

# DENGUEWATCH: A SYSTEM FOR REAL-TIME DENGUE MONITORING AND FORECASTING IN ILOILO PROVINCE

A Special Problem Proposal  
Presented to  
the Faculty of the Division of Physical Sciences and Mathematics  
College of Arts and Sciences  
University of the Philippines Visayas  
Miag-ao, Iloilo

In Partial Fulfillment  
of the Requirements for the Degree of  
Bachelor of Science in Computer Science by

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November 25, 2024

## Abstract

Dengue fever remains a significant public health concern in the Philippines, with cases rising dramatically in recent years. Nationwide outbreaks have placed immense strain on healthcare systems, underscoring the need for innovative approaches to surveillance and response. In Iloilo City, this national trend is reflected in a significant surge, with the Iloilo Provincial Health Office reporting 4,585 cases and 10 fatalities as of August 10, 2023—a 319% increase from the previous year’s 1,095 cases and one death. This research includes the development of a centralized system for monitoring and forecasting dengue trends in Iloilo City. This study explores the application of artificial intelligence (AI) for dengue prediction, using a deep learning approach with Long Short-Term Memory (LSTM) networks. The LSTM model is compared with traditional statistical methods, including non-seasonal and seasonal Autoregressive Integrated Moving Average (ARIMA) models and the Kalman Filter for state estimation algorithm in noisy data conditions. Forecasting was based on climate variables such as temperature, rainfall, relative humidity, and previous monthly case counts, with performance evaluated using Root Mean Square Error (RMSE). By integrating predictive analytics with real-time data visualization, the proposed system aims to support public health agencies, such as the Department of Health (DOH), by providing actionable insights for proactive intervention strategies. This AI-driven solution enhances traditional outbreak reporting systems by enabling timely, data-informed decisions to mitigate the impact of dengue in the region.

**Keywords:** ARIMA, artificial intelligence, dengue prediction, LSTM, Kalman Filter, deep learning, climate variables, public health, outbreak mitigation

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# Chapter 1

## Introduction

### 1.1 Overview

From 2020 to 2022, dengue cases declined due to reduced surveillance during the COVID-19 pandemic, but cases surged in 2023 as restrictions were lifted. This year saw an increase in dengue outbreaks worldwide, with over five million cases and more than 5,000 deaths reported in over 80 countries. (Bosano, 2023) Dengue is endemic in the Philippines, leading to longer and more widespread seasonal outbreaks. Globally, dengue infections have increased significantly, posing a major public health challenge. The World Health Organization (Organization, 2024) reported a ten-fold rise in cases between 2000 and 2019, with a peak in 2019 when the disease spread across 129 countries.

Iloilo City and Province are intensifying efforts to curb the rising dengue cases. As of August 10, 2023, the Iloilo Provincial Health Office recorded 4,585 cases and 10 deaths, a 319% increase from last year's 1,095 cases and one death. Governor Arthur Defensor Jr. confirmed that the province has reached the dengue outbreak threshold based on Department of Health (DOH) criteria, and a formal declaration is pending. Local government units (LGUs) have been informed, and the province's disaster management office is on blue alert, indicating disaster mode. (Lena, 2024)

In Iloilo City, 649 dengue cases were recorded during the same period, with two deaths. Cases cluster in 40 out of 180 barangays, meaning multiple cases are being reported in these areas over several weeks. The city's health officer, Dr. Roland Jay Fortuna, reported high utilization of non-COVID-19 hospital beds, reaching over 76%, prompting concerns about hospital capacity.

This study explores the monitoring and forecasting of dengue outbreaks by analyzing key factors such as temperature, relative humidity, and historical dengue cases, using different models. The findings aim to provide an advanced, AI-driven alternative for dengue prevention and control, targeting agencies like the Department of Health (DOH). By aligning with the national AI Roadmap, particularly in Iloilo City, this research aspires to improve outbreak responses through cutting-edge technology rather than traditional reporting methods.

## **1.2 Problem Statement**

Dengue remains a critical public health challenge worldwide, with cases increasing due to the easing of COVID-19 restrictions and heightened global mobility. While a temporary decline in cases was observed during the pandemic (2020–2022) due to reduced surveillance efforts, 2023 marked a resurgence, with over five million cases and more than 5,000 deaths reported across 80 countries. In dengue-endemic regions like the Philippines, the threat is particularly severe. In Iloilo City and Province, dengue cases rose by 319% as of August 2023, overwhelming local health-care systems. This surge strained resources, with over 76% of non-COVID-19 hospital beds occupied by dengue patients, highlighting the urgent need for effective predictive tools. The lack of a reliable system to monitor and forecast dengue outbreaks contributes to delayed interventions, exacerbating public health risks and healthcare burdens in the region.

## **1.3 Research Objectives**

### **1.3.1 General Objective**

This study aims to develop an AI-based dengue forecasting and monitoring system for Iloilo City and Province. The researchers will train and compare multiple deep learning models to predict dengue case trends based on climate data and historical dengue cases to help public health officials in possible dengue case outbreaks.

### **1.3.2 Specific Objectives**

Specifically, this study aims to:



1. Gather dengue data from the Iloilo Provincial Health Office and climate data from online sources. Combine and aggregate these data into a unified dataset to facilitate comprehensive dengue case forecasting.
2. Evaluate deep learning models for predicting dengue cases. Compare the performance of these models to determine the most accurate forecasting approach.
3. Develop a web-based analytics dashboard that integrates a predictive model and provides data management system for dengue cases in Iloilo City and the Province.

## 1.4 Scope and Limitations of the Research

This study aims to gather dengue data from the Iloilo Provincial Health Office and climate data from online sources such as PAGASA or [weatherandclimate.com](http://weatherandclimate.com). These data will be preprocessed, cleaned, and combined into a unified dataset to facilitate comprehensive dengue case forecasting. However, the study is limited by the availability and completeness of historical data. Inconsistent or missing data points may introduce biases and reduce the quality of predictions. Furthermore, the granularity of the data, such as weekly or monthly formats, depends on the formats provided by the sources.

To evaluate deep learning models for predicting dengue cases, the study will train and compare the performance of various models, using metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). While these models aim to provide accurate forecasts, their performance is heavily influenced by the quality and size of the dataset. Limited or low-quality data may lead to suboptimal predictions. Additionally, the models cannot fully account for external factors such as public health interventions or socio-economic conditions which may impact dengue transmission dynamics.

The study also involves developing a web-based analytics dashboard that integrates predictive models and provides a data management system for dengue cases in Iloilo City and the Province. This dashboard will offer public health officials an interactive interface to visualize dengue trends, input new data, and identify risk areas. However, its usability depends on feedback from stakeholders, which may vary based on their familiarity with analytics tools. Moreover, external factors such as limited internet connectivity or device availability in remote areas may affect the system's adoption and effectiveness. While the dashboard provides valuable insights, it cannot incorporate all factors influencing dengue

transmission, emphasizing the need for ongoing validation and refinement.

## 1.5 Significance of the Research

This study’s development of an AI-based dengue forecasting and monitoring system has wide-reaching significance for various stakeholders in Iloilo City:

- **Public Health Agencies:** Organizations like the Department of Health (DOH) and local health units in Iloilo City and Province stand to benefit greatly from the system. With dengue predictions, we can help these agencies optimize their response strategies and implement targeted prevention measures in high-risk areas before cases escalate.
- **Local Government Units (LGUs):** LGUs can use the system to support their disaster management and health initiatives by proactively addressing dengue outbreaks. The predictive insights allow for more efficient planning and resource deployment in barangays and communities most vulnerable to outbreaks, improving overall public health outcomes.
- **Healthcare Facilities:** Hospitals and clinics, which currently face high bed occupancy rates during dengue season will benefit from early outbreak forecasts that can help in managing patient inflow and ensuring adequate hospital capacity.
- **Researchers and Policymakers:** This AI-driven approach contributes valuable insights for researchers studying infectious disease patterns and policymakers focused on strengthening the national AI Roadmap. The system’s data can support broader initiatives for sustainable health infrastructure and inform policy decisions on resource allocation for dengue control.
- **Community Members:** By reducing the frequency and severity of outbreaks, this study ultimately benefits the community at large. This allows for timely awareness campaigns and community engagement initiatives, empowering residents with knowledge and preventative measures to protect themselves and reduce the spread of dengue.

# Chapter 2

## Review of Related Literature

### 2.1 Existing System: RabDash DC

RabDash, developed by the University of the Philippines Mindanao, is a web-based dashboard for rabies data analytics. It combines predictive modeling with genomic data, enabling local health authorities to optimize interventions and allocate resources more effectively. RabDash's modules include trend visualization, geographic hotspot mapping, and predictive forecasting, utilizing Long Short-Term Memory (LSTM) models for time-series forecasting (RabDashDC, 2024).

For DengueWatch, RabDash serves as a strong inspiration, particularly in its monitoring, historical trend visualization, and forecasting capabilities. These features align well with the needs of dengue control efforts, providing real-time insights into outbreak trends and enabling more effective, data-driven decision-making. RabDash's architecture is relevant to the DengueDash, as dengue outbreaks similarly require time-series forecasting models. By using LSTM, RabDash effectively models trends in outbreak data, which provides a framework for adapting LSTM to dengue forecasting. Research indicates that LSTM models outperform traditional methods, such as ARIMA and MLP, in handling the complexities of time-dependent epidemiological data (Ligue & Ligue, 2022).

### 2.2 Deep Learning

The study of (Ligue & Ligue, 2022) highlights how data-driven models can help predict dengue outbreaks. The authors compared traditional statistical meth-

ods, such as non-seasonal and seasonal autoregressive integrated moving average (ARIMA), and traditional feed-forward network approach using a multilayer perceptron (MLP) model with a deep learning approach using the long short-term memory (LSTM) architecture in their prediction model. They found that the LSTM model performs better in terms of accuracy. The LSTM model achieved a much lower root mean square error (RMSE) compared to both MLP and ARIMA models, proving its ability to capture complex patterns in time-series data (Ligue & Ligue, 2022). This superior performance is attributed to LSTM’s capacity to capture complex, time-dependent relationships within the data, such as those between temperature, rainfall, humidity, and mosquito populations, all of which contribute to dengue incidence (Ligue & Ligue, 2022).

## 2.3 Kalman Filter

The Kalman Filter is another powerful tool for time-series forecasting that can be integrated into our analysis. It provides a recursive solution to estimating the state of a linear dynamic system from a series of noisy measurements. Its application in epidemiological modeling can enhance prediction accuracy by accounting for uncertainties in the data (Li et al., 2022). Studies have shown that Kalman filters are effective in predicting infectious disease outbreaks by refining estimates based on observed data. A study published in *Frontiers in Physics* utilized the Kalman filter to predict COVID-19 deaths in Ceará, Brazil. They found that the Kalman filter effectively tracked the progression of deaths and cases, providing critical insights for public health decision-making (Ahmadini et al., 2021). Another research article in *PLOS ONE* focused on tracking the effective reproduction number ( $R_t$ ) of COVID-19 using a Kalman filter. This method estimated the growth rate of new infections from noisy data, demonstrating that the Kalman filter could maintain accurate estimates even when case reporting was inconsistent (Arroyo-Marioli, Bullano, Kucinskis, & Rondón-Moreno, 2021).

Our study will compare ARIMA, seasonal ARIMA, Kalman Filter, and LSTM models using our own collected dengue case data along with weather data to identify the most effective model for real-time forecasting.

## 2.4 Weather Data

The relationship between weather patterns and mosquito-borne diseases is inherently nonlinear, meaning that fluctuations in disease cases do not respond propor-

tionally to changes in climate variables (Colón-González, Fezzi, Lake, & Hunter, 2013). Weather data, such as minimum temperature and accumulated rainfall, are strongly linked to dengue case fluctuations, with effects observed after several weeks due to mosquito breeding and virus incubation cycles. Integrating these lagged weather effects into predictive models can improve early warning systems for dengue control (Cheong, Burkart, Leitão, & Lakes, 2013). A study also suggests that weather-based forecasting models using variables like mean temperature and cumulative rainfall can provide early warnings of dengue outbreaks with high sensitivity and specificity, enabling predictions up to 16 weeks in advance (Hii, Zhu, Ng, Ng, & Rocklöv, 2012).

We will utilize weather data, including variables such as temperature, rainfall, and humidity, as inputs for our dengue forecasting model. Given the strong, non-linear relationship between climate patterns and dengue incidence, these weather variables, along with their lagged effects, are essential for enhancing prediction accuracy and providing timely early warnings for dengue outbreaks.

## 2.5 Chapter Summary

This chapter reviewed key literature relevant to our study, focusing on existing systems, predictive modeling techniques and the role of weather data in forecasting dengue outbreaks. We examined systems like RabDash DC, which integrates predictive modeling with real-time data to inform public health decisions, providing a foundational structure for our Dengue Watch System. Additionally, deep learning approaches, particularly Long Short-Term Memory (LSTM) networks, were highlighted for their effectiveness in time-series forecasting, while alternative methods such as ARIMA and Kalman Filters were considered for their ability to model complex temporal patterns and handle noisy data.

The literature further underscores the significance of weather variables—such as temperature and rainfall—in forecasting dengue cases. Studies demonstrate that these variables contribute to accurate outbreak prediction models. Leveraging these insights, our study will incorporate both weather data and historical dengue case counts to build a reliable forecasting model.

# Chapter 3

## Research Methodology

This chapter lists and discusses the specific steps and activities that will be performed to accomplish the project. The discussion covers the activities from pre-proposal to Final SP Writing.

### 3.1 Research Activities

#### 3.1.1 System Development Framework

The Agile Model is the birthchild of both iterative and incremental approaches in Software Engineering. It aims to be flexible and effective at the same time by being adaptable to change. It's also important to note that small teams looking to construct and develop projects quickly can benefit from this kind of methodology. As the Agile Method focuses on continuous testing, quality assurance is a guarantee since bugs and errors are quickly identified and patched.

#### 3.1.2 Design, Building, Testing, and Integration

##### Design and Development

After brainstorming and researching the most appropriate type of application to accommodate both the prospected users and the proposed solutions, the team has decided to proceed with a web application. Given the time constraints and

available resources, we believe this is the most pragmatic and practical move. The next step is to select modern and stable frameworks that align with the fundamental ideas we have learned at the university. The template obtained from WVCHD was meticulously analyzed to create use cases and develop a preliminary well-structured database that adheres to the requirements needed to produce a quality application. The said use cases serve as the basis of general features. Part by part, these are converted into code, and with the help of selected libraries and packages, it resulted in the desired outcome that may still modified and extended since it is continuously being developed.

### **Testing and Integration**

Each feature is rigorously user-tested to ensure quality assurance, with particular emphasis on prerequisite features, as development cannot progress properly if these fail. Moreover, integration between each feature serves as a pillar for a cohesive user experience. Presently, we have not been able to use performance metrics to measure the system's performance, as developing and connecting the core features is the utmost priority.

## **3.2 Model and Algorithm**

### **Data Preprocessing and Feature Selection:**

- Clean and preprocess the dataset, handling missing values and outliers.
- Select important features such as temperature, rainfall, and humidity.

### **Model Selection and Justification:**

- Train an LSTM model due to its efficiency in handling long-term data relationships.
- Compare performance with ARIMA, SARIMA, and Kalman Filter.

### **Seasonal ARIMA (SARIMA):**

- Set seasonal parameters based on observed seasonality in cases.

- Apply SARIMA to capture short-term and seasonal trends.

#### **Kalman Filter:**

- Use Kalman Filter for real-time updates and handle missing values dynamically.

#### **LSTM (Long Short-Term Memory) Neural Network:**

- Build a sequential LSTM model with tuned hyperparameters.

#### **Model Evaluation:**

- Evaluate performance with Mean Absolute Error (MAE), RMSE, and R-squared metrics.

## **3.3 Development Tools**

### **3.3.1 Software**

#### **Github**

GitHub is a cloud-based platform that tracks file changes using Git, an open-source version control system (*About GitHub and Git - GitHub Docs*, n.d.). It is used in the project to store the application's source code, manage the system's source version control, and serve as a repository for the Latex files used in the actual research.

#### **Visual Studio Code**

Visual Studio Code is a free, lightweight, and cross-platform source code editor developed by Microsoft (*Why Visual Studio Code?*, 2021). As VS Code supports this project's programming and scripting languages, it was chosen as the primary source code editor.



## Django

Django is a free and open-sourced Python-based web framework that offers an abstraction to develop and maintain a secure web application. As this research aims to create a well-developed and maintainable application, it is in the best interest to follow an architectural pattern that developers and contributors in the future can understand. Since Django adheres to Model-View-Template (MVT) that promotes a clean codebase by separating data models, business logic, and presentation layers, it became the primary candidate for the application's backbone.

## Next.js

A report by Statista (2024) claims that React is the most popular front-end framework among web developers. However, React has limitations that can be a nuisance in rapid software development, which includes routing and performance optimizations. This is where Next.js comes in—a framework built on top of React. It offers solutions for React's deficiency, making it a rising star in the framework race.

## Postman

As the application heavily relies on the Application Programming Interface (API) being thrown by the backend, it is a must to use a development tool that facilitates the development and testing of the API. Postman is a freemium API platform that offers a user-friendly interface to create and manage API requests (*What is Postman? Postman API Platform*, n.d.).

### 3.3.2 Hardware

The web application is continuously being developed on laptop computers with minimum specifications of an 11th-generation Intel i5 CPU and 16 gigabytes of RAM.

### 3.3.3 Packages

#### Django REST Framework

Django Rest Framework (DRF) is a third-party package for Django that provides a comprehensive suite of features to simplify the development of robust and scalable Web APIs (Christie, n.d.). These services include Serialization, Authentication and Permissions, Viewsets and Routers, and aBrowsable API .

#### Leaflet

One of the features of the web application is the ability to map the number of cases using a Choropleth Map. Leaflet is the only free, open-sourced, and most importantly, stable JavaScript package that can do the job. With its ultra-lightweight size, it offers a comprehensive set of features that does not trade off performance and usability (*Leaflet — an open-source JavaScript library for interactive maps*, n.d.).

#### Chart.js

Another feature of the application is to provide users with informative, approachable data storytelling that is easy for everyone to understand. The transformation of pure data points and statistics into figures such as charts is a big factor. Thus, there is a need for a package that can handle this feature without compromising the performance of the application. Chart.js is a free and open-source JavaScript package that is made to meet this criteria as it supports various types of charts (*Chart.js*, n.d.).

#### Tailwind CSS

Using plain CSS in production-quality applications can be counterproductive. Therefore, CSS frameworks were developed to promote consistency and accelerate the rapid development of web applications (Joel, 2021). One of these is Tailwind, which offers low-level utility classes that can be applied directly to each HTML element to create a custom design (*Tailwind CSS - Rapidly build modern websites without ever leaving your HTML.*, n.d.). Given the limited timeline for this project, using this framework is a wise choice due to its stability and popularity among developers.

## Shadcn

Shadcn offers a collection of open-source UI boilerplate components that can be directly copied and pasted into one’s project. With the flexibility of the provided components, Shadcn allows developers to have full control over customization and styling. Since this is built on top of Tailwind CSS and Radix UI, it is supported by most modern frontend frameworks, including Next.js (Shadcn, n.d.).

### 3.4 Calendar of Activities

A Gantt chart showing the schedule of the activities is included below. Each bullet represents approximately one week of activity.

Table 3.1: Timetable of Activities

Activities (2024)	Aug	Sept	Oct	Nov	Dec
Project Initiation and Team Formation	●●				
Literature Review and Data Gathering	●●	●●●●			
Data Cleaning and Feature Selection		●●		●	
Creating System Dashboard		●●	●●●●	●	
Analysis and Interpretation of Results			●		
Documentation		●	●●●●	●	

## Chapter 4

# Preliminary Results/System Prototype

### 4.1 Data Gathering

The data for dengue case prediction was gathered from a variety of reliable sources, enabling a comprehensive dataset spanning from January 2016 to September 2024. This dataset includes 452 rows of data, each containing weekly records of dengue cases along with corresponding meteorological variables, such as rainfall, temperature, and humidity.

1. **Dengue Case Data:** The primary source of historical dengue cases came from the Humanitarian Data Exchange and the Western Visayas Center for Health Development (WVCHD). The dataset, accessed through Freedom of Information (FOI) requests, provided robust case numbers for the Western Visayas region. The systematic collection of these data points was essential for establishing a reliable baseline for model training and evaluation.
2. **Weather Data:** Weekly weather data was obtained by web scraping from Weather Underground, allowing access to rainfall, temperature, and humidity levels that correlate with dengue prevalence.

```
data.head()
```

	Time	Rainfall	Temperature	Humidity	Cases
0	2016-01-04	0.034	28.100000	81.671429	19
1	2016-01-11	0.000	28.310000	81.685714	23
2	2016-01-18	0.000	28.033333	80.400000	31
3	2016-01-25	0.420	26.527778	85.985714	26
4	2016-02-01	5.660	27.444440	84.680000	10

Figure 4.1: Snippet of the Combined Dataset

## 4.2 Preliminary Model Training

The proposed Dengue Watch system utilized four distinct models to forecast weekly dengue cases: Long Short-Term Memory (LSTM) networks, Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Kalman Filter. Each model was trained on a dataset containing 452 weeks of historical dengue cases from 2016 to 2024, with meteorological variables such as temperature, humidity, and rainfall.

To optimize predictive performance, hyperparameter tuning was conducted individually for each model, refining parameters to achieve the most accurate and reliable forecasts. Following training, the models were rigorously evaluated against the dataset using a set of key performance metrics, including Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

The table below provides a summary and comparative analysis of each model's results across these metrics, offering insights into the strengths and limitations of each forecasting technique for dengue case prediction in Iloilo City.

Model	MSE	RMSE
<b>LSTM</b>	<b>342.59</b>	<b>18.51</b>
<b>Seasonal ARIMA (2, 0, 2) (0, 1,1)</b>	<b>1198</b>	<b>34.62</b>
<b>ARIMA (2, 0, 3)</b>	<b>1983.16</b>	<b>44.53</b>
<b>Kalman Filter</b>	<b>2755.77</b>	<b>52.49</b>

Table 4.1: Comparison of Models

### 4.2.1 LSTM Model

The LSTM model architecture consisted of an input layer, a single LSTM layer with 64 units and ReLU activation, followed by a dense layer with a single output neuron to predict the dengue case count. Key hyperparameters included:

- Window Size: 10 weeks, representing the time steps used in the sequence data for each prediction.
- Epochs: 50 epochs were used for training, balancing sufficient training time with computational efficiency.
- Batch Size: 1, allowing the model to process one sequence at a time, which is beneficial for small datasets but increases training time.
- Optimizer: The Adam optimizer was chosen for its adaptive learning capabilities and stability in training. A custom learning rate of 0.0001 was set to ensure gradual convergence and minimize risk of overfitting.

**Data Division for Training and Testing** The dataset was split into training and test sets to evaluate the model's performance and generalizability:

- Training Set: 85% of the data (385 sequences) was used for model training, enabling the LSTM to learn underlying patterns in historical dengue case trends and their relationship with weather variables.
- Test Set: The remaining 15% of the data (67 sequences) was reserved for testing

Upon testing, the LSTM model produced an MSE of 342.59 and an RMSE of 18.51, showing its capability to generalize to unseen data. The close alignment of actual and predicted values in the test set plot supports this observation, suggesting that the model successfully captured critical temporal trends that correlate with dengue outbreaks.

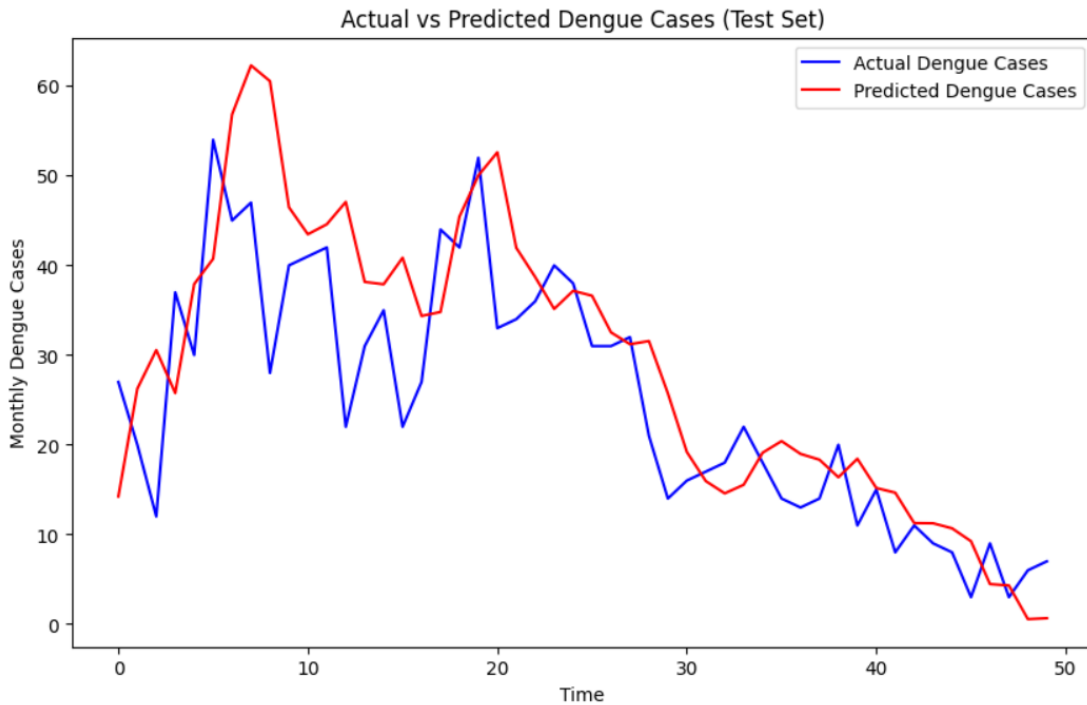


Figure 4.2: LSTM Prediction Results for Test Set

## Training and Testing Data Division for ARIMA and Seasonal Arima

Both models utilized an **80%-20% split** to evaluate generalizability:

- **Training Set:** 80% of the data was used for training, allowing the models to learn underlying patterns in the dataset.
- **Test Set:** 20% of the data was reserved for testing, providing an unbiased assessment of the models' performance on unseen data.

### 4.2.2 ARIMA Model

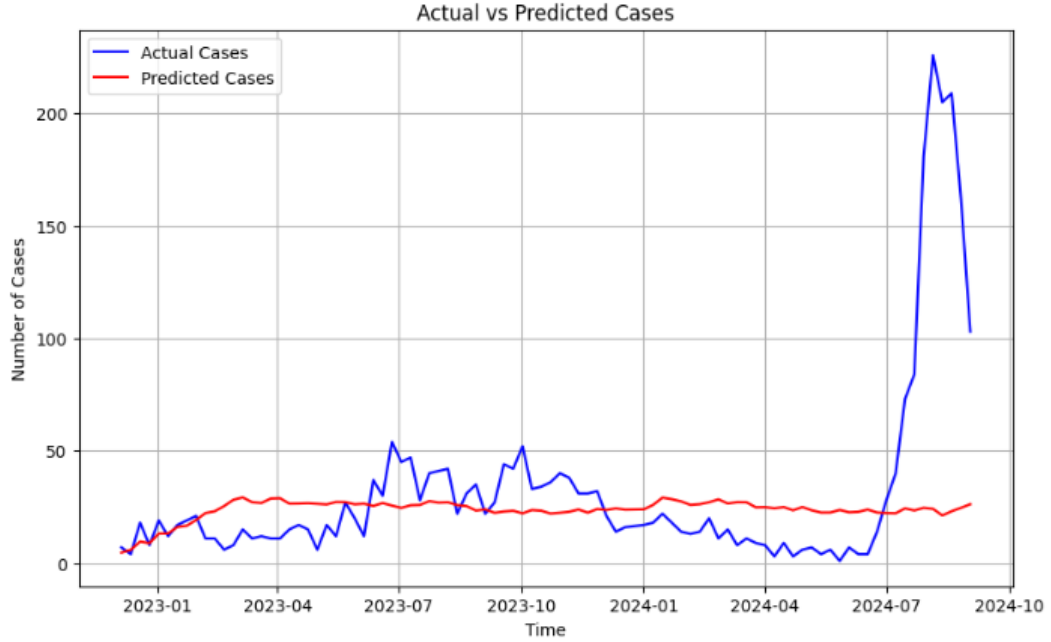


Figure 4.3: ARIMA Prediction Results for Test Set

The ARIMA model was developed to capture non-seasonal trends in the data. To determine the best model configuration, grid search was used to explore various combinations of ARIMA parameters, ultimately selecting **ARIMA(2, 0, 3)**. The model was iteratively refined over **400 iterations** to ensure convergence to an optimal solution. Key details are as follows:

1. **Data Preprocessing:** Prepare the dataset by handling any missing values and scaling the data if necessary to improve model convergence and stability.
2. **Hyperparameter Tuning:** Use a grid search on potential ARIMA parameters  $(p, d, q)$  to identify the configuration that minimizes error. The optimal parameters were found to be **(2, 0, 3)**.
3. **Model Training:**
  - Set the number of iterations to 400 to ensure thorough training and convergence.
  - Train the ARIMA model on 80% of the data and reserve 20% for testing.



4. **Evaluation:** After training, the ARIMA model was evaluated on the test data, yielding the following performance metrics:

- **MSE (Mean Squared Error):** 1983.16
- **RMSE (Root Mean Squared Error):** 44.53

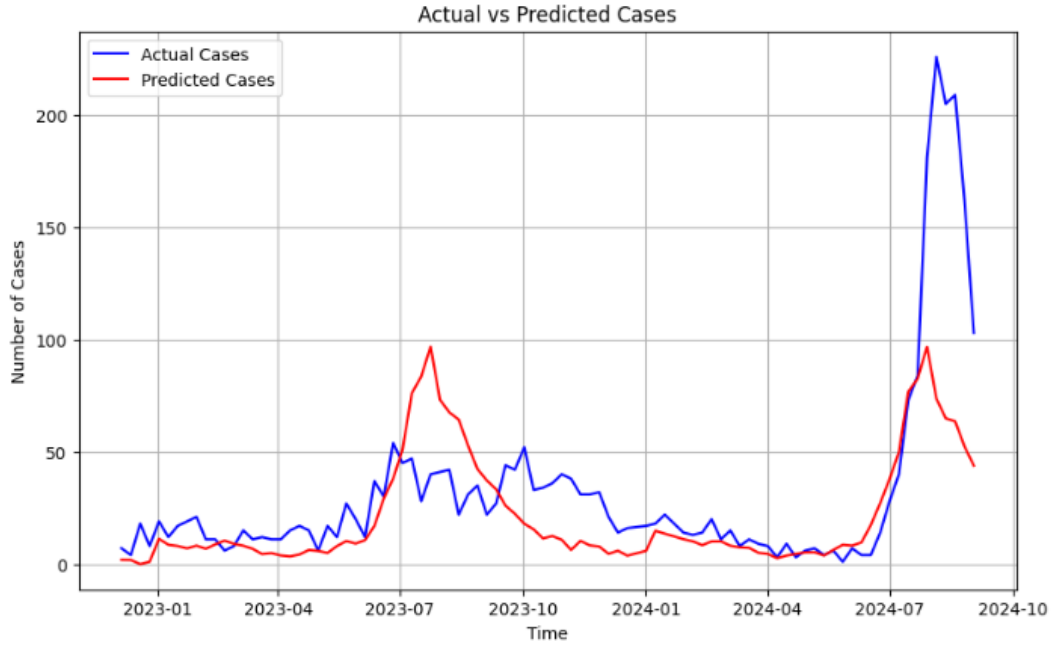


Figure 4.4: Seasonal ARIMA Prediction Results for Test Set

### 4.2.3 Seasonal ARIMA Model

1. **Data Preprocessing:** Prepare the dataset by handling any missing values and scaling the data if necessary to improve model convergence and stability.
2. **Hyperparameter Tuning:** Use a grid search on potential ARIMA parameters  $(p, d, q)$  to identify the configuration that minimizes error. The optimal parameters were found to be **(2, 0, 3)**.
3. **Model Training:**
  - Set the number of iterations to 400 to ensure thorough training and convergence.
  - Train the ARIMA model on 80% of the data and reserve 20% for testing.

4. **Evaluation:** After training, the ARIMA model was evaluated on the test data, yielding the following performance metrics:

- **MSE (Mean Squared Error):** 1983.16
- **RMSE (Root Mean Squared Error):** 44.53

These metrics demonstrate that the ARIMA model effectively captured non-seasonal temporal patterns in the data.

## Seasonal ARIMA (SARIMA) Model

This model incorporates seasonal parameters, which were tuned using grid search to find the best configuration: **SARIMA(2, 0, 2)(0, 1, 1)[52]**. As with ARIMA, **400 iterations** were applied to ensure a robust fit.

### Steps to Create the SARIMA Model:

1. **Data Preprocessing:** Ensure data readiness by filling any missing values and scaling as needed.
2. **Seasonality Analysis:** Examine the dataset for seasonal patterns. A periodicity of **52 weeks** was identified, making SARIMA a suitable choice for capturing yearly seasonality.
3. **Hyperparameter Tuning:** Conduct grid search to identify the best set of parameters  $(p, d, q)(P, D, Q)[S]$ , where:
  - **(p, d, q)** are the non-seasonal parameters,
  - **(P, D, Q)** are the seasonal parameters, and
  - **S** is the season length.

The optimal configuration found was **(2, 0, 2)(0, 1, 1)[52]**.

4. **Model Training:**
  - Set the iteration count to 400 for enhanced model robustness.
  - Train the model on the 80% training dataset and reserve the remaining 20% for testing.
5. **Evaluation:** The SARIMA model yielded the following error metrics:

- **MSE:** 1198
- **RMSE:** 34.62

The SARIMA model outperformed the ARIMA model in terms of lower MSE and RMSE values, indicating its effectiveness in capturing the seasonal patterns in the data.

#### 4.2.4 Kalman Filter Model

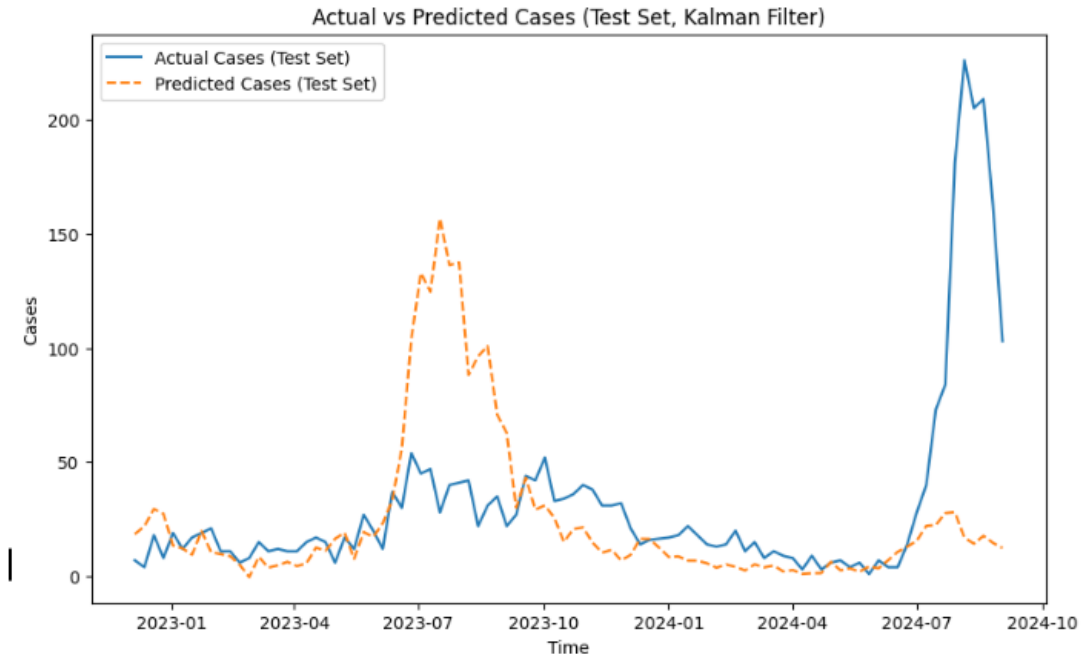


Figure 4.5: Kalman Filter Prediction Results for Test Set

### Kalman Filter Methodology with Matrix Calculations

**Measurement Acquisition:** Obtain the measurement  $z_k$  of the system's state with associated confidence. This measurement matrix provides a noisy observation of the true state.

The dataset was split into training and test sets to evaluate the Kalman Filter's performance and generalizability:

- **Training Set:** 80% of the data was used for training, enabling the Kalman Filter model to capture key patterns.
- **Test Set:** The remaining 20% of the data was reserved for testing.

### Prediction Step:

- Predict the next state:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k$$

where  $A$  is the state transition matrix and  $B$  is the control matrix.

- Update the state covariance:

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q$$

where  $Q$  is the process noise covariance matrix.

### Compute Residual: Calculate the residual

$$y_k = z_k - H\hat{x}_{k|k-1}$$

where  $H$  is the observation matrix. This residual represents the new information from the measurement.

### Scaling Factor (Kalman Gain):

- Compute the Kalman Gain:

$$K_k = P_{k|k-1}H^T(H P_{k|k-1}H^T + R)^{-1}$$

where  $R$  is the measurement noise covariance matrix.

- The Kalman Gain determines the weight of the measurement relative to the prediction.

### State Update:

- Update the state estimate:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k y_k$$

blending the prediction and measurement.

### Uncertainty Update:

- Update the state covariance:

$$P_{k|k} = (I - K_k H) P_{k|k-1}$$

where  $I$  is the identity matrix.

**Model Evaluation:** Upon testing, the Kalman Filter produced a Mean Squared Error (MSE) of 2755.77 and a Root Mean Squared Error (RMSE) of 52.49.

## 4.3 Guest Interface

The Guest Interface is intended for all visitors of the web application. It shows the related statistics for dengue cases in a particular area and time. As the system is still in its testing phase, the data and charts shown in Figure 4.2 are generated from Python’s Faker library.

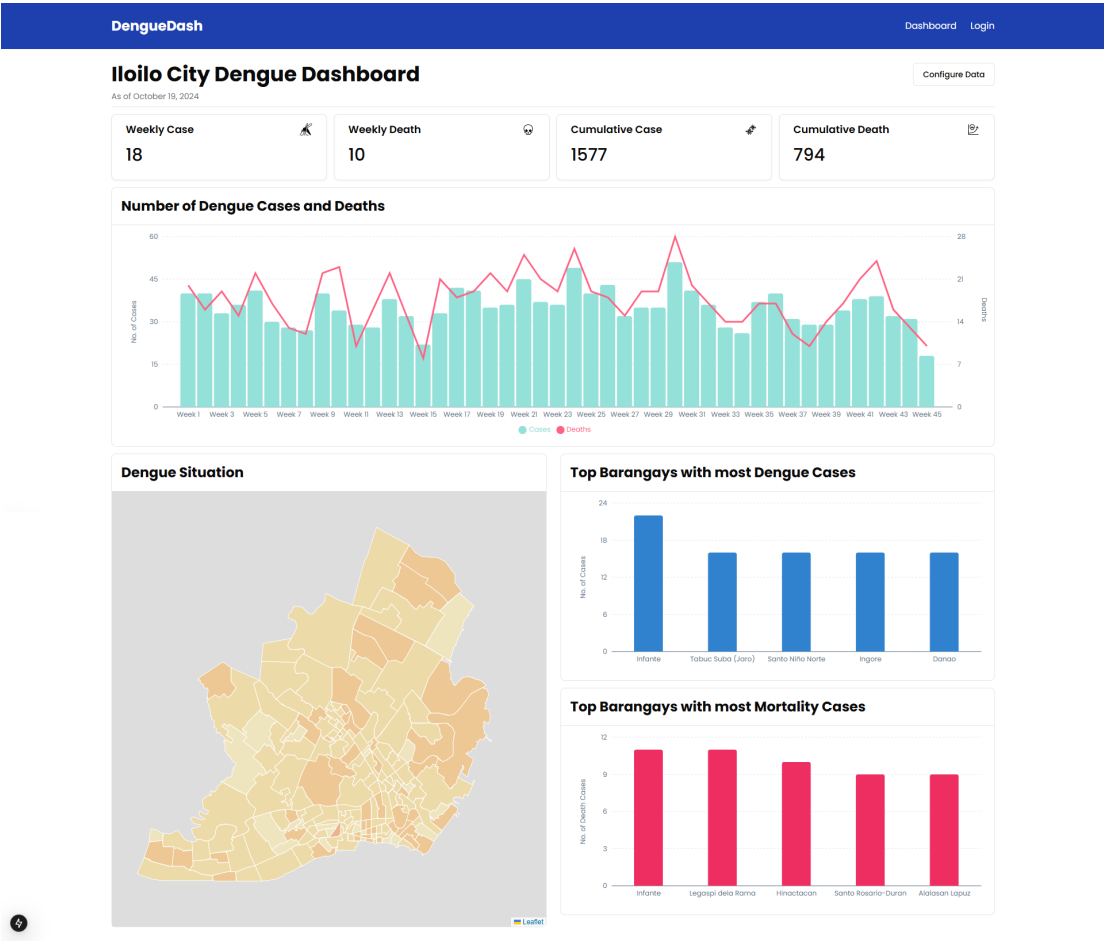
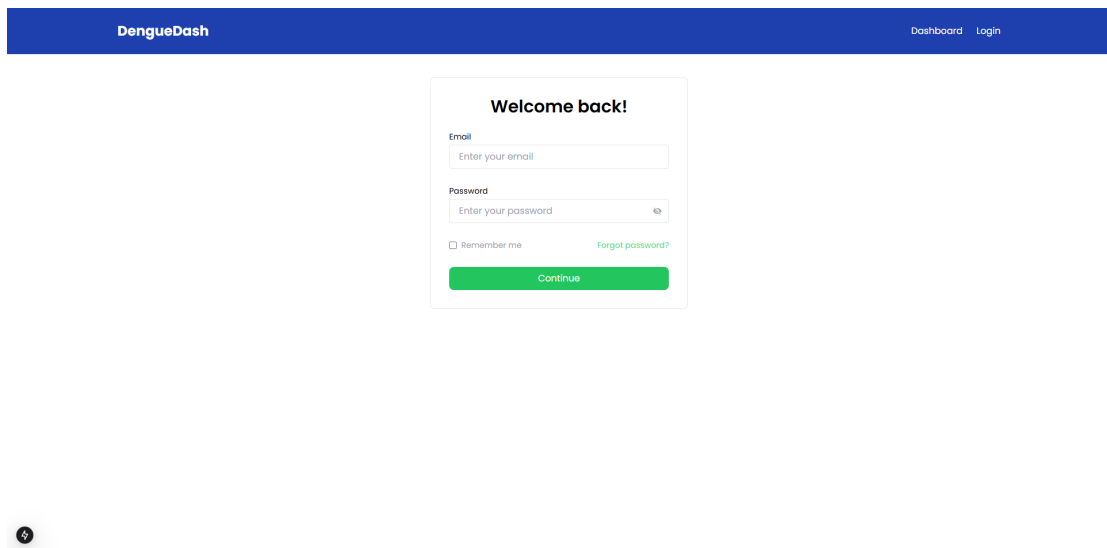


Figure 4.6: Dashboard for Guests

## 4.4 Personnel Interface

### 4.4.1 User Authentication, and Login

To protect the data's integrity in production, it has been decided that the registration process will not be visible. Instead, an admin must register a user using a different interface. As of the moment, registering a user is done using API via Postman. In the login process, the system implements HTTP-only cookies that save the access token to protect against XSS attacks. After proper credentials have been provided, it will redirect to the user's home page.



The screenshot shows the login interface for DengueDash. The header is a solid blue bar containing the site name 'DengueDash' and navigation links for 'Dashboard' and 'Login'. The login form is centered on the page and features a 'Welcome back!' greeting. It includes an email input field, a password input field with a visibility toggle, a 'Remember me' checkbox, a 'Forgot password?' link, and a prominent green 'Continue' button.

Figure 4.7: Login Page for Users

DengueDash

Modules

Analytics

Forms

Case Report Form

Data Tables

Settings

shadcn

m@example.com

0

Building Your Application

Data Fetching

Personal Information

Clinical Status

Personal Detail

First Name

Middle Name

Last Name

Suffix

Sex

Civil Status

Date of Birth

Current Address

House No.

Street

Barangay

City

Province

Permanent Address

Same as Current Address

House No.

Street

Barangay

City

Province

Vaccination

Date of First Vaccination

Date of Last Vaccination

Back

Next

Figure 4.8: First Part of Case Report Form

26



DengueDash

Building Your Application

Data Fetching

Modules

Analytics

Forms

Case Report Form

Data Tables

Settings

shadcn

m@example.com

0

Personal Information

Clinical Status

Consultation

Date Admitted/Consulted/Seen

Pick a date

Is Admitted?

Yes

Date Onset of illness

Pick a date

Clinical Classification

No warning signs

Laboratory Results

NSI

Pending Result

Date done (NSI)

Pick a date

IgG ELISA

Pending Result

Date done (IgG ELISA)

Pick a date

IgM ELISA

Pending Result

Date done (IgM ELISA)

Pick a date

PCR

Pending Result

Date done (PCR)

Pick a date

Outcome

Case Classification

Confirmed

Outcome

Alive

Date of Death

Pick a date

Back

Submit

Figure 4.9: Second Part of Case Report Form

DengueDash

Building Your Application

Data Fetching

Modules

Analytics

Forms

Data Tables

Dengue Reports

Another Report

Settings

shadcn

m@example.com

0

Case ID	Name	Barangay	City	Date Consulted	Clinical Classification	Case Classification
2401038	Vargas, Dorothy Heather	Santa Rosa	Iloilo City	2024-11-07	With warning signs	Suspect
2401012	Villanueva, Sarah Victor	Aguinaldo	Iloilo City	2024-11-07	No warning signs	Probable
24009788	Marshall, Nicole Anthony	Buhang	Iloilo City	2024-11-07	With warning signs	Confirmed
24009770	Waller, Jason Alyssa	Calaparan	Iloilo City	2024-11-07	No warning signs	Confirmed
24010529	Hernandez, David Melanie	Abeto Mirasol Taft South (Quirino Abeto)	Iloilo City	2024-11-06	Severe dengue	Suspect
24008490	Reynolds, Kenneth David	Simon Ledesma	Iloilo City	2024-11-06	No warning signs	Suspect
24010103	Bender, Courtney Allen	Baldoza	Iloilo City	2024-11-05	No warning signs	Confirmed
24010946	Ray, Christopher Christopher	Tagbac	Iloilo City	2024-11-05	With warning signs	Suspect
24010226	Davis, Abigail Antonio	Monica Blumentritt	Iloilo City	2024-11-05	Severe dengue	Confirmed
24010162	Benton, Amanda Sean	Taytay Zone II	Iloilo City	2024-11-05	No warning signs	Suspect

< Previous

1

2

...

1106

Next >

Figure 4.10: Dengue Reports

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# Appendix A

## Appendix Title

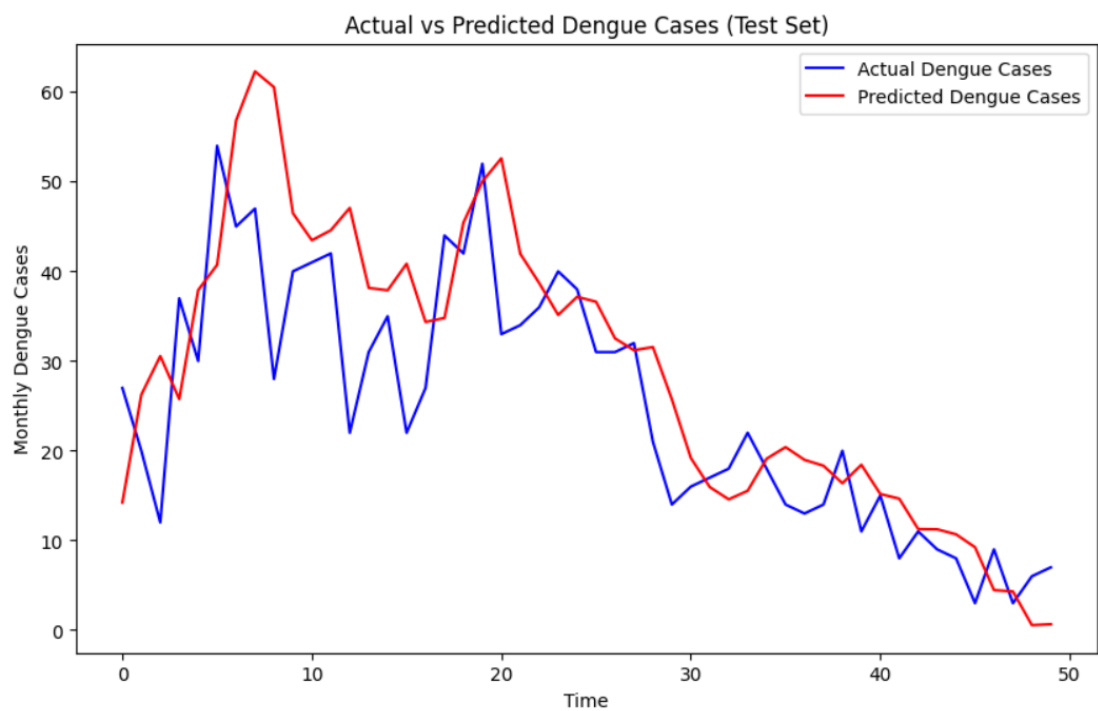


Figure A.1: LSTM Prediction Results for Test Set

# Appendix B

## Resource Persons

**Mr. Firstname1 Lastname1**

Role1

Affiliation1

emailaddr1@domain.com

**Ms. Firstname2 Lastname2**

Role2

Affiliation2

emailaddr2@domain.net

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