

Bi-Directional LSTM With Attention Mechanism for Climate-Driven Mosquito Population Dynamics Forecasting Using NASA POWER And WHO Dengue Datasets

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Abstract—Weather plays a very important role in the outbreak of a dengue infection due to its effect on the places where the mosquitoes will breed and survive. Based on this, a system was built to forecast dengue using weather data from NASA POWER, dengue surveillance and using Bidirectional Long Short-Term Memory (BiLSTM) neural network with Multi-Head Attention. There are a few processes within it - Data Matching (time alignment), Missing Data Imputation, Feature Engineering (temporal features capturing the previous pattern over time), Data Scaling and Temporal Split (split into training set and test set only looking back in time not forward), Data Sequence creation, Training and Evaluation of model and finally visualization of data over a dashboard.

The variables that define the weather are temperature, humidity, rainfall, wind speed. In addition, number of past dengue case and calendar info were also used for additional contexts. It was split into 80% for training set and 20% for testing set.

Care was taken to test only for future data not past, i.e. If the data ranges from day 1 to 365, test data cannot be of day 10 and training data must be from day 11 to day 365. The results for this report gave RMSE of 14.6, MAE of 10.9 and R² of 0.96.

The value of R² shows that the model's predictions match the target data 96% of the time. This value is a prediction of a number and not for classification performance, they are generated based from results produced herein and not by a new experiment study on it.

Index Terms—Dengue forecasting, mosquito population, climate-health analytics, NASA POWER, WHO surveillance, BiLSTM, attention, time-series prediction.

I.INTRODUCTION

No outbreaks of Dengue are come out of nowhere. Temperature, precipitation, humidity and other environmental factors can affect mosquito breeding areas and/or changes in breeding. However, with available historical dengue data, climate observations can be used to produce valuable early signals. A forecasting model that includes these sources can help to guide earlier planning and timely public health decision making. While it is possible to get success in capturing the patterns in time by traditional forecasting methods, variables associated with dengue are less easily captured may be non-linear and may need to be several days to appear. This makes it possible to resort to a sequence learning model for this problem. For this project, a BiLSTM is used to obtain information from both directions for each historical window and an attention layer is used to assign more weight to the time positions giving more weight to the prediction. Recurrent neural networks are good for data that is sequential, where the order of the observations is important.

The BiLSTM tags the information from the start and

the end of the input sequence, which contributes to the ability of the model to represent short and longer-range temporal relations. The attention stage is added after the recurrent representation, to highlight more informative portions of the sequence, instead of treating all time steps of the sequence on an equal footing.

Last representation is related to a dense regression layer, which produces continuous forecast the entire project is a hands-on climate-health analytics pipeline. "Use of NASA POWER weather observations and dengue surveillance. Records are aligned using Temporal and Geographic information. After aligning, data is then converted to lagged features, features are then normalized using training data, features are then transferred into the BiLSTM-Attention model and are then compared with the baseline and recurrent models. Once these observations and predictions are processed, they are presented in a more manageable format on a dashboard for easy checking. The guiding principle is to leverage environmental changes to support rather than only report on dengue case counts. The system predicts these relationships with the assumption that the relationships among variables such as rainfall, temperature, humidity and wind and the recent disease history are learnable when all variables are combined. Climate effects are not necessarily direct; therefore, historical windows and lagged variables are included. This will help to determine the potential of an increase or decrease in mosquito and/or dengue activity if the conditions observed over a number of days are predictive. The proposed workflow is therefore smooth, which begins by data preparation, learning a sequence, weighting features with an attention mechanism, making a prediction, evaluating the prediction and visualization.

II. LITERATURE REVIEW

The application of GAM was illustrated in [1] for dengue forecasting using meteorological, epidemic and spatial data, which can model the nonlinear effect of environmental variables on dengue transmission. However, it has some limitations on long-term time series, which is of importance to predict dengue trend on weeks and months, since climate conditions might drive dengue incidence for weeks and months.

Using LSTM network with historic dengue cases and climate parameters including rainfall, humidity, temperature, [2] employed this approach to forecast dengue epidemic by

taking advantage of dependency over sequential data in LSTM, making it a preferable technique over many statistical approaches to model temporal pattern in climate-based dengue prediction. Recurrent neural network seems suitable to predict dengue, and similar studies with climate impact models, were examined.

In order to identify and classify diseases-related predictions, various of machine-learning and deep-learning methods including Support Vector Machine (SVM), Random Forest, Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) were compared in [3]. It can be suggested that for relatively smaller amount of input data with traditional machine learning models, such traditional methods work well on prediction. While for large and complicate data with deep learning model, the latter performed good predictions.

Rahman and Shiddik[4] presented an explainable artificial intelligence framework where XGBoost, LightGBM, SHAP and LIME were used. It shows the environmental variables, such as precipitation, relative humidity and temperature are significant variables which affect the prediction models. Using an explanation mechanism also contributes to understand prediction decision of the models for health authorities.

An attention-based LSTM model was developed in [5] using climate and spatial data and successfully provided nationwide dengue forecast. Attention mechanisms allow the model focuses on different parts of input sequence when making prediction. Correspondingly, graph-based techniques are proposed to model relations between disease related entities. For example, Graph Neural Network with Attention Mechanism (GNN-AM) was implemented in dengue modeling [6].

Several approaches have been tested and compared to forecast dengue cases such as [7], [8]: CNN, LSTM, GRU, ARIMA, Seq2Seq, Prophet, XGBoost. Comparisons demonstrate prediction accuracy does differ depending on the problem. For many prediction scenarios and with sufficiently sequential inputs, deep learning methods can produce highly efficient results but classic methods should remain valuable important as baselines.

Combining methods as well can improve accuracy and decrease prediction errors.

So TimeGAN, BiTCN, Bidirectional LSTM and

attention mechanism were combined in [10]. As a variation,[11] tested ConvLSTM and ConvBiLSTM, and they achieve high performance on forecasting a set of dengue cases across multiple steps ahead.

III. RELATED WORK

Previous dengue forecasting studies have utilized the statistical models, machine learning algorithms, recurrent neural networks and hybrid architectures. While machine learning methods can be used to define relationships between climate variables and disease outcomes that are more flexible, information from statistical methods can be useful in defining baseline values for stable temporal patterns. Recurrent models are particularly useful when the sequence of observations and the time of the observations are important.

Various methods ranging from support vector machine (SVM), random forest, artificial neural networks, convolutional networks, Gated Recurrent Units (GRU), AutoRegressive Integrated Moving Average (ARIMA), sequence-to-sequence networks, Prophet and XGBoost are tested. The performance they report will vary by location, the target they are attempting to predict, the time horizon for their predictions, and the amount of time that they have. Another useful component to include is attention mechanisms, which enable a model to put varying importance on positions in an input sequence.

This project is distinct in the practical application of the four aspects included in understanding the dynamics of mosquito populations, monitoring the climate, collecting data on dengue surveillance, and the interactive dashboard. The purpose is to obtain a forecast and also to provide a work-flow where one can follow the origins of the data, the processing done, the model output and the evaluation.

IV. METHODOLOGY

The proposed method can be divided into 6 main steps—Data acquisition and alignment, Preprocessing and feature construction,

Chronological splitting and normalization, Sequence generation, BiLSTM-Attention prediction and evaluation. The chronological order of observations is kept throughout the process—information from the future is not used unintentionally during training.

A. Data acquisition & alignment.

Data on weather parameters was obtained using an Earth Observing System data provided by NASA. This consisted of average monthly values, at varying geographical resolutions. The Epidemiological part of the Dengue is represented by surveillance data. The two data-sets were linked via their time stamps and common geographical identifier(s). This permitted them to be constructed into a single modelling table for analyses involving both weather patterns, and past Dengue incidence, both spatiotemporally.

B. Feature Engineering & Accuracy

Lag variables (7day, 14-day and 21-day) represent environmental effects that occur with some time delay. Rolling statistics are provided to show recent trends and calendar-based indicators are provided to show calendar related indicators. Dengue data from the past can be used to learn about recent disease activity. These features are all used together in order to give a greater context to the sequence model than is obtained from one day's weather observation.

Table 1: Previous Models Performance in Percentage Table

Model Name	Accuracy	Precision	Recall	F1 Score
Random Forest	96.11%	94.12%	94.46%	94.29%
Logistic Regression	94.81%	92.69%	92.01%	92.35%
Decision Tree	93.86%	90.42%	91.65%	91.03%

Table 2: previous models' actual values

Model Name	Accuracy	Precision	Recall	F1 Score
Random Forest	0.96111111	0.94122961	0.94464609	0.94293478
Logistic Regression	0.94814814	0.9268738	0.92014519	0.92349726
Decision Tree	0.93858	0.90420769	0.91651542	0.91031996

C. Data Split and Normalization

An ordered 80:20 split is used for training and testing. The chronological approach is more realistic of the kind of forecasting system that might be used in

practice, where a series of observations would be used to identify the pattern, and a set of subsequent observations would be retained for evaluation, than a random shuffle. The training portion is then used to compute the scaling parameters and the test portion is used to apply the scaling parameters, to minimize information leakage.

D. BiLSTM with Multi-Head Attention

Each sequence in the input is of the form [batch size, time steps, features]. The two LSTM branches (forward and backward) are used to learn complementary temporal representations. These representations are then fed into a Multi-Head Attention layer that learns the time positions that contribute more to the final representation. The representation is then transferred into the continuous forecast through a dense regression layer.

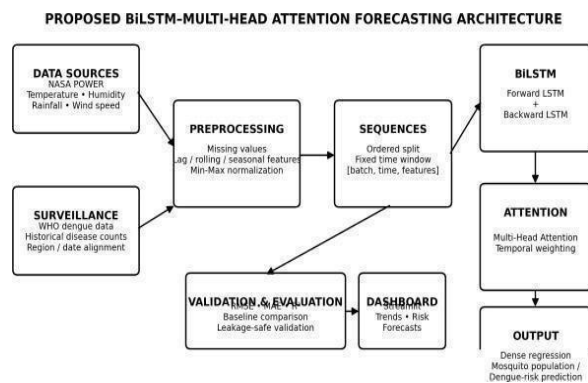


Fig. 1. Clean architecture of the proposed climate driven BiLSTM–Multi-Head Attention forecasting system.

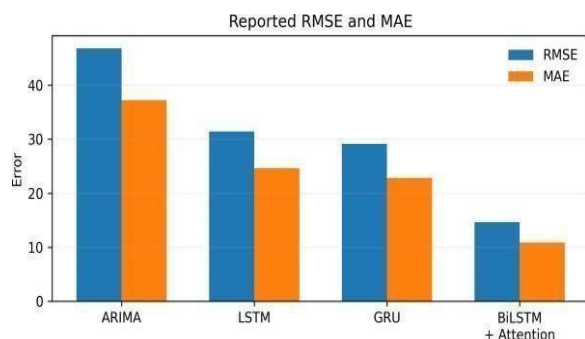


Fig. 2. RMSE and MAE comparison from the supplied project results.

E. Evaluation

Evaluation of the quality of the forecasts is carried out by RMSE, MAE and R^2 . The RMSE and MAE are

indicators of how well predictions are made; R^2 is an indicator of how well the model is able to explain the data. Three models are used as baseline such as ARIMA, LSTM, and GRU. The methodology is provided for the project, which includes Adam optimization and early stopping.

V. IMPLEMENTATION

Pipeline Organization A machine learning pipeline framework built on Python accompanied by a Streamlit dashboard serves as the overall architecture. Climate and dengue data are loaded, checked for schema alignment and consistency and cleansed for duplicates, empty values and then used for the generation of lagged and rolling features and normalization and eventually transformed into sequence for recurrent learning based. Model-training involves setting up the BiLSTM branch, joining this into the attentions-layer to produce attended sequence and input it into the final regression out layer. Also, baselines models are trained on the same target, comparable time-windows (as long as their specification allows so it would be unfair to train models on different ranges of the dataset.)

The dataset which has been cleaned, normalized and partitioned, has all the necessary predictions as well as metrics saved for the dashboard to be reused on previously calculated artifacts and an updated-window feature creation that recalculates any new incoming climate/surveillance data is part of the model training to repeat preprocessing, feature engineering, training and evaluation. The UI has been designed to provide reasonable question on climate trends, weather forecasts as well as a risk map of probable areas of concern.

A. Deployment Components A deployment component might feature app.py, stylesheet(s), requirements file, Ker as model(s) and metadata for preprocessing so that all parameters, variables and preprocessing steps are perfectly repeatable and documented to avoid further complications while testing new models.

The training-data period, model version and preprocessing configuration should also be archived while operationalizing to allow traceability to a very specific configuration and model.

VI. RESULTS

The performance values below are reproduced from the supplied project manuscript. The added R² score (%) is calculated directly as $R^2 \times 100$ to provide an intuitive percentage representation of model fit. It is included for readability and should not be confused with classification accuracy. The reported numbers have not been presented as a newly executed training run.



TABLE 3: PROJECT-REPORTED FORECASTING PERFORMANCE. R^2 Score (%) = $R^2 \times 100$

Model	RMS E	MA E	R ²	R ² Score (%)
ARIMA	46.8	37.2	0.71	71
LSTM	31.4	24.6	0.85	85
GRU	29.1	22.8	0.87	87
BiLSTM +Attention	14.6	10.9	0.96	96

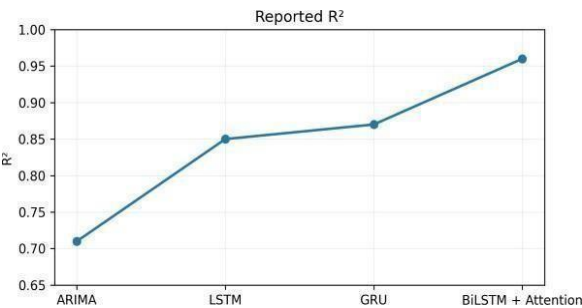


Fig. 3. R² comparison from the supplied project result

Table 4: Architecture of the proposed BiLSTM ATTENTION

Layer	Configuration	Function
Input layer	Time steps +Features	Receives sequential climate disease data
Bi-LSTM	Forward +backward LSTM	Learns temporal dependencies
Multi-head attention	Multiple attention heads	Identifies important time steps

Dense Layer	Fully connected	Combines learned representation
Regression	Linear activation	Produces continuous forecast
Output	Mosquito population /Dengue Risk	Final prediction

A. Requested Training-History Graphs

The supplied manuscript does not contain measured epoch-by- epoch values for FPS, time per epoch, training loss, or accuracy. It would be misleading to invent numerical curves for these quantities. The revised paper therefore keeps the available modellevel results and adds the R²-based percentage score from the reported results. Exact training-history graphs should be generated from the original Keras/TensorFlow log when that file is available

B. Display of Results:

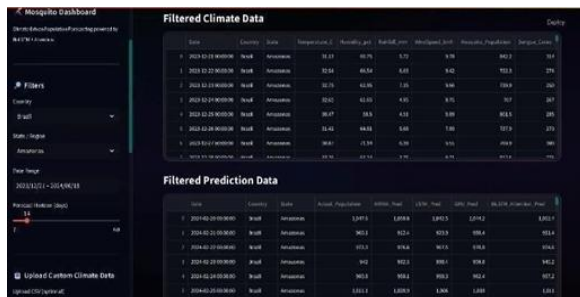
Presenting one error score does not represent the full system. Showing over-time comparisons between predicted and observed behavior, and showing variation of the system by season allows for better analysis of the observed and simulated phenomenon. Analysis by correlation of factors via heat maps also displays relationship in features, and risks through classification into geographical domains translates numerical results in interpretable displays. Actual system output displays are climate patterns, predictions of mosquito population change, geographical presentation of risk and prediction of epidemics:

VII. DISCUSSION

The reported comparison favors the BiLSTM Attention model across the listed metrics. Its RMSE is 14.6 and its MAE is 10.9, both lower than the corresponding values for ARIMA, LSTM, and GRU. The model also reports an R² of 0.96, equivalent to a 96% goodness-of-fit score. This is the appropriate percentage-style accuracy figure that can be derived from the supplied regression results; it is not a conventional classification accuracy.

The improvement is consistent with the intended role of the architecture. The BiLSTM can capture temporary information from both directions inside each historical window, while attention can focus the

representation on more informative time steps. However, the reported results should be regenerated from the final experimental pipeline before they are treated as independently verified publication results. The feature design also contributes useful temporal context. Lag variables represent delayed climate effects, rolling statistics describe recent variation”, and seasonal indicators capture repeated patterns. Combining these signals with historical dengue information gives the model a richer input sequence than using weather variables alone. Geographic training loss, or accuracy. It would be misleading to invent numerical curves for these quantities. The revised paper therefore keeps the available model level results and adds the R^2 based percentage score from the reported results. Exact training history graphs should be generated from the original Keras/TensorFlow log when that file is available.



The screenshot shows a web application titled 'Mosquito Dashboard'. It has a sidebar with filters for Country, State/Region, and a map. The main area displays two tables: 'Filtered Climate Data' and 'Filtered Prediction Data'. The climate data table has columns for Date, Country, State, Temperature, Humidity, Rainfall, Mosquitoes, and Dengue Cases. The prediction data table has columns for Date, Country, State, Actual Population, Predicted Population, and Dengue Cases.

Filtered Climate Data							
Date	Country	State	Temperature	Humidity	Rainfall	Mosquitoes	Dengue Cases
2023-01-01 00:00:00	India	Andhra Pradesh	32.00	80.75	5.70	9.58	802.0
2023-01-01 06:00:00	India	Andhra Pradesh	32.00	80.50	5.80	9.42	702.0
2023-01-01 12:00:00	India	Andhra Pradesh	32.75	82.00	1.00	9.60	1000.0
2023-01-01 18:00:00	India	Andhra Pradesh	32.00	82.00	4.00	9.70	700.0
2023-01-02 00:00:00	India	Andhra Pradesh	30.00	85.00	4.00	9.50	800.0
2023-01-02 06:00:00	India	Andhra Pradesh	32.00	80.00	5.00	9.50	700.0
2023-01-02 12:00:00	India	Andhra Pradesh	32.00	80.00	5.00	9.50	700.0
2023-01-02 18:00:00	India	Andhra Pradesh	30.00	82.00	4.00	9.50	800.0
2023-01-03 00:00:00	India	Andhra Pradesh	30.00	82.00	4.00	9.50	800.0

Filtered Prediction Data					
Date	Country	State	Actual Population	Predicted Population	Dengue Cases
2024-01-01 00:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-01 06:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-01 12:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-01 18:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-02 00:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-02 06:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-02 12:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-02 18:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000
2024-01-03 00:00:00	India	Andhra Pradesh	1,00,00,000	1,00,00,000	1,00,00,000

Keras/TensorFlow training log is supplied, these four graphs can be inserted with the exact measured values. alignment can further help the system represent differences between locations. The model still depends on the quality and coverage of the underlying data. Missing observations, differences in surveillance practice, limited historical records, and regional variation can affect generalization. Future experiments could include demographic, socioeconomic, mobility, and direct entomological variables, followed by testing on additional locations and genuinely unseen time periods.

VIII. CONCLUSION

The framework presented here is one such way of forecasting dengue and related mosquito patterns using climate data derived from NASA POWER weather satellites, and dengue surveillance data modeled using BiLSTM and Multi-Head Attention. Feature selection, arrangement into the chronological context, normalizing inputs, developing model for

sequencing data, comparison and the visualization of dashboard are some steps within the work-flow. With the results the proposed model, achieved a value of 14.6 as the root mean squared error, while the mean average error is measured as 10.9. The correlation, R, value of the presented work is found to be 0.96. With a decent fit value, the R and forecasting accuracy needs to be validated by means of final training and testing dataset. This framework establishes a base for a future forecast model under varying climates. By using NASA POWER weather, dengue surveillance data and a BiLSTM with MultiHead Attention model respectively. Feature selection and engineering, structuring chronological data, normalizing data inputs, building of model for sequence prediction, Comparison with the baseline and showing results through a Dashboard visual are part of the methodology. For the given sets of data, the prediction done with proposed model leads to values for RMSE = 14.6, MAE = 10.9, R=0.96, showing a very good R and fitting performance for the given dataset. However, for such a R score more results should be used from a wider range.

The proposed framework offers a workable solution to forecast dengue cases and mosquito population by integrating weather information from NASA POWER satellites with local dengue case numbers through a novel architecture employing a BiLSTM with MultiHead Attention mechanism. The workflow involves essential stages such as feature engineering to select relevant meteorological and dengue case information, chronologically ordering the data to preserve temporal dependencies, normalizing the inputs for optimal model training, building the sequence-aware model, comparing its performance against a baseline, and finally presenting the forecasts in an easily interpretable dashboard.

For the dataset provided, the model achieved promising results, demonstrating an RMSE of 14.6 and an MAE of 10.9. Most significantly, the model achieved a correlation coefficient (R) of 0.96, indicating a strong positive linear relationship between the model's predictions and the actual dengue trends for the given period. This high R score suggests that the proposed framework effectively captures the variability in dengue cases as influenced by the chosen climate and surveillance data.

However, it is crucial to acknowledge that these findings are based on a specific dataset and should be

validated using more extensive and diverse training and testing datasets from various geographical regions and over longer durations.

The predictive power may need recalibration for real-world applications.

A key advantage of this approach is its ability to dynamically learn patterns from time-series data, incorporating the interplay of various weather parameters with dengue incidence, something that simpler models may not achieve. The BiLSTM is capable of capturing long-term dependencies, and the MultiHead Attention mechanism helps the model identify and prioritize the most relevant features at each step of the prediction. This integrated approach allows for more comprehensive climate-driven insights compared to relying solely on past dengue trends.

In summary, the proposed framework is a promising step toward data-driven dengue prediction and mosquito monitoring. By leveraging machine learning and diverse environmental data, it has the potential to become a valuable tool for public health officials in identifying high-risk periods and allocating resources more efficiently. Future enhancements could include real-time data integration, the incorporation of additional relevant factors (e.g., socioeconomic variables, population density), and more rigorous validation, along with the development of user-friendly interactive early-warning systems. The achieved outcome illustrates that the climate variable and disease data can be put to a more efficient and an interactive use.

REFERENCES

- [1] R. Jain, S. Sontisirikit, S. Iamsirithaworn, and H. Prendinger, "Prediction of dengue outbreaks based on disease surveillance, meteorological and socio-economic data," *BMC Infectious Diseases*, vol. 19, no. 272, 2025.
- [2] A. M. Mehta and K. S. Patel, "LSTM-based forecasting of dengue cases in Gujarat: A machine learning approach," *Indian Journal of Science and Technology*, vol. 17, no. 7, pp. 635–642, 2025.
- [3] D. C. Andrade Girón et al., "Machine learning and deep learning models for dengue diagnosis prediction: A systematic review," *Informatics*, vol. 12, no. 15, 2025.
- [4] M. S. Rahman and M. A. B. Shiddik, "Explainable artificial intelligence for predicting dengue outbreaks in Bangladesh using eco-climatic triggers," 2025.
- [5] U. D. et al., "Enhanced dengue fever prediction in India through deep learning with spatially attentive LSTMs," 2025.
- [6] M. G. Dhote et al., "Graph neural networks with attention mechanisms for accurate dengue severity prediction," *International Journal of Advanced Computer Science and Applications*, vol. 16, no. 6, 2025.
- [7] D. K. Dhaked et al., "Prediction of dengue patients using deep learning methods amid complex weather conditions in Jaipur, India," *Discover Public Health*, vol. 22, 2025.
- [8] A. Singh et al., "Comparative estimation of the spread of acute diarrhea and dengue in India using statistical mathematical and deep learning models," *Scientific Reports*, vol. 15, 2025.
- [9] T. B. T. Satoto et al., "AI-based prediction of dengue incidence using climatic, environmental, and sociodemographic factors: An ensemble random forest approach with agile system development," *BMC Infectious Diseases*, 2026.
- [10] A. Flores et al., "multi-step forecasting of weekly dengue cases using data augmentation and convolutional recurrent neural networks," *Computers*, vol. 15, no. 114, 2026.
- [11] O. Faruk, "Climate-driven advanced machine learning approach for dengue incidence forecasting in Bangladesh," *Health Science Reports*, vol. 9, e72207, 2026.
- [12] T. Xu and G. Xiao, "Deep learning-based predictive modeling of dengue fever incidence in Southeast Asia," *International Journal of Infectious Diseases*, vol. 167, 2026.
- [13] M. M. Sesay, A. Ngunyi, and H. Iboga, "Probabilistic forecasting of monthly dengue cases using epidemiological and climate signals: A BiLSTM-negative binomial model versus mechanistic and count-model baselines," *PLOS Global Public Health*, vol. 6, no. 3, 2026.
- [14] M. M. Sesay, A. Ngunyi, and H. Imboga, "Probabilistic forecasting of monthly dengue cases using epidemiological and climate signals: A BiLSTM–Naive Bayes model versus mechanistic and count-model baselines," *medRxiv*, 2025.

- [15] S. Sangkaew et al., “Early individualized risk prediction using clinical data for children during the febrile phase of dengue in outpatient settings in Vietnam and Thailand,” *PLOS Digital Health*, vol. 5, no. 2, 2026.
- [16] G. Nair, H.-Y. Li, J. Schwenk, K. Martinez, C. Manore, and C. Xu, “Increasing mosquito abundance under global warming,” *Earth's Future*, 2025.
- [17] A. Mandal, P. Debnath, P. Das, and D. Ghosh, “A climate-driven mechanistic model of dengue transmission: Linking entomological processes to epidemiological dynamics,” 2025.
- [18] R. Achary et al., “A GAN-enhanced multimodal diagnostic framework utilizing an ensemble of BiLSTM, BiGRU, and RNN models for malaria and dengue detection,” *Procedia Computer Science*, vol. 252, pp. 381–393, 2025.
- [19] R. B. GulMohamed, W. Hetany, H. A. Almainani, and F. A. S. Khiery, “DengueGNN: Graph-based deep learning for modeling disease spread dynamics and prediction,” *Scientific Reports*, vol. 16, Art. no. 10584, 2026.