Dengue Dynamics in Bangladesh: Unveiling Insights through Statistical and Machine Learning Analysis

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Abstract. Dengue fever remains a significant public health concern in Bangladesh, with recurring outbreaks posing substantial challenges to healthcare systems and communities. This study provides a concise overview of a comprehensive study aimed at unravelling the dynamics of dengue in Bangladesh through a synergistic combination of statistical and machine learning analyses. By applying statistical techniques, we first identify temporal and spatial patterns, uncovering seasonal trends, hotspot regions, and fluctuations in dengue incidence. The trend of safe childbirth practices gradually increased between 2000 to 2023. Dhaka, the capital city of Bangladesh, and its surrounding areas in the Dhaka Division showed a high number of dengue cases and deaths. The knowledge and awareness level about dengue was significantly higher for educated respondents (OR = 1.89, 1.21 – 1.97), residing in semi-urban regions (OR = 1.35, 0.93 – 1.41), female (OR = 1.39, 1.14 – 1.62), living in Dhaka division (OR = 3.72, 2.89 – 3.88), and housewife (OR = 1.52, 1.26 – 1.89). This initial analysis allows us to pinpoint high-risk areas and periods, facilitating targeted intervention strategies. In tandem with traditional statistical methods, we harness the power of machine learning to develop a predictive model which is capable of forecasting dengue outbreaks with enhanced accuracy. In conclusion, this study represents a comprehensive effort to deepen our understanding of dengue dynamics in Bangladesh. By combining statistical analyses with machine learning technique, we aim to provide actionable insights that can inform public health policies and interventions. Our findings have the potential to guide the allocation of resources, improve preparedness, and ultimately mitigate the impact of dengue fever in Bangladesh, offering a valuable framework for addressing similar challenges in other regions grappling with vector-borne diseases.

Keywords: dengue · DGHS · ML · socio-demographic · FBProphet.

1 Introduction

Dengue fever, a tropical disease transmitted by vectors, spreads rapidly and frequently [1]. According to the World Health Organization, dengue remains among the top 10 global health threats [2]. Several factors, including population growth, high population density, unplanned urbanization, climate change, inadequate water distribution, and insufficient vector control measures, have contributed to the global increase in dengue cases [3]. The Aedes mosquito is the primary vector responsible for transmitting this chronic disease among humans [4]. Dengue infection is often asymptomatic, occurring more than 50Bangladesh is one of the 12 countries in Southeast Asia where dengue is notably more prevalent [7]. The Southeast Asian and Western Pacific regions together account for 75 percent of global dengue cases, primarily due to their favorable climate for mosquito population growth [8]. With a population exceeding 165 million, Bangladesh, situated in South Asia, faces recurrent dengue outbreaks [9]. The term "Dacca fever" was coined to describe the initial dengue outbreak in Bangladesh, which occurred in East Pakistan in 1964. In 2000, the first recognized dengue outbreak in Bangladesh resulted in 5551 cases and 93 fatalities, establishing dengue as an endemic disease in the country. Since 2022, dengue fever cases have been on the rise in various nations, including Bangladesh, with the highest incidence occurring in Dhaka, the capital city [10]. Researchers have employed spatial analytical tools to investigate the correlation between the geographic distribution of Aedes mosquitoes and recent dengue infections in Dhaka, Bangladesh [11]. Another study has also explored the association between the geographic distribution of Aedes mosquitoes and recent dengue infections in Dhaka, Bangladesh [12]. Socio-demographic factors play a pivotal role in influencing the transmission and prevalence of dengue in Bangladesh. According to a recent study, residing in an urban area, having a lower socioeconomic status, living in households with inadequate sanitation, and having a history of dengue fever infection were all linked to an elevated risk of dengue fever in Bangladesh [13]. Furthermore, the study revealed that the risk of dengue fever was heightened during the monsoon season and in regions with a high mosquito population density. In Bangladesh, children and young adults were noted to be at a higher risk of dengue infection [14]. In a separate investigation, it was found that males were 1.5 times more likely to contract dengue than females [15]. Urban residents faced double the risk of dengue infection compared to their rural counterparts [16]. This discrepancy can be attributed to several factors, such as greater population density, increased mosquito breeding sites, and limited access to clean water and sanitation. Individuals from the lowest socioeconomic quintile were also 1.5 times more susceptible to dengue infection than those from the highest quintile [17]. This discrepancy is likely due to various factors, including crowded and unsanitary living conditions, reduced access to healthcare, and lower usage of mosquito nets. Additionally, other socio-demographic factors like education level, occupation, and travel history have also been associated with dengue infection in Bangladesh [18-19]. Machine learning (ML) is a dynamically advancing field poised to transform the landscape of infectious disease prevention and control [20]. ML algorithms offer the capability to scrutinize vast and intricate datasets, uncovering patterns and trends that traditional statistical methods would struggle to discern, if not render unattainable [21]. Recent years have witnessed a surging adoption of ML in the examination of dengue fever within the context of Bangladesh [22]. Utilizing ML algorithms, dengue data from diverse sources, encompassing hospital records, governmental reports, and social media, have undergone analysis [23]. ML stands as a potent instrument capable of enhancing our comprehension of dengue fever dynamics in Bangladesh, thereby facilitating the formulation of more effective prevention and control strategies. Ongoing research is essential for the development and validation of ML models aimed at predicting dengue outbreaks and identifying the risk factors for dengue fever infection. This study aimed to explore the intricacies of dengue transmission in Bangladesh and construct a machine learning model for predicting dengue outbreaks. The discoveries from this research hold promise for enhancing the accuracy of dengue prediction, forecasting, and control strategies in Bangladesh. The knowledge gleaned from this study has the potential to offer evidence-based policy recommendations, which could serve as valuable guidance for governmental and healthcare authorities in their endeavors to combat dengue effectively.

2 Methodology

2.1 Data collection and processing

This study employed both primary and secondary data sources. Secondary data for this research were obtained from the Directorate General of Health Services (DGHS) in Bangladesh, while primary data were gathered from dengue patients admitted to specific public and private hospitals during the period between August and September 2023. The majority of the data were collected within Dhaka city, while the remaining data were sourced from various other regions, including Rajshahi, Barisal, Chittagong, Khulna, and Mymensingh. To facilitate data collection, a pre-coded questionnaire was devised and subsequently approved after undergoing a pretest involving a sample of 50 participants. The sample size was estimated as:

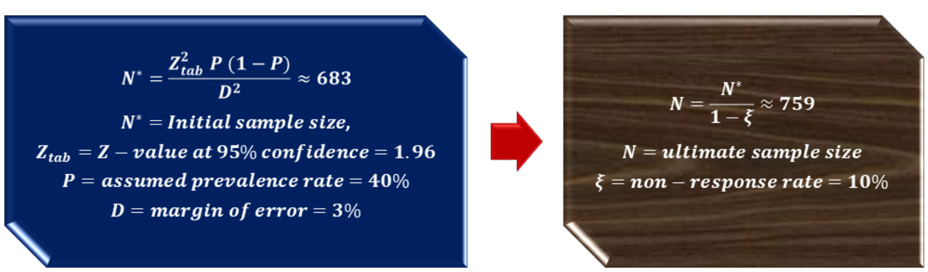


Fig. 1: Estimation process of sample size

The data underwent preprocessing to ensure its cleanliness and suitability for analysis. This process encompassed actions such as outlier removal, error correction, and categorical variable encoding. Survey participants who did not answer all the questions or departed before the interview's completion were omitted from the dataset. A small fraction of them was unable to provide complete responses due to limited awareness. As a result, our final sample size was established at 699 participants, which was considered adequate to fulfill our study's objectives with a 95% confidence level.

2.2 Study variables

The data was divided into two distinct sections: one detailing the socio-demographic characteristics of the respondents and the other addressing their knowledge and awareness regarding various aspects of dengue and its prevention. The socio-demographic profile encompassed information on age (categorized as below 18 years, 18 to 40 years, 40 to 60 years, and above 60 years), gender (classified as male or female), educational attainment (grouped into illiterate, primary, secondary, and higher), place of residence (categorized as rural, semi-urban, or urban), financial status (grouped as poor, middle-class, or rich), division (including Sylhet, Barishal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, and Rangpur), and occupation (divided into categories such as student, housewife, service, and others). The survey questionnaire collected both quantitative and qualitative information, thereby bolstering the overall credibility and acceptability of the research findings.

2.3 Statistical analyses

Various statistical techniques were employed to examine the data, encompassing descriptive statistics, correlation analysis, and regression analysis. Initially, summary measures were computed to evaluate the percentage distribution of variable categories. Subsequently, Pearson correlation coefficients (r) were computed to gauge the presence of multicollinearity among the variables. It's noteworthy that all correlation values were below 0.5, signifying the absence of multicollinearity [24].

$$r = \frac{Covariance(X_1 X_2)}{\sqrt{Variance(X_1) Variance(X_2)}})$$

Logistic regression analysis is the predominant regression method used when dealing with a binary outcome variable. Unlike some other techniques, it doesn't rely on assumptions about the distributions of explanatory variables. It offers an estimated measure of association, considering the impact of other variables. By exponentiating the regression coefficients, we can interpret them as odds ratios (OR) for the respective variables. In statistical terms, the equation can be expressed as follows:

$$E(O) = \frac{e^{\phi E}}{1 + e^{\phi E}}$$

where O = outcome variable, E_j = explanatory variables, ϕ_j = corresponding parameters.

To pinpoint the significant factors linked to dengue awareness and knowledge among the respondents, a logistic regression model was employed. All necessary analyses were carried out using IBM SPSS version 25.0.

2.4 FBProphet Forecasting Model

In this study, we utilized the Prophet forecasting tool as a machine learning model, developed by Facebook's Core Data Science team, to predict time-series data [27].Prophet operates on an additive model, that decomposes a given time-series into three main components: trend, seasonality, and holidays. Mathematically, this can be represented as

$$y(t) = g(t) + s(t) + h(t) +_t$$

Where $g(t)$ accounts for the non-periodic changes and represents the trend component, $s(t)$ captures the periodic oscillation indicating seasonality, and $h(t)$ reflects the effects of holidays. The error term $_t$ accommodates any anomalies not covered by the model. Prophet's flexibility allows it to handle missing data points and outliers gracefully. Moreover, its capacity to incorporate yearly, weekly, and daily seasonality, as well as holiday effects, makes it uniquely suited for a wide range of forecasting scenarios. To tune the model, Prophet offers intuitive parameters like changepoint prior scale for adjusting trend flexibility and seasonality prior scale to control the seasonality component's fit. We adopted default hyperparameters in the initial model and made subsequent refinements based on diagnostic metrics to achieve an optimal forecast.

3 Result and Discussion

3.1 Trends of Dengue Outbreak in Bangladesh

Figure 2 depicts the occurrences of dengue cases and related deaths in Bangladesh from 2000 to 2022. In the year 2000, the mortality rate was approximately 100, a figure that nearly halved in 2001. In 2002, there was an uptick in both case and mortality rates, followed by a significant decrease in 2003 when both rates became nearly negligible. In 2004, there was a slight resurgence in both rates, but they plummeted to almost zero in 2005. The case frequency remained relatively consistent from 2005 to 2014, with a slight increase in the death frequency during this period. The following years exhibited a near-constant case frequency. Then, there was a modest increase in both frequencies from 2014 to 2016, followed by a sharp drop in 2017 when the frequency approached zero. In 2018, both frequencies began to surge rapidly, with the death frequency surpassing 250 and the case frequency nearing 150 by 2019. Subsequently, both frequencies plummeted rapidly, reaching nearly zero by 2020. However, from 2020 to 2022, both frequencies experienced an upward trend, with the death frequency in 2022 surpassing that of 2019. It is noteworthy that 2022 emerged as the year with the highest number of deaths.

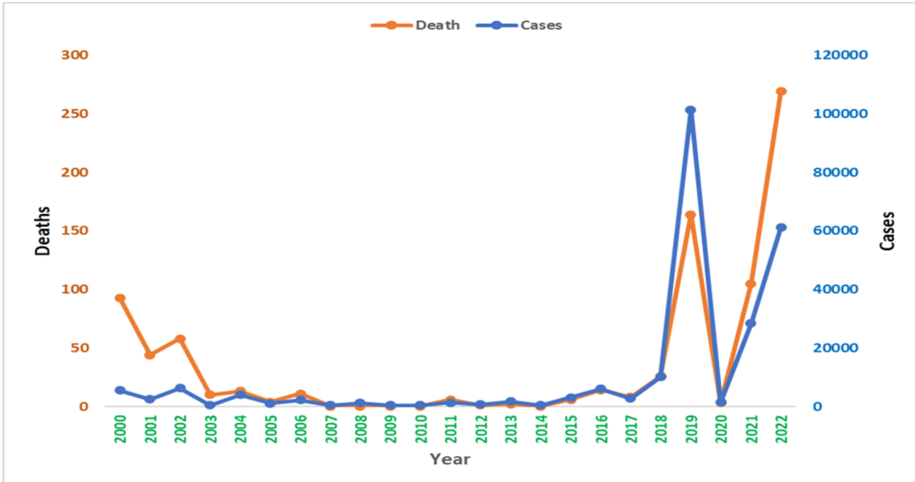


Fig. 2: Trend of Dengue Cases and Deaths in Bangladesh between 2000 to 2022

3.2 Distribution of Dengue Outbreak in 2023

Dengue fever has claimed the lives of over 1,000 people in Bangladesh this year, a staggering increase of nearly fourfold compared to the entire previous year. Figure 3 illustrates the frequencies of dengue cases and related fatalities recorded from January to September 2023. In the initial nine months of 2023, no fewer than 1017 individuals have succumbed to the mosquito-borne disease, while approximately 209000 have contracted it. This marks the most severe outbreak of this disease in the country since the first documented epidemic in the year 2000. As evident, there has been a consistent rise in both dengue cases and fatalities from January through August, reaching a peak in August. This pattern aligns with the typical occurrence of dengue outbreaks in Bangladesh, which typically coincide with the rainy season, spanning from May to September. It is important to note that the number of dengue cases and deaths reported in Bangladesh is likely to be an underestimate, as many people do not seek medical care for mild cases. Dengue cases typically start to rise in July, reaching their zenith in either August or September. A concurrent increase in the number of deaths is also typical during this period. Bangladesh experiences its monsoon season, usually spanning from June to September, and it is during this period that dengue cases typically surge. The warm and humid climate prevalent during this season creates ideal breeding grounds for mosquitoes, contributing to the rise in dengue cases. Inadequate sanitation conditions in Bangladesh, including open drains and the presence of garbage dumps, can exacerbate the transmission of dengue.

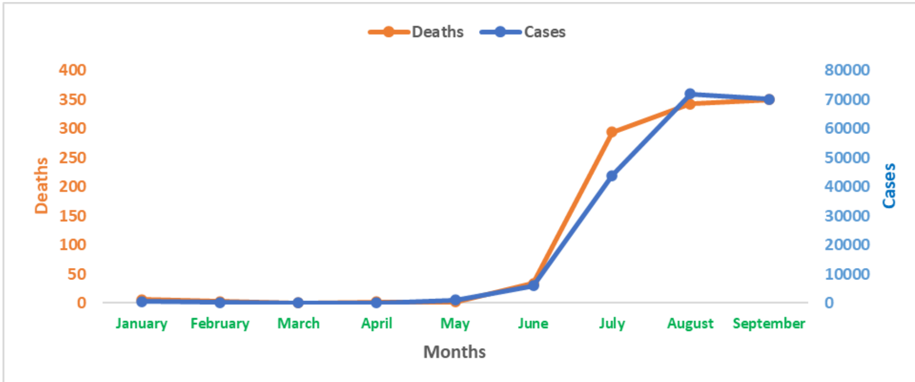


Fig. 3: Trend of Dengue Cases and Deaths month wise in Bangladesh between January-September 2023

3.3 Outcomes from Survey Data

Socio-demographic profile of the respondents Table 1 shows the distribution of the respondents according to selected socio-demographic variables. Notably, Dhaka accounts for the majority, with 53.8% of the 699 respondents being from this division. Chittagong follows with nearly one-fifth (20.1%) of the cases. Conversely, Sylhet division contributes only 1%, and Mymensingh records a negligible frequency of 0.9%. This data underscores that Dhaka is the division with the highest Dengue infection rate compared to the others. Among the 699 respondents, there were 406 males (58.1%) and 293 females (41.9%). The majority (71.7%) fell within the 18-40 years age group, while a minority (2.7%) were above 60 years old. Most respondents resided in urban areas (59.5%), with 21.2% in semi-urban areas, and the remaining 19% in rural regions. In terms of education, 9.2% had no formal education, while more than half (55%) were highly educated. The occupational distribution showed that 36.2% were students, 18.6% held jobs, and only 1.3% were engaged in farming. The majority of respondents belonged to the middle-class category, constituting nearly two-third of all respondents (65.6%), whereas only 17.7% came from higher-class families.

Knowledge and awareness level of the respondents Among the total respondents, an overwhelming majority (92.4%) were aware of Dengue fever. Approximately 87% attributed mosquito bites as the primary cause of Dengue Fever. When asked about the timing of mosquito bites, around three-fifths (62.8%) believed that Dengue causes mosquitoes to bite mostly during the daytime. An even larger majority (81.7%) of respondents believed that Dengue is not contagious. When asked about common symptoms of dengue, the most frequent response was high fever (30.6%). More than half of the respondents (64.1%) indicated that they were knowledgeable about the Aedes mosquito.

Table 1: Socio-demographic profile of the respondents

		Frequency	Percentage (%)
Sex	Male	406	58.1
	Female	293	41.9
Age	Below 18 years	91	13.0
	18 to 40 years	501	71.7
	40 to 60 years	88	12.6
	Above 60 years	19	2.7
Residential origin	Rural	133	59.8
	Semi-Urban	148	21.2
	Urban	418	19.0
Education	Illiterate	64	9.2
	Primary	121	17.3
	Secondary	129	18.5
	Higher	385	55.0
Occupation	Student	253	36.2
	Housewife	127	18.2
	Service	182	26.0
	Others	137	19.6
Financial status	Poor	118	16.6
	Middle class	459	65.6
	Rich	124	17.7

Findings of logistic regression model The results presented in Table 3 from the logistic regression analysis reveal that female respondents showed significantly higher level of knowledge and awareness about dengue [OR = 1.39, 1.14 − 1.62] in comparison to their male counterparts. These findings are consistent with prior studies that have also reported a similar trend [14, 20]. Under specific conditions, men may demonstrate lesser safe attitudes and behaviors when compared to women, which can be attributed to gender psychology [25]. Another contributing factor could be masculinity, a significant determinant of men's safety-related actions [25]. Table 3 also tells that educated respondents had significantly higher level of knowledge and awareness about dengue compared to those with no education. These outcomes are consistent with previous works which highlight the positive effect of education on knowledge and awareness about dengue [15, 18]. Individuals with higher levels of education are often more knowledgeable about dengue, its symptoms, and prevention measures. The effect of education on level of knowledge and awareness about dengue among the people in Bangladesh incorporates many dimensions of health sector. Education augments health awareness and endorses positive behavior changes. It advances access to healthcare amenities and improves health outcomes.

Dengue is prevalent in major urban centers where mosquitoes, the carriers of the disease, closely interact with densely populated human communities. As indicated by the findings in Table 3, individuals residing in semi-urban areas [OR = 1.35, 0.93 − 1.41] and urban environments [OR = 1.14, 0.98 − 1.29] ex-

Table 2: Knowledge and awareness level of the respondents

		Frequency	Percentage (%)
Familiar with Dengue Fever	Yes	646	92.4
	No	53	7.6
Responsible for Dengue fever	Mosquito's bite	608	87.0
	Others	17	2.4
	Don't know	74	10.6
Most common time for mosquito bites	Day	502	71.8
	Night	42	6.0
	Don't know	154	22.0
Dengue is a contagious disease	Yes	128	18.3
	No	571	81.7
Signs and symptoms of Dengue fever	High fever	489	38.8
	Acute body aches	242	19.2
	Diarrhea and vomiting	241	19.1
	Others	289	22.9
Can detect Aedes	Yes	448	64.1
	No	251	35.9
Dengue requires hospitalization	Yes	577	82.5
	No	122	17.5
Tests are needed to diagnose Dengue fever	Yes	404	57.8
	No	295	42.2
Protection from mosquito bites	Use Spray/Coil/Cream	511	51.0
	Use Net	426	42.5
	Do nothing	65	6.5

Table 3: Findings of logistic regression model

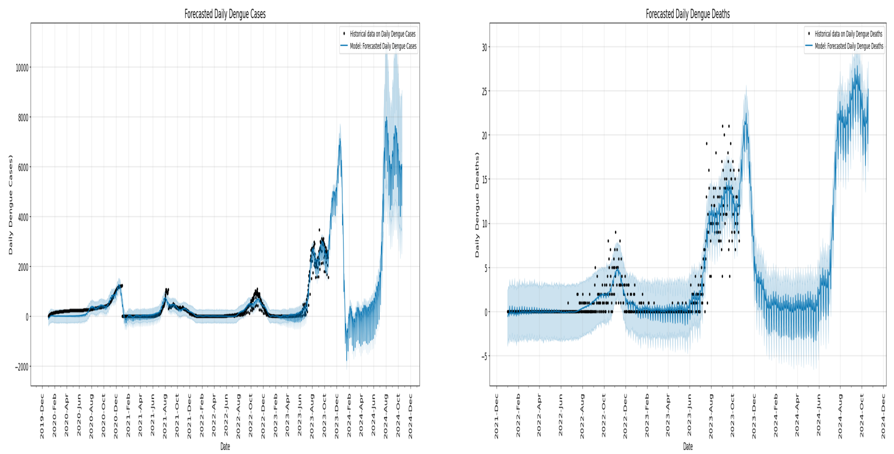
		Odds ratio	95% confidence interval
Sex	Male	1	
	Female	1.39**	[1.14, 1.62]
Age	Below 18 years	1	
	18 to 40 years	0.73**	[0.43, 1.02]
	40 to 60 years	0.86*	[0.58, 1.19]
	Above 60 years	0.92*	[0.36, 0.99]
Residential origin	Rural	1	
	Semi-Urban	1.35*	[0.93, 1.41]
	Urban	1.14**	[0.98, 1.29]
Education	Illiterate	1	
	Primary	1.89**	[1.21, 1.97]
	Secondary	1.18*	[0.82, 1.81]
	Higher	1.03**	[0.93, 1.38]
Occupation	Student	1	
	Housewife	1.52**	[1.26, 1.89]
	Service	1.03*	[0.89, 1.27]
	Others	1.13	[0.72, 1.59]
Financial status	Poor	1	
	Middle class	0.83**	[0.47, 1.01]
	Rich	0.94**	[0.44, 1.18]
Division	Mymensingh (RC)	1	
	Chittagong	1.41**	[1.13, 1.65]
	Dhaka	3.72**	[2.89, 3.88]
	Khulna	1.19	[0.85, 1.41]
	Rajshahi	1.14	[0.94, 1.38]
	Rangpur	1.01	[0.51, 1.33]
	Sylhet	0.87	[0.24, 1.15]
	Barisal	1.07	[0.43, 1.59]
**p-value<0.01,*p-value<0.05			

hibit notably greater likelihood of possessing knowledge and awareness regarding dengue in contrast to their rural counterparts. This result aligns with the conclusions drawn from previous studies [15,16]. Middle-class [OR = 0.83, 0.47 − 1.01] and rich [OR = 0.94, 0.44 − 1.18] respondents showed significantly lower levels of dengue knowledge and awareness when contrasted with those in the lower socioeconomic strata as they were less likely to correctly recognize clinical symptoms of dengue fever and understand its modes of transmission and prevention. This discrepancy may be attributed to the fact that individuals with greater financial resources often have access to superior healthcare facilities [17, 18] and may have limited or no direct experience with the disease. In line with many other diseases, the ability to identify dengue symptoms plays a crucial role in enabling early diagnosis, treatment, and improved clinical outcomes. This study has identified a noteworthy connection between age and the level of dengue knowledge and awareness. Individuals aged 18 years and older exhibited a lower inclination to recognize the seriousness of dengue and the necessity for hospitalization compared to those under 18 years of age. Interestingly, a contrasting study conducted in Bangladesh [26] discovered that individuals between the ages of 45 and 60 were more likely to express a positive attitude toward taking precautionary measures for dengue prevention than those under 25 years old. It's important to note that while this study defined attitude as the sentiment regarding the severity of dengue and the need for hospitalization due to the disease, the other study [26] regarded attitude as the collective sentiments of community members toward dengue prevention and control. Consequently, the variations in how different studies measured these factors naturally led to differing outcomes. Nevertheless, it's reasonable to assume that perspectives on dengue transmission are subject to change, particularly among young individuals, given the significant fluctuations in both dengue infections and associated fatalities observed in recent years. Respondents from Dhaka and Chittagong had significantly better dengue knowledge and awareness level than other divisions in Bangladesh. Most of the respondents living in those two divisions were facilitated better than other divisions in various aspects which ultimately had positive impact on knowledge and awareness level. The results of other relevant studies support it as well [22,25].

3.4 Forecasting Daily Cases and Deaths with FBProphet

Here we use the daily dengue cases data from January 01, 2020 to October 20, 2023 and daily deaths used to dengue from January 01, 2022 to October 20, 2023 [28] to predict the next one year of daily cases and deaths implementing FBProphet forecasting model. Figure-4 shows that the disease will spread in its height form to nearly 7000 in a day within the next two months and decrease afterward; and will increase again from July 2024 towards December 2024 as like as the previous years. A similar scenario has been shown in Figure-5 for the daily deaths due to dengue. Daily deaths can be raised up to 23 a day within the next two months and decrease afterward. Furthermore, daily deaths increase again from July 2024 towards December 2024 and can be raised up to 27 in a day.

The model fits into the training dataset and outperforms with testing dataset (Figure-4).



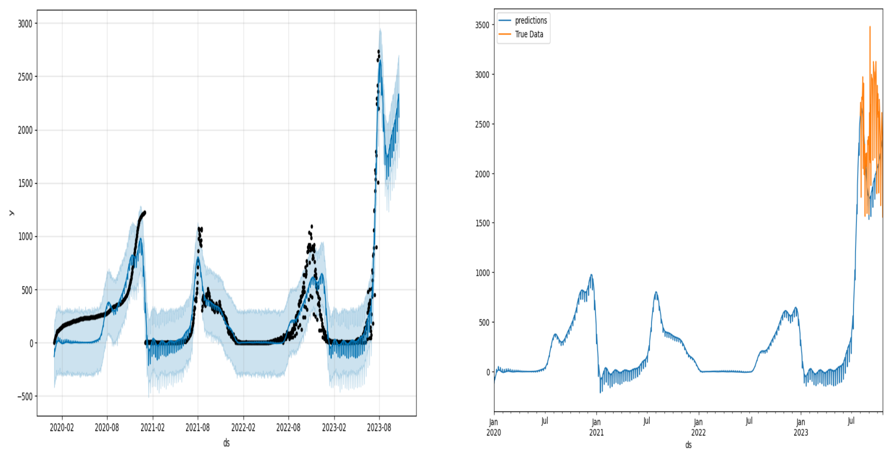
(a) Forecasted daily Dengue Cases

(b) Forecasted daily Dengue Deaths

Fig. 4: Forecasted daily Dengue Scenario

4 Conclusion

This study uncovered several significant findings regarding the dengue epidemic in Bangladesh. It identified a pronounced seasonality in the epidemic, primarily occurring during the monsoon season. Furthermore, it revealed spatial disparities, with certain regions experiencing higher dengue rates than others. The increasing complexity and unpredictability of the epidemic were attributed to multiple factors, including climate change, urbanization, and the emergence of new mosquito strains. In response to these findings, the study advocates for a range of interventions to combat the dengue epidemic in Bangladesh. These interventions encompass enhanced surveillance and monitoring of dengue cases, targeted vector control measures, public awareness campaigns for dengue prevention, and improved healthcare access for dengue patients. Additionally, the study emphasizes the importance of further research to develop more effective prevention and control strategies. Furthermore, the study's incorporation of machine learning analysis underscores the potential of data-driven approaches in forecasting and managing dengue outbreaks. This innovation holds significant promise for public health authorities, enabling more efficient resource allocation and timely intervention implementation.



(a) (b)

Fig. 5: Train-Test Performance with FBProphet

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