graphical user interface (GUI). Streamlit is a web framework aimed at efficiently deploying models and visualizations using the Python language, which is fast and minimalistic but has a decent interface and is user-friendly. There are built-in widgets for user input, such as image uploads, sliders, text input, and other familiar hypertext markup languages (HTML) elements, like checkboxes and radio buttons. Whenever a user interacts with a Streamlit application, the Python script is rerun from top to bottom. It is an important concept to keep in mind when considering the various application states to choose.

Streamlit is a free application, and users do not need to have advanced front-end development knowledge to operate it. It can run on the Anaconda editor and Python 3.7 series and above. Still, it does not support the Jupyter Notebook editor, so it must be converted to a Pycharm or Visual Code editor. The homepage display in the Streamlit application can be separated into two parts, namely buttons for menu selection and visual chart display. It necessitates the use of the NumPy and Pandas libraries in order to display graphics. The graph output is in line with the machine learning method data processing results using a combination of LSTM and GRU hidden layers. Buttons function to select datasets from country categories, animal types, hidden layer architecture, optimizer, as well as options for epochs and predictions in the next few years.

III. RESULT AND DISCUSSION

Machines are capable of learning from time-series data. Therefore, a training dataset of 70% to 80% of the total dataset was taken from the existing datasets. Furthermore, from the learning outcomes, the machine was tested to predict the testing dataset (20% to 30%). The prediction results of the testing dataset were measured for the error value with the value of the actual testing dataset (target data). The error value obtained was used to correct (update) the weight value. The new weight value was used in the prediction of the next iteration.

The raw manure management data was obtained from *fao.org*. The food and Agriculture Organization (FAO) works with other countries to overcome hunger and poverty and reduce the effects of climate change. The data taken was annual data, from 1961 to 2021, containing 12,480 rows. The process and results of data extraction from *fao.org* are shown in Fig. 5. This raw data consists of five column features: item, element, year, unit, and value.

Fig. 6 is the graph of CO_2eq emissions from 1961 to 2018 for all livestock. Of the fifteen livestock, the highest emission data were selected: cattle, non-dairy cattle, and poultry birds. Another factor used in determining these three objects is references from research that has been carried out, which took samples from 25 cattle farms in the Netherlands from 2006 to

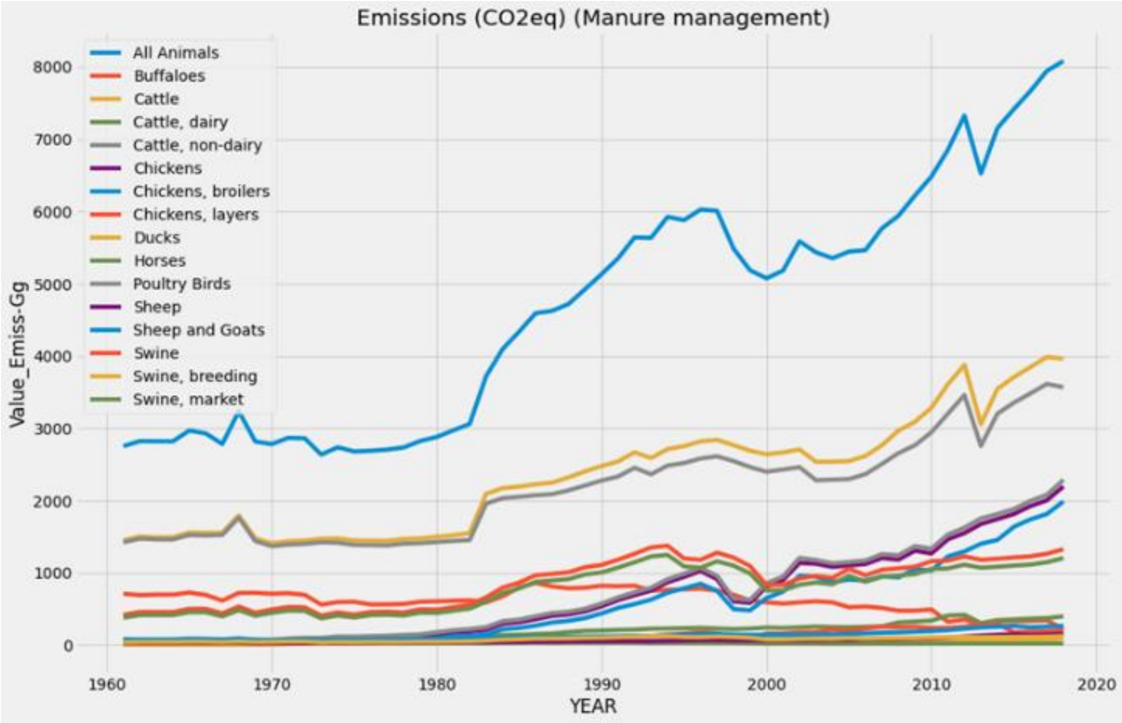

Fig. 6 CO_2eq emissions in Indonesia by animal.

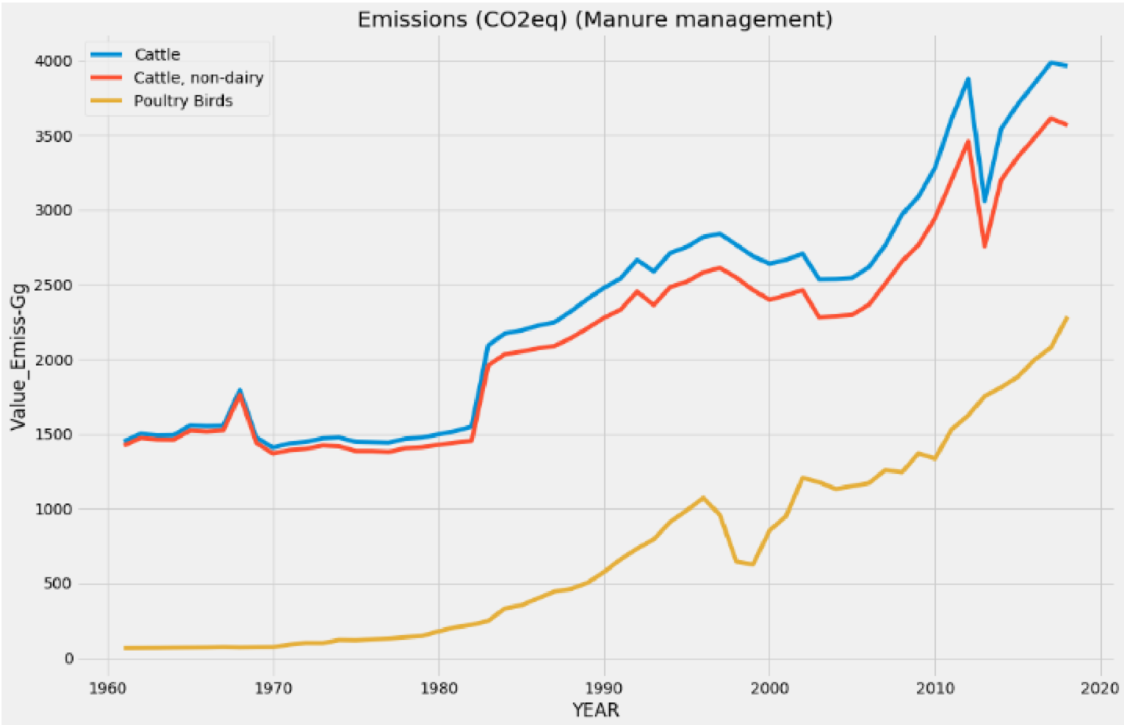

Fig. 7 CO_2eq emissions in Indonesia by high emitter.

2018 [16]. Another study took objects on farms in Northern Germany [28].

Fig. 7 shows the trend of increasing CO_2eq emissions from the three most dominant livestock, namely, cattle, non-dairy cattle, and poultry birds. Indonesia has made numerous efforts to achieve the Sustainable Development Goals (SDGs) and the Paris Agreement goals. Several innovative policies and actions have been issued to change food and land-use systems in order to reduce GHG emissions, conserve and restore biodiversity, promote healthy diets, adapt to climate change, and meet other environmental constraints [29].

The increase in GHG has an impact on increasing the average temperature of the earth, which can lead to climate change, trigger disasters with more frequent and greater

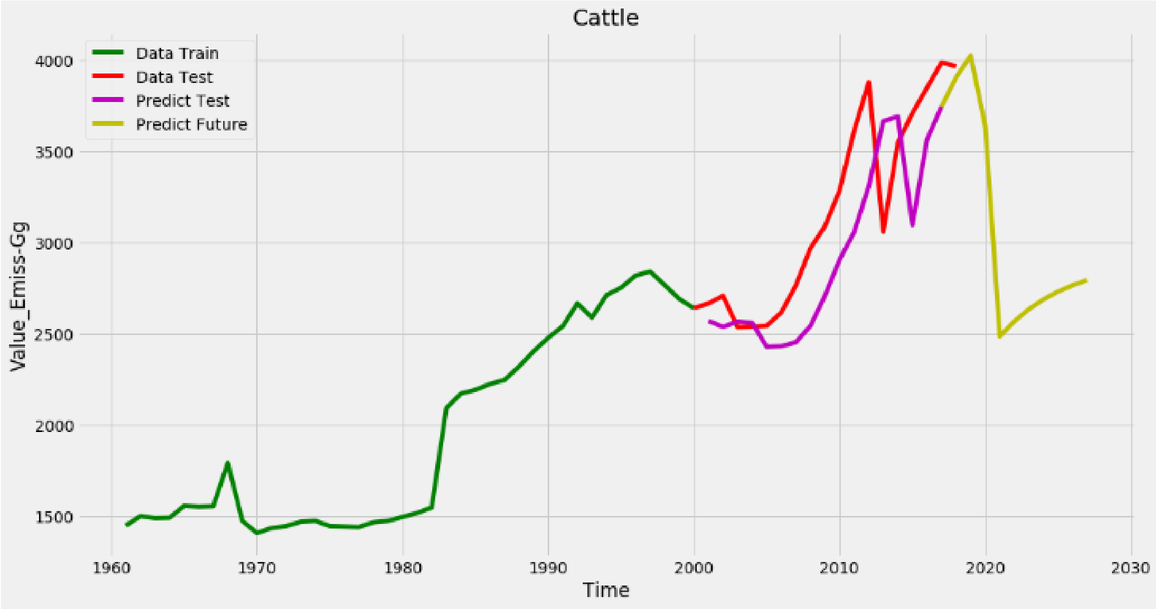

Fig. 8 Predict future cattle.

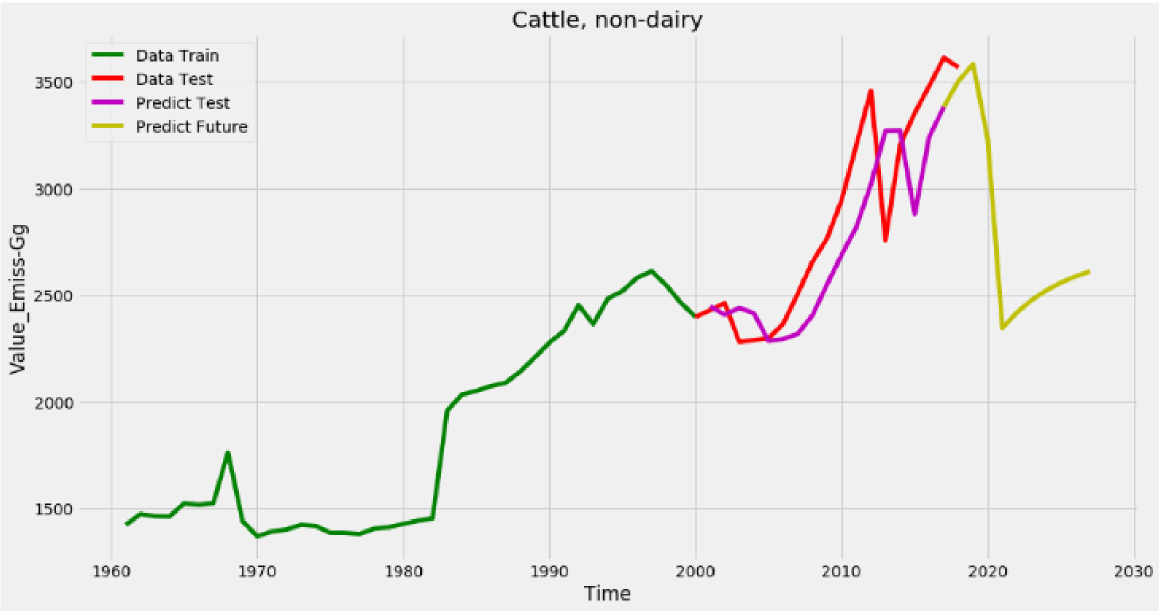

Fig. 9 Predict future non-dairy cattle.

frequency. It can threaten the sustainability of global ecosystems [30]. The IPCC has stated that global warming will impact various aspects of the economy and development, especially in developing countries, including Indonesia. As the largest archipelagic country with extensive lowlands and small islands, Indonesia is one of the most vulnerable countries to the negative impacts of climate change. Indonesia faces the risk of losing small islands and narrowing coastal areas due to rising sea levels that will threaten cities along the coastline [29].

The optimization results of the hidden layer combination of manure management from the cattle category are as follows. As seen in Fig. 8 and Table II, with ten epochs using layer four of the mixture (LSTM, GRU, LSTM, GRU), the resulting RMSE is 425,170. The characteristics of the epoch are a challenge for machine learning methods that have been tested with relatively little data [31]. The future prediction chart shows a downward trend, starting from 2019 to reaching the lowest point in 2021. In 2021, it was the second year of the pandemic. The Indonesian economy experienced a positive trend [32]. Seen in the graph of CO_2eq emissions, there is an increase (predictive graph)

TABLE II
OPTIMIZATION OF CATTLE HIDDEN LAYER COMBINATION

Combination of Hidden Layers	Epoch	RMSE
LSTM, GRU, LSTM, GRU	5	956.065
	10	**425.170**
	15	436.719
	20	586.875

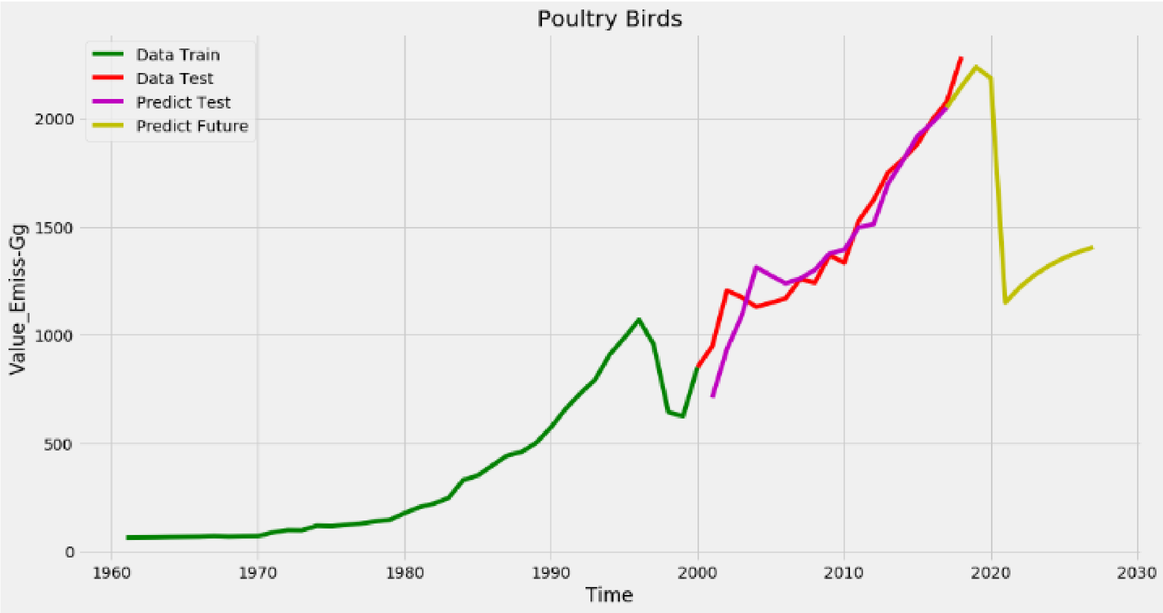

Fig. 10 Predict future poultry birds.

TABLE III
OPTIMIZATION OF HIDDEN LAYER COMBINATION OF NON-DAIRY CATTLE

Combination of Hidden Layers	Epoch	RMSE
GRU, GRU, GRU, GRU	5	550.549
	10	369.885
	15	**360.848**
	20	367.339

TABLE IV
OPTIMIZATION OF HIDDEN LAYER COMBINATION OF POULTRY BIRDS

Combination of Hidden Layers	Epoch	RMSE
GRU, GRU, LSTM, LSTM	5	969.337
	10	345.169
	15	**325.145**
	20	375.852

followed by improving economic conditions (the need for animal nutrition in the community increases) [33].

The results of the optimization of the hidden layer combination of manure management from the non-dairy cattle categories with fifteen epochs and one layer (GRU, GRU, GRU, GRU) with an RMSE value of 360.848 are shown in Fig. 9 and Table III. Predictions in 2020 show a reduction in CO_2eq emissions by up to 50%. It is possible due to the pandemic declared in early March 2020. One of the factors for the decline in people's purchasing power during the pandemic was the soaring price of beef and the increase in the rupiah exchange rate, which reached Rp17,000 [34].

The optimization of the hidden layer combination of manure management from the poultry birds category is shown in Fig. 10 and Table IV, with fifteen epochs and three layers (GRU, GRU, LSTM, LSTM) with an RMSE value of 325.145. One of the categories of poultry birds is broilers. At the beginning of the pandemic, the price of broilers fell drastically, far below the cost of goods sold (COGS). The contributing factors are panic selling and large-scale social restrictions (LSSR) [35]. This drastic reduction in public consumption reduces CO_2eq emissions from the poultry birds sector.

Fig. 11 is an artificial intelligent manure management dashboard. This user interface makes it easy for users to view simulations and predictions of GHG emissions in Indonesia. The calling of the Streamlit dashboard is done using Anaconda Prompt, tested on localhost computing.

IV. CONCLUSION

The experimental results show that, machine learning methods using a combination of hidden layers can perform simulations and predictions in the future for GHG mitigation options in manure management. Of fifteen livestock that emit GHG emissions, three livestock emitting the highest emissions from 1961 to 2021 are cattle, non-dairy cattle, and poultry birds. The significant reduction in CO2eq emissions in 2020 was caused by lower public consumption as a result of supply chain constraints caused by PSBB (COVID-19 pandemic policy).

This experiment is expected to add value to the development of better decision support tools and models for assessing emission trends in the livestock sector. This paper may also contribute to the development of CO2eq emission mitigation strategies during manure storage, resulting in more sustainable fertilizer management practices. The difficulty in using machine learning to process data is that the data is relatively large, whereas this secondary data is only 58 rows for each farm animal. Characteristics with limited data are linear, with RMSE results that are not yet optimal. The use of primary datasets from several farms can be an option to add input to machine learning methods.

The development of machine learning methods and other optimizers needs to be tested in further research to obtain optimal results. To compare trends in CO2eq emissions and determine future mitigation measures, datasets from different

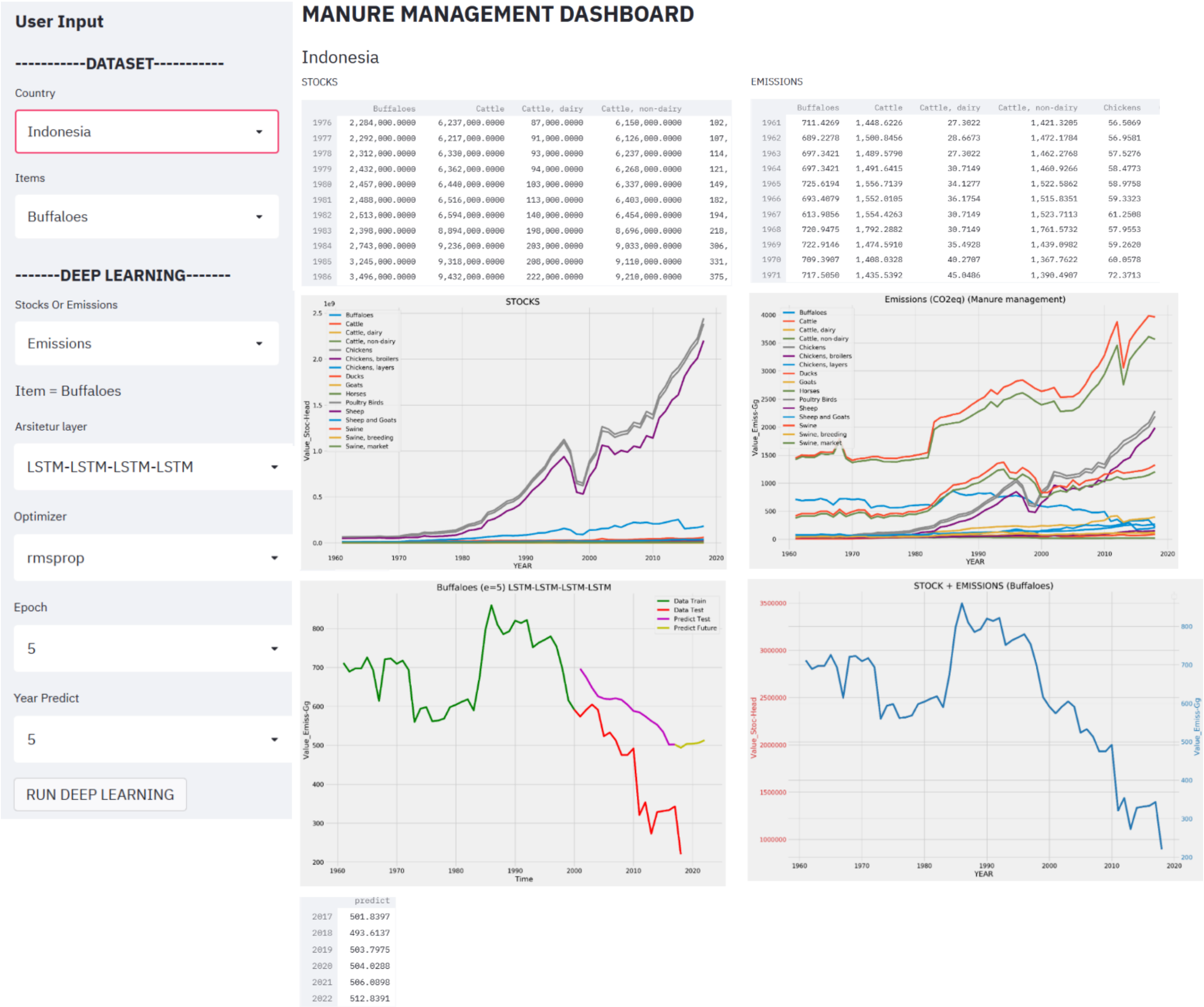

Fig. 11 Streamlit user interface.

countries with an equivalent level of classification of gross national income (GNI) must be processed.

Conflict of Interest

The author declares that there is no conflict of interest.

Author Contribution

Conceptualization, Widi Hastomo and Nur Aini; methodology, Widi Hastomo and Adhitio Satyo Bayangkari Karno; software, Widi Hastomo and Adhitio Satyo Bayangkari Karno; formal analysis, Widi Hastomo and L.M. Rasdi Rere; investigation, Widi Hastomo and Adhitio Satyo Bayangkari Karno; validation, L.M. Rasdi Rere and Nur Aini; data curation, Widi Hastomo and Adhitio Satyo Bayangkari Karno; the original draft, Widi Hastomo, Nur Aini, Adhitio Satyo Bayangkari Karno and L.M. Rasdi Rere; writing-reviewing and editing, Widi Hastomo, Adhitio Satyo Bayangkari Karno, Nur Aini and L.M. Rasdi Rere; visualization, Widi Hastomo and Adhitio Satyo Bayangkari Karno; supervision, L.M. Rasdi Rere; project administration, Nur Aini; acquisition of funding, Widi Hastomo and Nur Aini.

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