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Transformer-based Deep Learning for COVID-19 Prediction Based on Climate Variables in Indonesia

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Abstract*—Recent research on the effect of climate variables on coronavirus (COVID-19) transmission has emerged. Climate change can potentially cause new viral outbreaks, illness, and death. This study contributes to COVID-19 disease prevention efforts. This study makes two contributions: (1) we investigated the impact of climate variables on the number of COVID-19 cases in 34 Indonesian provinces, and (2) we developed a transformer-based deep learning model for time series forecasting for the number of positive COVID-19 cases the following day based on climate variables in 34 Indonesian provinces. We obtained data from March 15, 2020, to July 22, 2021, on the number of positive COVID-19 cases and climate change variables (wind, temperature, humidity) in Indonesia. To examine the effect of climate change on the number of positive COVID-19 cases, we employed 15 scenarios for training. The experiment results of the proposed model show that the combination of wind speed and humidity has a weakly positive correlation with positive COVID-19 incidence; however, the temperature has a considerably negative association with positive COVID-19 incidences. Compared to the other testing scenarios, the transformer-based deep learning model produced the lowest MAE of 175.96 and the lowest RMSE of 375.81. This study demonstrates that the transformer model works well in several provinces, such as Sumatra, Java, Papua, Bali, West Nusa Tenggara, East Nusa Tenggara, East Kalimantan, and Sulawesi, but not in Central Kalimantan, West Sulawesi, South Sulawesi, and North Sulawesi.

***Keywords*— COVID-19 prediction; climate variables; transformer-based deep learning.**

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I. INTRODUCTION

The recent coronavirus (COVID-19) pandemic resulted in a significant loss of human life across the globe. COVID-19 infection is typically characterized by a variety of symptoms, including fever, cough, lethargy, sore throat, shortness of breath, and malaise [1]. Age and comorbidities such as hypertension, diabetes, obesity, cardiovascular disease, and respiratory disorders are thought to increase the severity of COVID-19. In contrast, some people infected with the virus are asymptomatic [2]. In some countries, the incidence of COVID-19 infections has decreased, while in others, such as France [3] and several countries in Asia, including Indonesia [4], a new wave of COVID-19 infections has occurred. Several factors play a role in determining whether the number of new COVID-19 cases is increasing or decreasing in specific geographic areas.

The rapid global spread of the virus resulted in numerous fatalities and the stagnation of numerous sectors [5]. Climate variables are thought to affect COVID-19 transmission and incidence. When COVID-19 first emerged, most experts predicted that the new coronavirus, SARS-CoV-2, would not survive in hot environments or in high temperatures [6]. However, the coronavirus has spread throughout both hot and cold environments. Several studies predicted that temperature, weather, and climate would affect COVID-19 incidence [7]. Some of these studies show that countries located at high latitudes or farther from the equator are more vulnerable to the spread of COVID-19 when compared to tropical countries [6]. According to Paraskevis et al. [8], the ideal conditions for the spread of the coronavirus are temperatures around 5 - 15°C. A number of studies indicate that a combination of temperature, humidity, and wind speed may contribute to the spread of COVID-19 [9]. In addition to potentially prolonging the half-life and viability of the coronavirus, another potential mechanism associated with low temperature and humidity is droplet stabilization and the velocity of spread to the nasal mucosa [10].

As of October 30, 2021, the number of positive COVID-19 cases in Indonesia reached 4 million, with 143 thousand deaths. Rosario et al. [11] revealed that COVID-19 outbreaks in Brazil are closely linked to weather conditions. Sunlight radiation was found to have a strong correlation to the incidence of COVID, whereas wind temperature and speed had a moderate correlation, and climate factors gradually mitigated the pandemic's effects. Brazil is a tropical country with a high number of COVID cases which has decreased and increased at different times [12]. There are many similarities between Indonesia and Brazil, both being tropical countries. These similarities have attracted researchers interested in predicting COVID-19 cases in every province in Indonesia based on weather data. Another study by Tosepu et al. [13] looked at the relationship between the weather and COVID-19 cases in Jakarta, Indonesia. Based on temperature, humidity, and rainfall data collected from January to March 29, 2020, the study discovered that temperature is the most influential factor in the number of COVID-19 cases in Jakarta.

Forecasting COVID-19 occurrence is crucial so that public health agencies can plan and prepare for pandemics. Various approaches have been developed over the years to forecast time series data. Deep learning has recently outperformed classic machine learning models in several tasks [14]. Deep learning methods have been effectively applied to time series forecasting problems and be a successful solution due to their ability to address huge data problems and automatically learn the temporal connections in time series [15]. Transformer is one of the deep learning models with the potential to outperform existing cutting-edge time series models [16]. Transformers have been applied to datasets with long historical information to solve various problems [17], [18], [19], [20], [21], and [22]. According to a recent study, Transformer produces the best results for the time series regression problem compared to other models [23]. This study employs a transformer-based deep learning algorithm to predict the number of COVID-19 incidences in all Indonesian provinces depending on local weather. The purpose of utilizing a Transformer is to avoid the vanishing gradient problem or gradient changes that are so small that the model is considered not to be learning [16]. The following are the contributions of this study.

- We investigate the influence of climate variables on the number of COVID-19 cases in 34 Indonesian provinces.
- We develop a transformer-based deep learning model for time series forecasting to predict the number of positive COVID-19 cases the following day based on climate variables in 34 Indonesian provinces.

This paper evaluates the model using RMSE and MAE [24]. The remainder of this paper is presented as follows:

- The related studies are presented in section 2.
- Section 3 details the experiment.
- In section 4, the numerical results and the analysis are presented.
- Section 5 summarizes the findings and makes recommendations for future research.

II. Materials and Methods

Several investigations have been conducted to build a COVID-19 prediction model. Iloanusi [25] developed an LSTM model and a random forest model to forecast the number of COVID-19 cases in 36 countries. They used a variety of data sources, namely COVID-19 case data from worldmeters.info and weather data obtained from the National Aeronautics and Space Administration (NASA). Their study revealed that while LSTM produced better prediction results for COVID-19 cases, the random forest was more suitable for some countries. The study also found that temperature significantly impacted the prediction of COVID-19 cases, making it the most influential factor.

Bhimala et al. [26] developed a deep learning univariate LSTM model to forecast the number of COVID-19 cases in India using official COVID-19 case data from the Indian government and weather data from the NCEP/NCAR reanalysis data from April 1, 2020, to July 30, 2020. In March 2021, Batool et al. [27] examined how temperature and humidity can be used to predict COVID-19 cases in Iran. The research demonstrated that LSTM has the lowest MSE, RMSE, and MAPE compared to other approaches.

Kolozsvari et al. [28] investigated the second wave of COVID-19 cases using RNN deep learning. Khennou et al. [29] used deep learning to forecast COVID-19 cases in Canada based on weather conditions. The study utilized three types of data: weather data, the number of daily data tests, and COVID-19 case data. The study results showed that LSTM and GRU achieved the lowest RMSE, MAE, and MAPE compared to ARIMA.

We identified that there is much research on COVID-19 prediction. To our knowledge, this is the first study to forecast COVID-19 cases in every province in Indonesia while considering climate variables. Furthermore, none of the existing studies have used transformers to forecast the number of COVID-19 cases. Therefore, this study presents a COVID-19 prediction method in 34 Indonesian provinces using transformer-based deep learning, considering climate variables.

A. Dataset

This study utilized positive COVID-19 case counts from all Indonesian provinces [30]. To examine the influence of weather and COVID-19 spread in Indonesia, we utilized the global climate and weather data from ERA5-Land [31]. We obtained data from March 15, 2020, to July 22, 2021, consisting of *10-meter U wind component, 10-meter V wind component, 10-meter wind speed, total precipitation, surface solar radiation downward clear-sky, 2-meter temperature*, and *2-meter humidity*. We collected 509 daily data points and employed a window size parameter of 7 with a time lag of 1 data point. Data from March 15, 2020, to April 2, 2021, was used for training, and the remainder was used for testing. Fig. 1 depicts the temperatures throughout Indonesia for seven days, from March 15, 2020, to March 21, 2020.

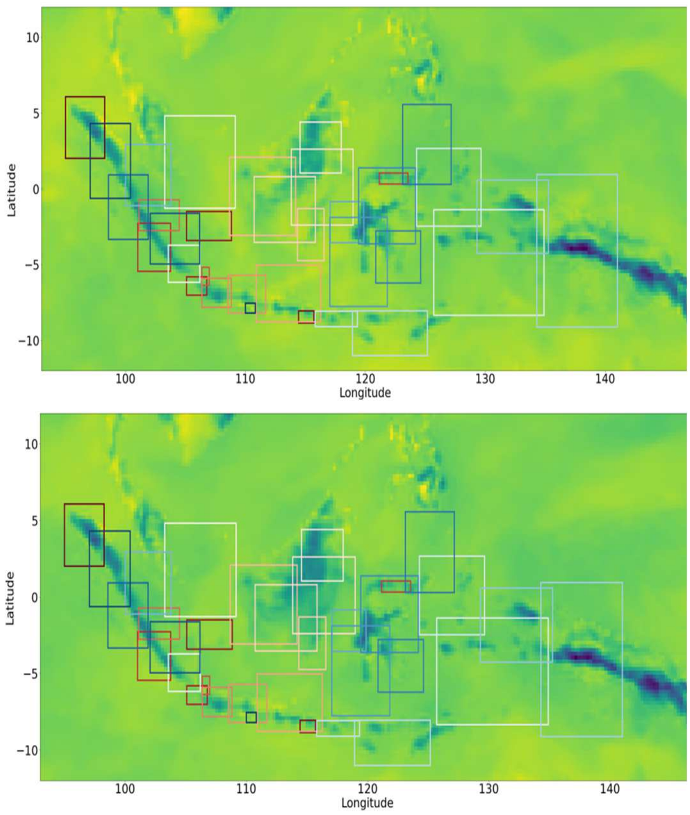


Fig. 1 Temperature Samples in Indonesia from March 15 2020, to March 21, 2020

B. *Feature Correlation*

It is important to select appropriate features in deep learning model training. This study uses Rank-Spearman correlation to examine the correlation between weather and the number of COVID-19 cases. The Spearman rank correlation is shown in Equation 1 [32].

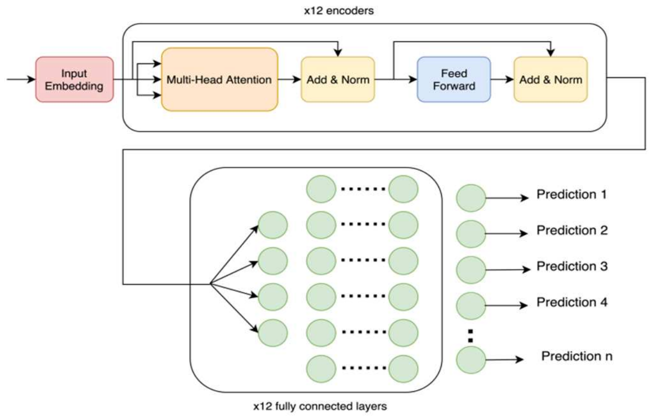
$$r_s = 1 - \frac{6\Sigma_1^{d^2}}{N(N^2-1)} \quad (1)$$

where r_s is the Spearman rank correlation value, d is the margin of each pair value and N is the Spearman rank pair values.

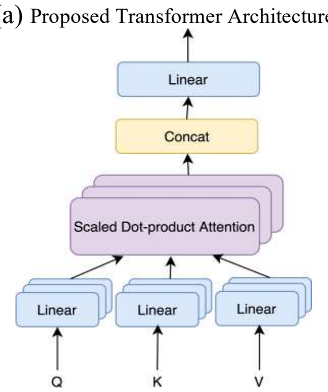
C. *Transformer*

The Transformer was first introduced in 2017 [16]. It consists of two parts, the decoder and the encoder. Decoders receive inputs of (*x1, x2, ..., xn*) and produce outputs of (*z1, z2, ..., zn*) as inputs from decoders. Decoders generate sequences of (*y1, y2, ..., yn*). Transformers are typically composed of three layers: stacked self-attention, point-wise convolution, and the fully connected layer. However, for simplicity, we only applied encoders in our study. Fig. 2(a) depicts our proposed Transformer architecture, consisting of 12 encoders followed by 128 fully connected layers, and the last layer comprising 34 nodes. The last layer uses a linear activation function that aims to predict the number of daily positive cases of COVID-19 in all provinces in Indonesia.

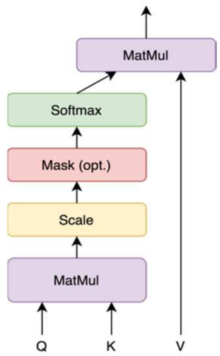
In the Transformer, the attention module consists of multi-head attention in which there is scaled dot-product attention. Transformer requires three inputs: query, keys and value, which are notated as *Q, K* and *V*. The three inputs are paired together. The result of the attention is the vector. Vectors are the combined result of all three inputs.



(a) Proposed Transformer Architecture



(b) Multi-Head Attention Illustration



(c) Scaled Dot-product Attention Illustration

Fig. 2 Proposed Transformer Model: (a) Proposed Transformer Architecture; (b) Multi-Head Attention Illustration; (c) Scaled Dot-product Attention Illustration

Multi-head attention receives three inputs which s go through to the linear operations first. Queries and keys have dk and values with dimensions d_v. All three inputs are processed first by the scaled dot-product attention in each dimension. The process results of each dimension are combined using concatenate operations. Fig. 2(b) provides an overview of multi-head attention for the Transformer. The mathematical equations of multi-head attention are given in equations 2 and 3.

MultiHead(Q, K, V) = C¨oncat(head1, ..., headh)WO (2)

where

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V) \quad (3)$$

and,

$$Attention(Q, K, V) = softmax(\frac{QK^T}{sqrtd_k})V \qquad (4)$$

Scaled dot-product attention uses three inputs, namely query and key input, with dimensions d_k and value with dimensions d_v. The first step of the scaled dot-product process is to perform the dot-product operation between query and key, followed by a division operation with $sqrtd_k$. The results of the operation are then processed using the SoftMax activation function. Fig. 2(c) provides an overview of the scaled dot-product attention on the Transformer. Equation 4 denotes the mathematical equation of the scaled dot-product.

D. *Hyperparameters*

Selecting the right parameters ensures the deep learning model performs well. The number of epochs used to train the Transformer is 100, with a learning rate of 0.001. Adaptive Moment Estimation (ADAM) was selected as the optimizer for this training. ADAM is the combined result of momentum optimization [33] and RMSProp [34]. ADAM's advantage is that convergence and more efficient computing accelerates the training process of the deep learning model [35]. The equation to calculate ADAM is as follows:

$$\vartheta_{t+1} = \vartheta_t + \frac{\eta}{\sqrt{\hat{s}+\epsilon}}\widehat{m} \qquad (5)$$

where ϑ_{t+1} is the weight after optimization, ϑ_t is the weight before the optimization process, η is the learning rate, $\hat{s}$ is RMSProp and $\widehat{m}$ is momentum optimization.

E. *Loss Function*

The loss function used is MAE, one of the regression model evaluation metrics. MAE was chosen as the loss function because MAE is more resistant to data outliers [24]. The MAE principle considers the average difference in absolute value between the predicted result and the actual value. The smaller the MAE value produced, the better the model at making predictions. MAE is calculated as follows:

$$\mathrm{MAE} = \frac{\sum_{n=1}^{N} |r'_n - r_n|}{N} \qquad (6)$$

where N is the amount of data, r'_n is a prediction result from the deep learning model and r_n is the target value.

F. *Performance Evaluation*

We used root mean square error (RMSE) and mean average error (MAE) to assess the model. Both assessment measures are used because RMSE performs well when examining model capabilities in certain circumstances and MAE performs better in others [24]. The smaller the MAE and RMSE values, the better the performance of the model. RMSE is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{n=1}^{N} (r'_n - r_n)^2}{N}} \qquad (7)$$

G. *Training Scenario*

The training scenario in this study evaluates the effect of each feature on the performance of the deep learning model. The training consists of 15 scenarios, as shown in Table 1.

III. Results and Discussion

We examined the influence of weather data on the incidence of COVID-19 in 34 Indonesian provinces. As depicted in Fig. 3, the findings reveal that wind speed and humidity have a weakly positive correlation with positive COVID-19 incidences. Temperature, on the other hand, has a strong negative correlation with positive COVID-19 incidences. China also observed that transmission increased when the temperature reduced and that an increasing temperature correlated with decreased infection rates and outbreak size [36], [37].

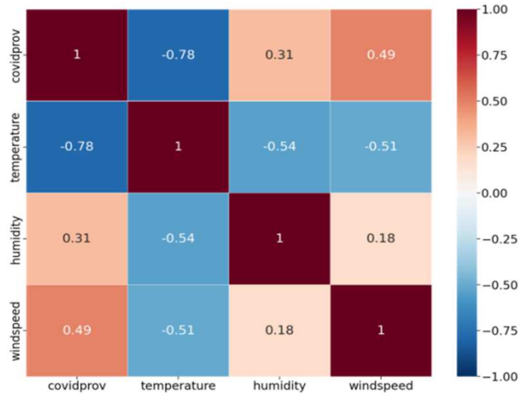


Fig. 3 Feature Correlation.

Table 1 shows that the transformer-based deep learning model achieved the lowest MAE of 175.96, as shown in Fig. 4 and the lowest RMSE of 375.81 in scenario 7 by employing two features, namely temperature and the number of positive cases in each province in Indonesia.

TABLE I
TRAINING SCENARIO AND TESTING RESULT

No	**Scenario Name**	**Number of Positive Cases per Province**	**Humidity**	**Wind Speed**	**Temperature**	**Metric Evaluation**	
						MAE	**RMSE**
1	Scenario 1	✓				180.83	403.898
2	Scenario 2		✓			336.48	789.93
3	Scenario 3			✓		336.29	797.03
4	Scenario 4				✓	325.83	761.37
5	Scenario 5	✓	✓			182.89	394.15
6	Scenario 6	✓		✓		183.94	404.76
7	Scenario 7	✓			✓	175.96	375.81
8	Scenario 8		✓	✓		352.54	814.33
9	Scenario 9		✓		✓	337.68	793.02
10	Scenario 10			✓	✓	355.73	831.20
11	Scenario 11	✓	✓	✓		182.58	388.64
12	Scenario 12	✓	✓		✓	181.67	386.47
13	Scenario 13	✓		✓	✓	189.89	433.19
14	Scenario 14		✓	✓	✓	355.63	821.60
15	Scenario 15	✓	✓	✓	✓	183.34	410.69

Fig. 5 and Fig. 6 show the prediction results for the province sample with the largest and lowest errors, respectively. We evaluated the Transformer model using fifteen different scenarios. The temperature scenario demonstrates an inverse association with the incidence of positive COVID-19.

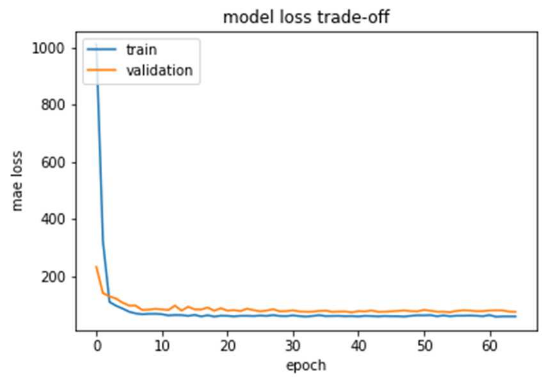


Fig. 4 MAE of temperature and the number of positive cases scenario

Fig. 5 shows that when wind speed combined with temperature parameter is taken into account, the proposed Transformer model is able to forecast the positive incidences of COVID-19 in Banten. However, the model does not predict positive incidences very precisely because there is a large discrepancy between the test prediction and the actual target. As shown in Table 1, when temperature and wind speed are used in Scenario 10, the MAE is 355.73, and the RMSE is 831.20. In contrast, a strong correlation exists between temperature and COVID-19 case number changes. Fig. 6 shows that temperature parameters are effective predictors of COVID-19 incidence in Kaltim, as the proposed Transformer model can predict more accurately COVID-19 incidence in Kaltim, as indicated by the reduced MAE and RMSE in Table 1.

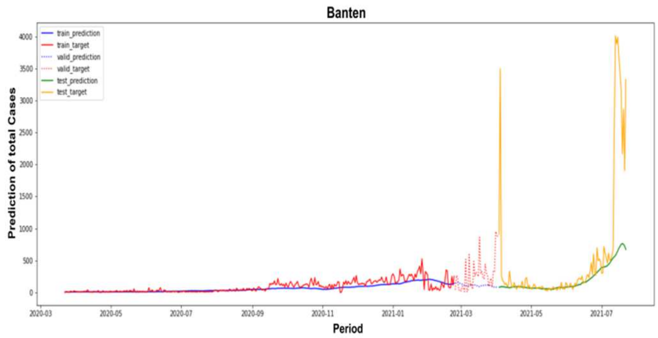


Fig. 5 Result sample of wind speed and temperature scenario (scenario 10)

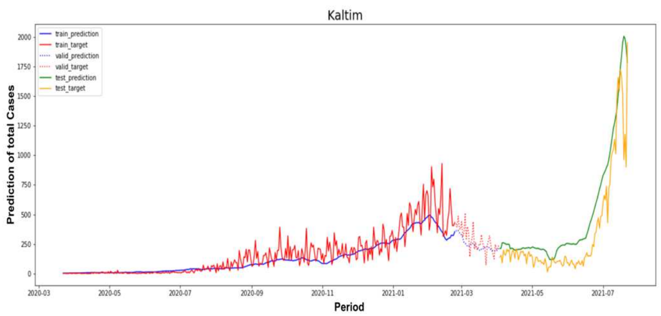
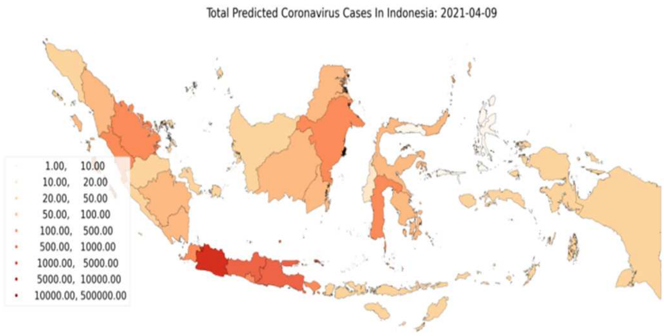


Fig. 6 Result sample of temperature and the number of positive cases scenario (scenario 7)

Since scenario 7 in Table 1 had the smallest MAE and RMSE, we selected scenario 7 for all provinces in Indonesia. Fig. 7a shows the actual confirmed cases of COVID-19 on April 9, 2021, while Fig. 7b shows the prediction of the Transformer model and scenario 7 of COVID-19 incidences on April 9, 2021. The results show that the Transformer model works well in several provinces, such as Sumatra, Java, Papua, Bali, West Nusa Tenggara, East Nusa Tenggara, East Kalimantan, and Sulawesi, but not for Central Kalimantan, West Sulawesi, South Sulawesi, and North Sulawesi. In addition, Transformers do not always perform well when predicting COVID-19 cases throughout Indonesia. Fig. 7 shows that the number of COVID-19 cases predicted by Transformer in the Maluku Islands differs greatly from the target value.

(a) Number of confirmed COVID-19 cases in Indonesia



(b) Predicted number of COVID-19 cases in Indonesia by Transformer

Fig. 7 (a) Number of confirmed COVID-19 cases in Indonesia; (b) Predicted number of COVID-19 cases in Indonesia using Transformer

IV. Conclusion

This study makes two contributions: (1) we investigated the influence of climate variables on the number of COVID-19 incidences in 34 Indonesian provinces; (2) we developed a transformer-based deep learning model for time series forecasting to predict the number of positive COVID-19 cases the following day based on climate variables in each province of Indonesia. The findings reveal that wind speed and humidity correlate negatively with positive COVID-19 incidence. However, temperature exhibits a considerable negative association with positive COVID-19 incidences.

Compared to the other testing scenarios, the transformer-based deep learning model produced the lowest MAE of 175.95 and the lowest RMSE of 375.81 in Scenario 7. Future studies will attempt to improve the forecasting quality by increasing the data so that deep learning models can learn patterns from varying trends, such as the increase and decrease in the number of COVID-19 cases. Moreover, we will tune the hyperparameters and modify the model to improve the outcomes.

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