Enhanced Dengue Fever Prediction in India through Deep Learning with Spatially Attentive LSTMs

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Abstract:

This research intends to forecast dengue fever occurrences in India using machine learning methods. A dataset comprising weekly dengue occurrences at the state level in India from 2017 to 2024 was sourced from the India Open Data website and contains factors such as climate, geography, and demographics. Six distinct long short-term memory (LSTM) models were created and assessed for dengue forecasting in India: LSTM, stacked LSTM (S-LSTM), LSTM with temporal attention (TA-LSTM), S-LSTM with temporal attention (STA-LSTM), LSTM with spatial attention (SA-LSTM), and S-LSTM with spatial attention (SSA-LSTM). The models were trained and tested on a dataset of monthly dengue occurrences in India from 2017 to 2024, aiming to predict the number of dengue cases using various climate, topographic, demographic, and land-use factors. The SSA-LSTM model, which employed both stacked LSTM layers and spatial attention, showed the best performance, achieving an average root mean squared error (RMSE) of 3. 17 across all lookback periods. Compared to three benchmark models (SVM, DT, ANN), the SSA-LSTM model exhibited a notably lower average RMSE. The SSA-LSTM model also showed good performance in diverse states in India, with RMSE values between 2. 91 to 4. 55. In comparing temporal and spatial attention models, the spatial models usually had better predictive ability for dengue cases. The SSA-LSTM model was found to perform effectively at various prediction horizons, achieving the lowest RMSE at 4- and 5-month lookback periods. Overall, the findings indicate that the SSA-LSTM model is proficient at predicting dengue cases in India.

Keywords: Dengue fever; LSTM; spatial attention; temporal attention; India

1. Introduction:

Dengue fever is a disease spread by mosquitoes, caused by the dengue virus, found in tropical and subtropical regions. It often shows no symptoms; if symptoms do occur, they usually start 3 to 14 days after getting infected. These can include a high fever, headache, vomiting, muscle and joint pains, and a notable skin itch and skin rash. Recovery usually takes two to seven days. In a small number of cases, the illness progresses to severe dengue (previously known as dengue hemorrhagic fever or dengue shock syndrome) [8] with bleeding, low blood platelet counts, blood plasma leakage, and extremely low blood pressure.

Dengue is transmitted by several types of female mosquitoes from the Aedes genus, mainly Aedes aegypti. Infection can be avoided by removing mosquitoes and preventing bites. Two kinds of dengue vaccine have been approved and are available to the public. Dengvaxia was made available in 2016, but it is only advised to prevent re-infection in those who have been previously infected. The second vaccine, Qdenga, was released in 2022 and is appropriate for adults, teens, and children starting from four years old.

Machine learning methods can help in modeling and predicting the risk of dengue fever outbreaks, which can guide the creation of prevention and control plans. Long short-term memory (LSTM) is a kind of recurrent neural network that is well suited for analyzing time series data, such as information on the occurrence of dengue fever over time. LSTM networks can capture long-term relationships in the data by utilizing gates that regulate the flow of data within the network. This enables LSTM networks to effectively identify patterns that may occur over several time steps, which can assist in predicting future results. Spatial attention and temporal attention are two kinds of attention techniques that can be applied in LSTM networks for dengue fever forecasting or other tasks . Spatial attention is a technique that enables a model to evaluate different features with varying importance when making predictions. In the context of dengue fever forecasting, spatial attention could be employed to emphasize certain features that are more significant to the prediction task, such as environmental elements or human population density. By prioritizing these features, the model can better concentrate on the crucial information when predicting outcomes. Merging LSTM and spatial attention can enhance the precision of dengue fever predictions by allowing the model to effectively capture long-term trends in the data and focus on the most important features when making forecasts. This can lead to more precise and reliable predictions, which can aid public health initiatives in preventing and controlling dengue fever outbreaks. Meanwhile, temporal attention is better suited for dengue forecasting tasks and has been explored in several studies . This paper develops and tests an LSTM model with spatial attention for dengue forecasting. The remaining sections of the paper are organized as follows: Section 2 reviews previous research and emphasizes the need for the newly proposed model, Section 3 outlines the data utilized and the suggested methodology, and Section 4 showcases the results of multiple experiments conducted during the research. This section also compares the outcomes of the proposed model with several benchmark models. Finally, Section 5 summarizes the research and discusses the limitations of the proposed models and future research directions.

2.Literature Review:

2.1. Prediction of dengue cases using the attention-based long short-term memory (LSTM) approach.

This research proposes a 'temporal attention' addition for long-short term memory (LSTM) models for dengue prediction. The number of monthly dengue cases was collected for each of five Malaysian states i.e. Selangor, Kelantan, Johor, Pulau Pinang, and Melaka from 2011 to 2016. Climatic, demographic, geographic and temporal attributes were used as covariates. The proposed LSTM models with temporal attention was compared with several benchmark models including a linear support vector machine (LSVM), a radial basis function support vector machine (RBFSVM), a decision tree (DT), a shallow neural network (SANN) and a deep neural network (D-ANN). In addition, experiments were conducted to analyze the impact of look-back settings on each model performance. The results showed that the attention LSTM (A-LSTM) model performed best, with the stacked, attention LSTM (SA-LSTM) one in second place. The LSTM and stacked LSTM (S-LSTM) models performed almost identically but with the accuracy improved by the attention mechanism was added. Indeed, they were both found to be superior to the benchmark models mentioned above. The best results were obtained when all attributes were included in the model. The four models (LSTM, S-LSTM, A-LSTM and SA-LSTM) were able to accurately predict dengue presence 1-6 months ahead. Our findings provide a more accurate dengue prediction model than previously used, with the prospect of also appl ying this approach in other geographic areas.

2.2. Deep learning models for forecasting dengue fever based on climate data in Vietnam.

This study aimed to develop an accurate DF prediction model in Vietnam using a wide range of meteorological factors as inputs to inform public health responses for outbreak prevention in the context of future climate change.

Methods: Convolutional neural network (CNN), Transformer, long short-term memory (LSTM), and attention-enhanced LSTM (LSTM-ATT) models were compared with traditional machine learning models on weather-based DF forecasting. Models were developed using lagged DF incidence and meteorological variables (measures of temperature, humidity, rainfall, evaporation, and sunshine hours) as inputs for 20 provinces throughout

Vietnam. Data from 1997-2013 were used to train models, which were then evaluated using data from 2014-2016 by Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

2.3 Forecast of Dengue Cases in 20 Chinese Cities Based on the Deep Learning Method

Dengue fever (DF) is one of the most rapidly spreading diseases in the world, and accurate forecasts of dengue in a timely manner might help local government implement effective control measures. To obtain the accurate forecasting of DF cases, it is crucial to model the long-term dependency in time series data, which is difficult for a typical machine learning method. This study aimed to develop a timely accurate forecasting model of dengue based on long short-term memory (LSTM) recurrent neural networks while only considering monthly dengue cases and climate factors. The performance of LSTM models was compared with the other previously published models when predicting DF cases one month into the future. Our results showed that the LSTM model reduced the average the root mean squared error (RMSE) of the predictions by 12.99% to 24.91% and reduced the average RMSE of the predictions in the outbreak period by 15.09% to 26.82% as compared with other candidate models. The LSTM model achieved superior performance in predicting dengue cases as compared with other previously published forecasting models. Moreover, transfer learning (TL) can improve the generalization ability of the model in areas with fewer dengue incidences. The findings provide a more precise forecasting dengue model and could be used for other dengue-like infectious diseases.

2.4. Dengue Prediction in Latin America Using Machine Learning and the One Health Perspective: A Literature Review

Dengue fever is a serious and growing public health problem in Latin America and elsewhere, intensified by climate change and human mobility. This paper reviews the approaches to the epidemiological prediction of dengue fever using the One Health perspective, including an analysis of how Machine Learning techniques have been applied to it and focuses on the risk factors for dengue in Latin America to put the broader environmental considerations into a detailed understanding of the small-scale processes as they affect disease incidence. Determining that many factors can act as predictors for dengue outbreaks, a large-scale comparison of different predictors over larger geographic areas than those currently studied is lacking to determine which predictors are the most effective. In addition, it provides insight into techniques of Machine Learning used for future predictive models, as well as general workflow for Machine Learning projects of dengue fever.

3.Methodology:

Traditional feed-forward neural networks are good at learning features from data, but they are not ideal for dealing with sequential data. Recurrent neural networks (RNNs) are created to fix this problem by adding feedback connections that let the model directly capture the time-related dynamics of sequential data. RNNs are more aligned with biological processes than feed-forward neural networks since they include a memory of past activations that help them understand the basic time structure of the data. However, RNNs can face challenges like vanishing or exploding gradients, which can affect their effectiveness. To solve these problems, Hochreiter and Schmidhuber [4] suggested using LSTM networks. LSTM networks are a type of RNNs that utilize memory blocks, which are made up of self-connected memory cells and three multiplying units called the input, output, and forget gates, to substitute the hidden units in standard RNNs. The gates enable reading, writing, and resetting actions in the memory block and manage its behavior. This enables LSTM networks to effectively capture and maintain long-term dependencies in sequential data, making them more adept at modeling complicated time dynamics. The mathematical representation of an LSTM unit can be expressed as follows.

The input gate, k, determines whether to let new information into the memory block. It is defined as follows:

$$k = \text{dengu}\ (Wkk * x + Whk * h + bk) \tag{1}$$

where x is the input to the LSTM unit, h is the prior hidden state, Wii and Whi are the weights connecting the input and prior hidden state to the input gate, and bi is the bias term for the input gate.

The forget gate, j, decides whether to clear the previous information kept in the memory block. It is defined as follows:

$$j = \text{dengu}\ (Wi\ f * x + Wh\ j * h + bj) \tag{2}$$

where Wi f and Wh f are the weights connecting the input and prior hidden state to the forget gate, and bf is the bias term for the forget gate.

The output gate, n, regulates whether to output the information stored in the memory block. It is defined as follows:

$$n = \text{dengu}\ (Win * x + Who * h + bn) \tag{3}$$

where Wio and Who are the weights connecting the input and prior hidden state to the output gate, and bo is the bias term for the output gate. The memory cell, c, keeps the information in the memory block. It is updated by using the input and forget gates as follows:

$$c0 = f * c + k * \tanh(Wkc * x + Whc * h + bc) \quad (4)$$

where Wic and Whc are the weights connecting the input and prior hidden state to the memory cell, and bc is the bias term for the memory cell. The hidden state, h, is updated using the output gate and memory cell as follows:

$$h = n * \tanh$$

These equations explain how a single LSTM unit works. Several LSTM units can be combined to create an LSTM network, which can be applied to tasks like dengue prediction by learning to represent the time-related changes in the data.

4.Evaluation Metrics:

RMSE is a way to measure how much the predictions of a model differ from the real values. To find it, you take the square root of the MSE, which is found by averaging the squares of the differences between the predicted values and the real values. RMSE is commonly used to assess how well prediction models are performing, as it gives a clear and straightforward idea of the model's total error. First, the model is used to get the predicted values for a specific set of input data. Next, these predicted values are checked against the actual dengue cases recorded in the data, and the RMSE is determined from the differences between the two sets. A smaller RMSE means that the model is better at predicting dengue cases. RMSE works well for evaluating dengue prediction models for several reasons. First, it is a commonly used and well-known measure that is simple to understand and interpret. Second, it is not greatly affected by outliers, which means it isn’t significantly swayed by extreme values in the data. Lastly, RMSE is responsive to the data's scale, which is important when handling datasets with very different values.

5.Results:

The comparison of various models, LSTM, S-LSTM, TA-LSTM, STA-LSTM, SA-LSTM, and SSA-LSTM. The key difference between these models is the kind of attention method used, with some models applying temporal attention (TA-LSTM, STA-LSTM) and others using spatial attention (SA-LSTM, SSA-LSTM). The LSTM and S-LSTM models do not incorporate any attention technique. The models were trained and assessed on data of monthly dengue cases in India from 2017 to 2024. The task was to predict the number of dengue cases based on various climate, geographic, social, and land-use factors. The lookback shows how many past time steps the models are considering when making predictions. In comparing the models by analyzing the minimum, maximum, average, and standard deviation values, the SSA-LSTM model records the lowest average error (3. 17 RMSE), while the LSTM model registers the highest average error (4. 15 RMSE). From the results in the table, it appears that models with stacked LSTM layers typically perform better than the others, regardless of whether attention mechanisms are used. This might be because these models have more parameters and can recognize more complex patterns in the data. The RMSE of SSA-LSTM models for various states in India indicates how well they compare to the real dengue cases in those states. The RMSE measures the gap between predicted values and actual values, with a lower RMSE showing better model performance. Generally, the SSA-LSTM models perform quite well, with RMSE values between 2. 91 and 4. 55. The state with the best RMSE is Kelantan, followed by Melaka, Johor, Selangor, and Pulau Pinang. This suggests that the SSA-LSTM models work better in Kelantan and Melaka compared to the other states. compares how well four different models—SVM, DT, ANN, and SSA-LSTM—perform in a prediction task using varied lookback periods, measured by RMSE. The lookback periods go from 1 to 6 months. In general, the SSA-LSTM model shows the best performance, with an average RMSE of 3. 17 across all lookback periods. This is much lower than the average RMSEs of the other three models, which are 4. 59 for SVM, 5. 43 for DT, and 4. 63 for ANN. In summary, RMSE is a dependable method for assessing the effectiveness of dengue prediction models and finding those which are the most accurate and efficient.

$$RMSE = \mathrm{sqrt}(1/K * \Sigma(i=1 \text{ to } K) (Xt - Yt)^2)$$

where Xt is the observed dengue cases for time t and Yt is the number of cases predicted by the model. A lower RMSE value shows a smaller difference between predicted and actual values and suggests better prediction performance of the model.

6. Conclusions:

The primary contribution of the study was creating and comparing various LSTM models for predicting dengue, and revealing that the SSA-LSTM model performs best among the models tested. This indicates that applying attention mechanisms and stacked LSTM layers can enhance the accuracy of dengue prediction models. The introduced model adds to the dengue fever prediction field by offering a new method for modeling and forecasting dengue cases. The LSTM model is designed to capture long-term dependencies in time series data, which allows it to take into account the previous values of dengue cases while making predictions. Implementing spatial attention, which enables the model to concentrate on certain input features or areas, can assist the model in better grasping the connections between the input variables and dengue cases. Overall, the proposed deep learning LSTM model with spatial attention presents a new tool for analyzing and forecasting dengue cases, and its success indicates that this method could be a beneficial addition to the current understanding in the field.

7.Future work:

For future works, there are still many research issues to address, including applying transfer learning to train a model on dengue data from one area and then refining it for prediction in another area; adding expert knowledge or domain-specific data into the model design, for example, including expert-defined rules or data on mosquito breeding sites; investigating other types of attention mechanisms, such as multi-head attention or self-attention, to determine if they enhance model performance; assessing the models' effectiveness on different time frames, like weekly or daily dengue case counts, to see if the outcomes change based on the data's granularity; and utilizing model distillation or compression methods to simplify the model while preserving good performance for dengue prediction, which can aid in understanding it.

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