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Explainable artificial intelligence for predicting dengue outbreaks in Bangladesh using eco-climatic triggers☆

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A R T I C L E I N F O

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A B S T R A C T

Background: Dengue represents a significant public health threat in Bangladesh, characterized by its complex ecological transmission dynamics. To improve dengue prevention and control efforts, firstly, we employ state-of-the-art artificial intelligence (AI) methods to identify the roles of eco-climatic factors in predicting dengue outbreaks in Bangladesh.

Methods: We utilize high-performance machine learning (ML) models, XGBoost and LightGBM, combined with explainable AI (XAI) methodologies to evaluate the predictive performance and impact of various dengue determinants in Bangladesh from 2000 to 2023. The LightGBM and XGBoost models were also utilized to predict dengue cases and early warning trends from 2024 to 2030. Climatic, socio-demographic, and landscape features were used to train these models; SHapley Additive Explanations (SHAP) values and LIME (Local Interpretable Model-agnostic Explanations) were used to interpret the results.

Findings: Between 2000 and 2023, Bangladesh experienced the highest number of dengue cases in August, while November saw the most fatalities. The XGBoost model excelled in predicting dengue outbreaks, achieving an AUC score of 0.89, a Log Loss of 0.64. Key predictors identified by the model include population density, precipitation, temperature, and land-use patterns. Additionally, Local Interpretable Model-agnostic Explanations (LIME) provided insights into the model's predictions, highlighting the significance of population density, relative humidity, and minimum temperature in dengue outbreaks.

Interpretation: This study showcases the potential of XAI in uncovering the complexities of dengue outbreaks, providing a robust tool for public health interventions. Our AI-driven framework can be utilized to generate prompt and timely alerts to prevent imminent dengue and other infectious disease outbreaks.

Introduction

Dengue, known for being the most rapidly spreading mosquito-borne disease, has become a significant threat to global public health [1]. The World Health Organization (WHO) has identified dengue as one of the top ten global health threats [2,3].This is particularly concerning because there is currently no specific treatment or vaccinev to prevent dengue virus (DENV) [2,3]. Although Sanofi Pasteur's dengue vaccine has been authorized in 24 countries and included in public immunization programs in the Philippines and Brazil, it still does not provide a comprehensive solution to the dengue challenge [4]. Dengue has spread to 125 countries, resulting in 400 million infections and 40,000 deaths annually [5]. Approximately 70 % of dengue cases occur in endemic regions of tropical and subtropical nations, especially in Southeast and South Asia [5].

Bangladesh, a South Asian country with a population exceeding 165 million, has experienced annual dengue outbreaks since 2000, with epidemics intensifying in recent years [6]. Dengue, also referred to as "Dacca fever," was initially identified in Bangladesh (then East Pakistan) in the 1960s [7]. Since 2010, higher temperatures and the rainy season from May to September have been linked to increased dengue incidences. Two of the deadliest outbreaks occurred in 2019 and 2022, and the current outbreak is expected to be the most extensive to date [8]. Between 1 January and 30 September 2023, Bangladesh documented 203,406 dengue cases and 989 fatalities, significantly exceeding the incidence rates of previous years for the same period [9]. In the past

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three months, from July to September, the number of recorded dengue cases this year was 1.9 times higher than the total cases reported in all of 2019, the last significant outbreak [9]. The increase and spread of dengue cases remain unclear due to complex transmission pathways and key disease drivers. Bangladesh's climate is becoming more favorable to DENV and other vector-borne diseases like chikungunya and malaria because of excessive rainfall, flooding, waterlogging, rising temperatures, and unusual changes in traditional seasons [6]. The ecology of dengue transmission is complicated. The spatial and temporal spread of DENV is significantly influenced by several risk factors, including climate, socioeconomic status, landscape features, and human activities [10–12]. Climate-based models facilitate the development of early warning systems for dengue to avert potential outbreaks during extreme climatic conditions; however, simultaneously recognizing climate, socioeconomic, and land use/land cover characteristics is crucial to enhance dengue prevention and control initiatives. This type of study is rare in the literature and merits further investigation in Bangladesh [10].

Machine learning (ML) and artificial intelligence (AI) methods for detecting key factors and forecasting infectious illnesses have recently gained popularity [10,13,14]. As a result, current methodologies that combine ML and explainable AI present a good chance to assess the influence of climatic, socioeconomic, and landscape factors on dengue risk. However, these methods have not been frequently employed in DENV research; the majority have been used in small, regional studies with little explanatory power. These high-performance machine learning models have a key disadvantage in that they are complicated and opaque (i.e., black-box models), making it difficult to draw recommendations for public health policies from them [13]. Thus, XAI can aid in understanding the immensely complex biophysical, environmental, and social factors that influence diseases like DENV, which would otherwise be very difficult to comprehend.

Due to multiple risk factors, Bangladesh has lately seen several severe dengue epidemics [6,15]. National public health catastrophes may occur if appropriate preventative measures are not enacted, due to inadequate outbreak preparedness, insufficient community awareness of DENV, and deficient healthcare infrastructure. The alarming trends in dengue incidence and mortality in the country require public health policymakers to intensify their focus on dengue dynamics in South Asia, improve surveillance systems and diagnostic capabilities, and devise tools and methodologies for strategic resource distribution and management initiatives [8]. The development of early warning systems (EWS) and its predictive ability to manage infectious disease outbreaks is critical to public health practice [16]. In light of continuous environmental and climatic changes, anticipating disease outbreaks using eco-climatic parameters is critical for effective preparedness and response [17]. As a result, the findings of this study may be used to parameterize EWS by using the ecoclimatic triggers of DENV outbreaks, allowing for the creation of precise and efficient preventative strategies to reduce the impact of dengue in Bangladesh and other endemic countries.

In recent studies, there has been a significant rise in the application of AI and ML methodologies to predict and control infectious disease outbreaks, particularly focusing on dengue [18,15]. These models have shown promise in identifying complex patterns in high-dimensional data, enabling more accurate forecasts of disease transmission. However, despite advancements in predictive capabilities, a significant gap remains in the area of model interpretability, often referred to as the "black-box" problem [19,20]. This lack of transparency makes it challenging for public health professionals to trust and act upon the predictions made by these models, especially when the rationale behind the predictions is not easily understood [21,22]. While climate-based models of dengue are well-established [23–25], the integration of enhanced interpretability techniques in predictive frameworks remains limited. This study addresses this gap by incorporating explainable AI methodologies to improve the transparency and applicability of dengue forecasting models.

Explainable Artificial Intelligence has emerged as a potential solution to this challenge. The methodology of XAI aims to make complex ML models more transparent and interpretable, allowing humans to understand the underlying processes that lead to model predictions [26]. Recent studies propose frameworks like TIFU (Transparency and Interpretability for Understandability), which shift the focus from simple explainability to a deeper, more actionable understanding of how models operate [19]. These advancements are particularly important in safety-critical domains like healthcare, where it is essential to not only predict outcomes accurately but also to ensure that the predictions are grounded in a comprehensible and transparent rationale [19,20].

Notwithstanding progress in XAI, a substantial gap persists in the literature concerning the incorporation of XAI methodologies into predictive models for dengue outbreaks. While research exists on the application of machine learning models in predicting infectious diseases, limited studies explore the role of explainability and transparency in these models, particularly in the context of public health applications [18]. Systematic reviews emphasize the growing importance of XAI across various domains but highlight the need for further research in health-related fields where transparency is critical for adoption and decision-making [20]. Similarly, recent studies discuss the potential of AI in modeling vector-borne diseases, including dengue, but call for more research on the explainability and transparency of these models [15].

Moreover, while studies have demonstrated the effectiveness of XAI in improving predictive models for health-related applications such as suicide risk assessment, there remains limited exploration of its application to dengue prediction, particularly in resource-constrained settings like Bangladesh [27]. This identifies a gap in study findings about the application of sophisticated ML models and XAI approaches to anticipate and mitigate the effect of dengue epidemics. Existing studies, such as Sarma et al. demonstrated the application of machine learning algorithms in forecasting dengue transmission, but they did not use XAI in their models [18]. The objective of this research is to address a vacuum in dengue outbreak prediction by undertaking a thorough comparison analysis of ML models, especially XGBoost and LightGBM, for predicting dengue outbreaks in Bangladesh. This study assesses the prediction accuracy of these models by employing XAI methodologies to ensure that the model outputs are both interpretable and actionable for health professionals in the community. By analyzing eco-climatic, socioeconomic, and landscape factors, this study aims to identify key drivers of dengue transmission and provide transparent insights to inform targeted public health interventions. Ultimately, this study seeks to contribute to the development of reliable, interpretable, and actionable AI-driven systems for dengue prediction and outbreak management in Bangladesh and similar endemic countries.

Novelty and contributions of the study

This study introduces a pioneering AI-driven methodology for predicting dengue outbreaks in Bangladesh, combining advanced machine learning models (XGBoost and LightGBM) with Explainable AI (XAI) techniques. Unlike conventional statistical approaches, this method uncovers complex, non-linear interactions within epidemiological data, significantly boosting predictive accuracy.

Key contributions

1. **AI-Driven Epidemic Forecasting:** Leveraging a two-decade dataset (2000–2023), this study offers a long-term perspective on dengue transmission dynamics.
2. **SHAP-Based Explainability:** The integration of SHapley Additive exPlanations (SHAP) values ensures transparency in model decision-making, enabling actionable insights.

3. **Multifactorial Analysis**: Unlike previous studies focusing on isolated variables, this research incorporates climatic, socio-economic, and landscape factors for a holistic understanding.
4. **Public Health Impact:** By enabling early warning systems, these AI-driven predictions strengthen Bangladesh's dengue surveillance framework and inform targeted interventions.

This study contributes to the advancement of dengue prediction by integrating AI techniques with epidemiological analysis, offering valuable insights for disease monitoring in dengue-endemic regions.

Materials and methods

Data collection

Dengue deaths and cases, climate, socio-demographics, and landscape characteristics were all gathered between January 2000 and December 2023. The predictive models were developed with a variety of variables, including dengue cases, climate (temperature, relative humidity, rainfall, surface pressure, and wind speed), sociodemographic factors (population density, gross domestic product, gross national income, poverty headcount ratio, adult literacy rate, total unemployment, access to electricity, population growth), and landscape (forest area, agricultural land, and arable land) features (Table 1). Official press releases from the Directorate General of Health Services (DGHS), Ministry of Health and Family Welfare, Bangladesh, and the Institute of Epidemiology, Disease Control and Research (IEDCR), Bangladesh, provided confirmations of dengue cases and the associated deaths. https://old.dghs.gov.bd/index.php/en/data and https://iedcr.gov.bd/surveillances/ were the two portals from which we collected and compiled all the published data. This study's climate factors are obtained from the National Aeronautics and Space Administration (NASA: https://data.giss.nasa.gov/) monthly estimated dataset. This study retrieved socio-demographic and landscape factors from the World Bank (https://data.worldbank.org/).

Table 1
Explanatory and outcome variables used in the training and testing datasets for the dengue model in Bangladesh from 2000 to 2023.

Category	Code	Variables	Source	Temporal granularity
	Year	Year		
Dengue	Cases	Cases	DGHS and IEDCR	Monthly
	Deaths	Deaths	DGHS and IEDCR	Monthly
Climate variables	x1	Mean temperature (°C)	NASA	Monthly
	x2	Minimum temperature (°C)	NASA	Monthly
	x3	Maximum temperature (°C)	NASA	Monthly
	x4	Relative humidity (%)	NASA	Monthly
	x5	Rainfall (mm)	NASA	Monthly
	x6	Surface Pressure (kPa)	NASA	Monthly
	x7	Wind Speed at 50 Meters Maximum (m/s)	NASA	Monthly
Socio-demographic variables	x8	Population density	World Bank	Yearly
	x9	Gross Domestic Product (Billion US$)	World Bank	Yearly
	x10	Gross National Income (K US$)	World Bank	Yearly
	x11	Poverty head-count ratio (% of population)	World Bank	Yearly
	x12	Adult literacy rate (% of population)	World Bank	Yearly
	x13	Total unemployment (% of total labor force)	World Bank	Yearly
	x14	Access to electricity (% of population)	World Bank	Yearly
	x15	Population Growth	World Bank	Yearly
Landscape variables	x16	Forest area (% of total land area)	World Bank	Yearly
	X17	Agricultural land (% of total land area)	World Bank	Yearly
	X18	Arable Land (% of the total land area)	World Bank	Yearly

Data preprocessing

Splitting dataset

In this study, we considered only outbreaks of dengue cases (≥344,905 cases) in Bangladesh from January 2000 to December 2023. The cutoff for outbreak classification was determined based on a percentile approach, categorizing values above the mean as 1 and below the mean as 0, ensuring a standardized threshold for defining outbreak severity. The 2000–2019 data were used to train the model, while the 2020–2023 data were chosen to test it. The analysis was conducted using R, a widely used statistical programming language, with the following libraries: dplyr and caret for data preprocessing and model training, rpart for decision tree modeling, xgboost and lightgbm for gradient boosting techniques, e1071 for support vector regression, and lime and SHAPforxgboost for implementing Explainable AI techniques. Visualisations of model performance and feature importance were created using ggplot2. Furthermore, DALEX was employed for model elucidation and interpretation, offering an in-depth comprehension of model behavior and aiding in the assessment of model performance via visual representations of the impact of various features on predictions.

Model selections

Six machine learning classifiers were evaluated Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Naïve Bayes Classifier (Naive), Decision Tree (DT), Support Vector Machine (SVM), Generalized Linear Model (GLM) with a logistic regression (LR) link function, to predict dengue outbreaks (Table S1). These models were chosen for their demonstrated capability to manage complex, non-linear interactions within eco-climatic, socio-demographic, and landscape data. To develop our models, we divided the datasets into training (2000–2019) and testing (2020−2023) sets. The final model, selected based on its highest AUC score during validation, was utilized to predict the test. To ensure interpretability, XAI approaches were employed, SHapley Additive Explanations (SHAP) values, and Local Interpretable Model-Agnostic Explanations (LIME). SHAP values were analyzed first to identify and provide detailed insights into the contributions of each feature, pinpointing the primary drivers behind dengue outbreaks. Finally, the LIME framework was employed to dissect the individual impacts of features, offering granular analyses of their contributions to predictions across 18 variables (Table 1). By combining these methods, the study ensured a transparent and comprehensive understanding of the model's predictive behavior and the key factors influencing dengue epidemics. To assess the model's performance in predicting dengue cases and deaths outbreak, five evaluation metrics were utilized: accuracy (Acc), precision (Prec), sensitivity/recall (Sens), specificity (Spec), and F1 score (F1) (Fig. S1-S2, Table S1-S9),.

LIME explanations for model predictions

The application of Local Interpretable Model-Agnostic Explanations (LIME) elucidates the intricate influence of individual features on model predictions [28]. This method enhances our understanding of how the model uses various features, providing a transparent and interpretable framework. In this study, LIME dissected the contributions of 18 features to the model's dengue case predictions (Table 1).

Cross-validation, model training and hyperparameter optimization

To ensure model robustness and mitigate overfitting or underfitting, this study employed 10-fold cross-validation for each model's training dataset. This computationally intensive yet reliable technique divides the dataset into 10 equal subsets, using nine for training and one for testing in each iteration, repeating the process 10 times to obtain a comprehensive evaluation of model performance. Additionally, Hyper-parameters were tuned using grid search, and the optimal configuration was selected based on the highest Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) score. The top two models with the highest AUC scores were selected for predictions on the test dataset. This meticulous approach to model selection and tuning ensured that the machine learning models were accurately and reliably predicting dengue outbreaks in Bangladesh, leveraging climatic, socio-economic, and landscape variables. For Details of the models and their hyper-parameters See Table S2-S10.

Results

The outbreaks of dengue cases and deaths from 2000 to 2023 revealed significant variations across different months and years. August consistently exhibited the highest number of dengue cases, peaking at 52,636 cases. Other months with notably high cases include October (30,879 cases) and November (29,652 cases). The month with the highest number of deaths was November, recording 173 deaths, followed closely by October with 135 deaths and September with 87 deaths (Fig. 1, S3-S4). Yearly analysis demonstrated dramatic increases in dengue cases in 2019 and 2023. The 2019 dengue outbreak in Bangladesh was the first deadliest on record, with 101,324 reported cases and 166 deaths. In 2023, the country documented a cumulative 203,406 dengue cases and 989 fatalities from January 1 to September 30 (Fig. 1, S3-S5).

Climate, socio-demographic and landscape characteristics

The density plots of climate, socio-demographic, and landscape factors demonstrate significant distributions across various parameters. For instance, mean temperature exhibits a peak around the median value of 27.5 °C, while minimum and maximum temperatures show varied distributions, reflecting seasonal changes. Relative humidity (mean: 75.9 %, min: 45.2 %, max: 91.8 %) and rainfall (mean: 6.04 mm, min: 0.0 mm, max: 32.5 mm) display broader distributions, indicating substantial variation over time. Economic factors, such as gross domestic product (mean: 190.0 billion US dollars, min: 53.4 billion US dollars, max: 486.0 billion US dollars) and gross national income (mean: 1224.0 thousand US dollars, min: 440.0 thousand US dollars, max: 2820.0 thousand US dollars), present wide ranges, reflecting economic diversity (Fig. S6).

Other factors, including wind speed at 50 m maximum (mean: 9.92

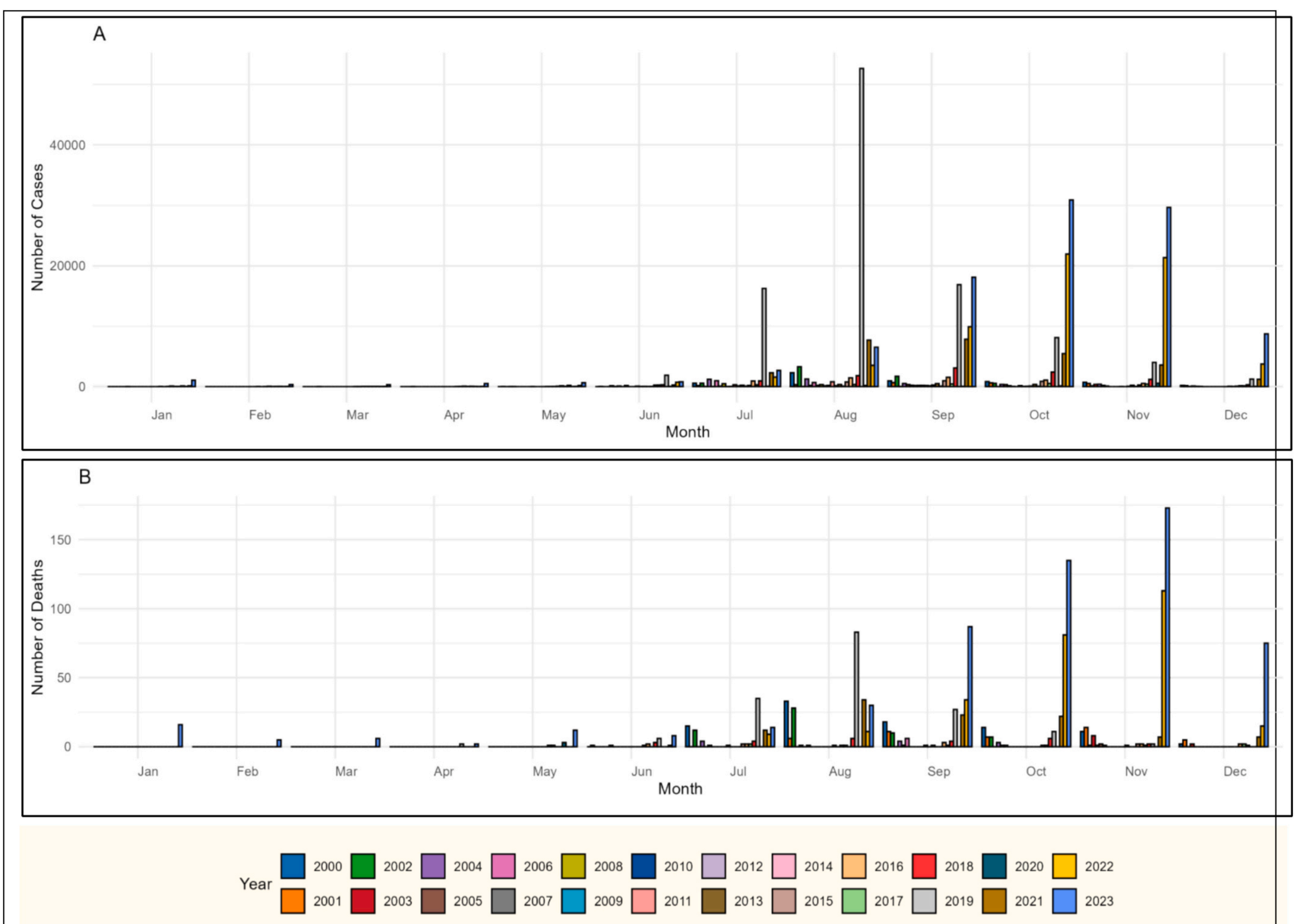

Fig. 1. Monthly A) dengue cases and B) dengue deaths from 2000 to 2023.

m per second, min: 4.36 m per second, max: 20.6 m per second), population density (mean: 1140.0 persons per square kilometer, min: 981.0 persons per square kilometer, max: 1278.0 persons per square kilometer), poverty head-count ratio (mean: 33.1 %, min: 18.2 %, max: 48.9 %), adult literacy rate (mean: 62.0 %, min: 47.5 %, max: 74.9 %), total unemployment (mean: 4.28 %, min: 3.3 %, max: 5.4 %), access to electricity (mean: 65.1 %, min: 32.0 %, max: 100.0 %), population growth (mean: 1.27 %, min: 1.0 %, max: 2.0 %), forest area (mean: 14.5 %, min: 14.5 %, max: 14.8 %), agricultural land (mean: 72.0 %, min: 70.1 %, max: 76.1 %), and arable land (mean: 60.8 %, min: 58.9 %, max: 64.2 %) also display distinct patterns of distribution (Fig. S6). Detailed summary statistics of these factors are provided in Table S10.

Correlation between dengue and climate, socio-demographic and landscape variables

Mean temperature showed a positive correlation with both dengue cases ($r = 0.65$) and deaths ($r = 0.62$), suggesting higher temperatures may contribute to increased dengue. Minimum and maximum temperatures were moderately correlated with cases ($r = 0.48$ and $r = 0.52$) and deaths ($r = 0.45$ and $r = 0.50$). Relative humidity displayed a strong positive correlation with cases ($r = 0.70$) and deaths ($r = 0.68$), supporting the role of moisture-rich environments in dengue transmission. Rainfall also demonstrated positive correlations with cases ($r = 0.58$) and deaths ($r = 0.55$). Socio-demographic factors revealed that population density had a strong positive correlation with cases ($r = 0.78$) and deaths ($r = 0.75$). Gross domestic product and Gross national income showed weaker positive correlations with dengue cases and deaths. The poverty headcount ratio had a positive correlation with cases (r = 0.55) and deaths ($r = 0.50$), while adult literacy rate showed a weak negative correlation with cases ($r = -0.25$) and deaths ($r = -0.22$). These findings underscore the complex interaction between environmental factors and socio-economic conditions in influencing dengue incidence and mortality (Fig. S7 and Table S11).

Model selection

Based on the training set (2000–2019), Light Gradient Boosting Machine (LightGBM) demonstrated the highest predictive performance, achieving an AUC of 0.998, accuracy of 0.971, and strong sensitivity (0.961) and specificity (0.985). Extreme Gradient Boosting (XGBoost) followed closely with an AUC of 0.996 and accuracy of 0.955, showcasing its ability to effectively handle non-linear interactions in the dataset. Decision Tree (DT) and Naïve Bayes (NB) also demonstrated moderate predictive capability, achieving AUCs of 0.968 and 0.956, respectively. Support Vector Machine (SVM) performed slightly lower, with an AUC of 0.952, while the Generalized Linear Model (GLM) had the weakest performance in this set, with an AUC of 0.877, reflecting its limited ability to capture complex patterns (Fig. 2 and Table S8). For the testing set (2020–2023), model evaluation was conducted using Log Loss and AUC metrics to validate the predictive performance. XGBoost emerged as the strongest model, achieving a Log Loss of 0.64 and an AUC of 0.89, highlighting its robustness in handling complex, non-linear relationships within the data. LightGBM, which performed well in the training phase, also retained strong predictive capability with a Log Loss of 0.61 and an AUC of 0.84. The GLM model exhibited satisfactory performance (Log Loss of 0.48, AUC of 0.84), while Decision Tree (DT) maintained an AUC of 0.82. The Naïve Model, included as a baseline, showed limited predictive ability with an AUC of 0.50, confirming its reduced efficacy for dengue prediction. Support Vector Regression (SVR) was not applicable in this analysis (Fig. S1 and Table S9). These findings confirm the reliability of XGBoost and LightGBM as optimal models for predicting dengue outbreaks, demonstrating their ability to generalize effectively from training to testing phases.

The XGBoost and LightGBM using XAI techniques to predict dengue outbreaks

The summary plot of the most important eco-climatic features identified by SHAP values highlights their importance and the direction of their influence. Climatic factors such as wind speed at 50 m and mean temperature are pivotal in predicting dengue outbreaks, with wind speed showing a significant positive SHAP value (Fig. 3, A). The total feature importance for the LightGBM and XGBoost models demonstrates the key predictors that influence model accuracy. Population density appears as a critical element in both models, highlighting the importance of socio-demographic factors in defining predictive ability. Furthermore, agricultural land and relative humidity are key predictors of significant SHAP values (Fig. 3,B).

The Shapley values for various predictors offer a comprehensive

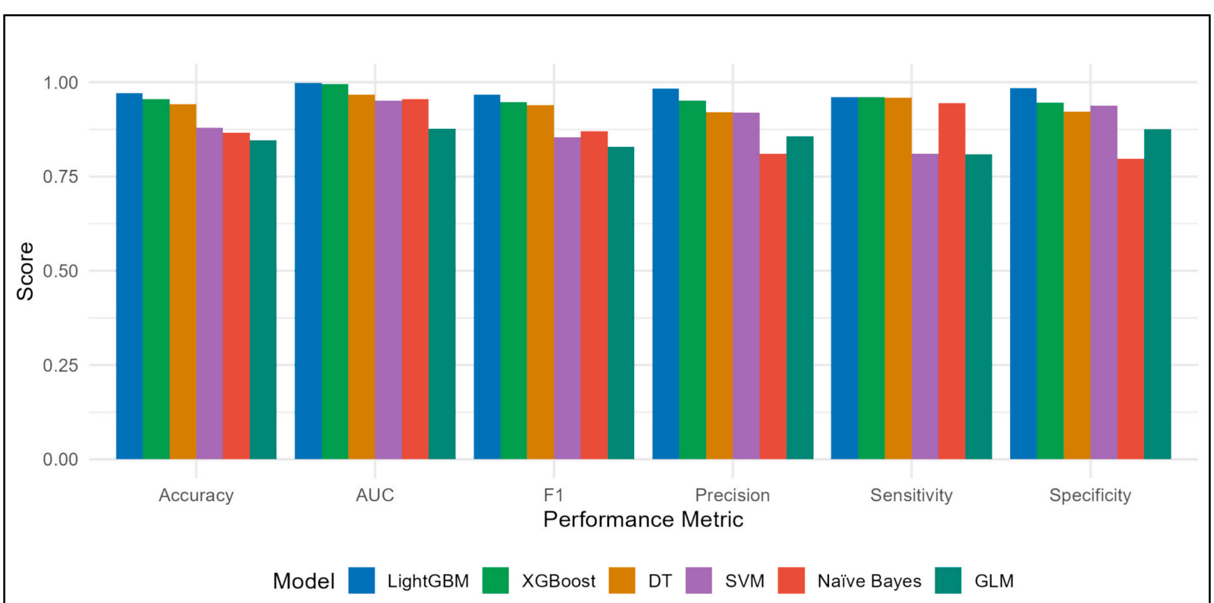

Fig. 2. The performance metrics for the training sets (2000–2019); LightGBM:Light Gradient Boosting Machine; XGBoost:Gradient Boosting; DT:Decision Tree; Naïve Bays: Naïve Bayes Classifier; SVM: Support Vector Machine; GLM: Generalized linear model.

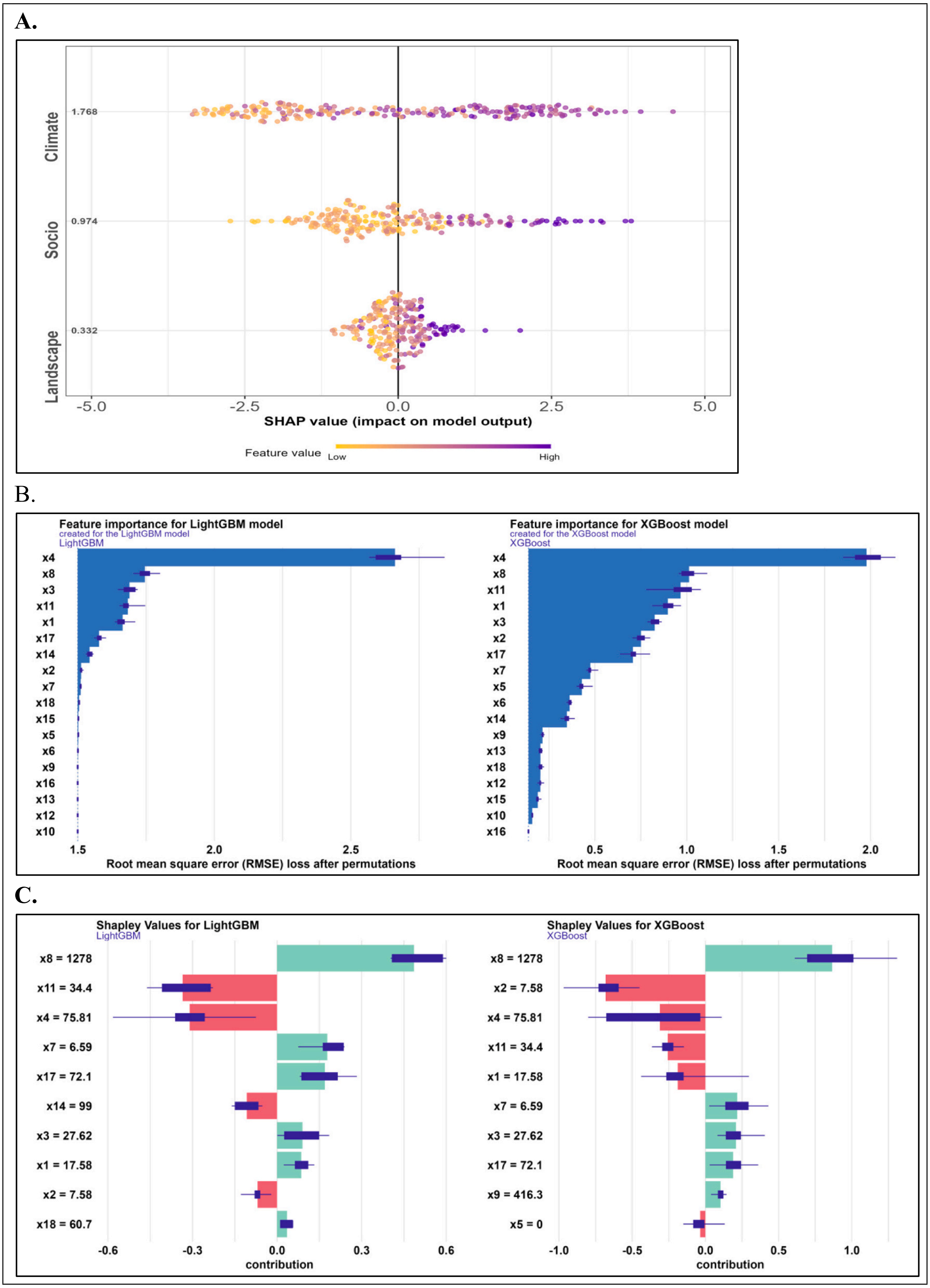

Fig. 3. A) Summary plot: principal SHAP predicted features of eco-climatic factors from the XAI model, Bangladesh 2000–2023. B) Feature importance for LightGBM and XGBoost models. C) Shaply values or LightGBM and XGBoost models. X1: Mean temperature (°C); X2: Minimum temperature (°C); X3: Maximum temperature (°C); X4: Relative humidity (%); X5: Rainfall (mm); X6: Surface Pressure (kPa); X7: Wind Speed at 50 Meters Maximum (m/s); X8: Population density; X9: Gross Domestic Product (Billion US$); X10: Gross National Income (K US$); X11: Poverty head-count ratio (% of population); x12: Adult literacy rate (% of population); X13: Total unemployment (% of total labor force); X14: Access to electricity (% of population); X15: Population growth; X16: Forest area (% of total land area); X17: Agricultural land (% of total land area); X18: Arable Land (% of the total land area).

evaluation of each feature's additional contribution to the models' predictions. In the XGBoost model, gross domestic product (Min: 0.02, Q1: 0.06, Median: 0.09, Mean: 0.09, Q3: 0.11, Max: 0.17) and agricultural land (Min: 0.06, Q1: 0.14, Median: 0.18, Mean: 0.19, Q3: 0.22, Max: 0.34) exhibit significant positive SHAP values, indicating a strong association with dengue incidences. Conversely, mean temperature (Min: -0.44, Q1: −0.32, Median: −0.23, Mean: -0.23, Q3: −0.17, Max: 0.15) and relative humidity (Min: -0.71, Q1: −0.40, Median: −0.26, Mean: -0.27, Q3: −0.05, Max: 0.16) display negative SHAP values (Fig. 3, C). Summary statistics of SHAP values for the models illustrate the distribution and spread of SHAP values across different features (Fig. S8, Table S12 - S13).

For instance, population density (value: 1278) reveals a mean SHAP value of 0.85 (Min: 0.40, Q1: 0.69, Median: 0.79, Q3: 1.07, Max: 1.30) in the XGBoost model and 0.42 (Min: 0.40, Q1: 0.41, Median: 0.48, Q3: 0.59, Max: 0.59) in the LightGBM model, emphasizing its significance in predicting dengue incidences. Additional critical features include agricultural land (value: 72.1, XGBoost mean SHAP value: 0.19, LightGBM mean SHAP value: 0.16) and rainfall (value: 0, LightGBM mean SHAP value: 0.009). Other notable features with their respective values include wind speed (value: 6.59), maximum temperature (value: 27.62), and surface pressure (value: 101.3). These findings underscore the crucial role of specific features in influencing the model's predictions, providing insights for model refinement and ensuring accurate forecasts. Population density stands out as the most significant contributor, with the XGBoost model capturing these contributions more effectively. (Fig. 3, C).

LIME for model predictions

In this study, LIME analyzed the contributions of 18 features to the model's dengue case predictions (Fig. 4). For instance, in case 1, minimum temperature (−1.71, weight: −0.65), relative humidity (−0.01, weight: −0.67), and population density (1.74, weight: 0.86) emerged as significant factors. Lower values of minimum temperature and relative humidity negatively impacted predicted log cases, while higher population density values increased predictions. This pattern was consistent across cases, underscoring the pivotal roles of these features. In case 2, the negative impact of relative humidity (−1.24, weight: −1.66) was more pronounced, further decreasing predicted log cases, while minimum temperature (−1.65, weight: −0.62) continued to show a notable negative effect. Population density (1.74, weight: 1.2) again demonstrated a strong positive influence, increasing predictions. In case 3, maximum temperature (1.58, weight: −1) significantly lowered predictions, whereas mean temperature (0.61, weight: 0.36) had a positive impact.

LIME explanations comprehensively understand the model's predictive behavior, emphasizing the importance of minimum temperature, relative humidity, and population density. These insights are vital for model refinement and ensuring accurate predictions (Fig. 3 and Table S14).

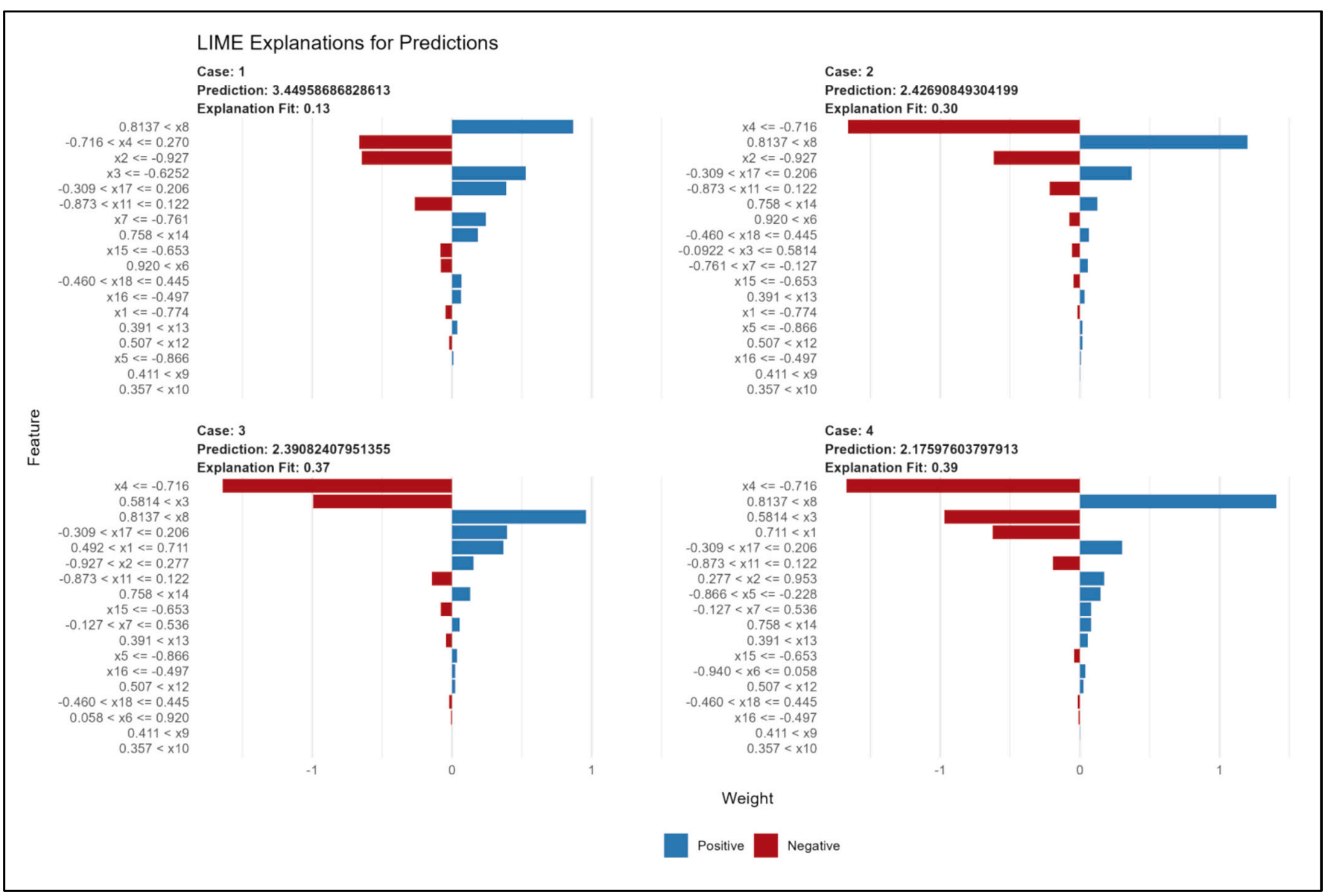

Fig. 4. LIME explanations for model predictions. X1: Mean temperature (°C); X2: Minimum temperature (°C); X3: Maximum temperature (°C); X4: Relative humidity (%); X5: Rainfall (mm); X6: Surface Pressure (kPa); X7: Wind Speed at 50 Meters Maximum (m/s); X8: Population density; X9: Gross Domestic Product (Billion US$); X10: Gross National Income (K US$); X11: Poverty head-count ratio (% of population); x12: Adult literacy rate (% of population); X13: Total unemployment (% of total labor force); X14: Access to electricity (% of population); X15: Population growth; X16: Forest area (% of total land area); X17: Agricultural land (% of total land area); X18: Arable Land (% of the total land area).

Predictive accuracy and early warning trends analysis using XGBoost and LightGBM

The LightGBM and XGBoost models were utilized to predict dengue cases and provide early warnings from 2024 to 2030 (Fig. 5). The analysis revealed that months such as October (avg. predicted cases: 11,275.52 XGBoost, 7165.41 LightGBM) and November (avg. predicted cases: 14,082.53 XGBoost, 8595.23 LightGBM) consistently trigger warnings of high dengue activity, indicating peak risks during these periods (Table S15). In contrast, months like June (avg. predicted cases: 1074.31 XGBoost, 1313.72 LightGBM) and August (avg. predicted cases: 299.51 XGBoost, 1759.70 LightGBM) show comparatively lower activity, despite LightGBM predicting elevated infections in August (Table S15).

The XGBoost model demonstrates stronger predictive accuracy, with an R^2 value of 0.84 for dengue cases compared to the LightGBM model, which has an R^2 value of 0.095 for dengue cases (Fig. 5). Forecasts for future years (2024–2030) further highlight XGBoost's reliability in delivering precise predictions and consistent early warnings compared to LightGBM (Table S15). The comparison with recent 2024 dengue outcomes confirms the models' ability to capture peak risk trends, reinforcing their reliability for surveillance and early intervention strategies. XGBoost aligns closely with observed dengue case surges, effectively identifying high-risk periods with greater precision. This consistency underscores its value in forecasting outbreak patterns and supporting timely public health responses(Fig. S9 and Table S17).

Discussion

The integration of XAI techniques has significantly improved the interpretability of machine learning models for dengue outbreak forecasting. By utilizing SHAP values, this study identified key predictive factors and their relative importance, offering valuable insights into disease transmission dynamics. Previous research has established that environmental variables such as temperature, humidity, and precipitation play a critical role in dengue outbreaks. However, this study goes

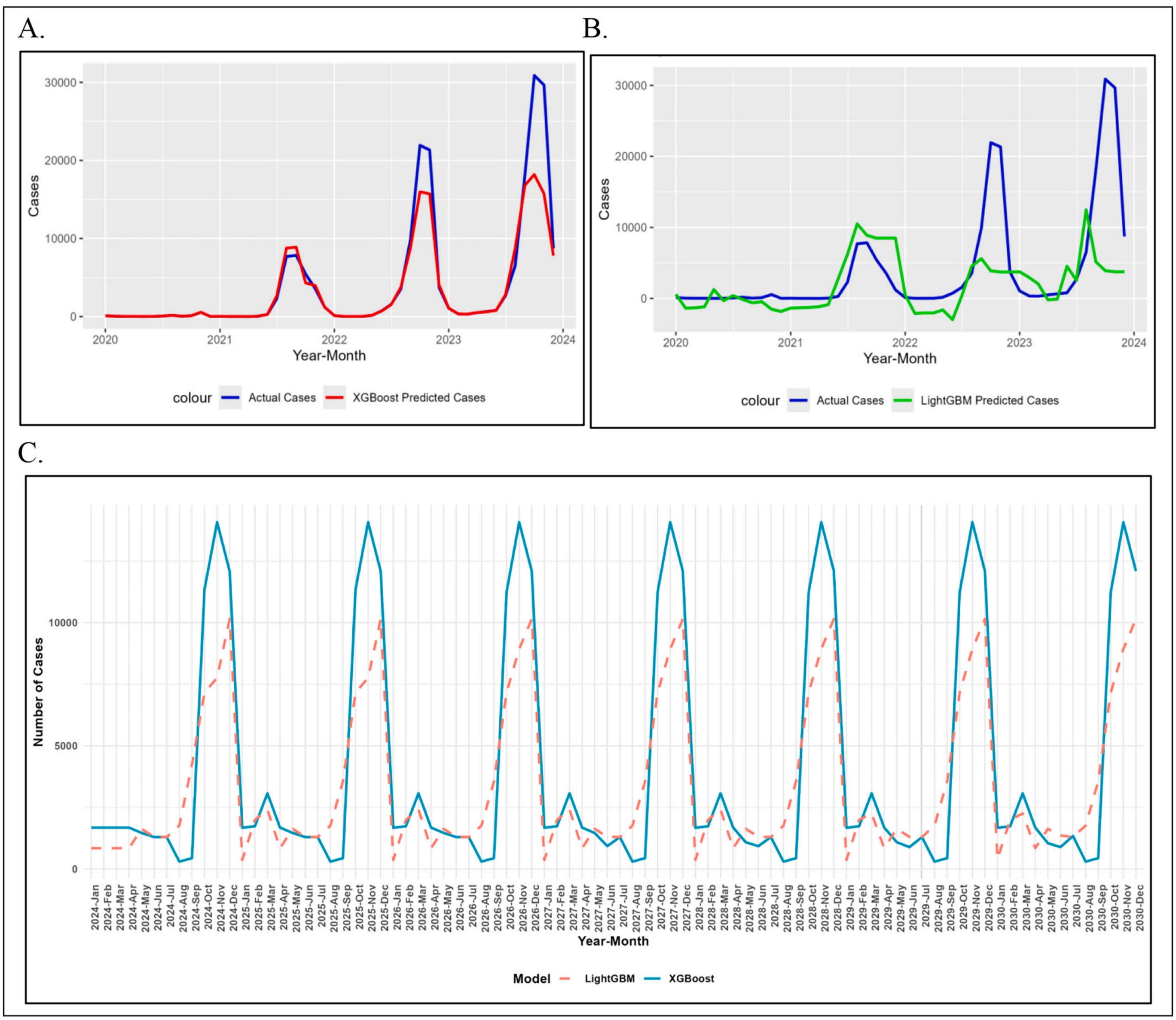

Fig. 5. Actual vs predicted dengue Cases A) XGBoost: monthly actual vs predicted dengue cases. (B) LightGBM: monthly actual vs predicted dengue cases (Train set: 2000–2019, Test set: 2020–2023; R^2 values – XGBoost: 0.84, LightGBM: 0.095). (C) Future dengue case predictions & early warning (2024–2030) using LightGBM and XGBoost models.

beyond conventional analysis by quantifying individual contributions using SHAP values, thereby reinforcing the necessity of advanced ML-driven approaches. Such quantification provides a more refined understanding of how specific climatic conditions intensify transmission, particularly in the context of socio-economic disparities [29] [30] [31]. The interpretability of these models ensures that epidemiological forecasts are transparent and actionable, empowering public health officials with data-driven interventions rather than relying on opaque predictive models [32]. Beyond climate factors, socio-demographic variables such as population density and land use patterns emerged as significant contributors to dengue outbreaks, reinforcing the importance of integrating environmental and human behavioral factors into predictive models [33] [34] Seasonal trends in dengue outbreaks highlight specific months with heightened transmission risks, aligning with known vector dynamics and climate-driven variations. [35] [29,34,36]. Such predictive clarity is crucial for early warning systems, allowing policymakers to allocate resources proactively before outbreak escalation [37] The comparative analysis of XGBoost and LightGBM revealed that ensemble-based models optimize predictions by accounting for complex interactions within epidemiological interactions. XGBoost exhibited superior predictive accuracy, making it a valuable tool for real-time outbreak forecasting and rapid-response planning, whereas LightGBM demonstrated strong predictive capabilities in identifying early warning signals for outbreak trends, making it a key asset for anticipatory surveillance measures [38] [39] [40]. These results are particularly relevant for low-resource settings where access to timely and reliable forecasts can significantly impact disease control efforts [41] [42,32]. The implementation of LIME provided further interpretability of AI-driven predictions, enabling localized explanations that enhance model credibility in public health decision-making. However, challenges related to stability in feature attribution highlight the need for more robust alternatives, such as Deterministic LIME (DLIME) and frameworks integrating Shapley values [32,43] [28]. These enhancements improve reliability, ensuring that AI-driven models remain practical for deployment in epidemiological surveillance. Additionally, the advancements in feature attribution methods underscore the broader movement within the ML community toward more transparent and interpretable models [44]. Early warning analysis consistent seasonal trends in dengue outbreaks, reinforcing the importance of proactive intervention programs. The predictive accuracy of the models was validated through retrospective assessments, demonstrating their reliability for forecasting outbreak trends [45]. [46]. Compared to traditional statistical models, the advantages of AI-driven forecasting become evident, particularly in terms of adaptability to changing epidemiological landscapes and improved precision in disease risk mapping [47] [46].

While AI-enhanced forecasting enhances dengue surveillance, its effectiveness ultimately depends on integration into real-world health frameworks. Future improvements in dengue Early Warning Systems should incorporate behavioral and landscape characteristics, along with enhanced vector surveillance, to refine predictions further. The combination of XAI techniques and ML models represents a powerful approach for epidemiological modeling, balancing interpretability with predictive performance to support effective public health planning [48–50] [55] [56][57].

Limitations

This study relies on historical epidemiological and climate data, which may not fully account for underreporting biases in dengue cases. While XGBoost and LightGBM performed well, the models focus primarily on environmental and socio-demographic factors, omitting key elements like human behavioral patterns, vector abundance, and healthcare accessibility, which could enhance future predictions. Although SHAP and LIME improve interpretability, LIME's instability due to random perturbations may affect consistency. Further refinements, such as Deterministic LIME (DLIME), could enhance reliability. Lastly, model validation was done using historical datasets, and real-time integration into public health surveillance systems would strengthen practical applications.

Conclusion

This study highlights the potential of AI-driven machine learning models in dengue outbreak forecasting. By integrating XGBoost and LightGBM with SHAP values, we improve interpretability, identifying key environmental and socio-demographic factors influencing dengue transmission. XGBoost exhibits strong predictive accuracy, while LightGBM enhances early warning capabilities, offering valuable insights for public health planning. Despite limitations, such as data biases and the exclusion of behavioral factors, this approach provides a foundation for refining dengue prediction systems. Future models should incorporate vector abundance, healthcare access, and human dynamics to improve real-world applications. The use of XAI techniques ensures transparency, strengthening trust in AI-driven disease forecasting. By advancing ML-based epidemiological models, this study supports timely interventions, helping mitigate dengue outbreaks and improve preparedness in resource-limited settings.

Availability of data and materials

All necessary data and source codes are available at https://github.com/siddikur2022/XAI-Dengue-Outbreak-Prediction.

CRediT authorship contribution statement

Md. Siddikur Rahman: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Md. Abu Bokkor Shiddik:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis.

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Declaration of competing interest

All authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloepi.2025.100210.

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