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Nowcasting of Chili Pepper (*Capsicum frutescens* L.) Prices in East Java Province Using Multi-Layer Perceptron Method

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Abstract. The aims of study is to predict the price of chili pepper at the provincial level in East Java by looking for the best input variable from three types of input variables, price of chili pepper at the regency and city levels, natural factors, and word search index on Google Trends as an approach to the causes of chili pepper price fluctuations. The Multi-Layer Perceptron method, accompanied by a search for the best combination of model parameters is selected to get the model with the best nowcasting ability. The result shows that the best model for nowcasting is characterized by: the input variable is price of chili pepper at the regency and city levels with three hidden layers and 32, 45, and 51 neurons in each hidden layer, maximum iteration is 200 iterations, maximum iteration when the model not increase in performance for applying early stopping is 20 iterations, non-linear activation used is RELU (Rectified Linear Unit), and optimization function used is ADAM optimizer. The accuracy of nowcasting in this study is highly accurated with MAPE smaller than 10%.

1. Introduction

East Java is one of the provinces with the highest consumption of chili in Indonesia, especially in commodity chili pepper. According to BPS data from 2014 to 2018, the lowest consumption of chili pepper was 2.08 kg/capita/year in 2014, while the highest was 4.2 kg/capita/year in 2016 [1]. Increasing of consumption rate is accompanied by a high population as well. In 2020, East Java was 6th ranked with the highest per capita chili pepper consumption, 2.061 kg/capita/year, below Gorontalo, North Sulawesi, Lampung, Bali and Central Sulawesi. [2]. Even though it is 6th ranked, the population of East Java is far more than the provinces that ranked above it. In 2020, the total chili pepper consumption in East Java reached 5.5% of national production [3] [4]. High chili consumption means high demand, that will lead to plummeting chili price, and harm the consumer ability to buy the product. Therefore the adequate production quantity is needed to balance the demand side of the chili.

The Department of Industry and Trade (Disperindag) of East Java is responsible to monitor the price of chili pepper in East Java. Chili is one of the main groceries that mentioned in Presidential Regulation (PERPRES) Number 71 Year 2015, hence the government has important role to make sure that people can have chili in their daily meal. Chili has proven as main contributor to inflation in Indonesia, especially in East Java [5]. Every day, they calculate the average chili prices from all regencies and cities in East Java to get provincial-level chili price data and publish it in SISKAPERBAPO (Sistem Informasi Ketersediaan dan Perkembangan Bahan Pokok) website. The big difference of chili pepper production is the leading cause of the big price difference between regencies and cities. For example, in March 2019, Blitar City produced 13,865 quintals of chili pepper, and Pasuruan Regency only produced

65 quintals [6]. An example of a big price difference occurred on February 12, 2020. The price of chili pepper in Lumajang Regency was 43,333/kg, while in Probolinggo Regency was 68,000/kg, even though the two areas are neighboring regency. The data shows that the fluctuation of chili price between region and provincial level is correlated. So, provincial level chili price is important to predict the fluctuation of chili price in regency and city level. The data that regency and city level is correlated with provincial level chili price shown in Figure 1.

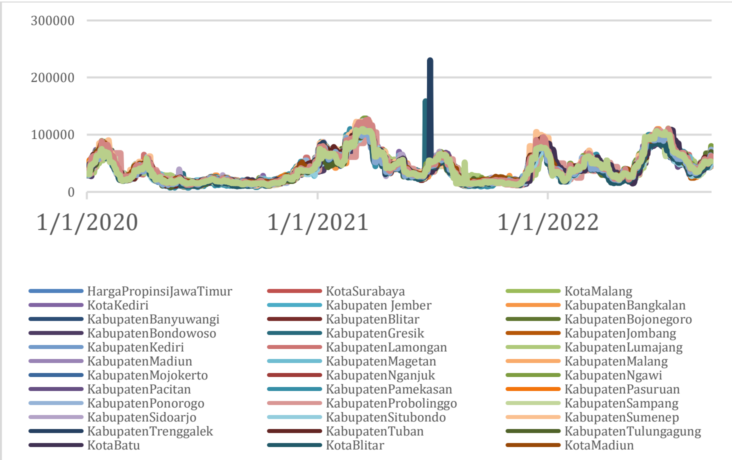

Figure 1. Graph of Chili Pepper Price in Provincial, Regency, and City Level in East Java

According to the Central Bureau of Statistics (BPS), the development of chili commodities is constrained by four issues, one of that is weather/climate/natural factors [6]. Chili is a plant that is highly affected by the weather [7]. The harvested area and production of chili are greatly affected by it. Therefore, the availability of chili pepper in the market becomes unstable, and the price fluctuates. For example, on May 2020, the Meteorological, Climatological, and Geophysical Agency (BMKG) said that many regions in East Java entered the rainy season, and production dropped. On the contrary, on October 2020, production rise because the weather was dry. In Figure 2, the fluctuations of chili pepper production in 2020-2021 are presented from the publication titled "Horticultural Statistics" for 2020 and 2021 by BPS [8], [9]. Figure 3 shows the provincial chili pepper prices from January 1, 2020, to September 17, 2022.

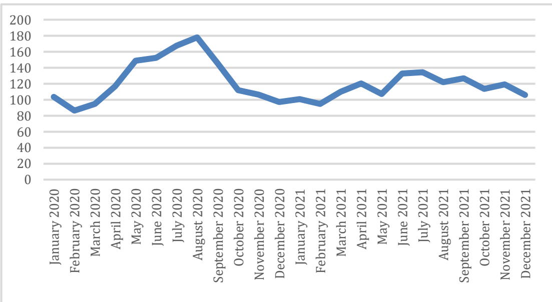

Figure 2. Production of Chili pepper in East Java, 2018 – 2020 [8], [9]

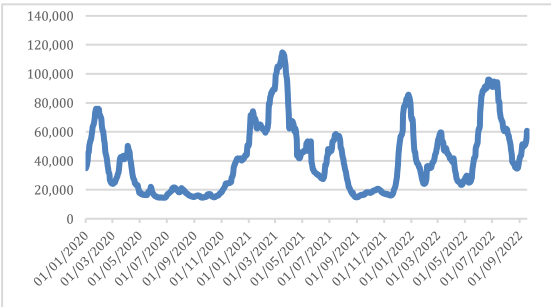

Figure 3. Graph of Provincial Level Chili Pepper Prices from 1 January 2020 to 17 September 2022 [10]

The household sector is the largest chili pepper consumer when compared to other sectors. According to the Head of the East Java Agriculture and Food Security Office, in 2022 the chili pepper demand for households is around 85%-90% while industrial demand is only 10%-15% of total production [11].

However, the household consume fresh chili pepper, not processed or preserved [6]. Therefore, this phenomenon is prone to oversupply and overdemand.

Chili pepper price usually causes inflation and deflation in East Java. The Official Statistics News (BRS) of East Java in June 2022 reported that this commodity was the main cause of inflation with a share of 19% and the percentage of change in price is 88.21%. [5]. Apart from the provincial level, chili pepper also caused inflation in 6 cities where the Consumer Price Index (CPI) is calculated in there, namely Banyuwangi, Sumenep, Kediri, Malang, Probolinggo and Madiun in January 2020 [12]. Not only causing inflation, in May 2020, chili pepper was the main cause of deflation in East Java particularly in Probolinggo Regency and Surabaya City [13].

According to the Ministry of Agriculture's Strategic Plan (RENSTRA) for 2020-2021, chili is an important commodity for maintaining food security, hence the price stabilization is needed to prevent inflation. [2]. According to Presidential Regulation (PERPRES) Number 71 Year 2015, chili is a basic commodity for agricultural products whose the availability and price must be controlled. [14]. But, the Department of Industry and Trade of East Java Province, which is responsible for monitoring the price of chili pepper, sometimes has delay in monitoring it (from SISKAPERBAPO website).

Especially when compared to the consumer habit in East Java. Most people shop in the morning until around 12 AM while the price data is usually completely collected around 2 PM. This time gap, makes the government difficult to take immediate action needed to stabilize the prices. The data should available in daily period because chili pepper price is very fluctuative in daily range, the fact is shown in Figure 3.

In order to solve this problem, our research applies nowcasting with Artificial Neural Network (ANN) named Multi Layer Perceptron (MLP). The method is chosen because of its reliability. Pardede and Herawan [15] summarized 30 journals regarding classification and prediction using MLP and the results showed that the best performance has an accuracy of 100%, the lowest is 62.89%, and the average accuracy is 91.98%. If we compare with clasical method, machine learning is very experienced to handle big data, especially a task that need a complex calculation. Especially, Multi Layer Perceptron has ability to map input variable patterns and generalize them so as to minimize overfitting or underfitting, tolerant of noisy data, accommodates non-linearity, and can be run in parallel at high speed [16]. To obtain data on the chili pepper price at the regency and city levels, the Department of Industry and Trade recorded in every market in 38 regencies and cities in East Java. Then, calculated the average price of chili pepper at the regency and city level. Meanwhile, to obtain the price of chili pepper at the provincial level, the Department of Industry and Trade calculates the average price of chili pepper in 38 regencies and cities in East Java. From the explanation above, the price of chili pepper at the regency and city levels clearly influences the price of chili pepper at the provincial level, so it is necessary to select chili pepper prices from several regencies and cities to be used as input variables in the nowcasting modeling.

BPS statement said the development of the chili commodity is constrained by the weather/climate is proven with scientific research's statement that the weather affects the growth of chilies [7]. This will cause the amount of chili pepper production. For example, in May 2020, many areas in East Java are entering the dry season, so their production increased, and in October 2020, when many areas are entering the rainy season, their production dropped dramatically [17][18]. Data on natural factors was chosen as an approach to total production due to the unavailability of daily chili pepper production data.

As a comparison, the word search index on Google Trends are keywords that are relevant to the demand of chili pepper is also used as an input variable in the nowcasting modeling. According to Choi and Varian [19], Google Trends is a new branch of econometrics widely used to see trends in public consumption.

From the explanation above, the objectives of this research are: Obtaining the best input variables for nowcasting modeling of chili pepper prices in East Java Province; Obtaining the best model parameters of the nowcasting for the chili pepper price in East Java Province; Nowcasting the price of chili pepper in East Java Province using the best nowcasting model.

2. Methods

2.1. Source and Data Collecting

Chili pepper price data at the provincial level in East Java was taken from the Siskaperbapo (Sistem Informasi Ketersediaan dan Perkembangan Bahan Pokok) website by the East Java Department of Industry and Trade with the link https://siskaperbapo.jatimprov.go.id/. chili pepper price per market in each regency and city in East Java is obtained from the Siskaperbapo website. The data is processed into price data at the regency and city levels. Natural factor data was obtained from the BMKG website with the link https://dataonline.bmkg.go.id/. Word search index data on Google Trends is obtained from the Google Trends web with the link https://trends.google.com/trends/. We use daily data, 991 days from 1 January 2020 to 17 September 2022 as research limitation.

2.2. Data Imputation

Several data in natural factor data are missing due to measurement constraints experienced by BMKG, so imputation is needed. The imputation method used in this study is mid-point imputation. Mid-point imputation is performed at the midpoint of an interval [20]. The imputation mechanism in this study is finding the average value of 3 data before and 3 data after from missing data. This imputation method was chosen because BMKG usually analyses natural factor data from one day to seven days [21]. The details of data with missing values are shown in Table 1. Then, data is imputed.

Table 1. Total Missing Value in Natural Factors Data

Variable	Total Missing Value
Average temperature (°C)	14
Average humidity (%)	15
Rainfall(mm)	66
Sun exposure duration (hours)	14
Average wind speed (m/s)	13

2.3. Data Splitting

Data splitting is the process of separating data into train data and test data. Neural network requires training data to train the model to get the best weight in ANN. Then the model that have been trained are tested for their performance using test data.

At this stage, the separation of train data and test data is carried out. The proportion of train data and test data is 8:2 according to Pareto Law. Both train data and test data are divided into independent variables and dependent variables because MLP is a supervised learning. In Table 2, Table 3, and Table 4, the dependent and independent variables of each input variable are presented.

In city and regency levels of chili price input variables, the independent variables are choosen using LASSO regression. We select variables that affect the price of provincial chili pepper price. The variables is price of chili pepper in Surabaya, Jember, Banyuwangi, Madiun and Ngawi, all in lag 1 (lag 1 from nowcasted data).

Table 2. Table of Variable Types in City and Regency Levels of Chili Price Input Variables

Dependent Variable	Independent Variable
Province Level Rawit Chili Prices	Chili pepper Prices at Province Level Lag 1
	Price of Chili Pepper in Surabaya City Lag 1
	Price of Chili pepper in Jember Regency Lag 1
	Price of Chili pepper in Banyuwangi Regency Lag 1
	Price of Chili pepper in Madiun Regency Lag 1
	Price of Chili pepper in Ngawi Regency Lag 1

The natural factor input variables are choosen from variables that scientifically proved will affect the chili production [22], [23], [24], [25]. Those variables is average temperature, average humidity, length of sunlight, average wind speed and rainfall. All of those variables are in lag 1 form.

Table 3. Table of Variable Types in Natural Factor Input Variables

Dependent Variable	Independent Variable
Province Level Rawit Chili Prices	Chili pepper Prices at Province Level Lag 1
	Average Temperature Lag 1
	Average Humidity Lag 1
	Length of Sunlight Lag 1
	Average Wind Speed Lag 1
	Rainfall Lag 1

We use words combination appeared in Table 4 as those words are the Indonesian words that closely associated with people who will search chili price information. This research used word index of 4 to select relevant words with chili pepper price.

Table 4. Table of Variable Types in Word Search Index in Google Trends Input Variables

Dependent Variable	Independent Variable
Province Level Rawit Chili Prices	Chili pepper Prices at Province Level Lag 1
	"harga cabe" Lag 1
	"harga cabai" Lag 1
	"harga cabe rawit" Lag 1
	"harga cabe sekarang" Lag 1
	"harga cabe hari ini" Lag 1

2.4. Feature Selection

Feature Selection is the process of removing uninformative and redundant input variables in the model because that can reduce the effectiveness of the model [26]. The feature selection method used in this study is LASSO (Least Absolute Shrinkage and Selection Operator). The advantages of that method are not too sensitive to outliers and computationally efficient [25]. The formula for that feature selection is presented in Formula 1.

$$\sum_{I=1}^{n}(Y_i - \hat{Y}_i)^2 + \lambda \sum_{j=1}^{n} |\hat{\beta}_j| \quad (1)$$

Where Yi is the actual data, Ŷi is predicted data, λi is penalty, and B̂j is the magnitude of the regression coefficient of each variable.

Feature selection was only carried out on the input variable price of chili pepper at the regency and city levels because the number of variables was too many, 38 variables. The selected variables were the price of chili paper at Surabaya City, Jember Regency, Banyuwangi Regency, Madiun Regency and Ngawi Regency.

2.5. Normalization

One of the main problems of neural network at training phase is the gradient that expands or disappears suddenly [27]. This problem arises because the range of data between variables is not uniform, so it requires data normalization. The type of data normalization commonly used in neural network is min-max normalization. The formula of min-max normalization is presented in Formula 2.

$$x_{norm} = \frac{x - min(x)}{max(x) - min(x)} \quad (2)$$

Where $\mathbf{X_{norm}}$ is the value of the normalization results, **x** is value to be normalized, **min(x)** is minimum value in the dataset, and **max(x)** is maximum value in the dataset. The results is data with a uniform range, zero to one.

2.6. Nowcasting Modeling

At this stage, nowcasting modeling is carried out with various model parameters to find the best parameters. The best model is chosen from the smallest average MSE value on cross-validation at the validation stage. The results of modeling with various input variables and model parameters by taking the best model for each number of hidden layers are shown in Tables 5 to 7.

3. Result

This research is trying to find the best model parameter of MLP to reach best nowcasting result. Table 5, 6, and 7 show the best linear function, number of neuron in 1st until 5th hidden layer, learning rate type, maximum iteration, iterations that are run when the model's performance does not improve for early stopping, and optimization type. For the result, we add the comparison of the goodness measurement like Average computation time per cross-validation, Standard deviation of computation time per cross-validation, Average MSE per cross-validation in the training phase, MSE standard deviation per cross-validation in the training phase, Average MSE per cross-validation in the validation phase, and MSE standard deviation per cross-validation in the validation phase for all hidden layers in this study.

Table 5. Selection of The Best Model of City Levels of Chili Price Input Variables

Parameter	2 Hidden layers	3 Hidden layers	4 Hidden layers	5 Hidden layers
Non-linear activation function	relu	relu	relu	relu
Number of neurons in 1st *hidden layer*	relu	relu	relu	relu
Number of neurons in 2nd *hidden layer*	32	32	12	32
Number of neurons in 3rd *hidden layer*	45	45	24	45
Number of neurons in 4th *hidden layer*		51	48	51
Number of neurons in 5th *hidden layer*			96	54
Learning rate type (only when SGD optimization type)	adaptive	adaptive	constant	adaptive
Maximum iteration	200	200	300	100

Parameter	2 Hidden layers	3 Hidden layers	4 Hidden layers	5 Hidden layers
Iterations that are run when the model's performance does not improve for *early stopping*	20	20	20	15
Optimization type	ADAM	ADAM	ADAM	ADAM
Average computation time per *cross-validation*	0.2282075	0.2916216	0.5146835	0.3433096
Standard deviation of computation time per *cross-validation*	0.0695171	0.1046189	0.1557653	0.1017512
Average MSE per *cross-validation* in the training phase	0.0002548	0.0002552	0.000227	0.0002319
MSE standard deviation per *cross-validation* in the training phase	0.0000288	0.0000550	0.0000314	0.0000518
Average MSE per *cross-validation* in the validation phase	0.0002761	0.0002750	0.0002803	0.0002761
MSE standard deviation per *cross-validation* in the validation phase	0.0001386	0.0001306	0.0001886	0.0001610

Table 6. Selection of The Best Model of Natural Factors Data Input Variables

Parameter	2 Hidden layers	3 Hidden layers	4 Hidden layers	5 Hidden layers
Non-linear activation function	tanh	tanh	tanh	tanh
Number of neurons in 1st *hidden layer*	32	32	32	32
Number of neurons in 2nd *hidden layer*	45	45	45	45
Number of neurons in 3rd *hidden layer*		51	51	51
Number of neurons in 4th *hidden layer*			54	54
Number of neurons in 5th *hidden layer*				56
Learning rate type (only when SGD optimization type)	constant	adaptive	constant	adaptive
Maximum iteration	100	100	300	300
Iterations that are run when the model's performance does not improve for early stopping	20	20	20	20
Optimization type	ADAM	ADAM	ADAM	ADAM
Average computation time per cross-validation	0.569774	0.590175	0.886361	1.362758
Standard deviation of computation time per cross-validation	0.208795	0.106247	0.199291	0.535182
Average MSE per cross-validation in the training phase	0.000341	0.000358	0.000347	0.00037
MSE standard deviation per cross-validation in the training phase	0.000052	0.000048	0.000054	0.000033
Average MSE per cross-validation in the validation phase	0.000411	0.000408	0.00036	0.000388
MSE standard deviation per cross-validation in the validation phase	0.000271	0.000242	0.000181	0.000229

Table 7. Selection of the Best Model of Word Search Index in Google Trend Input Variables

Parameter	2 Hidden layers	3 Hidden layers	4 Hidden layers	5 Hidden layers
Non-linear activation function	tanh	tanh	tanh	tanh
Number of neurons in 1st *hidden layer*	32	32	32	32
Number of neurons in 2nd *hidden layer*	45	45	45	45
Number of neurons in 3rd *hidden layer*		51	51	51
Number of neurons in 4th *hidden layer*			54	54
Number of neurons in 5th *hidden layer*				56
Learning rate type (only when SGD optimization type)	constant	adaptive	constant	constant
Maximum iteration	100	100	300	200
Iterations that are run when the model's performance does not improve for early stopping	10	10	20	20
Optimization type	ADAM	ADAM	ADAM	ADAM
Average computation time per cross-validation	0.324298	0.368883	0.630395	1.094747
Standard deviation of computation time per cross-validation	0.102377	0.044253	0.061126	0.234273
Average MSE per cross-validation in the training phase	0.000347	0.000354	0.000357	0.00039
MSE standard deviation per cross-validation in the training phase	0.000038	0.000052	0.00005	0.000051
Average MSE per cross-validation in the validation phase	0.000343	0.000358	0.000346	0.000408
MSE standard deviation per cross-validation in the validation phase	0.000173	0.000178	0.000195	0.000191

Figure 4 presents a comparison graph of the average MSE value for each cross-validation at the validation stage with the validation data for each of the best models for each input variable.

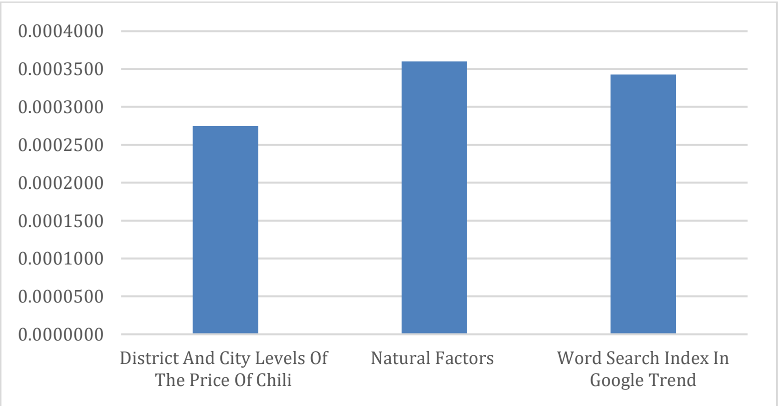

Figure 4. MSE Average Value for Each Cross-validation at the Best Model Validation Stage for Each Type of Input Variable

The best model obtained is the model with the activation function tanh, hidden layer of 3 layers with neurons on 32, 45, and 51 neurons and on each hidden layer, adaptive learning rates, maximum iteration of 200 iterations, the number of iterations that will be executed if the model does not experience an increase in performance to do early stopping is 20 iterations, and the type of optimization used is ADAM. The average MSE result for each cross-validation during validation was 0.000275 with a standard deviation of 0.0001306. The average MSE result for each cross-validation during training was 0.0002552 with a standard deviation of 0.0000550. The difference between the average MSE for each cross-validation during the validation and training stage is slight. It indicates that the model is not overfitting. The model was trained to recognize patterns from the data and obtain the loss curve/error curve presented in Figure 5.

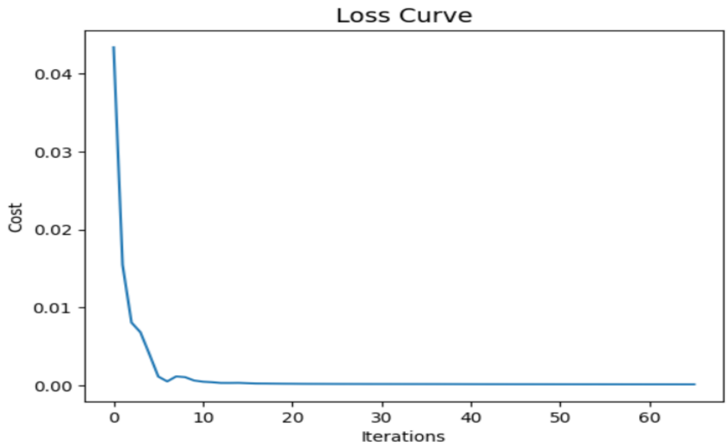

Figure 5. Loss Curve During Model Training

When it has reached 15 iterations, the resulting curve moves constantly, which means the model is approaching convergence. Then at the 68th iteration, the training was stopped because the model had reached convergence.

The best model obtained after the training stage is tested using 191 test data. The result is presented in Figure 6.

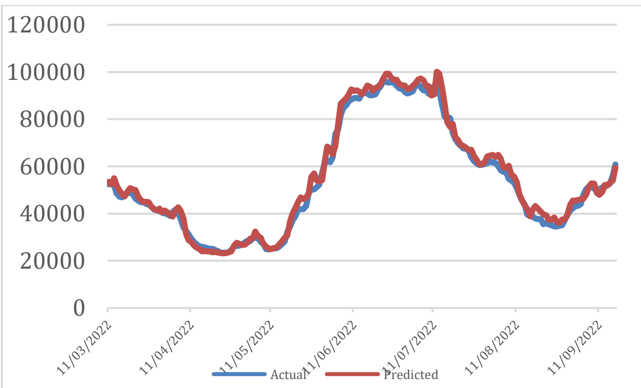

Figure 6. Comparison of Nowcasting Results with Original Data

RMSE, MSE and MAPE obtained are 2,564,935, 6,578,892,883, and 3%. According to Lewis [28], MAPE below 10% indicates that the model's prediction is highly accurate.

4. Conclusion

Our study show that the nowcasting is highly accurate, shown from the MAPE that only 3% with convergent loss curve. That result indicates that the model is good enough to nowcast the chilli pepper price in East Java. The government may use this model to predict the chili price in Jawa Timur Province.

Insight may also be taken from the prediction results, for example, if the prediction says that chilli pepper price wil increase sharply tomorrow, the government may provide more chilli pepper in the market to stabilize the price. And if the prediction says the reverse, the government can buy chilli pepper in market to increase the price.

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