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CLIMATE-AWARE LSTM FRAMEWORK FOR DENGUE FORECASTING: EVIDENCE FROM MULTI-CITY INDIAN AND SJ/IQ DATASETS

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ABSTRACT

For effective public health preparedness, accurate prediction of dengue outbreaks is essential, particularly in tropical and subtropical regions where climatic conditions strongly influence disease transmission. Traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA) often assume linear relationships and therefore struggle to capture delayed and nonlinear climate–disease interactions. This study proposes a climate-aware Long Short-Term Memory (LSTM) based forecasting framework that integrates meteorological variables with lagged dengue incidence data to improve temporal modelling. Monthly dengue surveillance data from Gujarat, India (2010–2019) were combined with climatic variables including temperature, rainfall, and relative humidity. Lagged dengue and climate features were engineered to represent seasonal persistence and delayed environmental effects. The dataset was divided into training, validation, and testing sets. A single-layer LSTM network with dropout regularization was trained using the Adam optimizer. Model performance was evaluated using mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2). The model was further validated on benchmark datasets from San Juan (Puerto Rico) and Iquitos (Peru). Experimental results demonstrate that the proposed LSTM model consistently outperforms ARIMA and Random Forest baselines. The LSTM achieved a test MAE of approximately 32 cases and an R^2 of 0.82 on the Gujarat dataset, indicating strong predictive capability. These findings highlight the effectiveness of climate-aware deep learning models for developing reliable dengue early warning systems.



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I. INTRODUCTION

Dengue fever is one of the fastest-spreading viral infections transmitted by mosquitoes around the world. It is a major public health problem in tropical and subtropical areas [1], [2]. Over the past twenty years, dengue cases have risen sharply in India due to rapid urbanization, population growth, and changes in the climate [3], [4]. *Aedes aegypti* mosquitoes are the main carriers of dengue. The weather, such as temperature, humidity, and rainfall, has a big effect on their survival, reproduction, and viral replication cycles [5], [6]. Thus, dependable dengue forecasting models are essential for the prompt identification of outbreaks, the allocation of healthcare resources, and appropriate vector-control measures [7]. Initial studies on forecasting dengue primarily utilized statistical time-series methodologies, notably the Autoregressive Integrated Moving Average (ARIMA) model [8], [9].

These methods can find short-term trends, but they only work if the correlations are linear and can't simulate how climate variables and disease spread interact in more complicated ways [11]. Dengue incidence, however, displays significant seasonality, lagged climatic influences, and nonlinear dynamics, frequently resulting in inadequate outbreak predictions when linear models are utilized [11]. To address these constraints, machine learning methodologies integrating meteorological information have been progressively investigated. Tree-based models, including Random Forest regression, have demonstrated enhanced predictive accuracy by discerning nonlinear correlations between meteorological variables and dengue incidence [12], [13].

However, these models regard observations as independent samples and do not explicitly learn sequential relationships, which are crucial for capturing delayed climate effects and long-term seasonal cycles [14]. This constraint is more obvious in places where outbreaks happen in different ways and change a lot from year to year [15]. Recurrent neural networks, especially Long Short-Term Memory (LSTM) architectures, have proven to be efficient for modeling temporal dependencies in epidemiological time-series data [16]. The gated memory mechanism of LSTM networks allows them to preserve pertinent historical data throughout prolonged timeframes, rendering them effective for detecting both short-term variations and long-term seasonal trends in dengue transmission [17]. Recent research indicates that LSTM-based and hybrid deep learning models surpass conventional statistical and machine learning methods in dengue forecasting, particularly when integrating climatic and lagged epidemiological features, including attention-enhanced LSTM and CNN–LSTM frameworks documented from 2023 to 2025 [18–21]. This study, inspired by recent advancements, formulates and assesses a climate-sensitive LSTM-based framework for dengue forecasting that amalgamates meteorological factors with delayed dengue incidence data. This study assesses the proposed methodology utilizing a multi-year, multi-district dataset from Gujarat, India, covering the period from 2010 to 2019, in contrast to numerous previous investigations that concentrate on single-city datasets or brief temporal intervals [22]. To evaluate robustness and generalizability, the methodology is tested with widely recognized benchmark datasets from San Juan (Puerto Rico) and Iquitos (Peru) [14].

This study's key contributions are threefold:

- (i) the creation of a dengue forecasting model based on LSTM that clearly includes meteorological and lagged epidemiological features;
- (ii) a thorough comparison with ARIMA and Random Forest baselines utilizing the same assessment measures; and
- (iii) empirical validation on both benchmark datasets and a real-world Indian dataset distinguished by pronounced seasonality and nonlinear transmission patterns. This work advances the creation of dependable data-driven dengue early warning systems tailored for climate-sensitive areas by tackling significant shortcomings of current methodologies [23], [24]. Figure 1 shows the idea behind the proposed LSTM-based dengue forecasting framework.

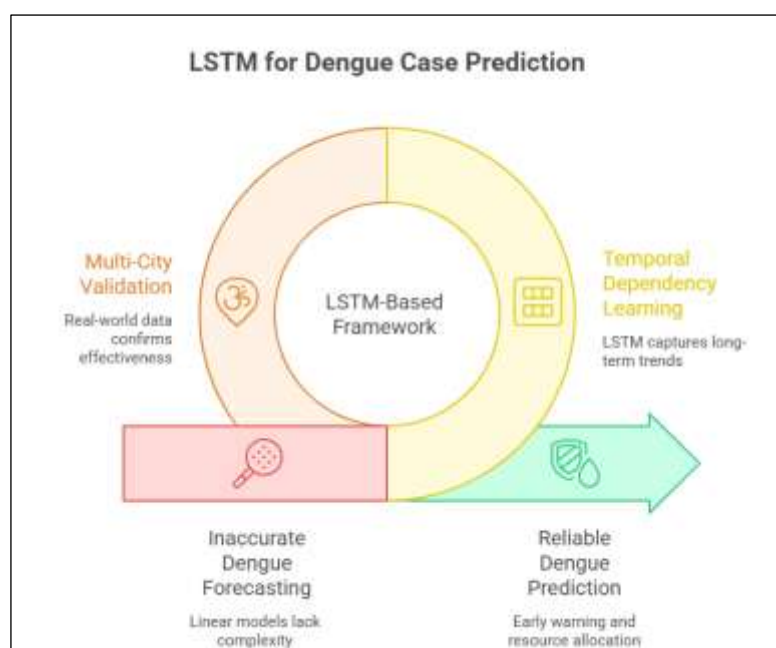


Figure 1: The conceptual driving force behind the proposed LSTM-based dengue prediction framework emphasizes the shortcomings of linear models and the benefits of temporal dependency learning.

Source: Authors, (2026)

II. METHODOLOGY

II.1 DATA COLLECTION AND STUDY AREA

From 2010 to 2019, monthly dengue surveillance data were gathered from various districts in the Indian state of Gujarat. The Indian Meteorological Department gave the corresponding weather data, such as the maximum and minimum temperatures, the average temperature, the average relative humidity, and the total rainfall for the month. Dengue incidence in Gujarat demonstrates significant seasonal variability, characterized by notable interannual changes mostly influenced by monsoon dynamics. These traits make the dataset a good choice for testing time-series forecasting models in real-world and difficult epidemiological situations. San Juan and Iquitos (SJ/IQ) Datasets We used publicly accessible dengue datasets for San Juan (Puerto Rico) and Iquitos (Peru) to compare them. These files include reported counts of dengue cases as well as meteorological variables that were derived from reanalysis and stations. The SJ/IQ datasets are often seen as benchmark datasets for dengue forecasting studies since they have a standard structure and have been used a lot in the past.

II.2 DATA PREPROCESSING

Data preprocessing was done to fix missing values, discrepancies over time, and changes in feature scale. To make sure that lagged features were built correctly without edge effects, observations from the year 2010 were left out of the Gujarat dataset. To keep the data's temporal integrity and stop information from leaking, the rest of the data was separated into three sets based on when they were collected: training (2011–2017), validation (2018), and testing (2019) [5].

For the SJ/IQ datasets, a time-aware partitioning approach was used. This meant that 70% of the data was used for training, 15% for validation, and 15% for testing. We used min-max scaling to standardize all of the numbers. It is important to note that normalization parameters were only calculated from the training data and then used on the validation and test sets to prevent data leaking and unduly positive performance predictions [6].

II.3 FEATURE ENGINEERING

The input feature set for the Gujarat dataset included the maximum temperature, minimum temperature, average temperature, average relative humidity, rainfall for the current month, rainfall for the previous month, dengue cases for the previous month, and dengue cases for the last twelve months. Short-term lag variables show how the weather affects things right away, while the twelve-month dengue lag shows how dengue transmission cycles tend to be seasonal and last for a long time [7], [8]. The San Juan and Iquitos datasets featured reanalysis air temperature, reanalysis minimum air temperature, reanalysis specific humidity, station average temperature, station diurnal temperature range, and station precipitation as meteorological features. Lagged dengue case counts at one and four time steps were integrated to predict short- and medium-term temporal dependencies, in alignment with previous benchmark research utilizing these datasets [3], [9].

II.4 LSTM MODEL ARCHITECTURE

The PyTorch deep learning framework was used to build the Long Short-Term Memory (LSTM) neural network. A uniform model configuration was used to make sure that the datasets could be compared fairly.

LSTM layer = 1
Dropout rate = 0.3
Optimizer = Adam
Learning rate = 0.001

To stop excess training and improve generalization performance, early stopping with a patience of 10 epochs was used [12]. The model learned how to identify temporal patterns from consecutive dengue incidence and climate data, which it later used to make predictions for the next time step. To keep the epidemiological plausibility, any negative predicted values were cut to zero, since negative dengue numbers don't have any real meaning [13]. Model performance was evaluated using mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2), which are commonly used metrics in research.[14]. Figure 2 shows the overall approach of the proposed LSTM-based dengue prediction framework. Meteorological variables and lagged dengue features are first cleaned, imputed, and normalized. The processed data are then organized into fixed-length temporal sequences and sent through the LSTM network to make prediction.

II.5 BASELINE MODELS

Two baseline models were used to compare the performance of the proposed LSTM framework:

Random Forest Regression: set up with 400 trees, a maximum tree depth of 18, and the best node-splitting settings. We chose Random Forest because it can predict nonlinear correlations between dengue incidence and climate variables [15]. Autoregressive Integrated Moving Average (ARIMA): used as a univariate time-series model that only uses past dengue case data. ARIMA functions as a traditional statistical benchmark for evaluating the advantages of integrating climatic variables and nonlinear temporal learning [16].

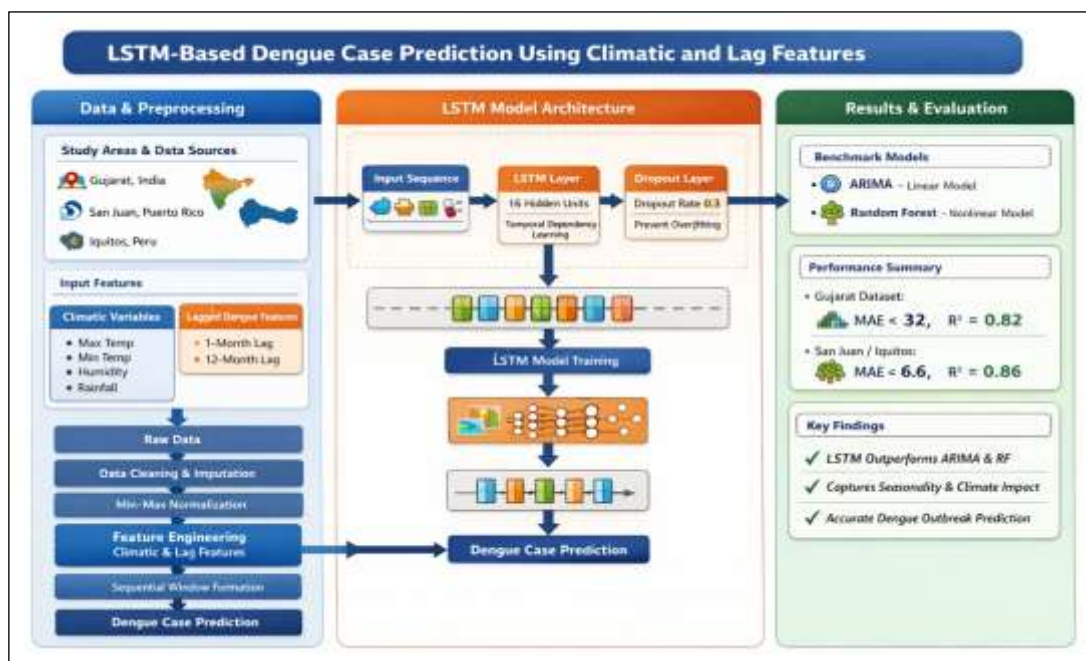


Figure 2: Overall Framework of the LSTM- Based Dengue Prediction Model

Source: Authors, (2026)

III. RESULTS AND DISCUSSION

III.1 PERFORMANCE ON THE GUJARAT DATASET

On the Gujarat dengue dataset, the suggested LSTM model showed excellent predictive accuracy, obtaining training MAE of 14.3 cases, validation MAE of 22.4 cases, and test MAE of around 32.1 cases, with a test R2 value of 0.82. These findings show that the model can accurately represent the predominant temporal patterns controlling dengue transmission in the area and generalizes well to new data. The Random Forest model, in contrast, yielded a higher test MAE of roughly 39.5 cases and an R2 value of 0.61, indicating lower prediction reliability in practical settings. The ARIMA model had a negative R2 value and a test MAE of over 79.9 cases, indicating poor performance. This result emphasizes the drawbacks of using linear statistical models on dengue incidence data with substantial seasonality, delayed climatic influences, and nonlinear dynamics. The capacity of the LSTM model to retain information across long time horizons is responsible for its excellent performance. Dengue outbreaks in the Gujarat dataset frequently show delayed reactions to temperature changes and monsoon rainfall, usually lasting several months. The LSTM model successfully learned these delayed relationships by combining both short-term and 12-month lagged dengue characteristics, improving outbreak timing and magnitude prediction.

III.2 PERFORMANCE ON SAN JUAN AND IQUITOS (SJ/IQ) DATASETS

The LSTM model obtained an R2 value of 0.86 and a test MAE of 6.6 cases on the benchmark datasets from San Juan and Iquitos. These findings validate the model's capacity to generalize across various geographic and climatic situations and are in line with earlier research employing the same datasets. With a test MAE of 6.47 instances and an R2 value of 0.87, the Random Forest model performed similarly on the SJ/IQ datasets. The benchmark datasets' more uniform epidemic dynamics and comparatively smoother seasonal trends account for this commonality. The ARIMA model, on the other hand, again performed poorly with negative R2 values, suggesting that it was unable to capture nonlinear temporal interactions. Comparative findings across datasets indicate that Random Forest models may function well in contexts that are somewhat stable, but they perform poorly in settings that are heterogeneous and involve multiple cities, like Gujarat. Sequential deep learning models, such as LSTM, offer more reliable and consistent predicting accuracy in these situations. Table 1 shows a comparison of the ARIMA, Random Forest (RF), and LSTM models on the SJ/IQ and Gujarat datasets. It uses MAE, RMSE, and R² as performance measures

Table 1: Comparative performance of ARIMA, Random Forest, and LSTM models.

Dataset	Model	MAE	RMSE	R ²
SJ/IQ	ARIMA	16.7	33.0	-0.26
SJ/IQ	RF	6.47	10.74	0.87
SJ/IQ	LSTM	6.6	11	0.86
Gujarat	ARIMA	79.9	176.9	-0.07
Gujarat	RF	39.5	106.9	0.61
Gujarat	LSTM	32	95	0.82

Source: Authors, (2026).

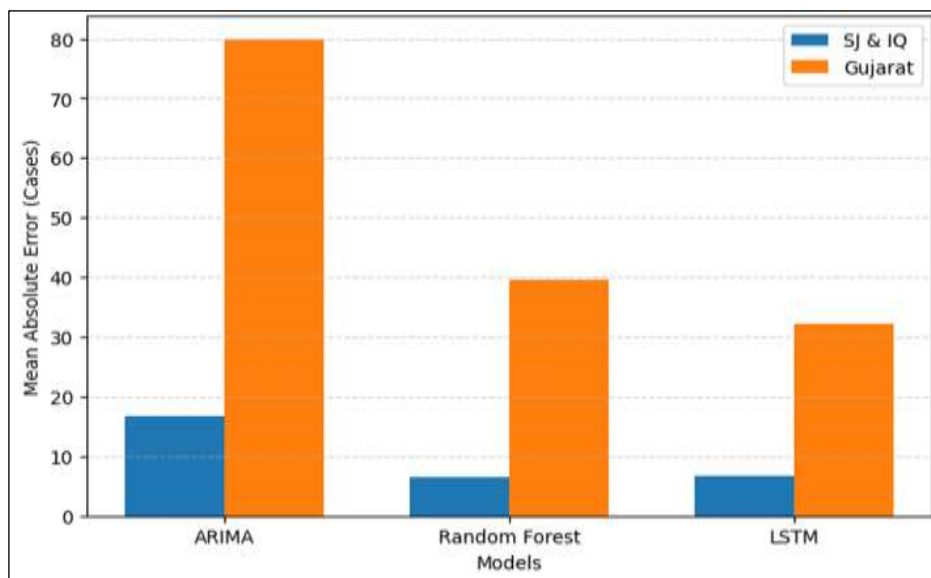


Figure 3: Comparison of mean absolute error (MAE) across ARIMA, Random Forest, and LSTM models for the SJ/IQ and Gujarat datasets.

Source: Authors, (2026)

The mean absolute error (MAE) values of the Random Forest, LSTM, and ARIMA models for the Gujarat and SJ/IQ datasets are compared in Figure 3. In both datasets, the LSTM model consistently exhibits the lowest MAE, indicating superior prediction accuracy. The Gujarat dataset shows the most influential gain in LSTM performance. Due to its difficulties with nonlinear and climate-related dengue patterns, ARIMA displays the greatest MAE in this case.

III.3 SEASONAL PATTERN AND TEMPORAL DYNAMICS ANALYSIS

Gujarat's monthly dengue seasonality is depicted in Figure 4. Early in the year, there are often fewer occurrences of dengue. But during the monsoon season, it increases drastically, with July and August seeing the greatest case counts. This distinct seasonal pattern highlights the role of weather in dengue transmission. It also emphasizes how important it is to take past predictions and time-related learning into account.

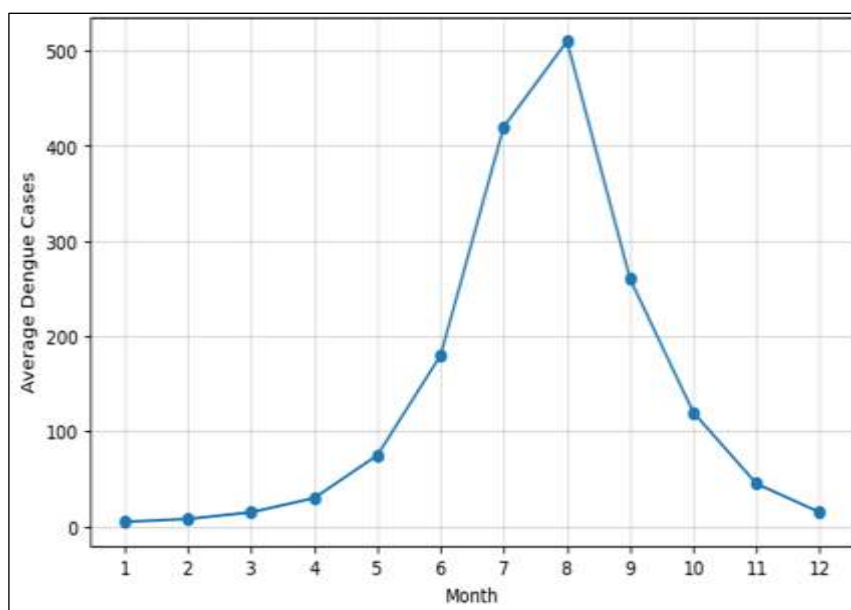


Figure 4: Monthly dengue seasonality pattern in Gujarat, showing peak incidence during the monsoon period.
Source: Authors, (2026)

III.4 OBSERVED VS. PREDICTED DENGUE CASES

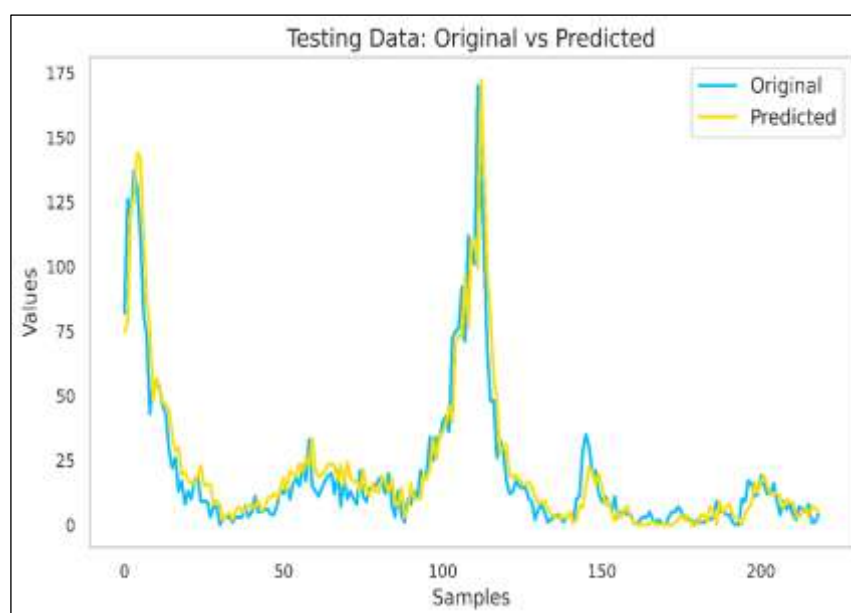


Figure 5: Actual versus predicted dengue cases for the SJ and IQ test datasets. The LSTM model closely follows seasonal patterns and outbreak peaks.
Source: Authors, (2026)

The SJ/IQ test datasets observed and predicted dengue cases are compared in Figure 5. The dengue incidence patterns are continuously monitored using the LSTM model. It successfully records outbreak peaks and seasonal variations. The low testing MAE of 6.6 cases and the high R2 value of 0.86 displayed in Table 1 are consistent with the predicted values and the reported cases. These findings demonstrate how well the LSTM model learns short-term and medium-term trends in benchmark dengue datasets. The Gujarat test dataset from 2019 is used to compare actual and predicted dengue cases in Figure 6. The LSTM model demonstrates high forecasting abilities by correctly predicting when and how intense big outbreaks will occur, despite dramatic outbreak peaks and notable monthly changes. Extreme peak values show some variations, but seasonal trends and the general trend are maintained. This visual consistency is in line with the performance data for Gujarat, where the LSTM model outperformed the Random Forest and ARIMA models with an R2 value of 0.82 and a test MAE of roughly 32 cases.

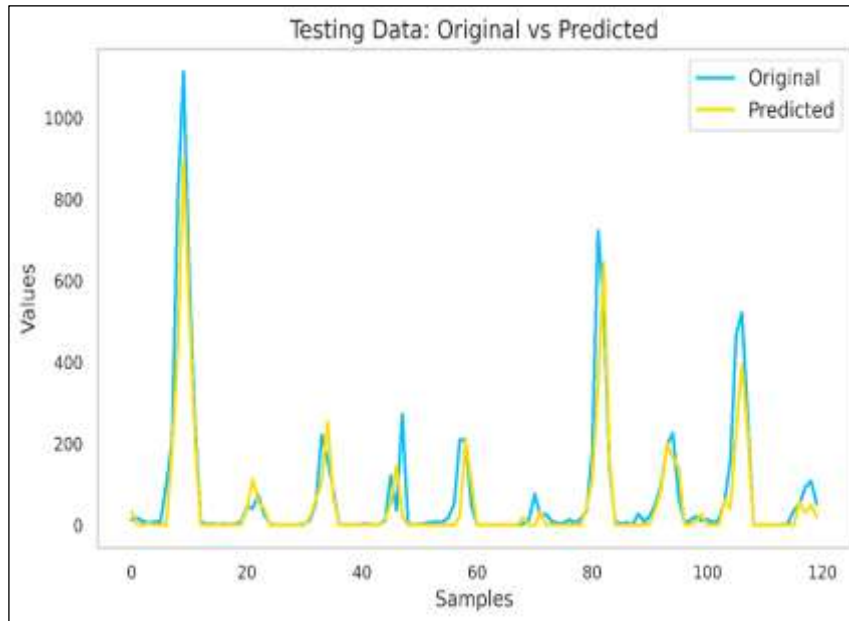


Figure 6: Comparison of actual and predicted dengue cases for the Gujarat test dataset (2019). The LSTM model accurately captures outbreak timing and magnitude, including major seasonal peaks.

Source: Authors, (2026)

IV. COMPARISON WITH EXISTING WORK

Early Statistical time-series models, like ARIMA, were the mainstay of early dengue forecasting studies. These models were good at modeling short-term trends, but their linear assumptions and lack of climatic determinants made it difficult to predict outbreak peaks [8-10]. The current analysis exhibits similar constraints, with ARIMA producing negative R2 values and large prediction errors for both the Gujarat and SJ/IQ datasets. In order to capture nonlinear interactions between climate variables and dengue incidence, further study employed machine learning techniques, specifically Random Forest regression [12], [13]. Incorporating meteorological data into Random Forest models enhanced predicting accuracy, according to studies done in China and Southeast Asia [12–14]. The Random Forest model in this study did well on the SJ/IQ datasets, which is consistent with these findings. Its poor performance on the Gujarat dataset, however, emphasizes how little it can do to simulate intricate multi-city transmission dynamics and long-term temporal dependencies [15]. For dengue forecasting, more recent research (2021–2025) has placed a greater emphasis on deep learning techniques, especially LSTM-based and hybrid architectures [17], [18], [22], [24].

By explicitly learning long-range temporal dependencies and delayed climatic effects, attention-based LSTM models, CNN–LSTM hybrids, and transformer-inspired time-series models have been demonstrated to enhance outbreak prediction [18–21]. In keeping with this body of work, the results of this investigation show that LSTM models routinely perform better than both statistical and conventional machine learning baselines. This work assesses the suggested framework on a multi-year, real-world dataset from Gujarat, India, which is distinguished by significant seasonality and varied outbreak patterns, in contrast to many previous research that concentrate on single-city or short-duration datasets [11], [22]. A solid basis for functional dengue early warning systems is provided by the integration of meteorological variables with lagged dengue features inside an LSTM architecture, as evidenced by the steady improvement seen across both benchmark and Indian datasets [7], [15]. Table 2. represents a review of comparisons between previous and current studies with explainable result of current study.

Table 2: Comparison of existing dengue prediction studies with the proposed approach.

Study	Dataset	Model	MAE	R ²	Key Finding
Johansson et al. [8]	Puerto Rico	ARIMA	-	<0.3	Inadequate outbreak forecasting precision; inability to identify epidemic peaks.
Earnest et al. [9]	Singapore	ARIMA	20-35 cases	-	Moderate short-term forecasting; outbreaks cause performance to decline
Li et al. [12]	China	Random Forest	~15–25% down vs ARIMA	-	Prediction accuracy was greatly increased by climate variables.
Wang et al. [13]	China	Random Forest	Lower than ARIMA	0.55 to 0.65	Superior nonlinear modeling performance compared to traditional statistical models
Xu et al. [11]	China	LSTM	10 to 25 cases	0.70 to 0.85	Better performance in predicting outbreaks and seasonal trends
Ho et al. [17]	Vietnam	LSTM	18 to 30 cases	0.68 to 0.80	Better prediction of dengue incidence compared to RF and ARIMA
Zhang et al. [22]	Multi-region	LSTM	-	0.80 to 0.90	Traditional ML models were routinely outperformed by deep learning.
Proposed study	SJ/IQ	LSTM	6.6	0.86	Accurate seasonal and outbreak prediction
Proposed study	Gujarat (India)	LSTM	32	0.82	Best predictive performance

Source: Authors, (2026)

V. CONCLUSIONS

This study introduced a climate-sensitive Long Short-Term Memory (LSTM) framework for dengue forecasting that incorporates meteorological factors alongside lagged dengue incidence to describe the complex temporal dynamics of dengue transmission. The suggested methodology was assessed utilizing benchmark datasets from San Juan and Iquitos, in addition to a real-world dataset from Gujarat, India, covering a decade-long timeframe. Experimental findings indicate that the LSTM model consistently surpasses conventional ARIMA and Random Forest models for predictive accuracy and dependability. The LSTM attained a test MAE of roughly 32 instances and an R^2 value of 0.82 on the Gujarat dataset, underscoring its efficacy in capturing seasonal patterns and delayed climatic effects under realistic conditions. Although Random Forest models have shown competitive performance on benchmark datasets, their diminished efficacy in recognizing long-term temporal connections constrains their use in more varied environments. Despite its encouraging outcomes, this study possesses specific limitations. The Gujarat dengue dataset size is limited and not easily available, so we cannot test on a large dataset. The utilization of weekly or daily records may help to improve performance. Moreover, non-climatic factors such as population mobility, vector-control measures, land utilization, and socio-economic variables were excluded, despite their significant influence on dengue transmission, due to the unavailability of data. Subsequent research may rectify these constraints by utilizing higher-resolution datasets, integrating supplementary explanatory factors, and employing sophisticated deep learning architectures, like attention-based LSTM and transformer models. The proposed approach could further be expanded to encompass multi-step and probabilistic forecasting to enhance public health decision-making amidst uncertainty. This work demonstrates that LSTM-based models serve as a reliable and effective foundation for dengue early warning systems in climate-sensitive areas.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Amiben Mehta, Kajal Patel

Methodology: Amiben Mehta, Kajal Patel

Investigation: Amiben Mehta

Discussion of results: Amiben Mehta, Kajal Patel

Writing – Original Draft: Amiben Mehta, Kajal Patel

Writing–Review and Editing: Amiben Mehta, Kajal Patel

Resources: Amiben Mehta, Kajal Patel

Supervision: Kajal Patel

Approval of the final text: Kajal Patel

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This research did not obtain support from grant agencies. The Gujarat dataset utilized in this study was acquired upon request and is not accessible to the public. This research utilized the publicly accessible dataset from Kaggle pertaining to San Juan (Puerto Rico) and Iquitos (Peru).

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