

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

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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 focuses on developing a centralized system for monitoring and forecasting dengue trends in Iloilo City, incorporating graphical visualizations such as heatmaps, trends, and historical graphs. The study explores the application of artificial intelligence (AI) in dengue prediction, utilizing deep learning models. The performance of the Long Short-Term Memory (LSTM) model is compared with traditional statistical methods, including non-seasonal and seasonal Autoregressive Integrated Moving Average (ARIMA) models and the Kalman Filter. Evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE) were used to identify the most effective model for integration into the system. Forecasting is based on climate variables such as temperature, rainfall, relative humidity, and previous monthly case counts. The LSTM model emerged as the best performer with an RMSE of 18.51, demonstrating its suitability for time-series predictions, while the Kalman Filter showed the poorest performance with an RMSE of 52.49. 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 (WHO, 2023), 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 reported a ten-fold rise in cases between 2000 and 2019, with a peak in 2019 when the disease spread across 129 countries (WHO, 2024).

Iloilo City and Province are intensifying efforts to curb the rising dengue cases (Lena, 2024). 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). Local government units (LGUs) have been informed, and the province's disaster management office is on blue alert, indicating disaster mode. (Perla, 2024)

In Iloilo City, 649 dengue cases were recorded this year 2024, 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. 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 will be in a weekly format.

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, Kucinskas, & 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.

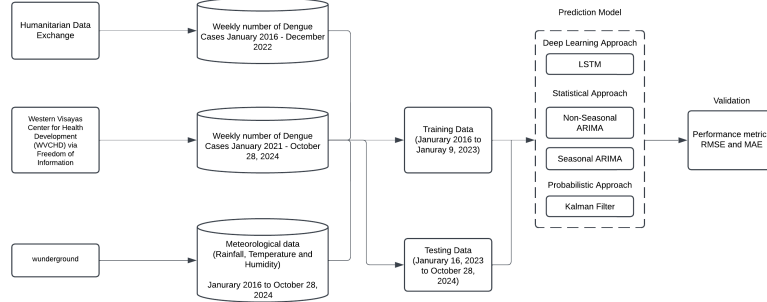


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

This summarizes the workflow for forecasting the number of weekly dengue cases. This workflow focuses on using statistical, deep learning, and probabilistic models to forecast the number of reported dengue cases. The approach involves deploying several models for prediction, including ARIMA and Seasonal ARIMA as statistical approaches, LSTM as a deep learning approach, and the Kalman Filter as a probabilistic approach. These methods are compared with each other to determine the most accurate model.

3.1 Research Activities

3.1.1 Gather Dengue Data and Climate Data to Create a Complete Dataset for Forecasting

Acquisition of Dengue Case Data

The historical dengue case dataset used in this study was obtained from the Humanitarian Data Exchange and the Western Visayas Center for Health Development (WVCHD) via Freedom of Information (FOI) requests. Also, the collection of weather data was done by utilizing web scraping techniques to extract weekly weather data (e.g., rainfall, temperature, and humidity) from Weather Underground (wunderground.com).

Data Fields

- **Time.** Represents the specific year and week corresponding to each entry in the dataset.
- **Rainfall.** Denotes the observed average rainfall, measured in millimeters, for a specific week.
- **Humidity.** Refers to the observed average relative humidity, expressed as a percentage, for a specific week.
- **Temperature.** Represents the observed average temperature, measured in degrees Celsius, for a specific week.
- **Cases.** Refers to the number of reported dengue cases during a specific week.

Data Integration and Preprocessing

The dengue case data was integrated with the weather data to create a comprehensive dataset, aligning the data based on corresponding timeframes. The dataset underwent a cleaning process to address any missing values, outliers, and inconsistencies to ensure its accuracy and reliability. To ensure that all features and the target variable were on the same scale, a MinMaxScaler was applied to normalize both the input features (rainfall, temperature, humidity) and the target variable (dengue cases).

Exploratory Data Analysis (EDA)

- Analyze trends, seasonality, and correlations between dengue cases and weather factors.
- Create visualizations like time series plots and scatterplots to highlight relationships and patterns in the data.

3.1.2 Develop and Evaluate Deep Learning Models for Dengue Case Forecasting

The deep learning models were developed and trained to forecast weekly dengue cases using historical weather data (rainfall, temperature, and humidity) and dengue case counts. The dataset was normalized and divided into training and testing sets, ensuring temporal continuity to avoid data leakage. The methodology for preparing and training the model are outlined below.

Data Preprocessing

The raw dataset included weekly aggregated weather variables (rainfall, temperature, humidity) and dengue case counts. The "Time" column was converted to a datetime format to ensure proper temporal indexing. To standardize the data for training, MinMaxScaler was employed, normalizing the feature values and target variable to a range of 0 to 1. This step ensured that the models could efficiently process the data without being biased by feature scaling differences.

LSTM Model

To prepare the data for LSTM, a sliding window approach was utilized. Sequences of 10 weeks of normalized features were constructed as input, while the dengue case count for the subsequent week was set as the target variable. This approach ensured that the model leveraged temporal dependencies in the data for forecasting.

The LSTM model was designed using the TensorFlow and Keras libraries. The architecture comprised the following layers:

- Input Layer: Accepting sequences of 10 weeks with three features (rainfall, temperature, and humidity).

- LSTM Layer: A single LSTM layer with 64 units and ReLU activation, capturing temporal dependencies and feature interactions.
- Dense Output Layer: A fully connected layer with a single neuron to predict the dengue cases for the next week.

The model was trained for 50 epochs with a batch size of 1, enabling fine-grained weight updates. The training dataset consisted of 85% of the sequences, while the remaining 15% was used as the test set to evaluate model performance. Validation loss was monitored during training to assess model generalization.

After training, predictions on both the training and test datasets were rescaled to their original scale using the inverse transformation of MinMaxScaler. Model performance was evaluated using the mean squared error (MSE) and root mean squared error (RMSE).

Seasonal ARIMA (SARIMA):

The SARIMA (Seasonal ARIMA) model was utilized to forecast weekly dengue cases, incorporating seasonal patterns and exogenous weather variables (rainfall, temperature, and humidity). The dataset was divided into training (80%) and testing (20%) sets while maintaining temporal continuity for validation. The input data consisted of weekly dengue case counts as the target variable and weather-related features as exogenous regressors.

The SARIMA model's parameters were set as follows:

- Order: (2, 0, 2)
- Seasonal Order: (0, 1, 1, 52)

The SARIMA model was trained using the training dataset, including exogenous variables. The maximum number of iterations was set to 400 to ensure convergence during fitting.

The model's performance was assessed using regression metrics to evaluate its forecasting capability and ability to detect outbreaks:

- Mean Squared Error (MSE): Quantifies average squared prediction error.
- Root Mean Squared Error (RMSE): Measures average prediction error on the data's original scale.

ARIMA

The ARIMA model was employed to forecast weekly dengue cases using historical weather data (rainfall, temperature, and humidity) as exogenous variables and historical case counts as the primary dependent variable. The dataset was split into training (80%) and testing (20%) sets. To determine the optimal configuration for the ARIMA model, a grid search was conducted over the following parameter ranges:

- p (autoregressive order): 0 to 3
- d (differencing order): 0 to 2
- q (moving average order): 0 to 3

The combinations of these parameters were evaluated by fitting an ARIMA model for each set of (p, d, q) values. The model's performance was assessed using the mean squared error (MSE) between the predicted and actual dengue cases in the test set. The combination yielding the lowest MSE was selected as the optimal parameter configuration.

The fitted ARIMA model was used to forecast weekly dengue cases for the test dataset. Predictions were directly assigned to the PredictedCases column in the test dataset. Model performance was evaluated using the following metrics:

- Mean Squared Error (MSE): Quantifies average squared prediction error.
- Root Mean Squared Error (RMSE): Measures average prediction error on the data's original scale.

Kalman Filter:

- Input Variables: The target variable (Cases) was modeled using three regressors: rainfall, temperature, and humidity.
- Training and Testing Split: The dataset was split into 80% training and 20% testing to evaluate model performance.
- Observation Matrix: The Kalman Filter requires an observation matrix, which was constructed by adding an intercept (column of ones) to the regressors.

The Kalman Filter’s em method was employed for training, iteratively estimating model parameters over 10 iterations. The smooth method was used to compute the smoothed state estimates for the training data. Observation matrices for the test data were constructed similarly, ensuring compatibility with the trained model.

Model Evaluation and Optimization

- Compare the performance of all models to identify the most accurate forecasting approach.
- Iteratively optimize the selected model.

3.1.3 Integrate the Predictive Model into a Web-Based Data Analytics Dashboard

Dashboard Design and Development

- Design an intuitive, user-friendly web-based dashboard incorporating:
 - Interactive visualizations of yearly dengue case trends.
 - Data input and update forms for dengue and weather data.
 - Map display of dengue cases in each district in Iloilo City

Model Integration and Deployment

- Deploy the best-performing model within the dashboard as a backend service to enable real-time or periodic forecasting.

3.1.4 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.

3.1.5 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 Development Tools

3.2.1 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.).

3.2.2 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.

3.2.3 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.).

3.3 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	Jan	Feb	Mar	Apr	May
Project Initiation and Team Formation	••									
Literature Review and Data Gathering	••	••••								
Data Cleaning and Feature Selection		••		•	•					
Creating System Dashboard		••	••••	•						
Analysis and Interpretation of Results			•		•					
Create Admin Dashboard						•	•••			
Integrate the Best Model to the System						•	••••			
Extend Features to Accommodate a National Setting							•	••		
User Testing								••	•	
System Deployment									•••	
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
LSTM	342.59	18.51
Seasonal ARIMA (2, 0, 2) (0, 1,1)	1198	34.62
ARIMA (2, 0, 3)	1983.16	44.53
Kalman Filter	2755.77	52.49

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.

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.

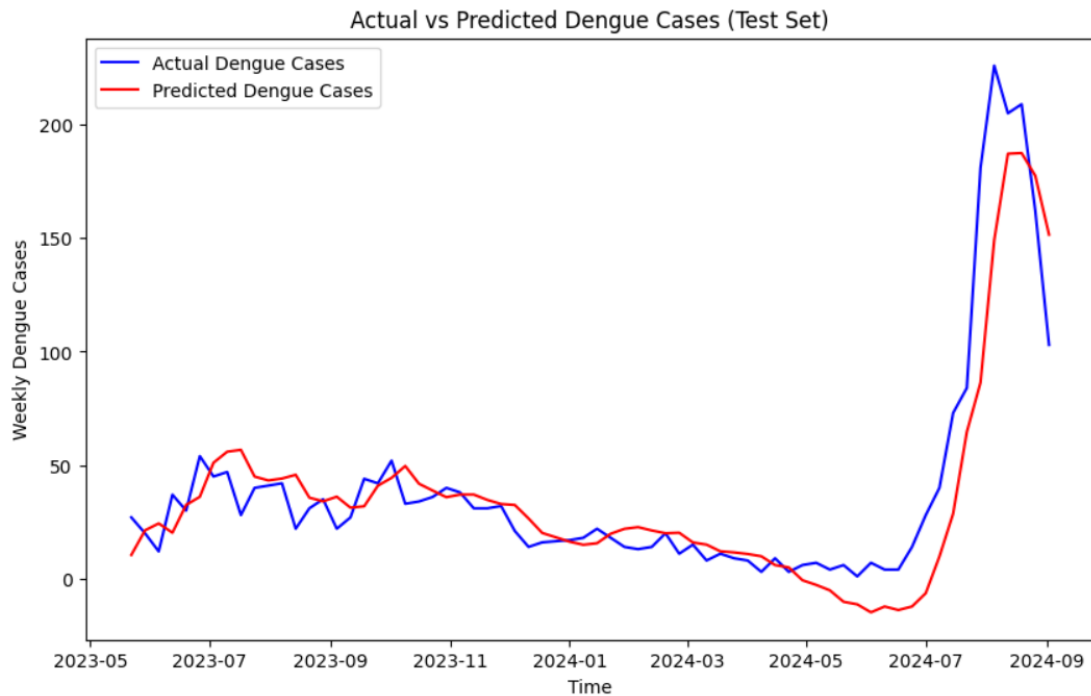


Figure 4.2: LSTM Prediction Results for Test Set

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

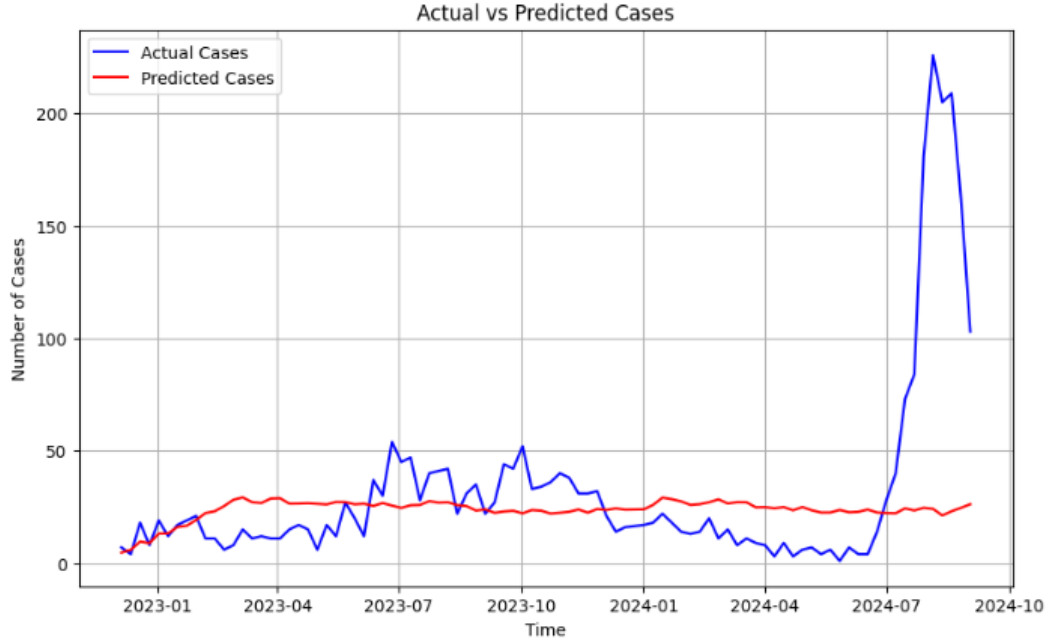


Figure 4.3: ARIMA Prediction Results for Test Set

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

Seasonal ARIMA (SARIMA) Model

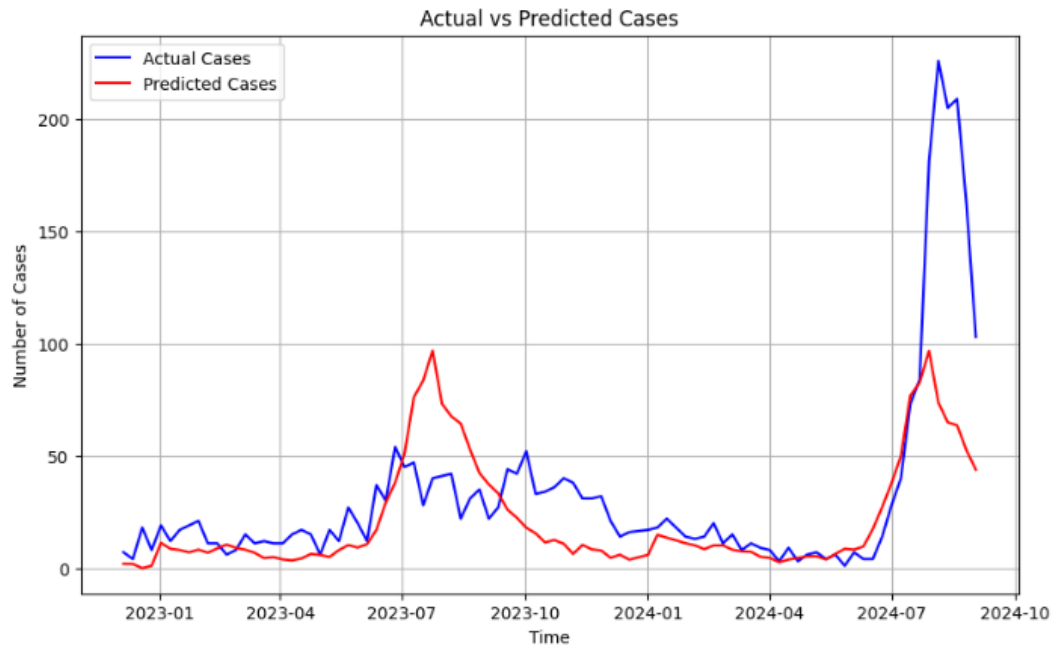


Figure 4.4: Seasonal ARIMA Prediction Results for Test Set

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.

4.2.3 Kalman Filter Model

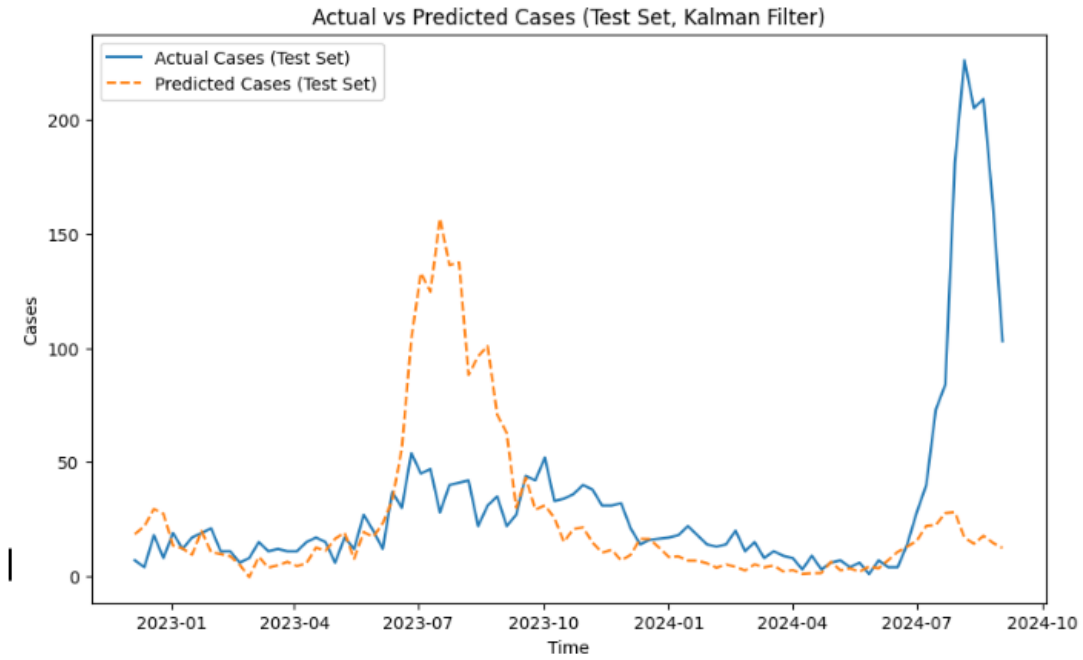


Figure 4.5: Kalman Filter Prediction Results for Test Set

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 System Prototype

4.3.1 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 converted into charts shown in Figure 4.6 are generated from Python’s Faker library.

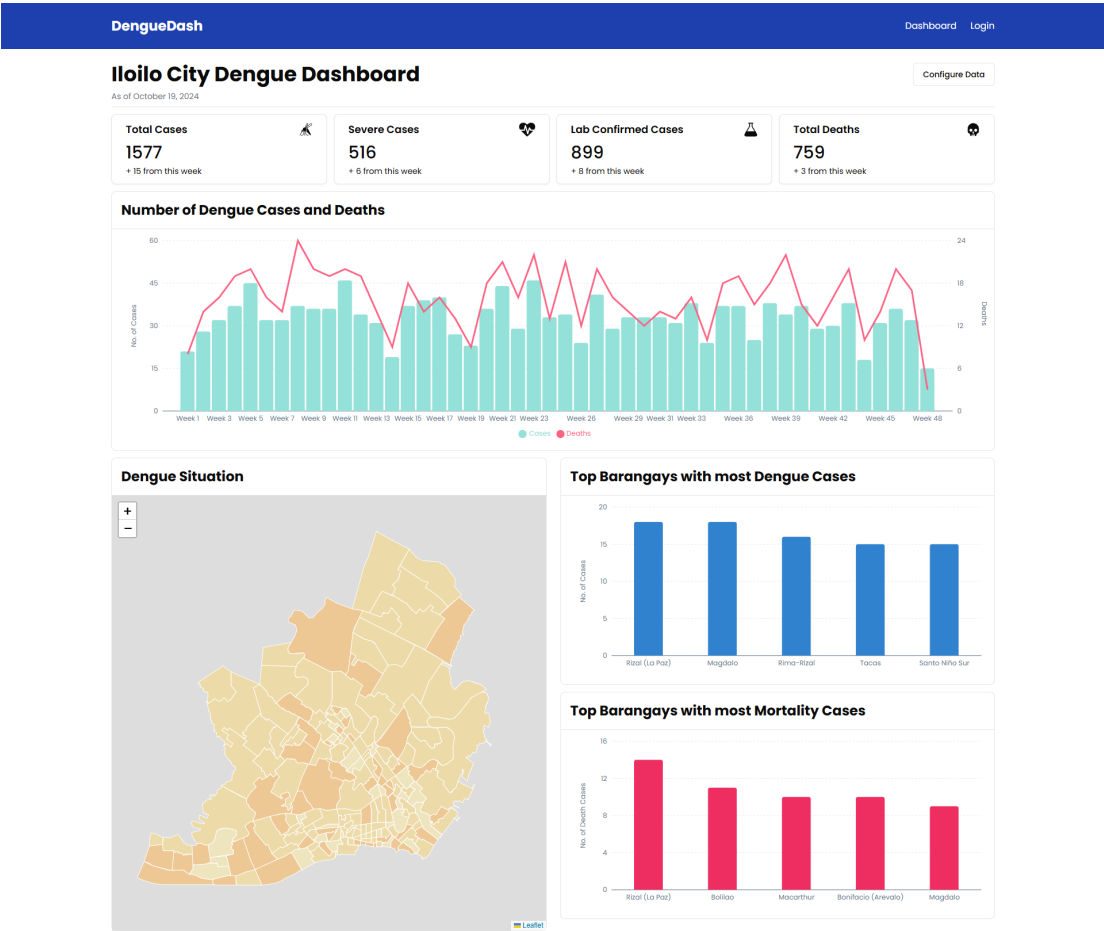


Figure 4.6: Dashboard for Guests

4.3.2 Personnel Interface

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 contains the JSON Web Tokens (JWT) to protect against XSS attacks. After proper credentials have been provided, it will redirect to the user's home page.

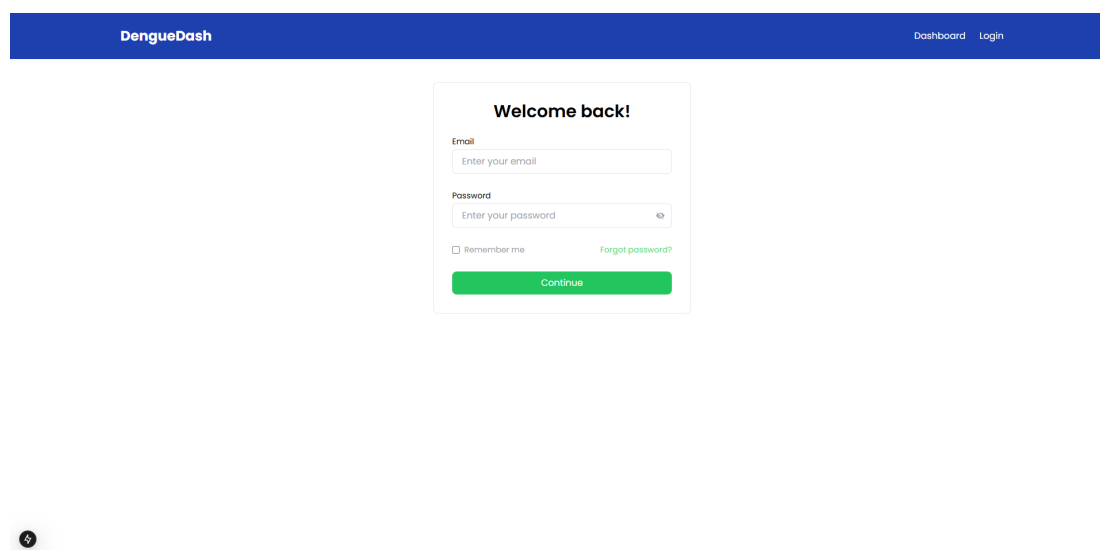


Figure 4.7: Login Page for Users

Encoder's View

Figures 4.8 and 4.9 show the digitized counterpart of the form obtained from the Iloilo Provincial Epidemiology and Surveillance Unit. As the system aims to support expandability for future features, some fields were modified to accommodate more detailed input. It is worth noting that all of the included fields adhere to the latest Philippine Integrated Disease and Surveillance Response (PIDSR) Dengue Forms, which the referenced form was based on. By doing this, it is assumed that the targeted users will have a familiarity when deployed on a national scale. On a further note, the case form includes the patient's basic information, dengue vaccination status, consultation details, laboratory results, and the outcome.

DengueDash

Modules

Analytics

Forms

Case Report Form

Data Tables

Settings

CN

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

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

DengueDash

Modules

Analytics

Forms

Case Report Form

Data Tables

Settings

CN

shadcn

m@example.com

0

Building Your Application

Data Fetching

Personal Information

Clinical Status

Consultation

Date Admitted/Consulted/Seen

Is Admitted?

Date Onset of Illness

Clinical Classification

Laboratory Results

NSI

Date done (NSI)

IgG ELISA

Date done (IgG ELISA)

IgM ELISA

Date done (IgM ELISA)

PCR

Date done (PCR)

Outcome

Case Classification

Outcome

Date of Death

Back

Submit

Figure 4.9: Second Part of Case Report Form

Once the data generated from the case report form is validated, it will be assigned as a new case and can be accessed through the Dengue Reports page, as shown in Figure 4.10. The said page displays basic information about the patient related to a specific case, including their name, address, date of consultation, and clinical and case classifications. It is also worth noting that it only shows cases the user is permitted to view. For example, in a local Disease Reporting Unit (DRU) setting, the user can only access records that the user created. On the other hand, in a consolidated surveillance unit such as a regional and provincial quarter, its users can view all the records that came from all the DRUs that report to them. Moving forward, Figure 4.11 shows the detailed case report of the patient on a particular consultation date.

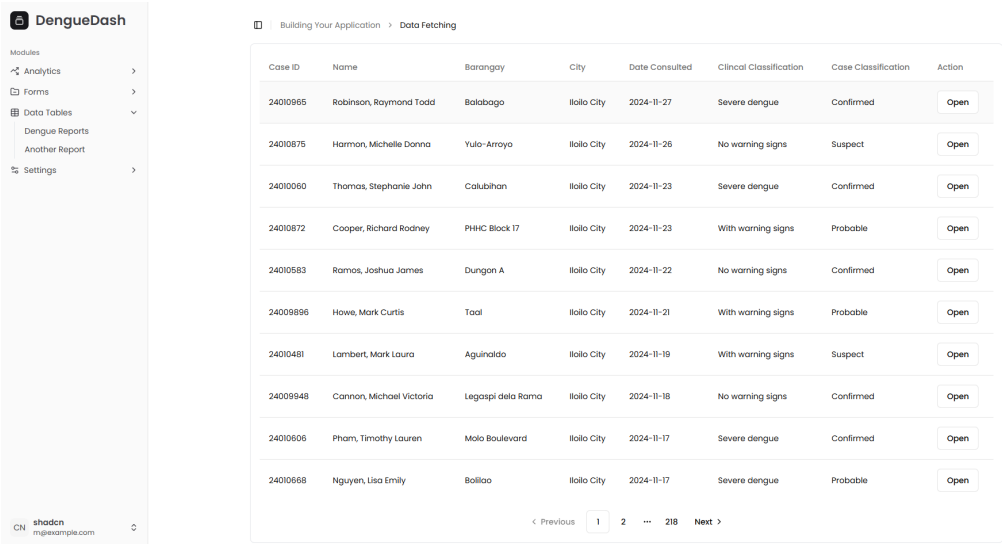


Figure 4.10: Dengue Reports

The image is a screenshot of a web application interface. At the top, there is a dark header bar with a logo on the left and the text 'DengueDash' on the right. Below the header, the main content area is divided into two sections. The first section, titled 'Modules', contains a list of items: 'Analytics', 'Forms', 'Data Tables', 'Dengue Reports', and 'Settings'. Each item has a small icon to its left and a right-pointing arrow. The 'Dengue Reports' item is highlighted with a blue background. The second section, titled 'Dengue Reports', shows a list of reports. The first report is 'Another Report', which is highlighted with a blue background. Below it, there is a table with columns for 'Report Name', 'Status', and 'Action'. The table contains one row with the value 'Another Report' in the 'Report Name' column, 'Completed' in the 'Status' column, and a right-pointing arrow in the 'Action' column. At the bottom of the page, there is a footer bar with the text 'shadcn' and 'myexampl.com' on the left, and a small icon on the right.

Building Your Application > Data Feeding	
 Personal Information	
Full Name Thomas, Stephanie John	Date of Birth September 19, 2010
Sex Male	Civil Status Separated
Full Address 4189 Rice Coves, Calubihan, Iloilo City, Iloilo	
 Vaccination Status	
First Dose February 11, 2024	Last Dose April 10, 2024
 Case Record #24010060	
Date of Consultation November 23, 2024	Patient Admitted? Yes
Date Onset of Illness November 22, 2024	Clinical Classification Severe dengue
 Laboratory Results	
NSI Pending Result	Date Done N/A
IgG Elisa Negative	Date Done November 29, 2024
IgM Elisa Equivocal	Date Done December 2, 2024
PCR Pending Result	Date Done N/A
 Outcome	
Case Classification Confirmed	Outcome Dead
Date of Death November 29, 2024	

Figure 4.11: Detailed Case Report

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Appendix A

Appendix Title

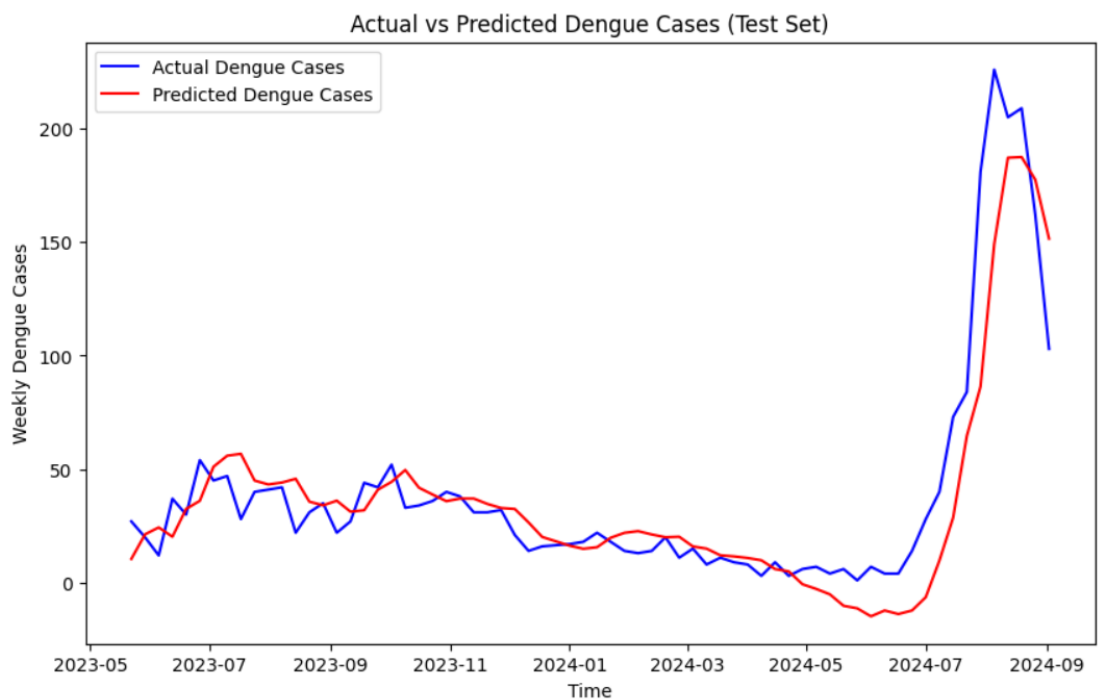


Figure A.1: LSTM Prediction Results for Test Set

Appendix B

Resource Persons

Mr. Firstname1 Lastname1

Role1

Affiliation1

emailaddr1@domain.com

Ms. Firstname2 Lastname2

Role2

Affiliation2

emailaddr2@domain.net

....