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Exploratory Data Analysis of Dengue Outbreaks in Bangladesh: Temporal and Spatial Trends from Positive Case Data

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***Abstract*—Dengue fever continues to be a global health crisis, affecting over 12 million individuals worldwide in 2024. In Bangladesh, the incidence of dengue has surged, with 321,179 cases reported in 2023 alone. This paper presents a comprehensive data analysis to identify the demographics most impacted by dengue in Bangladesh. We examine the prevalence of dengue across different age groups and socioeconomic statuses, distinguishing between the effects on developed versus underdeveloped regions. Additionally, we employ statistical methods to forecast dengue incidence in Bangladesh from 2024 to 2030. The insights derived from this analysis aim to enhance understanding of dengue trends and support public health strategies for future epidemic management.**

***Index Terms*—Dengue, Public Health, Data Analytics**

I. Introduction

Dengue fever, a vector-borne disease transmitted by Aedes mosquitoes, poses a significant public health challenge worldwide. In 2024, over 12 million cases of dengue were reported globally [1], highlighting the widespread impact of this disease. Bangladesh has experienced a notable increase in dengue cases, with 321,179 reported in 2023 alone [2]. This surge underscores the urgency of understanding the patterns and factors contributing to the rising incidence of dengue.

The disease's impact varies across different demographics, including age groups and socioeconomic statuses, which may influence susceptibility and disease severity. Additionally, the geographic distribution of dengue cases in both developed and underdeveloped regions of Bangladesh presents distinct challenges for public health interventions.

Different methods have been proposed to evaluate the link between climate and dengue transmission. For instance, Lambrechts et al. [3] and Mordecai et al. [4] employed laboratory entomological data, while Perkins et al. [5] used epidemiological case data. These approaches yield varying characterizations of how climatic factors influence dengue transmissibility.

Extensive research has highlighted the global impact of dengue fever and the increasing prevalence in endemic regions. While much of the existing literature focuses on epidemiological patterns and control measures [6], there is a significant gap in studies examining the perceived risk and preventive practices among youth, particularly in Bangladesh. Prior research emphasizes the importance of understanding public perception and behavior in managing dengue outbreaks [7]. Effective control strategies often depend on targeted interventions that influence community practices, especially among younger populations who can serve as agents of change [8]. This study seeks to fill this gap by investigating the perceived dengue risk and prevention practices among youth in Bangladesh, aiming to provide insights that could enhance public health strategies and interventions [9].

This paper aims to provide a detailed analysis of dengue fever in Bangladesh by examining demographic and geographic factors affecting disease prevalence. We analyze data to determine which age groups and socioeconomic statuses are most affected and assess the differences in disease impact between developed and underdeveloped regions. Furthermore, we employ statistical forecasting methods to project dengue incidence in Bangladesh from 2024 to 2030. By providing a comprehensive analysis of these factors, our study seeks to offer valuable insights for policymakers and health authorities to better address and mitigate the impact of dengue fever in the coming years.

II. LITERATURE REVIEW

Research on dengue fever has highlighted various trends, challenges, and advancements in understanding and managing the disease. Hasan et al. [10] documented a significant increase in dengue cases and deaths in Bangladesh from 2000 to 2022. They attributed this rise to global warming, including increased temperatures and altered rainfall patterns, which extended the dengue transmission season. The study emphasized the need for integrated vector management and community engagement to control dengue effectively.

In a subsequent study, Hasan et al. [11] used Poisson regression and autoregressive integrated moving average models to analyze the impact of meteorological factors on dengue cases. Their findings revealed a dramatic increase in cases and a decrease in the case fatality rate, highlighting the influence of temperature and rainfall on dengue incidence.

Prome et al. [12] explored the use of machine learning models to predict dengue cases across 11 districts in Bangladesh. They found that the support vector regression model with optimized hyperparameters performed best, demonstrating the potential of machine learning in forecasting dengue outbreaks and highlighting the value of explainable AI frameworks.

Barua et al. [13] discussed the evolving clinical characteristics of dengue fever, noting the need for early disease identification and accurate severity monitoring. They stressed the importance of epidemiological studies to assess current diagnostic and treatment approaches and called for further research to identify biomarkers linked to dengue treatment.

Shawon et al. [14] emphasized the necessity of a multifaceted approach to dengue control in Bangladesh. Their recommendations included targeted mosquito control efforts, a deeper understanding of local meteorological conditions, and enhanced diagnostic tools. They advocated for collaborative research to develop a comprehensive strategy to combat dengue and improve public health outcomes.

Akter et al. [15] focused on enhancing dengue prediction models using data from the Directorate General of Health Services (DGHS) between January 2016 and July 2021. Their study compared neural network models and ARIMA models, finding that the neural network model with five hidden layers provided the most accurate predictions. Islam et al. [16] They suggested that the neural network model could significantly impact reducing dengue-related mortality in Dhaka city and recommended public education on vaccination as a preventive measure.

Islam et al. [17] and Khan et al. [18] analyzed meteorological factors affecting dengue epidemics, using ARIMA models to identify correlations between weather variables and dengue incidence. Their results highlighted that increased rainfall was positively correlated with dengue cases, while higher humidity was associated with a reduction in cases. Their study emphasized the importance of incorporating weather data into national dengue prevention programs.

Childs et al. [19] and Rehman et al. [20] examined the causal impact of temperature on dengue spread across the Americas and Asia, using a dataset of nearly 1.5 million incidence records. They found a nonlinear relationship between temperature and dengue incidence, with peak incidence at 27.8°C. Their projections suggested a potential increase in dengue incidence due to climate change, emphasizing the need for strategies to mitigate future risks by reducing emissions.

Hamida et al. [21] proposed an Integrated Moving Average and Hierarchical Clustering (IMAHC) approach to predict dengue vulnerability based on historical data and various factors such as rainfall and population density. Their study demonstrated that the IMAHC method with Euclidean distance provided accurate predictions, highlighting the variability in factors affecting dengue susceptibility.

Mufti et al. [22] discussed the lack of antiviral medications for dengue and suggested plant-based constituents as potential therapeutic alternatives, emphasizing the need for broad-spectrum antiviral drugs.

Luang-Suarkia and Dagwinin [23] reported that dengue is hyperendemic in Papua New Guinea, with evidence of all four serotypes circulating since 1959. Their findings underscored the high prevalence of dengue and the need for prioritized intervention and control measures.

Andronico et al. [24] assess the forecasting performance of various models that describe how climate impacts the time-varying transmissibility of dengue virus (DENV) during a large epidemic in Reunion Island, [25,26] an overseas department of France in the Indian Ocean. Before this outbreak, DENV had been sporadically present on the island for 40 years despite the constant presence of Aedes albopictus. [27,28] The island had previously experienced a significant DENV epidemic (serotype 2) in 1977–1978, [29] as well as a major chikungunya virus (CHIKV) outbreak in 2005–2006. Both outbreaks affected about one-third of the population, demonstrating that substantial self-sustained arbovirus outbreaks were feasible. In early 2018, a sudden increase in dengue cases raised concerns among local authorities, given their previous experiences with CHIKV and DENV.

III. Methodology

This study employs a comprehensive methodology to analyze dengue fever trends and forecast future incidence in Bangladesh. Data is collected from two main sources: real-time data from local hospitals and the World Health Organization (WHO) website for January and February 2024, and historical data from the WHO covering the period from 2018 to 2023. The dataset comprises 20,000 records of confirmed dengue cases, detailed in Table 1.

TABLE I
Summary of Variables in the Dataset

Variable Name	Summary
Year	Category-wise year from 2009 to 2023
Category Name	Job category name
Count	Category-wise yearly job count
Gender	Male or Female
House Type	Building or Tin Shed
Area Type	Developed or Undeveloped
Age	Age of the patient
City Division Name	Division name of the city
Status	Positive or Negative
Dengue Test Report	NS1 or IGM

After data collection, we proceeded with a series of systematic steps to analyze and forecast dengue trends. First, the collected data was meticulously cleaned and prepared to ensure accuracy and consistency. This involved handling missing values, correcting inconsistencies, and standardizing data formats. Following data preparation, we conducted a descriptive analysis to identify general trends and patterns in dengue cases, focusing on demographic and geographic factors.

Next, we performed a risk factor analysis to explore the relationship between dengue incidence and various environmental factors such as temperature, rainfall, and humidity. Statistical tests, including chi-square and t-tests, were utilized to determine the significance of these risk factors.

For forecasting, we employed an ARIMA (AutoRegressive Integrated Moving Average) model, selected for its efficacy in time series analysis. The ARIMA model was used to predict dengue cases from 2024 to 2030, with parameters tuned based on historical data to optimize accuracy. The model's performance was validated using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

The final step involved deriving insights from the analysis and formulating recommendations. This included identifying peak periods and high-risk areas for dengue and proposing targeted public health strategies. The detailed methodology is illustrated in Fig. 1, which outlines the step-by-step process from data collection to insight generation and forecasting.

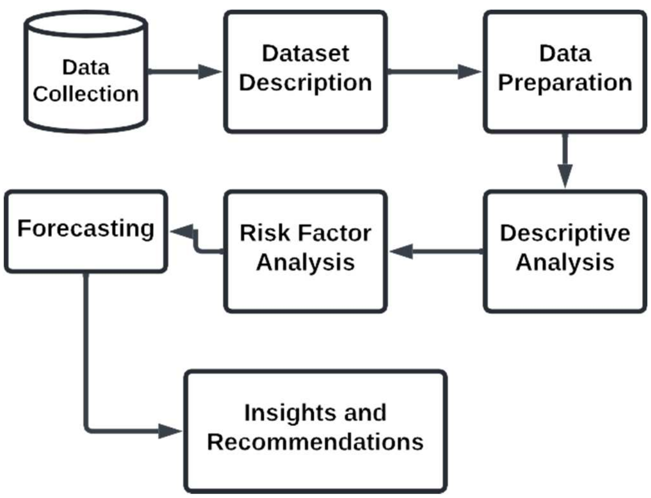

Fig. 1. Work progress of the study

To forecast dengue cases, we employed two time series models: ARIMA and ETS.

1) ARIMA Model: The ARIMA (AutoRegressive Integrated Moving Average) model is used for forecasting univariate time series data. It combines autoregressive (AR), differencing (I), and moving average (MA) components. The ARIMA model is defined as:

$$\text{ARIMA}(p, d, q) \tag{1}$$

where p is the order of the autoregressive part, d is the number of differences required for stationarity, and q is the order of the moving average part. The mathematical representation of the ARIMA model is:

$$\Phi(B)(1-B)^d Y_t = \Theta(B)\epsilon_t \tag{2}$$

where B is the backshift operator, ϕ_i are the autoregressive coefficients, ϑ_i are the moving average coefficients, and ϵ_t is the white noise error term.

2) ETS Model: The ETS (Error-Trend-Seasonality) model decomposes the time series into error, trend, and seasonal components to capture different patterns. The general form of the ETS model is:

$$Y_t = \text{Level}_t + \text{Trend}_t + \text{Seasonality}_t + \text{Error}_t \tag{3}$$

where:

- **Level** represents the baseline value.
- **Trend** indicates the direction of movement.
- **Seasonality** accounts for periodic patterns.
- **Error** denotes random fluctuations.

The mathematical formulation of the ETS model components is:

$$\text{Level}_t = \alpha Y_t + (1-\alpha)(\text{Level}_{t-1} + \text{Trend}_{t-1}) \tag{4}$$

$$\text{Trend}_t = \beta(\text{Level}_t - \text{Level}_{t-1}) + (1-\beta)\text{Trend}_{t-1} \tag{5}$$

$$\text{Seasonality}_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-m} \tag{6}$$

where α, β, and γ are the smoothing parameters, and m is the seasonal period.

Both models were applied to the data to compare their forecasting accuracy and determine the most effective model for predicting future dengue cases.

The performance of the forecasting models was evaluated using standard metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results were analyzed to identify the model providing the most accurate forecasts.

IV. Analysis and Result

In Fig. 2, we show the dengue test result distribution: 11,530 cases were positive and 8,470 cases negative. This distribution underscores the high prevalence of dengue in the dataset, setting the stage for analyzing contributing factors and impacts.

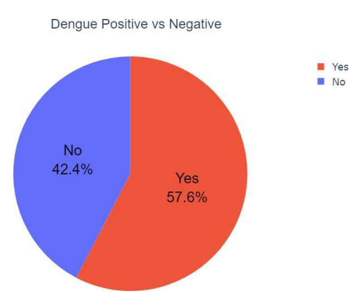

Fig. 2. Dengue Positive vs Negative

Fig. 3 shows the gender distribution of dengue-positive cases, with 5,680 females and 5,850 males. This highlights a nearly equal prevalence of dengue between genders.

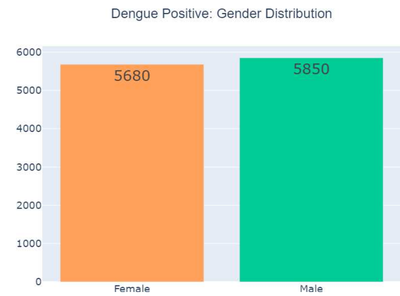

Fig. 3. Dengue Positive vs Negative

Fig. 4 illustrates the age-wise distribution of dengue-positive cases. The highest percentage falls within the 21-30 age range (28%), followed by 31-40 (22%) and 1-10 (16%). Other age groups show a decreasing trend, with the lowest percentage observed in the 71-80 age range (3%).

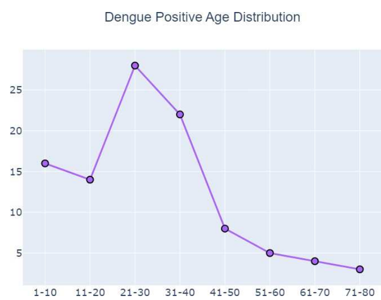

Fig. 4. Dengue Positive vs Negative

Fig. 5 presents the area type-wise distribution of dengue-positive cases. A significant majority of cases are from developed areas (8908 cases), while undeveloped areas account for 2622 cases, indicating a higher prevalence of dengue in developed regions.

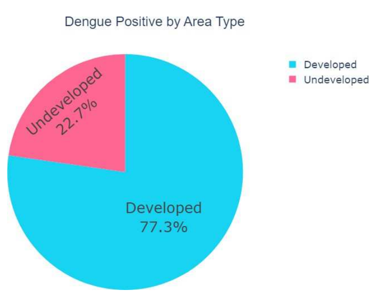

Fig. 5. Dengue Positive vs Negative

Fig. 6 shows dengue-positive cases by house type: 63.7% in buildings and 36.3% in tinshade homes, indicating a potential link between housing and dengue risk.

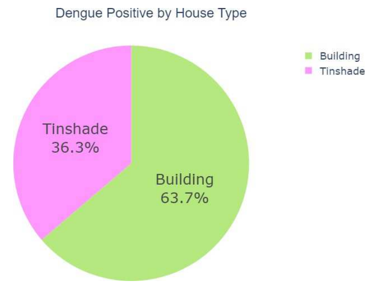

Fig. 6. Dengue Positive vs Negative

In Fig. 7 illustrates the distribution of dengue-positive cases across various divisions. The data reveals significant regional variations: Dhaka division reports the highest number of cases with 5,880, followed by Khulna with 1,644 cases. In contrast, the divisions with the fewest dengue-positive cases are Mymensingh (336) and Sylhet (552). The overall distribution highlights that Dhaka experiences a substantial burden of dengue, while other divisions such as Barishal, Chittagong, Rajshahi, and Rangpur have intermediate case numbers. This regional disparity underscores the need for targeted intervention strategies in the most affected areas.

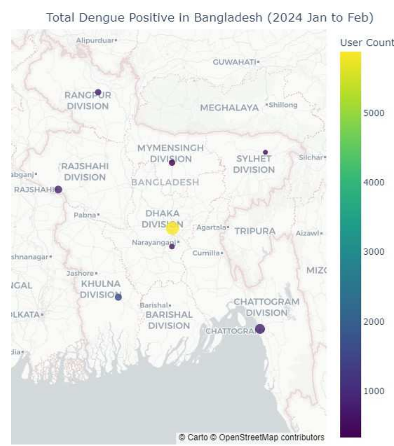

Fig. 7. Dengue Positive vs Negative

In Fig. 8, dengue cases in Bangladesh from 2018 to 2023 show a fluctuating trend with a sharp rise in 2019 (101,354 cases) and a significant peak in 2023 (321,179 cases). This highlights the growing burden of dengue in recent years.

In Fig. 9, dengue-related deaths in Bangladesh from 2018 to 2023 show a concerning upward trend, with the highest number of deaths recorded in 2023 (1,705 deaths). This increase underscores the rising severity of dengue outbreaks over recent years and highlights the urgent need for enhanced preventive measures and healthcare interventions.

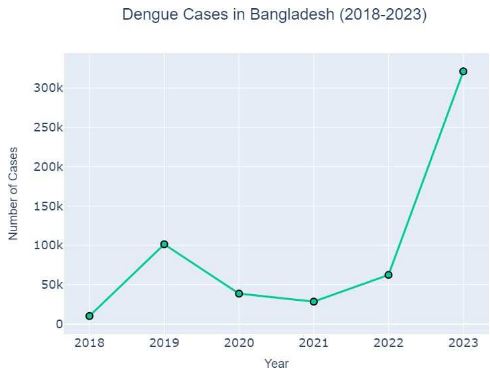

Fig. 8. Dengue Positive vs Negative

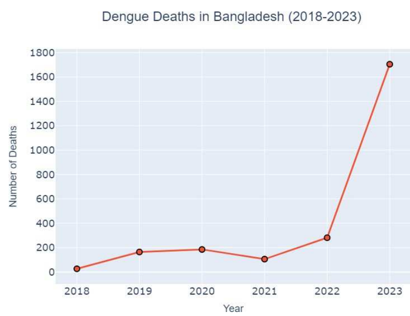

Fig. 9. Dengue Positive vs Negative

Table 2 shows the dengue case fatality rates in Bangladesh from 2018 to 2023. While the total number of cases fluctuated significantly, with a peak of 321,179 cases in 2023, the case fatality rate ranged between 0.16% and 0.53%. The highest fatality rate was recorded in 2023, indicating a concerning increase in the severity of dengue cases over time.

TABLE II
DENGUE CASE FATALITY RATE IN BANGLADESH (2018-2023)

Year	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
Cases	10,148	101,354	38,654	28,429	62,382	321,179
Deaths	26	164	185	105	281	1,705
CFR (%)	0.26	0.16	0.47	0.37	0.45	0.53

Fig 10 presents ARIMA model forecasts for dengue cases from 2024 to 2030. The predictions show a substantial increase in cases, rising from approximately 502,000 in 2024 to a peak of around 849,000 in 2029, before slightly decreasing to 834,000 in 2030. This trend underscores a continuing upward trajectory in dengue incidence over the forecast period.

Fig 11 shows the forecasts for dengue cases from 2024 to 2030 using the ETS model. The projections indicate a steady increase, starting at approximately 411,525 cases in 2024 and reaching around 958,618 cases by 2030. The forecast suggests a continuous rise in dengue incidence over the period, with the most significant increase occurring towards the end of the decade.

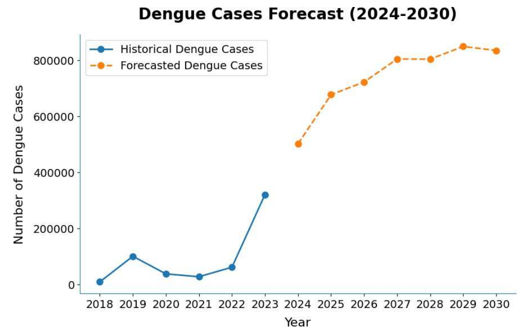

Fig. 10. Dengue Cases Forecast (2024-2030)

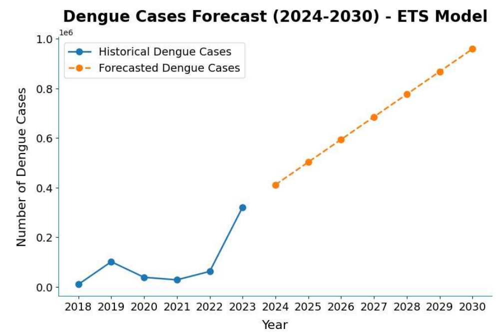

Fig. 11. Dengue Cases Forecast (2024-2030)

Our analysis of dengue fever data reveals significant insights into the disease's prevalence and distribution. The overall dengue positivity rate is approximately 57.6%, with a nearly balanced gender distribution (49.3% females and 50.7% males). The disease predominantly affects individuals aged 21-30 years and shows notable regional variations, with 77.3% of cases occurring in developed areas. The annual case numbers demonstrate a sharp increase, particularly in 2023, while the average case fatality rate ranges from 0.16% to 0.53%, averaging 0.37%.

The ARIMA model (Fig. 10) predicts dengue cases will rise from approximately 502,000 in 2024 to a peak of 849,000 in 2029, then slightly decline to 834,000 in 2030. In contrast, the ETS model (Fig. 11) shows a continuous increase, starting at 411,525 in 2024 and reaching 958,618 by 2030. The ARIMA model suggests a peak by 2029, followed by a slight decline, indicating potential stabilization, whereas the ETS model forecasts a steady rise. This divergence highlights the uncertainty in long-term predictions and underscores the need for robust disease management strategies. Both models emphasize the importance of ongoing surveillance and proactive public health interventions to mitigate the rising trend of dengue cases, with tailored strategies needed to address regional variations in dengue trends and reduce the disease burden effectively.

V. CONCLUSION

This study highlights the need for improved dengue fever management, with significant variations in incidence based on regional and socio-economic factors. Both the ARIMA and

ETS models provide valuable forecasts, but they show different trajectories for future dengue cases, underlining the uncertainty in long-term predictions. Despite these differences, the findings emphasize the urgent need for proactive public health interventions and tailored disease management strategies to mitigate the rising burden of dengue.

Future research should integrate additional factors, such as climate change, vector control measures, and demographic shifts, to enhance the accuracy of predictive models. Moreover, evaluating the long-term effectiveness of public health interventions, alongside incorporating more detailed regional and socio-economic data, will offer crucial insights. These improvements will aid in developing more effective and targeted dengue control strategies to address the evolving challenges posed by the disease.

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