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Dengue out break Prediction Based on Artificial Neural Networking Model using Climatic Parameters

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Abstract

Purpose: Dengue fever is a vector-borne tropical disease radically amplifiedby 30 times in occurrence between 1960 and 2010. The upsurge is considered to be because of urbanization, population growth and climate change. Therefore, Meteorological parameters (temperature, precipitation and relative humidity) have impact on the occurrence and outbreaks of dengue fever. There are not many studies that enumerate the relationship between the dengue cases in a particular locality and the meteorological parameters.This study explores the relationship between the dengue cases and the meteorological parameters.In prevalent localities, it is essential to alleviate the outbreaks using modelling techniques for better disease control.

Materials and Methods: An artificial neural network (ANN) model was developed for predicting the number of dengue cases by knowing the meteorological parameters.The model was trained with 7 years of dengue fever data of Kamrup and Lakhimpur district of Assam, India. The practicality of the model was corroborated using independent data set with satisfactory outcomes.

Result and conclusion: It was apparent from the sensitivity analysis that precipitation is more sensitive to the number of dengue cases than other meteorological parameters. This model would assist dengue fever alleviation and control in the long run.

Keywords: Artificial neural network; Nonlinear models; Meteorological parameters; Dengue; Aedes mosquito.

Introduction

Dengue fever is a vector-borne disease that is one of the most important public health riskscaused by the all four serotypes of dengue virus DENV-1, DENV-2, DENV-3 and DENV-4. Globally there are 100 to 400 million cases of infections annually in tropical and subtropical regions [1-3]. Aedes aegypti and Aedes albopictus mosquitoes are responsible for the diseases transmission [1,2,4]. As the Ae. Aegypti mosquitoes have adjusted to urban settings, the control and mitigation of the disease has become very difficult [5-7]. The epidemics of dengue fever in India have turn out to be more commonand have rapidly spread to new areaswhere dengue was not generallyin existence [8]. Ensuing epidemics have been reported in different parts of India, especially in urban settings [9].An important shift has been observed in the range of the dengue affected area where it is not constrained to urban areas only but has spread to rural expanses [10].The increase in the burden of dengue cases in

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India has been associated with the deviations in environmental aspects, unforeseen urbanization, population resistantissues and insufficient vector control actions which have shaped promising settings for dengue virus spread [8].There are quite a few studies that conveyed the shifting spatial patterns in the transmission of dengue fever with the causes,stretching from the increase mobility of individuals and goods, proliferating vectors and pathogens to changes in climatic conditions [10-13]. Meteorological parameters like temperature, relative humidity and precipitation are important factors in mosquito population and disease transmission dynamics [14]. Temperature impacts the growth multiplicative performance of mosquitoes and precipitationdelivers the water that helps as surroundings for larvae whereas humidity indulgence inprolonged existence of the mosquitoes and reduce the viral growth period leading to quicker virus replication and better transmission intensity [14-16].It is also evident from the past literatures that the risk of dengue transmission is highly seasonal and increases primarily when vector incursion reaches its peak [17,18]. The association between meteorological parameters and dengue fluctuates across the areas [19,20]. For tropical and subtropical region like India, dengue is highly seasonal but inadequate numbers of researches have been carried out to estimate the effect of meteorological parameters on the number of dengue cases.

There are some studies regarding linear and nonlinear methods simulating intricate associations between climatic parameters and dengue fever incidence [1,21,22]. Though, the linear methods are frequently inept to simulate complex relations between these parameters [23,24]. Nonlinear methods have usually given away comparatively better results than linear models [25-27].

The objective of the study is to establish a predictive model for the occurrence of dengue fever and number of cases as a function of meteorological parameters like precipitation, temperature and relative humidity. Two study areas were chosen in this study which were can be studied independently. An artificial neural network (ANN) model was developed for predicting the number of cases as a function of precipitation, temperature and relative humidity which was additionally corroborated with the independent set of dengue cases. ANN use mixtures of predictor variables of meteorological parameters to simulate association with target variable the number of dengue fever cases. This model can be adjusted to integrate the data such that advance the functional associations between meteorological parameters and the number of dengue fever cases.The model would be useful for predicting the potential outbreaks of dengue fever with known meteorological parameters and comprehend the dengue fever dynamics and advance epidemiological observation which is the innovative feature of the study.

Methodology

Description of the Study Area

The study areas were the Kamrup district and Lakhimpur district in thesub-basin of river Brahmaputra, Assam, North-east India, with their geographic location between 25°31'3.434"N and 26°44'55.122"N Latitude and 90°56'14.324"E and 92°6'10.578"E Longitude and 26°31'3.254"N and 27°28'32.471"N Latitude and 93°51'54.414"E and 94o57'24.874"E Longitude respectively. Kamrup district has an average precipitation of 172 cm per year, with annual average maximum temperatures of 32°Cand minimum 19°C,average relative humidity is 82%. Lakhimpur district has an average precipitation of 277 cm per year, with annual average maximum temperatures of 29°C and minimum 18°C and the average relative humidity is 87%. For the months of May to October weather is wet and from December to March it is dry in both the study areas.

Dengue Fever Cases

Dengue fever data for both the study areas were obtained from the department of epidemiology from the year 2012-2018 for seven years. The phenology of dengue cases for both the study areas is comparable, with cases typically increasing in August-October and decreasing around December and January which follows the rainy season at both the study areas. The number of dengue cases differs in different years due to various serotypes articulating themselves in different times and the vulnerability of population with movement to affected areas. The number of dengue cases in Lakhimpur district is minuscule in comparison to the Kamrup district as one area has been chosen as exceedingly exposed to dengue fever and other is slightly exposed.

Meteorological data

Precipitation, relative humidity and minimum and maximum temperatures were obtained from the Indian Meteorological Department (IMD) from the year 2012-2018 for seven years.

Development of artificial neural network (ANN) model for Dengue Fever Cases

Neural networks comprise artificial neurons in a multi-layered architecture to institute correlation between the input and the output parameters.A network is trained encompassing an iterative process by which the network provides the suitable inputs along with anexact output for each of the inputs [28]. In the wake of the training, the subsequent set has been learned with the learning weights are slightlyadjusted while each ofthe iterations carried out and the cycle is settled when the appropriate weights have been achieved.

In the study, ANN was carried out to relatemeteorological parameters with the number of dengue cases. ANN has been used to predict the dengue cases for the study areas as a

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function of precipitation, relative humidity and temperature. ANN toolbox available with MATLAB v 2015A, has been used for the formation of the relationship between the number of dengue cases and meteorological parameters precipitation, relative humidity and temperature. The network was constructed and trained with various learning algorithms where multilayer feed-forward-back-propagation network with Levenberg–Marquardt's learning rule found to be the most competent and precise in estimating the output in comparison with the other algorithms with the lowest mean square errors (MSE) with 5 neurons as shown in figure 1. The maximum possible iterations had been set to 50,000 where the advancement in successive learning iterations was determined by MSE, as expressed in Eq. 1,

$$MSE = \frac{1}{N_d}\sum_{i=1}^{N}(O_s - O_A)^2 \tag{1}$$

where OS and OA were the simulated and predicted values respectively of the same unit and Nd was the total number of units. As obvious from figure 2, the number of neurons in the hidden layer was optimized to have the least MSE.Therefore, the network structure was a 3-5-1 architecture with three neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer where non-linear tan-sigmoid transfer function was used for the nodal connectors as shown in figure 2.

Results

Normalization of Input and Output

The normalization was conducted using the following expression given as,

$$S_j^n = 2\frac{S_j^a - S_j^{min}}{S_j^{max} - S_j^{min}} - 1 \tag{2}$$

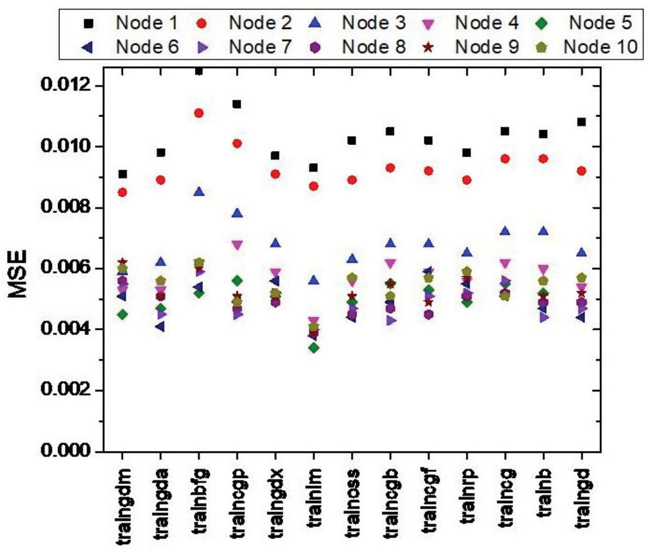

Figure 1: Training program of hidden layer transfer functions with MSE data

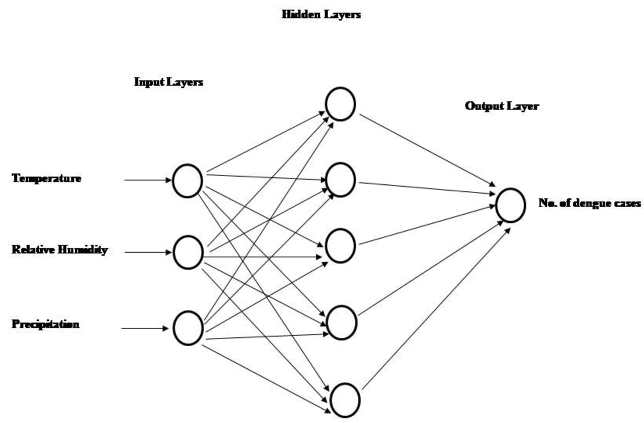

Figure 2: Structure of the Neural Network

where "S" _"j" ^"n" and "S" _"j" ^"a" were the jth values of input or output before and after normalization respectively whereas "S" _"j" ^"max" and "S" _"j" ^"min" are the maximum and minimum values of all before normalization.

Number of Hidden Neurons

Investigation was conducted to find out the optimal number of neuronsindispensable in the hidden layer. It was clear that the lowest MSE was in the case of Levenberg–Marquardt's training function with 5neurons in the hidden layer. Therefore, a 3-5-1 ANN architecture had been developed with threeinput neurons (precipitation, humidity and temperature) with one output node (No of dengue cases) and five hidden neurons tabulated in table 1.

Overview and Performance of the ANN Architecture

The architecture of the ANN can adjust its performance in agreement with the precise problem. So, ANN has the capability to captureoperative configuration from a particular dataset which is known as training where the connection weights of neurons change systematically to deliver the favored outcomes. The leading objective of the training is to discover the perfectconnection weights which would generate minimum MSE. Capability of neural structure for training, Testing and Validation phase shown in figure 3.

ANN Prediction Equation

A model equation was outlined with the weights and biases attained from trained ANN. The mathematical equation linking the input variables and the output could be expressed as

$$D_n = f_{sig}\left\{b_0 + \sum_{k=1}^{h}\left[w_k \times f_{sig}(b_k + \sum_{i=1}^{m} w_k P_i)\right]\right\} \tag{3}$$

where Dn was the normalized output variable,fsigis the sigmoid transfer function, b0is the bias at the output layer; Wkisthe connection weight between k[th] node of hidden layer

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Table 1: Training parameters in the study.

Sr. No.	Training parameters	Magnitudes and Selection
1	Training function	trainlm
2	Transfer function Hidden layer	tansig
3	Transfer function Output layer	tansig
4	Performance function	mse
5	Error after learning	0.001
6	Epochs	50,000
7	Number of neurons in input layer	3
8	Number of hidden layers	1
9	Number of neurons in hidden layer	5
10	Number of output layers	1

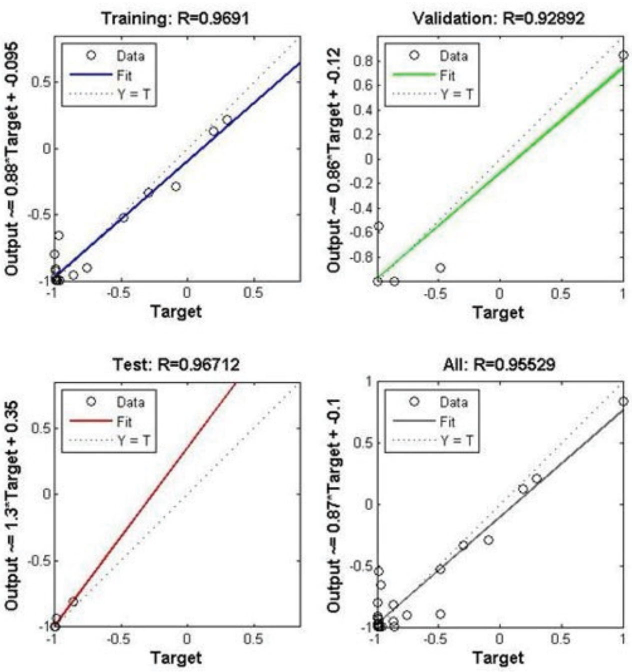

Figure 3: Capability of neural structure for training, testing and validation phase.

Table 2: Sensitivity index for dengue cases by Garson's algorithm (based on ANN)

S. No.	Input	Importance	Importance (%)	Rank
1	Precipitation	1.53549	30.7	3
2	Temperature	1.5874	31.7	2
3	Relative Humidity	1.87711	37.5	1

and the output node, bhkis the bias at the kth node of the hidden layer, mis the number of input variables, his the number of neurons in the hidden layer, Wikis the connection weight between ith layer of input and kth node of hidden layer, Piis the normalized input variables.

With the values of the connection weights and biases and subsequent ANN Prediction Equations of the model can be expressed.

The Dnvalue was in between −1 and 1 and that required to be denormalized as,

$$D = 0.5(Dn+1)\,(Dmax - Dmin) + Dmin \tag{4}$$

where, Dmaxand Dminwere the maximum and minimum value respectively of the dataset

Sensitivity study of meteorology and dengue cases

The goal of a sensitivity analysis is comparable to evaluating relative importance of explanatory variables, with a few differences. The relationships between explanatory and response variables as described by the model in the hope that the neural network has explained some real-world phenomenon. Itis note worthy for the choice of inducing input variables so as to give their ranking according to their importance. Garson's algorithm was used in this study to find the importance of inputs [27]. Using Garson's algorithm, we can get an idea of the magnitude and sign of the relationship between variables relative to each other. At first the input-hidden and hidden-output weights were disjointed, and the absolute values of the weights were used to differentiate the rank of input parameters. The three meteorological parameters are the inputs for the study. In the method, the products of the input-hidden and hidden-output connection weights were measured. The outcome is the standing of the input variables centered on their absolute values.

$$Input_X = \sum_{Y=A}^{F} \frac{\left| Hidden_X \right|}{\sum_{Z=1}^{9} \left| Hidden_Z \right|} \tag{5}$$

Accordingly, the above expression represents the estimation of variable importance for predictor variable X (where X = 1–3), using the weights connecting each of the input neurons Z (where Z = 1–3) to each of the hidden neurons N (where N = 1–5), and the latter to the single output neuron. The result of the sensitivity analysis conducted with the Garson's method to deliver the importance ranking to the input parameters was shown in table 2. Relative humidity has been found to be the most important input parameter followed by temperature and precipitation.

Discussion

There are fairly a few studies that conveyed the association between meteorological parameters and dengue fever though it vacillates across the areas [17-20].As the meteorological parameters like temperature, relative humidity and precipitation significantly influences mosquito population and spread of the disease, establishing a predictive model for the occurrence of dengue fever is essential [14].

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Though there are studies simulating associations between climatic parameters and dengue fever incidence with both linear and nonlinear methods, nonlinear methods like ANN have typically provided with relatively better results [21,25-27]. ANN model has also been used in Thailand, Singapore, Malaysia, North America to predict dengue fever cases with high accuracies [24,29-30]. The present study is the first such approach in India in that context with an ANN model has been developed for predicting the number of cases as a function of precipitation, temperature and relative humidity which was additionally corroborated with the independent set of dengue cases with two study areas chosen which were studied independently. A model equation has been developed with ANN for determining the number of dengue cases as a function of three meteorological parameters which would be useful for predicting the potential outbreaks of dengue fever and advance epidemiological observation. The sensitivity analysis of the meteorological parameters for predicting the vulnerability of dengue fever is also first such effort in the context of India.

Conclusions

The number of dengue cases was modeled in this study using meteorological parameters with a nonlinear neural network method. An Artificial neural network has been developed with a feed forward back propagation neural network to predict the number of dengue cases towards three meteorological parameters. The ANN model with the five hidden neurons is the optimal model based on training and testing data set. A model equation has been developed based on the trained weights of the ANN for determining the number of dengue cases as a function of three meteorological parameters. Based on sensitivity analysis as per the Garson's algorithm approaches, relative humidity is the most important input parameters for predicting the vulnerability of dengue fever.

There were numerous influences that were not deliberated in the predictive ability of the ANN models. Additional studies are desirable to include population vulnerability to dengue, vector and dengue virus dynamics into the models which advance the ability of simulations and comprehend related diseases that be influenced by meteorological changes. This is also perceived that meteorological parameters are not the only issues influencing the sudden changes in the dengue cases affecting the precision of the model. Future studies should increase the time period to comprehend the seasonal and spatial variances across dengue fever prevalent regions and can apply ANNs in that region to predict the number of cases.

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Author's contribution

BG has worked on the modeling software and designed the prediction model. MShelped in framing the manuscript, worked on dengue disease transmission pattern and acquired data from National Vector Borne Disease Control Programme (NVBDCP), Guwahati and regional metrologicalcentre. Both the authors have read and approved the manuscript.

Ethics approval and consent to participate

Ethical approval and consent to participate is not necessary for the publication.

Consent for publication

Authors declare consent for publication for this manuscript.

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