

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

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23

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

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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.

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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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55 search.

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65 perseverance, and determination to complete this research.

Abstract

67 Dengue fever remains a significant public health concern in the Philippines, with
68 cases rising dramatically in recent years. Nationwide outbreaks have placed immense
69 strain on healthcare systems, underscoring the need for innovative approaches to surveil-
70 lance and response. In Iloilo City, this national trend was reflected in a significant surge,
71 with the Iloilo Provincial Health Office reporting 4,585 cases and 10 fatalities as of Au-
72 gust 10, 2023, a 319% increase from the previous year's 1,095 cases and one death. This
73 rise overwhelmed local healthcare systems, with over 76% of non-COVID-19 hospital
74 beds occupied by dengue patients. The absence of a reliable system to monitor and fore-
75 cast dengue outbreaks contributed to delayed interventions, exacerbating public health
76 risks and the burden on medical resources. To address this gap, this study developed a
77 centralized system for monitoring and modernizing data management of dengue cases
78 in public health institutions, making it more efficient and modern. Using data gathered
79 from the Iloilo Provincial Health Office and online sources, several deep learning mod-
80 els were trained to predict dengue cases, utilizing weather variables and historical case
81 data as inputs. These models included Long Short-Term Memory (LSTM), ARIMA,
82 Seasonal ARIMA, Kalman Filter (KF), and a hybrid KF-LSTM model. The models un-
83 derwent time series cross-validation strategies to mimic real-world conditions as closely
84 as possible and were evaluated using metrics such as Mean Squared Error (MSE), Root
85 Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The LSTM model
86 demonstrated the best performance with the lowest RMSE of 16.90, followed by the
87 hybrid KF-LSTM model at 25.56. The LSTM model was then integrated into the sys-
88 tem to provide forecasting features that could support health institutions by offering
89 actionable insights for proactive intervention strategies.

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

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¹⁹⁸ **Chapter 1**

¹⁹⁹ **Introduction**

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

²⁰¹ Dengue cases surged globally in 2023 and continued to rise in 2025, with over
²⁰² five million cases and more than 5,000 deaths across 80 countries (Bosano, 2023).
²⁰³ The World Health Organization reported a ten-fold increase in cases from 2000
²⁰⁴ to 2019, peaking in 2019 with the disease affecting 129 countries (WHO, 2024).
²⁰⁵ In the Philippines, dengue remains endemic, leading to prolonged and widespread
²⁰⁶ outbreaks.

²⁰⁷ In Iloilo, dengue cases escalated dramatically. By August 2023, the provincial
²⁰⁸ health office reported 4,585 cases and 10 deaths, marking a 319% increase from
²⁰⁹ the previous year (Perla, 2024). Iloilo has reached the outbreak threshold, and
²¹⁰ local authorities are on blue alert. In Iloilo City, 649 cases were recorded in 2024,
²¹¹ with two deaths. Hospital capacity is strained, with non-COVID-19 hospital bed

212 occupancy exceeding 76%. This highlights the increasing pressure on healthcare
213 resources in the region.

214 In recent years, technology has played a growing role in improving disease
215 surveillance across the globe. Internationally, A study published in Frontiers
216 in Physics utilized the Kalman filter to predict COVID-19 deaths in Ceará, a,
217 Brazil(Ahmadi et al., 2021). A study also suggests that weather-based fore-
218 casting models using variables like mean temperature and cumulative rainfall can
219 provide early warnings of dengue outbreaks with high sensitivity and specificity,
220 enabling predictions up to 16 weeks in advance (Hii, Zhu, Ng, Ng, & Rocklöv,
221 2012). Locally, in Davao City, Ligue (2022) found that deep learning models can
222 accurately predict dengue outbreaks by capturing complex, time-dependent pat-
223 terns in environmental data. The study of Carvajal et. al. uses machine learning
224 methods to reveal the temporal pattern of dengue cases in Metropolitan Manila
225 and emphasizes the significance of relative humidity as a key meteorological fac-
226 tor, alongside rainfall and temperature, in influencing this pattern (Carvajal et
227 al., 2018).

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

²³⁵ **1.2 Problem Statement**

²³⁶ Dengue remains a critical public health challenge worldwide, with cases increasing
²³⁷ due to the easing of COVID-19 restrictions and heightened global mobility. While
²³⁸ a temporary decline in cases was observed during the pandemic (2020–2022) due
²³⁹ to reduced surveillance efforts, 2023 marked a resurgence, with over five million
²⁴⁰ cases and more than 5,000 deaths reported across 80 countries (Bosano, 2023).
²⁴¹ In Iloilo City and Province, dengue cases rose by 319% as of August 2023, over-
²⁴² whelming local healthcare systems. This surge strained resources, with over 76%
²⁴³ of non-COVID-19 hospital beds occupied by dengue patients (Perla, 2024), high-
²⁴⁴ lighting the urgent need for effective monitoring and predictive tools. Despite
²⁴⁵ all these studies, there remains a significant gap in the development of publicly
²⁴⁶ accessible systems that apply these predictive models in real-world settings. Most
²⁴⁷ existing studies remain confined to academic or theoretical contexts, with little
²⁴⁸ translation into practical tools for local communities and public health authorities.
²⁴⁹ In particular, there is a lack of research focused specifically on dengue prediction
²⁵⁰ and surveillance in Iloilo. While deep learning models have shown high accuracy
²⁵¹ in other regions, their application in the local context of Iloilo is minimal. The
²⁵² lack of a reliable system to monitor and forecast dengue outbreaks contributes to
²⁵³ delayed interventions, exacerbating public health risks and healthcare burdens in
²⁵⁴ the region.

²⁵⁵ **1.3 Research Objectives**

²⁵⁶ **1.3.1 General Objective**

²⁵⁷ This study aims to develop a centralized monitoring and analytics system for
²⁵⁸ dengue cases in Iloilo City and Province with data management and forecasting
²⁵⁹ capabilities. The researchers will train and compare multiple deep learning models
²⁶⁰ to predict dengue case trends based on climate data and historical dengue cases
²⁶¹ to help public health officials in possible dengue case outbreaks.

²⁶² **1.3.2 Specific Objectives**

²⁶³ Specifically, this study aims to:

- ²⁶⁴ 1. Gather dengue data from the Iloilo Provincial Health Office and climate data
²⁶⁵ (including temperature, rainfall, wind, and humidity) from online sources,
²⁶⁶ and combine and aggregate these into a unified dataset to facilitate compre-
²⁶⁷ hensive dengue case forecasting;
- ²⁶⁸ 2. Train and evaluate deep learning models for predicting dengue cases using
²⁶⁹ metrics such as Mean Absolute Error (MAE), Root Mean Squared Error
²⁷⁰ (RMSE), and Mean Squared Error (MSE), and determine the most accurate
²⁷¹ forecasting approach; and
- ²⁷² 3. Develop a web-based analytics dashboard that integrates the predictive
²⁷³ model, provides a data management system for dengue cases in Iloilo City

274 and the Province, and assess its usability and effectiveness through struc-
275 tured feedback from health professionals and policymakers.

276 1.4 Scope and Limitations of the Research

277 This study aims to gather dengue data from the Iloilo Provincial Health Office
278 and climate data from online sources such as PAGASA or weatherandclimate.com.

279 These data will be preprocessed, cleaned, and combined into a unified dataset to
280 facilitate comprehensive dengue case forecasting. However, the study is limited by
281 the availability and completeness of historical data. Inconsistent or missing data
282 points may introduce biases and reduce the quality of predictions. Furthermore,
283 the granularity of the data will be in a weekly format.

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

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

²⁹⁶ identify risk areas. However, its usability depends on feedback from stakeholders,
²⁹⁷ which may vary based on their familiarity with analytics tools. Moreover, exter-
²⁹⁸ nal factors such as limited internet connectivity or device availability in remote
²⁹⁹ areas may affect the system's adoption and effectiveness. While the dashboard
³⁰⁰ provides valuable insights, it cannot incorporate all factors influencing dengue
³⁰¹ transmission, emphasizing the need for ongoing validation and refinement.

³⁰² 1.5 Significance of the Research

³⁰³ This study's development of an AI-based dengue forecasting and monitoring sys-
³⁰⁴ tem has wide-reaching significance for various stakeholders in Iloilo City:

- ³⁰⁵ • Public Health Agencies: Organizations like the Department of Health (DOH)
³⁰⁶ and local health units in Iloilo City and Province stand to benefit greatly
³⁰⁷ from the system. With dengue predictions, we can help these agencies opti-
³⁰⁸ mize their response strategies and implement targeted prevention measures
³⁰⁹ in high-risk areas before cases escalate.
- ³¹⁰ • Local Government Units (LGUs): LGUs can use the system to support
³¹¹ their disaster management and health initiatives by proactively addressing
³¹² dengue outbreaks. The predictive insights allow for more efficient planning
³¹³ and resource deployment in barangays and communities most vulnerable to
³¹⁴ outbreaks, improving overall public health outcomes.
- ³¹⁵ • Healthcare Facilities: Hospitals and clinics, which currently face high bed
³¹⁶ occupancy rates during dengue season will benefit from early outbreak fore-

1.5. SIGNIFICANCE OF THE RESEARCH

7

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

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

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

³²⁹ Chapter 2

³³⁰ Review of Related Literature

³³¹ 2.1 Dengue

³³² Dengue disease is a tropical and subtropical mosquito-borne viral illness and is a
³³³ major health concern in the Philippines (Bravo, Roque, Brett, Dizon, & L'Azou,
³³⁴ 2014). The majority of individuals with dengue experience no symptoms. Fever is
³³⁵ the most common symptom, typically 4 to 7 days after being bitten by an infected
³³⁶ mosquito (Zhou & Malani, 2024). In recent years, the trend of dengue cases in
³³⁷ the Philippines has shown notable fluctuations, with periodic outbreaks occur-
³³⁸ ring every 3 to 5 years, often influenced by climatic and environmental changes.
³³⁹ According to the Department of Health (DOH), the number of reported cases
³⁴⁰ has steadily increased over the past decades, attributed to urbanization, popula-
³⁴¹ tion growth, and inadequate vector control measures (World Health Organization
³⁴² (WHO), 2018). Moreover, studies suggest that El Niño and La Niña events have
³⁴³ significant effects on dengue incidence, with warmer temperatures and increased

³⁴⁴ rainfall providing favorable breeding conditions for mosquitoes (Watts, Burke,
³⁴⁵ Harrison, Whitmire, & Nisalak, 2020). The study of Carvajal et. al. highlights
³⁴⁶ the temporal pattern of dengue cases in Metropolitan Manila and emphasizes the
³⁴⁷ significance of relative humidity as a key meteorological factor, alongside rainfall
³⁴⁸ and temperature, in influencing this pattern (Carvajal et al., 2018).

³⁴⁹ 2.2 Outbreak Definition

³⁵⁰ The definition of an outbreak is a critical factor in disease surveillance, as it
³⁵¹ determines the threshold at which an unusual increase in cases is considered a
³⁵² public health concern. Studies suggest that outbreak thresholds should be context-
³⁵³ specific, given the variability in transmission dynamics across different locations
³⁵⁴ (Runge-Ranzinger et al., 2016). Outbreak definitions defined using the Endemic
³⁵⁵ Channel often base thresholds on 2 standard deviations (SD) above the mean
³⁵⁶ number of historic dengue cases. Other studies (Hemisphere, 2015) also used an
³⁵⁷ alert threshold of a 5-year mean plus 2 standard deviations. A study by (Brady,
³⁵⁸ Smith, Scott, & Hay, 2015) discussed that definitions of dengue outbreaks differ
³⁵⁹ significantly across regions and time, making them inconsistent and incomparable.

³⁶⁰ From the studies above, this research implements an outbreak definition basing
³⁶¹ the threshold on 2 standard deviations (SD) above the mean number of historic
³⁶² dengue cases. It is important to note that for future outbreak definitions, addi-
³⁶³ tional local context like available hospital space etc., must be taken into account
³⁶⁴ for a more effective outbreak definition.

365 2.3 Existing System: RabDash DC

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

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

382 2.4 Deep Learning

383 The study of (Ligue & Ligue, 2022) highlights how data-driven models can help
384 predict dengue outbreaks. The authors compared traditional statistical meth-
385 ods, such as non-seasonal and seasonal autoregressive integrated moving average

386 (ARIMA), and traditional feed-forward network approach using a multilayer per-
387 ceptron (MLP) model with a deep learning approach using the long short-term
388 memory (LSTM) architecture in their prediction model. They found that the
389 LSTM model performs better in terms of accuracy. The LSTM model achieved a
390 much lower root mean square error (RMSE) compared to both MLP and ARIMA
391 models, proving its ability to capture complex patterns in time-series data (Ligue
392 & Ligue, 2022). This superior performance is attributed to LSTM's capacity
393 to capture complex, time-dependent relationships within the data, such as those
394 between temperature, rainfall, humidity, and mosquito populations, all of which
395 contribute to dengue incidence (Ligue & Ligue, 2022).

396 2.5 Kalman Filter

397 The Kalman Filter is another powerful tool for time-series forecasting that can be
398 integrated into our analysis. It provides a recursive solution to estimating the state
399 of a linear dynamic system from a series of noisy measurements. Its application
400 in epidemiological modeling can enhance prediction accuracy by accounting for
401 uncertainties in the data(Li et al., 2022). Studies have shown that Kalman filters
402 are effective in predicting infectious disease outbreaks by refining estimates based
403 on observed data. A study published in Frontiers in Physics utilized the Kalman
404 filter to predict COVID-19 deaths in Ceará, Brazil. They found that the Kalman
405 filter effectively tracked the progression of deaths and cases, providing critical in-
406 sights for public health decision-making (Ahmadini et al., 2021). Another research
407 article in PLOS ONE focused on tracking the effective reproduction number (R_t)
408 of COVID-19 using a Kalman filter. This method estimated the growth rate of

409 new infections from noisy data, demonstrating that the Kalman filter could main-
410 tain accurate estimates even when case reporting was inconsistent(Arroyo-Marioli,
411 Bullano, Kucinskas, & Rondón-Moreno, 2021).

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

415 2.6 Weather Data

416 The relationship between weather patterns and mosquito-borne diseases is inher-
417 ently nonlinear, meaning that fluctuations in disease cases do not respond propor-
418 tionally to changes in climate variables(Colón-González, Fezzi, Lake, & Hunter,
419 2013) Weather data, such as minimum temperature and accumulated rainfall, are
420 strongly linked to dengue case fluctuations, with effects observed after several
421 weeks due to mosquito breeding and virus incubation cycles. Integrating these
422 lagged weather effects into predictive models can improve early warning systems
423 for dengue control(Cheong, Burkart, Leitão, & Lakes, 2013). A study also sug-
424 gests that weather-based forecasting models using variables like mean temperature
425 and cumulative rainfall can provide early warnings of dengue outbreaks with high
426 sensitivity and specificity, enabling predictions up to 16 weeks in advance(Hii et
427 al., 2012).

428 This study utilizes weather data, including variables such as temperature,
429 rainfall, and humidity, as inputs for our dengue forecasting model. Given the
430 strong, nonlinear relationship between climate patterns and dengue incidence,

⁴³¹ these weather variables, along with their lagged effects, are essential for enhancing
⁴³² prediction accuracy and providing timely early warnings for dengue outbreaks.

⁴³³ 2.7 Chapter Summary

⁴³⁴ This chapter reviewed key literature relevant to our study, focusing on existing
⁴³⁵ systems, predictive modeling techniques and the role of weather data in forecast-
⁴³⁶ ing dengue outbreaks. We examined systems like RabDash DC, which integrates
⁴³⁷ predictive modeling with real-time data to inform public health decisions, provid-
⁴³⁸ ing a foundational structure for our Dengue Watch System. Additionally, deep
⁴³⁹ learning approaches, particularly Long Short-Term Memory (LSTM) networks,
⁴⁴⁰ were highlighted for their effectiveness in time-series forecasting, while alternative
⁴⁴¹ methods such as ARIMA and Kalman Filters were considered for their ability to
⁴⁴² model complex temporal patterns and handle noisy data.

⁴⁴³ The literature further underscores the significance of weather variables—such
⁴⁴⁴ as temperature and rainfall—in forecasting dengue cases. Studies demonstrate
⁴⁴⁵ that these variables contribute to accurate outbreak prediction models. Lever-
⁴⁴⁶ aging these insights, our study will incorporate both weather data and historical
⁴⁴⁷ dengue case counts to build a reliable forecasting model.

⁴⁴⁸ Chapter 3

⁴⁴⁹ Research Methodology

⁴⁵⁰ This chapter lists and discusses the specific steps and activities that were per-
⁴⁵¹ formed to accomplish the project. The discussion covers the activities from pre-
⁴⁵² proposal to Final SP Writing.

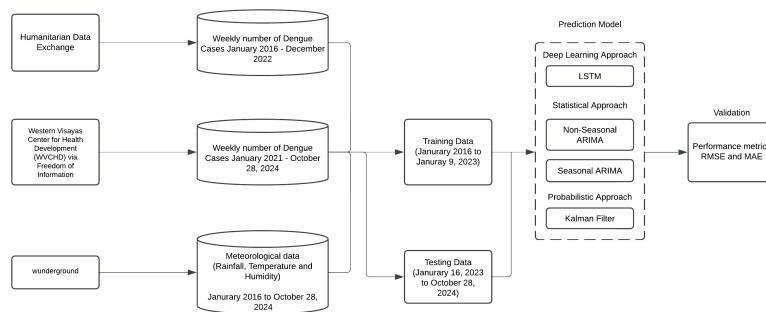


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

⁴⁵³ This summarizes the workflow for forecasting the number of weekly dengue
⁴⁵⁴ cases. This workflow focuses on using statistical, deep learning, and probabilistic
⁴⁵⁵ models to forecast the number of reported dengue cases. The approach involves
⁴⁵⁶ deploying several models for prediction, including ARIMA and Seasonal ARIMA

457 as statistical approaches, LSTM as a deep learning approach, and the Kalman
458 Filter as a probabilistic approach. These methods are compared with each other
459 to determine the most accurate model.

460 **3.1 Research Activities**

461 **3.1.1 Gather Dengue Data and Climate Data to Create a
462 Complete Dataset for Forecasting**

463 **Acquisition of Dengue Case Data**

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

473 Moreover, using a weekly interval provided more data points for training the
474 models compared to a monthly format. This is particularly critical in time series
475 modeling, where larger datasets help improve the robustness of the model and its
476 ability to generalize to new data. Also, the collection of weather data was done

477 by utilizing web scraping techniques to extract weekly weather data (e.g., rainfall,
478 temperature, and humidity) from Weather Underground (wunderground.com).

479

480 **Data Fields**

481 • **Time.** Represents the specific year and week corresponding to each entry
482 in the dataset.

483 • **Rainfall.** Denotes the observed average rainfall, measured in millimeters,
484 for a specific week.

485 • **Humidity.** Refers to the observed average relative humidity, expressed as
486 a percentage, for a specific week.

487 • **Max Temperature.** Represents the observed maximum temperature, mea-
488 sured in degrees Celsius, for a specific week.

489 • **Average Temperature.** Represents the observed average temperature,
490 measured in degrees Celsius, for a specific week.

491 • **Min Temperature.** Represents the observed minimum temperature, mea-
492 sured in degrees Celsius, for a specific week.

493 • **Wind.** Represents the observed wind speed, measured in miles per hour
494 (mph), for a specific week.

495 • **Cases.** Refers to the number of reported dengue cases during a specific
496 week.

497 Data Integration and Preprocessing

498 The dengue case data was integrated with the weather data to create a com
499 prehensive dataset, aligning the data based on corresponding timeframes. The
500 dataset undergoed a cleaning process to address any missing values, outliers, and
501 inconsistencies to ensure its accuracy and reliability. To ensure that all features
502 and the target variable were on the same scale, a MinMaxScaler was applied to
503 normalize both the input features (climate data) and the target variable (dengue
504 cases).

505 Exploratory Data Analysis (EDA)

- 506 • Analyzed trends, seasonality, and correlations between dengue cases and
507 weather factors.
- 508 • Created visualizations like time series plots and scatterplots to highlight
509 relationships and patterns in the data.

510 Outbreak Detection

511 To detect outbreaks, we computed the outbreak threshold value of dengue cases
512 using the formula,

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

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

514 **3.1.2 Develop and Evaluate Deep Learning Models for**
515 **Dengue Case Forecasting**

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

521 **Data Preprocessing**

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

528 **LSTM Model**

529 The dataset was split into training and test sets to evaluate the model's perfor-
530 mance and generalizability:

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

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

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

544 LSTM units:

- min value: 32
 - max value: 128
 - step: 16
 - sampling: linear

549 Learning Rate:

- min value: 0.0001
 - max value: 0.01
 - step: None
 - sampling: log

554 The tuner was instantiated with:

555 • **max trials = 10:** Limiting the search to 10 different configurations

556 • **executions per trial = 3:** Running each configuration thrice to reduce
557 variance

558 • **validation split = 0.2:** Reserving 20% of the training data for validation

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

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

575 After training, predictions on both the training and test datasets were rescaled
576 to their original scale using the inverse transformation of MinMaxScaler. Model

577 performance was evaluated using the mean squared error (MSE), root mean
578 squared error (RMSE) and mean absolute error (MAE).

579 **ARIMA**

580 The ARIMA model was utilized to forecast weekly dengue cases, leveraging histor-
581 ical weather data—including rainfall, maximum temperature, and humidity—as
582 exogenous variables alongside historical dengue case counts as the primary depen-
583 dent variable. The dataset was partitioned into training (80%) and testing (20%)
584 sets while maintaining temporal consistency.

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

- 587 • Autoregressive order (p): 0 to 3
588 • Differencing order (d): 0 to 2
589 • Moving average order (q): 0 to 3

590 Each combination of (p,d,q) was used to fit an ARIMA model, and perfor-
591 mance was evaluated based on the mean squared error (MSE) between the pre-
592 dicted and actual dengue cases on the test set. The parameter set that achieved
593 the lowest MSE was selected as the final model configuration.

594 Following model selection, the best-fit ARIMA model was retrained on the
595 training set and subsequently used to forecast dengue cases for the test period.
596 The predictions were assigned to the **PredictedCases** column in the test dataset.

597 Model performance was further assessed using key evaluation metrics, including
598 MSE, root mean squared error (RMSE), and mean absolute error (MAE). Visual
599 comparisons between actual and predicted dengue cases were produced through
600 line plots to better illustrate the model's forecasting accuracy.

601 Seasonal ARIMA (SARIMA)

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

620 **Kalman Filter:**

621 • Input Variables: The target variable (Cases) was modeled using three re-
622 gressors: rainfall, max temperature, and humidity.

623 • Training and Testing Split: The dataset was split into 80% training and
624 20% testing to evaluate model performance.

625 • Observation Matrix: The Kalman Filter requires an observation matrix,
626 which was constructed by adding an intercept (column of ones) to the re-
627 gressors.

628 The Kalman Filter's Expectation-Maximization (EM) method was employed
629 for training, iteratively estimating model parameters over 10 iterations. After
630 training, the smoothing method was used to compute the refined state estimates
631 across the training data. Observation matrices for the test data were constructed
632 in the same manner as for the training set, ensuring compatibility with the learned
633 model parameters. On the test data, the Kalman Filter applied these parameters
634 to predict and correct the estimated dengue cases, providing more stable and
635 accurate forecasts compared to direct regression models. Additionally, a hybrid
636 Kalman Filter–LSTM (KF-LSTM) model was developed to combine the strengths
637 of both approaches. In this setup, the LSTM model was first used to predict
638 dengue cases based on historical data and weather features. The Kalman Filter
639 was then applied as a post-processing step to the LSTM predictions, smoothing
640 out noise and correcting potential errors.

641 **3.1.3 Integrate the Predictive Model into a Web-Based**
642 **Data Analytics Dashboard**

643 **Dashboard Design and Development**

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

648 **Model Integration and Deployment**

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

651 **3.1.4 System Development Framework**

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

658 Design and Development

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

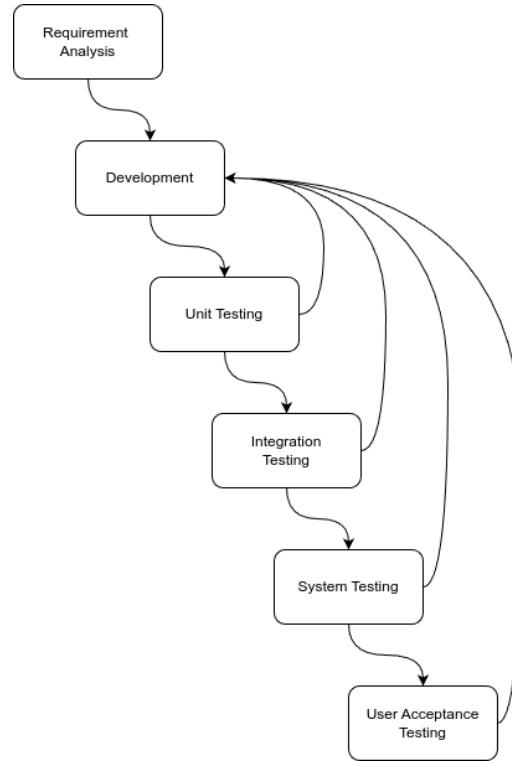
672 **Testing and Integration**

Figure 3.2: Testing Process for DengueWatch

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

701 Django

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

710 Next.js

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

717 Postman

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

⁷²² Postman? Postman API Platform, n.d.).

⁷²³ 3.2.2 Hardware

⁷²⁴ The web application was developed on laptop computers with minimum specifications of an 11th-generation Intel i5 CPU and 16 gigabytes of RAM. Furthermore,
⁷²⁵ an RTX 3060 mobile GPU was also utilized to retrain the integrated model locally.
⁷²⁶

⁷²⁷ 3.2.3 Packages

⁷²⁸ Django REST Framework

⁷²⁹ Django Rest Framework (DRF) is a third-party package for Django that provides a
⁷³⁰ comprehensive suite of features to simplify the development of robust and scalable
⁷³¹ Web APIs (Christie, n.d.). These services include Serialization, Authentication
⁷³² and Permissions, Viewsets and Routers, and a Browsable API .

⁷³³ Leaflet

⁷³⁴ One of the features of the web application is the ability to map the number
⁷³⁵ of cases using a Choropleth Map. Leaflet is the only free, open-sourced, and
⁷³⁶ most importantly, stable JavaScript package that can do the job. With its ultra-
⁷³⁷ lightweight size, it offers a comprehensive set of features that does not trade
⁷³⁸ off performance and usability (*Leaflet — an open-source JavaScript library for*
⁷³⁹ *interactive maps*, n.d.).

740 Chart.js

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

748 Tailwind CSS

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

757 Shadcn

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

⁷⁶¹ styling. Since this is built on top of Tailwind CSS and Radix UI, it is supported
⁷⁶² by most modern frontend frameworks, including Next.js (Shadcn, n.d.).

⁷⁶³ **Zod**

⁷⁶⁴ Data validation is integral in this web application since it will handle crucial data
⁷⁶⁵ that will be used for analytical inferences and observations. Since Zod is primarily
⁷⁶⁶ used for validating and parsing data, it ensures proper communication between
⁷⁶⁷ the client and the server (Zod, n.d.).

⁷⁶⁸ **3.3 Application Requirements**

⁷⁶⁹ **3.3.1 Backend Requirements**

⁷⁷⁰ **Database Structure Design**

⁷⁷¹ Determining how data flows and how it would be structured is crucial in creating
⁷⁷² the system as it defines how extendible and flexible it would be for future features
⁷⁷³ and updates. Thus, creating a comprehensive map of data ensures proper nor-
⁷⁷⁴ malization that eliminates data redundancy and improves data integrity. Figure
⁷⁷⁵ 3.3 depicts the designed database schema that showcases the relationship between
⁷⁷⁶ the application's entities.

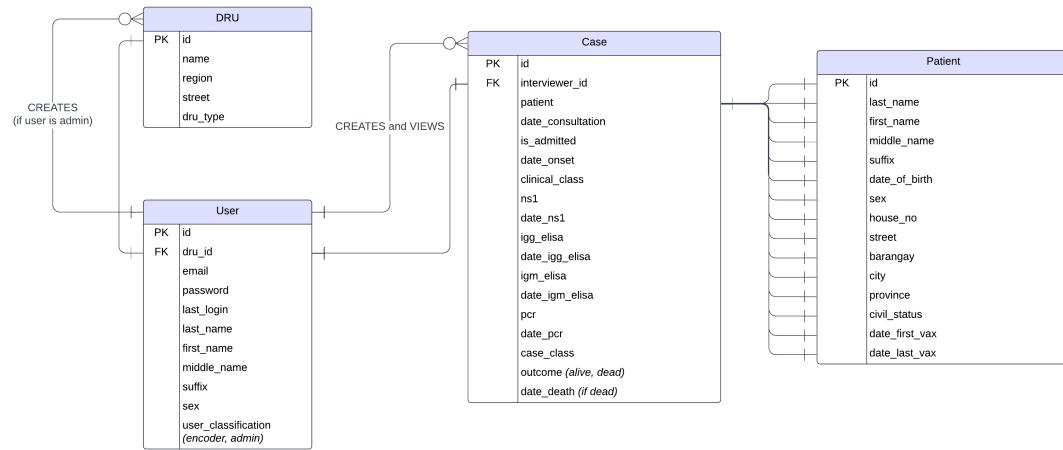


Figure 3.3: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

⁷⁷⁷ 3.3.2 User Interface Requirements

⁷⁷⁸ Admin Interface

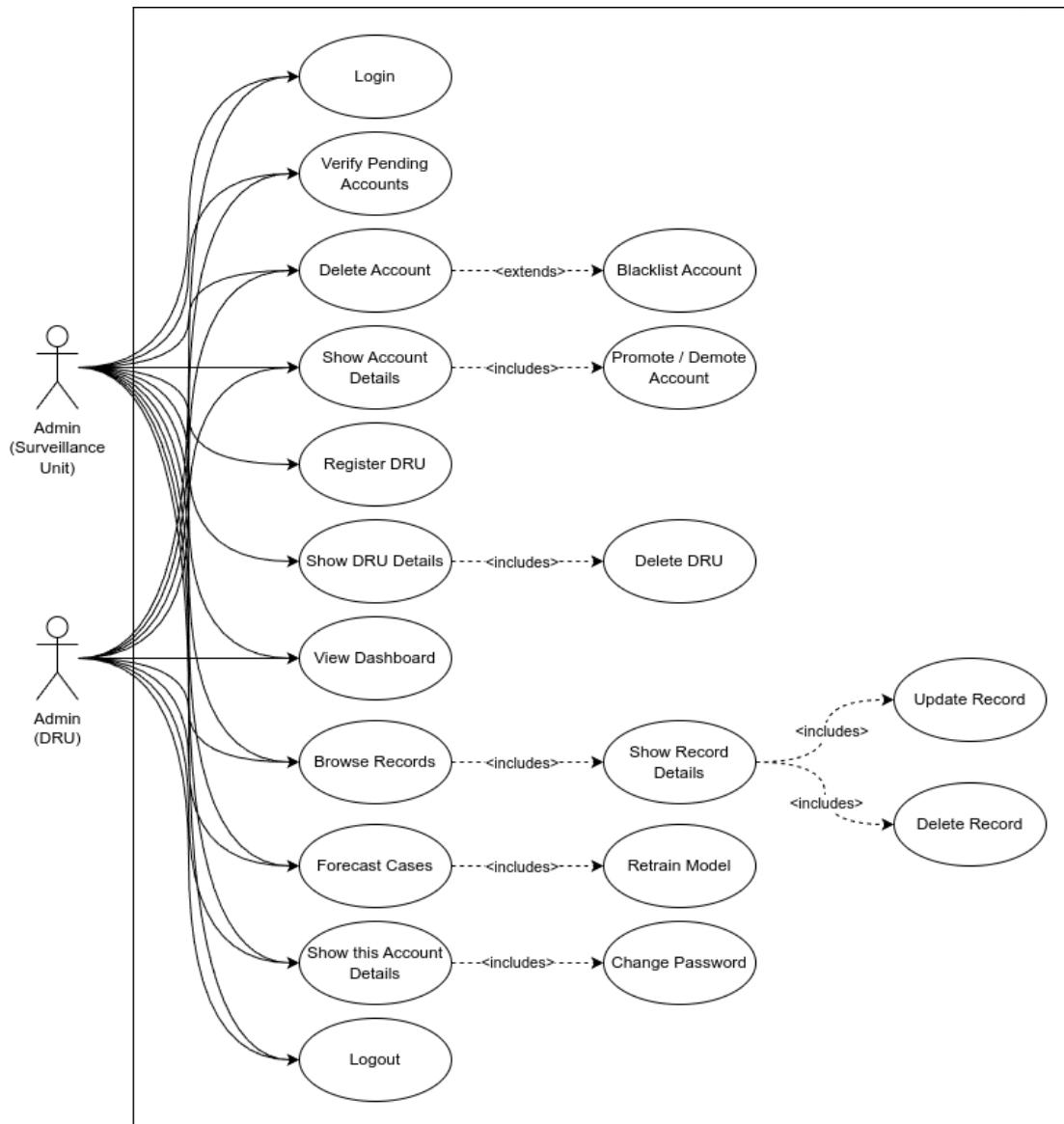


Figure 3.4: Use Case Diagram for Admins

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

⁷⁸⁹ **Encoder Interface**

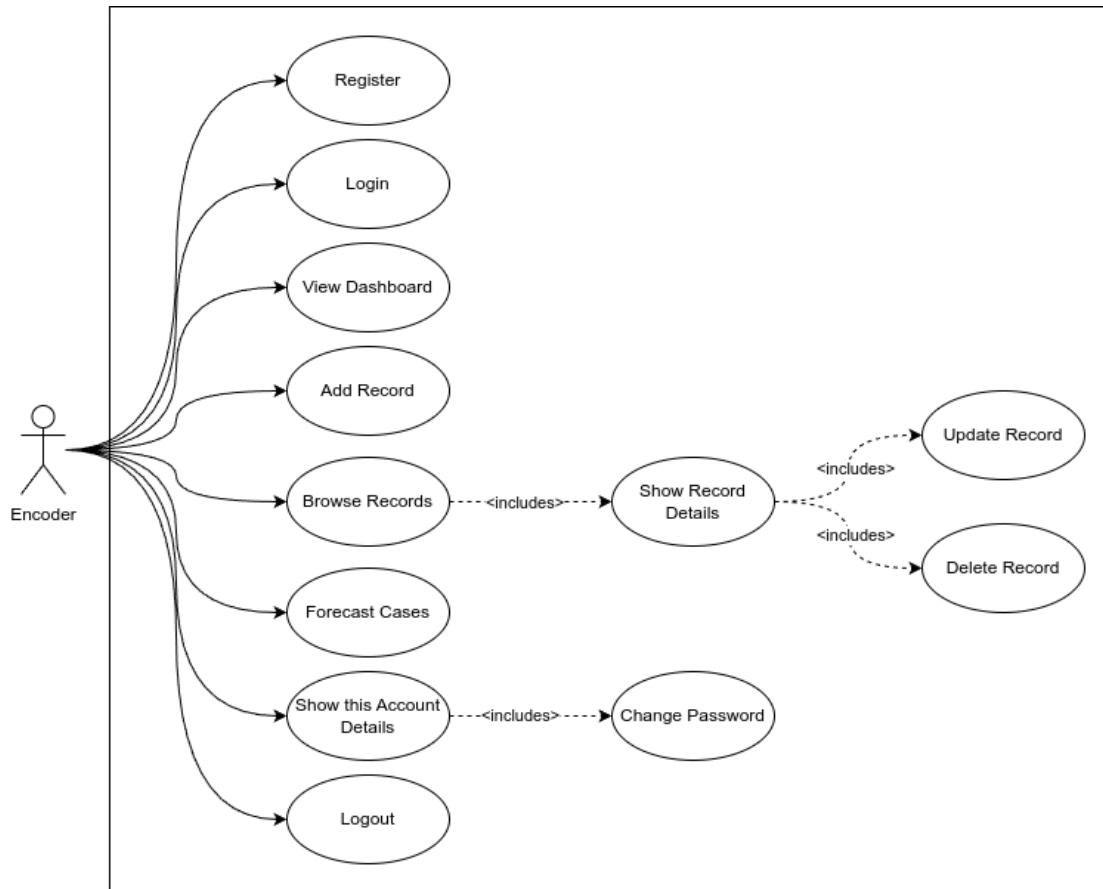


Figure 3.5: Use Case Diagram for Encoder

⁷⁹⁰ Figure 3.5, on the other hand, illustrates the use cases for the system's primary
⁷⁹¹ users. These users can register but must wait for further verification to access the
⁷⁹² application. Similar to the previous interfaces, encoders can browse and manage
⁷⁹³ records, as well as forecast the consolidated cases under a specific surveillance or
⁷⁹⁴ disease reporting unit, but they are not allowed to retrain the model. Lastly, they
⁷⁹⁵ are the only type of user that can file and create dengue cases by filling out a form
⁷⁹⁶ with the required details.

797 3.3.3 Security and Validation Requirements**798 Password Encryption**

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

807 Authentication

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

813 Data Validation

814 Both the backend and frontend should validate the input from the user to preserve
815 data integrity. Thus, Zod is implemented in the latter to help catch invalid inputs
816 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.

822 **Chapter 4**

823 **Results and Discussion/System**

824 **Prototype**

825 **4.1 Data Gathering**

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

- 831 1. Dengue Case Data: The primary source of historical dengue cases came
832 from the Humanitarian Data Exchange and the Western Visayas Center for
833 Health Development (WVCHD). The dataset, accessed through Freedom of
834 Information (FOI) requests, provided robust case numbers for the Western

835 Visayas region. The systematic collection of these data points was essential
 836 for establishing a reliable baseline for model training and evaluation.

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

| data.head() | | | | | | | | | |
|-------------|------------|----------|----------------|--------------------|----------------|-------|-----------|-------|--|
| | Time | Rainfall | MaxTemperature | AverageTemperature | MinTemperature | Wind | Humidity | Cases | |
| 0 | 2011-01-03 | 9.938571 | 29.444400 | 25.888890 | 23.888900 | 11.39 | 86.242857 | 5 | |
| 1 | 2011-01-10 | 8.587143 | 30.000000 | 26.705556 | 24.444444 | 7.32 | 88.028571 | 4 | |
| 2 | 2011-01-17 | 5.338571 | 30.000000 | 26.616667 | 25.000000 | 7.55 | 84.028571 | 2 | |
| 3 | 2011-01-24 | 5.410000 | 30.555556 | 26.483333 | 20.555556 | 10.67 | 80.971429 | 7 | |
| 4 | 2011-01-31 | 2.914286 | 28.333333 | 25.283333 | 18.650000 | 11.01 | 74.885714 | 2 | |

Figure 4.1: Snippet of the Combined Dataset

840 4.2 Exploratory Data Analysis

841 From Figure 4.2, the dataset consists of 720 weekly records with 8 columns:

- 842 • **Time.** Weekly timestamps (e.g. "2011-w1")
- 843 • **Rainfall.** Weekly average rainfall (mm)
- 844 • **MaxTemperature, AverageTemperature, MinTemperature.** Weekly
845 temperature data (C)
- 846 • **Wind.** Wind speed (m/s)
- 847 • **Humidity.** Weekly average humidity (%)

| # | Column | Non-Null Count | Dtype |
|---|--------------------|----------------|----------------|
| 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 |
| dtypes: datetime64[ns](1), float64(6), int64(1) | | | |
| memory usage: 45.1 KB | | | |

Figure 4.2: Data Contents

- 848 • **Cases.** Reported dengue cases

849 From the statistics in figure 4.3, the number of cases ranges from 0 to 319.
 850 The average number of dengue cases per week is 23.74, with a median of 12 cases
 851 and a standard deviation of 37.14. The distribution is highly skewed, with some
 852 weeks experiencing significant number of cases (up to 319 cases). Rainfall shows
 853 a wide variation (0 to 445mm), while temperature remains relatively stable, with
 854 an average of 28.1 degree celsius. Humidity levels ranges from 73% to 89% with
 855 a mean of 81.6%.

| | 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% | 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 | NaN | 35.448846 | 2.616379 | 0.999800 | 1.291659 | 2.446703 | 2.831674 | 37.144813 |

Figure 4.3: Dataset Statistics

856 Figure 4.4 illustrates the trend of weekly dengue cases over time. The data

reveals periodic spikes in the number of cases, suggesting a seasonal pattern in dengue cases. Notably, peak cases are observed during certain periods approximately 3 years, potentially aligning with specific climatic conditions such as increased rainfall or temperature changes. This underscores the importance of incorporating climate variables into the forecasting model.

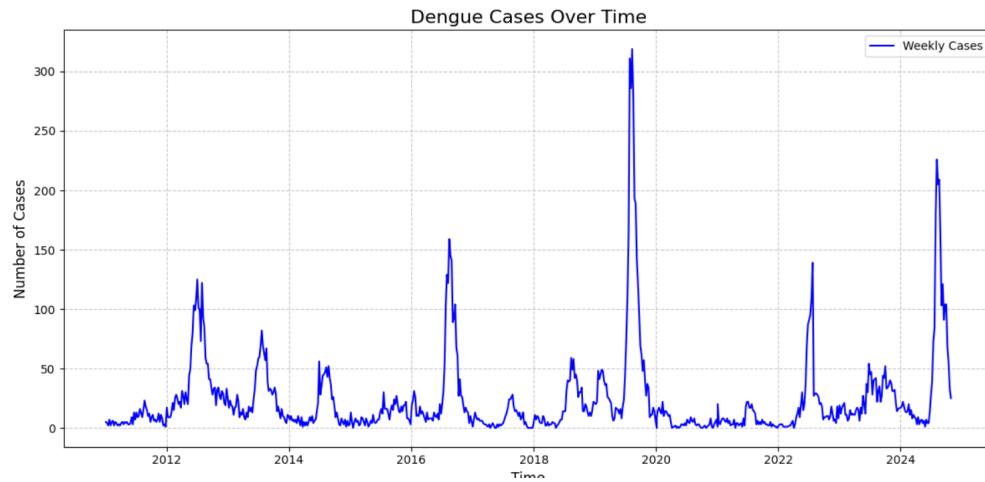


Figure 4.4: Trend of Dengue Cases

Figure 4.5 shows the ranking of correlation coefficients between dengue cases and selected features, including rainfall, humidity, maximum temperature, average temperature, minimum temperature, and wind speed. Among these, rainfall exhibits the highest positive correlation with dengue cases (correlation coefficient 0.13), indicating that increased rainfall may contribute to higher cases counts. This aligns with existing studies suggesting that stagnant water from heavy rainfall creates breeding grounds for mosquitos. It is followed by humidity (0.10), suggesting that higher humidity levels may enhance mosquito reproduction, leading to more dengue cases. Temperature has a weak to moderate positive correlation with dengue cases, with maximum temperature (0.09) showing a stronger relationship than average and minimum temperature.

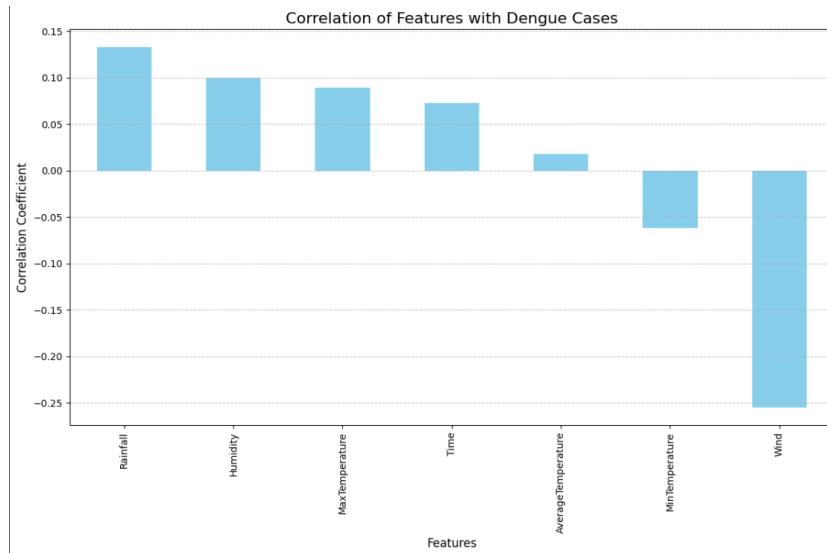


Figure 4.5: Ranking of Correlations

873 Figure 4.6 shows the distributions of each feature while Figure 4.7 shows scat-
874 terplots of each feature against the number of cases. The distributions of Rainfall,
875 Max Temperature, Min Temperature, and Wind appear skewed, which is common
876 for many real-world variables. This skewness can distort correlation estimates, as
877 Pearson correlation assume linear relationships and are more reliable when vari-
878 ables follow a symmetric or approximately normal distribution (Bobbitt, 2021).
879 Applying a log transformation can help normalize these distributions, improve
880 linearity, and thus lead to more meaningful and accurate correlation analysis.

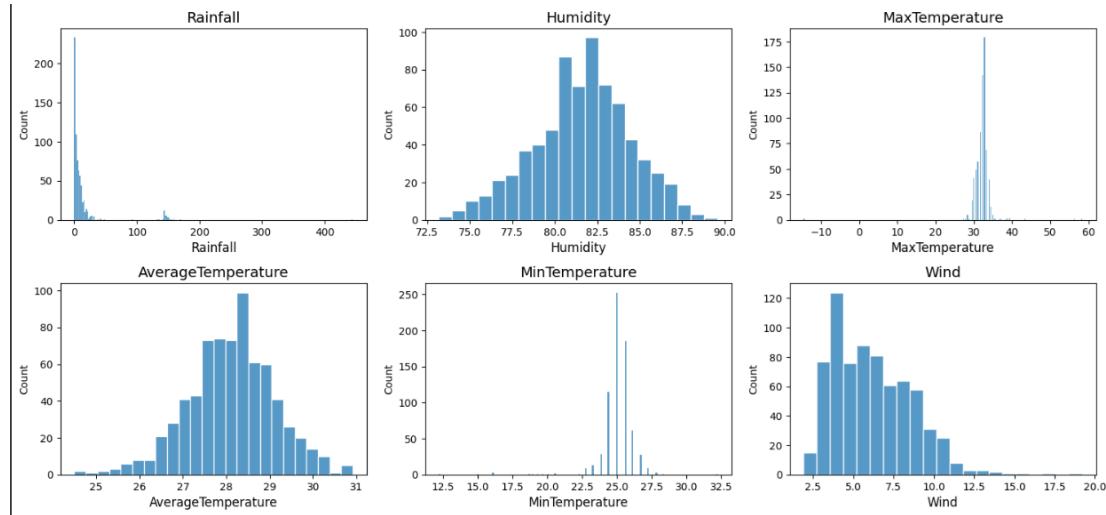


Figure 4.6: Pre-Transform Feature Distributions

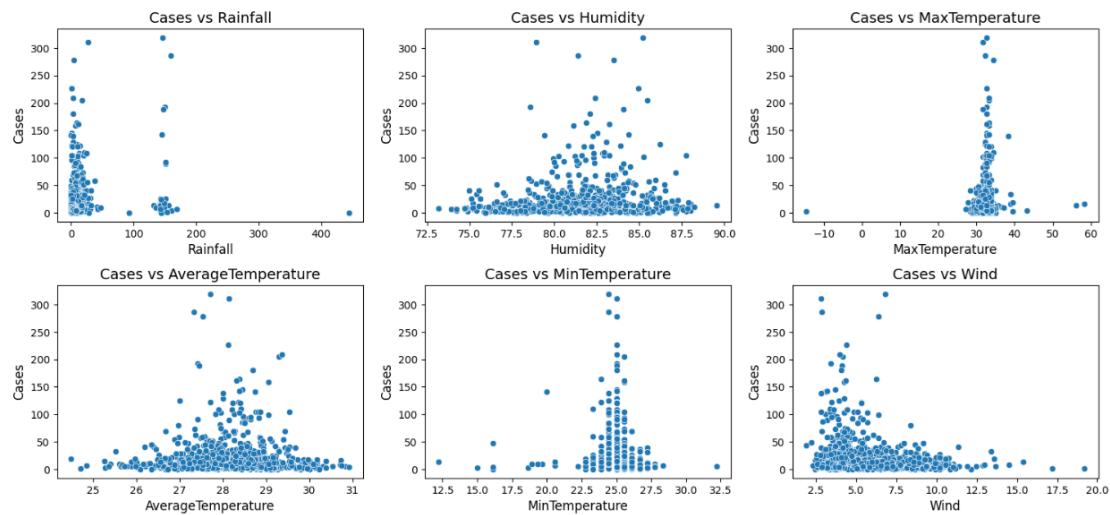


Figure 4.7: Scatterplots

881 After applying a log transformation, Figure 4.8 shows the new distributions for
 882 the previously skewed distributions, while Figure 4.9 shows the new scatterplots
 883 of each feature against the number of cases. Now, all distributions exhibit a
 884 somewhat normal distribution which is ideal for computing linear computations
 885 such as Pearson's correlation.

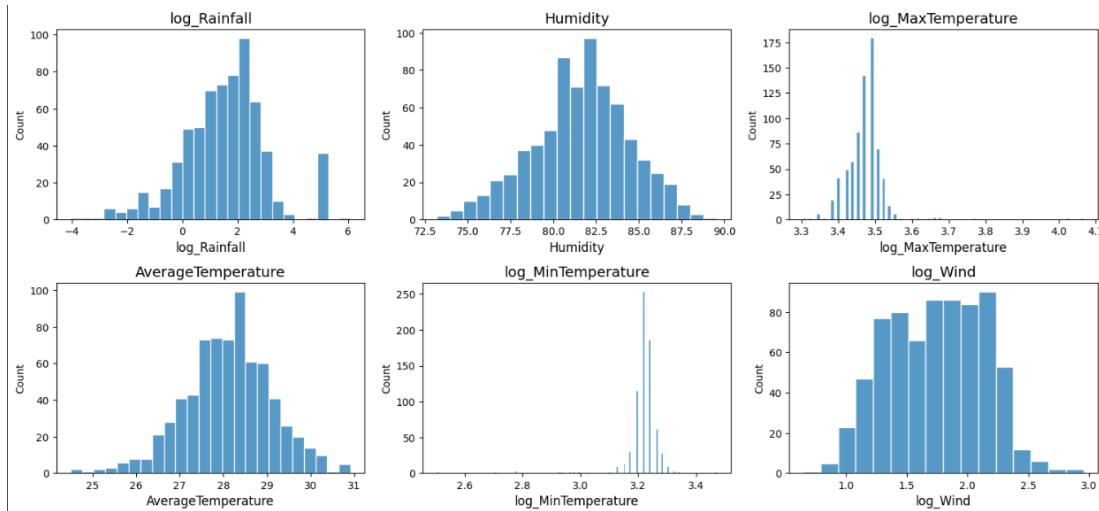


Figure 4.8: Post-Transform Feature Distributions

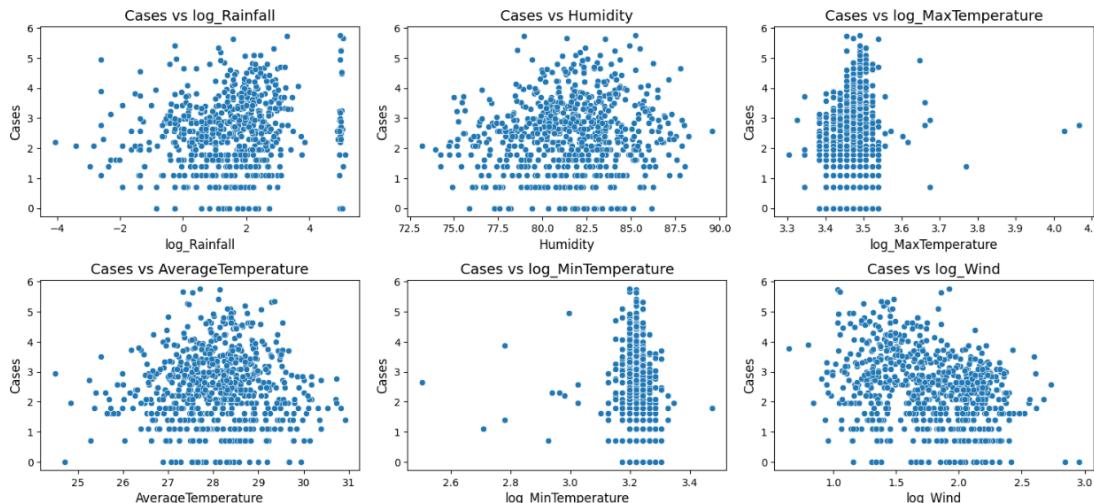


Figure 4.9: Transformed Distributions: Scatterplots

886 Figure 4.10 presents the recomputed correlation coefficients between dengue

cases and the log-transformed weather features. Rainfall shows the strongest correlation at 0.16, followed by Max Temperature at 0.12, and Humidity at 0.10. While other features are included, their correlation values are very small and not considered meaningful. Although the individual correlations are weak, they provide valuable signals that, when combined in a multivariate model, may contribute meaningfully to predictive performance., As a result, Rainfall, Max Temperature, and Humidity are selected as the key features for model training.

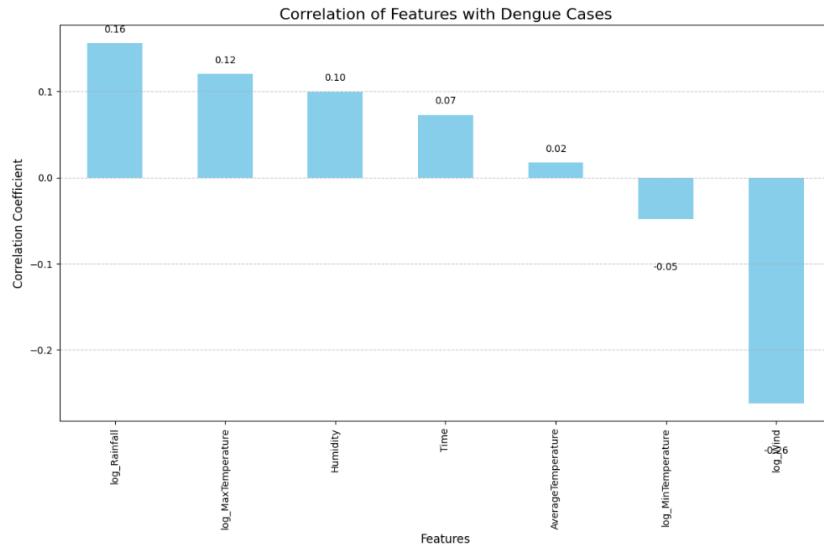


Figure 4.10: Ranking of Correlations with New Distributions

4.3 Outbreak Detection

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

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

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

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

$$= 98.03407 \quad (4.4)$$

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

898 This result indicates that dengue cases exceeding 98 in Iloilo City can be
899 considered an outbreak. However, it is important to note that this threshold
900 serves only as a baseline. Additional parameters, such as the number of hospital
901 beds available in the city, must be considered to compute a more effective threshold
902 and develop an appropriate response strategy.

903 4.4 Model Training Results

904 The models were evaluated using three metrics: MSE, RMSE, and MAE. The
905 table below provides a summary and comparative analysis of each model's results
906 across these metrics, offering insights into the strengths and limitations of each
907 forecasting technique for dengue case prediction in Iloilo City. The lower values
908 of the three metrics indicate better forecasting performance. Table 4.1 shows that
909 the models performed differently on testing data. LSTM outperformed the other
910 models with the lowest RMSE, MSE, and MAE while the other three models had
911 relatively higher values for the three metrics.

| Method | LSTM | Seasonal ARIMA | ARIMA | Kalman Filter | KF-LSTM |
|-----------------|--|----------------|---------|---|--------------|
| Testing MSE | 285.54 | 1261.20 | 1521.48 | 1474.82 | 785.35 |
| Testing RMSE | 16.90 | 34.45 | 39.00 | 38.40 | 25.56 |
| Testing MAE | 9.45 | 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 4.1: Comparison of different models for dengue prediction

912 4.4.1 LSTM Model

913 The LSTM model was tuned for the following parameters: learning rate and units.
 914 The hyperparameter tuning was conducted for each window size, finding the best
 915 parameters for each window size. Further evaluating which window size is most
 916 suitable for the prediction model, Table 4.2 shows the evaluation metrics for each
 window size used in the LSTM model training.

| Window Size | MSE | RMSE | MAE | R ² |
|-------------|---------------|--------------|-------------|----------------|
| 5 | 285.54 | 16.90 | 9.45 | 0.83 |
| 10 | 334.63 | 18.29 | 9.85 | 0.80 |
| 20 | 294.85 | 17.17 | 9.35 | 0.83 |

Table 4.2: Comparison of Window Sizes

917

918 The results indicate that a window size of 5 weeks provides the most accurate
 919 predictions, as evidenced by the lowest MSE and RMSE values. Furthermore, the
 920 R² score of 0.83 indicates that 83% of the variability in the target variable (cases)
 921 is explained by the independent variables (the inputs) in the model, making it a
 922 reliable configuration overall.

923 As shown in Table 4.3, the results from time series cross-validation indicate
 924 consistent performance trends, with a window size of 5 yielding the highest average
 925 RMSE across all folds compared to the other window sizes.

926 Figure 4.11 illustrates the model's performance in predicting dengue cases

| 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 4.3: Time-Series Cross Validation Results: Comparison of Window Sizes

for each fold using a window size of 5. As shown in the plot, the training set progressively increases with each fold, mimicking a real-world scenario where more data becomes available over time for dengue prediction. Figure 4.12 demonstrates that the predicted cases closely follow the trend of the actual cases, indicating that the LSTM model successfully captures the underlying patterns in the data. It is also evident that as the fold number increases and the training set grows, the accuracy of the predictions on the test set improves. Despite the test data being unseen, the model exhibits a strong ability to generalize, suggesting it effectively leverages past observations to predict future trends.

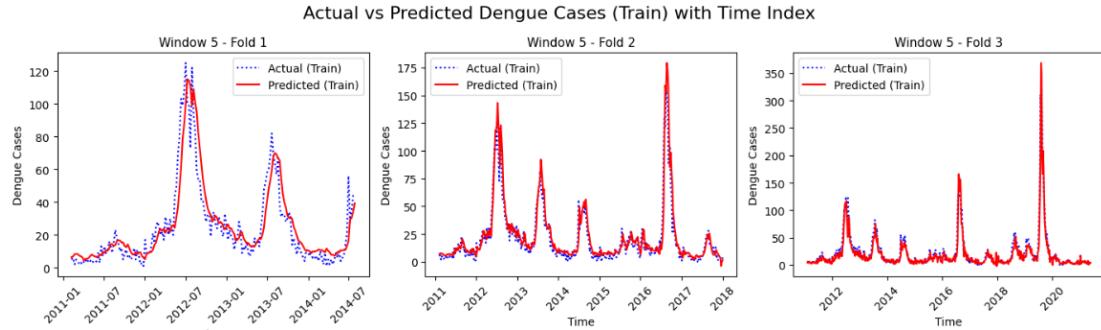


Figure 4.11: Training Folds - Window Size 5

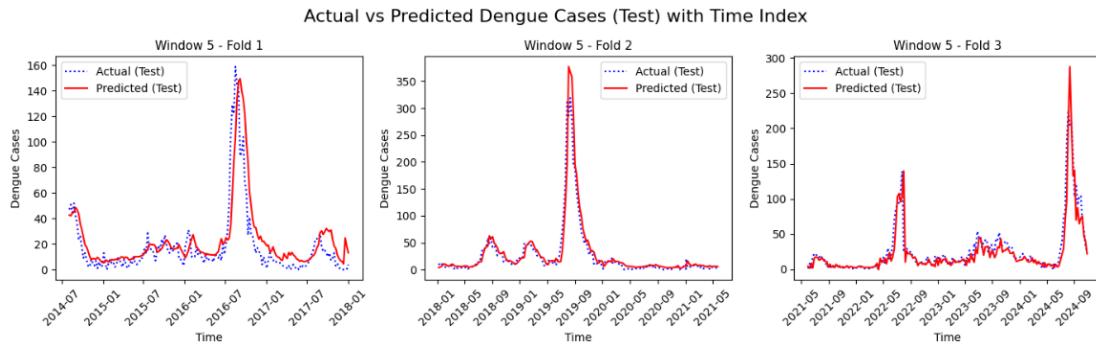


Figure 4.12: Testing Folds - Window Size 5

936 4.4.2 ARIMA Model

937 The ARIMA model was developed to capture non-seasonal trends in the data.
 938 To determine the best model configuration, grid search was used to explore vari-
 939 ous combinations of ARIMA parameters, ultimately selecting **ARIMA(1, 2, 2)**.
 940 The model was iteratively refined over **400 iterations** to ensure convergence to
 941 an optimal solution. Figure 4.13 illustrates the comparison between actual and
 942 predicted dengue cases in the test set. As shown in the plot, the ARIMA model
 943 struggled to capture the non-linear characteristics and abrupt spikes in the data.
 944 Consequently, it failed to accurately reflect the fluctuations and outbreak patterns
 945 seen in the actual case counts.

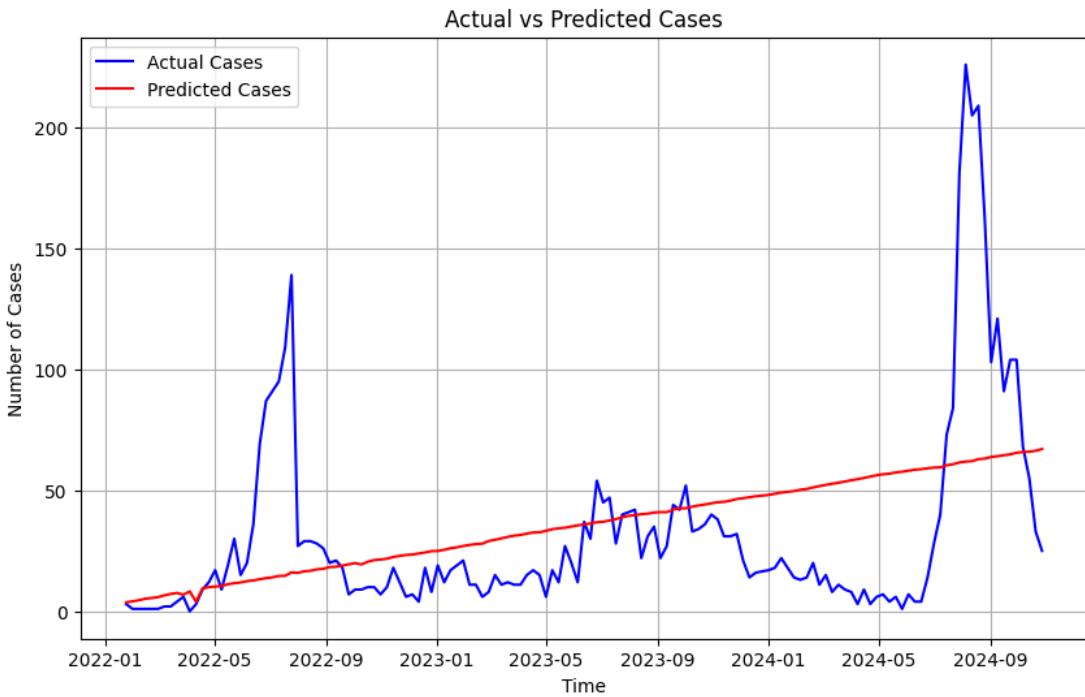


Figure 4.13: ARIMA Prediction Results for Test Set

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

- 948 • **MSE (Mean Squared Error):** 1521.48
- 949 • **RMSE (Root Mean Squared Error):** 39.01
- 950 • **MAE (Mean Absolute Error):** 25.80

951 4.4.3 Seasonal ARIMA (SARIMA) Model

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

954 data.

955 This model incorporates seasonal parameters, which were tuned using grid
 956 search to find the best configuration: **SARIMA(2, 0, 2)(0, 1, 1)[52]**. As with
 957 ARIMA, **400 iterations** were applied to ensure a robust fit. As shown in Figure
 958 4.14, the SARIMA model demonstrates a notable improvement in performance.
 959 Unlike its non-seasonal counterpart, it effectively captures the general trend and
 960 aligns more closely with the peaks observed in the actual dengue cases, indicating
 961 its ability to model seasonal dynamics.

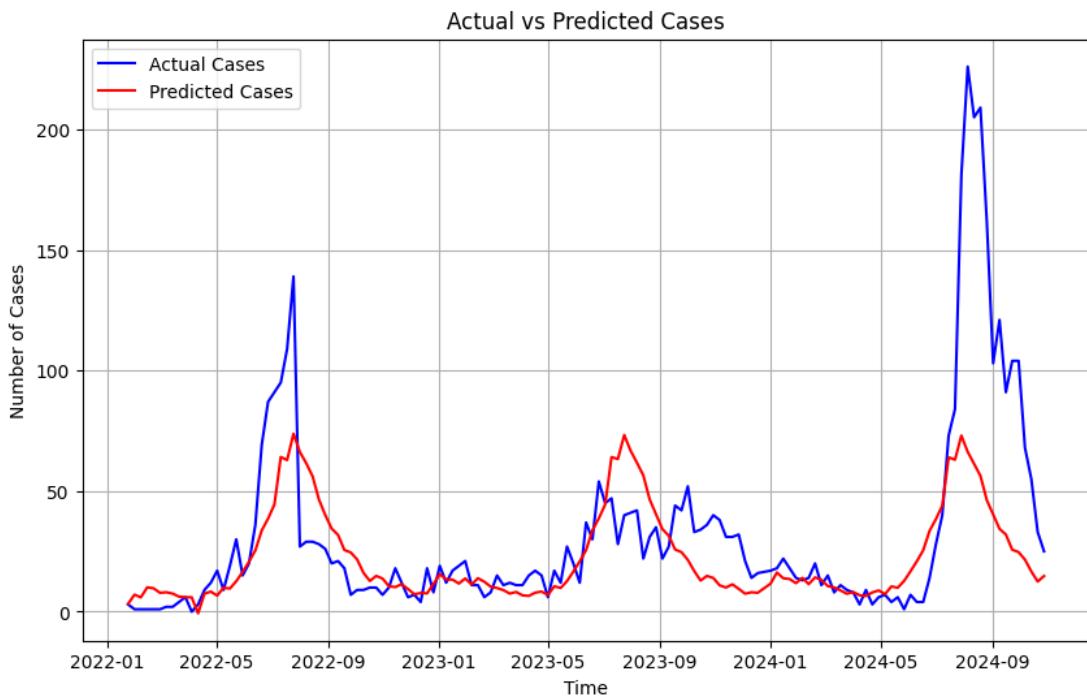


Figure 4.14: Seasonal ARIMA Prediction Results for Test Set

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

964 • **MSE:** 1109.69

965 • **RMSE:** 33.31

966 • **MAE:** 18.09

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

971 After training the model, the SARIMA model was validated using the same
972 Time Series Cross-Validation strategy employed in the LSTM model. Table 4.4
973 presents the performance metrics for each fold, as well as the average metrics
974 across all folds. The average RMSE and MAE values were close to those obtained
975 during the initial training phase, indicating that the SARIMA model performed
976 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 4.4: Comparison of SARIMA performance for each fold

977 4.4.4 Kalman Filter Model

978 Figure 4.15 shows the comparison between the actual dengue cases and the pre-
979 dicted values on the test set. As illustrated in the plot, the Kalman Filter model
980 demonstrates a moderate ability to follow the general trend of the actual data.

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

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

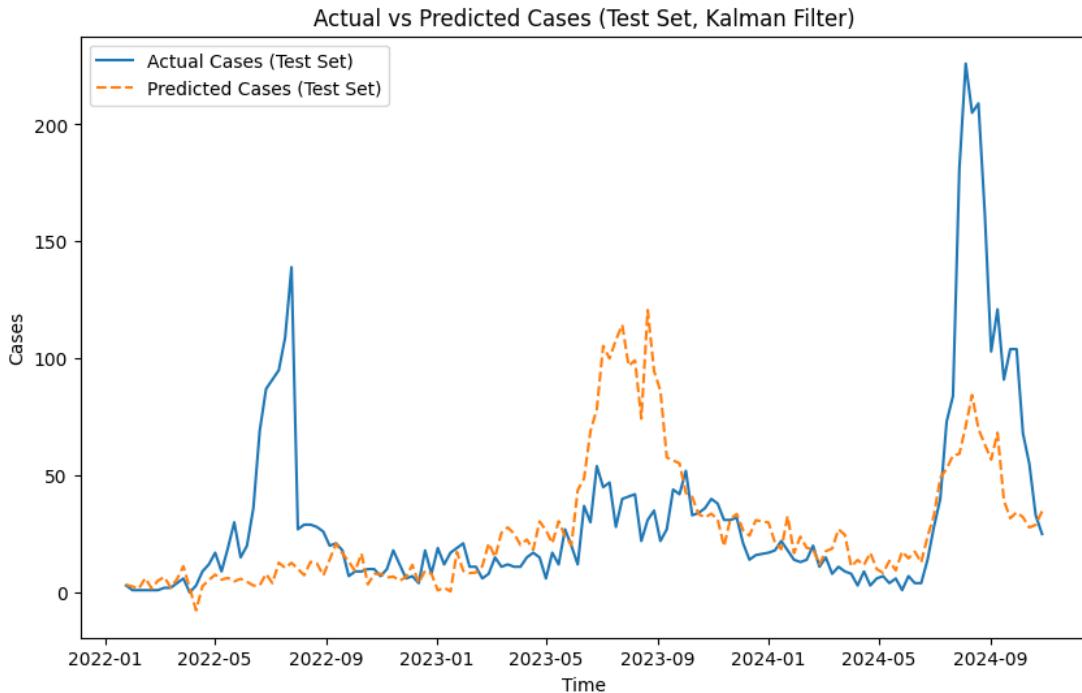


Figure 4.15: Kalman Filter Prediction Results for Test Set

986 The Kalman Filter was then combined with the LSTM model in order to see
 987 improvements in its predictions. Table 4.5 shows the metrics across three folds
 988 using the same Time Series Cross Validation Strategy employed in the previous
 989 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 4.5: Comparison of KF-LSTM performance for each fold

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

993 4.5 Model Simulation

994 To evaluate the LSTM model’s real-world forecasting ability, a simulation was
 995 conducted to predict dengue cases for the year 2025. The model was trained
 996 exclusively on data from 2011 to 2024, using both dengue cases and weather vari-
 997 ables. Importantly, the actual dengue case values for 2025 were never included
 998 during training. Instead, only the weather variables collected for 2025 were input
 999 into the model to generate predictions for that year. After prediction, the fore-
 1000 casted dengue cases for 2025 were compared against the true observed cases to
 1001 assess the model’s accuracy. Figure 4.16 shows that the predicted values closely
 1002 follow the trend, although it may overestimate the dengue cases in some weeks.

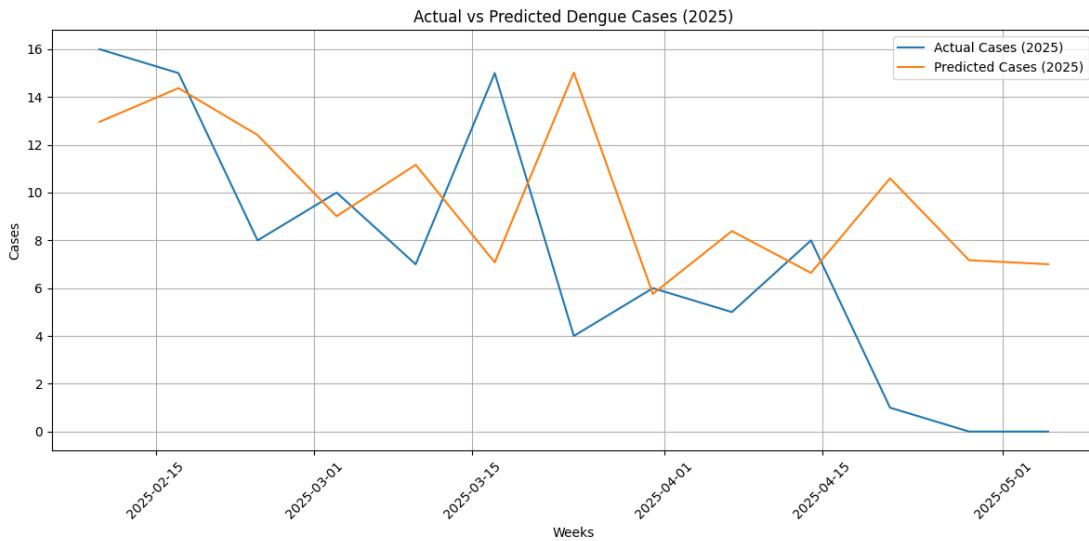


Figure 4.16: Predicted vs Actual Dengue Cases 2025

1003 4.6 System Prototype

1004 4.6.1 Home Page

1005 The Home Page is intended for all visitors of the web application. The Analytics
1006 Dashboard, which displays relevant statistics for dengue cases at a certain year
1007 and location, is the primary component highlighted, as seen in Figure 4.17. This
1008 component includes a combo chart that graphs the number of dengue cases and
1009 deaths per week in a specific year, a choropleth map that tracks the number of
1010 dengue cases per location, and various bar charts that indicate the top locations
1011 affected by dengue.

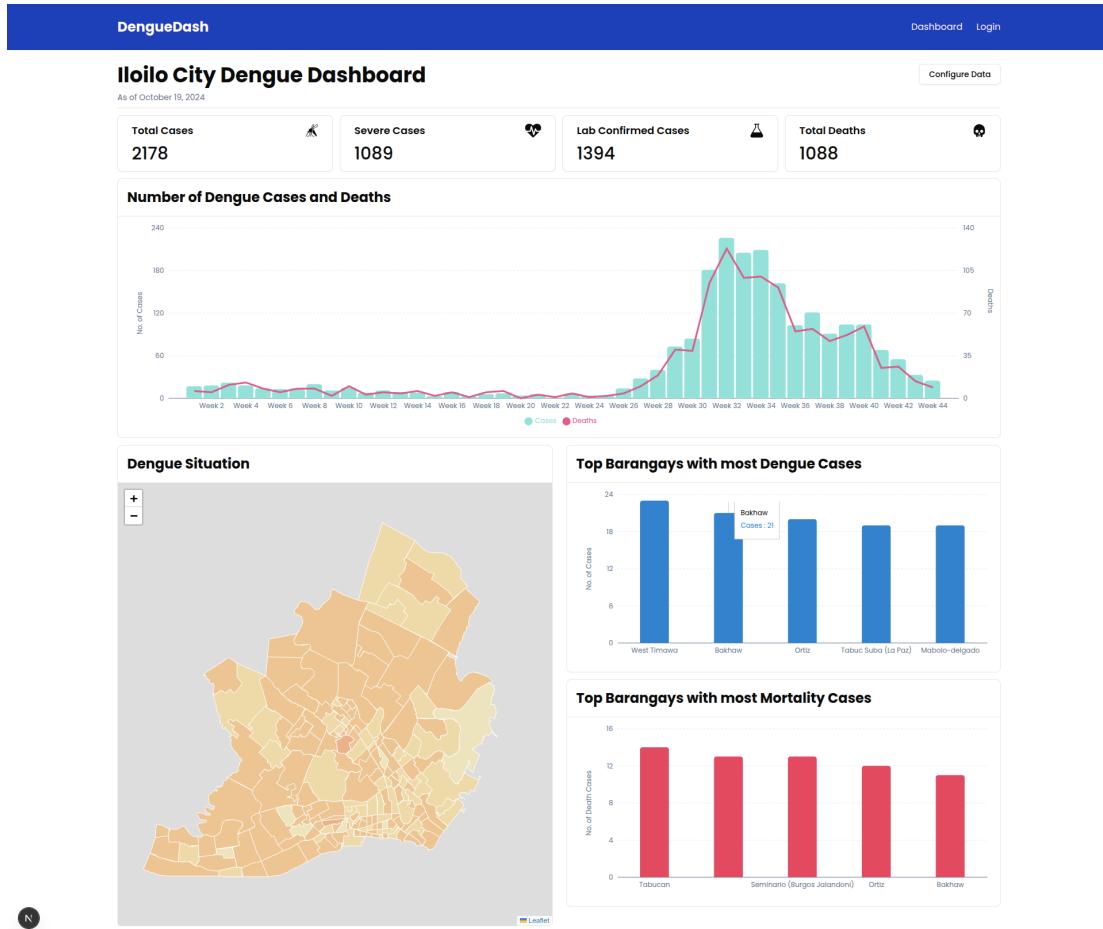


Figure 4.17: Home Page

¹⁰¹² 4.6.2 User Registration, Login, and Authentication

¹⁰¹³ The registration page, as shown in Figure 4.18, serves as a gateway to access the
¹⁰¹⁴ authenticated pages of the web application. Only prospective encoders can create
¹⁰¹⁵ an account since administrator accounts are only made by existing administra-
¹⁰¹⁶ tor accounts to protect the data's integrity in production. After registering, the
¹⁰¹⁷ "encoder account" cannot access the authorized pages yet as it needs to be veri-
¹⁰¹⁸ fied first by an administrator managing the unit the user entered. Once verified,

1019 the user can log in to the system through the page shown in Figure 4.19. Af-
1020 ter entering the correct credentials, which consist of an email and password, the
1021 system uses HTTP-only cookies containing JSON Web Tokens (JWT) to prevent
1022 vulnerability to Cross-site Scripting (XSS) attacks. It will then proceed to the
1023 appropriate page the type of user belongs to.

The screenshot shows the 'DengueDash' application's sign-up interface. At the top, there is a blue header bar with the 'DengueDash' logo on the left and 'Dashboard' and 'Login' links on the right. Below the header is a white form titled 'sign Up' with the sub-instruction 'Create your account to get started'. The form contains several input fields: 'First Name' (John), 'Middle Name (Optional)' (David), 'Last Name' (Doe), 'Sex' (Select gender), 'Email' (john@example.com), 'Region' (Select region), 'Surveillance Unit' (Select surveillance unit), 'DRU' (Select DRU), 'Password' (a field with placeholder text 'Must be at least 8 characters long'), and 'Confirm Password' (an empty field). At the bottom of the form is a large black button labeled 'Create Account'.

Figure 4.18: Sign Up Page

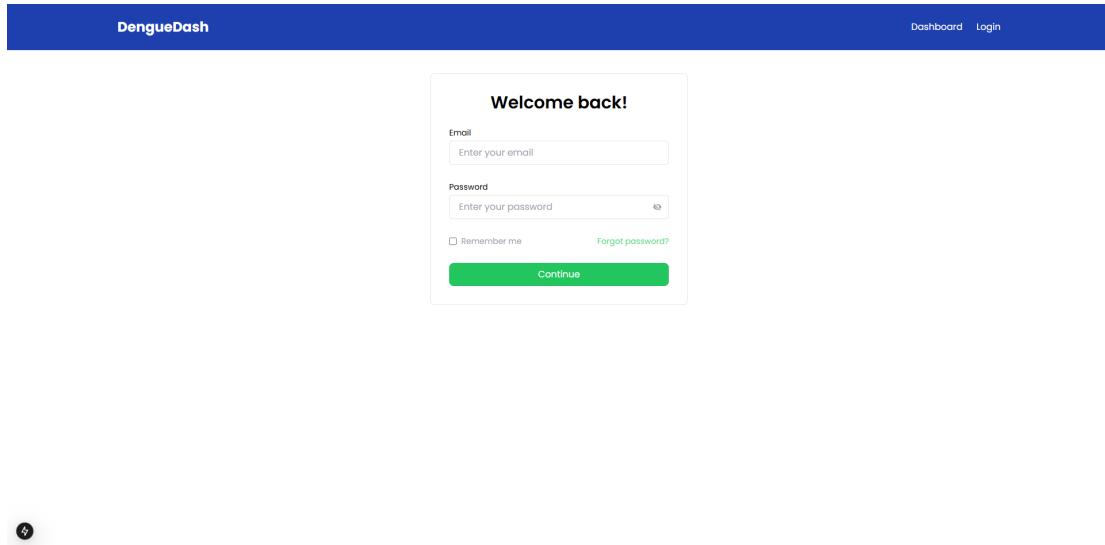


Figure 4.19: Login Page

₁₀₂₄ **4.6.3 Encoder Interface**

₁₀₂₅ **Case Report Form**

₁₀₂₆ Figures 4.20 and 4.21 show the digitized counterpart of the form obtained from the
₁₀₂₇ Iloilo Provincial Epidemiology and Surveillance Unit. As the system aims to sup-
₁₀₂₈ port expandability for future features, some fields were modified to accommodate
₁₀₂₉ more detailed input. It is worth noting that all of the included fields adhere to the
₁₀₃₀ latest Philippine Integrated Disease and Surveillance Response (PIDS) Dengue
₁₀₃₁ Forms, which the referenced form was based on. By doing this, if implemented
₁₀₃₂ on a national scale, the transition between targeted users will be easier. More-
₁₀₃₃ over, the case form includes the patient's basic information, dengue vaccination
₁₀₃₄ status, consultation details, laboratory results, and the outcome. On the other
₁₀₃₅ hand, encoders can also create case records using a "bulk upload" feature that

1036 makes use of a formatted CSV file template. As shown in Figure 4.22, an encoder
 1037 can download the template using the "Download Template" button, and insert
 1038 multiple records inside the file, then upload it by clicking the "Click to upload"
 1039 button. The web application automatically checks the file for data inconsistencies
 1040 and validation.

The screenshot shows the 'Case Report Form' page in the DengueDash application. The left sidebar has a 'Case Report Form' item under 'Forms' selected. The main content area has a 'Personal Information' tab active. It contains sections for 'Personal Detail' (with fields for First Name, Middle Name, Last Name, Suffix, Sex, and Civil Status), 'Address' (with fields for Region, Province, City, Barangay, Street, and House No.), and 'Vaccination' (with fields for Date of First Vaccination and Date of Last Vaccination). A 'Bulk Upload' button is located at the top right of the form area.

Figure 4.20: First Part of Case Report Form

The screenshot shows the 'Case Report Form' page within the DengueDash application. The left sidebar contains navigation links for 'Analytics', 'Forms' (selected), 'Data Tables', and 'Settings'. The top right features a 'Bulk Upload' button. The main content area is titled 'Case Report Form' and includes tabs for 'Personal Information' (selected) and 'Clinical Status'. The 'Clinical Status' tab is currently active, displaying sections for 'Consultation' and 'Laboratory Results'. In the 'Consultation' section, there are fields for 'Date Admitted/Consulted/Seen' (with a 'Pick a date' button) and 'Is Admitted?' (a dropdown menu). The 'Laboratory Results' section contains four rows, each with a test name (NS1, IgG ELISA, IgM ELISA, PCR) and a dropdown menu showing 'Pending Result'. To the right of these dropdowns are fields for 'Date done (NS1)', 'Date done (IgG ELISA)', 'Date done (IgM ELISA)', and 'Date done (PCR)' respectively, each with a 'Pick a date' button. Below these sections is the 'Outcome' section, which includes 'Case Classification' (dropdown menu) and 'Outcome' (dropdown menu). A 'Date of Death' field with a 'Pick a date' button is also present. At the bottom right are 'Previous' and 'Submit' buttons.

Figure 4.21: Second Part of Case Report Form

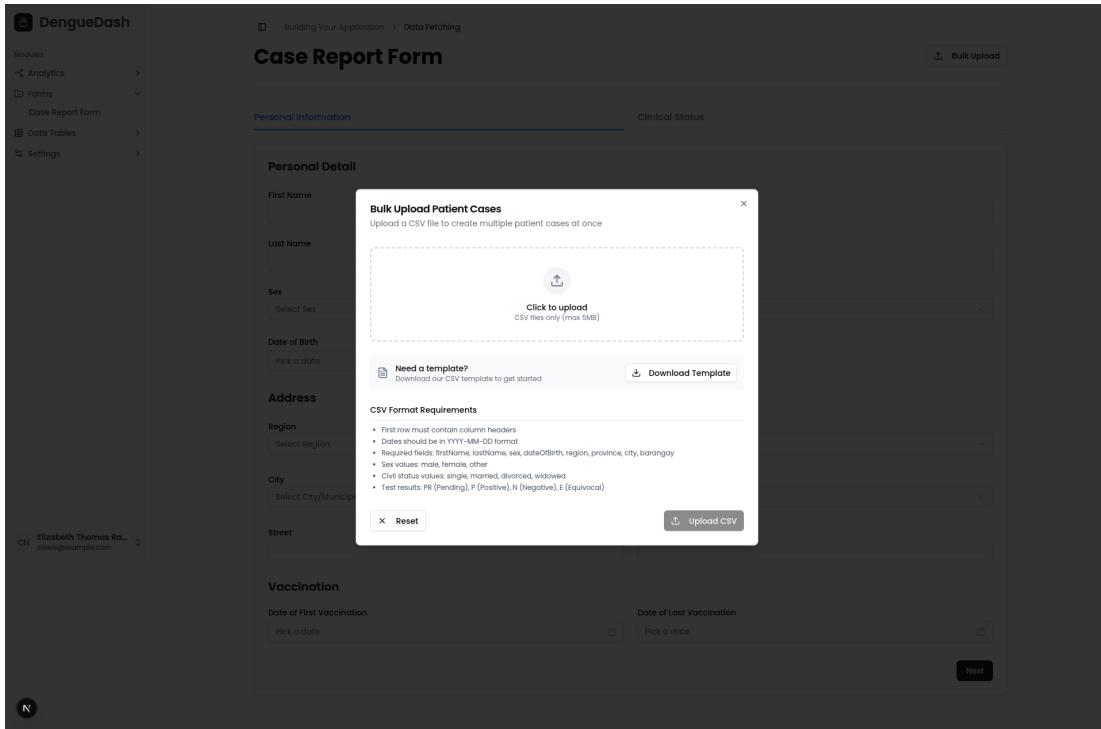


Figure 4.22: Bulk Upload of Cases using CSV

¹⁰⁴¹ Browsing, Update, and Deletion of Records

¹⁰⁴² Once the data generated from the case report form or the bulk upload is vali-
¹⁰⁴³ dated, it will be assigned as a new case and can be accessed through the Dengue
¹⁰⁴⁴ Reports page, as shown in Figure 4.23. The said page displays basic information
¹⁰⁴⁵ about the patient related to a specific case, including their name, address, date
¹⁰⁴⁶ of consultation, and clinical and case classifications. It is also worth noting that
¹⁰⁴⁷ it only shows cases the user is permitted to view. For example, in a local Disease
¹⁰⁴⁸ Reporting Unit (DRU) setting, the user can only access records that belong to
¹⁰⁴⁹ the same DRU. On the other hand, in a consolidated surveillance unit such as a
¹⁰⁵⁰ regional, provincial, or city quarter, its users can view all the records from all the

1051 DRUs that report to them. Moving forward, Figure 4.24 shows the detailed case
 1052 report of the patient on a particular consultation date.



The screenshot displays the DengueDash application's interface. On the left, a sidebar titled "DengueDash" lists "Modules": Accounts, DRU, Analytics, Data Tables (with "Dengue Reports" selected), and Settings. The main content area is titled "Dengue Reports" and shows a table of 137 entries. The table columns are: Case ID, Name, Barangay, City, Date Consulted, Clinical Classification, Case Classification, and Action (with an "Open" button). The first few rows of data are:

| Case ID | Name | Barangay | City | Date Consulted | Clinical Classification | Case Classification | Action |
|----------|---------------------------|----------------------------------|-----------------------|----------------|-------------------------|---------------------|-----------------------|
| 25017095 | Hedges, Destiny Michelle | Palo Benedicto Rizal (Mandurias) | ILOILO CITY (Capitol) | 2024-11-03 | Severe dengue | Probable | <button>Open</button> |
| 25017077 | Cuevas, Robert Rebecca | Democracia | ILOILO CITY (Capitol) | 2024-11-03 | With warning signs | Confirmed | <button>Open</button> |
| 25017090 | Middleton, Joseph Michael | Tanza-Esperanza | ILOILO CITY (Capitol) | 2024-11-01 | With warning signs | Suspect | <button>Open</button> |
| 25017089 | Medina, Michael Paige | Tacas | ILOILO CITY (Capitol) | 2024-11-01 | With warning signs | Probable | <button>Open</button> |
| 25017081 | Love, Paula Kimberly | Magsaysay | ILOILO CITY (Capitol) | 2024-11-01 | With warning signs | Suspect | <button>Open</button> |
| 25017073 | Smith, Anna Andrea | Desamparados | ILOILO CITY (Capitol) | 2024-11-01 | Severe dengue | Confirmed | <button>Open</button> |
| 25017094 | Morrison, Michael Sarah | El 98 Castilla (Claudio Lopez) | ILOILO CITY (Capitol) | 2024-10-31 | Severe dengue | Probable | <button>Open</button> |
| 25017093 | Barnes, Charles Robert | Rima-Rizal | ILOILO CITY (Capitol) | 2024-10-31 | With warning signs | Suspect | <button>Open</button> |

At the bottom, there are navigation links: < Previous, 1, 2, ..., 2137, Next >.

At the very bottom left, there is a footer: CN Iloilo City Epidemiol... ilocepss@gmail.com

Figure 4.23: Dengue Reports

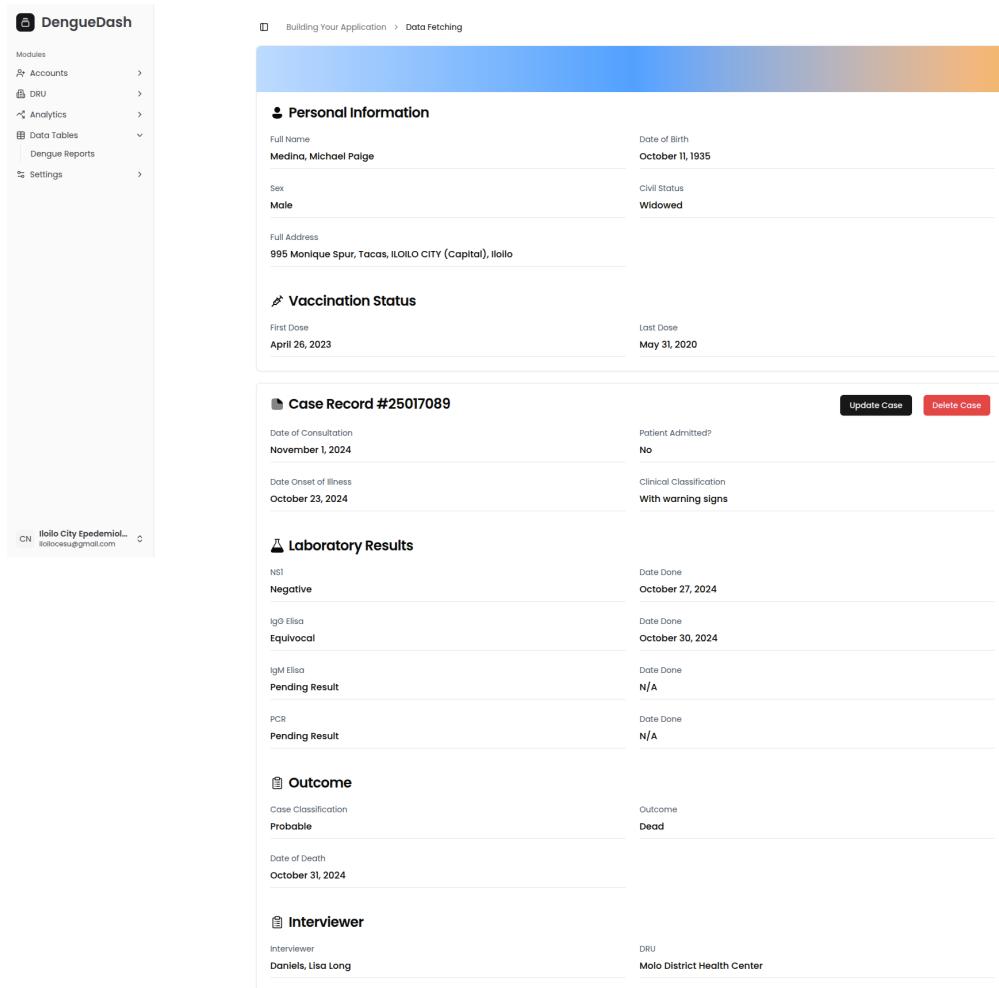


Figure 4.24: Detailed Case Report

1053 To update the case, the user can click the "Update Case" button, where a
 1054 dialog will appear, and the updateable fields will be shown. It is worth noting
 1055 that in this case, only fields under Laboratory Results and Outcome are included
 1056 since they are the only ones that are time-based, where the result may change in
 1057 the future. After updating, a prompt will show confirming the action of the user.
 1058 Moving forward, to delete a case record, the user must click the "Delete Case"
 1059 button, and a prompt verifying the action will appear. After confirming, the case

4.6. SYSTEM PROTOTYPE

65

1060 will be deleted permanently.

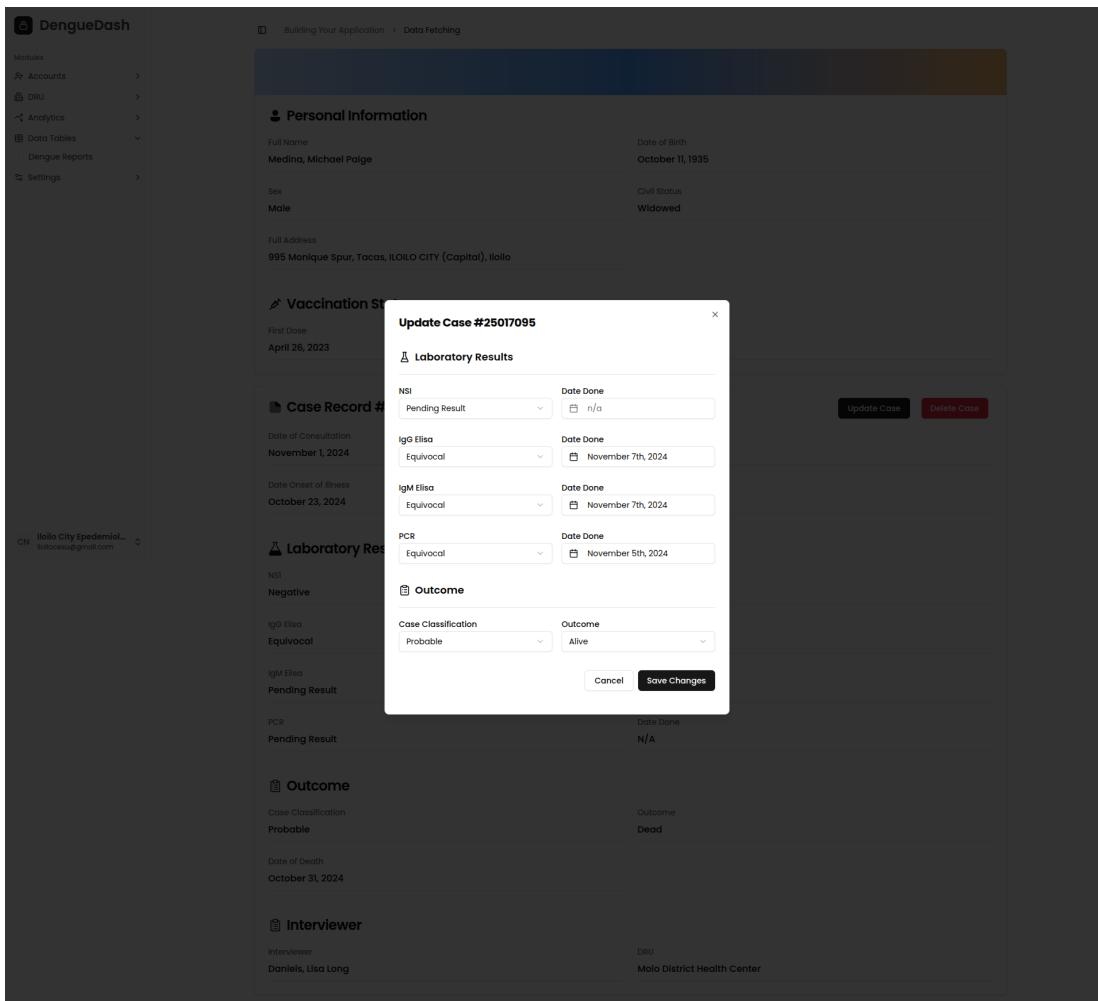


Figure 4.25: Update Report Dialog

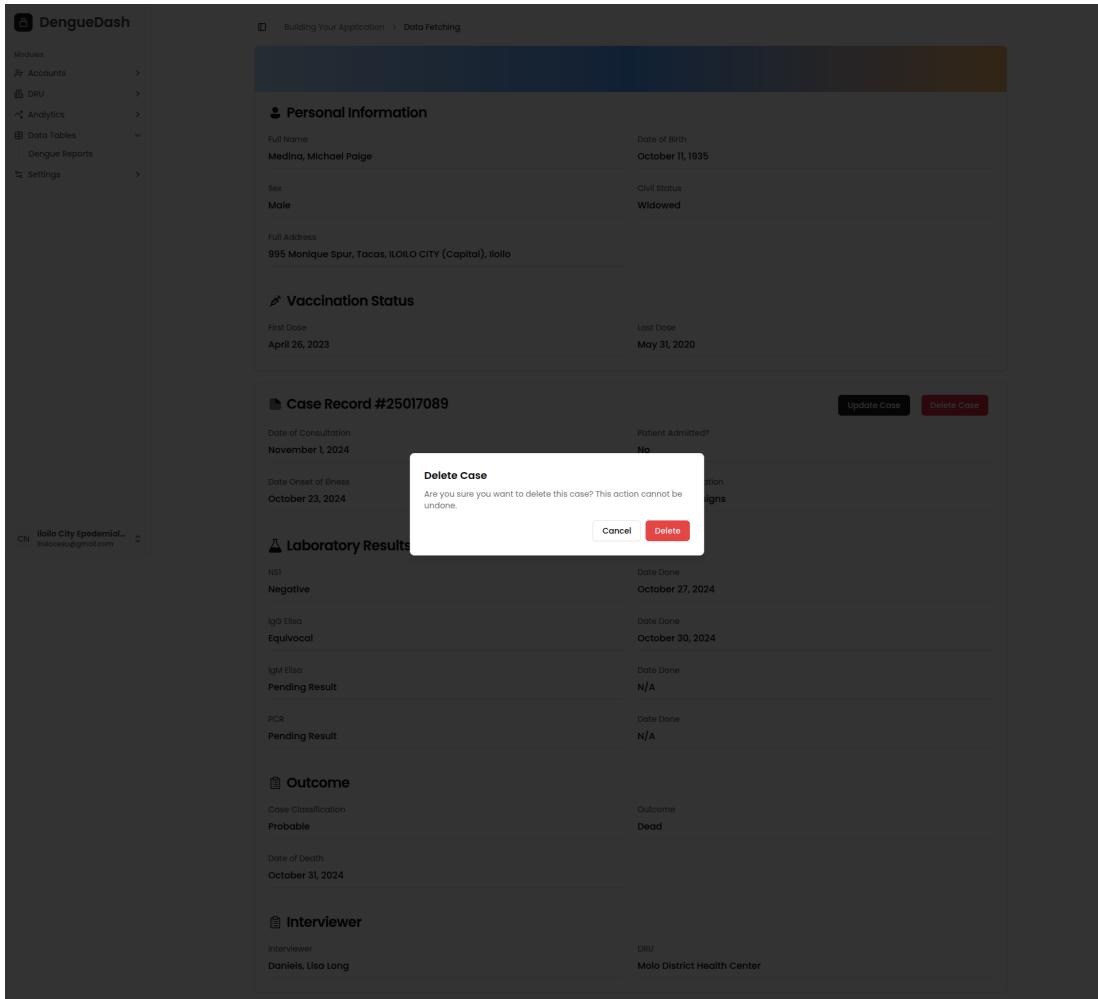


Figure 4.26: Delete Report Alert Dialog

1061 **Forecasting**

1062 The piece de resistance of the web application's feature is the Forecasting Page.
 1063 This is where users can forecast dengue cases for the next following weeks. To
 1064 predict, the application utilizes the exported LSTM model in a Keras format
 1065 derived from training the consolidated data from the database. It requires the
 1066 recent weekly dengue cases and weather variable data (temperature, humidity, and

₁₀₆₇ rainfall) based on the window size. This allows the web application to display a line
₁₀₆₈ chart with the anticipated number of dengue cases over the following four weeks.
₁₀₆₉ Moving forward, the Forecasting page, as shown in Figure 4.27, introduces a user-
₁₀₇₀ friendly interface that shows the current cases for the week and the predictions for
₁₀₇₁ the next two weeks with a range of 90 percent to 110 percent confidence interval
₁₀₇₂ that is presented in a simple but organized manner. There is also a line chart
₁₀₇₃ that shows the number of cases from the last 5 weeks plus the forecasted weekly
₁₀₇₄ cases. In addition, the current weather data for a specific week is also shown, as
₁₀₇₅ well as the forecasted weather data fetched from the OpenWeather API. Lastly,
₁₀₇₆ locations where dengue cases have been reported for the current week are listed
₁₀₇₇ in the Location Risk Assessment component.

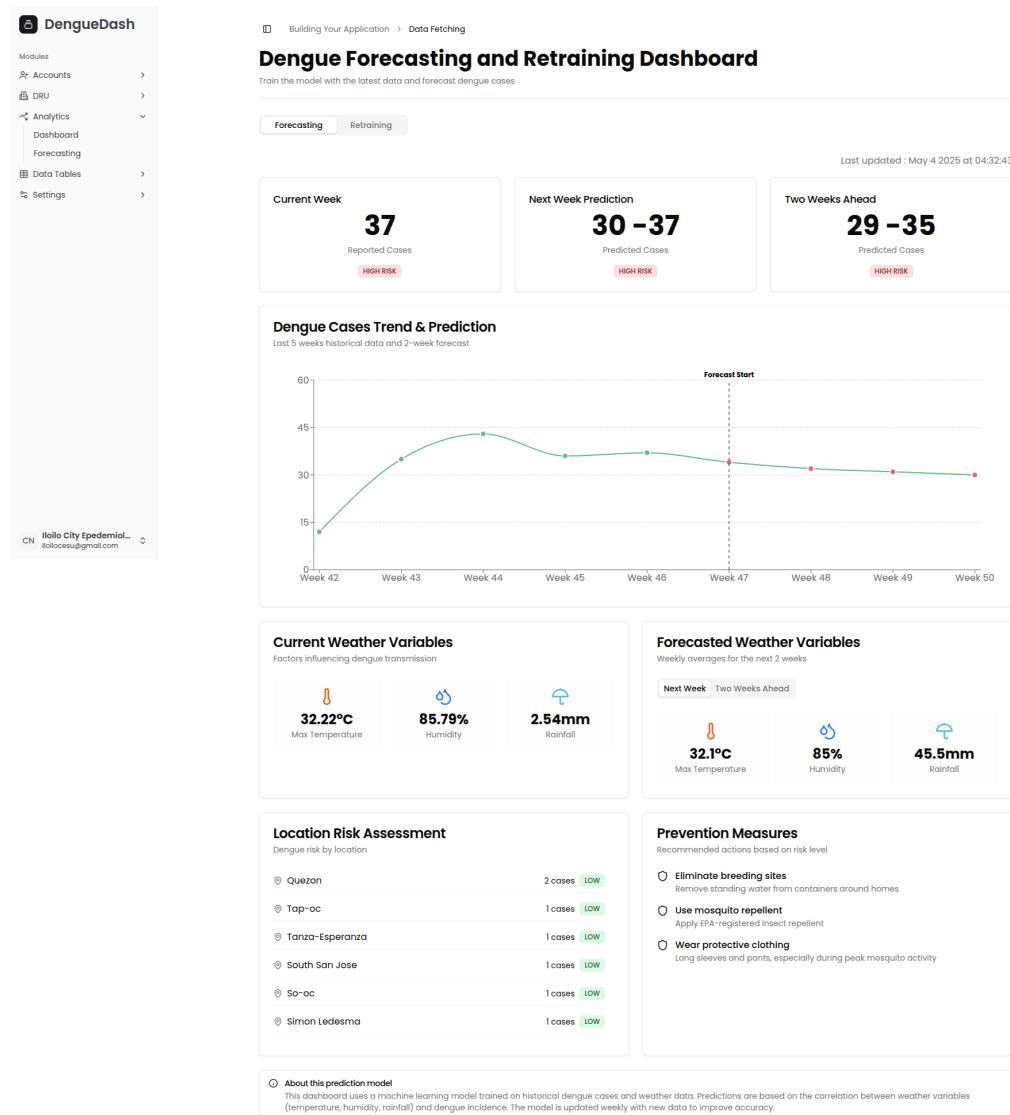


Figure 4.27: Forecasting Page

1078 4.6.4 Admin Interface**1079 Retraining**

1080 With LSTM being the best-performing model among the models used in forecast-
1081 ing dengue cases, it is the model chosen to power the prediction and retraining
1082 of the consolidated data within the web application. Since the retraining process
1083 consumes a lot of processing power and requires a more advanced understanding
1084 of how it works, it was decided that the said feature should only be available
1085 to admin users. Furthermore, the retraining component in the Forecasting page
1086 includes three additional components that include the configuration of LSTM pa-
1087 rameters (Figure 4.28), the actual retraining of the consolidated data from the
1088 database (Figure 4.29), and the results of the retraining that shows the current
1089 and previous model metrics depending on the parameters entered (Figure 4.30).
1090 It is also worth noting that when trained, the model used a seeded number to
1091 promote reproducibility.

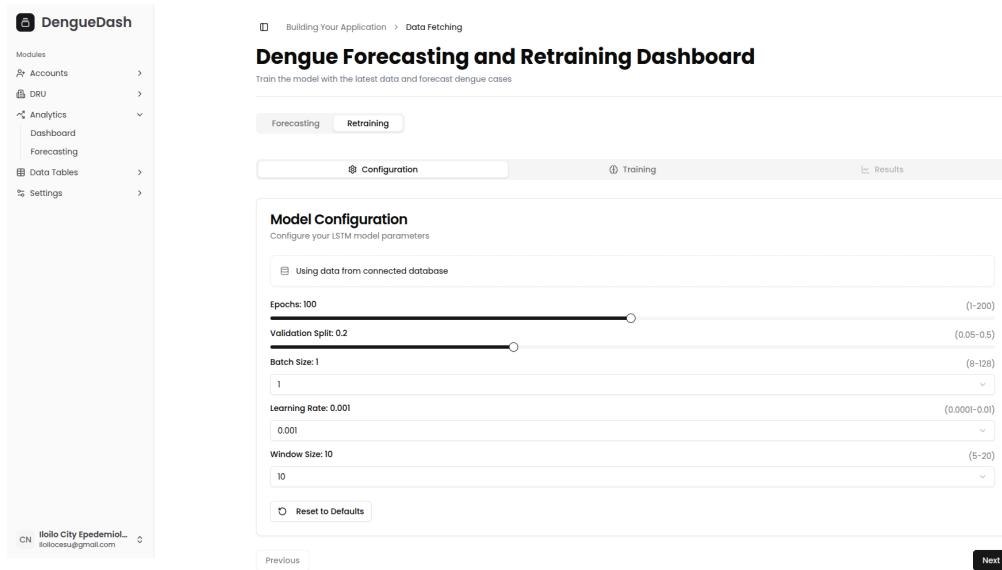


Figure 4.28: Retraining Configurations

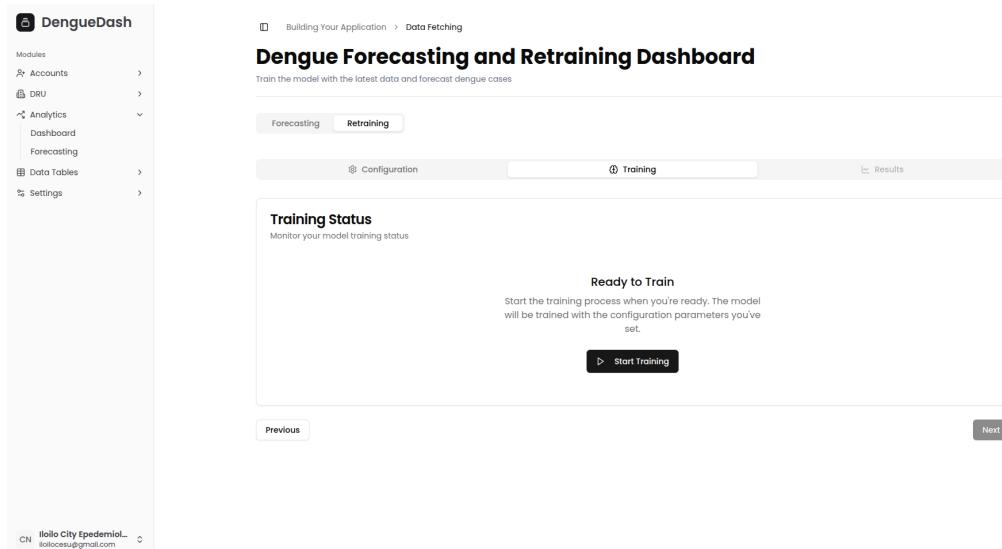


Figure 4.29: Start Retraining

The screenshot shows the 'Dengue Forecasting and Retraining Dashboard' interface. The left sidebar lists modules: Accounts, DRU, Analytics (Dashboard, Forecasting), Data Tables, and Settings. The main header is 'Dengue Forecasting and Retraining Dashboard' with a sub-header 'Train the model with the latest data and forecast dengue cases'. Below this are tabs for 'Forecasting' (selected) and 'Retraining'. A navigation bar at the top includes 'Configuration', 'Training', and 'Results'. The central area is titled 'Model Results' with a subtitle 'View the model's performance metrics and charts'. It features two side-by-side tables: 'Current Model Metrics' and 'Previous Model Metrics'. The 'Current Model Metrics' table contains:

| | Value |
|------------------|---------|
| MSE: | 296.999 |
| RMSE: | 17.234 |
| MAE: | 10.138 |
| R ² : | 0.826 |

The 'Previous Model Metrics' table contains:

| | Value |
|------------------|---------|
| MSE: | 311.420 |
| RMSE: | 17.647 |
| MAE: | 9.711 |
| R ² : | 0.818 |

A 'Metrics' button is located above the tables, and a 'Charts' button is to its right. At the bottom left is a 'Previous' button.

Figure 4.30: Retraining Results

1092 **Managing Accounts**

1093 Proper management of accounts is important to protect the integrity and confi-
 1094 dentiality of data. Thus, it is crucial for administrators to track their users and
 1095 control the flow of information. As discussed in the user registration of encoders,
 1096 admin users from a specific DRU or surveillance have the power to grant them ac-
 1097 cess to the web application. Figure 4.32 illustrates the interface for this scenario,
 1098 as the admins can approve or reject their applications. Once approved, these users
 1099 can access the features given to encoders and may be promoted to have admin-
 1100 istrative access, as shown in Figure 4.33. When deleting an account, the user's
 1101 email will be blacklisted and illegible to use when creating another account, and
 1102 all the cases reported by this user will be soft-deleted. The same figure also shows
 1103 the expanded details of the user, which include personal information and brief
 1104 activity details within the system.

| Name | Email | Role | Sex | Actions |
|-----------------------|---------------------------|---------|--------|-----------------------|
| Cheryl Hernandez King | omarpatterson@example.net | Encoder | Female | <button>Open</button> |

Figure 4.31: List of Verified Accounts

The screenshot shows the DengueDash application interface. On the left is a sidebar with a navigation menu:

- Modules
 - Accounts
 - Manage Accounts
 - Analytics
 - Data Tables
 - Settings

At the bottom of the sidebar, it says "CN Saint Paul's Hospital saintpaul@gmail.com".

The main content area has a breadcrumb navigation: Building Your Application > Data Fetching. The title is "Manage Accounts". Below the title is a button bar with "Verified", "Pending" (which is highlighted), and "Blacklisted". A table lists user information:

| Name | Email | Sex | Created At | Actions |
|----------------|--------------------------|------|------------|--|
| John David Doe | testereee@example.gov.ph | Male | 2025-04-26 | <button>Approve</button> <button>Delete</button> |

Figure 4.32: List of Pending Accounts

The screenshot shows the DengueDash application interface. On the left is a sidebar with a navigation menu:

- Modules
 - Accounts
 - Manage Accounts
 - Analytics
 - Data Tables
 - Settings

At the bottom of the sidebar, it says "CN Saint Paul's Hospital saintpaul@gmail.com".

The main content area has a breadcrumb navigation: Building Your Application > Data Fetching. The title is "User Profile". Below the title is a subtitle "View and manage user details". A table displays user details:

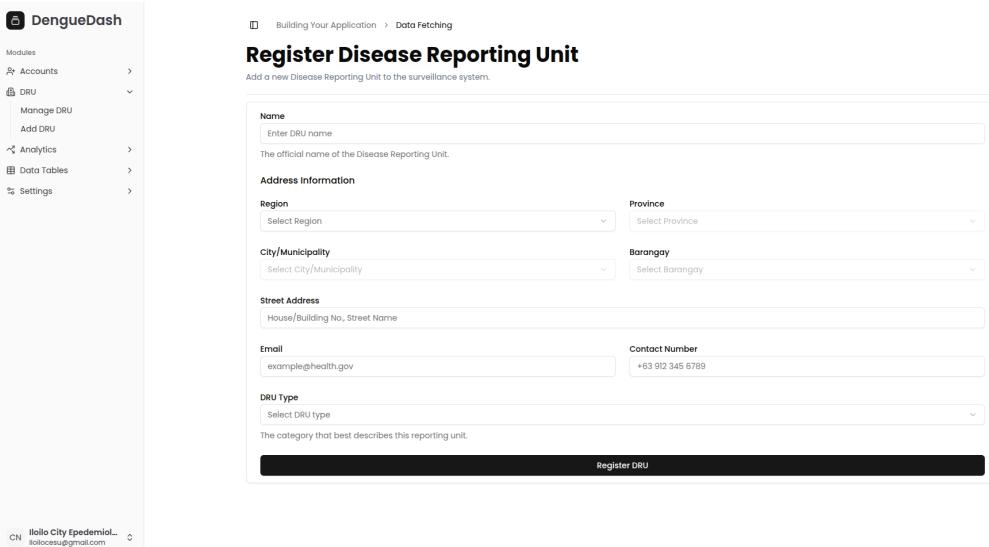
| | |
|---|---|
| Name John David Doe | Email testereee@example.gov.ph |
| Sex Male | Role Encoder |
| Hospital (ORU) Saint Paul's Hospital | |
| Created At April 26 2025 at 16:19:07 | Updated At April 26 2025 at 16:21:16 |
| | Last Login N/A |

Below the table are two buttons: "Promote to Admin" and "Delete User".

Figure 4.33: Account Details

1105 Managing DRUs

1106 Unlike the registration of encoder accounts, the creation of Disease Reporting
 1107 Units can only be done within the web application, and the user performing the
 1108 creation must be an administrator of a surveillance unit. Figure 4.34 presents the
 1109 fields the admin user must fill out, and once completed, the new entry will show
 1110 as being managed by that unit, as shown in Figure 4.35. Figure 4.36, on the other
 1111 hand, shows the details provided in the registration form as well as its creation
 1112 details. There is also an option to delete the DRU, and when invoked, all the
 1113 accounts being managed by it, and the cases reported under those accounts will
 1114 be soft-deleted.



The screenshot displays the DengueDash web application interface. On the left, a sidebar menu lists modules: Accounts, DRU (selected), Analytics, Data Tables, and Settings. The main content area is titled 'Register Disease Reporting Unit' and contains the following fields:

- Name:** A text input field labeled 'Enter DRU name' with the placeholder 'The official name of the Disease Reporting Unit.'
- Address Information:**
 - Region:** A dropdown menu labeled 'Select Region'.
 - Province:** A dropdown menu labeled 'Select Province'.
 - City/Municipality:** A dropdown menu labeled 'Select City/Municipality'.
 - Barangay:** A dropdown menu labeled 'Select Barangay'.
- Street Address:** A text input field labeled 'House/Building No., Street Name'.
- Email:** A text input field containing 'example@health.gov'.
- Contact Number:** A text input field containing '+63 912 345 6789'.
- DRU Type:** A dropdown menu labeled 'Select DRU type' with the placeholder 'The category that best describes this reporting unit.'

A large black button at the bottom right is labeled 'Register DRU'.

Figure 4.34: Disease Reporting Unit Registration

4.6. SYSTEM PROTOTYPE

75

The screenshot shows the DengueDash application interface. On the left is a sidebar with the following navigation:

- Modules
- Accounts
- DRU
 - Manage DRU
 - Add DRU
- Analytics
- Data Tables
- Settings

Below the sidebar, the user information is displayed: CN Iloilo City Epidemiol... and iloilocesu@gmail.com.

The main content area has a breadcrumb navigation: Building Your Application > Data Fetching. The title is "Manage Disease Reporting Units". Below the title, it says "View and manage Disease Reporting Units".

| DRU Name | Email | Action |
|-----------------------------|------------------------------|-----------------------|
| Molo District Health Center | molodistricthealth@gmail.com | <button>Open</button> |
| Jaro 1 Health Center | jarohealth@gmail.com | <button>Open</button> |
| Saint Paul's Hospital | saintpaul@gmail.com | <button>Open</button> |

Figure 4.35: List of Disease Reporting Units

The screenshot shows the DengueDash application interface. On the left is a sidebar with the following navigation:

- Modules
- Accounts
- DRU
 - Manage DRU
 - Add DRU
- Analytics
- Data Tables
- Settings

Below the sidebar, the user information is displayed: CN Iloilo City Epidemiol... and iloilocesu@gmail.com.

The main content area has a breadcrumb navigation: Building Your Application > Data Fetching. The title is "Disease Reporting Unit Profile". Below the title, it says "View and manage DRU details".

| | |
|---|---------------------------------------|
| Name of DRU Molo District Health Center | Email molodistricthealth@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 | |

At the bottom, there are two timestamped entries:

- Created At: April 26 2025 at 13:07:00
- Updated At: April 26 2025 at 13:07:00

A red button at the bottom right is labeled "Delete DRU".

Figure 4.36: Disease Reporting Unit details

₁₁₁₅ **4.7 User Testing**

₁₁₁₆ To evaluate the usability of the system, the System Usability Scale (SUS) was
₁₁₁₇ utilized. SUS is a Likert-scale-based questionnaire comprising 10 items that are
₁₁₁₈ critical to assessing system usability. A total of five participants completed the sur-
₁₁₁₉vey. Their responses were processed following the step-by-step calculation method
₁₁₂₀adopted from (Babich, 2015). The resulting usability scores for each participant
₁₁₂₁are shown in Table 4.6.

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

Table 4.6: Computed System Usability Scores per Participant

₁₁₂₂ The average System Usability Scale (SUS) score across systems is typically
₁₁₂₃ 68 (Babich, 2015). In this testing, the system achieved an average SUS score
₁₁₂₄ of 88.5, indicating a highly positive user experience. This score suggests that
₁₁₂₅ participants found the system not only enjoyable to use but also intuitive enough
₁₁₂₆ to recommend to others. Furthermore, it demonstrates that the system is suitable
₁₁₂₇ for real-world applications without presenting significant complexity for first-time
₁₁₂₈ users.

¹¹²⁹ Chapter 5

¹¹³⁰ Conclusion

¹¹³¹ The development of DengueWatch marks a transformative leap forward in public
¹¹³² health technology, providing Iloilo City with a centralized system to combat one
¹¹³³ of the most persistent mosquito-borne diseases. Previously, data was recorded
¹¹³⁴ manually on paper, making tracking and analysis slow and error-prone. Dengue-
¹¹³⁵ Watch digitizes this process, enabling faster, more accurate monitoring. More
¹¹³⁶ than an academic project, DengueWatch serves as a practical solution aimed at
¹¹³⁷ shifting the approach from reactive outbreak response to proactive prevention. By
¹¹³⁸ combining deep learning models with real-time climate data integration, the sys-
¹¹³⁹ tem achieves a level of accuracy and usability that makes it viable for real-world
¹¹⁴⁰ deployment.

¹¹⁴¹ At the heart of DengueWatch is a Long Short-Term Memory (LSTM) neu-
¹¹⁴² ral network, which outperformed traditional forecasting models such as ARIMA
¹¹⁴³ and Kalman Filter. The LSTM model achieved a Root Mean Square Error
¹¹⁴⁴ (RMSE) of 16.90, compared to 39.00 and 38.40 for ARIMA and Kalman, respec-

1145 tively—demonstrating a substantial improvement in predictive capability. This
1146 advantage stems from the LSTM’s ability to capture long-term dependencies and
1147 model nonlinear relationships between environmental factors and disease patterns.

1148 The analysis also revealed that climate indicators, particularly rainfall and
1149 humidity, play a significant role in dengue outbreaks, typically leading to a surge
1150 in cases three to five weeks after anomalies are detected. By incorporating these
1151 lagged effects, DengueWatch achieved an explanatory power of 83% ($R^2 = 0.83$),
1152 offering a game-changing advantage for early intervention and resource allocation.

1153 Usability testing further underscored DengueWatch’s readiness for real-world
1154 deployment. The system achieved an average System Usability Scale (SUS) score
1155 of 88.5, significantly above the industry benchmark of 68. This indicates that
1156 users found the system intuitive, efficient, and suitable for operational use in
1157 public health contexts. Key features such as a user-friendly dashboard, a two-week
1158 forecasting window aligned with mosquito life cycles, and automated outbreak
1159 alerts ensure that the system supports timely, effective responses.

1160 Beyond its immediate application in Iloilo City, the framework behind Dengue-
1161 Watch holds the potential for broader impact. With minor adaptations, it can
1162 be scaled nationally through integration with Department of Health surveillance
1163 systems.

1164 DengueWatch exemplifies how deep learning can bridge the gap between data
1165 science and life-saving interventions. It empowers health workers to act preemp-
1166 tively, policymakers to allocate resources strategically, and communities to en-
1167 gage in early preventive measures. As climate change accelerates the spread of
1168 vector-borne diseases, systems like DengueWatch will become indispensable in

1169 safeguarding public health. This system not only demonstrates the power of AI
1170 in epidemiological forecasting but also lays the foundation for a smarter, more
1171 resilient approach to combating infectious diseases in the years ahead.

¹¹⁷² Chapter 6

¹¹⁷³ References

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1254 **Appendix A**

1255 **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

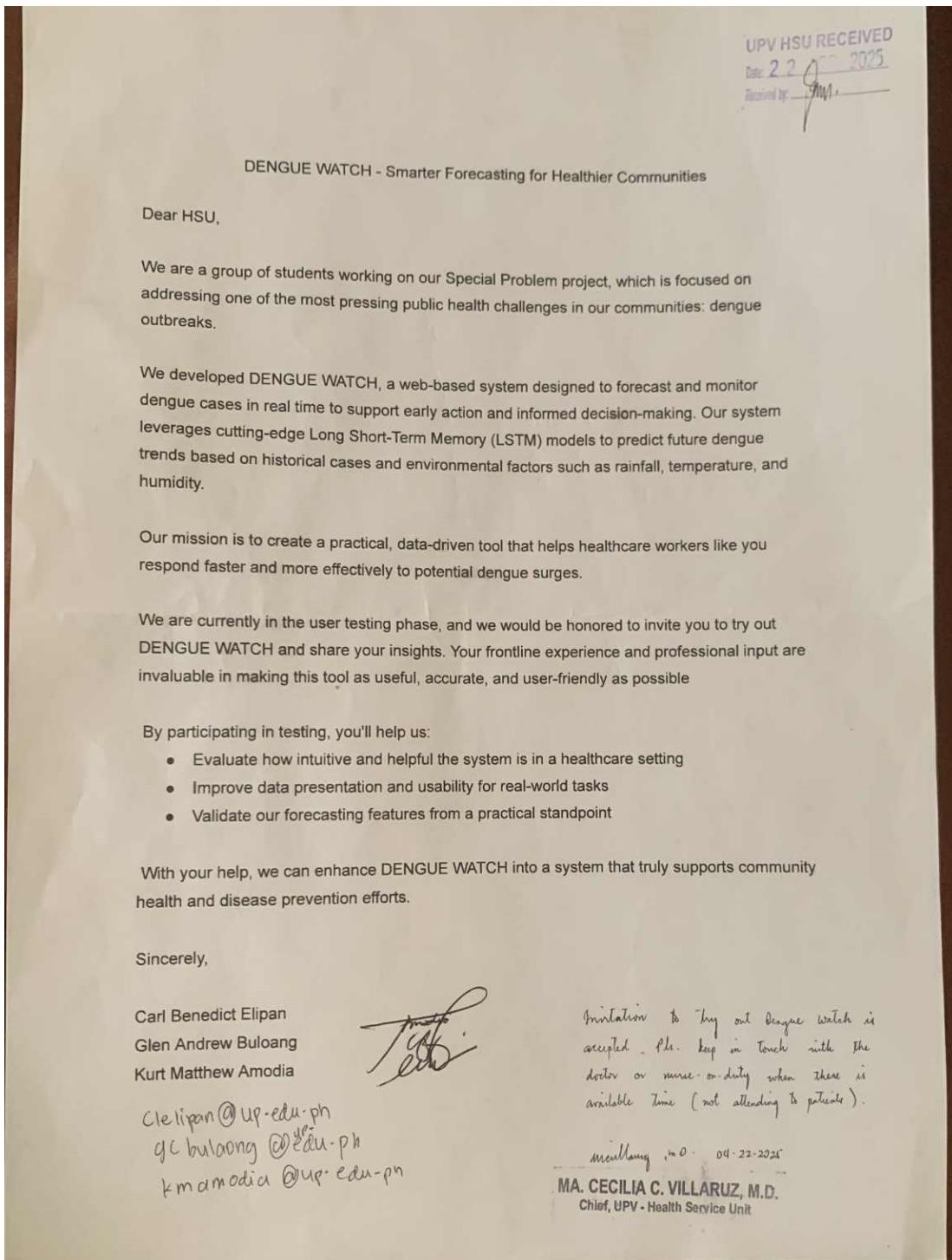


Figure A.3: Letter of Approval for User Testing in UPV HSU

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