

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

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13 AMODIA, Kurt Matthew A.
14 BULAONG, Glen Andrew C.
15 ELIPAN, Carl Benedict L.

16 Francis DIMZON, Ph.D.
17 Adviser

18 June 2025

19

Approval Sheet

20

The Division of Physical Sciences and Mathematics, College of Arts and
Sciences, University of the Philippines Visayas

22

certifies that this is the approved version of the following special problem:

23

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

25

26

Approved by:

Name

Signature

Date

Francis D. Dimzon, Ph.D. _____
(Adviser)

27

Ara Abigail E. Ambita _____
(Panel Member)

Kent Christian A. Castor _____
(Division Chair)

28 Division of Physical Sciences and Mathematics
29 College of Arts and Sciences
30 University of the Philippines Visayas

31 **Declaration**

32 We, Kurt Matthew A. Amodia, Glen Andrew C. Bulaong, and Carl Benedict
33 L. Elipan, hereby certify that this Special Problem has been written by us and
34 is the record of work carried out by us. Any significant borrowings have been
35 properly acknowledged and referred.

Name

Signature

Date

Kurt Matthew A. Amodia



June 2, 2025

(Student)

Glen Andrew C. Bulaong



June 2, 2025

(Student)

Carl Benedict L. Elipan



June 2, 2025

(Student)

Dedication

38 We dedicate this special problem to all the teachers who have guided us
39 throughout our academic journey. Your knowledge and mentorship have laid the
40 foundation for this research, and for that, we are truly grateful.

41 To our families, friends, and classmates, thank you for your unwavering sup-
42 port, encouragement, and belief in us. Your presence has been a constant source
43 of strength.

44 Most especially, we dedicate this work to the health offices and frontline per-
45 sonnel who continue to battle dengue cases with courage and dedication. Your
46 tireless efforts and sacrifices are an inspiration. We hope that this research, in its
47 own small way, can contribute to your work and make a meaningful difference in
48 your fight against this disease.

49

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Abstract

67 Dengue fever remains a significant public health concern in the Philippines, with
68 cases rising dramatically in recent years. Iloilo City experienced a surge in cases, with
69 4,585 reported cases and 10 deaths as of August 10, 2023, a 319% increase from the
70 previous year's 1,095 cases and one death. This rise overwhelmed local healthcare facil-
71 ities, with over 76% of non-COVID-19 hospital beds occupied by dengue patients. The
72 lack of a reliable monitoring and forecasting system delayed interventions, worsening
73 the public health burden. To address this, the study developed a centralized system to
74 modernize data management and monitoring of dengue cases in public health institu-
75 tions. Using data from the Iloilo Provincial Health Office and online sources, several
76 deep learning models were trained to forecast dengue cases on weather variables and
77 historical data. Models tested included LSTM, ARIMA, Seasonal ARIMA, Kalman Fil-
78 ter (KF), and a hybrid KF-LSTM, evaluated with time series cross-validation and error
79 metrics like MSE, RMSE, and MAE. The LSTM model performed best, achieving the
80 lowest RMSE of 20.15, followed by the hybrid KF-LSTM with 25.56. The LSTM model
81 was integrated into the system, providing forecasting capabilities to support proactive
82 interventions and better resource planning in health institutions.

83 **Keywords:** Dengue, Deep Learning, Monitoring, Prediction

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¹⁸⁹ **Chapter 1**

¹⁹⁰ **Introduction**

¹⁹¹ **1.1 Overview of the Current State of Technology**

¹⁹² Dengue cases surged globally in 2023 and continued to rise in 2025, with over
¹⁹³ five million cases and more than 5,000 deaths across 80 countries (Bosano, 2023).

¹⁹⁴ The World Health Organization reported a ten-fold increase in cases from 2000
¹⁹⁵ to 2019, peaking in 2019 with the disease affecting 129 countries (WHO, 2024).

¹⁹⁶ In the Philippines, dengue remains endemic, leading to prolonged and widespread
¹⁹⁷ outbreaks.

¹⁹⁸ In Iloilo, dengue cases escalated dramatically. By August 2023, the provincial
¹⁹⁹ health office reported 4,585 cases and 10 deaths, marking a 319% increase from
²⁰⁰ the previous year (Perla, 2024). Iloilo has reached the outbreak threshold, and
²⁰¹ local authorities are on blue alert. In Iloilo City, 649 cases were recorded in 2024,
²⁰² with two deaths. Hospital capacity is strained, with non-COVID-19 hospital bed

203 occupancy exceeding 76%. This highlights the increasing pressure on healthcare
204 resources in the region.

205 In recent years, technology has played a growing role in improving disease
206 surveillance across the globe. Internationally, a study published in *Frontiers*
207 in Physics utilized the Kalman filter to predict COVID-19 deaths in Ceará,
208 Brazil(Ahmadini et al., 2021). A study also suggests that weather-based fore-
209 casting models using variables like mean temperature and cumulative rainfall can
210 provide early warnings of dengue outbreaks with high sensitivity and specificity,
211 enabling predictions up to 16 weeks in advance (Hii, Zhu, Ng, Ng, & Rocklöv,
212 2012). Locally, in Davao City, Ligue (2022) found that deep learning models can
213 accurately predict dengue outbreaks by capturing complex, time-dependent pat-
214 terns in environmental data. The study of Carvajal et. al. uses machine learning
215 methods to reveal the temporal pattern of dengue cases in Metropolitan Manila
216 and emphasizes the significance of relative humidity as a key meteorological fac-
217 tor, alongside rainfall and temperature, in influencing this pattern (Carvajal et
218 al., 2018).

219 Most studies remain theoretical or academic, with limited translation into
220 practical tools that communities and local health authorities can use for early
221 warning and response. An example of such application is RabDash, developed by
222 the University of the Philippines Mindanao. RabdashDC (2024) is a web-based
223 dashboard for rabies data analytics. However, while RabDash demonstrates the
224 potential of applying advanced analytics in public health, similar systems are
225 lacking in the context of dengue.

²²⁶ **1.2 Problem Statement**

²²⁷ Dengue remains a critical public health challenge worldwide, with cases increasing
²²⁸ due to the easing of COVID-19 restrictions and heightened global mobility. While
²²⁹ a temporary decline in cases was observed during the pandemic (2020–2022) due
²³⁰ to reduced surveillance efforts, 2023 marked a resurgence, with over five million
²³¹ cases and more than 5,000 deaths reported across 80 countries (Bosano, 2023).
²³² In Iloilo City and Province, dengue cases rose by 319% as of August 2023, over-
²³³ whelming local healthcare systems. This surge strained resources, with over 76%
²³⁴ of non-COVID-19 hospital beds occupied by dengue patients (Perla, 2024), high-
²³⁵ lighting the urgent need for effective monitoring and predictive tools. Despite
²³⁶ all these studies, there remains a significant gap in the development of publicly
²³⁷ accessible systems that apply these predictive models in real-world settings. Most
²³⁸ existing studies remain confined to academic or theoretical contexts, with little
²³⁹ translation into practical tools for local communities and public health authorities.
²⁴⁰ In particular, there is a lack of research focused specifically on dengue prediction
²⁴¹ and surveillance in Iloilo. While deep learning models have shown high accuracy
²⁴² in other regions, their application in the local context of Iloilo is minimal. The
²⁴³ lack of a reliable system to monitor and forecast dengue outbreaks contributes to
²⁴⁴ delayed interventions, exacerbating public health risks and healthcare burdens in
²⁴⁵ the region.

²⁴⁶ **1.3 Research Objectives**

²⁴⁷ **1.3.1 General Objective**

²⁴⁸ This study aims to develop a centralized monitoring and analytics system for
²⁴⁹ dengue cases in Iloilo City and Province with data management and forecasting
²⁵⁰ capabilities. The researchers will train and compare multiple deep learning models
²⁵¹ to predict dengue case trends based on climate data and historical dengue cases
²⁵² to help public health officials in dengue surveillance.

²⁵³ **1.3.2 Specific Objectives**

²⁵⁴ Specifically, this study aims to:

- ²⁵⁵ 1. gather dengue data from the Iloilo Provincial Health Office and climate data
²⁵⁶ (including temperature, rainfall, wind, and humidity) from online sources,
²⁵⁷ and combine and aggregate these into a unified dataset to facilitate compre-
²⁵⁸ hensive dengue case forecasting;
- ²⁵⁹ 2. train and evaluate deep learning models for predicting dengue cases using
²⁶⁰ metrics such as Mean Absolute Error (MAE), Root Mean Squared Error
²⁶¹ (RMSE), and Mean Squared Error (MSE), and determine the most accurate
²⁶² forecasting approach; and
- ²⁶³ 3. develop a web-based analytics dashboard that integrates the predictive model,
²⁶⁴ provides a data management system for dengue cases in Iloilo City and the

265 Province, and assess its usability and effectiveness through structured feed-
266 back from health professionals and policymakers.

267 1.4 Scope and Limitations of the Research

268 This study aims to gather dengue data from the Iloilo Provincial Health Office
269 and climate data from online sources such as PAGASA or weatherandclimate.com.
270 These data will be preprocessed, cleaned, and combined into a unified dataset to
271 facilitate comprehensive dengue case forecasting. However, the study is limited by
272 the availability and completeness of historical data. Inconsistent or missing data
273 points may introduce biases and reduce the quality of predictions. Furthermore,
274 the granularity of the data will be in a weekly format.

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

283 The study also involves developing a web-based analytics dashboard that in-
284 tegrates predictive models and provides a data management system for dengue
285 cases in Iloilo City and the Province. This dashboard will offer public health
286 officials an interactive interface to visualize dengue trends, input new data, and

287 identify risk areas. However, its usability depends on feedback from stakeholders,
288 which may vary based on their familiarity with analytics tools. Moreover, exter-
289 nal factors such as limited internet connectivity or device availability in remote
290 areas may affect the system's adoption and effectiveness. While the dashboard
291 provides valuable insights, it cannot incorporate all factors influencing dengue
292 transmission, emphasizing the need for ongoing validation and refinement.

293 1.5 Significance of the Research

294 This study's development of an AI-based dengue forecasting and monitoring sys-
295 tem has wide-reaching significance for various stakeholders in Iloilo City:

- 296 • Public Health Agencies: Organizations like the Department of Health (DOH)
297 and local health units in Iloilo City and Province stand to benefit greatly
298 from the system. With dengue predictions, we can help these agencies opti-
299 mize their response strategies and implement targeted prevention measures
300 in high-risk areas before cases escalate.
- 301 • Local Government Units (LGUs): LGUs can use the system to support
302 their disaster management and health initiatives by proactively addressing
303 dengue outbreaks. The predictive insights allow for more efficient planning
304 and resource deployment in barangays and communities most vulnerable to
305 outbreaks, improving overall public health outcomes.
- 306 • Healthcare Facilities: Hospitals and clinics, which currently face high bed
307 occupancy rates during dengue season will benefit from early outbreak fore-

1.5. SIGNIFICANCE OF THE RESEARCH

7

308 casts that can help in managing patient inflow and ensuring adequate hos-
309 pital capacity.

310 • Researchers and Policymakers: This AI-driven approach contributes valua-
311 ble insights for researchers studying infectious disease patterns and policy-
312 makers focused on strengthening the national AI Roadmap. The system's
313 data can support broader initiatives for sustainable health infrastructure
314 and inform policy decisions on resource allocation for dengue control.

315 • Community Members: By reducing the frequency and severity of outbreaks,
316 this study ultimately benefits the community at large. This allows for timely
317 awareness campaigns and community engagement initiatives, empowering
318 residents with knowledge and preventative measures to protect themselves
319 and reduce the spread of dengue.

³²⁰ Chapter 2

³²¹ Review of Related Literature

³²² 2.1 Dengue

³²³ Dengue disease is a tropical and subtropical mosquito-borne viral illness and is a
³²⁴ major health concern in the Philippines (Bravo, Roque, Brett, Dizon, & L'Azou,
³²⁵ 2014). The majority of individuals with dengue experience no symptoms. Fever is
³²⁶ the most common symptom, typically 4 to 7 days after being bitten by an infected
³²⁷ mosquito (Zhou & Malani, 2024). In recent years, the trend of dengue cases in
³²⁸ the Philippines has shown notable fluctuations, with periodic outbreaks occur-
³²⁹ ring every 3 to 5 years, often influenced by climatic and environmental changes.
³³⁰ According to the Department of Health (DOH), the number of reported cases
³³¹ has steadily increased over the past decades, attributed to urbanization, popula-
³³² tion growth, and inadequate vector control measures (World Health Organization
³³³ (WHO), 2018). Moreover, studies suggest that El Niño and La Niña events have
³³⁴ significant effects on dengue incidence, with warmer temperatures and increased

³³⁵ rainfall providing favorable breeding conditions for mosquitoes (Watts, David M
³³⁶ and Burke, Donald S and Harrison, Bruce A and Whitmire, Ralph E and Nisalak,
³³⁷ Ananda, 2020). The study of Carvajal et. al. highlights the temporal pattern of
³³⁸ dengue cases in Metropolitan Manila and emphasizes the significance of relative
³³⁹ humidity as a key meteorological factor, alongside rainfall and temperature, in
³⁴⁰ influencing this pattern (Carvajal et al., 2018).

³⁴¹ 2.2 Outbreak Definition

³⁴² The definition of an outbreak is a critical factor in disease surveillance, as it
³⁴³ determines the threshold at which an unusual increase in cases is considered a
³⁴⁴ public health concern. Studies suggest that outbreak thresholds should be context-
³⁴⁵ specific, given the variability in transmission dynamics across different locations
³⁴⁶ (Runge-Ranzinger et al., 2016). Outbreak definitions defined using the Endemic
³⁴⁷ Channel often base thresholds on 2 standard deviations (SD) above the mean
³⁴⁸ number of historic dengue cases. Other studies (Hemisphere, 2015) also used an
³⁴⁹ alert threshold of a 5-year mean plus 2 standard deviations. A study by (Brady,
³⁵⁰ Smith, Scott, & Hay, 2015) discussed that definitions of dengue outbreaks differ
³⁵¹ significantly across regions and time, making them inconsistent and incomparable.

³⁵² 2.3 Existing System: RabDash DC

³⁵³ RabDash, developed by the University of the Philippines Mindanao, is a web-
³⁵⁴ based dashboard for rabies data analytics. It combines predictive modeling with

355 genomic data, enabling local health authorities to optimize interventions and al-
356 locate resources more effectively. RabDash's modules include trend visualization,
357 geographic hotspot mapping, and predictive forecasting, utilizing Long Short-
358 Term Memory (LSTM) models for time-series forecasting (RabDashDC, 2024).

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

369 2.4 Deep Learning

370 The study of (Ligue & Ligue, 2022) highlights how data-driven models can help
371 predict dengue outbreaks. The authors compared traditional statistical meth-
372 ods, such as non-seasonal and seasonal autoregressive integrated moving average
373 (ARIMA), and traditional feed-forward network approach using a multilayer per-
374 ceptron (MLP) model with a deep learning approach using the long short-term
375 memory (LSTM) architecture in their prediction model. They found that the
376 LSTM model performs better in terms of accuracy. The LSTM model achieved a

³⁷⁷ much lower root mean square error (RMSE) compared to both MLP and ARIMA
³⁷⁸ models, proving its ability to capture complex patterns in time-series data (Ligue
³⁷⁹ & Ligue, 2022). This superior performance is attributed to LSTM's capacity
³⁸⁰ to capture complex, time-dependent relationships within the data, such as those
³⁸¹ between temperature, rainfall, humidity, and mosquito populations, all of which
³⁸² contribute to dengue incidence (Ligue & Ligue, 2022).

³⁸³ 2.5 Kalman Filter

³⁸⁴ The Kalman Filter is another powerful tool for time-series forecasting that can be
³⁸⁵ integrated into our analysis. It provides a recursive solution to estimating the state
³⁸⁶ of a linear dynamic system from a series of noisy measurements. Its application
³⁸⁷ in epidemiological modeling can enhance prediction accuracy by accounting for
³⁸⁸ uncertainties in the data(Li et al., 2022). Studies have shown that Kalman filters
³⁸⁹ are effective in predicting infectious disease outbreaks by refining estimates based
³⁹⁰ on observed data. A study published in Frontiers in Physics utilized the Kalman
³⁹¹ filter to predict COVID-19 deaths in Ceará, Brazil. They found that the Kalman
³⁹² filter effectively tracked the progression of deaths and cases, providing critical in-
³⁹³ sights for public health decision-making (Ahmadini et al., 2021). Another research
³⁹⁴ article in PLOS ONE focused on tracking the effective reproduction number (R_t)
³⁹⁵ of COVID-19 using a Kalman filter. This method estimated the growth rate of
³⁹⁶ new infections from noisy data, demonstrating that the Kalman filter could main-
³⁹⁷ tain accurate estimates even when case reporting was inconsistent(Arroyo-Marioli,
³⁹⁸ Bullano, Kucinskas, & Rondón-Moreno, 2021).

399 This study compares ARIMA, seasonal ARIMA, Kalman Filter, and LSTM
400 models using collected dengue case data along with weather data to identify the
401 most effective model for real-time forecasting.

402 2.6 Weather Data

403 The relationship between weather patterns and mosquito-borne diseases is inher-
404 ently nonlinear, meaning that fluctuations in disease cases do not respond propor-
405 tionally to changes in climate variables(Colón-González, Fezzi, Lake, & Hunter,
406 2013) Weather data, such as minimum temperature and accumulated rainfall, are
407 strongly linked to dengue case fluctuations, with effects observed after several
408 weeks due to mosquito breeding and virus incubation cycles. Integrating these
409 lagged weather effects into predictive models can improve early warning systems
410 for dengue control(Cheong, Burkart, Leitão, & Lakes, 2013). A study also sug-
411 gests that weather-based forecasting models using variables like mean temperature
412 and cumulative rainfall can provide early warnings of dengue outbreaks with high
413 sensitivity and specificity, enabling predictions up to 16 weeks in advance(Hii et
414 al., 2012).

415 This study utilizes weather data, including variables such as temperature,
416 rainfall, and humidity, as inputs for our dengue forecasting model. Given the
417 strong, nonlinear relationship between climate patterns and dengue incidence,
418 these weather variables, along with their lagged effects, are essential for enhancing
419 prediction accuracy and providing timely early warnings for dengue outbreaks.

420 2.7 Chapter Summary

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

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

⁴³⁵ Chapter 3

⁴³⁶ Research Methodology

⁴³⁷ This chapter lists and discusses the specific steps and activities that were per-
⁴³⁸ formed to accomplish the project. The discussion covers the activities from pre-
⁴³⁹ proposal to Final SP Writing.

⁴⁴⁰ Figure 3.1 summarizes the workflow for forecasting the number of weekly
⁴⁴¹ dengue cases. This workflow focuses on using statistical, deep learning, and prob-
⁴⁴² abilistic models to forecast the number of reported dengue cases. The approach
⁴⁴³ involves deploying several models for prediction, including ARIMA and Seasonal
⁴⁴⁴ ARIMA as statistical approaches, LSTM as a deep learning approach, and the
⁴⁴⁵ Kalman Filter as a probabilistic approach. These methods are compared with
⁴⁴⁶ each other to determine the most accurate model.

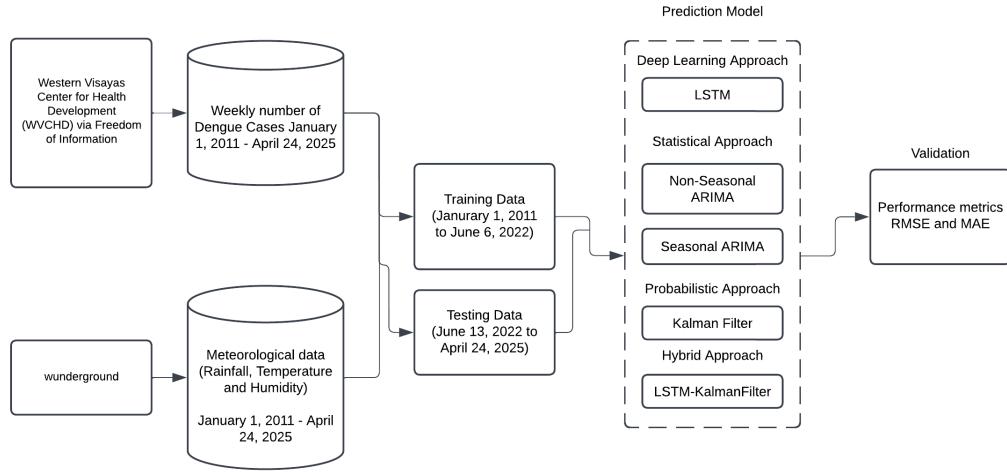


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

⁴⁴⁷ 3.1 Research Activities

⁴⁴⁸ 3.1.1 Dengue and Climate Data Collection

⁴⁴⁹ Acquisition of Dengue Case Data

⁴⁵⁰ The historical dengue case dataset used in this study was obtained from the Hu-
⁴⁵¹ manitarian Data Exchange and the Western Visayas Center for Health Develop-
⁴⁵² ment (WVCHD) via Freedom of Information (FOI) requests. The decision to use
⁴⁵³ weekly intervals was driven by the need for precision and timeliness in captur-
⁴⁵⁴ ing fluctuations in dengue cases and weather conditions. Dengue transmission is
⁴⁵⁵ influenced by short-term changes in weather variables such as rainfall and temper-
⁴⁵⁶ ature, which impact mosquito breeding and virus transmission cycles. A weekly
⁴⁵⁷ granularity allowed the model to better capture these short-term trends, enabling
⁴⁵⁸ more accurate predictions and responsive public health interventions.

459 Moreover, using a weekly interval provided more data points for training the
460 models compared to a monthly format. This is particularly critical in time series
461 modeling, where larger datasets help improve the robustness of the model and its
462 ability to generalize to new data. Also, the collection of weather data was done
463 by utilizing web scraping techniques to extract weekly weather data (e.g., rainfall,
464 temperature, and humidity) from Weather Underground (wunderground.com).

465

466 **Data Fields**

- 467 • **Time.** Represents the specific year and week corresponding to each entry
468 in the dataset.
- 469 • **Rainfall.** Denotes the observed average rainfall, measured in millimeters,
470 for a specific week.
- 471 • **Humidity.** Refers to the observed average relative humidity, expressed as
472 a percentage, for a specific week.
- 473 • **Max Temperature.** Represents the observed maximum temperature, mea-
474 sured in degrees Celsius, for a specific week.
- 475 • **Average Temperature.** Represents the observed average temperature,
476 measured in degrees Celsius, for a specific week.
- 477 • **Min Temperature.** Represents the observed minimum temperature, mea-
478 sured in degrees Celsius, for a specific week.
- 479 • **Wind.** Represents the observed wind speed, measured in miles per hour
480 (mph), for a specific week.

- 481 • **Cases.** Refers to the number of reported dengue cases during a specific
482 week.

483 **Data Integration and Preprocessing**

484 The dengue case data was integrated with the weather data to create a com
485 prehensive dataset, aligning the data based on corresponding timeframes. The
486 dataset undergoed a cleaning process to address any missing values, outliers, and
487 inconsistencies to ensure its accuracy and reliability. To ensure that all features
488 and the target variable were on the same scale, a MinMaxScaler was applied to
489 normalize both the input features (climate data) and the target variable (dengue
490 cases).

491 **Exploratory Data Analysis (EDA)**

492 Trends, seasonality, and correlations between reported dengue cases and weather
493 factors were thoroughly analyzed to identify potential relationships in the dataset.
494 To support and illustrate these findings, a series of visualizations, including time-
495 series plots and scatterplots, were developed, to highlight key patterns and rela-
496 tionships within the dataset.

497 **Outbreak Detection**

498 To detect outbreaks, we computed the outbreak threshold value of dengue cases
499 using the formula,

$$\text{Outbreak Threshold Value} = \mu + 2\sigma \quad (3.1)$$

500 where μ is the historical mean and σ is the standard deviation.

501 It is important to take note that definitions of dengue outbreaks differ signifi-
502 cantly across regions and time. This computation is subject to changes depending
503 on how the surveillance units detect outbreaks themselves.

504 **3.1.2 Develop and Evaluate Deep Learning Models for** 505 **Dengue Case Forecasting**

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

511 **Data Preprocessing**

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

⁵¹⁸ **LSTM Model**

⁵¹⁹ The dataset was split into training and test sets to evaluate the model's performance and generalizability:

⁵²¹ • **Training Set:** 80% of the data (572 sequences) was used for model training,
⁵²² enabling the LSTM to learn underlying patterns in historical dengue case
⁵²³ trends and their relationship with weather variables.

⁵²⁴ • **Test Set:** The remaining 20% of the data (148 sequences) was reserved for
⁵²⁵ testing

⁵²⁶ To prepare the data for LSTM, a sliding window approach was utilized. Sequences of weeks of normalized features were constructed as input, while the ⁵²⁷ dengue case count for the subsequent week was set as the target variable. This ⁵²⁸ approach ensured that the model leveraged temporal dependencies in the data for ⁵²⁹ forecasting. To enhance the performance of the LSTM model in predicting dengue ⁵³⁰ cases, Bayesian Optimization was employed using the Keras Tuner library. The ⁵³¹ tuning process aimed to minimize the validation loss (mean squared error) by ⁵³² adjusting key model hyper-parameters. Table 3.1 summarizes the search space ⁵³³ below:

Search Space	LSTM Units	Learning Rate
Min Value	32	0.0001
Max Value	128	0.01
Step	16	None
Sampling	Linear	Log
Tuner Configuration		
Max Trials	10	
Executions per Trial	3	
Validation Split	0.2	

Table 3.1: Hyperparameter Tuning: Search Space and Tuner Configuration

535 The hyperparameter tuning was conducted for three different window sizes of
536 data: 5, 10, and 20. This allows the model to have the optimal hyperparameters
537 used for each window size. Training was conducted over 100 epochs with early
538 stopping to prevent overfitting while maintaining computational efficiency. A
539 batch size of 1 was used, enabling the model to process individual sequences,
540 which is suitable for smaller datasets but results in longer training times. The
541 Adam optimizer, known for its adaptive learning capabilities and stability was
542 employed.

543 To validate the effectiveness of the model, cross-validation was implemented.
544 However, standard k-fold cross-validation randomly shuffles the data, which isn't
545 suitable for time series since the order of observations is important. To address
546 this, a time series-specific cross-validation strategy was used with TimeSeriesS-
547 plit from the scikit-learn library. This method creates multiple train-test splits
548 where each training set expands over time and each test set follows sequentially.
549 This approach preserves the temporal structure of the data while helping reduce
550 overfitting by validating the model across different time segments.

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

555 ARIMA

556 The ARIMA model was utilized to forecast weekly dengue cases, leveraging histor-
557 ical weather data—including rainfall, maximum temperature, and humidity—as

558 exogenous variables alongside historical dengue case counts as the primary dependent
559 variable. The dataset was partitioned into training (80%) and testing (20%)
560 sets while maintaining temporal consistency.

561 To identify the optimal ARIMA configuration, a comprehensive grid search
562 was performed across the following parameter ranges:

- 563 • Autoregressive order (p): 0 to 3
564 • Differencing order (d): 0 to 2
565 • Moving average order (q): 0 to 3

566 Each combination of (p,d,q) was used to fit an ARIMA model, and performance
567 was evaluated based on the mean squared error (MSE) between the predicted
568 and actual dengue cases on the test set. The parameter set that achieved
569 the lowest MSE was selected as the final model configuration.

570 Following model selection, the best-fit ARIMA model was retrained on the
571 training set and subsequently used to forecast dengue cases for the test period.
572 The predictions were assigned to the **PredictedCases** column in the test dataset.
573 Model performance was further assessed using key evaluation metrics, including
574 MSE, root mean squared error (RMSE), and mean absolute error (MAE). Visual
575 comparisons between actual and predicted dengue cases were produced through
576 line plots to better illustrate the model's forecasting accuracy.

577 Seasonal ARIMA (SARIMA)

578 The SARIMA modeling process began with data preprocessing, which included
579 handling missing values through interpolation or imputation, and standardizing
580 features to ensure stable model training. The dataset was then split into training
581 and testing sets in an 80:20 ratio, preserving the temporal order of observations.
582 Seasonality analysis was conducted using time series decomposition and autocor-
583 relation plots, which revealed a periodicity of 52 weeks—justifying the adoption
584 of a seasonal model. To fine-tune the model, a grid search was performed over a
585 range of SARIMA parameters $(p,d,q)(P,D,Q)[S]$, while stationarity was validated
586 using the Augmented Dickey-Fuller (ADF) test. The model was then trained
587 on the dataset using rainfall, temperature, and humidity as exogenous variables,
588 with convergence ensured by setting a maximum number of iterations. Residual
589 diagnostics were used to confirm that residuals were uncorrelated, indicating a
590 good model fit. For evaluation, forecasts were compared against actual values,
591 and results were visualized with line plots. Finally, to validate the model's gener-
592 alizability across different time periods, Time Series Cross-Validation with three
593 folds was applied. This allowed assessment of the model's performance on multi-
594 ple time segments, providing insights into its robustness in real-world forecasting
595 scenarios.

596 Kalman Filter:

- 597 • Input Variables: The target variable (Cases) was modeled using three re-
598 gressors: rainfall, max temperature, and humidity.
- 599 • Training and Testing Split: The dataset was split into 80% training and

- 600 20% testing to evaluate model performance.
- 601 • Observation Matrix: The Kalman Filter requires an observation matrix,
602 which was constructed by adding an intercept (column of ones) to the re-
603 gressors.

604 The Kalman Filter’s Expectation-Maximization (EM) method was employed
605 for training, iteratively estimating model parameters over 10 iterations. After
606 training, the smoothing method was used to compute the refined state estimates
607 across the training data. Observation matrices for the test data were constructed
608 in the same manner as for the training set, ensuring compatibility with the learned
609 model parameters. On the test data, the Kalman Filter applied these parameters
610 to predict and correct the estimated dengue cases, providing more stable and
611 accurate forecasts compared to direct regression models. Additionally, a hybrid
612 Kalman Filter–LSTM (KF-LSTM) model was developed to combine the strengths
613 of both approaches. In this setup, the LSTM model was first used to predict
614 dengue cases based on historical data and weather features. The Kalman Filter
615 was then applied as a post-processing step to the LSTM predictions, smoothing
616 out noise and correcting potential errors.

617 **Model Evaluation**

- 618 • **MSE** represents the average of the squared differences between predicted
619 and actual values. It penalizes larger errors more heavily.
- 620 • **RMSE**, the square root of MSE, provides a more interpretable value in the
621 same units as the target (i.e., number of dengue cases).

- 622 • **MAE** calculates the average magnitude of the errors without considering
623 their direction, giving a more straightforward understanding of the average
624 prediction error.

625 **Model Simulation:**

626 After identifying the best-performing model among all the trained deep learning
627 models, a simulation was conducted. Using the same parameters from the initial
628 training, the selected model was retrained with the original dataset along with
629 new data up to January 2025. The retrained model was then used to forecast
630 dengue cases for the period from February 2025 to May 2025. Listing 3.1 shows
631 a code snippet of the model training.

Listing 3.1: Code Snippet for Model Training

```
632           # Fit on train set
633           history = model.fit(
634           X_train, y_train,
635           epochs=100,
636           batch_size=1,
637           validation_split=0.2,
638           callbacks=[early_stop],
639           verbose=1
640       )
641
642           # Predict on 2025
643           y_pred_test = model.predict(X_test, verbose=0)
```

644 **3.1.3 Integrate the Predictive Model into a Web-Based**

645 **Data Analytics Dashboard**

646 **Dashboard Design and Development**

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

651 **Model Integration and Deployment**

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

654 **3.1.4 System Development Framework**

655 The Agile Model is the birthchild of both iterative and incremental approaches

656 in Software Engineering. It aims to be flexible and effective at the same time by

657 being adaptable to change. It's also important to note that small teams looking

658 to construct and develop projects quickly can benefit from this kind of method-

659 ology. As the Agile Method focuses on continuous testing, quality assurance is a

660 guarantee since bugs and errors are quickly identified and patched.

661 Design and Development

662 After brainstorming and researching the most appropriate type of application to
663 accommodate both the prospected users and the proposed solutions, the team
664 has decided to proceed with a web application. Given the time constraints and
665 available resources, it has been decided that the said means is the most pragmatic
666 and practical move. The next step is to select modern and stable frameworks
667 that align with the fundamental ideas learned by the researchers in the university.
668 The template obtained from WVCHD and Iloilo Provincial Epidemiology and
669 Surveillance Unit was meticulously analyzed to create use cases and develop a
670 preliminary well-structured database that adheres to the requirements needed
671 to produce a quality application. The said use cases serve as the basis of general
672 features. Part by part, these are converted into code, and with the help of selected
673 libraries and packages, it resulted in the desired outcome that may still modified
674 and extended to achieve scalability.

675 **Testing and Integration**

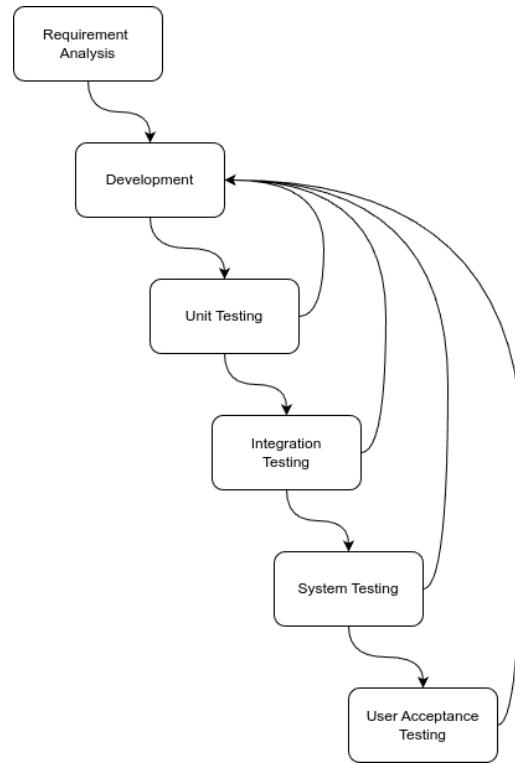


Figure 3.2: Testing Process for DengueWatch

676 Implementing testing is important to validate the system's performance and ef-
677 ficacy. Thus a series of tests were conducted to identify and resolve bugs during
678 the developmental phase. Each feature was rigorously tested to ensure quality as-
679 surance, with particular emphasis on prerequisite features, as development cannot
680 progress properly if these fail. Because of this, integration between each feature
681 serves as a pillar for a cohesive user experience. Since dengue reports include
682 confidential information, anonymized historical dengue reports were used to train
683 the model and create the foundational architecture of the system. By using func-
684 tional tests, data validation and visualization can be ensured for further continual

improvements. Security testing is also important as it is needed to safeguard confidential information when the system is deployed. It includes proper authentication, permission views, and mitigating common injection attacks. Finally, a user acceptance test from the prospected users, in this case, doctors, nurses, and other health workers is crucial to assess its performance and user experience. It enables the developers to confirm if the system meets the needs of the problem.

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.

704 Django

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

713 Next.js

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

720 Postman

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

⁷²⁵ Postman? Postman API Platform, n.d.).

⁷²⁶ 3.2.2 Hardware

⁷²⁷ The web application was developed on laptop computers with minimum specifications of an 11th-generation Intel i5 CPU and 16 gigabytes of RAM. Furthermore,
⁷²⁸ an RTX 3060 mobile GPU was also utilized to retrain the integrated model locally.
⁷²⁹

⁷³⁰ 3.2.3 Packages

⁷³¹ Django REST Framework

⁷³² Django Rest Framework (DRF) is a third-party package for Django that provides a
⁷³³ comprehensive suite of features to simplify the development of robust and scalable
⁷³⁴ Web APIs (Christie, n.d.). These services include Serialization, Authentication
⁷³⁵ and Permissions, Viewsets and Routers, and a Browsable API .

⁷³⁶ Leaflet

⁷³⁷ One of the features of the web application is the ability to map the number
⁷³⁸ of cases using a Choropleth Map. Leaflet is the only free, open-sourced, and
⁷³⁹ most importantly, stable JavaScript package that can do the job. With its ultra-
⁷⁴⁰ lightweight size, it offers a comprehensive set of features that does not trade
⁷⁴¹ off performance and usability (*Leaflet — an open-source JavaScript library for*
⁷⁴² *interactive maps*, n.d.).

743 Chart.js

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

751 Tailwind CSS

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

760 Shadcn

761 Shadcn offers a collection of open-source UI boilerplate components that can be
762 directly copied and pasted into one's project. With the flexibility of the provided
763 components, Shadcn allows developers to have full control over customization and

⁷⁶⁴ styling. Since this is built on top of Tailwind CSS and Radix UI, it is supported
⁷⁶⁵ by most modern frontend frameworks, including Next.js (Shadcn, n.d.).

⁷⁶⁶ **Zod**

⁷⁶⁷ Data validation is integral in this web application since it will handle crucial data
⁷⁶⁸ that will be used for analytical inferences and observations. Since Zod is primarily
⁷⁶⁹ used for validating and parsing data, it ensures proper communication between
⁷⁷⁰ the client and the server (Zod, n.d.).

⁷⁷¹ 3.3 Application Requirements

⁷⁷² 3.3.1 Backend Requirements

⁷⁷³ Database Structure Design

⁷⁷⁴ Determining how data flows and how it would be structured is crucial in creating
⁷⁷⁵ the system as it defines how extendible and flexible it would be for future features
⁷⁷⁶ and updates. Thus, creating a comprehensive map of data ensures proper nor-
⁷⁷⁷ malization that eliminates data redundancy and improves data integrity. Figure
⁷⁷⁸ 3.3 depicts the designed database schema that showcases the relationship between
⁷⁷⁹ the application's entities.

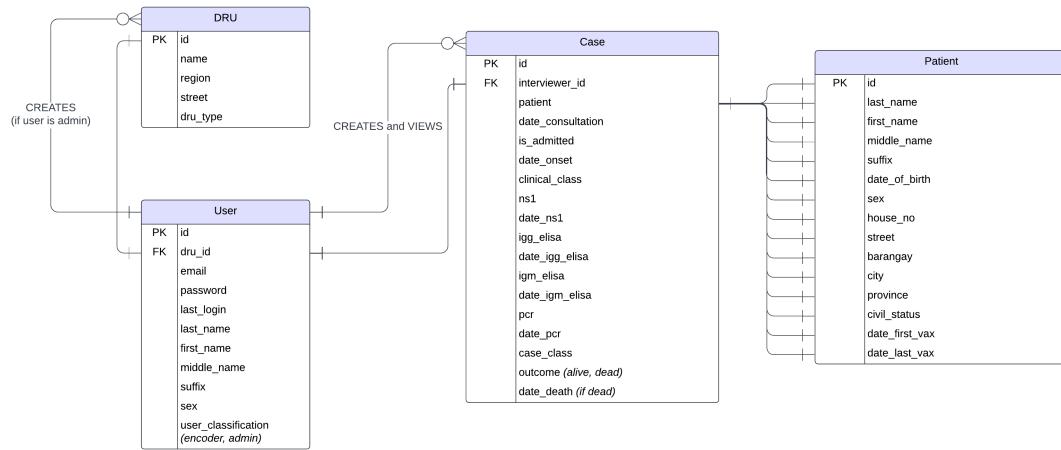


Figure 3.3: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

780 **3.3.2 User Interface Requirements**

781 **Admin Interface**

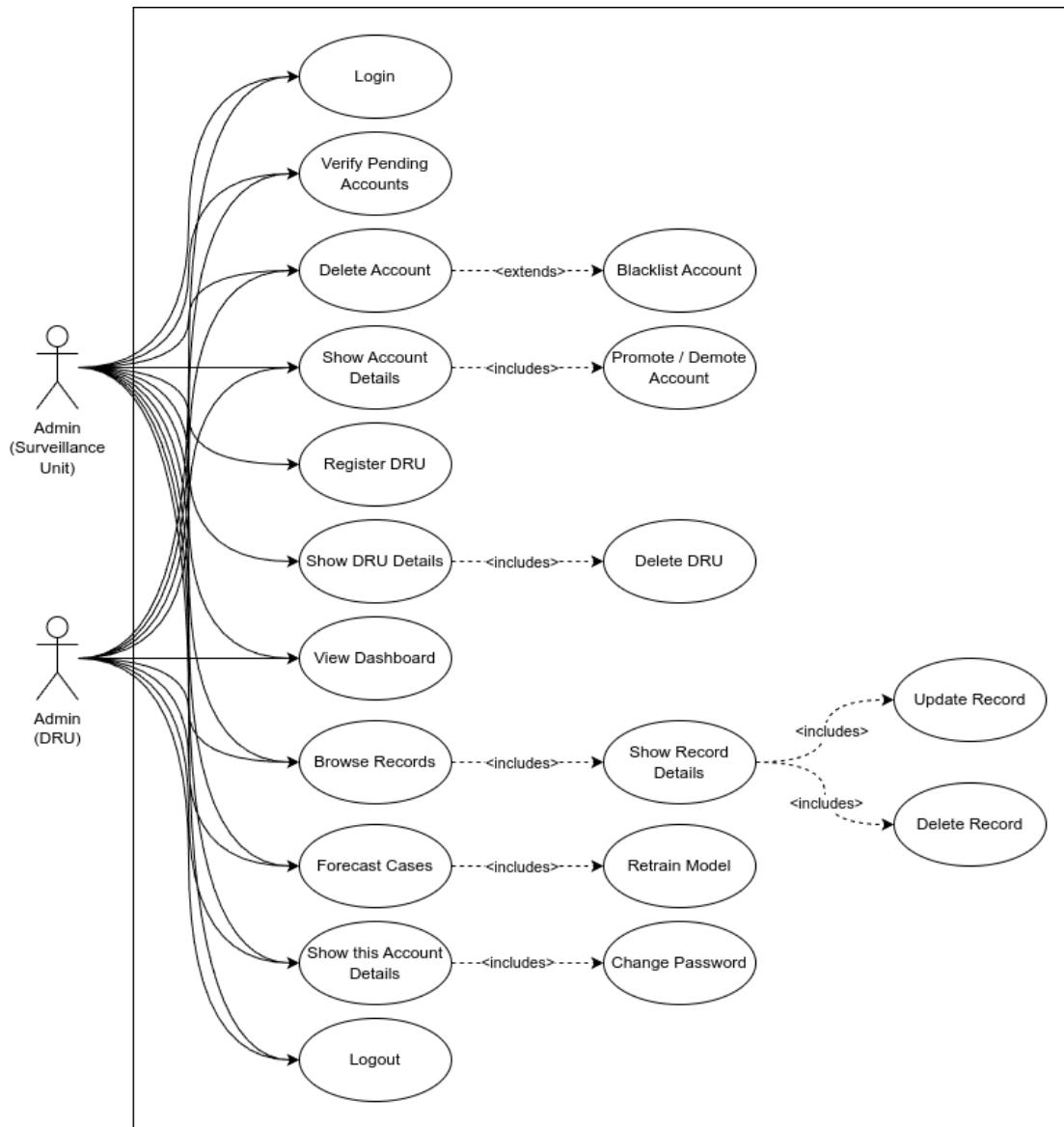


Figure 3.4: Use Case Diagram for Admins

782 Figure 3.4 shows the actions of an admin for a specific Disease Reporting Unit
783 (DRU) and an admin for a specific Surveillance Unit can take in the application.
784 Both of them include the management of accounts, browsing records, and fore-
785 casting and retraining all the consolidated data under their supervision. Most
786 importantly, these users must verify the encoders who register under their ju-
787 risdiction before allowing their account to access the application in the name of
788 safeguarding the integrity of the data. The only advantage of the latter type of ad-
789 ministrator is that it has a one-step higher authorization as it manages the DRUs.
790 In addition, only the authorized surveillance unit administrator can register and
791 create a DRU to uphold transparency and accountability.

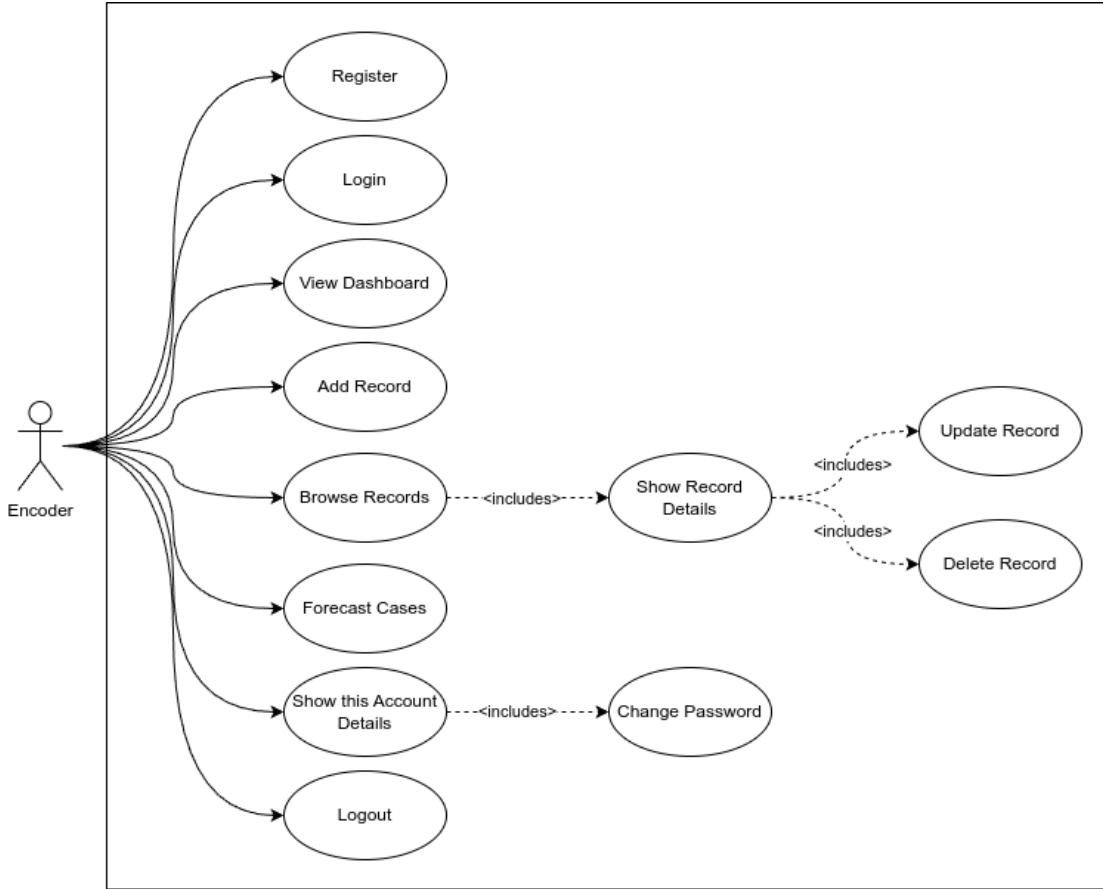
792 **Encoder Interface**

Figure 3.5: Use Case Diagram for Encoder

793 Figure 3.5, on the other hand, illustrates the use cases for the system's primary
 794 users. These users can register but must wait for further verification to access the
 795 application. Similar to the previous interfaces, encoders can browse and manage
 796 records, as well as forecast the consolidated cases under a specific surveillance or
 797 disease reporting unit, but they are not allowed to retrain the model. Lastly, they
 798 are the only type of user that can file and create dengue cases by filling out a form
 799 with the required details.

3.3.3 Security and Validation Requirements

801 Password Encryption

802 Storing passwords as plain text in the database is a disgrace and a mortal sin in
803 production. It is important to implement precautionary methods such as hashing
804 and salting, followed by encryption with a strong algorithm, to prevent bad actors
805 from using the accounts for malicious transactions. By default, Django generates
806 a unique random salt for each password and encrypts it with Password-Based Key
807 Derivation Function 2 (PBKDF2) with a SHA256 hash function. Utilizing these
808 techniques ensures that in the event of a data breach, cracking these passwords
809 would be time-consuming and useless for the attackers.

810 Authentication

811 DengueWatch utilizes JSON Web Tokens (JWT) to authenticate the user. Since
812 the mechanism operates in a stateless manner, tokens are served only after a
813 successful login, eliminating the need for the server to keep a record of the token,
814 which is vulnerable to session hijacking. In addition, these tokens are signed with
815 a secret key, ensuring they have not been tampered with.

816 Data Validation

817 Both the backend and frontend should validate the input from the user to preserve
818 data integrity. Thus, Zod is implemented in the latter to help catch invalid inputs
819 from the user. By doing this, the user can only send proper requests to the server

which streamlines the total workflow. On the other hand, Django has also a built-in validator that checks the data type and ensures that the input matches the expected format on the server side. These validation processes ensure that only valid and properly formatted data is accepted, which reduces the risk of errors and ensures consistency across the web application.

825 **Chapter 4**

826 **Results and Discussion**

827 **4.1 Data Gathering**

828 The data for dengue case prediction was gathered from a variety of reliable sources,
829 enabling a comprehensive dataset spanning from January 2011 to October 2024.
830 This dataset includes 720 rows of data, each containing weekly records of dengue
831 cases along with corresponding meteorological variables, such as rainfall, temper-
832 ature, and humidity.

833 1. Dengue Case Data: The primary source of historical dengue cases came
834 from the Humanitarian Data Exchange and the Western Visayas Center for
835 Health Development (WVCHD). The dataset, accessed through Freedom of
836 Information (FOI) requests, provided robust case numbers for the Western
837 Visayas region. The systematic collection of these data points was essential
838 for establishing a reliable baseline for model training and evaluation.

839 2. Weather Data: Weekly weather data was obtained by web scraping from
 840 Weather Underground, allowing access to rainfall, temperature, wind, and
 841 humidity levels that correlate with dengue prevalence.

Time	Rainfall	MaxTemperature	AverageTemperature	MinTemperature	Wind	Humidity	Cases
2011-01-03	9.938571	29.444400	25.888890	23.888900	11.39	86.242857	5
2011-01-10	8.587143	30.000000	26.705556	24.444444	7.32	88.028571	4
2011-01-17	5.338571	30.000000	26.616667	25.000000	7.55	84.028571	2
2011-01-24	5.410000	30.555556	26.483333	20.555556	10.67	80.971429	7
2011-01-31	2.914286	28.333333	25.283333	18.650000	11.01	74.885714	2

Table 4.1: Snippet of the combined dataset

842 4.2 Exploratory Data Analysis

843 From Table 4.2, the dataset consists of 720 weekly records with 8 columns:

- 844 • **Time.** Weekly timestamps (e.g. “2011-w1”)
- 845 • **Rainfall.** Weekly average rainfall (mm)
- 846 • **MaxTemperature, AverageTemperature, MinTemperature.** Weekly
 847 temperature data (°C)
- 848 • **Wind.** Wind speed (m/s)
- 849 • **Humidity.** Weekly average humidity (%)
- 850 • **Cases.** Reported dengue cases

851 From the statistics in Table 4.3, the number of cases ranges from 0 to 319.

852 The average number of dengue cases per week is 23.74, with a median of 12 cases
 853 and a standard deviation of 37.14. The distribution is highly skewed, with some

#	Column	Non-Null Count	Data Type
0	Time	720 non-null	datetime64[ns]
1	Rainfall	720 non-null	float64
2	MaxTemperature	720 non-null	float64
3	AverageTemperature	720 non-null	float64
4	MinTemperature	720 non-null	float64
5	Wind	720 non-null	float64
6	Humidity	720 non-null	float64
7	Cases	720 non-null	int64

Table 4.2: Data Schema: Column Names, Non-Null Counts, and Data Types

854 weeks experiencing significant number of cases (up to 319 cases). Rainfall shows
 855 a wide variation (0 to 445mm), while temperature remains relatively stable, with
 856 an average of 28.1 degree celsius. Humidity levels ranges from 73% to 89% with
 857 a mean of 81.6%.

Statistic	Time	Rainfall	MaxTemperature	AverageTemperature	MinTemperature	Wind	Humidity	Cases
Count	720	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000
Mean	2017-12-02 11:22:00	13.957499	32.191142	28.110319	25.038472	6.172417	81.609442	23.744444
Min	2011-01-03 00:00:00	0.000000	-14.600000	24.494444	12.222222	1.910000	73.185714	0.000000
25%	2014-06-21 06:00:00	1.270000	31.666667	27.504167	25.000000	4.117500	79.885713	5.000000
50% (Median)	2017-12-07 12:00:00	4.318000	32.222222	28.161111	25.000000	5.725000	81.771429	12.000000
75%	2021-05-11 18:00:00	10.414000	32.777778	28.751389	25.555556	7.860000	83.503571	26.000000
Max	2024-10-28 00:00:00	445.008000	58.333333	30.916667	32.222222	19.200000	89.571429	319.000000
Std Dev	N/A	35.448846	2.616379	0.999800	1.291659	2.446703	2.831674	37.144813

Table 4.3: Descriptive Statistics of the Combined Dataset

858 Figure 4.1 illustrates the trend of weekly dengue cases over time. The data
 859 reveals periodic spikes in the number of cases, suggesting a seasonal pattern in
 860 dengue cases. Notably, peak cases are observed during certain periods approx-
 861 imately 3 years, potentially aligning with specific climatic conditions such as
 862 increased rainfall or temperature changes. This underscores the importance of
 863 incorporating climate variables into the forecasting model.

864 Figure 4.2 presents a time series subplot that combines rainfall and dengue
 865 cases to highlight potential non-linear associations between the two variables. In
 866 this figure, raw rainfall data is represented by blue scatter points (aligned with

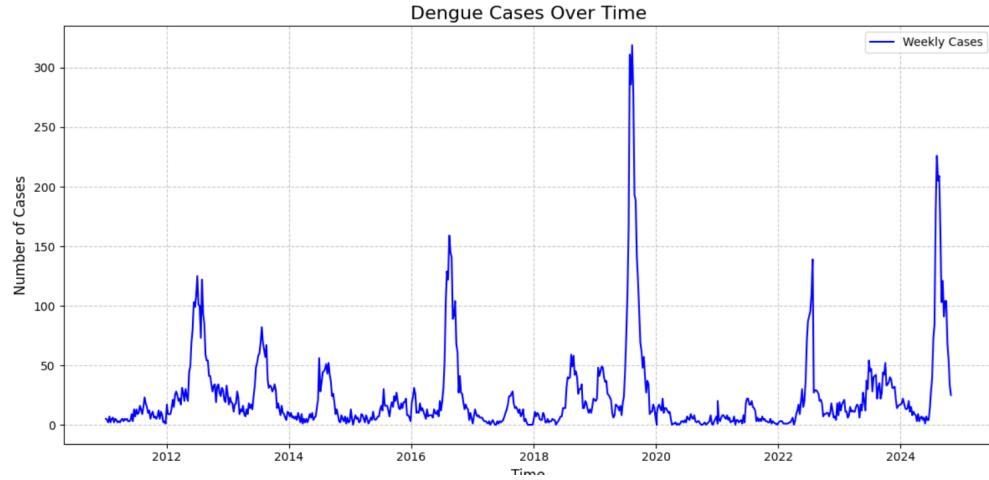


Figure 4.1: Trend of Dengue Cases

the left y-axis), while a blue solid line traces its 4-week rolling average to reveal underlying trends. Simultaneously, the red dashed line illustrates the smoothed trajectory of dengue cases (aligned with the right y-axis), also using a 4-week rolling average to reduce short-term fluctuations and emphasize longer-term patterns.

Notably, the plot suggests a recurring pattern. Periods of increased rainfall often precede or coincide with spikes in dengue cases. This observed relationship supports existing literature which proposes that higher rainfall contributes to the proliferation of mosquito breeding sites, particularly in stagnant water, thereby elevating the risk of dengue transmission.

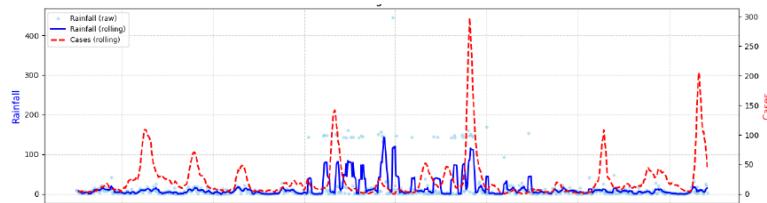


Figure 4.2: Rainfall and Dengue Cases Over Time

The KDE plots in Figure 4.3 illustrate the distributions of meteorological vari-

ables during outbreak and normal dengue weeks. The x-axes represent the actual values of each feature, while the y-axes show density, indicating how frequently values occur within each category. The graphs reveal that outbreak weeks tend to have moderately higher rainfall than weeks with no outbreak. This is evident in the way the curve for outbreak weeks is positioned slightly to the right of the curve for normal weeks. In terms of temperature, the distributions for both normal and outbreak weeks appear very similar; however, upon closer inspection, the curve for maximum temperature shows a slightly higher density at higher values during outbreak weeks. The same is true for humidity, with outbreak weeks showing greater density at higher humidity levels. These patterns suggest that dengue outbreaks are more likely to occur during warm, humid periods with relatively high rainfall. Based on these observations, rainfall, maximum temperature, and humidity were selected as the meteorological features for training the predictive models.

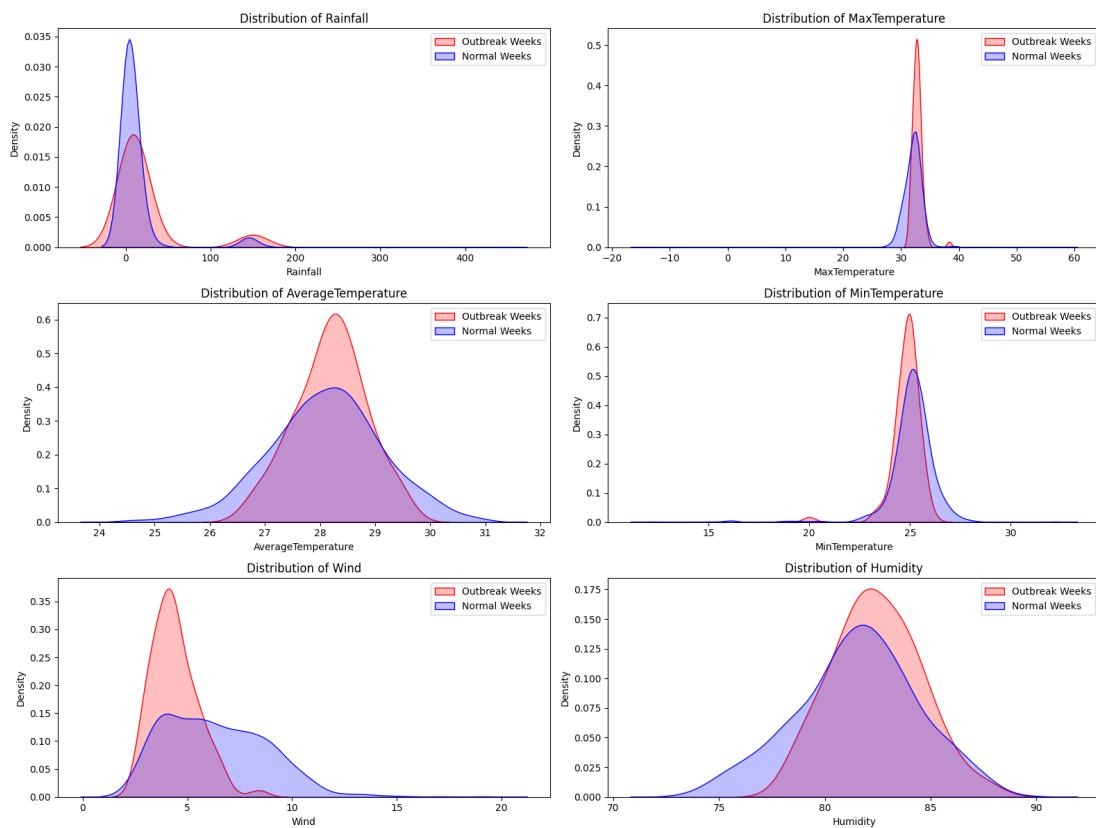


Figure 4.3: Kernel Density Estimate Plots of Meteorological Features

892 4.3 Outbreak Detection

893 To identify outbreaks, the researchers calculated the outbreak threshold value
894 using the historical mean as the endemic channel. The threshold is determined
895 using the formula:

$$\text{Outbreak Threshold Value} = \mu + 2\sigma \quad (4.1)$$

$$= 23.744444 + 2(37.144813) \quad (4.2)$$

$$= 23.744444 + 74.289626 \quad (4.3)$$

$$= 98.03407 \quad (4.4)$$

896 where μ is the historical mean and σ is the standard deviation.

897 This result indicates that dengue cases exceeding 98 in Iloilo City can be
898 considered an outbreak. However, it is important to note that this threshold
899 serves only as a baseline.

900 4.4 Model Training Results

901 The models were evaluated using three commonly used regression metrics: Mean
902 Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute
903 Error (MAE). These metrics help assess how accurately each model forecasts
904 dengue cases based on historical data. Table 4.4 presents a comparative analysis

905 of the models using these metrics.

- 906 • **MSE** represents the average of the squared differences between predicted
907 and actual values. It penalizes larger errors more heavily.
- 908 • **RMSE**, the square root of MSE, provides a more interpretable value in the
909 same units as the target (i.e., number of dengue cases).
- 910 • **MAE** calculates the average magnitude of the errors without considering
911 their direction, giving a more straightforward understanding of the average
912 prediction error.

913 In simpler terms, lower values in these metrics indicate that the model is
914 making more accurate predictions.

Method	LSTM	Seasonal ARIMA	ARIMA	Kalman Filter	KF-LSTM
Testing MSE	406.03	1261.20	1521.48	1474.82	785.35
Testing RMSE	20.15	34.45	39.00	38.40	25.56
Testing MAE	12.61	18.73	25.80	22.33	14.55
Best Parameters	Window Size: 5 Learning Rate: 0.01 Units: 64	(2,0,2)(0,1,1)	(1,2,2)	Observation Covariance: 10.0 Transition Covariance: 0.1 × Identity	Same as LSTM

Table 4.4: Comparison of different models for dengue prediction

915 As shown in Table 4.4, the LSTM model consistently achieved the lowest MSE
916 (406.03), RMSE (20.15), and MAE (12.61) among all evaluated models. This
917 suggests that, on average, the LSTM's predictions were about 12 to 20 cases away
918 from the actual values, which is a strong indication of reliability for practical use
919 in public health decision-making.

920 In contrast, traditional time series models like Seasonal ARIMA and ARIMA
921 showed higher errors, indicating less accurate predictions. For example, the Sea-
922 sonal ARIMA model had an RMSE of 34.45, which implies that its forecasts devi-

923 ated from actual dengue case counts by around 34 cases on average, a significant
 924 discrepancy for health officials planning resource allocation.

925 The Kalman Filter and hybrid KF-LSTM models showed moderate perfor-
 926 mance. Although they did not outperform LSTM, the hybrid model (KF-LSTM)
 927 still reduced errors compared to the standalone Kalman Filter.

928 These results highlight the potential of LSTM-based models to provide timely
 929 and accurate forecasts that can support early intervention, resource planning, and
 930 policy formulation to combat dengue outbreaks in Iloilo City.

931 4.4.1 LSTM Model

932 The LSTM model was tuned for the following parameters: learning rate and units.
 933 The hyperparameter tuning was conducted for each window size, finding the best
 934 parameters for each window size. Further evaluating which window size is most
 935 suitable for the prediction model, Table 4.5 shows the evaluation metrics for each
 window size used in the LSTM model training.

Window Size	MSE	RMSE	MAE	R ²
5	406.03	20.15	12.61	0.76
10	1037.77	32.21	26.79	0.39
20	427.39	20.67	13.61	0.75

Table 4.5: Comparison of Window Sizes

936

937 The results indicate that a window size of 5 weeks provides the most accurate
 938 predictions, as evidenced by the lowest MSE and RMSE values. Furthermore, the
 939 R² score of 0.76 indicates that 76% of the variability in the target variable (cases)
 940 is explained by the independent variables (the inputs) in the model, making it a

941 reliable configuration overall.

942 As shown in Table 4.6, the results from time series cross-validation indicate
943 consistent performance trends, with a window size of 5 yielding the highest average
944 RMSE across all folds compared to the other window sizes.

Window Size	Average RMSE	Average MAE	Average R ²
5	16.69	9.06	0.79
10	17.08	10.40	0.75
20	16.93	8.75	0.81

Table 4.6: Time-Series Cross Validation Results: Comparison of Window Sizes

945 Figure 4.4 illustrates the model’s performance in predicting dengue cases for
946 each fold using a window size of 5. As shown in the plot, the training set pro-
947 gressively increases with each fold, mimicking a real-world scenario where more
948 data becomes available over time for dengue prediction. Figure 4.5 demonstrates
949 that the predicted cases closely follow the trend of the actual cases, indicating
950 that the LSTM model successfully captures the underlying patterns in the data.
951 It is also evident that as the fold number increases and the training set grows, the
952 accuracy of the predictions on the test set improves. Despite the test data being
953 unseen, the model exhibits a strong ability to generalize, suggesting it effectively
954 leverages past observations to predict future trends.

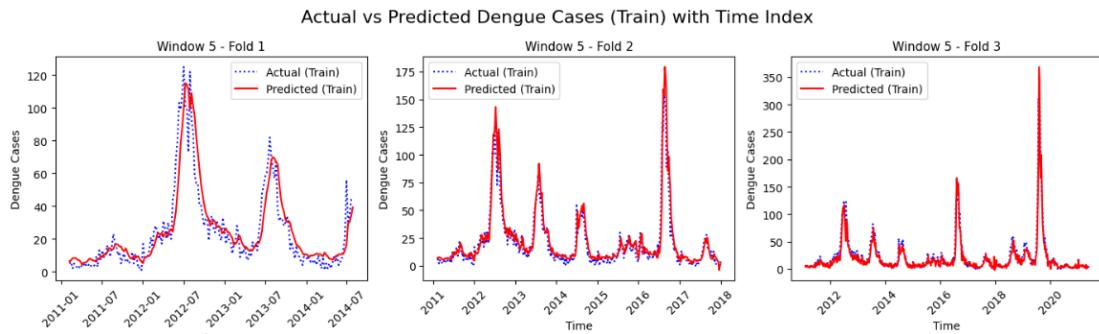


Figure 4.4: Training Folds - Window Size 5

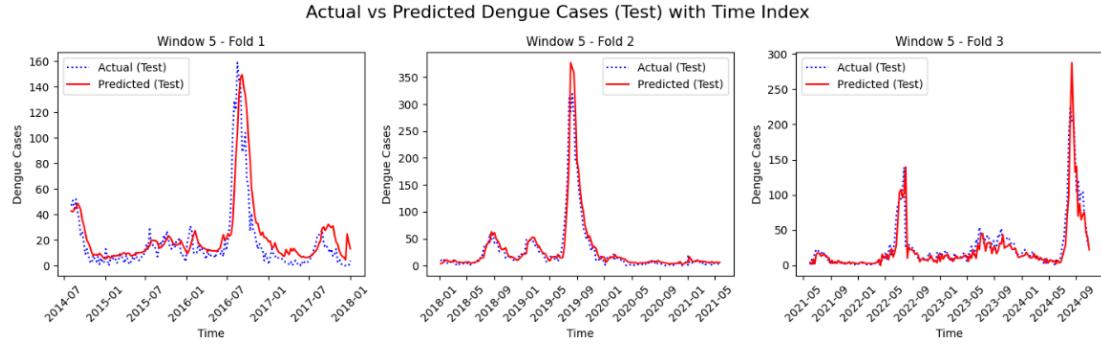


Figure 4.5: Testing Folds - Window Size 5

955 4.4.2 ARIMA Model

956 The ARIMA model was developed to capture non-seasonal trends in the data.
 957 To determine the best model configuration, grid search was used to explore vari-
 958 ous combinations of ARIMA parameters, ultimately selecting **ARIMA(1, 2, 2)**.
 959 The model was iteratively refined over **400 iterations** to ensure convergence to
 960 an optimal solution. Figure 4.6 illustrates the comparison between actual and
 961 predicted dengue cases in the test set. As shown in the plot, the ARIMA model
 962 struggled to capture the non-linear characteristics and abrupt spikes in the data.
 963 Consequently, it failed to accurately reflect the fluctuations and outbreak patterns
 964 seen in the actual case counts.

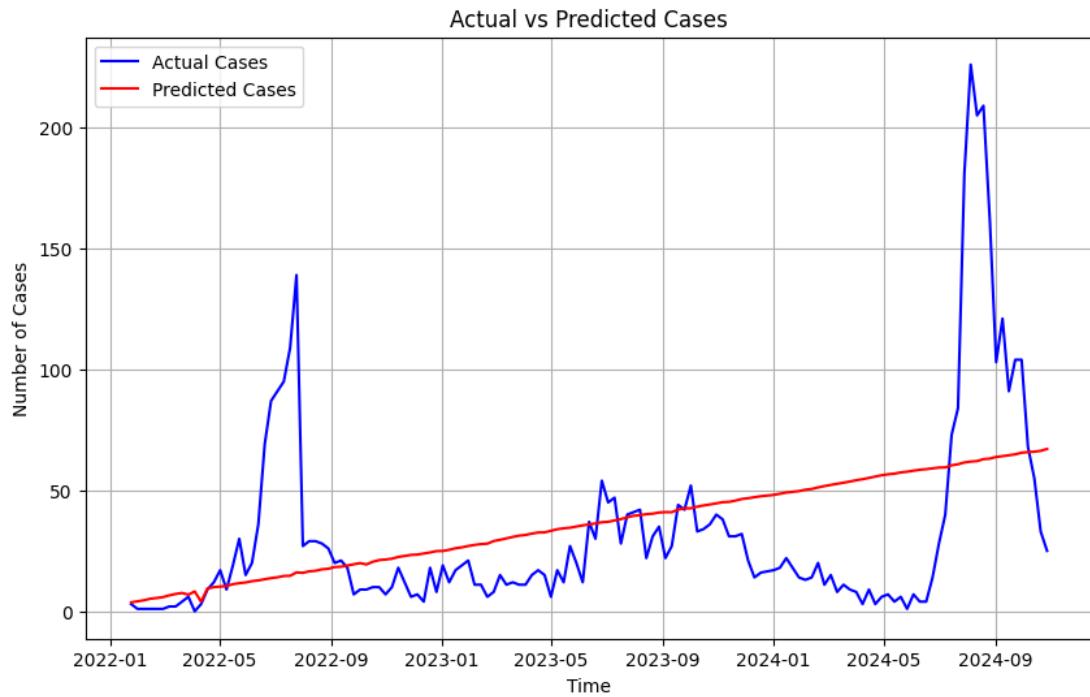


Figure 4.6: ARIMA Prediction Results for Test Set

965 The model's performance was assessed using regression metrics to evaluate its
 966 forecasting capability. The ARIMA model yielded the following error metrics:

- 967 • **MSE (Mean Squared Error):** 1521.48
- 968 • **RMSE (Root Mean Squared Error):** 39.01
- 969 • **MAE (Mean Absolute Error):** 25.80

970 4.4.3 Seasonal ARIMA (SARIMA) Model

971 To address the limitations of the ARIMA model, a Seasonal ARIMA (SARIMA)
 972 model was developed to capture both non-seasonal and seasonal variations in the

973 data.

974 This model incorporates seasonal parameters, which were tuned using grid
 975 search to find the best configuration: **SARIMA(2, 0, 2)(0, 1, 1)[52]**. As with
 976 ARIMA, **400 iterations** were applied to ensure a robust fit. As shown in Figure
 977 4.7, the SARIMA model demonstrates a notable improvement in performance.
 978 Unlike its non-seasonal counterpart, it effectively captures the general trend and
 979 aligns more closely with the peaks observed in the actual dengue cases, indicating
 980 its ability to model seasonal dynamics.

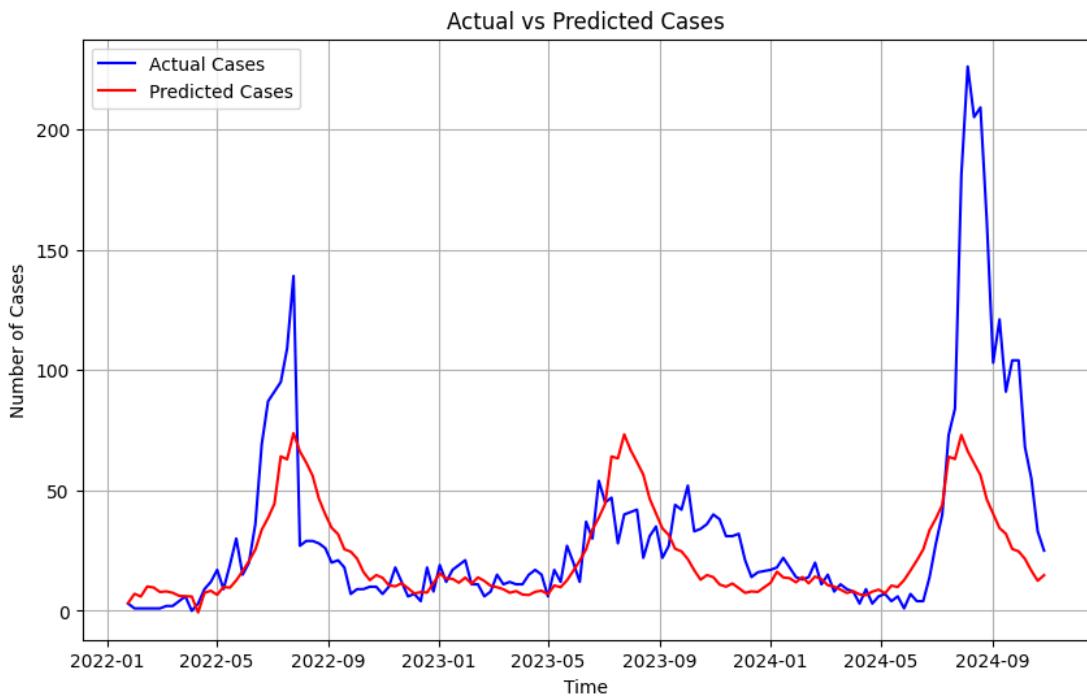


Figure 4.7: Seasonal ARIMA Prediction Results for Test Set

981 The model's performance was assessed using regression metrics to evaluate its
 982 forecasting capability. The SARIMA model yielded the following error metrics:

983 • **MSE:** 1109.69

984 • **RMSE:** 33.31

985 • **MAE:** 18.09

986 The lower error values, when compared to the ARIMA model, highlight the
 987 SARIMA model's superior capability in forecasting dengue cases. Its effective-
 988 ness in capturing seasonal patterns contributed to a more accurate representation
 989 of the actual cases.

990 After training the model, the SARIMA model was validated using the same
 991 Time Series Cross-Validation strategy employed in the LSTM model. Table 4.7
 992 presents the performance metrics for each fold, as well as the average metrics
 993 across all folds. The average RMSE and MAE values were close to those obtained
 994 during the initial training phase, indicating that the SARIMA model performed
 995 consistently across different time segments.

Fold	MSE	RMSE	MAE
1	659.68	25.68	16.00
2	2127.49	46.12	21.30
3	996.43	31.56	18.89
Average	1261.20	34.45	18.73

Table 4.7: Comparison of SARIMA performance for each fold

996 4.4.4 Kalman Filter Model

997 Figure 4.8 shows the comparison between the actual dengue cases and the pre-
 998 dicted values on the test set. As illustrated in the plot, the Kalman Filter model
 999 demonstrates a moderate ability to follow the general trend of the actual data.

1000 While it effectively captures some rising and falling patterns, it still struggles to
 1001 accurately replicate the sharp peaks and extreme values found in the real case
 1002 counts. This limitation is particularly noticeable during the large spikes in 2022
 1003 and 2024. The model's performance was evaluated using standard regression met-
 1004 rics. The results are as follows:

$$\text{MSE} = 1474.82, \quad \text{RMSE} = 38.40, \quad \text{MAE} = 22.34$$

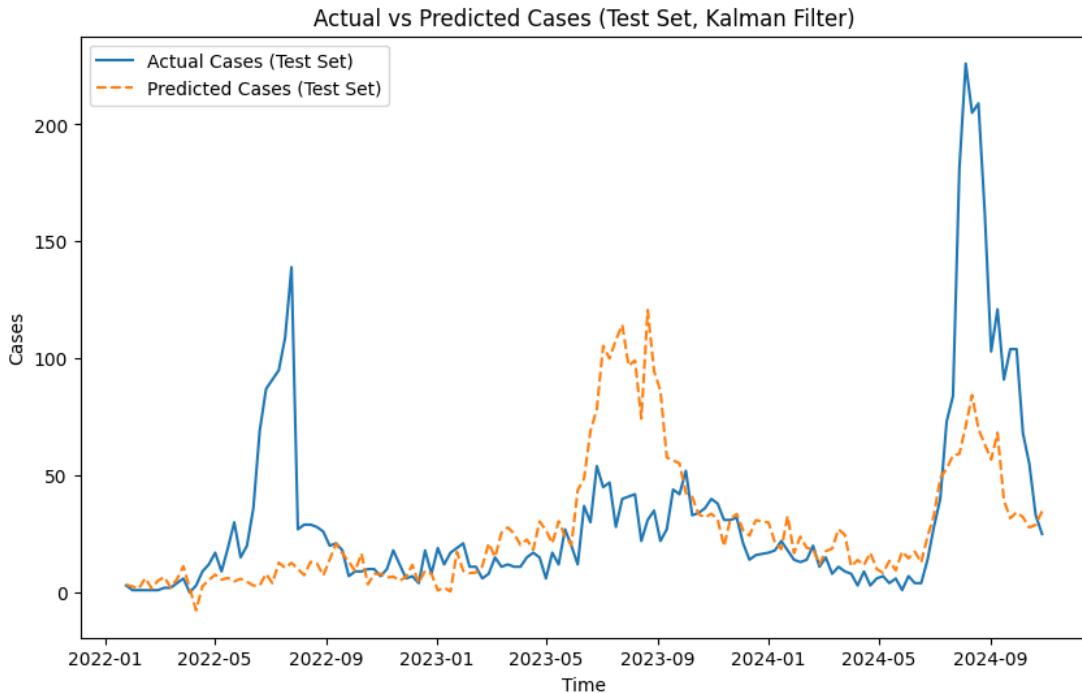


Figure 4.8: Kalman Filter Prediction Results for Test Set

1005 The Kalman Filter was then combined with the LSTM model in order to see
 1006 improvements in its predictions. Table 4.8 shows the metrics across three folds
 1007 using the same Time Series Cross Validation Strategy employed in the previous
 1008 models to see how it performed on different time segments.

Fold	MSE	RMSE	MAE
1	113.59	10.66	6.42
2	752.51	27.43	12.11
3	1489.95	38.60	25.13
Average	785.35	25.56	14.55

Table 4.8: Comparison of KF-LSTM performance for each fold

1009 As can be seen in the table above, the performance of the hybrid model demon-
1010 strated improvements in all metrics as compared to just using the Kalman Filter
1011 alone.

1012 4.5 Model Simulation

1013 To evaluate the LSTM model’s real-world forecasting ability, a simulation was
1014 conducted to predict dengue cases for the year 2025. The model was retrained
1015 exclusively, using the parameters found from the initial training, on data from 2011
1016 to January 2025, using both dengue cases and weather variables. Importantly, the
1017 actual dengue case values for 2025 were never included during training. Instead,
1018 only the weather variables collected for 2025 were input into the model to generate
1019 predictions for that year. After prediction, the forecasted dengue cases for 2025
1020 were compared against the true observed cases to assess the model’s accuracy.
1021 Figure 4.9 shows that the predicted values closely follow the trend, although it
1022 may overestimate the dengue cases in some weeks.

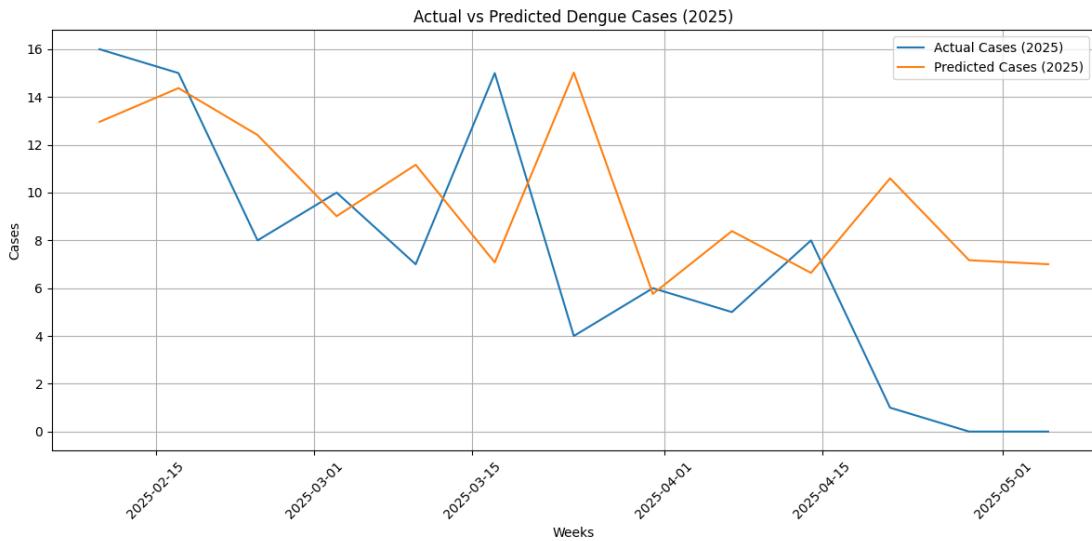


Figure 4.9: Predicted vs Actual Dengue Cases 2025

1023 Retraining the model is essential to ensure it remains accurate and responsive
 1024 to the evolving trends of dengue case patterns over time. Ideally, the model should
 1025 be updated whenever new data becomes available to capture recent dynamics.
 1026 However, given the computational cost associated with retraining, a more practical
 1027 approach is to update the model on a monthly basis. This allows the incorporation
 1028 of approximately four weeks' worth of new data, providing a meaningful update
 1029 to the model's predictive capabilities without excessive resource consumption.
 1030 Furthermore, this schedule aligns with the typical data release cycle of provincial
 1031 health offices, which, based on the researchers' experience, usually occurs monthly.
 1032 This balance between accuracy and efficiency ensures that the model remains both
 1033 up-to-date and manageable in real-world deployment.

1034 4.6 System Prototype

1035 4.6.1 Home Page

1036 The Home Page is intended for all visitors to the web application. The Analytics
1037 Dashboard, which displays relevant statistics for dengue cases at a certain time
1038 and location, is the primary component highlighted, as seen in Figure 4.10. This
1039 component includes a combo chart that graphs the number of dengue cases and
1040 deaths per week in a specific year, along with the outbreak threshold. It also
1041 features a choropleth map that tracks the number of dengue cases per barangay in
1042 a location and various bar charts that indicate the top constituent places affected
1043 by dengue.

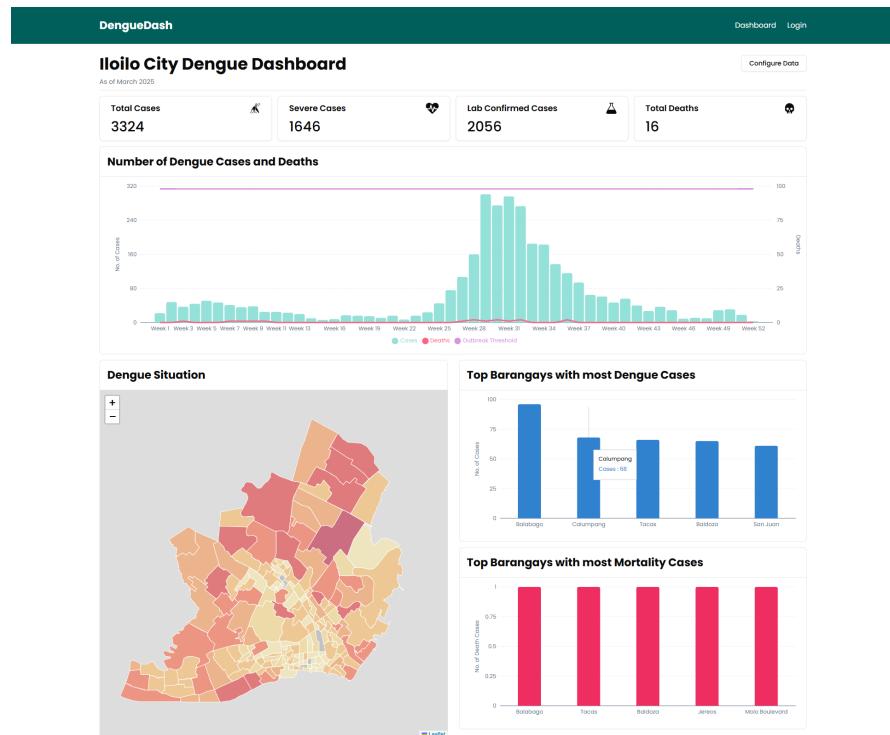
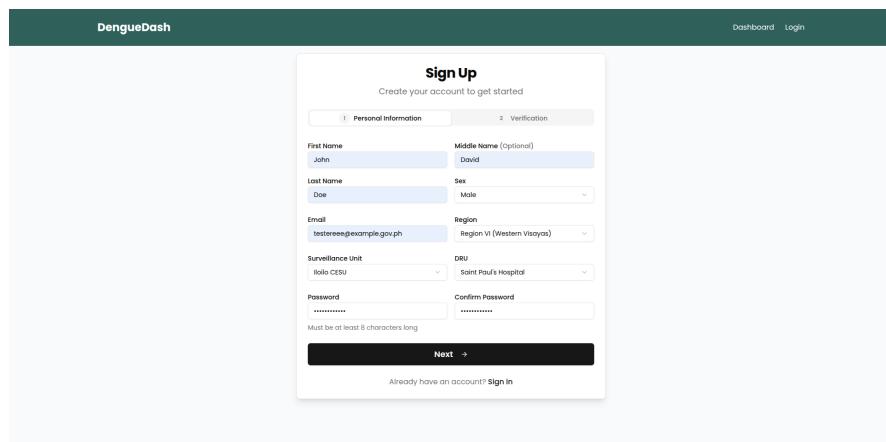


Figure 4.10: Home Page

¹⁰⁴⁴ **4.6.2 User Registration, Login, and Authentication**

¹⁰⁴⁵ The registration page, as shown in 4.11 and 4.12, serves as a gateway to access
¹⁰⁴⁶ the authenticated pages of the web application. Only prospective encoders can
¹⁰⁴⁷ register an account, as administrator accounts are created by existing administra-
¹⁰⁴⁸ tor accounts to protect the integrity of the data in production. After registering,
¹⁰⁴⁹ the "encoder account" cannot access the authorized pages yet as it needs to be
¹⁰⁵⁰ verified first by an administrator managing the unit the user entered. Because
¹⁰⁵¹ of this, proper identification (user's picture and employee identification card) is
¹⁰⁵² mandatory to help the admins verify the identity of the registrant. Once verified,
¹⁰⁵³ the user can log in to the system through the page shown in Figure 4.13. Af-
¹⁰⁵⁴ ter entering the correct credentials, which consist of an email and password, the
¹⁰⁵⁵ system uses HTTP-only cookies containing JSON Web Tokens (JWT) to prevent
¹⁰⁵⁶ vulnerability to Cross-site Scripting (XSS) attacks. It will then proceed to the
¹⁰⁵⁷ appropriate page for the type of user it belongs to. Logging out, on the other
¹⁰⁵⁸ hand, will remove both the access and refresh tokens from the browser and will
¹⁰⁵⁹ blacklist the latter token to make it unusable for security purposes.



The screenshot shows the 'Sign Up' page of the DengueDash application. At the top, there is a dark header bar with the DengueDash logo on the left and 'Dashboard' and 'Login' links on the right. Below the header is a large white form area with a title 'Sign Up' and a subtitle 'Create your account to get started'. The form is divided into two tabs: 'Personal Information' (which is active, indicated by a blue border) and 'Verification' (indicated by a grey border). The 'Personal Information' tab contains fields for First Name ('John'), Middle Name ('David'), Last Name ('Doe'), Sex ('Male'), Email ('testereee@example.gov.ph'), Region ('Region VI (Western Visayas)'), Surveillance Unit ('Iloilo CESU'), DRU ('Saint Paul's Hospital'), Password (a masked password), and Confirm Password (a masked password). A note at the bottom of the form says 'Must be at least 8 characters long'. At the bottom of the form is a large black 'Next →' button. Below the button, a small link says 'Already have an account? [Sign in](#)'.

Figure 4.11: Personal Information Tab of Sign Up Page

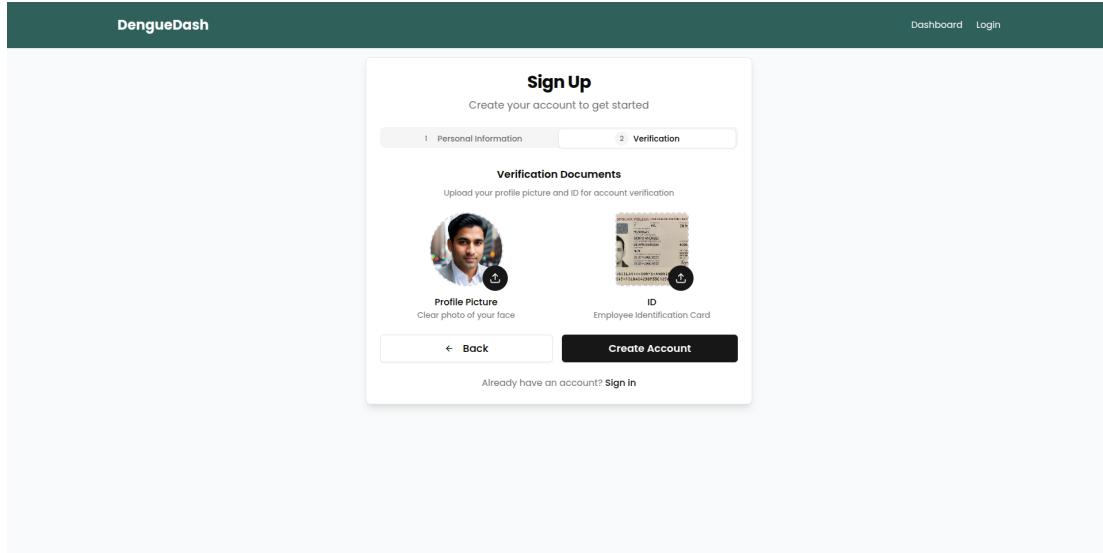


Figure 4.12: Verification Tab of Sign Up Page

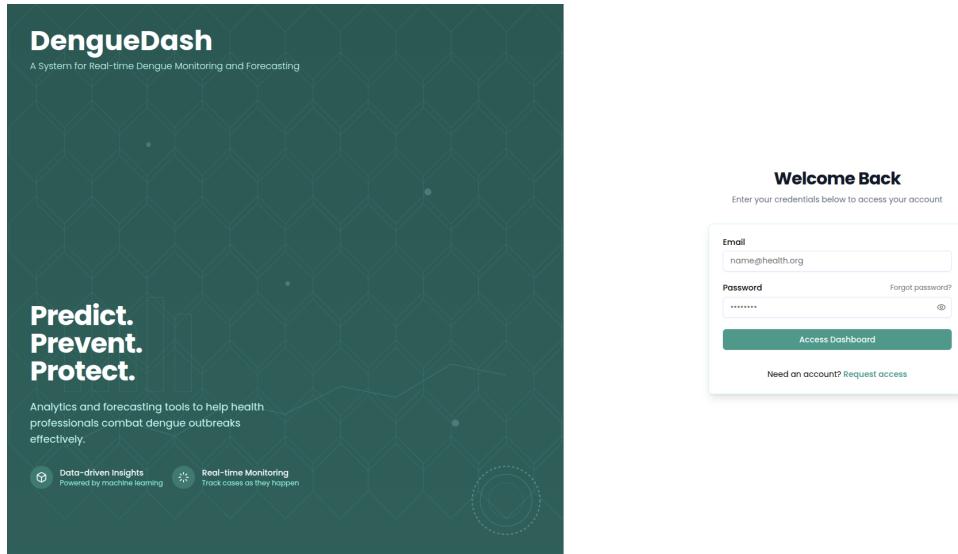


Figure 4.13: Login Page

1060 4.6.3 Encoder Interface**1061 Case Report Form**

1062 Figures 4.14 and 4.15 show the digitized counterpart of the form obtained from the
1063 Iloilo Provincial Epidemiology and Surveillance Unit. As the system aims to sup-
1064 port expandability for future features, some fields were modified to accommodate
1065 more detailed input. It is worth noting that all of the included fields adhere to the
1066 latest Philippine Integrated Disease and Surveillance Response (PIDS) Dengue
1067 Forms, which the referenced form was based on. By doing this, if implemented
1068 on a national scale, the transition between targeted users will be easier. More-
1069 over, the case form includes the patient's basic information, dengue vaccination
1070 status, consultation details, laboratory results, and the outcome. On the other
1071 hand, encoders can also create case records using a "bulk upload" feature that
1072 makes use of a formatted CSV file template. As shown in Figure 4.16, an encoder
1073 can download the template using the "Download Template" button, and insert
1074 multiple records inside the file, then upload it by clicking the "Click to upload"
1075 button. The web application automatically checks the file for data inconsistencies
1076 and validation.

CHAPTER 4. RESULTS AND DISCUSSION

DengueDash

Modules

- Analytics
- Forms
 - Case Report Form
- Data Tables

Forms > Case Report Form

Case Report Form

Personal Information

Personal Detail

First Name	Middle Name
Last Name	Suffix
Sex	Civil Status
Select Sex	Select Civil Status

Date of Birth

Pick a date

Address

Region	Province
Select Region	Select Province
City	Barangay
Select City/Municipality	Select Barangay
Street	House No.

Vaccination

Date of First Vaccination	Date of Last Vaccination
Pick a date	Pick a date

Clinical Status

Next

Figure 4.14: First Part of Case Report Form

DengueDash

Modules

- Analytics
- Forms
 - Case Report Form
- Data Tables

Forms > Case Report Form

Case Report Form

Personal Information

Clinical Status

Consultation

Date Admitted/Consulted/Seen	Is Admitted?
Pick a date	Select

Date Onset of illness	Clinical Classification
Pick a date	Select

Laboratory Results

NS1	Date done (NS1)
Pending Result	Pick a date
IgG ELISA	Date done (IgG ELISA)
Pending Result	Pick a date
IgM ELISA	Date done (IgM ELISA)
Pending Result	Pick a date
PCR	Date done (PCR)
Pending Result	Pick a date

Outcome

Case Classification	Outcome
Select	Select

Date of Death

Pick a date

Previous **Submit**

Figure 4.15: Second Part of Case Report Form

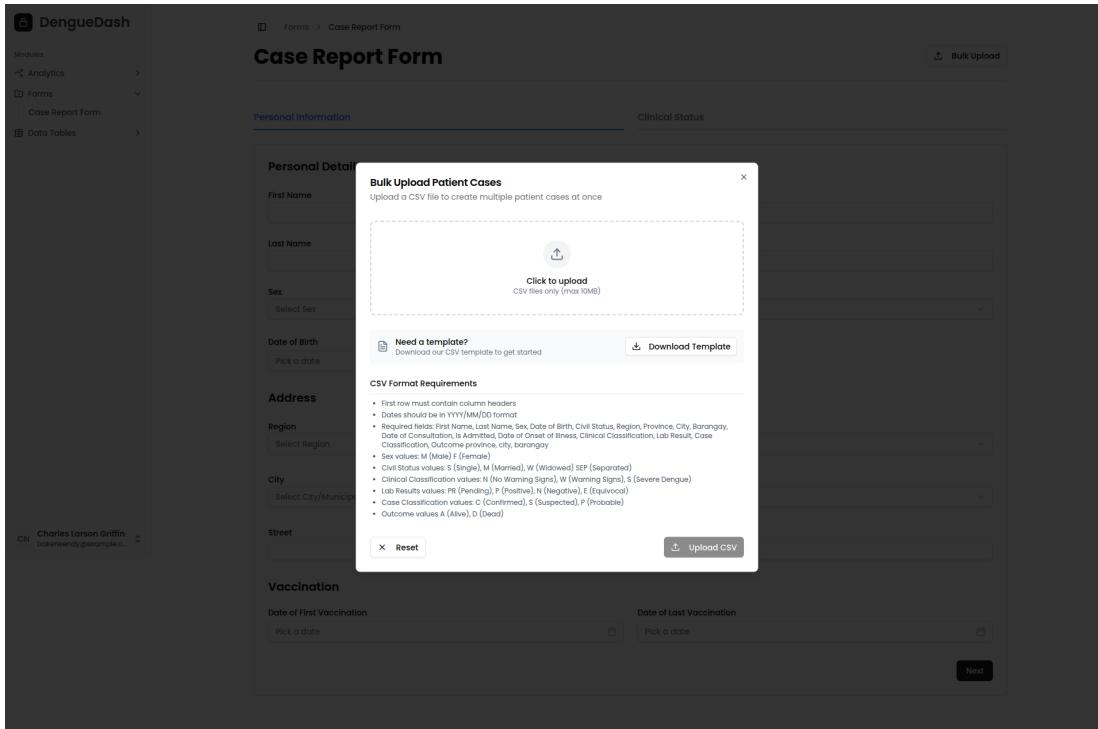


Figure 4.16: Bulk Upload of Cases using CSV

1077 Browsing, Update, and Deletion of Records

1078 Once the data generated from the case report form or the bulk upload is vali-
1079 dated, it will be assigned as a new case and can be accessed through the Dengue
1080 Reports page, as shown in Figure 4.17. The said page displays basic information
1081 about the patient related to a specific case, including their name, address, date
1082 of consultation, and clinical and case classifications. It is also worth noting that
1083 it only shows cases that the user is permitted to view. For example, in a local
1084 Disease Reporting Unit (DRU) setting, the user can only access records that be-
1085 long to the same DRU. Additionally, users can search for cases by name, location,
1086 date of consultation, or classifications associated with the specific query, making

1087 it easier to find pertinent information quickly and efficiently. On the other hand,
 1088 in a consolidated surveillance unit such as a regional, provincial, or city quarter,
 1089 its users can view all the records from all the DRUs that report to them. Moving
 1090 forward, Figure 4.18 shows the detailed case report of the patient on a particular
 1091 consultation date.

Case ID	Name	Barangay	City	Date Consulted	Clinical Classification	Case Classification	Action
25017062	Corey, Cassie Jonathan	Magsaysay	ILOILO CITY (Capital)	2024-12-28	With warning signs	Confirmed	<button>Open</button>
25017082	Kirk, Dominique Jacqueline	Rizal Palapala II	ILOILO CITY (Capital)	2024-12-28	Severe dengue	Confirmed	<button>Open</button>
25017067	Henderson, Joel Lindsey	Santa Rosa	ILOILO CITY (Capital)	2024-12-27	Severe dengue	Confirmed	<button>Open</button>
25017077	H Flynn, Christina Shannon	Tabuc Suba (Jaro)	ILOILO CITY (Capital)	2024-12-27	Severe dengue	Confirmed	<button>Open</button>
25017070	Green, Monique Mark	West Habog-habog	ILOILO CITY (Capital)	2024-12-26	With warning signs	Confirmed	<button>Open</button>
25017061	Thomas, Lisa Jared	San Pedro (Molo)	ILOILO CITY (Capital)	2024-12-24	With warning signs	Confirmed	<button>Open</button>
25017079	Esparza, Nicole Stephanie	Tabucan	ILOILO CITY (Capital)	2024-12-24	Severe dengue	Confirmed	<button>Open</button>
25017069	James, Emily Sara	Libertad, Santa Isabel	ILOILO CITY (Capital)	2024-12-23	With warning signs	Confirmed	<button>Open</button>

Figure 4.17: Dengue Reports

The screenshot shows a web-based application interface for 'DengueDash'. On the left, a sidebar lists 'Modules' such as Analytics, Forms, Data Tables, and the current 'Dengue Reports'. A user profile 'Charles Larson Griffin' is shown at the bottom of the sidebar. The main content area is titled 'Data Tables > Dengue Reports' and displays a 'Personal Information' section with fields for Full Name (Doe, John David), Date of Birth (April 29, 2025), Sex (Male), and Civil Status (Married). It also shows a 'Vaccination Status' section with First Dose (May 7, 2025) and Last Dose (May 13, 2025). Below these is a 'Case Record #25016448' section with fields for Date of Consultation (April 30, 2025), Patient Admitted? (No), Date Onset of Illness (April 29, 2025), and Clinical Classification (With warning signs). The 'Laboratory Results' section lists pending results for NS1, IgG Elisa, IgM Elisa, and PCR. The 'Outcome' section shows Case Classification (Probable) and Outcome (Dead). Finally, the 'Interviewer' section lists the interviewer as Griffin, Charles Larson, with DRU Saint Paul's Hospital.

Personal Information	
Full Name	Doe, John David
Date of Birth	April 29, 2025
Sex	Male
Civil Status	Married
Full Address	1231 Ice Ice Baby, Bulak Sur, BATAD, ILOILO

Vaccination Status	
First Dose	May 7, 2025
Last Dose	May 13, 2025

Case Record #25016448	
Date of Consultation	April 30, 2025
Patient Admitted?	No
Date Onset of Illness	April 29, 2025
Clinical Classification	With warning signs

Laboratory Results	
NS1	Date Done N/A
IgG Elisa	Date Done N/A
IgM Elisa	Date Done N/A
PCR	Date Done N/A

Outcome	
Case Classification	Outcome
Probable	Dead
Date of Death	
May 13, 2025	

Interviewer	
Interviewer	DRU
Griffin, Charles Larson	Saint Paul's Hospital

Figure 4.18: Detailed Case Report

1092 To update the case, the user can click the "Update Case" button, where a
 1093 dialog will appear, and the updateable fields will be shown. It is worth noting
 1094 that in this case, only fields under Laboratory Results and Outcome are included
 1095 since they are the only ones that are time-based, where the result may change
 1096 in the future. After updating, a prompt will show confirming the user's action.
 1097 Moving forward, to delete a case record, the user must click the "Delete Case"
 1098 button, and a prompt verifying the action will appear. After confirming, the case

1099 will be deleted permanently.

The screenshot shows the DengueDash application interface. On the left, there's a sidebar with 'Modules' listed: Analytics, Forms, Data Tables, and Dengue Reports. The 'Dengue Reports' section is expanded, showing a list of cases. One case, 'Case Record #25016548', is selected and shown in a modal dialog. The dialog has tabs for 'Personal Information', 'Vaccination Status', 'Case Record', 'Laboratory Results', 'Outcome', and 'Interviewer'. The 'Laboratory Results' tab is active, displaying results for NS1, IgG Elisa, IgM Elisa, and PCR. The 'Outcome' tab shows the case is 'Confirmed' and 'Alive'. The 'Interviewer' tab shows 'Griffin, Charles Larson' as the interviewer at 'Saint Paul's Hospital'. At the bottom of the dialog, there are 'Cancel' and 'Save Changes' buttons.

Figure 4.19: Update Report Dialog

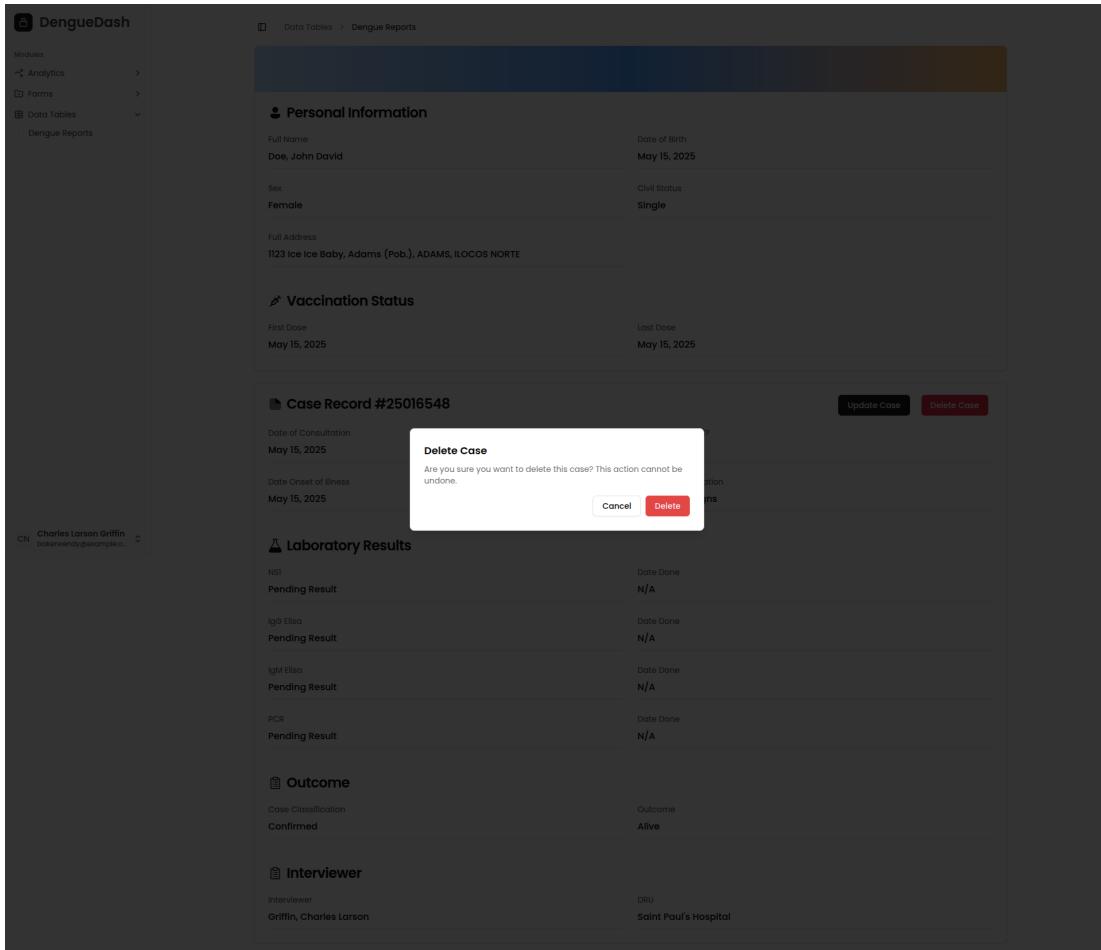


Figure 4.20: Delete Report Alert Dialog

1100 Forecasting

- 1101 The pièce de résistance of the web application's features is the Forecasting Page.
- 1102 This is where users can forecast dengue cases for the next few weeks. To predict,
- 1103 the application utilizes the exported LSTM model in a Keras format derived from
- 1104 training the consolidated data from the database. The said file stores the model's
- 1105 architecture and the learned parameters, which include the weights and biases
- 1106 to predict cases without training the data again. Furthermore, it requires the

recent weekly dengue cases and weather variable data (temperature, humidity, and rainfall) to form a sequence based on the window size, and the forecasted weather data via OpenWeatherAPI. Due to the limitations posed to the current subscribed student plan in the said API, only two weeks of forecasted weather data can be fetched. As a result, the web application can predict dengue cases for the next two following weeks. Moving forward, the Forecasting page, as shown in Figure 4.21, introduces a user-friendly interface that shows the current cases for the week and the predictions for the next two weeks with a range of 90 percent to 110 percent confidence interval that is presented in a simple but organized manner. There is also a line chart that shows the number of cases from the last 5 weeks plus the forecasted weekly cases. In addition, the current weather data for a specific week is also shown, as well as the forecasted weather data fetched from the said API. Lastly, locations where dengue cases have been reported for the current week are listed in the Location Risk Assessment component.

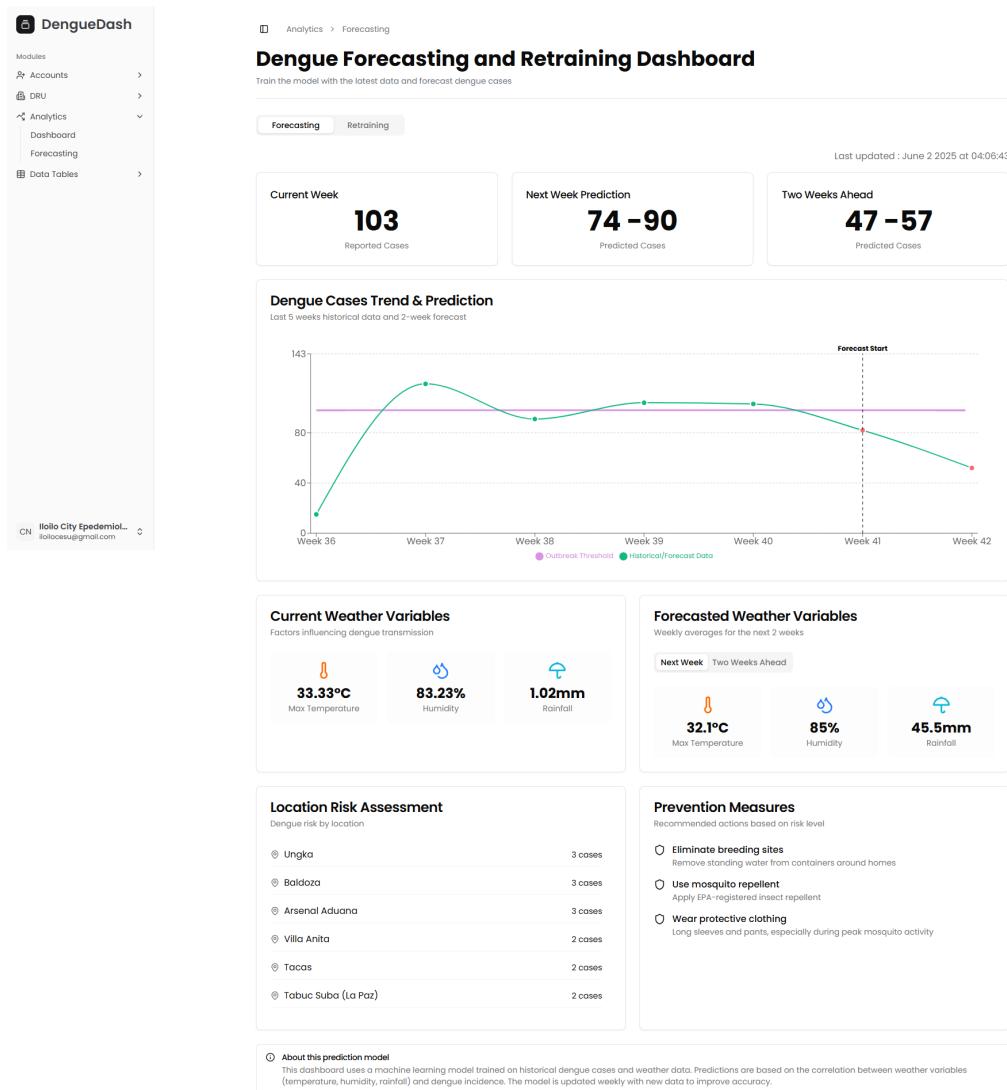


Figure 4.21: Forecasting Page

1121 4.6.4 Admin Interface

1122 Retraining

1123 With LSTM being the best-performing model among the models used in forecast-
1124 ing dengue cases, it is the model chosen to power the prediction and retraining
1125 of the consolidated data within the web application. Since the retraining process
1126 consumes a lot of processing power and requires a more advanced understanding
1127 of how it works, it was decided that the said feature should only be available to
1128 admin users of surveillance units. Furthermore, the retraining component in the
1129 Forecasting page includes three additional components that include the configura-
1130 tion of LSTM parameters (Figure 4.22), the actual retraining of the consolidated
1131 data from the database (Figure 4.23), and the results of the retraining that shows
1132 the current and previous model metrics depending on the parameters entered
1133 (Figure 4.24). It is also worth noting that when training, the model used a seeded
1134 number to promote reproducibility.

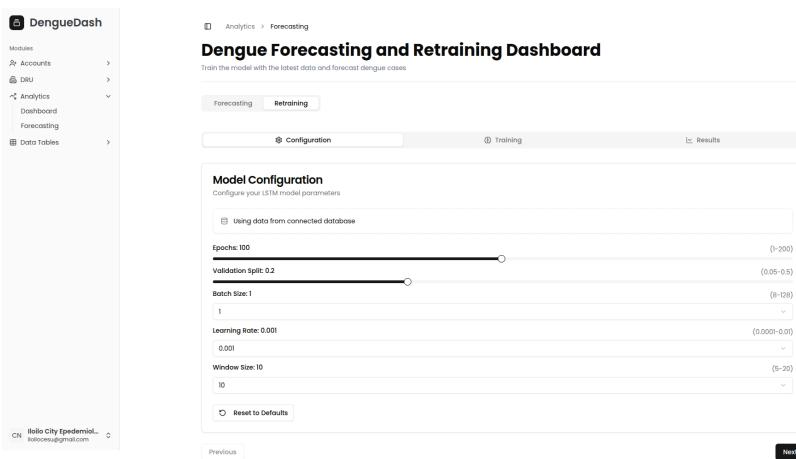


Figure 4.22: Retraining Configurations

4.6. SYSTEM PROTOTYPE

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The screenshot shows the Dengue Forecasting and Retraining Dashboard. The left sidebar lists modules: Accounts, DRU, Analytics (Dashboard, Forecasting), and Data Tables. The main header is "Dengue Forecasting and Retraining Dashboard". Below it, a sub-header says "Train the model with the latest data and forecast dengue cases". A navigation bar at the top has tabs: Forecasting (selected), Retraining, Configuration, Training (selected), and Results. A large central box is titled "Training Status" with the sub-section "Ready to Train". It contains the text: "Start the training process when you're ready. The model will be trained with the configuration parameters you've set." Below this is a "Start Training" button. Navigation buttons "Previous" and "Next" are at the bottom. A user profile at the bottom left shows "ilolo City Epidemiol..." and "ilolocesu@gmail.com".

Figure 4.23: Start Retraining

The screenshot shows the same dashboard as Figure 4.23, but the "Results" tab is selected in the navigation bar. The main content area is titled "Model Results" with the sub-section "View the model's performance metrics and charts". It features two tables: "Current Model Metrics" and "Previous Model Metrics".

Current Model Metrics		Previous Model Metrics	
MSE:	268.308	MSE:	302.741
RMSE:	16.319	RMSE:	17.399
MAE:	9.526	MAE:	10.620
R ² :	0.843	R ² :	0.822

Navigation buttons "Previous" and "Next" are at the bottom. A user profile at the bottom left shows "ilolo City Epidemiol..." and "ilolocesu@gmail.com".

Figure 4.24: Retraining Results

1135 **Managing Accounts**

1136 Proper management of accounts is important to protect the integrity and confidentiality of data. Thus, it is crucial for administrators to track their users and control the flow of information. As discussed in the user registration of encoders, 1139 admin users from a specific DRU or surveillance unit have the power to grant 1140 them access to the web application. Figure 4.26 illustrates the interface for this 1141 scenario, as the admins can approve or reject their applications. Once approved, 1142 these users can access the features given to encoders and may be promoted to 1143 have administrative access, as shown in Figure 4.27. Both Figure 4.26 and 4.27 1144 also show the expanded details of the user, which include personal information, 1145 proof of identification, and brief activity details within the system. When deleting 1146 an account, the user's email will be blacklisted and illegible to use when creating 1147 another account, and all the cases reported by this user will be soft-deleted. How- 1148 ever, the blacklist status can be reverted by clicking the "Unban" button, which 1149 would make the user of the email able to register to the web application again as 1150 shown in Figure 4.28.

Name	Email	Role	Sex	Actions
Daniel Santiago Brandt	Brandon02@example.org	Encoder	Female	<button>Open</button>

Figure 4.25: List of Verified Accounts

User Approval

View and manage pending accounts

John David Doe
Encoder

SEX
Male

EMAIL
bakerwendy@gmail.com

HOSPITAL (DRU)
Saint Paul's Hospital

CREATED AT
June 1 2025 at 17:28:48

UPDATED AT
June 1 2025 at 17:28:48

LAST LOGIN
N/A

Approve **Delete**

Figure 4.26: Encoder Approval Page

User Profile

View and manage user details

John David Doe
Encoder

SEX
Male

EMAIL
poliver@example.net

HOSPITAL (DRU)
Saint Paul's Hospital

CREATED AT
June 1 2025 at 12:25:44

UPDATED AT
June 1 2025 at 16:31:58

LAST LOGIN
N/A

Promote to Admin **Delete User**

Figure 4.27: Account Management

Email	Date Added	Actions
testereee@example.gov.ph	2025-05-15	<button>Unban</button>

Figure 4.28: List of Blacklisted Accounts

1151 Managing DRUs

1152 Unlike the registration of encoder accounts, the creation of Disease Reporting
 1153 Units can only be done within the web application, and the user performing the
 1154 creation must be an administrator of a surveillance unit. Figure 4.29 presents the
 1155 fields the admin user must fill out, and once completed, the new entry will show
 1156 as being managed by that unit, as shown in Figure 4.30. Figure 4.31, on the other
 1157 hand, shows the details provided in the registration form as well as its creation
 1158 details. There is also an option to delete the DRU, and when invoked, all the
 1159 accounts being managed by it, and the cases reported under those accounts will
 1160 be soft-deleted.

Register Disease Reporting Unit

Add a new Disease Reporting Unit to the surveillance system.

Name Enter DRU name The official name of the Disease Reporting Unit.	Province Select Province
Region Select Region	Barangay Select Barangay
City/Municipality Select City/Municipality	Street Address House/Building No., Street Name
Email example@health.gov	Contact Number +63 912 345 6789
DRU Type Select DRU type The category that best describes this reporting unit.	

Register DRU

Figure 4.29: Disease Reporting Unit Registration

Manage Disease Reporting Units

View and manage Disease Reporting Units

DRU Name	Email	Action
Molo District Health Center	molodistricthealth@gmail.com	Open
Jaro Health Center	jarohealth@gmail.com	Open
Saint Paul's Hospital	saintpaul@gmail.com	Open

Figure 4.30: List of Disease Reporting Units

The screenshot shows the DengueDash application interface. On the left is a sidebar with navigation links: Accounts, DRU (selected), Analytics, and Data Tables. The main content area is titled "Disease Reporting Unit Profile" and shows the following details:

Name of DRU	Molo District Health Center	Email	moldistrictthealth@gmail.com
Address	M.H. Del Pilar Street, Molo, Molo, ILOILO CITY (Capital), ILOILO	Contact Number	09123456782
Region	Region VI (Western Visayas)	Surveillance Unit	Iloilo CESU
DRU Type	CHO/MHO/PHO		
Created At	May 5 2025 at 04:47:11	Updated At	May 5 2025 at 04:47:11

At the bottom right of the main content area is a red button labeled "Delete DRU". In the bottom left corner of the entire window, there is a user profile placeholder with the text "ilolo City Epidemiol..." and "iloloceus@gmail.com".

Figure 4.31: Disease Reporting Unit details

¹¹⁶¹ 4.7 User Testing

¹¹⁶² To evaluate the usability of the system, the System Usability Scale (SUS) was
¹¹⁶³ utilized. SUS is a Likert-scale-based questionnaire comprising 10 items that are
¹¹⁶⁴ critical to assessing system usability. A total of five participants completed the sur-
¹¹⁶⁵vey. Their responses were processed following the step-by-step calculation method
¹¹⁶⁶ adopted from (Babich, n.d.). The resulting usability scores for each participant
¹¹⁶⁷ are shown in Table 4.9.

¹¹⁶⁸ The average System Usability Scale (SUS) score across systems is typically
¹¹⁶⁹ 68 (Babich, n.d.). In this testing, the system achieved an average SUS score
¹¹⁷⁰ of 88.5, indicating a highly positive user experience. This score suggests that
¹¹⁷¹ participants found the system not only enjoyable to use but also intuitive enough

Participant	Usability Score
1	95.0
2	90.0
3	85.0
4	87.5
5	85.0
Average	88.5

Table 4.9: Computed System Usability Scores per Participant

₁₁₇₂ to recommend to others. Furthermore, it demonstrates that the system is suitable
₁₁₇₃ for real-world applications without presenting significant complexity for first-time
₁₁₇₄ users.

¹¹⁷⁵ Chapter 5

¹¹⁷⁶ Conclusion

¹¹⁷⁷ The development of DengueWatch marks a transformative leap forward in public
¹¹⁷⁸ health technology, providing Iloilo City with a centralized system to combat one
¹¹⁷⁹ of the most persistent mosquito-borne diseases. Previously, data was recorded
¹¹⁸⁰ manually on paper, making tracking and analysis slow and error-prone. Dengue-
¹¹⁸¹ Watch digitizes this process, enabling faster, more accurate monitoring. More
¹¹⁸² than an academic project, DengueWatch serves as a practical solution aimed at
¹¹⁸³ shifting the approach from reactive outbreak response to proactive prevention. By
¹¹⁸⁴ combining deep learning models with real-time climate data integration, the sys-
¹¹⁸⁵ tem achieves a level of accuracy and usability that makes it viable for real-world
¹¹⁸⁶ deployment.

¹¹⁸⁷ At the heart of DengueWatch is a Long Short-Term Memory (LSTM) neural
¹¹⁸⁸ network, which outperformed traditional forecasting models such as ARIMA and
¹¹⁸⁹ Kalman Filter. The LSTM model achieved a Root Mean Square Error (RMSE) of
¹¹⁹⁰ 20.15, followed by the hybrid KF-LSTM model with an RMSE of 25.56, demon-

strating a substantial improvement in predictive capability. Consequently, the LSTM model was selected for integration into the DengueWatch system. Re-training the model monthly strikes a balance between maintaining accuracy and managing computational costs. It allows the model to incorporate new trends from the latest four weeks of data and aligns with the typical monthly data release schedule of provincial health offices.

Usability testing further underscored DengueWatch's readiness for real-world deployment. The system achieved an average System Usability Scale (SUS) score of 88.5, significantly above the industry benchmark of 68. This indicates that users found the system intuitive, efficient, and suitable for operational use in public health contexts. Key features such as a user-friendly dashboard and a two-week forecasting window ensure that the system supports timely, effective responses.

Beyond its immediate application in Iloilo City, the framework behind DengueWatch holds the potential for broader impact. With minor adaptations, it can be scaled nationally through integration with Department of Health surveillance systems.

₁₂₀₈

Chapter 6

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1289 **Appendix A**

1290 **Data Collection Snippets**

Time	Rainfall	MaxTemperature	AverageTemperature	MinTemperature	Wind	Humidity	Cases
2011-w1	9.938571429	29.4444	25.88889	23.8889	11.39	86.24285714	5
2011-w2	8.587142857	30	26.70555556	24.44444444	7.32	88.02857143	4
2011-w3	5.338571429	30	26.61666667	25	7.55	84.02857143	2
2011-w4	5.41	30.55555556	26.48333333	20.55555556	10.67	80.97142857	7
2011-w5	2.914285714	28.33333333	25.28333333	18.65	11.01	74.88571429	2
2011-w6	3.44	31.11111111	27.53333333	25	3.69	85.27142857	5
2011-w7	1.444285714	30	27.06111111	25	6.69	82.1	6
2011-w8	0.7685714286	30.55555556	27.03333333	25	7.82	76.18571429	2
2011-w9	4.064285714	30.55555556	26.75	24.44444444	6.64	84.1	5
2011-w10	1.252857143	31.11111111	27.7	25.55555556	7.92	80.18571429	4
2011-w11	7.068571429	28.33333333	26.03888889	23.88888889	10.35	85.7	2
2011-w12	3.567142857	30.55555556	26.4	24.44444444	9.57	87.74285714	3
2011-w13	2.745714286	30	26.61666667	25	10.05	86.25714286	2
2011-w14	0.09285714286	30	27.44444444	25	8.25	76.32857143	4
2011-w15	1.008571429	31.11111111	26.89444444	22.77777778	7.93	80.64285714	5
2011-w16	0.8771428571	31.66666667	28.43333333	24.44444444	4.76	80.35714286	3
2011-w17	2.15	32.77777778	28.87222222	25.55555556	5.54	81.77142857	5
2011-w18	3.062857143	32.77777778	28.62777778	25	5.15	81.9	4
2011-w19	9.828571429	32.77777778	27.97222222	25	4.18	85.77142857	5
2011-w20	2.848571429	33.33333333	29.71111111	25.55555556	3.77	79.65714286	3
2011-w21	11.74142857	32.77777778	28.51111111	25	4.28	81.81428571	3
2011-w22	14.52857143	32.77777778	28.47222222	25.55555556	4.04	82.45714286	4
2011-w23	11.51714286	32.22222222	28.26111111	24.44444444	3.91	84.24285714	9
2011-w24	8.784285714	32.22222222	27.71111111	24.44444444	3.87	84.7	3
2011-w25	10.43714286	32.77777778	27.47777778	24.44444444	4.46	86.52857143	13
2011-w26	6.702857143	32.22222222	28.39444444	25	3.94	81.87142857	7
2011-w27	14.48	32.22222222	27.66666667	25	4.19	85.42857143	13
2011-w28	3.32	32.22222222	27.49444444	19.68333333	6.69	80.78571429	9
2011-w29	17.33714286	32.77777778	27.95555556	25	3.57	80.05714286	10
2011-w30	22.77	31.66666667	26.63888889	24.44444444	5.13	88.01428571	16
2011-w31	9.875714286	32.77777778	27.81111111	25	4.66	83.11428571	13

Figure A.1: Snippet of Consolidated Data

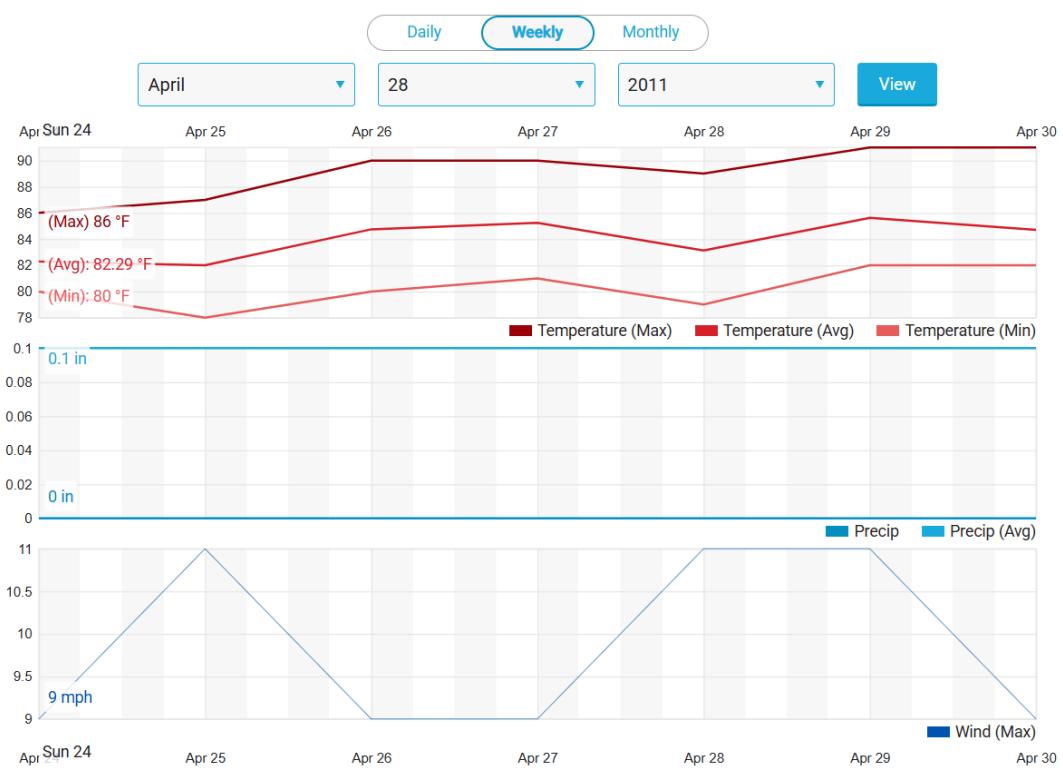


Figure A.2: Snippet of Weather Data Collection

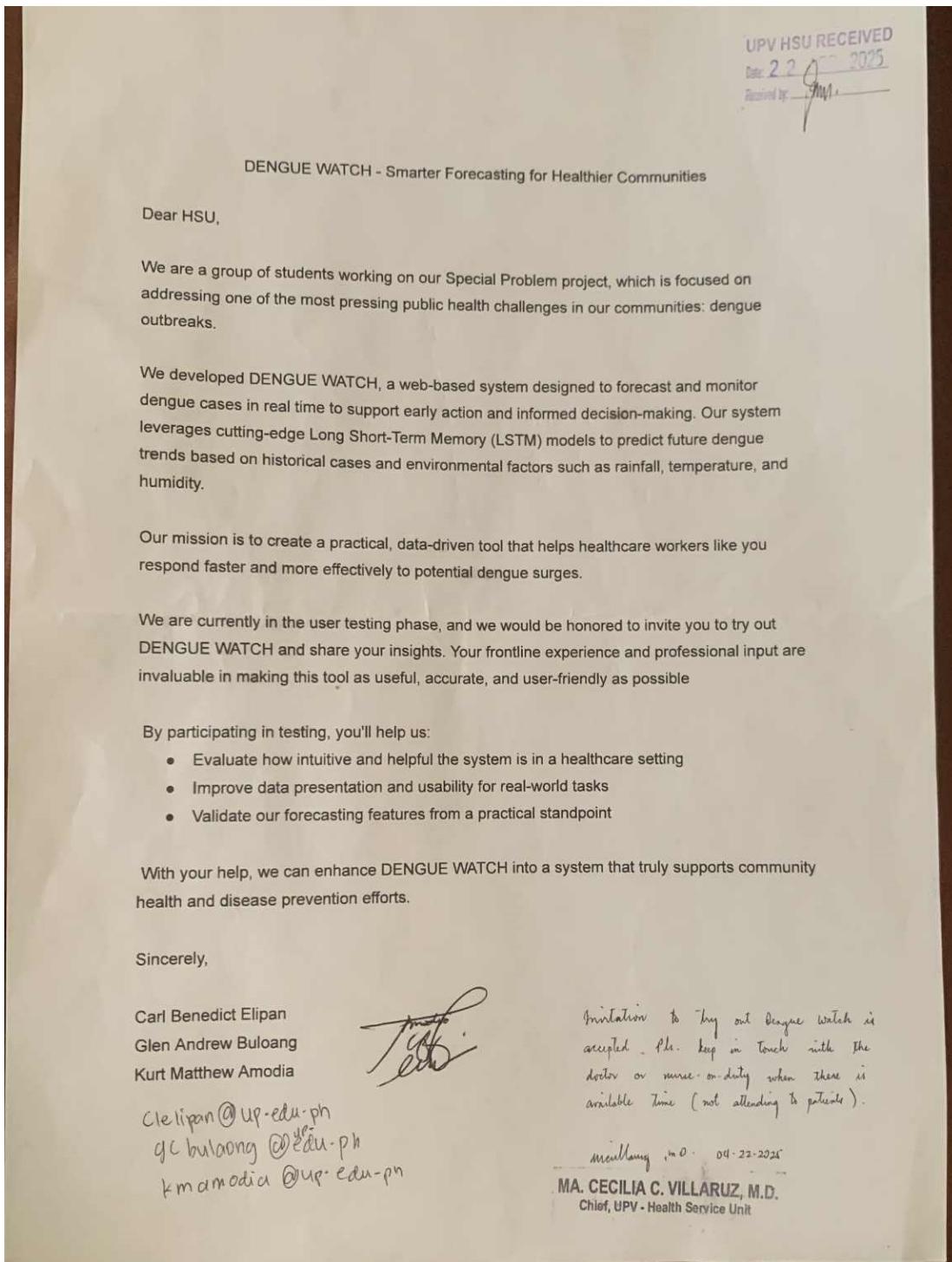


Figure A.3: Letter of Approval for User Testing in UPV HSU

Please enter your participant number: 2

System Usability Scale (SUS)

This is a standard questionnaire that measures the overall usability of a system. Please select the answer that best expresses how you feel about each statement after using the system today.

	Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
1. I think I would like to use DengueWatch frequently to monitor and forecast dengue cases.	<input type="checkbox"/>				
2. I found DengueWatch unnecessarily complex when entering or analyzing data.	<input type="checkbox"/>				
3. I thought DengueWatch was easy to use, even for someone unfamiliar with AI forecasting tools.	<input type="checkbox"/>				
4. I think I would need the support of an IT or technical person to use all the features of DengueWatch.	<input type="checkbox"/>				
5. I found the visualizations (charts, maps, graphs) in DengueWatch to be well-integrated and informative.	<input type="checkbox"/>				
6. I thought there was too much inconsistency in how different parts of the DengueWatch system behaved.	<input type="checkbox"/>				
7. I believe most public health workers would learn to use DengueWatch very quickly.	<input type="checkbox"/>				
8. I found DengueWatch very cumbersome to use when entering weekly case reports or viewing forecasts.	<input type="checkbox"/>				
9. I felt confident in using DengueWatch to get the information I needed for decision-making.	<input type="checkbox"/>				
10. I needed to learn a lot of things before I could get going with DengueWatch.	<input type="checkbox"/>				

How likely are you to recommend this website to others? (please circle your answer)

Not at all likely 0 1 2 3 4 5 6 7 8 9 10 Extremely likely

Please provide important comments about the website:

Figure A.4: System Usability Score Questionnaire