Predicting Dengue in the Philippines using an Artificial Neural Network

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ABSTRACT

Dengue fever is an infectious disease caused by *Flavivirus* transmitted by the Aedes mosquito. This disease predominantly occurs in the tropical and subtropical regions. With no specific treatment, the most effective way to prevent dengue is vector control. The dependence of the Aedes mosquito population on meteorological variables make the prediction of dengue infection possible using conventional statistical and epidemiologic models. However, with the increasing average global temperature, the predictability of these models may be lessened employing the need for an artificial neural network. This study uses an artificial neural network to predict the dengue incidence in the entire Philippines with humidity, rainfall, and temperature as independent variables. All generated predictive models have mean squared logarithmic error of less than 0.04.

KEYWORDS

Dengue, Philippines, artificial neural network, climate change

1. Introduction

wDengue fever is an infectious disease caused by *Flavivirus* transmitted by the vector mosquito Aedes. The dengue virus has 4 serotypes (DENV-1, DENV-2, DENV-3, DENV-4) which mostly occur in the urban and suburban areas in tropical and subtropical regions. It is estimated that 50 million people contract a dengue infection globally per annum. In the Philippines, an estimated 170,000 cases occur annually on average but in 2022, there are 220,705 dengue cases tallied. Currently, there are no specific treatments for dengue and the most effective way to prevent it is through vector control.[1–7]

The two most important vectors for dengue transmission are: Aedes aegypti and Aedes albopictus. The life cycle of these vectors is divided into egg, larva, pupa, and adult stages; which is heavily influenced by different meteorological, geological, and anthropological variables. The typical adult mosquito lays eggs just above the waterline of a stagnant water. It takes 48 hours in a warm, humid environment for the embryo to develop. Once developed, the eggs are tolerant to desiccation up to more than a year.[1] The adult mosquito then typically emerges after 10 days. The adult female mates and feeds on blood necessary for egg maturation. The blood meal biting activity takes place in the morning and afternoon.[8,9] However, blood meals also do occur at night in lighted rooms.

Temperature, rainfall, and relative humidity affect the transmission of dengue.[10] Annual rainfall of more than 200 cm provides the conducive environment for the growth of the Aedes mosquito population.[11] The Aedes mosquito population growth is more abundant up to 500 meters above sea level, although they can thrive up to 1,200 meters.[12] Climate variability strongly influences the dengue epidemic. A maximal temperature of more than 32°C and a maximal relative humidity of more than 95% influence the incubation period, feeding frequency, and longevity of the Aedes mosquito.[13] There is low mosquito mortality at temperatures between 15°C to 30°C. Pupae development occurs in less than 1 day at 32°C to 34°C, but takes 4 days at 22°C.[14–18]

With the dependence of the Aedes mosquito population dynamics on weather, variables such as climate change, undoubtedly, will have an impact on the spread of dengue infection. It is estimated that the average global temperature will increase by 2°C to 4.5°C by the year 2100.[19] There are many studies that predict dengue infection using weather variables. Different statistical models were employed such as: Poisson regression, autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA),[20,23] negative binomial, quasi-likelihood regression,[20,21] and distributed lag non-linear model (DLNM).[22] There are also attempts to employ machine learning techniques such as random forest and gradient boosting to make dengue infection predictions.[24–26] These predictive models have varying degrees of predictions on dengue incidence.

With the ease of accessibility and less expensive computing power available nowadays, there is increased application of artificial neural networks in making predictions in different areas of science. Coupled with the use of programming and software packages such as Python and TensorFlow, this research will attempt to predict dengue incidence in the Philippines using an artificial neural network

2. Materials and Methods

Study Setting

The study was conducted in all 17 administrative regions in the Philippines: Region 1 to 12 (including 4-A and 4-B), Autonomous Region of Muslim Mindanao (ARMM), Cordillera Autonomous Region (CAR), and CARAGA. The Philippines has two seasons: wet (June to October) and dry (November to May). However, there are four climate types in the Philippines based on modified Coronas classification: Type I (dry from November to April, we from May to October), Type II (seasonal rainfall from November to December), Type III (same as Type I but with maximum rainfall from May to October), and Type IV (evenly distributed rainfall annually).[27]

Data Collection

Data on dengue incidence is freely available on the Department of Health (DOH) website as PDF reports. These dengue reports are the sum of all case definitions of dengue cases with or without the confirmation of polymerase chain reaction. This is attributed to the limited resources available especially in remote and rural areas where dengue case definition is based on signs and symptoms only. The meteorological data such as: humidity (as %), rainfall (as mm), temperature (as °C) were requested from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) and were received as Excel files. Missing dengue values were addressed by getting the average value from the same region from different years but of the same week time frame. Missing meteorological values were filled using the average value from the same weather station and from a different year period but of the same month time frame. These files from DOH and PAGASA were encoded to comma separated value (CSV) files for data analysis. Dengue data were reported on a weekly basis from each administrative region while the meteorological data were reported on a monthly basis from each weather station where most administrative regions have two to three weather stations. To reconcile these differences, the weekly tally of dengue was summed up to reflect a monthly value while the meteorological values were averaged out from the weather stations to reflect the regional value. The data on dengue and weather variables are from the year 2013 to 2018.

Artificial Neural Network
Data were analyzed in Python 3 using Jupyter Notebook as the interface while also employing several libraries such as Numpy, Pandas, Keras, and TensorFlow. A training and test set were created for each region. The training set consists of data from 2013 to 2017 and the test set contains data from 2018. An artificial neural network was created with 1 input layer, 6 hidden layers, and 1 output layer, as shown in Figure 1. The input layer is composed of humidity, rainfall, and temperature. The output layer is composed of dengue incidence.

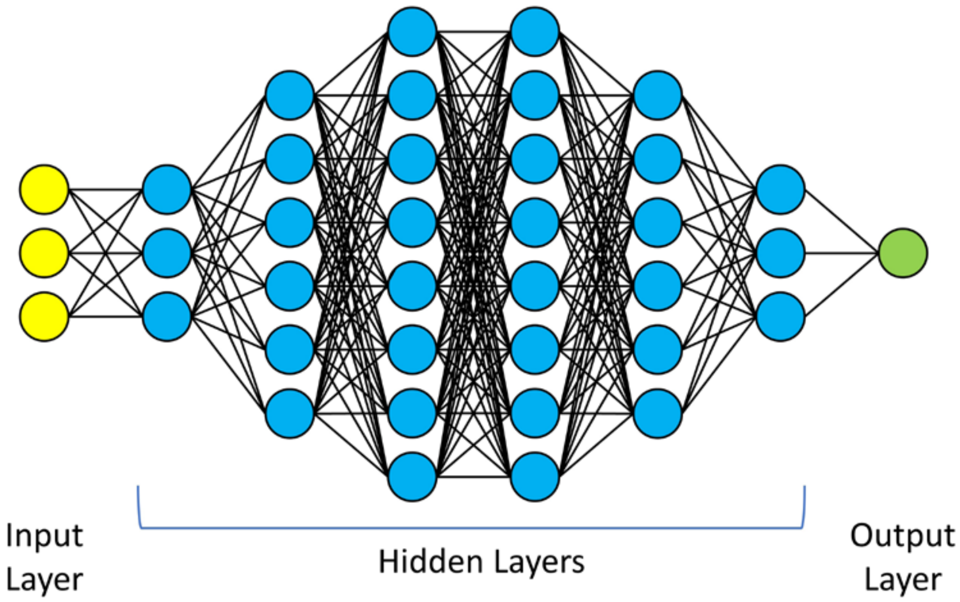


Figure 1: Artificial neural network architecture

The artificial neural network uses rectified linear unit (ReLU) as the activation function and adaptive moment estimation (Adam) as an optimizer. It was trained with batch size of 24 in 500 epochs for each administrative region. The created model from the training set was used to predict the dengue values in the test set. The prediction was evaluated using mean squared logarithmic error (MSLE).

3. Results

Table 1 shows the descriptive statistics of monthly humidity, rainfall, temperature, and dengue incidence for each administrative region. ARMM has the lowest average dengue incidence of 157.26 while Region 4-A has the highest at 2,616.97. NCR has the lowest average humidity of 75.24% while CAR has the highest at 87.25%. Region 12 has the lowest average rainfall of 81.99 mm, while Region 7 has the highest at 1,130.61 mm. CAR has the lowest average temperature of 19.47°C, while Region 11 has the highest at 28.7°C.

Table 1: Descriptive statistics of monthly humidity, rainfall, temperature, and dengue incidence in each administrative region of the Philippines (2013 to 2018).

Region	*Humidity (%)*				*Rainfall (mm)*				*Temperature (°C)*				*Dengue Incidence*			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
ARMM	76	2.69	68	80	160.07	90.76	2.8	393.4	28.22	0.66	26.8	29.9	157.26	80.76	16	495
CAR	87.25	4.12	78	96	307.52	400.32	0	1822.6	19.47	1.01	15.8	21.4	681.99	670.35	58	2965
CARAGA	82.74	3.11	76	89.33	298.01	200.62	47.4	1126.47	28.10	1.02	24.97	30.5	812.79	506.97	144	2574
NCR	75.24	7.16	61.33	89	195.18	201.78	0.1	890.6	28.45	1.26	25.03	30.97	1569.15	1329.74	78	7977
1	79.41	4.63	71.33	88.67	198.22	274.02	0	1069.93	27.61	1.22	23.87	29.9	1024.88	1013.94	99	4917.99
2	84.36	2.27	79.8	88.82	171.85	125.91	8.56	526.84	26.31	2.29	21.62	29.7	697.51	786.54	57	3821
3	79.70	3.93	71.67	87.83	249.67	189.07	23.72	803.02	27.75	1.21	24.58	30.27	2515.51	2202.24	139.98	13134
4-A	83.92	2.62	77	88.33	237.88	154.1	13.08	540.5	26.91	1.26	23.82	29.32	2616.97	2280.62	197.9	14568.15
4-B	81.37	3.17	73.67	86.83	183.92	139.7	12.08	599.25	27.93	0.75	26.30	29.82	769.62	580.72	102.5	3298.83
5	84.67	2.02	81	88.5	248.7	163.84	23.35	733.18	27.71	1.06	25.15	29.58	234.18	130.55	36	500
6	81.03	2.15	76	86.48	176.2	120.26	3	476.5	28.42	0.8	26.2	30.2	1424.78	1391.65	147	6924
7	81.52	2.75	75	86.09	1130.61	73.88	1.53	271.23	28.09	0.8	25.9	29.73	1687.05	1291.86	102	5307.99
8	85.02	2.56	78.17	90.53	297.37	199.86	33.17	1045.8	27.74	0.89	25.41	29.27	442.98	298.53	31.02	1840.02
9	81.66	2.32	75	86	163.37	103.66	2.65	522.2	28.3	0.47	26.6	29.3	518.76	216.22	184	1155
10	84.73	2.66	77.5	89.5	180.46	103.38	2.9	443.95	26.11	0.68	24.3	27.65	1078.71	699.18	344	3414
11	78.7	3.36	70	85	161.47	94.14	14.2	430.5	28.7	0.69	26.5	30.6	599.91	388.52	116	2581
12	77.53	4.72	65	84	81.99	51.8	0.1	256.8	27.99	0.93	26.5	31.1	1019.04	573.58	278	3443

ARMM – Autonomous Region in Muslim Mindanao
CAR – Cordillera Autonomous Region
NCR – National Capital Region

The Python code implementation of the artificial neural network in Figure 1 is shown below:

```
ann = tf.keras.models.Sequential()
ann.add(tf.keras.layers.Dense(units=3, activation='relu'))
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=8, activation='relu'))
ann.add(tf.keras.layers.Dense(units=8, activation='relu'))
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=3, activation='relu'))
ann.add(tf.keras.layers.Dense(units=1))
ann.compile(optimizer = 'adam', loss = 'mean_squared_logarithmic_error')
ann.fit(train_climate, train_dengue, batch_size = 24, epochs = 500)
```

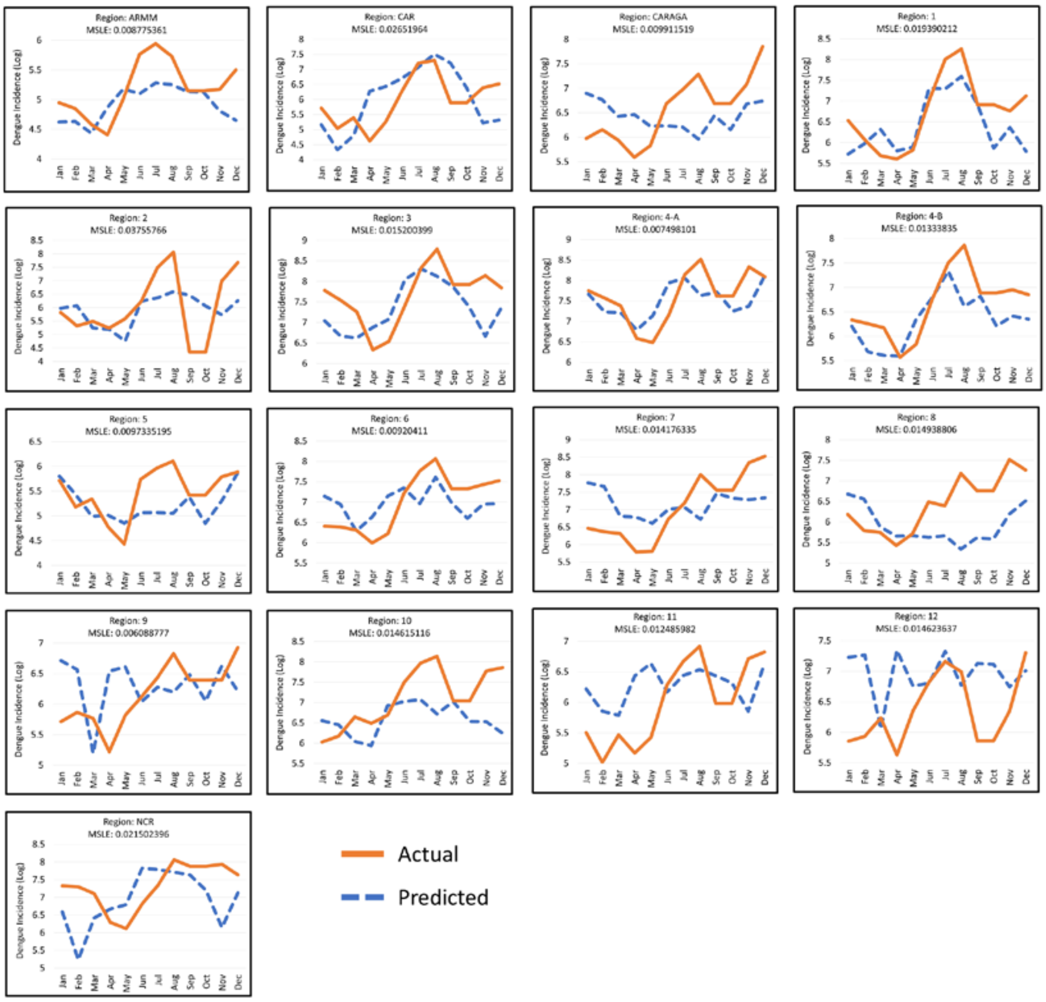
The resulting predictive models from the artificial neural network have a mean squared logarithmic error (MSLE) of less than 0.04 in all administrative regions. Table 2 provides the values of MSLE in each region. Region 9 has the lowest MSLE of 0.006, while Region 2 has the highest at 0.0376. Figure 2 provides a comparison of the actual and predicted dengue incidence in each administrative region using the generated predictive models.

Table 2: Mean squared logarithmic error of each administrative region in the Philippines.

Region	*MSLE*
ARMM	0.008775361
CAR	0.020651964
CARAGA	0.009911519
NCR	0.021502396
Region 1	0.019390212
Region 2	0.03755766
Region 3	0.015200399
Region 4-A	0.007498101
Region 4-B	0.01333835
Region 5	0.0097335195
Region 6	0.009920411

Region	*MSLE*
Region 6	0.009920411
Region 7	0.014176335
Region 8	0.014938806
Region 9	0.006088777
Region 10	0.014615116
Region 11	0.012485982
Region 12	0.014623637

Figure 2: Comparison of the actual and predicted dengue incidence in all administrative regions in the Philippines (2018).



4. Disscussion

Although there is a low MSLE in each administrative region, visual inspection of the actual and predicted dengue incidence revealed that there are predictive models that are better than the other. For example, the predictive model of Regions 4-A and 4-B provide really close predicted values to the actual values, especially at the peak incidence, while the predictive model of Region 2, 5 and 12 provide predicted values far from the actual values. The importance of using MSLE is that it uses the percentage difference between the log-transformed actual and predicted values. Small and big differences are treated the same. It should be noted that predictive models are unique to each region since they are trained separately and have their own artificial neural network even though they have the same network architecture. The administrative regions that have visually performed well are: ARMM, CAR, Region 1, 3, 4-A, and 4-B. The predictive models also had inefficiencies in identifying the peak dengue incidence which are evident in Region 2, 5, 10, and ARMM. The worst predictive models are in CARAGA, NCR and Regions 2, 7, 8, 9, 11, and 12.

Predictions made by an artificial neural network are different from statistical or epidemiological modeling. Artificial neural networks utilize a collection of artificial neurons that take the weighted inputs, pass it through an activation function, to produce an output.[28] In this study, there are three inputs: humidity, rainfall, and temperature; and there is one output which is a single value of dengue incidence. Given the three input values, and passing these values to an artificial neural network, what will be the predicted output. The rectified linear unit (ReLU)[29] is the activation function used to avoid having negative values for the dengue incidence. These multiple units and layers of computation can make better predictions.

There are several limitations that were encountered in this study. The study encompasses entire administrative regions, which means micro-climate variability from each city or municipality can be a contributing factor to the dengue incidence. The meteorological variables provided by PAGASA were limited to three (humidity, rainfall, temperature), although the request includes flood occurrence and average sunlight. These three significant meteorological variables appeared in the research studies done in the Philippines: one was done using general additive modeling, SARIMA, random forest, and gradient boosting in the national capital region; while the other one used quasi-Poisson regression combined with distributed lag nonlinear model in Davao region only.[24,30] Flood occurrence may help in dengue incidence prediction because flushing, which occurs when the water levels exceed the mosquito breeding site's threshold and wash away the mosquito larvae, can potentially reduce dengue incidence.[31] Average sunlight has an inconclusive relationship to dengue incidence using statistical model.[32] However, this might be proven otherwise if artificial neural network is used because it does not assume that the data has collinearity or is normally distributed unlike most common statistical models.

The impact of climate change can influence the transmission of dengue to other places other than the tropical and subtropical regions. By the end of this century, dengue epidemic potential for Aedes aegypti could occur in 10 European cities (Madeira, Malaga, Athens, Rome, Nice, Paris, London, Amsterdam, Berlin, Stockholm) with a continued current rate of greenhouse gas emission.[33] The complexities of weather and climate influences on dengue transmission are not easily modelled with a statistical approach[34] which makes an artificial neural network more helpful in predicting dengue incidence more accurately.

4. Conclusion

Close fidelity on the predicted and actual dengue incidence in some administrative regions in the Philippines prove that artificial neural networks can be implemented for predicting dengue. Further work can be done in optimizing the artificial neural network architecture: number of neurons, number of hidden layers, and additional input meteorological variables (flood occurrence, average sunlight). It is recommended that future research be focused on the city or municipal level of dengue cases and the

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