Dengue case forecasting using multi-step deep learning models with attention layers

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ABSTRACT

Dengue is a viral infection that is transmitted from mosquitoes to people. It is more common in regions with tropical and subtropical climates. Accurate dengue forecasting is important to make the right decisions on time. In this sense, in this study, deep learning models with attention mechanisms such as long short-term memory (LSTM), bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), and bidirectional GRU (BiGRU) were implemented, and to improve the accuracy of model results they were linearly interpolated. According to the results, in most cases, linear interpolation improved the implemented deep learning models with attention mechanisms in terms of mean squared error (RMSE), mean absolute percentage error (MAPE) and R2. For one-step predictions, improvements occurred between 0.08% and 0.13%, for two-step predictions between 8.55% and 22.81%, for three-step predictions between 0.26% and 23.88%, for four-steps between 0.15% and 4.79%, and between 0.11% and 0.19% for five-step predictions. Based on the obtained results, it is possible to experiment with other types of interpolations such as polynomial, spline, and inverse distance weighting (IDW).

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1. INTRODUCTION

Dengue is transmitted through the bite of an infected mosquito [1], [2]. It is a disease that affects people of all ages, with symptoms such as fever [3], headache [4], pain behind the eyes [5], pain in muscles and joints [6], and erythema [7]. The disease can progress to severe forms, mainly characterized by shock, respiratory distress [8], and severe organ damage [9]. In the Americas, the main responsible for transmitting dengue is the Aedes aegypti mosquito [10], [11].

In Peru, in recent years its spread has increased considerably, thus in 2021, 44791 cases were reported, in 2022, 63168 cases, in 2023, 265544 cases, and so far in 2024 there are 112659 cases. Forecasting the number of dengue cases is very important so that authorities can make the corresponding decisions [12] on time, this can help hospitals anticipate excess patients [13] among others. According to the literature, forecasting methods can be classified as statistical, machine learning, and deep learning. Among the statistical ones linear regression (LR), multiple linear regression (MLR), and ARIMA [14] are the best known. Among the machine learning ones, support vector regression (SVR), multi layer perceptron (MLP), random forest (RF), and XGBoosting are very common. And, among the deep learning ones, those based on recurrent neural networks [15] such as LSTM, GRU, BiLSTM, and BiGRU are widely used.

In this work, deep learning models based on RNNs were implemented including attention mechanisms and linear interpolation for different prediction steps, 1, 2, 3, 4, and 5 were proposed to improve the accuracy of dengue forecasting. According to the literature, the forecasting of dengue cases has been approached with statistical techniques and machine learning, including LASSO [16], RF [17], LSTM [12], [18], [19], GRU [20], BiLSTM [20], CNN [20], LSTM with attention mechanism [21], [22], some of them, just for 1-step forecasting, which means that the models predict just 1 week or 1 month depending on the frequency of the data. All related works were performed for dengue cases including Singapore, China, Puerto Rico, Colombia, Philippines, and Vietnam, none for Peru. According to the literature review, the attention mechanism was used with LSTM, hence this work explored this mechanism with other architectures such as BiLSTM, GRU, and BiGRU for different step sizes. Moreover, in related works, the results produced by the models were not modified to improve accuracy; in this work, the model results were smoothed with linear interpolation, because this helps to improve their accuracy in terms of RMSE, MAPE, and R^2, bringing them closer to real data. Table 1 shows the main differences between related works and this work.

Table 1. Differences between related works and this work

Related works	This work
Most of them worked with dengue data from Asian countries, and only two used data from Latin America (Colombia and Puerto Rico)	It worked with data from Peru
Only two of them used LSTM with attention mechanism.	It worked with four different deep learning models with attention mechanism.
They did not apply techniques to improve the results produced by the forecasting models.	Linear interpolation was applied to smooth and improve results.
Most of them reported their results in terms of RMSE.	The results were reported in terms of RMSE, MAPE, and R2.

The contributions of this work are listed below:

– Comparison of different RNN models such as LSTM, BiLSTM, GRU, and BiGRU with different step-sizes, and attention mechanisms for Peruvian dengue cases.
– RNN models with attention mechanism and linear interpolation to improve the accuracies of predictions in terms of RMSE, MAPE, and R^2.

The rest of the paper is structured in section 2, which describes the method to implement the deep learning models with attention mechanisms and linear interpolation. Section 3, describes the obtained results and discusses them. At the end, the respective conclusion of the work.

2. METHOD

2.1. Data collection

The dataset was obtained from MINSA's repository at the following link https://www.dge.gob.pe/sala-situacional-dengue/. This dataset contains weekly dengue cases in Peru from 2000 to 2023 year. The dataset was split into 3 subsets, training (84% 20 years), validation (4% 1 year), and testing (12% 3 years). Table 2 shows in detail the amount of data for each subset and Figure 1 shows graphically the dataset subsets.

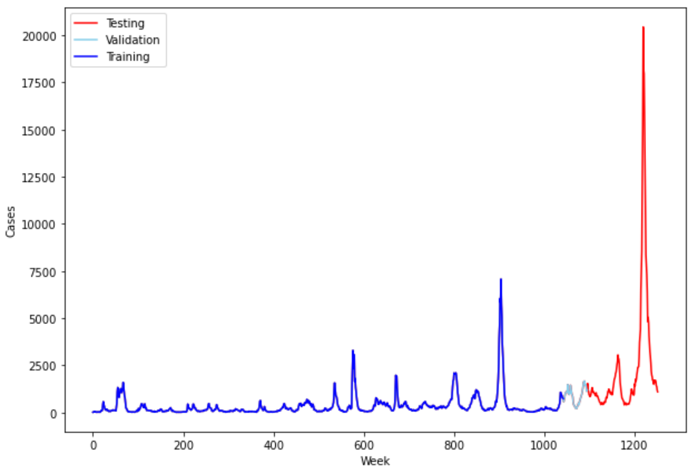


Figure 1. Dataset subsets: training, validation, and testing

Table 2. Dataset subsets: training, validation, and testing

Subset	Number of weeks	Percentage (%)
Training	1040	84
Validation	52	4
Testing	156	12

2.2. Data preparation

The data was prepared for the implementation of deep learning models, thus the data was normalized through the min/max normalization to ensure fast convergence, and (1) was used for this. While this study focuses on historical case data, future extensions could incorporate meteorological variables such as temperature [23], [24] and precipitation [25], which are known to influence dengue transmission patterns.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where x' is the scaled value, x is the value to be scaled, min(x) is the min value in the x vector, and max(x) is the max value in the x vector.

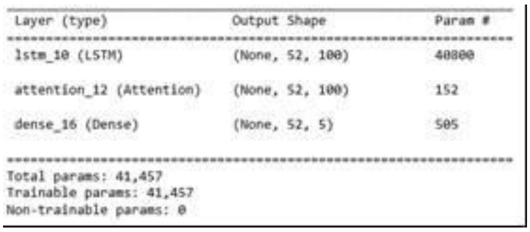
Data is structured in features and labels, 52 features are considered for each row, and depending on step size, labels contain 1, 2, 3, 4, or 5 columns.

2.3. Implementation of models

Deep learning models with attention mechanisms were implemented using the TensorFlow 2.9.0 library and Google Colab. The hyperparameters for each model are detailed in Table 3. According to Table 3, all models in their first layer present 100 units, the second layer corresponds to the attention mechanism, and the third layer is similar to the first layer but with 32 units. The last layer is a Dense layer with size units, size is the number of steps to be predicted. All models are compiled with 100 epochs, adam as optimizer, mse as loss function, and a batch size=52. Figure 2 shows the architecture with attention mechanism of the Figure 2(a) LSTM, Figure 2(b) BiLSTM, Figure 2(c) GRU, and Figure 2(d) BiGRU used in the experimentation of this work.

Table 3. Hyperparameters of models with attention mechanism

Model	Hyperparameters
LSTM	[100, ATT, 32, size], activation: relu, learning_rate: 0.001
BiLSTM	[100, ATT, 32, size], activation: relu, learning_rate: 0.001
GRU	[100, ATT, 32, size], activation: relu, learning_rate: 0.001
BiGRU	[100, ATT, 32, size], activation: relu, learning_rate: 0.001



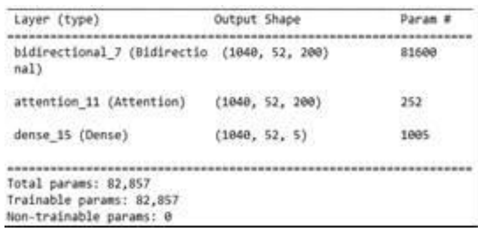
```
Layer (type)                 Output Shape          Param #
================================================================
lstm_10 (LSTM)               (None, 52, 100)       40800

attention_12 (Attention)     (None, 52, 100)       152

dense_16 (Dense)             (None, 52, 5)         505

================================================================
Total params: 41,457
Trainable params: 41,457
Non-trainable params: 0
```

(a)



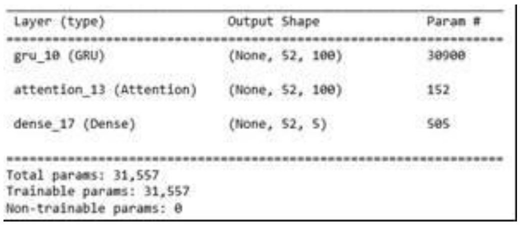
```
Layer (type)                 Output Shape          Param #
================================================================
bidirectional_7 (Bidirectio  (1040, 52, 200)       81600
nal)

attention_11 (Attention)     (1040, 52, 200)       252

dense_15 (Dense)             (1040, 52, 5)         1005

================================================================
Total params: 82,857
Trainable params: 82,857
Non-trainable params: 0
```

(b)



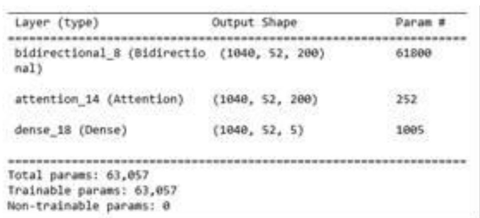
```
Layer (type)                 Output Shape          Param #
================================================================
gru_10 (GRU)                 (None, 52, 100)       30900

attention_13 (Attention)     (None, 52, 100)       152

dense_17 (Dense)             (None, 52, 5)         505

================================================================
Total params: 31,557
Trainable params: 31,557
Non-trainable params: 0
```

(c)



```
Layer (type)                 Output Shape          Param #
================================================================
bidirectional_8 (Bidirectio  (1040, 52, 200)       61800
nal)

attention_14 (Attention)     (1040, 52, 200)       252

dense_18 (Dense)             (1040, 52, 5)         1005

================================================================
Total params: 63,057
Trainable params: 63,057
Non-trainable params: 0
```

(d)

Figure 2. Architecture of the implemented models with attention mechanism:
(a) LSTM, (b) BiLSTM, (c) GRU, and (d) BiGRU

2.4. Linear interpolation

Linear interpolation [26] is a curve-fitting [27] method to construct new data points within the range of a discrete set of known data points. In this case, two points are used to generate a midpoint. For this purpose, a simplified (2) was used.

$$r_i = (r_{i-1} + r_{i+1})/2 \tag{2}$$

Where r_i is the interpolated value, r_{i-1} is the prior value and r_{i+1} is the next value.

The results of deep learning models were interpolated with linear interpolation. What was observed in the results of the deep learning models are the curves that give detail to the predictions, in many cases, these details negatively affect the accuracy of predictions compared with the real values, harming the accuracy of the models. For this reason, in many cases, smoothing these curves improves the model performance.

Linear interpolation is used for smoothing results, for this, considering an *r* vector of prediction results with *n* items, a counter *i* that starts at 1 and increments by two is considered, when *i=1*, the *i* position is interpolated using the *i-1* and the *i +1* values; then *i=3*, again the *i* position is interpolated with *i-1* and *i+1* values, and so on. The respective algorithm for this process is shown in Figure 3. Figure 4 is an example of what linear interpolation does with deep learning predictions. As can be seen for every three ítems of the result array, two of them were used for linear interpolation, and one of them was ignored (the middle one), the result shows that the interpolated curve better approximates the observed curve (ground truth).

```
procedure linearInterpolation(r)
begin
    n=len(r)-1
    i=1
    ir=[]
    while(i<n)
    begin
        m=(r[i-1]+r[i+1])/2
        ir.push(r[i-1])
        ir.push(m)
        i+=2
    end
    ir.push(r[n])
    return(ir)
end
```

Figure 3. Algorithm for linear interpolation

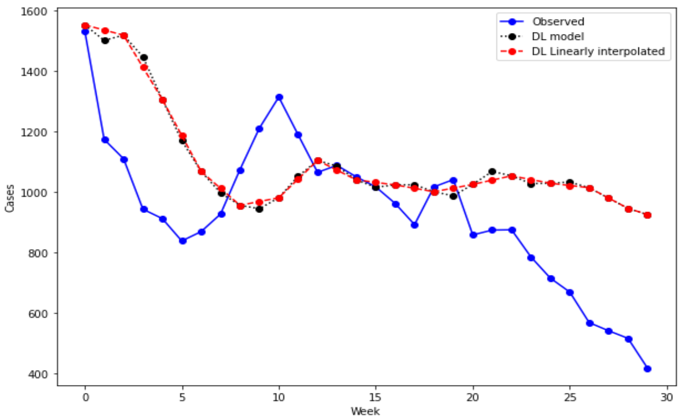


Figure 4. Deep learning results linearly interpolated

2.5. Evaluation

The implemented models were evaluated using metrics including root mean squared error (RMSE), mean absolute percentage error (MAPE), and R^2. RMSE is a metric to evaluate the error between the predicted and the test data regarding the original values (the number of dengue cases). MAPE is a metric to evaluate the results in percentage terms, it is more appropriate than RMSE to compare the results of related works that worked with different data. A model is better than another if the RMSE or MAPE is closer to 0. R^2 evaluates the correlation between the predicted data and the test data, the closer to 1, the better the predictions will be.

RMSE, MAPE, and R^2 were estimated through (3), (4), and (5) respectively.

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\boldsymbol{Pi}-\boldsymbol{Oi})^2}{\boldsymbol{n}}} \tag{3}$$

$$\boldsymbol{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(O_i-P_i)}{O_i} * \mathbf{100}\right| \tag{4}$$

$$R^2 = \sum_{i=1}^{n}(P_i-\bar{O})^2/\sum_{i=1}^{n}(O_i-\bar{O})^2 \tag{5}$$

Where *Pi* is the predicted vector, *Oi* is the observed vector, *n* the length of vectors, $\bar{O}$ the mean of the observed vector.

3. RESULTS AND DISCUSSION

In this section, it is explained the obtained results and at the same time the respective discussion is given.

3.1. Results

The obtained results are shown in Tables 4-6 and visually illustrated in Figure 5, which presents the comparison between the observed values and the multi-step prediction results obtained by different deep learning models. As shown in Figure 5(a)–(e), all models are able to capture the general trend of the observed data, particularly for short-term predictions, while prediction deviations become more noticeable as the forecasting horizon increases. According to Table 4, in terms of RMSE, it can be seen that for one-step prediction, the best RMSE was obtained by two models with linear interpolation, in this case liBiLSTM and liBiGRU with RMSEs of 778.25. Likewise, it can be seen that all deep learning models manage to improve with linear interpolation except LSTM, which slightly worsens its RMSE from 1172.76 to 1174.73.

For two-step predictions, all models improved, and liGRU obtained the best RMSE (679.14). In the case of three-step predictions, two models (LSTM and BiLSTM) manage to improve with linear interpolation, but two models fail to improve (GRU and BiGRU). The best RMSE (893.59) was obtained by a model with linear interpolation, in this case, it was liLSTM. For four-step predictions, as two-step predictions, all models managed to improve with linear interpolation, and liBiLSTM obtained the best RMSE (1200.27). Finally, for five-step predictions, no model manages to improve with linear interpolation, the best RMSE (1431.24) was obtained by BiGRU. For RMSE, from 20 model results, 13 were improved by linear interpolation.

According to Table 5, in terms of MAPE, for one-step predictions, linear interpolation improved all models. liGRU obtained the best MAPE (25.83%). For two-step and three-step, all models improved with linear interpolation except BiLSTM. liBiGRU obtained the best MAPEs (10.22% and 15.87 respectively). For four-step predictions, as one-step predictions, all models improved with linear interpolation, and liBiGRU obtained the best MAPE (18.48%). Finally, for five-step predictions, all models improved with linear interpolation, liBiLSTM was the exception. liBiGRU obtained the best MAPE (21.63%). For MAPE, from 20 model results, 17 were improved by linear interpolation.

According to Table 6, in terms of R^2, for one-step predictions, linear interpolation improved all model results. The models with linear interpolation liBiLSTM, liGRU, and liBiGRU obtained the best R^2 (0.96). For two-step predictions, all models improved with linear interpolation, BiLSTM was the exception, which kept the same R^2. For three-step predictions, just LSTM improved, and the other three worsened their R^2. BiGRU obtained the best R^2 (0.92). For four-step predictions, as one-step predictions, linear interpolation improved all model results. liBiLSTM obtained the best R^2 (0.94). Finally, for five-step predictions, one of the models kept the same R^2, and the other three worsened their R^2. For R^2, from 20 model results, 12 were improved by linear interpolation.

Table 4. Results in terms of RMSE

Model	Steps				
	1	2	3	4	5
LSTM	1172.76	1108.98	1641.57	1618.86	1892.90
BiLSTM	848.36	995.79	1484.81	1415.85	2237.15
GRU	993.54	1156.87	1274.85	167412	1886.57
BiGRU	811.60	1020.43	1130.07	1649.78	**1431.24**
liLSTM	1174.13	893.59	**893.59**	1310.02	1980.91
liBiLSTM	**778.25**	956.02	1309.32	**1200.27**	2289.17
liGRU	974.43	**679.14**	1550.51	1482.23	1979.02
liBiGRU	**778.25**	708.59	1263.86	1320.43	1474.72

Table 5. Results in terms of MAPE

Model	Steps				
	1	2	3	4	5
LSTM	38.37	53.05	42.07	41.41	26.95
BiLSTM	28.73	13.12	18.46	26.93	27.72
GRU	25.95	38.57	41.98	41.26	50.98
BiGRU	28.73	18.77	16.13	22.85	21.74
liLSTM	38.29	41.76	41.76	36.62	26.75
liBiLSTM	28.60	37.11	41.82	23.36	27.87
liGRU	**25.83**	15.76	18.10	41.11	50.40
liBiGRU	28.60	**10.22**	**15.87**	**18.48**	**21.63**

Table 6. Results in terms of R^2

Model	Steps				
	1	2	3	4	5
LSTM	0.92	0.91	0.85	0.81	0.83
BiLSTM	0.95	0.93	0.88	0.89	0.75
GRU	0.95	0.89	0.88	0.77	0.75
BiGRU	0.95	0.92	**0.92**	0.78	**0.90**
liLSTM	0.93	0.94	0.94	0.88	0.81
liBiLSTM	**0.96**	0.93	0.87	**0.94**	0.74
liGRU	**0.96**	**0.97**	0.87	0.82	0.74
liBiGRU	**0.96**	**0.97**	0.90	0.87	**0.90**

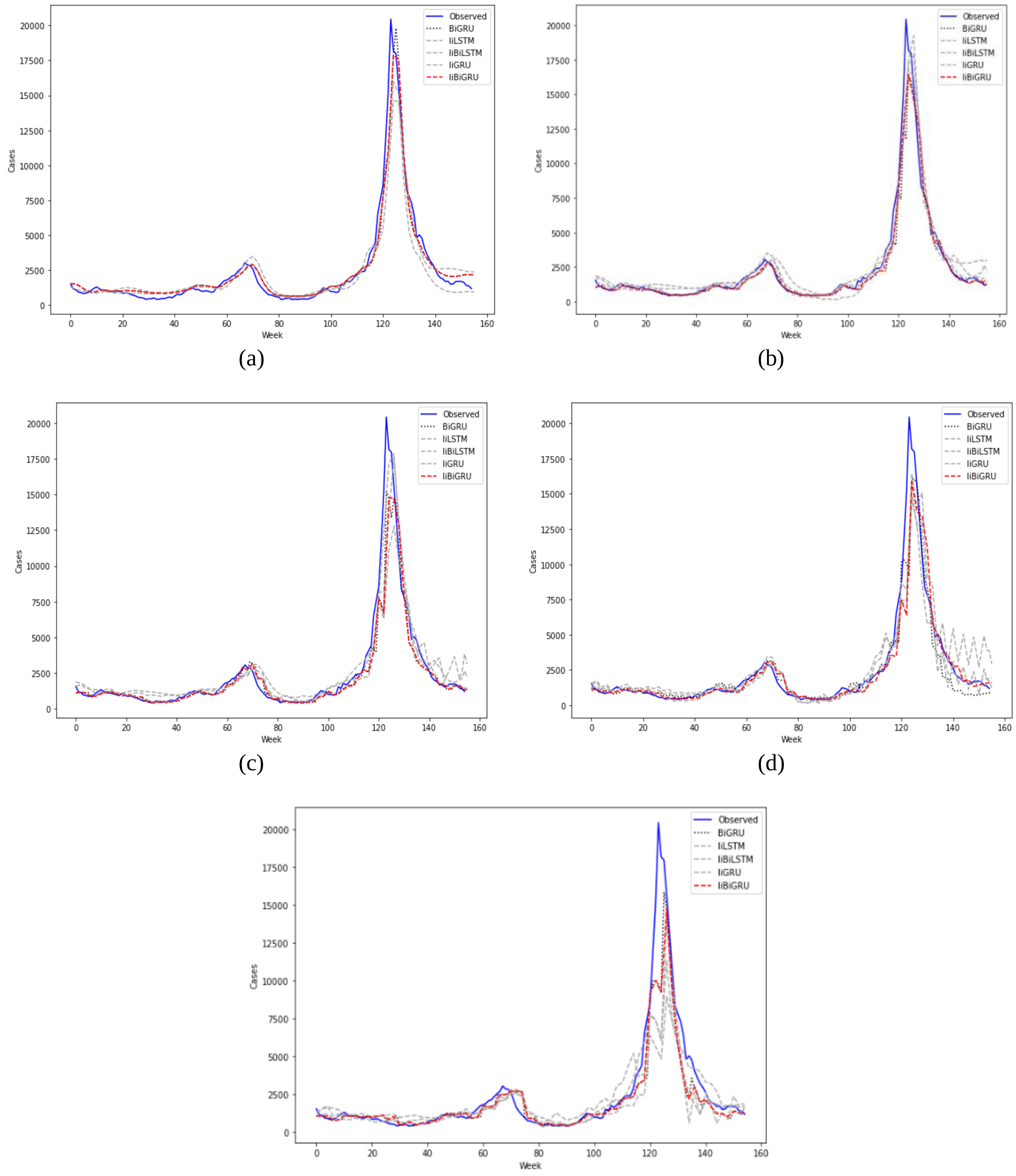


Figure 5. Prediction results: (a) one-step, (b) two-step, (c) three-step, (d) four-step, and (d) five-step

3.2. Discussions

According to the results, it can be seen that the greater the number of steps, the deviation between the predicted values and the real values is increased, harming the accuracy of the predictions, as can be seen graphically in Figure 4. This can be corrected in a certain way by using linear interpolation. According to Table 7, in terms of MAPE the proposed models achieve a MAPE between 10.22 and 28.60%, surpassing the works [16], [20]. RMSE is not recommended for comparisons, especially for models that worked with different datasets, since the datasets present different data for each week, producing smaller RMSEs in the predictions for those who do not have too many dengue cases per week and larger for those who have more dengue cases per week, unfortunately, it is not appropriated to compare with works [12], [18], [19], [21], [22]. Something similar happens with MAE reported in [17].

Something similar happens with MAE reported in [17]. Future improvements could consider incorporating meteorological variables such as temperature [23], [24] and precipitation [25] into multivariate deep learning models, as these factors are known to influence dengue transmission dynamics. Additionally, advanced architectures such as Transformers, which have shown success in other epidemiological forecasting tasks [28], could be explored to enhance prediction accuracy. Other interpolation methods beyond linear, such as polynomial, spline, or spatial interpolation techniques, may also be tested to further smooth and improve model outputs.

Table 7. Related work results

Work	Country	Technique	Freq.	Step size	Metric	Value
[16]	Singapore	LASSO	Weekly	[1,12]	MAPE	[17.00– 24.00]
[12]	China	LSTM	Monthly	[1,12]	RMSE	[54.06 - 43.10]
[18]	Puerto Rico	LSTM	Weekly	1	RMSE	15.67
[17]	Colombia	RF	Weekly	[1,12]	MAE	[13.86 – 26.76]
[19]	Philippines	LSTM	Monthly	1	RMSE	73.17
[21]	Vietnam	LSTM-ATT	Monthly	[1, 3]	RMSE	[0.529 - 9.544]
[20]	Singapore	RNN, GRU, LSTM, BiLSTM, CNN	Weekly	[1,4]	MAPE	[12.27-17.89]
[22]	Malasya	LSTM-ATT	Weekly	1	RMSE	3.10
Proposal	Peru	RNNs and Linear interpolation	Weekly	[1,5]	RMSE	[679.14-1431.24]
					MAPE	[10.22-28.60]

4. CONCLUSION AND FUTURE WORK

According to the results obtained, in most cases, linear interpolation improved the predictions made by deep learning models with attention mechanisms, therefore, it constitutes a good alternative for improvement, thus, in terms of RMSE, from 20 model results, 13 were improved by linear interpolation; in terms of MAPE, from 20 model results, 17 were improved; and, in terms of R^2, from 20 model results, 12 were improved. In the improved cases, for one-step predictions, improvements occurred between 0.08% and 0.13%, for two-step predictions between 8.55% and 22.81%, for three-step predictions between 0.26% and 23.88%, for four-steps between 0.15% and 4.79%, and between 0.11% and 0.19% for five-step predictions. For future work, some improvements that can be implemented would include the implementation of multivariate deep learning models with attention mechanisms, where meteorological variables such as temperature and precipitation could be considered. Likewise, the implementation of models based on Transformers that were used for other endemic cases could be taken into account. On the other hand, ensemble models could be implemented by combining deep learning-based models with machine learning models or statistical models that presented important results in other cases. In the interpolation field, other types of interpolations such as polynomial, spline, stineman, inverse distance weighting (IDW), and Kriging can be implemented instead of just linear interpolation.

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Authors state no funding involved.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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