Deep Learning Approach to Forecasting Dengue Cases in Davao City Using Long Short-term Memory (LSTM)

Kim Dianne B. Ligue¹* and Kristine Joy B. Ligue²

¹Department of Mathematics, Physics, and Computer Science, College of Science and Mathematics, University of the Philippines Mindanao, Davao City, Region XI 8000 Philippines
²Department of Health Davao Center for Health Development, Davao City, Region XI 8000 Philippines

Dengue is a mosquito-transmitted viral disease that causes mild to severe infection. In the tropics, the risk of high infection is driven by factors that influence its vector’s population density such as meteorological variables and unplanned rapid urbanization. In the Philippines, dengue remains endemic in all regions reporting hundreds of thousands of cases annually. The continuous development of data-based infectious disease prediction models plays a vital role in overcoming this persistent adversity. This study explored the application of artificial intelligence (AI) through a deep learning approach using the long short-term memory (LSTM) architecture in our prediction model. This is compared with the traditional feed-forward network approach using a multilayer perceptron (MLP) model and a statistical approach using non-seasonal and seasonal autoregressive integrated moving average (ARIMA). The forecasting models predicted the monthly number of reported dengue cases in Davao City using temperature, rainfall, relative humidity, and previous monthly cases. Model performance was evaluated using the root mean square error (RMSE). The LSTM model recorded the highest accuracy among the models, reporting two times lower RMSE than the MLP model and four times lower RMSE than the statistical models. This result demonstrated the feasibility of deep learning techniques to capture nonlinear characteristics of data and the ability of the LSTM to effectively incorporate information from longer past periods in its prediction.

Keywords: ARIMA, artificial neural network, climate, dengue, forecasting, long short-term memory

INTRODUCTION

Dengue is a mosquito-borne viral infection that predominantly occurs in tropical and subtropical climates around the world. Caused by the dengue virus (DENV), its clinical manifestation ranges from nonspecific viral syndrome to severe and fatal hemorrhaging. Symptoms of dengue infection include high fever (40 °C/ 104 °F) accompanied by at least two other symptoms, severe headache, muscle and joint pains, nausea, vomiting, swollen glands, or rash. Severe dengue infection is potentially fatal due to acute hemorrhaging, organ impairment, plasma leaking, or respiratory distress (WHO 2021).
Transmission of the five serotypes of DENV occurs via their interaction between human hosts and mosquito vectors (Shil et al. 2020). In the tropics, the risk of high infection is driven by meteorological variables and man-made factors such as unplanned rapid urbanization (WHO 2021). Entomological models were developed to investigate the suspected ecological factors such as temperature, relative humidity, rainfall, and their influence on the life cycle of mosquitoes. The development and survival rate of A. aegypti had a positive correlation to temperature and humidity. Precipitation causes stagnation of water in artificial and natural breeding grounds (Focks et al. 1993). The overarching influence of meteorological conditions led several researchers to study its relation to the population density of mosquito vectors and, consequently, to predict dengue transmission accurately using either statistical models or deterministic models (Teurlai et al. 2015).

Southeast Asia is one of the regions seriously affected by the global burden of disease (WHO 2021). In the Philippines, Dengue Hemorrhagic Fever was detected and described as early as the 1950s. Dengue continues to be considered a notifiable disease, predominantly infecting children (Bravo et al. 2014). In August 2019, the Philippines has reported almost 150,000 cases and more than 400,000 cases by the end of the year – the highest among its neighboring countries in Southeast Asia (DOH 2020; WHO 2021). Davao Region is one of the 17 regions in the country endemic with dengue (DOH 2020). This region is home to Davao City, the third most populous city in the Philippines with almost two million population and the largest city in terms of land area (PSA 2021). As the disease primarily thrives in densely populated urban areas, Davao City is the center of dengue incidence in the region. In 2019, Davao City reported 4,495 dengue cases, accounting for 50% of the total cases in the region. By the first half of 2021, the city already reported 1,431 dengue cases, representing a 66% increase compared to the same period last year.

Dengue prevention and control in the country stems from the Department of Health (DOH), the national agency for health. The DOH dengue program conducts continuous surveillance, case management and diagnosis, integrated vector management, outbreak response, health promotion and advocacy, and research to protect Filipinos against the threat of the disease. Surveillance of outbreaks is reported through the Philippine Integrated Disease Surveillance and Response (PIDS&R) with help from the DOH Regional Offices and the Research Institute for Tropical Medicine’s Department of Entomology (DOH 2021). Dengue alert is raised before the rainy season, hotspots are identified as clustering of cases for at least two consecutive weeks in the same area. Detected outbreaks are mitigated by active search and destruction of urban breeding sites, distribution of treated screens to communities, and continuous public campaigns warning against dengue. Although the department uses general weather patterns as one of the predicting variables for the disease, there is a limited number of studies investigating the climatic factors as an effective approach in the country (Bravo et al. 2014). The lack of advancements in the development of antiviral drugs or preventive means such as vaccines calls for the importance of utilizing readily available resources in forecasting dengue cases. Up-to-date and more reliable forecasting may strengthen the public health efforts of the government.

The recent explosion of various applications of AI – specifically, deep learning methods – has taken data mining to the next level. The neural network architecture helps capture the nonlinear characteristics of data (Grossberg 1988), so it has increasingly been used in forecasting. Using this emerging technique to examine highly complex relationships, such as between dengue cases and meteorological variables, is shown to produce more favorable results than the traditional statistical models, e.g. multiple regression models (Xu et al. 2020). Deep learning techniques are progressively being developed to further understand infectious disease dynamics such as the application of artificial neural networks (ANNs) to predict trends in the mosquito population (Lee et al. 2016). A recently trending deep learning application is the use of LSTM architecture to forecast datasets with temporal properties. LSTM is a type of recurrent neural network (RNN) that effectively describes and uncovers the pattern of long sequences such as time-series data (Hochreiter and Schmidhuber 1997). Asian countries have started to explore the use of LSTMs in forecasting dengue cases. Prediction models with LSTM have been proposed to forecast the reported number of dengue cases in Indonesia, India, and South Korea using climate variables (Chae et al. 2018; Chovatiya et al. 2019; Kurnianingsih et al. 2020). In China, Xu and colleagues (2020) proposed an LSTM model with transfer learning to produce accurate forecasts of dengue case count using monthly dengue cases and weather data in selected cities in China with fewer dengue cases. In the Philippines, the LSTM architecture was applied to develop an early warning system that forecasts dengue cases without the use of meteorological variables as external regressors, but results favored the authors’ proposed hybrid ARIMA-ANN model (Chakraborty et al. 2019). However, we suspect that the more careful selection of the LSTM model hyperparameters may further improve the forecast accuracy of the ARIMA-LSTM hybrid. In this study, an LSTM model is proposed to predict the number of reported dengue cases in Davao City using rainfall,
temperature, relative humidity, and previous monthly dengue cases. The building of an effective deep neural network model requires a detailed investigation of the model hyperparameters. This study examined the effect of varying the values of three hyperparameters: the number of time steps for the input, the number of hidden layers, and the number of nodes in each layer. In addition, a regularization technique was applied to help combat overfitting in the form of dropout.

The results of this study will be proposed as an alternative and up-to-date preventive approach against dengue to primary agencies overseeing the control and prevention of the disease, such as the DOH. Moreover, it is hoped that the results of this study contribute to the national goal of advancing AI in the country, especially in Mindanao, in line with the country’s recently announced AI Roadmap. Embracing such potential will allow policymakers to promptly address dengue outbreaks using the most advanced models as opposed to the conventional reporting system.

MATERIALS AND METHODS

Study Area and Dengue Cases

The morbidity data for human dengue in Davao City were obtained from the PIDSR of the DOH–Davao Center for Health Development (DCHD). Monthly dengue cases reported in the 11 administrative districts in Davao City were gathered over the last 13 years: from January 2008–June 2021. The monthly average cases for each district are shown in Figure 1a. Current data shows that similar patterns in the density of cases per district can be observed, although there is an increase in the monthly average cases in 2021 for some districts as exhibited in Figure 1b. In both maps, the district with the highest mean monthly dengue cases is Talomo District, which accounts for about 29% of the total mean monthly dengue cases in Davao City.

The total monthly dengue cases in Davao City from January 2008–June 2021 were used in the training and prediction of proposed models. Figure 2 plots the number of cases over time, in which noticeable outbreaks are observed to be more frequent between the years 2010–2015. The most recent spike was recorded last April 2019.

Figure 1. The monthly average number of reported dengue cases in Davao City [a] throughout the years 2008–2021 and [b] for the year 2021 only. Source: PIDSR of DOH-DCHD.
with more than 800 recorded cases. The highest number of cases in the city based on the record occurred in July 2010, with monthly reported cases of at least 1,700.

Meteorological Factors
In addition to the past number of monthly dengue cases, five meteorological variables (rainfall, minimum temperature, maximum temperature, mean temperature, and relative humidity) were considered as predictors for the model. The feature hyperparameters used in modeling are summarized in Table 1. Monthly data from January 2008–June 2020 were obtained from the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) of the Department of Science and Technology (DOST). PAGASA is the DOST’s attached government agency mandated to produce timely, accurate, and reliable weather-related information and services in the Philippines. To fill in the missing values needed to complement the time parameters of our dengue data, the monthly values for minimum temperature, maximum temperature, mean temperature, and relative humidity values from July 2020–June 2021 were extracted from timeanddate.com, and the values for rainfall were gathered from World Weather Online. Timeandate.com is a globally recognized top-ranking website for time and time zones based in Norway (Time and Date AS 2021), while World Weather Online provides global weather forecasts and weather content available for the public (World Weather Online 2021). The missing values from the data obtained from PAG-ASA – in particular, for the month of September 2017 – were also obtained from these sources. The monthly weather variables – rainfall, temperature, and relative humidity – in Davao City over the last 13 years are plotted in Appendix Figure I.

Methodology
This study explored a deep learning approach to forecasting the number of reported dengue cases in Davao City. To demonstrate the potential of deep learning models to forecasting, a statistical approach was also performed by fitting both non-seasonal and seasonal ARIMA models. Figure 3 describes the overall framework for this study.

Forecast models were constructed to predict the number of dengue cases for the current month using previous monthly meteorological and dengue case data. The data from January 2008–December 2018 were used as the training set. To combat overfitting, the data from January 2019–June 2021 were used as the test set during evaluation. The test set is not seen during training.

Attribution selection during data preprocessing is usually performed to reduce overfitting (Khalid et al. 2014). An attempt to cut down the list of five climate variables was conducted using high correlation filtering and low variance filtering. The minimum and mean temperatures were considered for removal, which showed the highest correlation at 75%. Moreover, the same two variables were identified to have the lowest variance. However, initial results indicated that removing these variables led to worse forecast accuracy. Multicollinearity is considered a problem when the coefficients are evaluated in a multiple regression analysis (Allen 1997), which is not an objective of this study. Since the goal is to improve forecast accuracy, all five climate variables were retained.

All deep learning models were written in Python (version 3.9.5) and implemented using Google’s TensorFlow 2.0 integrated with the Keras API. The statistical models were written in R. All experiments were run in a hardware environment with 64-bit Windows, Intel® Core™ i5-1135G7 CPU at 2.4 GHz, 2 GB dedicated GPU memory, and 20 GB of RAM capacity, with 9.9 GB shared GPU memory.

Deep learning approach: LSTM. The LSTM network model is an extension of the RNN architecture designed to have longer reference windows for sequence prediction. An LSTM layer consists of recurrently connected memory blocks that have a bigger capacity than RNNs. This is achieved by including a forget gate in an LSTM cell that

![Figure 2. The monthly number of reported dengue cases in Davao City from January 2008–June 2021. Source: PIDSR of DOH-DCHD.](image-url)

Table 1. Feature parameters used in the LSTM prediction models.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>$t$</td>
<td>mo</td>
</tr>
<tr>
<td>Rainfall</td>
<td>$x_t^{rf}$</td>
<td>mm</td>
</tr>
<tr>
<td>Minimum temperature</td>
<td>$x_t^{\text{min}}$</td>
<td>$^\circ$C</td>
</tr>
<tr>
<td>Maximum temperature</td>
<td>$x_t^{\text{max}}$</td>
<td>$^\circ$C</td>
</tr>
<tr>
<td>Mean temperature</td>
<td>$x_t^{\text{mean}}$</td>
<td>$^\circ$C</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>$x_t^{rh}$</td>
<td>%</td>
</tr>
<tr>
<td>Monthly dengue cases</td>
<td>$y_t$</td>
<td>Count</td>
</tr>
</tbody>
</table>
allows the model to store relevant previous information selectively (Hochreiter and Schmidhuber 1997). Unlike the traditional feed-forward networks, RNNs are a type of ANN that are sequence networks. Sequence networks specialize in learning characteristics of temporal data. The model is able to retain past information by keeping the information from its previous cell states. Hence, sequence networks have been used extensively to solve prediction problems, including time series forecasting (Tealab 2018).

In this study, we designed a deep learning model with LSTM layers that takes six input parameters to predict the dengue case count for the current month, as shown in Figure 4. The input vector sequence consists of five meteorological variables and the previous monthly dengue case count, which is represented by \(X_t = y_t, x_{t}^{\text{r}}, x_{t}^{\text{min}}, x_{t}^{\text{max}}, x_{t}^{\text{mean}}, x_{t}^{\text{h}}\) at a given time \(t\).

**Deep learning approach: MLP.** ANNs consist of densely interconnected artificial neurons designed to simulate the microstructure of the human brain. In this study, an equivalent MLP model – a type of ANN – is trained for every LSTM model evaluated. These MLPs are feed-forward networks, so information is passed in only one direction and is trained with backpropagation learning algorithms (Hardesty 2017). The MLP models in this study utilized dense layers so that each neuron receives input from all neurons in the previous output. To capture information from multiple timesteps, the MLP model takes the input in one single vector only. This is shown in Figure 5.

**Model formulation.** Figure 6 describes the process of selecting the optimal hyperparameters for the deep learning models. Considering different model hyperparameters, a total of 180 LSTM models and 216 MLP models were evaluated.

Numerous timesteps were considered in the attempt to capture the suspected seasonality of data. Using temperature as the basis, the Philippines is considered to have two major seasons – rainy and dry – each lasting about 6 mo (DOST-PAGASA 2021). Here, timesteps \(i = 1, 3, 6, 9,\) and \(12\) were considered. At \(i = 1\), the meteorological and number of dengue case data from the previous month are used as input for the model. At \(i = 6,\) data from the last 6 mo are used, which corresponds to the duration of one season. At \(i = 12,\) the seasonal characteristic of one yearly cycle is captured and used in the prediction. The timesteps at \(i = 3\) and \(9\) represent the values in between. For MLPs specifically, a model was also fitted using a set of input comprising only of meteorological data from the previous month. For simplicity, this is labeled as timestep \(i = 0.\)

The model architecture has three layers comprising of an input layer, an output layer with one node representing the 1-mo forecast, and at least one hidden layer. The LSTM models receive a \(6 \times i\) matrix as input data, while the MLP models take a single vector with \(6i\) data points for \(i = 1, 3, 6, 9, 12.\) At \(i = 0,\) the MLP models take a vector of five data points. Normalization of input data is performed to speed up learning (Stöttner 2019). The
**Figure 4.** The architecture for forecasting the monthly dengue case count using the LSTM network.

**Figure 5.** The architecture for forecasting the monthly dengue case count using the MLP network.
input data were transformed to values from 0–1 using the MinMaxScaler() function of the scikit-learn machine learning library written in Python.

Deep learning models were evaluated in this study considering up to four hidden layers as performed by Chae et al. (2018), who used LSTMs and ANNs to predict infectious diseases in South Korea. The numbers of nodes considered are 32 and 64 – the same as those of Chae et al. (2018) and Xu et al. (2020), respectively – as well as 128 nodes for comparison. Dropout regularization is considered to reduce possible overfitting due to the relatively small quantity of training data (Brownlee 2019). A dropout layer with rates 0, 20, and 40% was added after each hidden layer. In the case of multiple hidden layers, a uniform number of nodes and dropout rate were applied to each layer.

Other hyperparameters were fixed with batch size set at 12 to reflect the yearly transmission cycle of dengue cases, and the epoch size set at 50 the same as (Chovatiya et al. 2019). The adaptive momentum optimizer was used for model optimization with a learning rate set at the default rate of 0.001. The default activation functions – tanh and rectified linear unit (ReLu) – were used for LSTMs and MLPs, respectively.

**Statistical approach: ARIMA.** Forecasting using the ARIMA models is one of the most widely used statistical approaches to time series forecasting (Mahalakshmi et al. 2016). This makes it an excellent choice for comparison with our deep learning approach, as demonstrated in the dengue case forecasting study by Chae and colleagues (2018). It combines autoregression, differencing, and moving average models to perform its prediction. This allows the model to forecast using a linear combination of lagged values of both the response variable and forecast errors on differenced series. The general forecasting equation can be written as:

\[
y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t,
\]

where \(y'_t\) is the differenced series, \(\phi_i\) are the parameters of the autoregressive part of order \(p\), \(\theta_i\) are the parameters of the moving average process of order \(q\), and \(\varepsilon_t\) are forecast errors at a given time \(t\).

The non-seasonal ARIMA is represented as \(ARIMA (p, d, q)\) with \(p, d,\) and \(q\) as the order of the autoregressive part, order of the differencing, and order of the moving average process, respectively. Seasonality in the dengue case data was suspected so seasonal ARIMA (SARIMA) models were also fitted. In SARIMA, seasonal terms are included in the ARIMA models and are represented as \(ARIMA (p, d, q) (P, D, Q)_m\), where \((P, D, Q)\) is the seasonal part of the model and \(m\) is the number of observations per year.

The auto.arima() function in R was utilized to perform the statistical experiments. The function automatically searches over all possible models and returns the model of best fit according to the corrected Akaike’s information criterion (AICc) value. Both the “approximation” and “stepwise” arguments were set to “FALSE” to enable the most thorough search. The meteorological data were inputted as external regressors using the “xreg” argument. The rest of the arguments were set at default.

The Ljung-Box chi-square statistic was used to check any violation in the independence assumption of the residuals.

The auto.arima() function conducted a search over 42 non-seasonal ARIMA models to determine the model of best fit. Seasonality was also considered, and a search was conducted over 212 combined seasonal and non-seasonal ARIMA models.
Forecast accuracy. Model validation is performed by uniformly evaluating the RMSE for all models using the test set data. The RMSE is a preferred scale-dependent measurement because it is the same scale as the data (Hyndman and Koehler 2006). It is used extensively in measuring forecast accuracy, including recent studies in forecasting dengue cases count (Chae et al. 2018; Chovatiya et al. 2019; Xu et al. 2020). The RMSE aggregates the magnitude of prediction error so lower RMSE is preferred for a model. The computation is performed by averaging the squared differences between predicted values, \( \hat{y}_t \), and observed values, \( y_t \), at a given time \( t \) as follows (Mahalakshmi et al. 2016):

\[
RMSE = \left( N^{-1} \sum_{t=1}^{N} (y_t - \hat{y}_t)^2 \right)^{1/2}.
\] (2)

The ANNs are initialized with random numbers as weights at the start of the training, which leads to slightly different results (Brownlee 2020). So, 30 runs per model were performed in an attempt to capture the general forecast accuracy for each model. This amounts to a total of 11,880 runs considering 180 LSTM and 216 MLP models. For each run, we forecasted the last 18 mo and computed the RMSE. The model recorded with the lowest RMSE was identified as the best model.

For the statistical approach, the model identified with the best fit according to the AICc value was used to forecast using the test set data. The RMSE is then computed for comparison.

RESULTS

Top Models Based on Forecast Accuracy
A systematic exploration of deep learning and statistical models demonstrated the feasibility of the LSTM network in forecasting time-series data. Table 2 shows the best models identified for each subgroup. An LSTM model was identified with the lowest RMSE of 73.17, which is at least four times smaller than that of the ARIMA models. This is followed by the MLP model, which recorded an RMSE twice as large as that of the LSTM model, highlighting a notable difference even among deep learning methods. The statistical models ranked least, identifying the ARIMA \((3, 0, 0)\) and ARIMA \((3, 0, 0) \) \((2, 0, 0)_{12}\) as models with the best fit.

Figure 7 shows the forecasted values of each model graphed against observed values not seen by the models during training. The graph highlights the aptitude of deep learning models to capture nonlinear characteristics of temporal datasets. The ARIMA models produced overestimates which showed approximately linear predictions, failing to produce accurate forecasts.

DISCUSSION

Forecasting Using the Statistical Approach
Both non-seasonal and seasonal ARIMA indicated that using information from the last 3 mo led to the best predictions when forecasting the number of reported dengue cases in Davao City. Differencing was also not necessary, which implies that the dataset exhibited no obvious increasing or decreasing trend throughout the years. The models passed the Ljung-Box test at the 5% level of significance, indicating that the assumption on the independence of residuals is met, supporting the validity of the statistical results. To further compare the output between the ARIMA and SARIMA models, more information may be found in Appendix Table I that lists the model coefficients and in Appendix Table II that summarizes relevant performance measures, including the Bayesian information criteria (BIC) and the RMSE for the training set.

When seasonality was considered, a SARIMA model was identified with the lowest AICc value, suggesting that seasonality is indeed present, and that information from two years back is most influential to the prediction. However, both ARIMA models recorded about the same RMSE on the test set so considering seasonality

<table>
<thead>
<tr>
<th>Approach</th>
<th>Models</th>
<th>AICc</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistical</td>
<td>Non-seasonal ARIMA</td>
<td>ARIMA ((3, 0, 0))</td>
<td>1715.59</td>
</tr>
<tr>
<td></td>
<td>Seasonal ARIMA</td>
<td>ARIMA ((3, 0, 0) ) ((2, 0, 0)_{12})</td>
<td>1713.89</td>
</tr>
<tr>
<td>Deep learning</td>
<td>MLP</td>
<td>MLP with ( i = 12, 1 ) hidden layer with 64 nodes, 40% dropout rate</td>
<td>136.66</td>
</tr>
<tr>
<td></td>
<td>LSTM</td>
<td>LSTM with ( i = 12, 1 ) hidden layer with 32 nodes, no dropout</td>
<td>73.17</td>
</tr>
</tbody>
</table>
in the ARIMA modeling did not improve the forecast accuracy. Nevertheless, there is still a clear difference in prediction power between the statistical and deep learning approaches in favor of the latter. To further explore the deep learning approach, the next section discusses the effect of the different deep learning model attributes considered on forecast accuracy.

**Forecasting Using the Deep Learning Approach**

**Effect of deep learning model attributes to forecast accuracy.** Deep models were explored in this study considering up to four hidden layers. However, results showed that deeper models did not result in better forecasts (see Appendix Figure II). The MLP models maintained the same forecast accuracy as the number of layers increased, whereas the LSTM models produced poorer forecasts. This suggests that considering deeper models is unnecessary, which is a result that coincides with the findings of Bishop (1995). Training deeper LSTM models also take considerably more time. While an architecture having one hidden layer took 3–4 s to train, an architecture with four hidden layers took about 30–40 s. This result will grow exponentially as more data are used in the training. Thus, this study recommends the use of only one hidden layer in the model architecture and focuses the rest of the discussion based on the results of these models.

Considering the time step, the LSTM and MLP models generally performed about the same except at timestep \( i = 12 \), where the LSTM model showed a sizeable drop in RMSE, as seen in Figure 8. This highlights the strength of an LSTM network architecture to retain information from longer past periods, a capability inexistent in MLP networks. In fact, Figure 8 demonstrates that MLPs may outperform LSTMs when considering shorter past periods. However, the predictive power of MLPs plateaus as more past information is used in the modeling, unlike the LSTMs.

Meanwhile, using a different number of nodes and dropout rates do not considerably affect the forecast accuracy. This is evidenced by the box plots shown in Appendix Figures III and IV that display consistency across the different hyperparameter values considered.
Figure 9 shows the forecast accuracy of the models grouped by the hyperparameters considered in this study. A box plot is drawn based on the RMSE results of the 30 runs performed for each model. MLP modeling using only weather variables from the last month resulted in worse forecast accuracy than also using last month’s number of reported dengue cases together with the weather variables. This result coincides with the findings of Aburas et al. (2010) that predicted the number of dengue confirmed cases in Malaysia using neural networks.

Of the models considered, an LSTM model with timestep $i = 12$ and 1 hidden layer yielded the most accurate forecasts. Figure 10 zooms in on the forecast accuracy of these LSTM models that shows favor on the use of an LSTM model with 32 nodes in the hidden layer and no applied dropout regularization.
CONCLUSION

This study applied a deep learning approach to forecasting the next monthly total of reported dengue cases in Davao City. The LSTM model has showcased its ability to retain information from a long sequence of data. The model produced notably more accurate forecasts than the other approaches by efficiently referring to information from the past 12 mo to draw its prediction. Of the model attributes considered, the time step parameter displayed the most influence on the forecast accuracy. This hyperparameter dictates the input to the model, thus confirming the autoregressive characteristic of dengue case counts. Considering more than one hidden layer is also unnecessary to produce accurate forecasts.

The study showed a notable increase in forecast accuracy using the deep learning approach; however, there is still much room for improvement. This study used a relatively small dataset compared to the typical successful applications of machine learning algorithms, so it is suggested to use a larger dataset when available. The LSTM model architecture could also be further examined by tweaking other model hyperparameters such as increasing the number of epochs, changing the learning rate, and considering other optimizers. The use of other sequence model networks such as the gated recurrent units, which is another RNN network extension, or the transformer models could also be explored. Building on an optimized model, the application of transfer learning can also be investigated to improve the forecast accuracy for other regions with fewer dengue cases.

NOTES ON APPENDICES

The complete appendices section of the study is accessible at https://philjournsci.dost.gov.ph

REFERENCES


APPENDICES

Appendix Table I. Coefficients of the selected ARIMA and SARIMA models of best fit.

<table>
<thead>
<tr>
<th>Model</th>
<th>Type</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA (3, 0, 0) (non-seasonal ARIMA)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ar1</td>
<td>1.3194</td>
<td>0.0868</td>
<td>0.00e+00***</td>
<td></td>
</tr>
<tr>
<td>ar2</td>
<td>-0.8099</td>
<td>0.1276</td>
<td>2.19e-10***</td>
<td></td>
</tr>
<tr>
<td>ar3</td>
<td>0.2348</td>
<td>0.0858</td>
<td>0.0062**</td>
<td></td>
</tr>
<tr>
<td>rainfall</td>
<td>-0.0795</td>
<td>0.1033</td>
<td>0.4419</td>
<td></td>
</tr>
<tr>
<td>temp_max</td>
<td>8.5275</td>
<td>9.4625</td>
<td>0.3674</td>
<td></td>
</tr>
<tr>
<td>temp_min</td>
<td>31.7739</td>
<td>15.3193</td>
<td>0.0381*</td>
<td></td>
</tr>
<tr>
<td>temp_mean</td>
<td>-9.0405</td>
<td>17.4265</td>
<td>0.6039</td>
<td></td>
</tr>
<tr>
<td>rel_humidity</td>
<td>-5.0195</td>
<td>3.7182</td>
<td>0.1770</td>
<td></td>
</tr>
</tbody>
</table>

| ARIMA (3, 0, 0) (2, 0, 0)_{12} (seasonal ARIMA) |      |             |                |               |
| ar1                                             | 1.2522 | 0.0898 | 0.00e+00*** |
| ar2                                             | -0.7101 | 0.1302 | 4.92e-08*** |
| ar3                                             | 0.2045 | 0.0856 | 0.0168*      |
| sar1                                            | 0.0924 | 0.0852 | 0.2780       |
| sar2                                            | 0.2017 | 0.0857 | 0.0185*      |
| rainfall                                        | 9.3298 | 0.1060 | 0.3280       |
| temp_max                                        | 34.2918 | 14.8597 | 0.3359       |
| temp_min                                        | -9.7128 | 16.9563 | 0.0210*      |
| temp_mean                                       | -6.0324 | 3.9961 | 0.5668       |
| rel_humidity                                    | -5.0195 | 3.7182 | 0.1312       |

Signif. codes: 0.001***; 0.01**; 0.05*

Appendix Table II. Summarized performance measurements of the ARIMA and SARIMA models. AIC: Akaike’s information criterion; AICc: corrected Akaike’s information criterion; BIC: Bayesian information criterion.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Non-seasonal ARIMA</th>
<th>Seasonal ARIMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>ARIMA (3, 0, 0)</td>
<td>ARIMA (3, 0, 0) (2, 0, 0)_{12}</td>
</tr>
<tr>
<td>Information criteria</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>1714.12</td>
<td>1711.69</td>
</tr>
<tr>
<td>AICc</td>
<td>1715.59</td>
<td>1713.89</td>
</tr>
<tr>
<td>BIC</td>
<td>1740.06</td>
<td>1743.4</td>
</tr>
<tr>
<td>Error measure (RMSE)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training Set</td>
<td>148.2708</td>
<td>144.1685</td>
</tr>
<tr>
<td>Test Set</td>
<td>332.8844</td>
<td>333.6958</td>
</tr>
<tr>
<td>Ljung-Box test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>24.33</td>
<td>15.295</td>
</tr>
<tr>
<td>p-value</td>
<td>0.08255</td>
<td>0.3583</td>
</tr>
</tbody>
</table>

Philippine Journal of Science
Vol. 151 No. 3, June 2022
Ligue and Ligue: Forecasting Dengue Cases Using Deep Learning
Appendix Figure I. The monthly rainfall (in mm), maximum, minimum, and mean temperature (in °C), and the relative humidity (in %) of Davao City from January 2008–July 2021. Source: DOST-PAGASA.

Appendix Figure II. Forecast accuracy of LSTM and MLP models grouped by the number of hidden layers. Both model architectures considered time steps $i = 1, 3, 6, 9, 12$, with each layer consisting of 32, 64, or 128 number of nodes applied with 0, 20, or 40% dropout rate. The MLP models also considered a set of input comprising only of meteorological data from the previous month, labeled as time step $i = 0$. 
Appendix Figure III. Forecast accuracy of LSTM and MLP models grouped by the number of nodes per layer. Both model architectures considered time steps \( i = 1, 3, 6, 9, 12 \), with each layer consisting of 32, 64, or 128 number of nodes applied with 0, 20, or 40\% dropout rate. The MLP models also considered a set of input comprising only of meteorological data from the previous month, labeled as time step \( i = 0 \).

Appendix Figure IV. Forecast accuracy of LSTM and MLP models grouped by the dropout rate. Both model architectures considered time steps \( i = 1, 3, 6, 9, 12 \), with each layer consisting of 32, 64, or 128 number of nodes applied with 0, 20, or 40\% dropout rate. The MLP models also considered a set of input comprising only of meteorological data from the previous month, labeled as time step \( i = 0 \).