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FORECASTING EGG PRICES WITH CONVOLUTIONAL LONG SHORT-TERM MEMORY IN INDONESIA'S HIGH STUNTING PREVALENCE PROVINCE

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ABSTRACT

By 2030, to end all forms of malnutrition, targeting stunting and wasting in children under 5 years of age is one of the targets from Goal Number 2 in the SDGs. In Indonesia, one of the provinces with the highest stunting rate is East Nusa Tenggara, with a rate of 35.3%. One affordable source of protein and nutrition used as a solution to overcome malnutrition problems such as stunting is eggs. In this paper, we want to predict the egg price, which is a source of affordable protein in Indonesia. Weekly egg price modeling was carried out from 2018 to 2023 using Convolutional Long Short-Term Memory (LSTM). This study only used components such as the Adam optimizer, ReLU activation function, and Huber loss function, with a batch size and 32 neurons for Convolutional LSTM. This study also finds that the MAPE value obtained from the model is relatively small, with MAPE for training, validation, and testing of 1.97%, 1%, and 1.19% respectively. We forecast the prices for a 5-week period from December 11, 2023, to January 8, 2024. It shows that egg prices tend to continue to decline per week. Thus, we can say that a decrease in egg prices can be a good thing in providing more affordable nutrition for the community.

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1. INTRODUCTION

The Sustainable Development Goals (SDGs) are a series of 17 goals fixed by the United Nations and adopted by 193 countries in 2015. Through sustainable (economic, environmental, and social) development, their overall objective is to create a better world and a better life for all by 2030. Every year from 2016 until now, a report on the progress of the SDGs is conducted; one of the SDGs Goals we consider in this research is Goals Number 2: zero hunger [1]. The problem of hunger and food insecurity globally has shown an alarming increase since 2015, a trend aggravated by a combination of factors, including pandemics, conflict, climate change, and deepening inequality. By 2022, an estimated 735 million people, or 9.2% of the world's population, will be chronically hungry, a staggering increase compared to 2019. This data underscores the severity of the situation and points to a growing crisis [2].

One of the targets of SDG 2 is malnutrition (SDG 2.2), which aims to end all forms of malnutrition by 2030, including achieving internationally agreed targets on stunting and wasting in children under 5 years of age by 2025 and meeting the nutritional needs of adolescent girls, pregnant and lactating women, and the elderly [3]. There are 3 indicators in achieving SDG 2.2: (1) the prevalence of stunting by height in children under 5 years of age (SDG 2.2.1), (2) the prevalence of malnutrition by weight in children under 5 years of age (SDG 2.2.2), and (3) the prevalence of anemia in women aged 15 to 49 years based on pregnancy status (SDG 2.2.3). [4]. Based on Ty Beal et al. (2018), 'A review of child stunting determinants in Indonesia,' during the last decade, Indonesia has a high prevalence of child stunting, around 37% nationally [5]. Indah et al. (2018), 'Determinants of Stunting in Indonesia: A Review Article,' state that stunting is a social health problem that needs to be addressed seriously, especially considering the stagnation of stunting cases around 36.8% (2007) to 37.2% (2013) in Indonesia. Indonesians often consider their height or shortness to be hereditary. This incorrect perception requires serious attention from the community, government, and relevant authorities. Research shows that heredity only contributes 15%, while the largest factors are related to nutrition, growth hormones, and recurrent infections. Cigarette smoke and air pollution also influence stunted growth. Malnutrition as a direct factor, especially in children under five years old, has a short-term impact of increasing morbidity. This nutritional problem is chronic and will have an impact on cognitive function, such as low intelligence levels and the quality of human resources [6]. According to [7], 'Energy and protein intakes are associated with stunting among preschool children in Central Jakarta, Indonesia: a case-control study,' an experiment was conducted by conducting a case-control study design with a total sample of 121 children aged 25-30 months in Gambir and Sawah Besar sub-districts, Central Jakarta, where the prevalence of stunting is high. All children were exclusively breastfed for at least four months and had similar socioeconomic levels. Results showed that children with insufficient energy and protein intake had a higher risk of stunting compared to children with adequate intake. The percentage of children who had energy and protein intake below the recommendation was higher in the group of stunted children. Therefore, nutritional intake, especially energy and protein intake, is very important in preventing stunting. It is important to ensure that macronutrient intake is sufficient every day to prevent stunting in children.

Eggs are an economically affordable source of high-quality protein. In addition, eggs also contain essential vitamins and minerals necessary for a healthy diet and a healthy life. It is estimated that by 2050, the world's population will reach 9 billion people, with the highest population growth rates occurring in regions that suffer the most from food hunger. Eggs are considered part of the solution to overcoming nutritional problems in various parts of the world that are still experiencing undernutrition [8]. According to [9], 'The Impact of Increased Prices of Eggs on Consumer Purchases in Klaten Regency, Central Java, Indonesia,' aims to evaluate the impact of rising egg prices on consumer decisions and purchases. 57.5% of consumers decided to reduce the number of eggs purchased when egg prices increased, while 42.5% continued to purchase the same number of eggs. This shows that egg prices affect egg purchases, which in turn affects egg consumption levels.

Based on the Indonesian Nutrition Status Survey (SSGI) conducted by the Ministry of Health, see Figure 2, it was revealed that in 2022, the prevalence of stunting in children under five in Indonesia reached 21.6%. It has decreased by 2.8 points compared to the previous year. One of the provinces in Indonesia with the highest stunting rate is East Nusa Tenggara, with its rate of 35.3%. Even though it remains the highest, it has decreased from 2021, which amounted to 37.8% [10]. Therefore, in this research, egg price forecasting will be carried out, especially in EAST NUSA Tenggara, using the Convolutional LSTM to model the movement of egg prices in it for the next 5 weeks. In this paper, we highlight the importance of predicting the egg price as a source of affordable protein by using an LSTM-based model, ConvLSTM. The Convolutional LSTM (ConvLSTM) was proposed by [11] for the task of precipitation nowcasting. In this architecture, the matrix multiplication within the LSTM cell is replaced with a convolutional operation. It has been used in various kinds of research, the temperature dataset in Jakarta using ConvLSTM to forecast a 7-day scenario and perform 0.4113, 0.3277, and 0.9774 for RMSE, MAE, and CC, respectively [12]. [13], [14] showed that the forecasting accuracy of the ConvLSTM on a daily scale had surpassed the LSTM, CNN-LSTM, SVR, and MLP models. [15] compared the LSTM model to the casual backpropagation model (BP model) in the Kelantan River, Malaysia. The results showed that the LSTM model accurately predicted the Kelantan River's streamflow in either rainy or dry seasons. Based on previous research, this research aimed to show the results of ConvLSTM to predict the egg price in East Nusa Tenggara. By splitting the dataset into three parts, which are the training set, validation set, and testing set, the accuracy of each set is measured by the metric evaluation used in this research.

2. RESEARCH METHODS

In this section, the research method will be explaining the descriptions of the data sources and data analysis conducted by the researcher.

2.1 Research Dataset

The data is in time series form and is a secondary dataset from the National Strategic Food Price Information Centre (PIHPS). We used chicken egg prices in East Nusa Tenggara from January 8, 2018, to December 4, 2023. Initially, the data exploration was conducted to examine the data patterns descriptively and visually.

Table 1. Statistical Summary of Egg Price in East Nusa Tenggara

Statistical Measure	Egg Prices
Mean	29228.83
Standard Deviation	2954.73
Minimum	24300
Maximum	37300

Data source: https://www.bi.go.id/hargapangan/TabelHarga/PasarTradisionalDaerah

Based on **Table 1**, it is found that the highest egg price is IDR 37,300 the lowest price is IDR 24,300 and the average price is IDR 29,228.83 with a standard deviation of IDR 2,954.73.

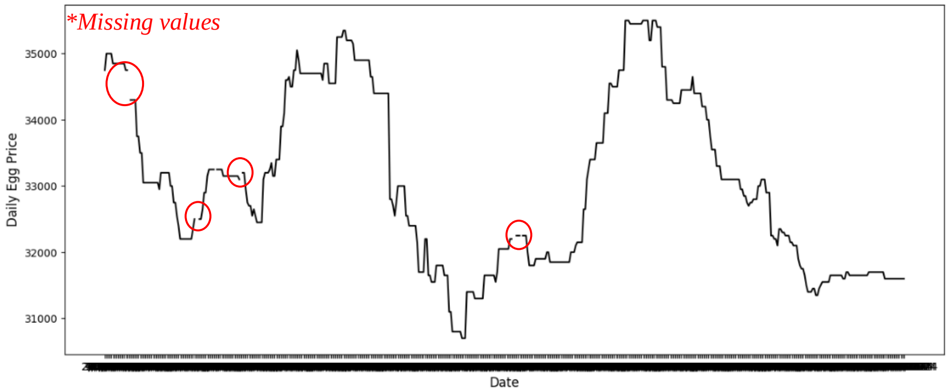


Figure 1. Daily Egg Price Time Series Plot in East Nusa Tenggara with Missing Values

From **Figure 1**, it can be observed that egg price in East Nusa Tenggara fluctuates, and there are some discontinuous lines. This indicates the presence of missing values in some time observations. Therefore, preprocessing is needed to fill in these missing data.

2.2 Research Design

In this study, the ConvLSTM modeling is used to forecast the egg price in East Nusa Tenggara. **Table 1** shows the summary of the data that contains 309 records of egg prices. Several steps need to be undertaken, which are:

a. Data preprocessing, handling missing data through interpolation, and splitting data into training, validating, and testing sets;

b. Modeling using ConvLSTM;

c. Evaluation of LSTM model metrics, which is MAPE;

d. Forecasting egg prices for the next 5 weeks.

2.2.1 Handling Missing Values

As a common occurrence in measured time-series datasets, missing values can be replaced using imputation methods to effectively improve the integrity of data. According to the common characteristics of missing values, the egg price dataset has an isolated missing value, which is the measured value of a variable that is missing in a data segment, but the neighboring values of the variable are known (as seen in **Figure 1**). The widely known interpolation methods include nearest neighbor, linear, and cubic spline interpolation. The cubic spline interpolation is the smoothest and most widely used method. The construction of a cubic spline interpolation function requires at least four neighboring known values; thus, two neighboring known values before and after $x_{i,j}$ are used as inputs **[16]**. According to **[17]**, the imputed value $\hat{x}_{i,j}$ can be calculated using an interpolation function f_{spline}.

$$\hat{x}_{i,j} = f_{spline}\left(x_{i-2,j}, x_{i-1,j}, x_{i+1,j}, x_{i+2,j}\right) \tag{1}$$

After handling the missing values, to prevent overfitting in the model, we divided the data into three parts: training data, validation data, and testing data. The proportions are 80% for training, 16% for validation, and 4% for testing.

2.2.2 Convolutional LSTM

Convolutional Long Short-Term Memory (ConvLSTM) is a variant of Long Short- Term Memory (LSTM) that integrates convolutional concepts, typically employed in models for processing spatial sequences, such as in image or video tasks. ConvLSTM combines ideas from LSTM with convolutional elements to preserve the spatial structure of input data **[11]**.

a. Forget Gate

$$f_t = \sigma\left(W_{fh} * h_{t-1} + W_{fx} * x_t + b_f\right) \tag{2}$$

The forget gate (f_t) determines how much information from the previous memory cell (c_{t-1}) should be forgotten. The $*$ symbolizes the convolution operation, where W_{fh} and W_{fx} are convolutional filters for the forget gate, and b_f is the bias vector.

b. Input Gate

$$i_t = \sigma(W_{ih} * h_{t-1} + W_{ix} * x_t + b_i) \tag{3}$$

The input gate (i_t) determines how much new information (g_t) will be accumulated into the memory cell.

c. Cell Candidate

d. $$g_t = tanh\left(W_{gh} * h_{t-1} + W_{gx} * x_t + b_g\right) \tag{4}$$

The cell candidate (g_t) is the new memory cell value that can be added to the current memory cell.

d. Update Cell State

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{5}$$

The update of the cell state (c_t) involves an element-wise multiplication operation $\odot$.

e. Output Gate

$$o_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t) \tag{6}$$

The output gate (o_t) determines how much information from the memory cell (c_t) will be revealed as the output (h_t).

f. Output

$$h_t = o_t \odot tanh\,(c_t) \tag{7}$$

This is the actual output at time step *t*, where $\odot$ denotes an element-wise multiplication operation.

2.2.3 Model Accuracy

Three common metrics used to measure the accuracy of a model in the context of statistical and machine learning modeling are Mean Absolute Percentage Error (MAPE). MAPE measures the average percentage error relative to the actual values. This metric is commonly used in a business context to assess the performance of a model in forecasting. Here is the mathematical formula for mean absolute percentage error [18].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{8}$$

3. RESULTS AND DISCUSSION

3.1 Prevalence of Stunting in Children Under Five in Indonesia

Based on the Indonesian Nutrition Status Survey (SSGI) conducted by the Ministry of Health, see **Figure 2**, it was revealed that in 2022, the prevalence of stunting in children under five in Indonesia reached 21.6%. It has decreased by 2.8 points compared to the previous year. WHO standards state that countries with stunting rates above 20% have chronic status.

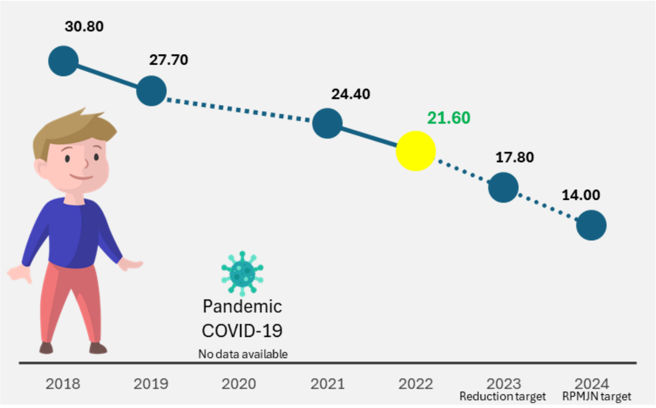


Figure 2. Indonesia's Stunting Prevalence
Source*: Indonesian Nutrition Status Survey Pocket Book 2022*

Prevalence is the total number of diseases in a certain population in a one-year period. Of the 33 provinces in Indonesia, only 11 provinces have a stunting rate below 20, as seen in **Figure 3**. Based on **Figure 2,** Indonesia targets that by 2024, the stunting prevalence rate will be 14%. Reducing the stunting rate from 21.6 to 14 by 2024 requires hard work from the government and society.

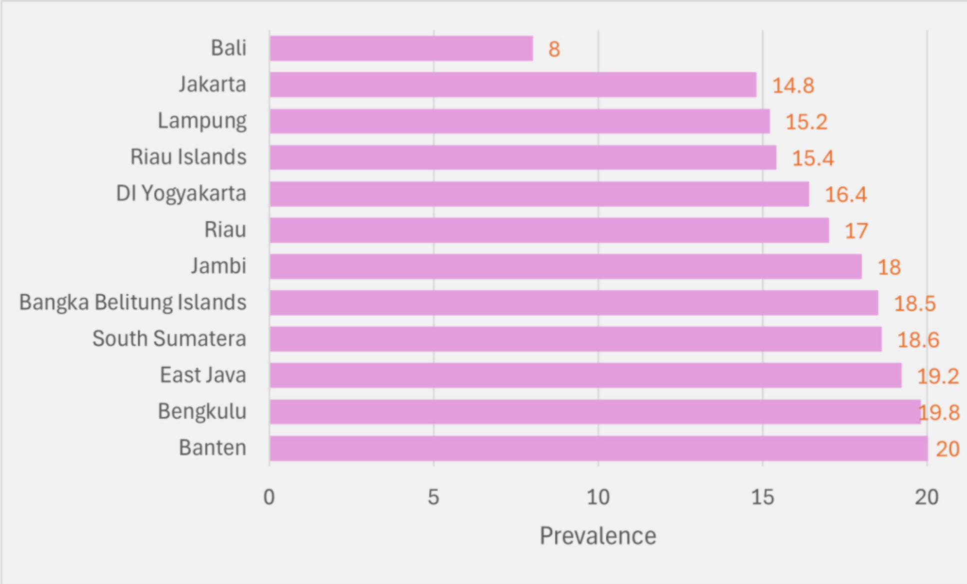


Figure 3. Eleven (11) Provinces with Stunting Prevalence ≤ 20
***Source**: Indonesian Nutrition Status Survey Pocket Book 2022*

3.2 Preprocessing Data

As seen in **Figure 1**, the egg price dataset has a total of 9 observations missing. The cubic spline interpolation is the smoothest and most widely used method, which we performed to estimate these missing data. After performing interpolation for missing data, the results plot is shown in **Figure 4**. Additionally, we split the data into three parts: training data (80%), validation data (16%), and testing data (4%). Data splitting is done to measure the accuracy of the model using MAPE.

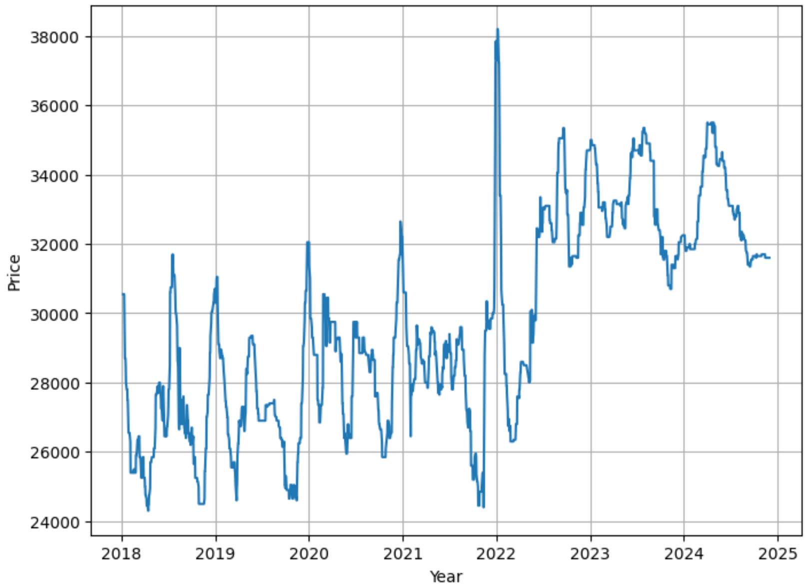


Figure 4. Time Series Plot Egg Price in East Nusa Tenggara Without Missing Values

3.3 Convolutional LSTM (ConvLSTM)

Convolutional LSTM is a neural network architecture that combines Convolutional layers and Long Short-Term Memory (LSTM) layers. This modeling using Convolutional LSTM is employed to predict chicken egg prices in East Nusa Tenggara Province. The components of the Convolutional LSTM model used are as follows.

Table 2. Components of the Convolutional LSTM Model

Optimizer	Activation	Batch Size	Loss Function	Neuron Size
Adam	RelU	32	Huber	32

The model consists of five layers. The first layer is Conv1D, with 32 filters designed to extract local features or identify specific patterns in the egg price data. The second and third layers are bidirectional layers, capturing temporal dependencies both forward and backward in the data. The fourth layer is a dense layer, a fully connected layer with 5 units. The final layer is a lambda layer responsible for generating the output values. The total number of parameters for this model is 4.437.

Table 3. Architecture of the Convolutional LSTM Model

Layer	Output (Shape)	Total Parameter
Conv1D	32	128
Bidirectional ke-1	16	2624
Bidirectional ke-2	16	1600
Dense	5	85
Lambda	5	0

From **Figure 6**, the graph shows that the loss has converged around Epoch 250. The losses for both training and validation are very close, indicating the absence of overfitting in this case. Additionally, both datasets have loss values approaching zero around Epoch 250. Therefore, the model is considered suitable for use as it has minimal loss values and no indications of overfitting.

After determining the complete architecture for ConvLSTM, we estimated egg price and compared it with the actual values in the training set. It has similar values that indicate the model has learned the patterns in the training set well. The same observation applies to the estimated results with the actual values in the validation set. Therefore, in the testing set, the predicted results with the testing set show quite similar outcomes, suggesting that the model performs well in predicting patterns from the testing data.

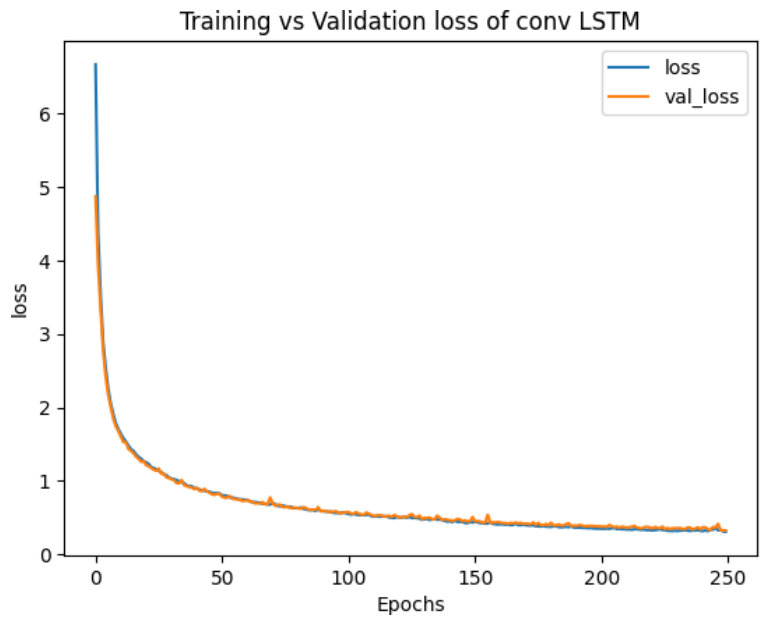
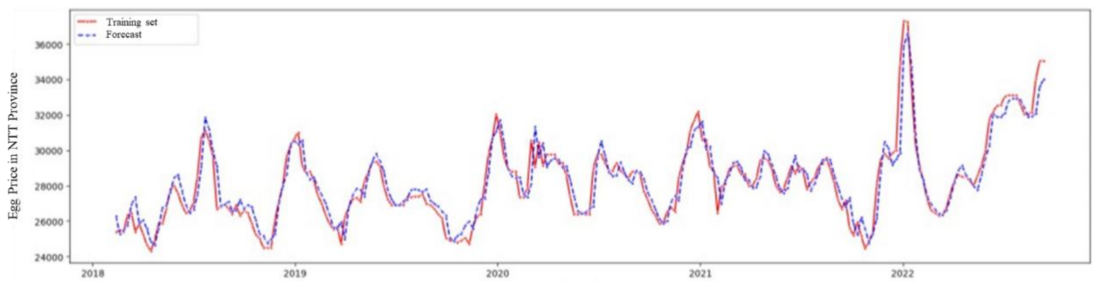
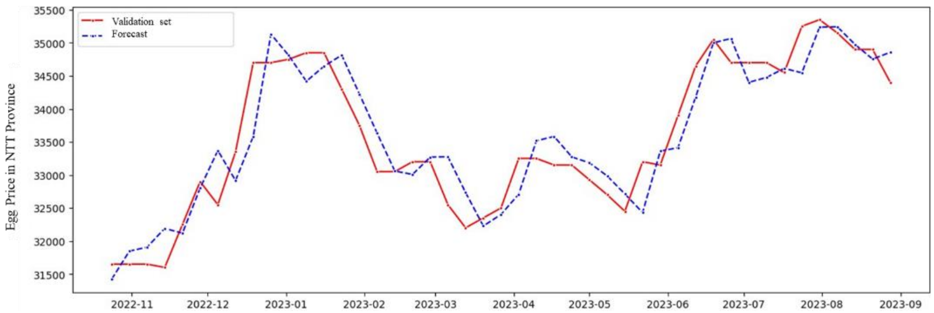


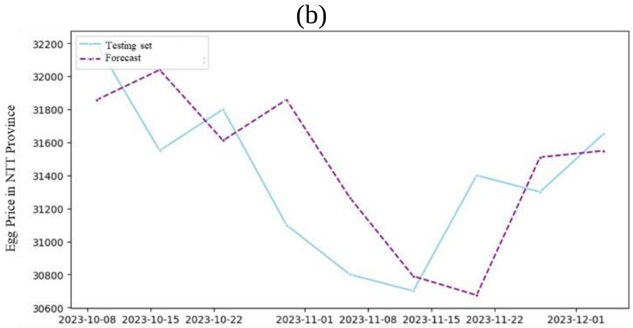
Figure 5. Training and Validation Loss Graph



(a)



(b)



(c)

Figure 6. Training and Validation Loss Graph, (A) Training Data, (B) Validation Data, (C) Testing Data

Accuracy metrics are used to measure the goodness of a model we built in the context of statistics and machine learning. From **Table 4**, it is observed that the MAPE values are relatively small for training, validation, and testing data. This indicates that the difference between predicted and actual values is relatively small, suggesting that the model is effective in predicting egg prices in East Nusa Tenggara.

Table 4. Accuracy Results for Training, Validation, and Testing Data

Data	MAPE
Training Data Accuracy	1.97%
Validation Data Accuracy	1%
Testing Data Accuracy	1.19%

3.4 Egg Price Prediction

After building the model using ConvLSTM, the next step is to forecast egg prices for the next 5 weeks in EAST NUSA Tenggara. The forecasting results are shown in the following **Table 5**.

Table 5. Accuracy Results for Egg Price Prediction

Date	Egg Price
December 11, 2023	31483.78
December 18, 2023	31154.10
December 25, 2023	31253.65
January 1, 2024	30641.43
January 8, 2024	30184.52

Forecasting egg prices for the next 5 weeks, namely on December 11, 18, and 25, 2023, and January 1 and 8, 2024, shows that the price continuously declines over time, even though there is a slight increase on 25 December 2023.

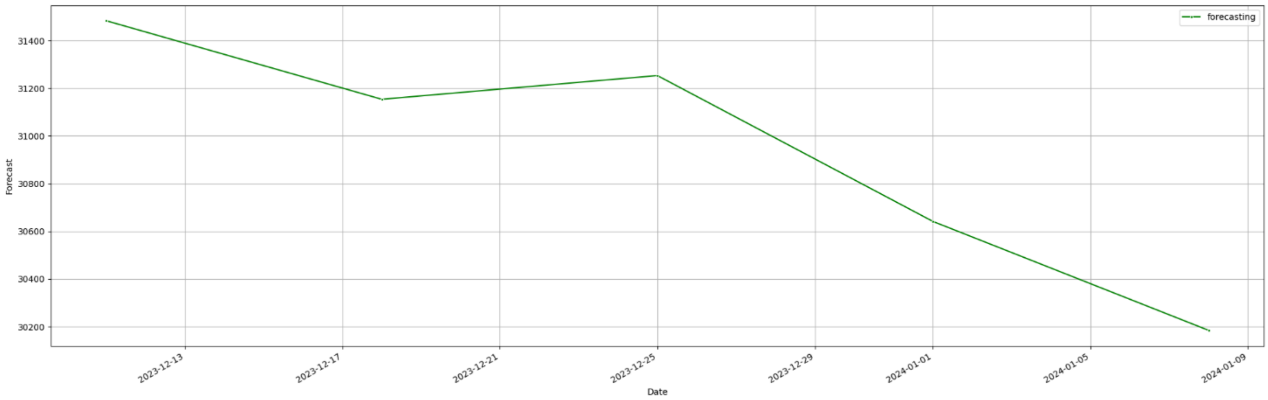


Figure 7. Forecasting Chicken Egg Prices in East Nusa Tenggara for The Next 5 Weeks

The overall chicken egg prices in East Nusa Tenggara from January 8, 2018, to January 8, 2024, can be seen in **Figure 7**. Thus, when we discuss the affordability of eggs for people around the highest stunting prevalence area, a decrease in egg prices can be a good thing in providing more affordable nutrition for the community.

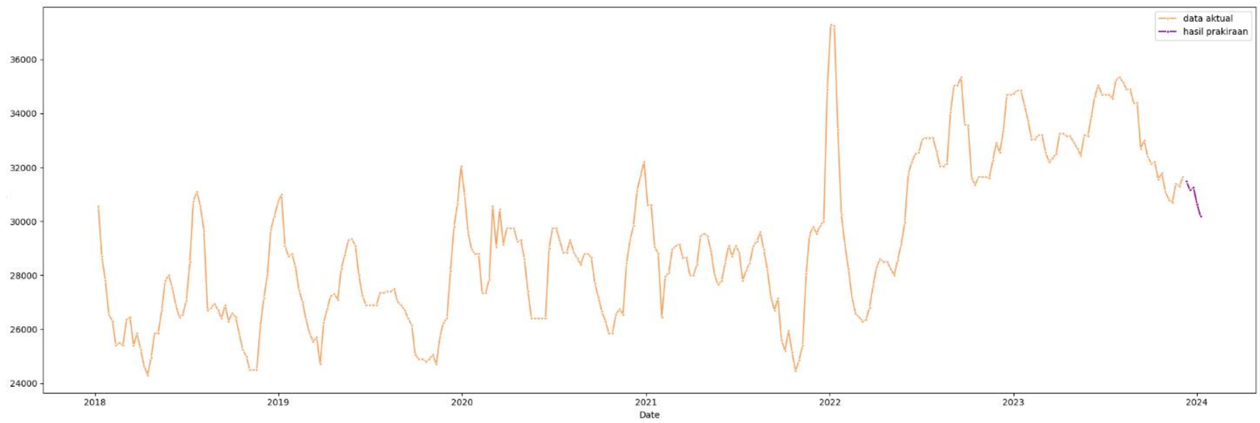


Figure 8. Chicken Egg Prices in East Nusa Tenggara: Actual Data and Forecast Results

Indonesia is an archipelagic country, making the availability of eggs in remote areas difficult, resulting in expensive egg prices. In fact, egg consumption by children is highly correlated with national egg availability, and both are a function of egg price. Therefore, production aggregation, with a minimum flock size of five thousand laying hens per farm, is a more promising way to increase availability in rural areas. Recent experience in countries such as Thailand confirms that this can be done and has impact **[19]**.

4. CONCLUSIONS

One of the provinces with the highest stunting rate in Indonesia is East Nusa Tenggara; its rate of 35.3% is way too far from the National Medium Term Development Plan (RPMJN) target, which is 14%. On the other hand, one of the affordable sources of high-quality protein in Indonesia is eggs. The modeling of egg prices in East Nusa Tenggara from January 8, 2018, to December 4, 2023, was conducted using Convolutional LSTM. It needs to be done so that the government has an image of egg prices, which will later be used for decision-making. From the forecasting results, we can conclude that for the next 5 weeks, December 11, 2023, to January 8, 2024, showed a consistent decrease. The decline in egg prices is expected to positively impact the accessibility of nutritious food for the community, contributing to improved public health and addressing health issues related to malnutrition, such as stunting.

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