

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

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Sciences, University of the Philippines Visayas

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

23

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

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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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63 research.

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

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

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¹⁹¹ **Chapter 1**

¹⁹² **Introduction**

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

¹⁹⁴ Dengue cases surged globally in 2023 and continued to rise in 2025, with over
¹⁹⁵ five million cases and more than 5,000 deaths across 80 countries (Bosano, 2023).

¹⁹⁶ The World Health Organization reported a ten-fold increase in cases from 2000
¹⁹⁷ to 2019, peaking in 2019 with the disease affecting 129 countries (WHO, 2024).

¹⁹⁸ In the Philippines, dengue remains endemic, leading to prolonged and widespread
¹⁹⁹ outbreaks.

²⁰⁰ In Iloilo, dengue cases escalated dramatically. By August 2023, the provincial
²⁰¹ health office reported 4,585 cases and 10 deaths, marking a 319% increase from
²⁰² the previous year (Perla, 2024). Iloilo has reached the outbreak threshold, and
²⁰³ local authorities are on blue alert. In Iloilo City, 649 cases were recorded in 2024,
²⁰⁴ with two deaths. Hospital capacity is strained, with non-COVID-19 hospital bed

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

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

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

228 1.2 Problem Statement

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

²⁴⁸ **1.3 Research Objectives**

²⁴⁹ **1.3.1 General Objective**

²⁵⁰ This study aims to develop a centralized monitoring and analytics system for
²⁵¹ dengue cases in Iloilo City and Province with data management and forecasting
²⁵² capabilities. The researchers will train and compare multiple deep learning models
²⁵³ to predict dengue case trends based on climate data and historical dengue cases
²⁵⁴ to help public health officials in possible dengue case outbreaks.

²⁵⁵ **1.3.2 Specific Objectives**

²⁵⁶ Specifically, this study aims to:

- ²⁵⁷ 1. gather dengue data from the Iloilo Provincial Health Office and climate data
²⁵⁸ (including temperature, rainfall, wind, and humidity) from online sources,
²⁵⁹ and combine and aggregate these into a unified dataset to facilitate compre-
²⁶⁰ hensive dengue case forecasting;
- ²⁶¹ 2. train and evaluate deep learning models for predicting dengue cases using
²⁶² metrics such as Mean Absolute Error (MAE), Root Mean Squared Error
²⁶³ (RMSE), and Mean Squared Error (MSE), and determine the most accurate
²⁶⁴ forecasting approach; and
- ²⁶⁵ 3. develop a web-based analytics dashboard that integrates the predictive model,
²⁶⁶ provides a data management system for dengue cases in Iloilo City and the

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

269 1.4 Scope and Limitations of the Research

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

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

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

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

295 1.5 Significance of the Research

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

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

1.5. SIGNIFICANCE OF THE RESEARCH

7

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

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

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

³²² Chapter 2

³²³ Review of Related Literature

³²⁴ 2.1 Dengue

³²⁵ Dengue disease is a tropical and subtropical mosquito-borne viral illness and is a
³²⁶ major health concern in the Philippines (Bravo, Roque, Brett, Dizon, & L'Azou,
³²⁷ 2014). The majority of individuals with dengue experience no symptoms. Fever is
³²⁸ the most common symptom, typically 4 to 7 days after being bitten by an infected
³²⁹ mosquito (Zhou & Malani, 2024). In recent years, the trend of dengue cases in
³³⁰ the Philippines has shown notable fluctuations, with periodic outbreaks occur-
³³¹ ring every 3 to 5 years, often influenced by climatic and environmental changes.
³³² According to the Department of Health (DOH), the number of reported cases
³³³ has steadily increased over the past decades, attributed to urbanization, popula-
³³⁴ tion growth, and inadequate vector control measures (World Health Organization
³³⁵ (WHO), 2018). Moreover, studies suggest that El Niño and La Niña events have
³³⁶ significant effects on dengue incidence, with warmer temperatures and increased

³³⁷ rainfall providing favorable breeding conditions for mosquitoes (Watts, David M
³³⁸ and Burke, Donald S and Harrison, Bruce A and Whitmire, Ralph E and Nisalak,
³³⁹ Ananda, 2020). The study of Carvajal et. al. highlights the temporal pattern of
³⁴⁰ dengue cases in Metropolitan Manila and emphasizes the significance of relative
³⁴¹ humidity as a key meteorological factor, alongside rainfall and temperature, in
³⁴² influencing this pattern (Carvajal et al., 2018).

³⁴³ 2.2 Outbreak Definition

³⁴⁴ The definition of an outbreak is a critical factor in disease surveillance, as it
³⁴⁵ determines the threshold at which an unusual increase in cases is considered a
³⁴⁶ public health concern. Studies suggest that outbreak thresholds should be context-
³⁴⁷ specific, given the variability in transmission dynamics across different locations
³⁴⁸ (Runge-Ranzinger et al., 2016). Outbreak definitions defined using the Endemic
³⁴⁹ Channel often base thresholds on 2 standard deviations (SD) above the mean
³⁵⁰ number of historic dengue cases. Other studies (Hemisphere, 2015) also used an
³⁵¹ alert threshold of a 5-year mean plus 2 standard deviations. A study by (Brady,
³⁵² Smith, Scott, & Hay, 2015) discussed that definitions of dengue outbreaks differ
³⁵³ significantly across regions and time, making them inconsistent and incomparable.

³⁵⁴ 2.3 Existing System: RabDash DC

³⁵⁵ RabDash, developed by the University of the Philippines Mindanao, is a web-
³⁵⁶ based dashboard for rabies data analytics. It combines predictive modeling with

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

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

371 2.4 Deep Learning

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

³⁷⁹ much lower root mean square error (RMSE) compared to both MLP and ARIMA
³⁸⁰ models, proving its ability to capture complex patterns in time-series data (Ligue
³⁸¹ & Ligue, 2022). This superior performance is attributed to LSTM's capacity
³⁸² to capture complex, time-dependent relationships within the data, such as those
³⁸³ between temperature, rainfall, humidity, and mosquito populations, all of which
³⁸⁴ contribute to dengue incidence (Ligue & Ligue, 2022).

³⁸⁵ 2.5 Kalman Filter

³⁸⁶ The Kalman Filter is another powerful tool for time-series forecasting that can be
³⁸⁷ integrated into our analysis. It provides a recursive solution to estimating the state
³⁸⁸ of a linear dynamic system from a series of noisy measurements. Its application
³⁸⁹ in epidemiological modeling can enhance prediction accuracy by accounting for
³⁹⁰ uncertainties in the data(Li et al., 2022). Studies have shown that Kalman filters
³⁹¹ are effective in predicting infectious disease outbreaks by refining estimates based
³⁹² on observed data. A study published in Frontiers in Physics utilized the Kalman
³⁹³ filter to predict COVID-19 deaths in Ceará, Brazil. They found that the Kalman
³⁹⁴ filter effectively tracked the progression of deaths and cases, providing critical in-
³⁹⁵ sights for public health decision-making (Ahmadini et al., 2021). Another research
³⁹⁶ article in PLOS ONE focused on tracking the effective reproduction number (R_t)
³⁹⁷ of COVID-19 using a Kalman filter. This method estimated the growth rate of
³⁹⁸ new infections from noisy data, demonstrating that the Kalman filter could main-
³⁹⁹ tain accurate estimates even when case reporting was inconsistent(Arroyo-Marioli,
⁴⁰⁰ Bullano, Kucinskas, & Rondón-Moreno, 2021).

⁴⁰¹ This study compares ARIMA, seasonal ARIMA, Kalman Filter, and LSTM
⁴⁰² models using collected dengue case data along with weather data to identify the
⁴⁰³ most effective model for real-time forecasting.

⁴⁰⁴ 2.6 Weather Data

⁴⁰⁵ The relationship between weather patterns and mosquito-borne diseases is inher-
⁴⁰⁶ ently nonlinear, meaning that fluctuations in disease cases do not respond propor-
⁴⁰⁷ tionally to changes in climate variables(Colón-González, Fezzi, Lake, & Hunter,
⁴⁰⁸ 2013) Weather data, such as minimum temperature and accumulated rainfall, are
⁴⁰⁹ strongly linked to dengue case fluctuations, with effects observed after several
⁴¹⁰ weeks due to mosquito breeding and virus incubation cycles. Integrating these
⁴¹¹ lagged weather effects into predictive models can improve early warning systems
⁴¹² for dengue control(Cheong, Burkart, Leitão, & Lakes, 2013). A study also sug-
⁴¹³ gests that weather-based forecasting models using variables like mean temperature
⁴¹⁴ and cumulative rainfall can provide early warnings of dengue outbreaks with high
⁴¹⁵ sensitivity and specificity, enabling predictions up to 16 weeks in advance(Hii et
⁴¹⁶ al., 2012).

⁴¹⁷ This study utilizes weather data, including variables such as temperature,
⁴¹⁸ rainfall, and humidity, as inputs for our dengue forecasting model. Given the
⁴¹⁹ strong, nonlinear relationship between climate patterns and dengue incidence,
⁴²⁰ these weather variables, along with their lagged effects, are essential for enhancing
⁴²¹ prediction accuracy and providing timely early warnings for dengue outbreaks.

422 2.7 Chapter Summary

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

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

⁴³⁷ Chapter 3

⁴³⁸ Research Methodology

⁴³⁹ This chapter lists and discusses the specific steps and activities that were per-
⁴⁴⁰ formed to accomplish the project. The discussion covers the activities from pre-
⁴⁴¹ proposal to Final SP Writing.

⁴⁴² Figure 3.1 summarizes the workflow for forecasting the number of weekly
⁴⁴³ dengue cases. This workflow focuses on using statistical, deep learning, and prob-
⁴⁴⁴ abilistic models to forecast the number of reported dengue cases. The approach
⁴⁴⁵ involves deploying several models for prediction, including ARIMA and Seasonal
⁴⁴⁶ ARIMA as statistical approaches, LSTM as a deep learning approach, and the
⁴⁴⁷ Kalman Filter as a probabilistic approach. These methods are compared with
⁴⁴⁸ each other to determine the most accurate model.

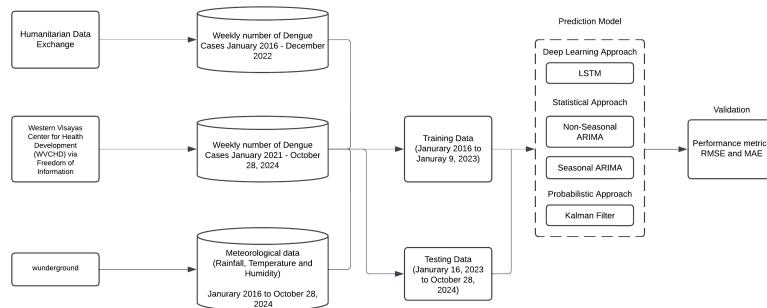


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

449 3.1 Research Activities

450 3.1.1 Dengue and Climate Data Collection

451 Acquisition of Dengue Case Data

The historical dengue case dataset used in this study was obtained from the Humanitarian Data Exchange and the Western Visayas Center for Health Development (WVCHD) via Freedom of Information (FOI) requests. The decision to use weekly intervals was driven by the need for precision and timeliness in capturing fluctuations in dengue cases and weather conditions. Dengue transmission is influenced by short-term changes in weather variables such as rainfall and temperature, which impact mosquito breeding and virus transmission cycles. A weekly granularity allowed the model to better capture these short-term trends, enabling more accurate predictions and responsive public health interventions.

461 Moreover, using a weekly interval provided more data points for training the
462 models compared to a monthly format. This is particularly critical in time series
463 modeling, where larger datasets help improve the robustness of the model and its

464 ability to generalize to new data. Also, the collection of weather data was done
465 by utilizing web scraping techniques to extract weekly weather data (e.g., rainfall,
466 temperature, and humidity) from Weather Underground (wunderground.com).

467

468 **Data Fields**

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

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

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

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

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

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

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

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

485 Data Integration and Preprocessing

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

493 Exploratory Data Analysis (EDA)

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

**499 3.1.2 Develop and Evaluate Deep Learning Models for
500 Dengue Case Forecasting**

501 The deep learning models were developed and trained to forecast weekly dengue
502 cases using historical weather data (rainfall, temperature, wind, and humidity)
503 and dengue case counts. The dataset was normalized and divided into training and
504 testing sets, ensuring temporal continuity to avoid data leakage. The methodology

505 for preparing and training the model are outlined below.

506 **Data Preprocessing**

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

513 **LSTM Model**

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

- 516 • **Training Set:** 80% of the data (572 sequences) was used for model training,
517 enabling the LSTM to learn underlying patterns in historical dengue case
518 trends and their relationship with weather variables.
- 519 • **Test Set:** The remaining 20% of the data (148 sequences) was reserved for
520 testing

521 To prepare the data for LSTM, a sliding window approach was utilized. Se-
522 quences of weeks of normalized features were constructed as input, while the
523 dengue case count for the subsequent week was set as the target variable. This
524 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:

529 **LSTM units:**

- 530 • min value: 32
- 531 • max value: 128
- 532 • step: 16
- 533 • sampling: linear

534 **Learning Rate:**

- 535 • min value: 0.0001
- 536 • max value: 0.01
- 537 • step: None
- 538 • sampling: log

539 The tuner was instantiated with:

- 540 • **max trials = 10:** Limiting the search to 10 different configurations
- 541 • **executions per trial = 3:** Running each configuration thrice to reduce variance

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

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

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

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

564 ARIMA

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

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

- 572 • Autoregressive order (p): 0 to 3
573 • Differencing order (d): 0 to 2
574 • Moving average order (q): 0 to 3

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

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

586 Seasonal ARIMA (SARIMA)

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

605 Kalman Filter:

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

609 20% testing to evaluate model performance.

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

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

626 **Model Simulation:**

627 After identifying the best-performing model among all the trained deep learning
628 models, a simulation was conducted. Using the same parameters from the initial
629 training, the selected model was retrained with the original dataset along with
630 new data up to January 2025. The retrained model was then used to forecast

631 dengue cases for the period from February 2025 to May 2025. Figure 3.2 shows a
632 code snippet of the model training.

```
# Fit on train set
history = model.fit(X_train, y_train,
                     epochs=100,
                     batch_size=1,
                     validation_split=0.2,
                     callbacks=[early_stop],
                     verbose=1)

# Predict on 2025
y_pred_test = model.predict(X_test, verbose=0)
```

Figure 3.2: Testing Folds - Window Size 5

633 3.1.3 Integrate the Predictive Model into a Web-Based 634 Data Analytics Dashboard

635 Dashboard Design and Development

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

640 Model Integration and Deployment

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

643 3.1.4 System Development Framework

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

650 Design and Development

651 After brainstorming and researching the most appropriate type of application to
652 accommodate both the prospected users and the proposed solutions, the team
653 has decided to proceed with a web application. Given the time constraints and
654 available resources, it has been decided that the said means is the most pragmatic
655 and practical move. The next step is to select modern and stable frameworks
656 that align with the fundamental ideas learned by the researchers in the university.
657 The template obtained from WVCHD and Iloilo Provincial Epidemiology and
658 Surveillance Unit was meticulously analyzed to create use cases and develop a
659 preliminary well-structured database that adheres to the requirements needed
660 to produce a quality application. The said use cases serve as the basis of general

661 features. Part by part, these are converted into code, and with the help of selected
662 libraries and packages, it resulted in the desired outcome that may still modified
663 and extended to achieve scalability.

664 **Testing and Integration**

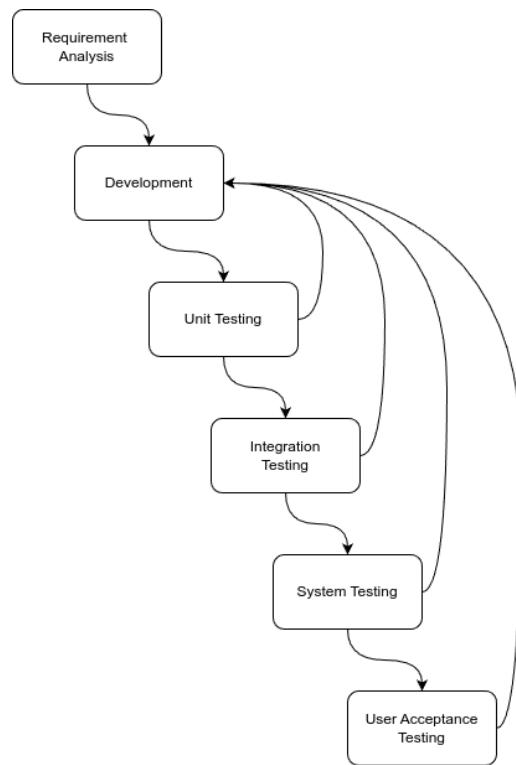


Figure 3.3: Testing Process for DengueWatch

665 Implementing testing is important to validate the system's performance and ef-
666 ficacy. Thus a series of tests were conducted to identify and resolve bugs during
667 the developmental phase. Each feature was rigorously tested to ensure quality as-
668 surance, with particular emphasis on prerequisite features, as development cannot
669 progress properly if these fail. Because of this, integration between each feature

670 serves as a pillar for a cohesive user experience. Since dengue reports include
671 confidential information, anonymized historical dengue reports were used to train
672 the model and create the foundational architecture of the system. By using func-
673 tional tests, data validation and visualization can be ensured for further continual
674 improvements. Security testing is also important as it is needed to safeguard
675 confidential information when the system is deployed. It includes proper authen-
676 tication, permission views, and mitigating common injection attacks. Finally, a
677 user acceptance test from the prospected users, in this case, doctors, nurses, and
678 other health workers is crucial to assess its performance and user experience. It
679 enables the developers to confirm if the system meets the needs of the problem.

680 **3.2 Development Tools**

681 **3.2.1 Software**

682 **Github**

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

688 Visual Studio Code

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

693 Django

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

702 Next.js

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

⁷⁰⁹ **Postman**

⁷¹⁰ As the application heavily relies on the Application Programming Interface (API)
⁷¹¹ being thrown by the backend, it is a must to use a development tool that facilitates
⁷¹² the development and testing of the API. Postman is a freemium API platform
⁷¹³ that offers a user-friendly interface to create and manage API requests (*What is*
⁷¹⁴ *Postman? Postman API Platform*, n.d.).

⁷¹⁵ **3.2.2 Hardware**

⁷¹⁶ The web application was developed on laptop computers with minimum specifica-
⁷¹⁷ tions of an 11th-generation Intel i5 CPU and 16 gigabytes of RAM. Furthermore,
⁷¹⁸ an RTX 3060 mobile GPU was also utilized to retrain the integrated model locally.

⁷¹⁹ **3.2.3 Packages**

⁷²⁰ **Django REST Framework**

⁷²¹ Django Rest Framework (DRF) is a third-party package for Django that provides a
⁷²² comprehensive suite of features to simplify the development of robust and scalable
⁷²³ Web APIs (Christie, n.d.). These services include Serialization, Authentication
⁷²⁴ and Permissions, Viewsets and Routers, and a Browsable API .

725 Leaflet

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

732 Chart.js

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

740 Tailwind CSS

741 Using plain CSS in production-quality applications can be counterproductive.
742 Therefore, CSS frameworks were developed to promote consistency and accelerate
743 the rapid development of web applications (Joel, 2021). One of these is Tailwind,
744 which offers low-level utility classes that can be applied directly to each HTML
745 element to create a custom design (*Tailwind CSS - Rapidly build modern web-*

⁷⁴⁶ *sites without ever leaving your HTML.*, n.d.). Given the limited timeline for this
⁷⁴⁷ project, using this framework is a wise choice due to its stability and popularity
⁷⁴⁸ among developers.

⁷⁴⁹ **Shadcn**

⁷⁵⁰ Shadcn offers a collection of open-source UI boilerplate components that can be
⁷⁵¹ directly copied and pasted into one's project. With the flexibility of the provided
⁷⁵² components, Shadcn allows developers to have full control over customization and
⁷⁵³ styling. Since this is built on top of Tailwind CSS and Radix UI, it is supported
⁷⁵⁴ by most modern frontend frameworks, including Next.js (Shadcn, n.d.).

⁷⁵⁵ **Zod**

⁷⁵⁶ Data validation is integral in this web application since it will handle crucial data
⁷⁵⁷ that will be used for analytical inferences and observations. Since Zod is primarily
⁷⁵⁸ used for validating and parsing data, it ensures proper communication between
⁷⁵⁹ the client and the server (Zod, n.d.).

760 **3.3 Application Requirements**

761 **3.3.1 Backend Requirements**

762 **Database Structure Design**

763 Determining how data flows and how it would be structured is crucial in creating
764 the system as it defines how extendible and flexible it would be for future features
765 and updates. Thus, creating a comprehensive map of data ensures proper nor-
766 malization that eliminates data redundancy and improves data integrity. Figure
767 3.4 depicts the designed database schema that showcases the relationship between
768 the application's entities.

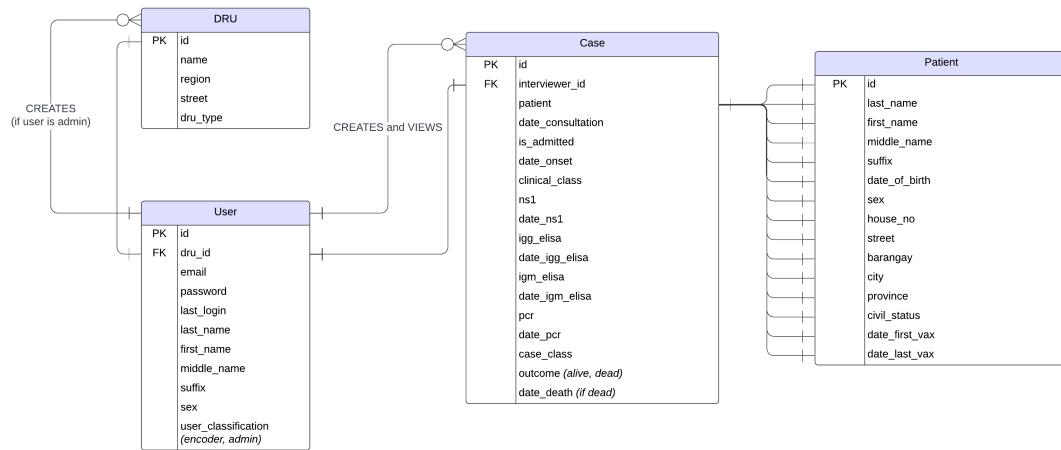


Figure 3.4: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

⁷⁶⁹ **3.3.2 User Interface Requirements**

⁷⁷⁰ **Admin Interface**

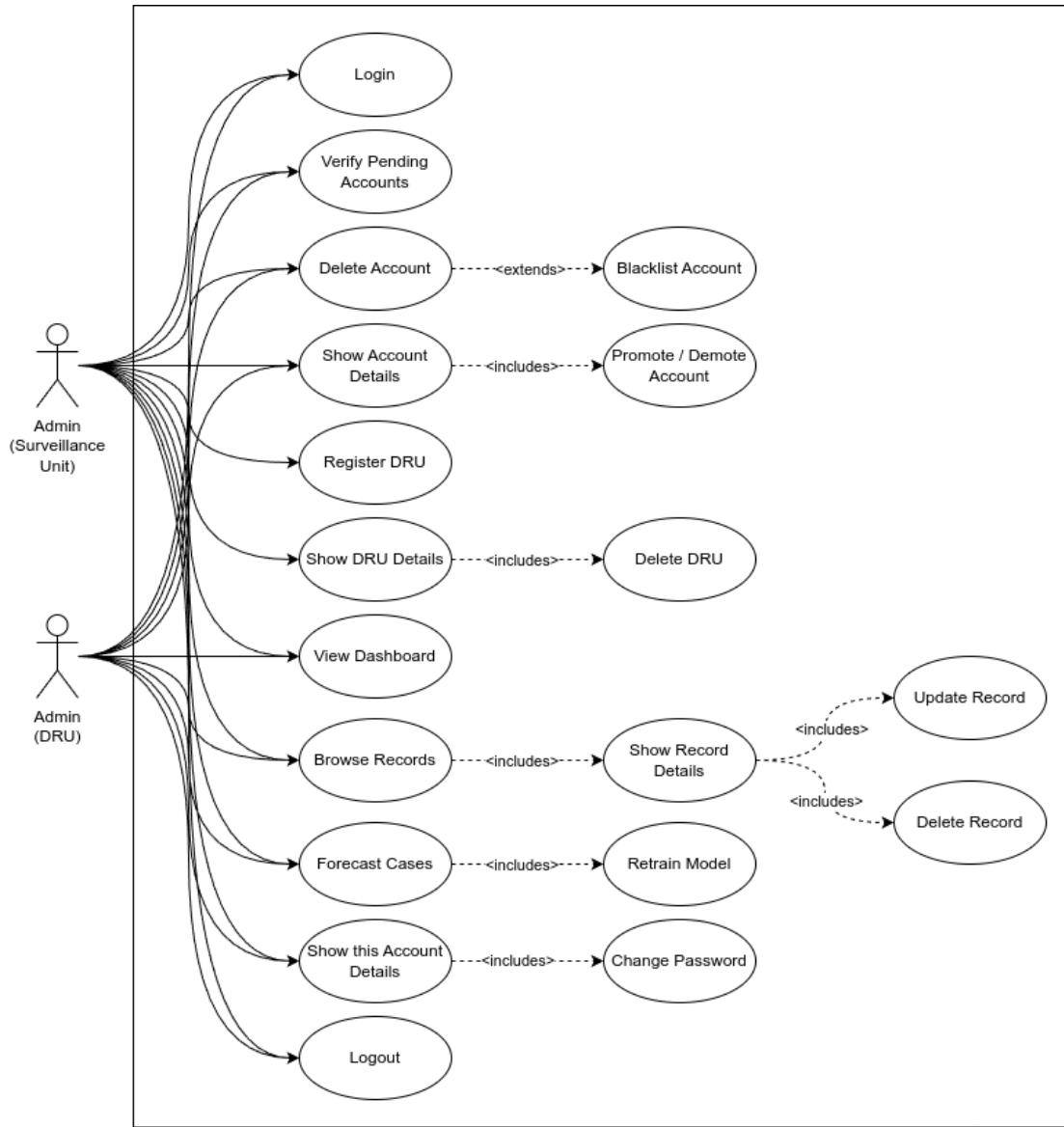


Figure 3.5: Use Case Diagram for Admins

771 Figure 3.5 shows the actions of an admin for a specific Disease Reporting Unit
772 (DRU) and an admin for a specific Surveillance Unit can take in the application.
773 Both of them include the management of accounts, browsing records, and fore-
774 casting and retraining all the consolidated data under their supervision. Most
775 importantly, these users must verify the encoders who register under their ju-
776 risdiction before allowing their account to access the application in the name of
777 safeguarding the integrity of the data. The only advantage of the latter type of ad-
778 ministrator is that it has a one-step higher authorization as it manages the DRUs.
779 In addition, only the authorized surveillance unit administrator can register and
780 create a DRU to uphold transparency and accountability.

⁷⁸¹ **Encoder Interface**

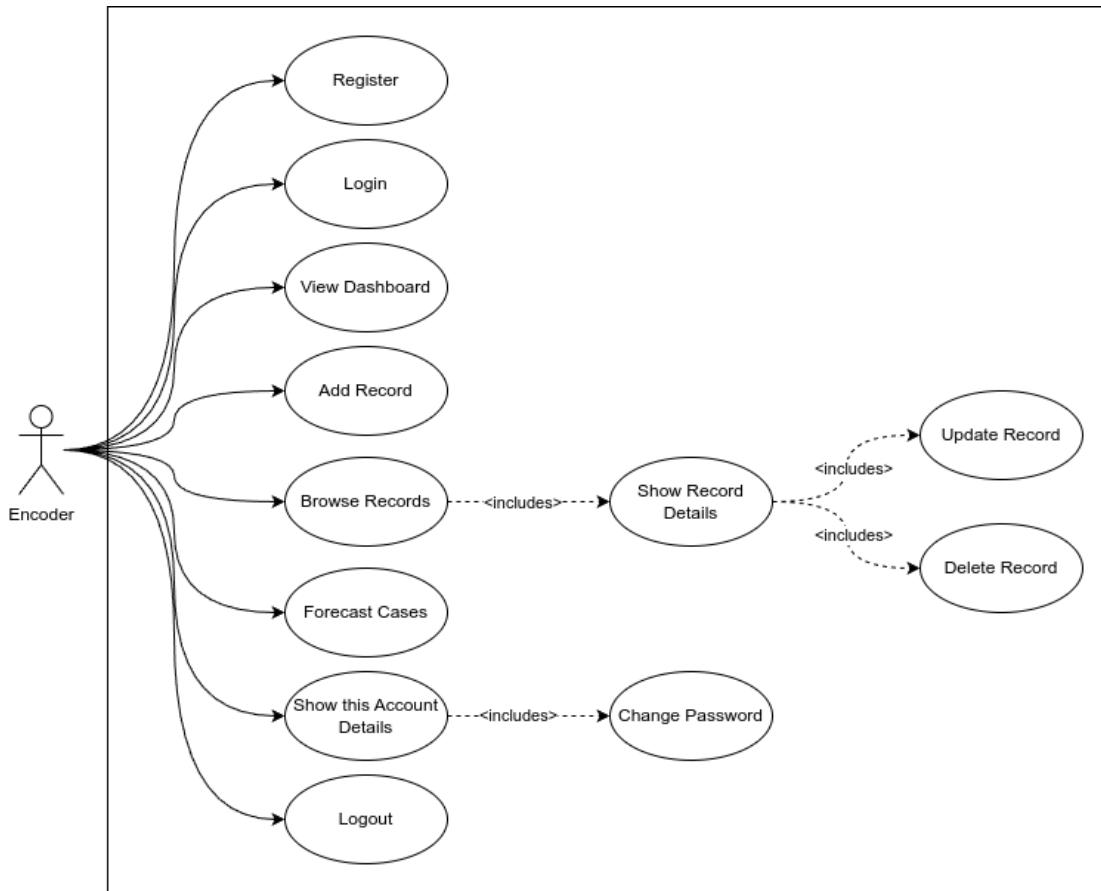


Figure 3.6: Use Case Diagram for Encoder

⁷⁸² Figure 3.6, on the other hand, illustrates the use cases for the system's primary
⁷⁸³ users. These users can register but must wait for further verification to access the
⁷⁸⁴ application. Similar to the previous interfaces, encoders can browse and manage
⁷⁸⁵ records, as well as forecast the consolidated cases under a specific surveillance or
⁷⁸⁶ disease reporting unit, but they are not allowed to retrain the model. Lastly, they
⁷⁸⁷ are the only type of user that can file and create dengue cases by filling out a form
⁷⁸⁸ with the required details.

789 3.3.3 Security and Validation Requirements**790 Password Encryption**

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

799 Authentication

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

805 Data Validation

806 Both the backend and frontend should validate the input from the user to preserve
807 data integrity. Thus, Zod is implemented in the latter to help catch invalid inputs
808 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.

⁸¹⁴ **Chapter 4**

⁸¹⁵ **Results and Discussion**

⁸¹⁶ **4.1 Data Gathering**

⁸¹⁷ The data for dengue case prediction was gathered from a variety of reliable sources,
⁸¹⁸ enabling a comprehensive dataset spanning from January 2011 to October 2024.
⁸¹⁹ This dataset includes 720 rows of data, each containing weekly records of dengue
⁸²⁰ cases along with corresponding meteorological variables, such as rainfall, temper-
⁸²¹ ature, and humidity.

⁸²² 1. Dengue Case Data: The primary source of historical dengue cases came
⁸²³ from the Humanitarian Data Exchange and the Western Visayas Center for
⁸²⁴ Health Development (WVCHD). The dataset, accessed through Freedom of
⁸²⁵ Information (FOI) requests, provided robust case numbers for the Western
⁸²⁶ Visayas region. The systematic collection of these data points was essential
⁸²⁷ for establishing a reliable baseline for model training and evaluation.

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

	Time	Rainfall	MaxTemperature	AverageTemperature	MinTemperature	Wind	Humidity	Cases
0	2011-01-03	9.938571	29.444400	25.888890	23.8888900	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

831 4.2 Exploratory Data Analysis

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

- 833 • **Time.** Weekly timestamps (e.g. “2011-w1”)
- 834 • **Rainfall.** Weekly average rainfall (mm)
- 835 • **MaxTemperature, AverageTemperature, MinTemperature.** Weekly
 836 temperature data (°C)
- 837 • **Wind.** Wind speed (m/s)
- 838 • **Humidity.** Weekly average humidity (%)
- 839 • **Cases.** Reported dengue cases

#	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

840 From the statistics in Figure 4.3, the number of cases ranges from 0 to 319.
 841 The average number of dengue cases per week is 23.74, with a median of 12 cases
 842 and a standard deviation of 37.14. The distribution is highly skewed, with some
 843 weeks experiencing significant number of cases (up to 319 cases). Rainfall shows
 844 a wide variation (0 to 445mm), while temperature remains relatively stable, with
 845 an average of 28.1 degree celsius. Humidity levels ranges from 73% to 89% with
 846 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: Summary Statistics for the Aggregated Dataset

847 Figure 4.4 illustrates the trend of weekly dengue cases over time. The data
 848 reveals periodic spikes in the number of cases, suggesting a seasonal pattern in
 849 dengue cases. Notably, peak cases are observed during certain periods approx-

850 imately 3 years, potentially aligning with specific climatic conditions such as
 851 increased rainfall or temperature changes. This underscores the importance of
 852 incorporating climate variables into the forecasting model.

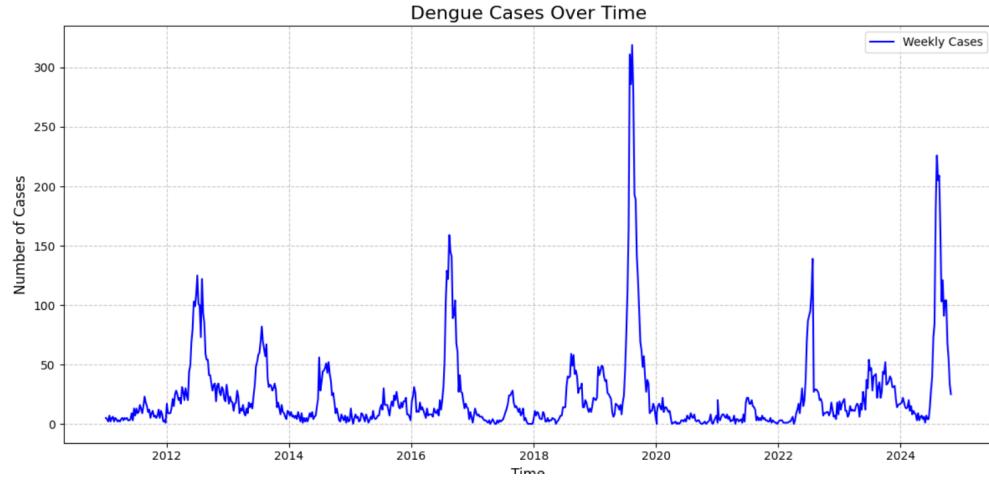


Figure 4.4: Trend of Dengue Cases

853 Figure 4.5 shows the ranking of correlation coefficients between dengue cases
 854 and selected features, including rainfall, humidity, maximum temperature, aver-
 855 age temperature, minimum temperature, and wind speed. Among these, rainfall
 856 exhibits the highest positive correlation with dengue cases (correlation coefficient
 857 0.13), indicating that increased rainfall may contribute to higher cases counts.
 858 This aligns with existing studies suggesting that stagnant water from heavy rain-
 859 fall creates breeding grounds for mosquitos. It is followed by humidity (0.10),
 860 suggesting that higher humidity levels may enhance mosquito reproduction, lead-
 861 ing to more dengue cases. Temperature has a weak to moderate positive corre-
 862 lation with dengue cases, with maximum temperature (0.09) showing a stronger
 863 relationship than average and minimum temperature.

864 Figure 4.6 shows the distributions of each feature while Figure 4.7 shows scat-
 865 terplots of each feature against the number of cases. The distributions of Rainfall,

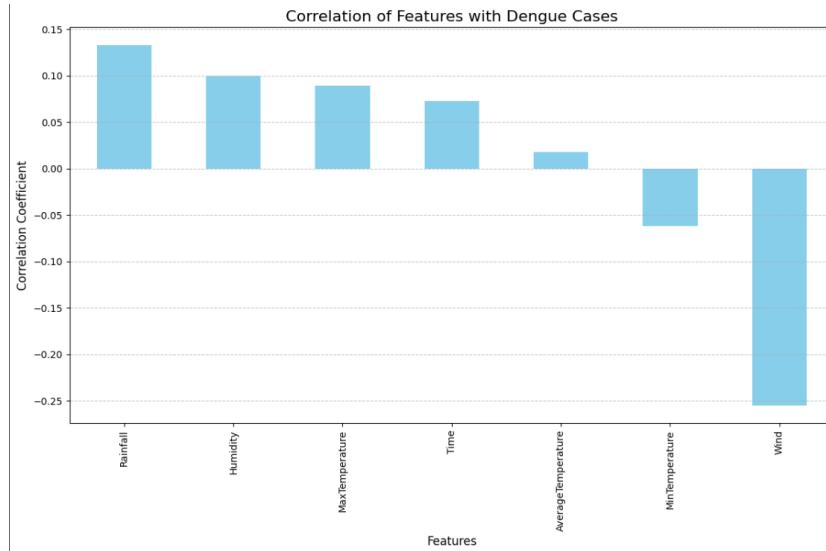


Figure 4.5: Ranking of Correlations

866 Max Temperature, Min Temperature, and Wind appear skewed, which is common
867 for many real-world variables. This skewness can distort correlation estimates, as
868 Pearson correlation assume linear relationships and are more reliable when vari-
869 ables follow a symmetric or approximately normal distribution (Bobbitt, 2021).
870 Applying a log transformation can help normalize these distributions, improve lin-
871 earity, and thus lead to more meaningful and accurate correlation analysis (Htoon,
872 2021).

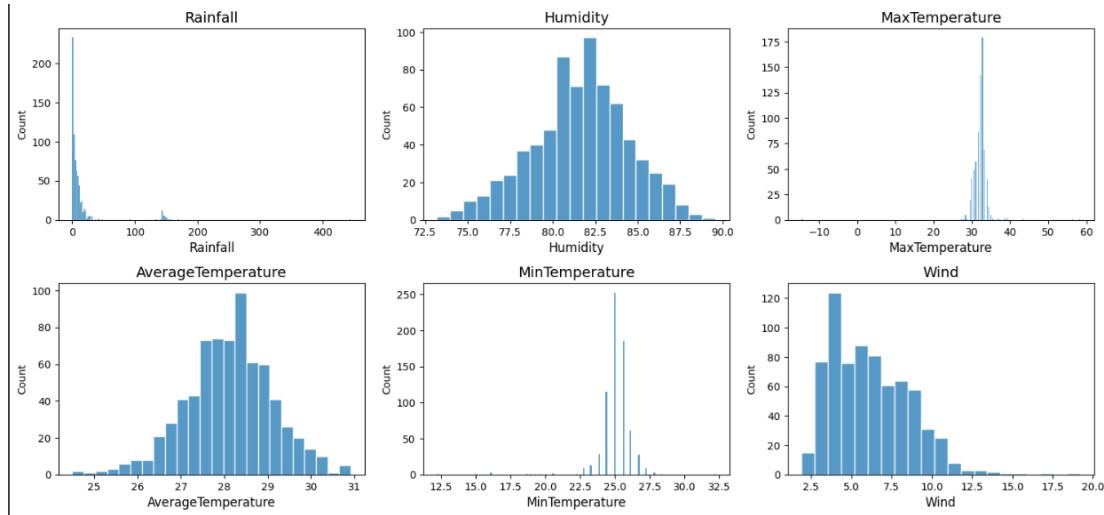


Figure 4.6: Pre-Transform Feature Distributions

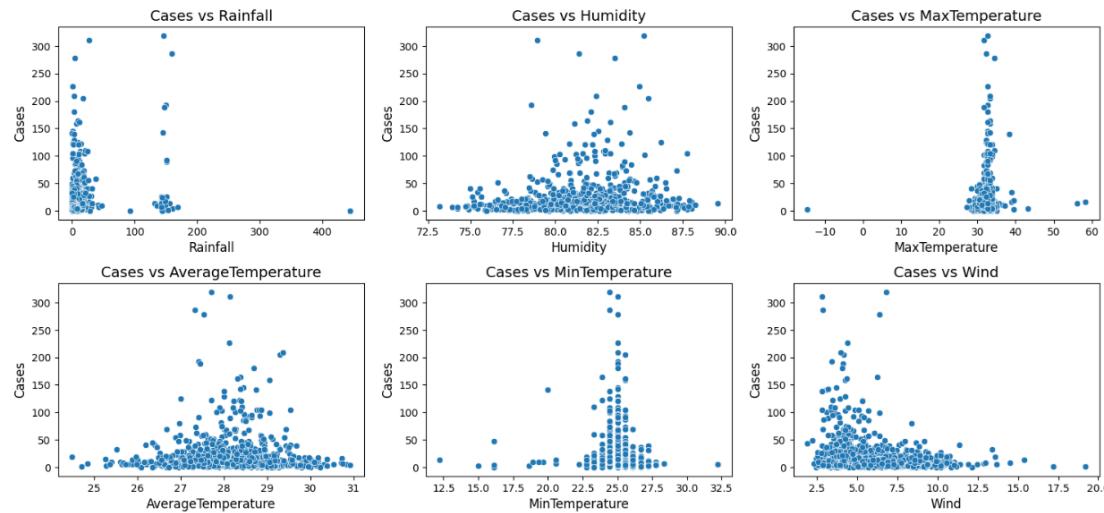


Figure 4.7: Pre-Transform Scatterplots

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

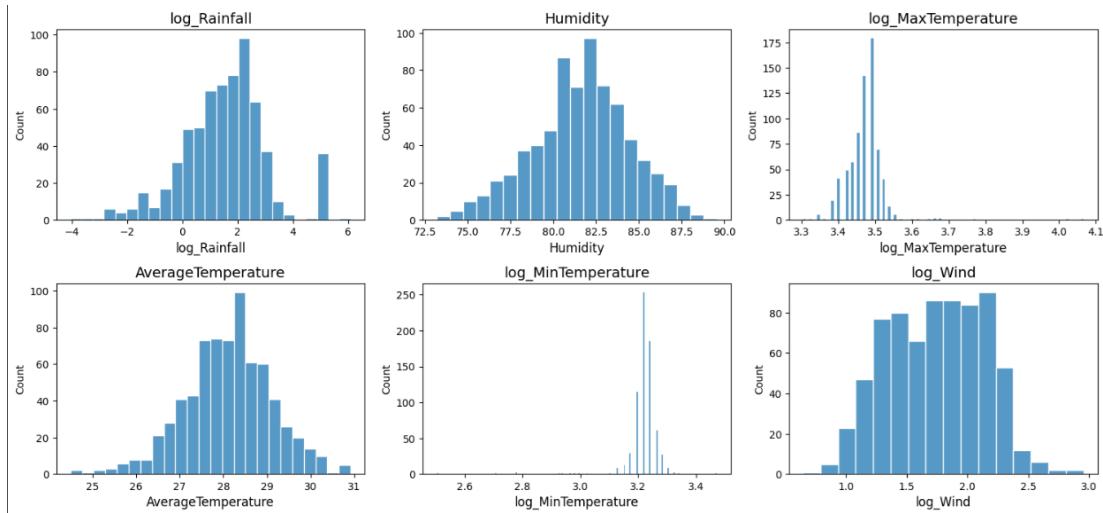


Figure 4.8: Post-Transform Feature Distributions

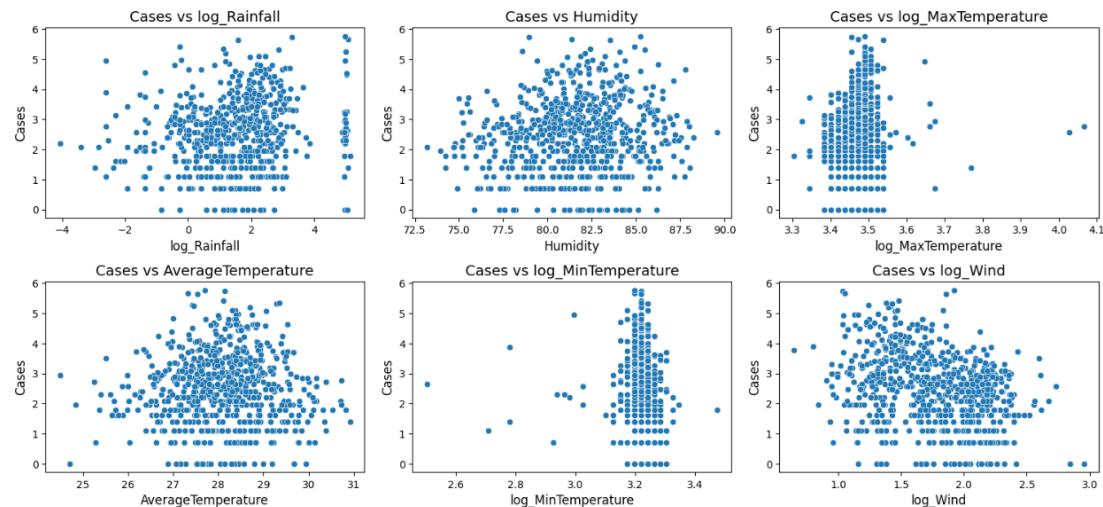


Figure 4.9: Transformed Distributions: Scatterplots

878 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. 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.

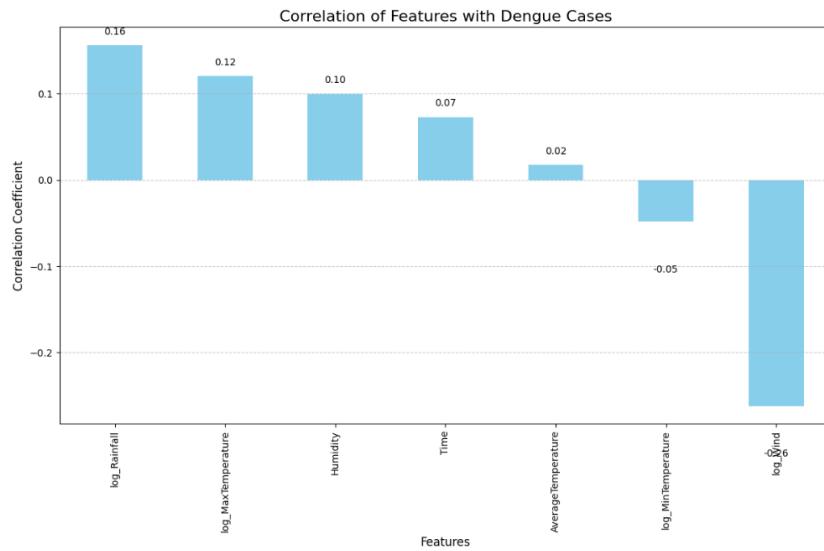


Figure 4.10: Ranking of Correlations with New Distributions

4.3 Model Training Results

The models were evaluated using three metrics: MSE, RMSE, and MAE. The table below provides a summary and comparative analysis of each model's results across these metrics, offering insights into the strengths and limitations of each forecasting technique for dengue case prediction in Iloilo City. The lower values of the three metrics indicate better forecasting performance. Table 4.1 shows that

892 the models performed differently on testing data. LSTM outperformed the other
 893 models with the lowest RMSE, MSE, and MAE while the other three models had
 894 relatively higher values for the three metrics.

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

Table 4.1: Comparison of different models for dengue prediction

895 4.3.1 LSTM Model

896 The LSTM model was tuned for the following parameters: learning rate and units.
 897 The hyperparameter tuning was conducted for each window size, finding the best
 898 parameters for each window size. Further evaluating which window size is most
 899 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	406.03	20.15	12.61	0.76
10	1037.77	32.21	26.79	0.39
20	427.39	20.67	13.61	0.75

Table 4.2: Comparison of Window Sizes

900
 901 The results indicate that a window size of 5 weeks provides the most accurate
 902 predictions, as evidenced by the lowest MSE and RMSE values. Furthermore, the
 903 R² score of 0.76 indicates that 76% of the variability in the target variable (cases)
 904 is explained by the independent variables (the inputs) in the model, making it a
 905 reliable configuration overall.

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

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

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

909 Figure 4.11 illustrates the model's performance in predicting dengue cases
 910 for each fold using a window size of 5. As shown in the plot, the training set
 911 progressively increases with each fold, mimicking a real-world scenario where more
 912 data becomes available over time for dengue prediction. Figure 4.12 demonstrates
 913 that the predicted cases closely follow the trend of the actual cases, indicating
 914 that the LSTM model successfully captures the underlying patterns in the data.
 915 It is also evident that as the fold number increases and the training set grows, the
 916 accuracy of the predictions on the test set improves. Despite the test data being
 917 unseen, the model exhibits a strong ability to generalize, suggesting it effectively
 918 leverages past observations to predict future trends.

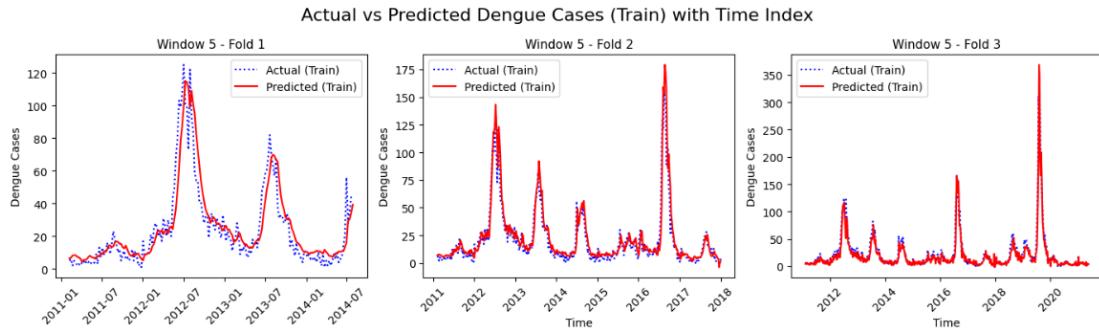


Figure 4.11: Training Folds - Window Size 5

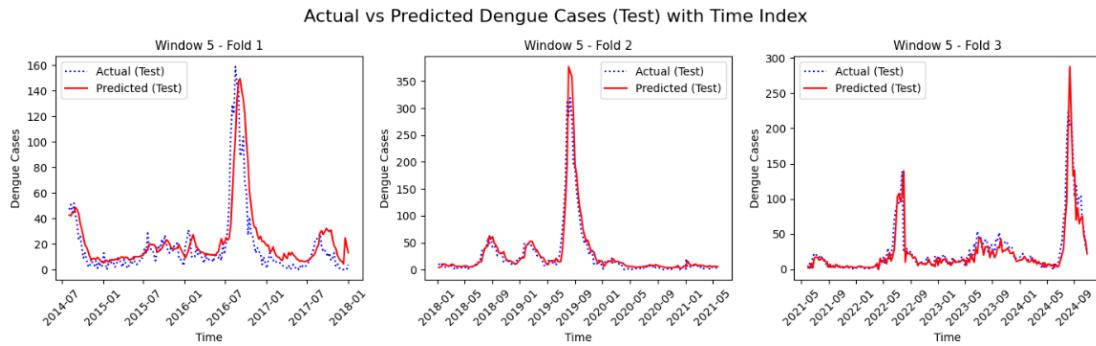


Figure 4.12: Testing Folds - Window Size 5

919 4.3.2 ARIMA Model

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

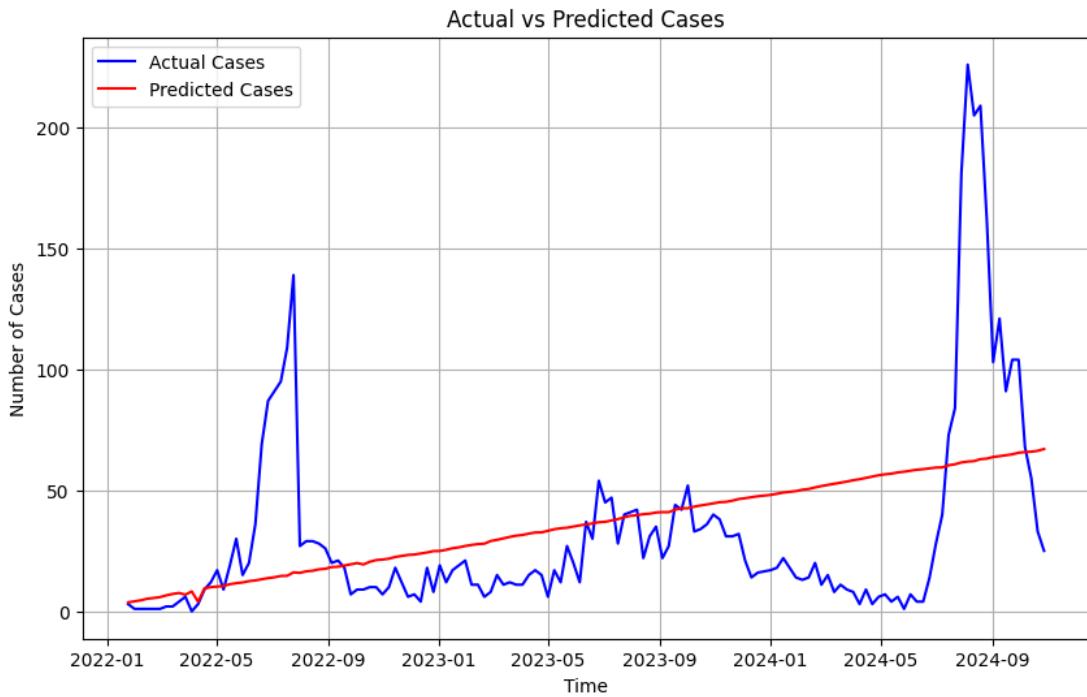


Figure 4.13: ARIMA Prediction Results for Test Set

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

- 931 • **MSE (Mean Squared Error):** 1521.48
- 932 • **RMSE (Root Mean Squared Error):** 39.01
- 933 • **MAE (Mean Absolute Error):** 25.80

934 4.3.3 Seasonal ARIMA (SARIMA) Model

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

937 data.

938 This model incorporates seasonal parameters, which were tuned using grid
939 search to find the best configuration: **SARIMA(2, 0, 2)(0, 1, 1)[52]**. As with
940 ARIMA, **400 iterations** were applied to ensure a robust fit. As shown in Figure
941 4.14, the SARIMA model demonstrates a notable improvement in performance.
942 Unlike its non-seasonal counterpart, it effectively captures the general trend and
943 aligns more closely with the peaks observed in the actual dengue cases, indicating
944 its ability to model seasonal dynamics.

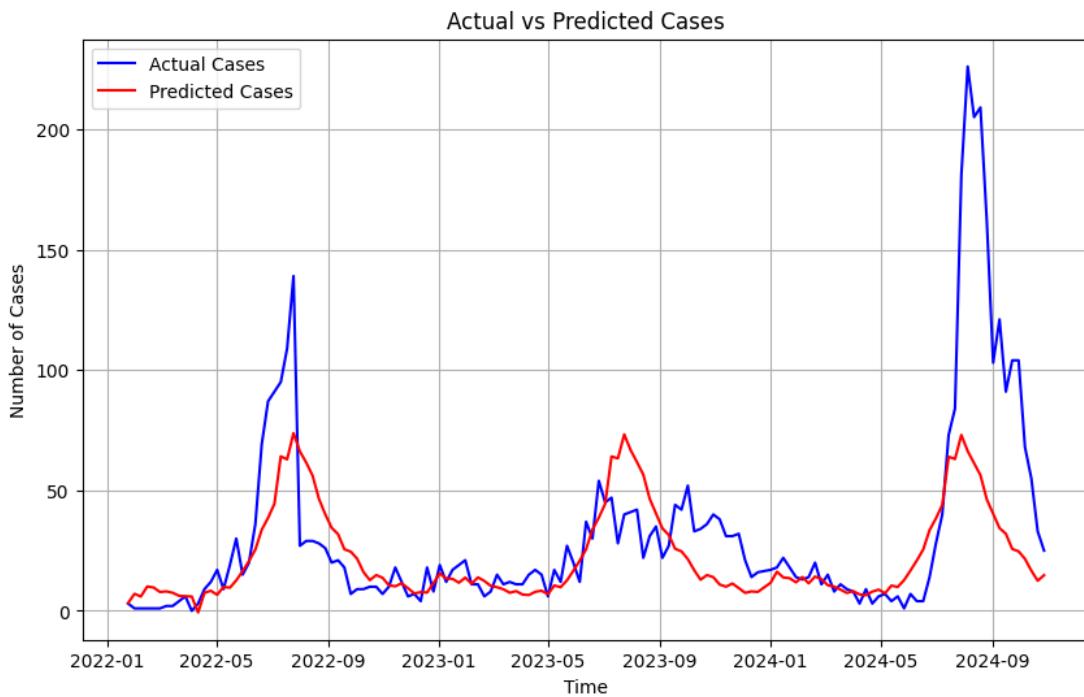


Figure 4.14: Seasonal ARIMA Prediction Results for Test Set

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

947 • **MSE:** 1109.69

948 • **RMSE:** 33.31

949 • **MAE:** 18.09

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

954 After training the model, the SARIMA model was validated using the same
 955 Time Series Cross-Validation strategy employed in the LSTM model. Table 4.4
 956 presents the performance metrics for each fold, as well as the average metrics
 957 across all folds. The average RMSE and MAE values were close to those obtained
 958 during the initial training phase, indicating that the SARIMA model performed
 959 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

960 4.3.4 Kalman Filter Model

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

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

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

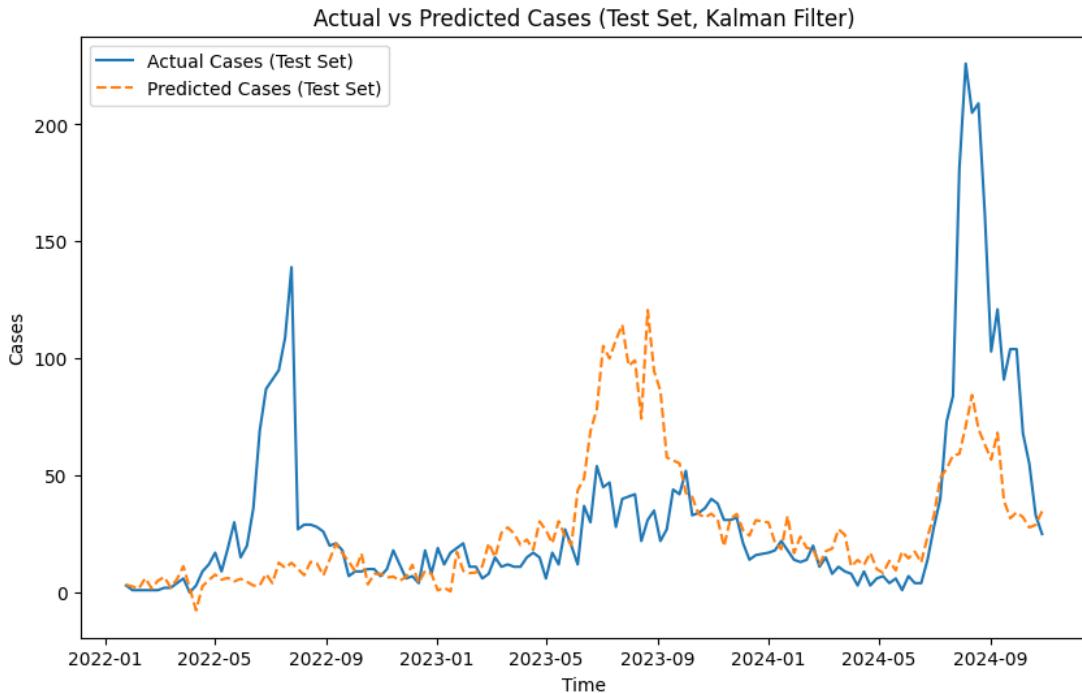


Figure 4.15: Kalman Filter Prediction Results for Test Set

969 The Kalman Filter was then combined with the LSTM model in order to see
 970 improvements in its predictions. Table 4.5 shows the metrics across three folds
 971 using the same Time Series Cross Validation Strategy employed in the previous
 972 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

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

976 4.4 Model Simulation

977 To evaluate the LSTM model’s real-world forecasting ability, a simulation was
 978 conducted to predict dengue cases for the year 2025. The model was retrained
 979 exclusively, using the parameters found from the initial training, on data from 2011
 980 to January 2025, using both dengue cases and weather variables. Importantly, the
 981 actual dengue case values for 2025 were never included during training. Instead,
 982 only the weather variables collected for 2025 were input into the model to generate
 983 predictions for that year. After prediction, the forecasted dengue cases for 2025
 984 were compared against the true observed cases to assess the model’s accuracy.
 985 Figure 4.16 shows that the predicted values closely follow the trend, although it
 986 may overestimate the dengue cases in some weeks.

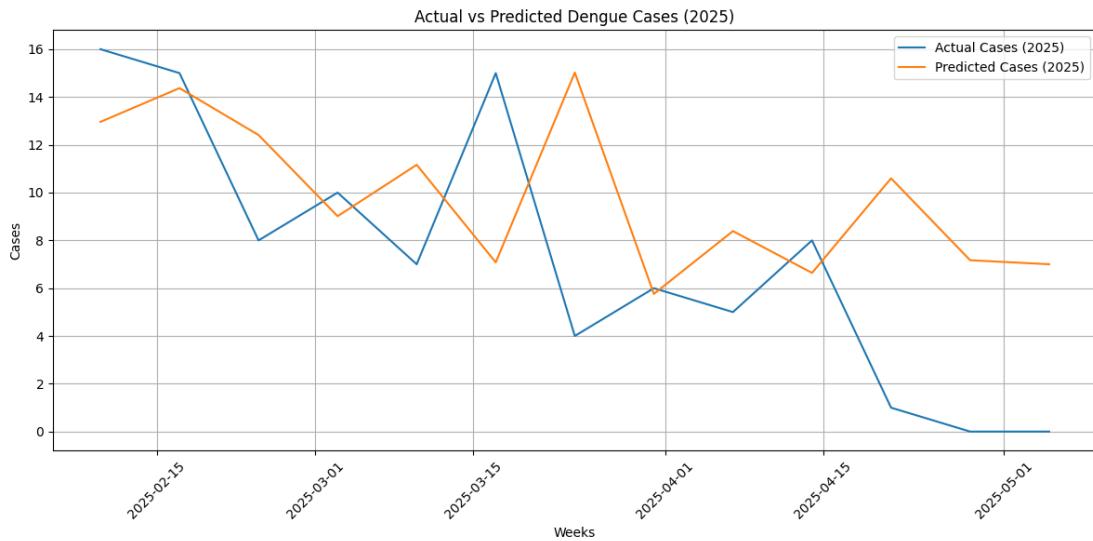


Figure 4.16: Predicted vs Actual Dengue Cases 2025

987 4.5 System Prototype

988 4.5.1 Home Page

989 The Home Page is intended for all visitors to the web application. The Analytics
990 Dashboard, which displays relevant statistics for dengue cases at a certain time
991 and location, is the primary component highlighted, as seen in Figure 4.17. This
992 component includes a combo chart that graphs the number of dengue cases and
993 deaths per week in a specific year, a choropleth map that tracks the number of
994 dengue cases per barangay in a location, and various bar charts that indicate the
995 top constituent places affected by dengue.

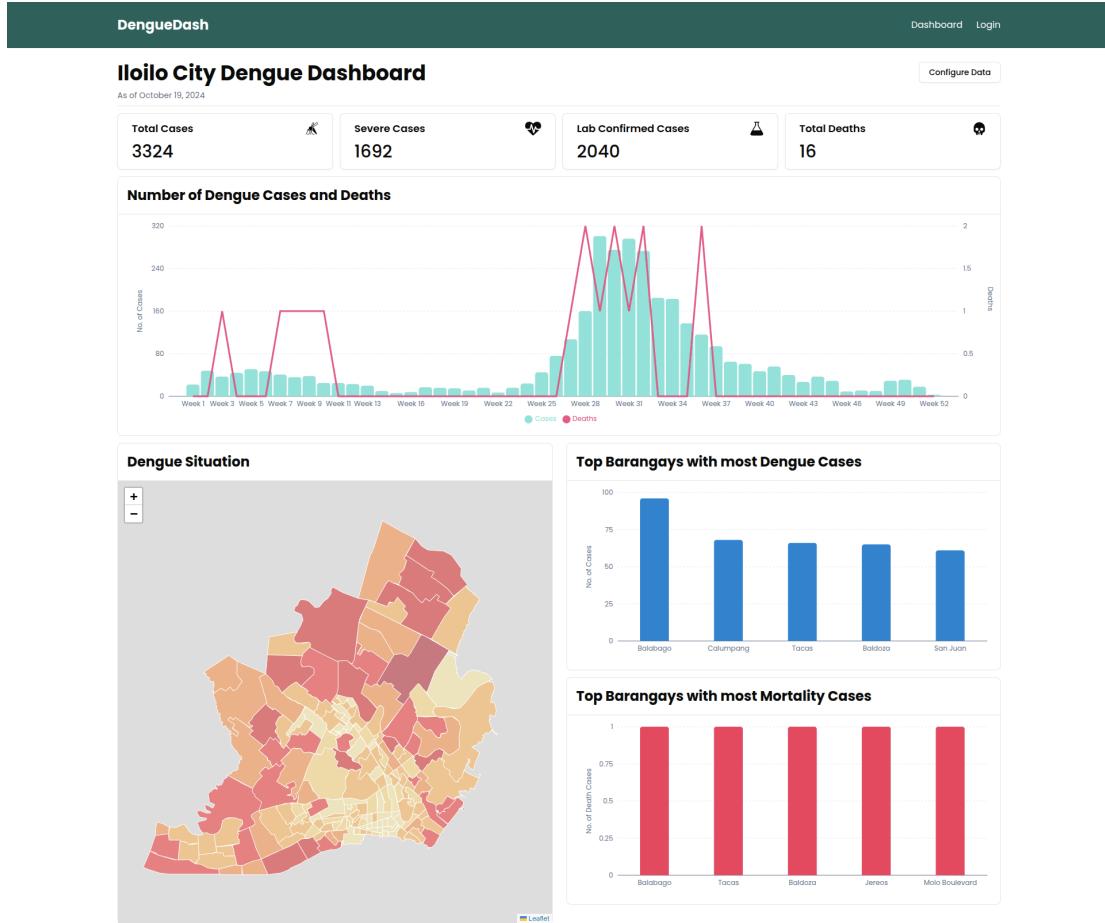


Figure 4.17: Home Page

4.5.2 User Registration, Login, and Authentication

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

1003 the user can log in to the system through the page shown in Figure 4.19. After
1004 entering the correct credentials, which consist of an email and password, the
1005 system uses HTTP-only cookies containing JSON Web Tokens (JWT) to prevent
1006 vulnerability to Cross-site Scripting (XSS) attacks. It will then proceed to the
1007 appropriate page for the type of user it belongs to. Logging out on the other
1008 hand, will remove both the access and refresh tokens from the browser, and will
1009 blacklist the latter token to make it unusable for security purposes.

The screenshot shows the 'Sign Up' page of the DengueDash application. At the top, there is a dark header bar with the text 'DengueDash' on the left and 'Dashboard Login' on the right. Below the header, the main form has a title 'Sign Up' and a subtitle 'Create your account to get started'. The form consists of several input fields arranged in a grid:

First Name	Middle Name (Optional)
John	David
Last Name	Sex
Doe	Select gender
Email	Region
john@example.com	Select region
Surveillance Unit	DRU
Select surveillance unit	Select DRU
Password	Confirm Password
Must be at least 8 characters long	

At the bottom of the form is a large black button labeled 'Create Account'. Below the button, there is a small link 'Already have an account? Sign in'.

Figure 4.18: Sign Up Page

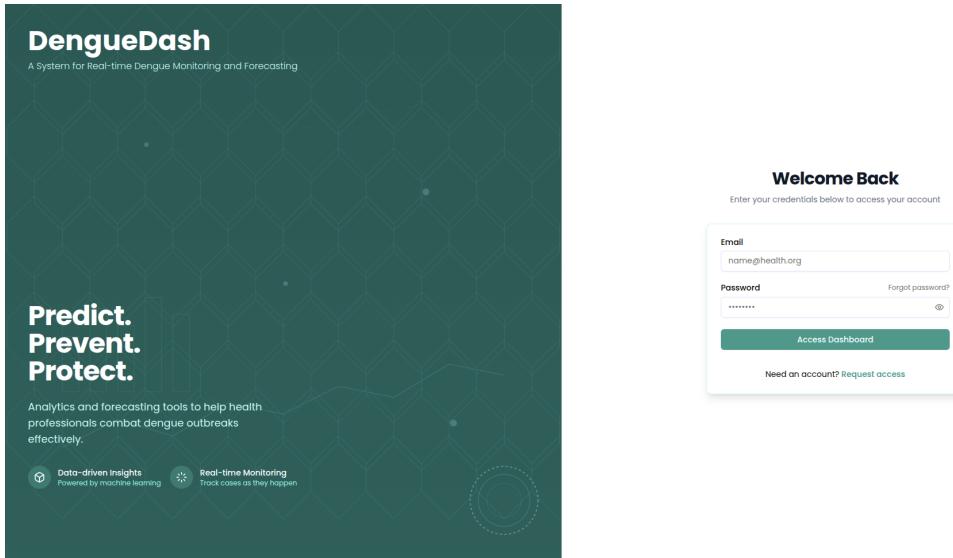


Figure 4.19: Login Page

4.5.3 Encoder Interface

Case Report Form

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

1022 makes use of a formatted CSV file template. As shown in Figure 4.22, an encoder
1023 can download the template using the "Download Template" button, and insert
1024 multiple records inside the file, then upload it by clicking the "Click to upload"
1025 button. The web application automatically checks the file for data inconsistencies
1026 and validation.

The screenshot shows the 'Case Report Form' page within the 'DengueDash' application. The left sidebar displays navigation links for 'Analytics', 'Forms' (selected), and 'Data Tables'. The main content area is titled 'Case Report Form' and contains three tabs: 'Personal Information' (selected), 'Clinical Status', and 'Vaccination'. The 'Personal Information' tab includes sections for 'Personal Detail' (with fields for First Name, Middle Name, Last Name, Suffix, Sex, Date of Birth, 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. On the far left, a user profile is visible: CN Charles Larson Griffin, bakerwendy@example.com.

Figure 4.20: First Part of Case Report Form

The screenshot shows the 'Case Report Form' page within the DengueDash application. The left sidebar includes 'Analytics', 'Forms' (selected), 'Case Report Form' (highlighted in blue), and 'Data Tables'. The top navigation bar shows 'Forms > Case Report Form'. A 'Bulk Upload' button is in the top right. The main area has tabs for 'Personal Information' (disabled) and 'Clinical Status' (selected). The 'Clinical Status' tab contains sections for 'Consultation' and 'Laboratory Results'. In 'Consultation', fields include 'Date Admitted/Consulted/Seen' (pick a date) and 'Is Admitted?' (select). In 'Laboratory Results', sections are provided for NS1 (Pending Result), IgG ELISA (Pending Result), IgM ELISA (Pending Result), and PCR (Pending Result). Each section has a 'Date done' field (pick a date). The 'Outcome' section includes 'Case Classification' (select) and 'Outcome' (select). A 'Date of Death' field (pick a date) is also present. At the bottom are 'Previous' and 'Submit' buttons.

Figure 4.21: Second Part of Case Report Form

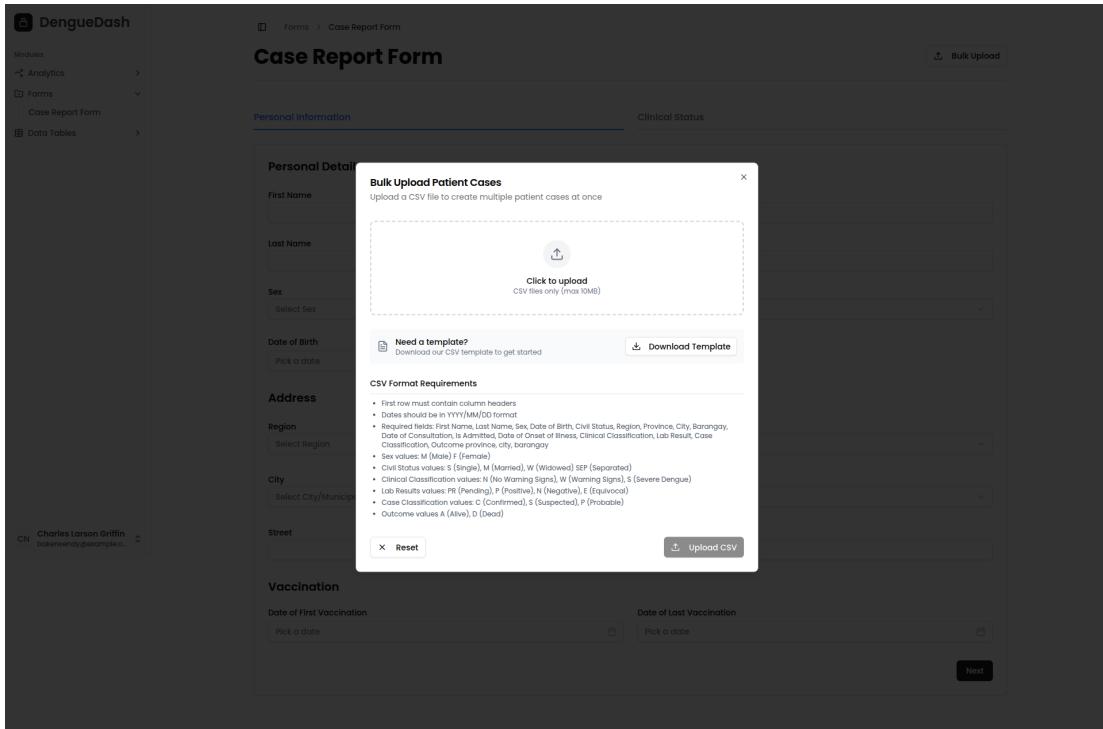


Figure 4.22: Bulk Upload of Cases using CSV

1027 Browsing, Update, and Deletion of Records

1028 Once the data generated from the case report form or the bulk upload is validated,
1029 it will be assigned as a new case and can be accessed through the Dengue Reports
1030 page, as shown in Figure 4.23. The said page displays basic information about
1031 the patient related to a specific case, including their name, address, date of con-
1032 sultation, and clinical and case classifications. It is also worth noting that it only
1033 shows cases that the user is permitted to view. For example, in a local Disease
1034 Reporting Unit (DRU) setting, the user can only access records that belong to
1035 the same DRU. On the other hand, in a consolidated surveillance unit such as a
1036 regional, provincial, or city quarter, its users can view all the records from all the

1037 DRUs that report to them. In addition, the user can also search for a case using
 1038 the name, location, date of consultation, or classifications that are associated with
 1039 the specific query, making it easier to find pertinent information quickly and effi-
 1040 ciently. Moving forward, Figure 4.24 shows the detailed case report of the patient
 1041 on a particular consultation date.

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

< Previous 1 2 ... 712 Next >

CN Robert Welch Johns... maryjanes@example.org

Figure 4.23: Dengue Reports

The screenshot shows the DengueDash application interface. On the left is a sidebar with 'DengueDash' logo and navigation links: 'Analytics', 'Forms', 'Data Tables' (selected), and 'Dengue Reports'. A user profile for 'Charles Larson Griffin' is shown. The main content area has a blue header 'Data Tables > Dengue Reports'. Below it is a 'Personal Information' section with fields for Full Name (Doe, John David), Date of Birth (April 29, 2025), Sex (Male), and Civil Status (Married). It also shows a 'Full Address' (1231 Ice Ice Baby, Bulak Sur, BATAD, ILOILO). A 'Vaccination Status' section shows First Dose (May 7, 2025) and Last Dose (May 13, 2025). The 'Case Record #25016448' section includes fields for Date of Consultation (April 30, 2025), Patient Admitted? (No), Date Onset of Illness (April 29, 2025), and Clinical Classification (With warning signs). The 'Laboratory Results' section lists pending results for NS1, IgG Elisa, IgM Elisa, and PCR. The 'Outcome' section shows Case Classification (Probable) and Outcome (Dead). The 'Interviewer' section lists Interviewer (Griffin, Charles Larson) and DRU (Saint Paul's Hospital). Buttons for 'Update Case' and 'Delete Case' are at the top right of the Case Record section.

Figure 4.24: Detailed Case Report

1042 To update the case, the user can click the "Update Case" button, where a
 1043 dialog will appear, and the updateable fields will be shown. It is worth noting
 1044 that in this case, only fields under Laboratory Results and Outcome are included
 1045 since they are the only ones that are time-based, where the result may change
 1046 in the future. After updating, a prompt will show confirming the user's action.
 1047 Moving forward, to delete a case record, the user must click the "Delete Case"
 1048 button, and a prompt verifying the action will appear. After confirming, the case

1049 will be deleted permanently.

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

Figure 4.25: Update Report Dialog

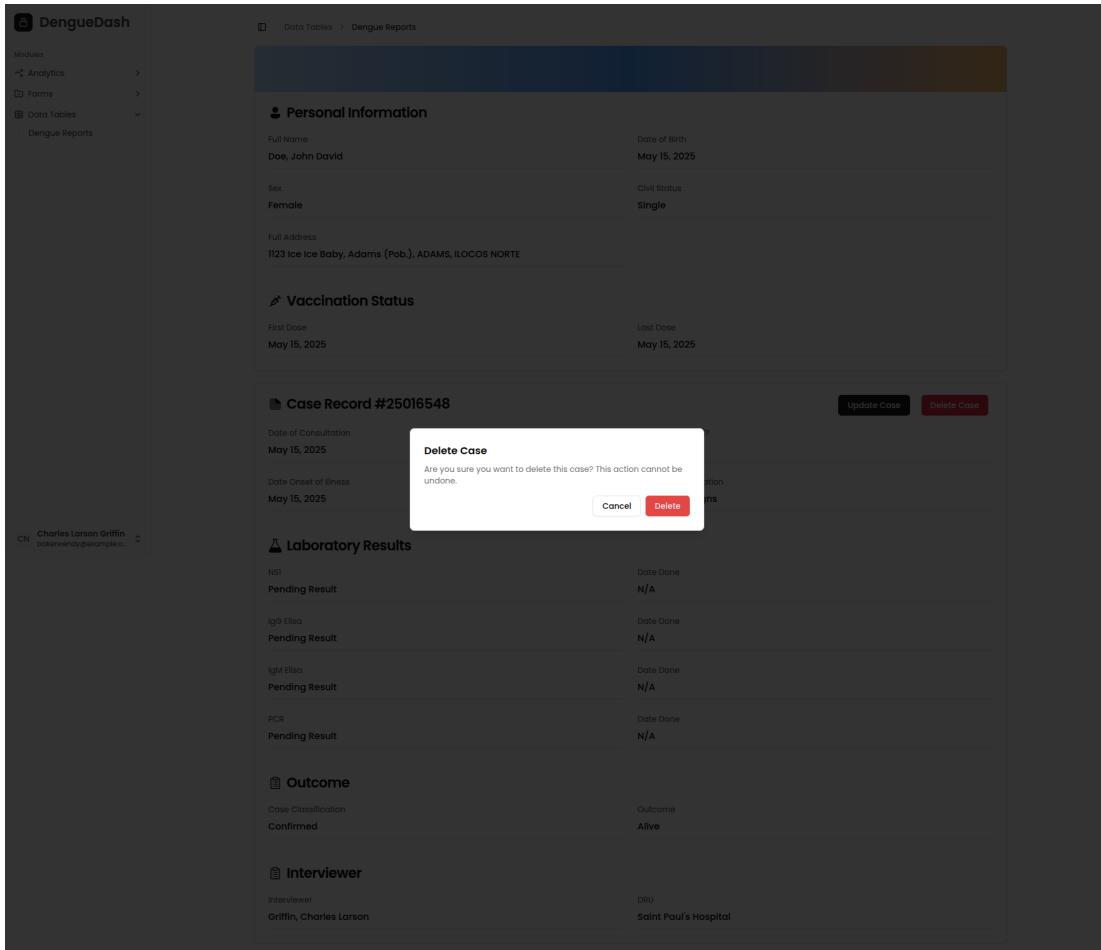


Figure 4.26: Delete Report Alert Dialog

1050 **Forecasting**

1051 The piece de resistance of the web application's feature is the Forecasting Page.
 1052 This is where users can forecast dengue cases for the next few weeks. To predict,
 1053 the application utilizes the exported LSTM model in a Keras format derived from
 1054 training the consolidated data from the database. The said file stores the model's
 1055 architecture and the learned parameters, which include the weights and biases, so
 1056 that it can predict cases without training the data again. Furthermore, it requires

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

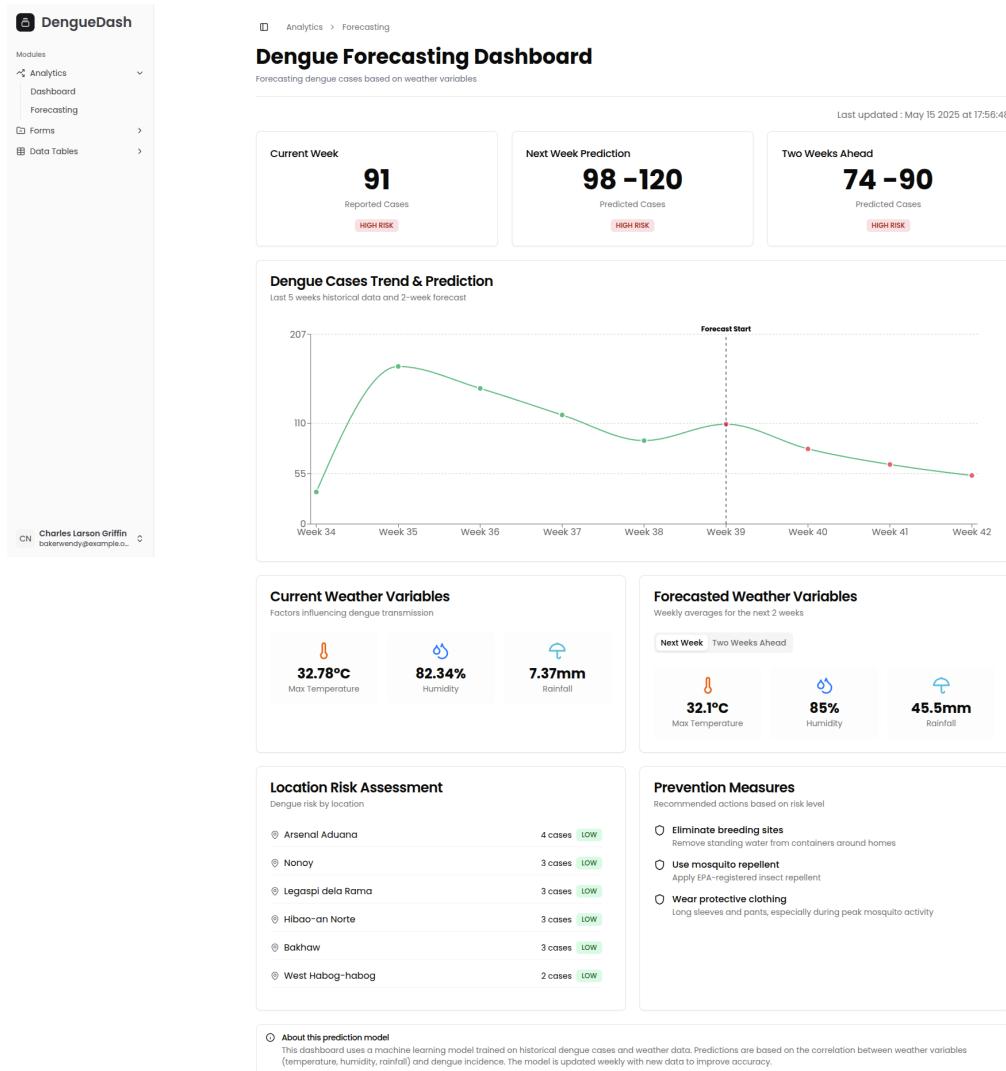


Figure 4.27: Forecasting Page

1069 4.5.4 Admin Interface

1070 Retraining

1071 With LSTM being the best-performing model among the models used in forecast-
 1072 ing dengue cases, it is the model chosen to power the prediction and retraining

of the consolidated data within the web application. Since the retraining process consumes a lot of processing power and requires a more advanced understanding of how it works, it was decided that the said feature should only be available to admin users of surveillance units. Furthermore, the retraining component in the Forecasting page includes three additional components that include the configuration of LSTM parameters (Figure 4.28), the actual retraining of the consolidated data from the database (Figure 4.29), and the results of the retraining that shows the current and previous model metrics depending on the parameters entered (Figure 4.30). It is also worth noting that when training, the model used a seeded number to promote reproducibility.

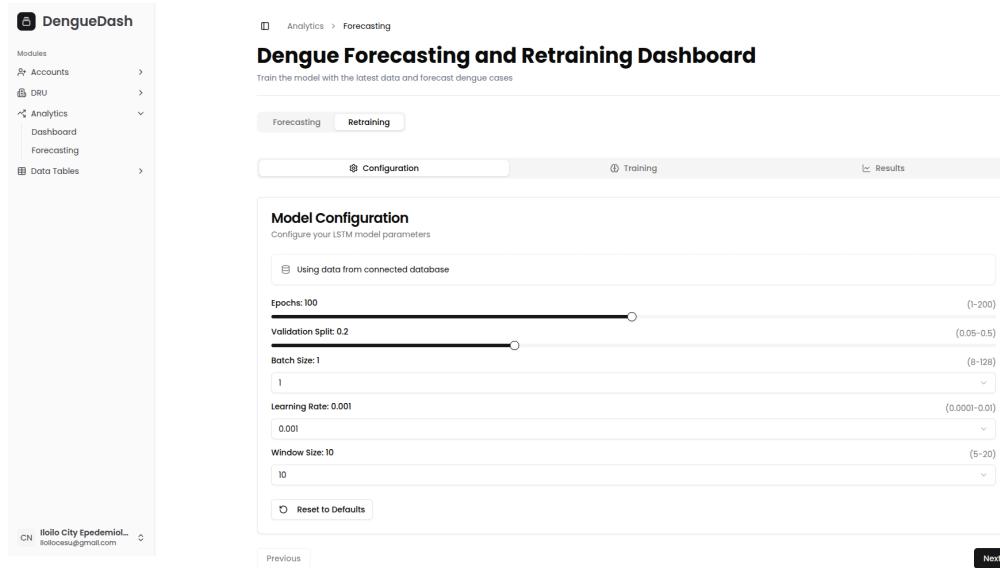


Figure 4.28: Retraining Configurations

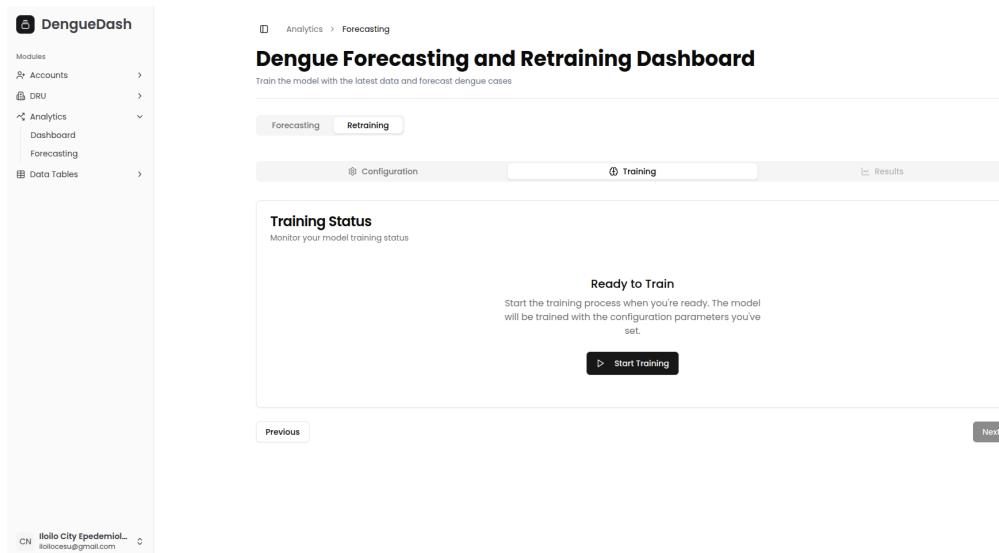


Figure 4.29: Start Retraining

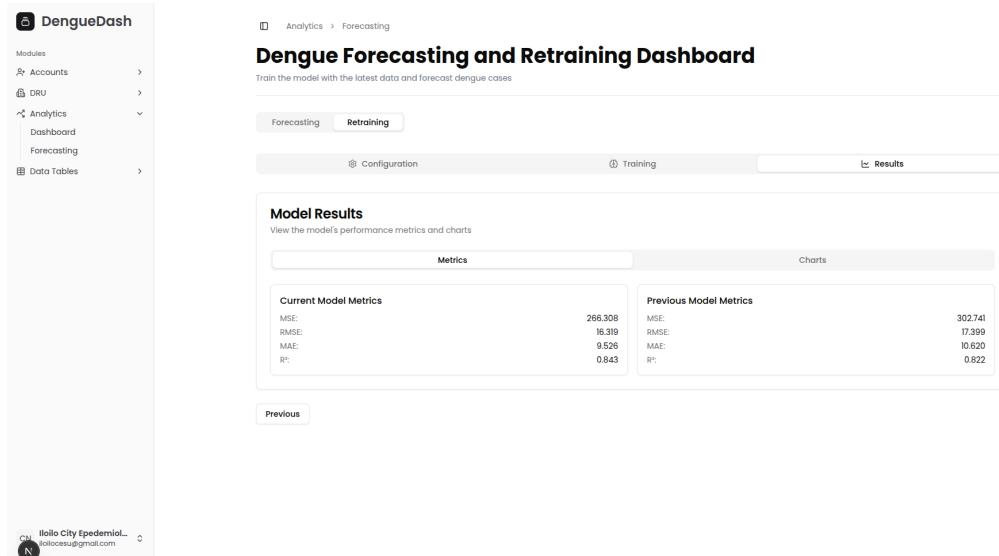


Figure 4.30: Retraining Results

1083 Managing Accounts

1084 Proper management of accounts is important to protect the integrity and confi-
1085 dentiality of data. Thus, it is crucial for administrators to track their users and
1086 control the flow of information. As discussed in the user registration of encoders,
1087 admin users from a specific DRU or surveillance unit have the power to grant
1088 them access to the web application. Figure 4.32 illustrates the interface for this
1089 scenario, as the admins can approve or reject their applications. Once approved,
1090 these users can access the features given to encoders and may be promoted to
1091 have administrative access, as shown in Figure 4.33. The same figure also shows
1092 the expanded details of the user, which include personal information and brief
1093 activity details within the system. When deleting an account, the user’s email
1094 will be blacklisted and illegible to use when creating another account, and all the
1095 cases reported by this user will be soft-deleted. However, the blacklist status can
1096 be reverted by clicking the ”Unban” button, which would make the user of the
1097 email be able to register to the web application again as shown in Figure 4.34.

The screenshot shows the DengueDash application interface. On the left is a sidebar with 'Modules' listed: Accounts (selected), DRU, Analytics, and Data Tables. Under 'Accounts', there's a 'Manage Accounts' option. At the bottom of the sidebar, it says 'CN iloilo City Epidemiol...' and 'iloiloeusu@gmail.com'. The main content area has a header 'Accounts > Manage' and 'Manage Accounts' with the sub-instruction 'View and manage registered and pending accounts'. Below this is a navigation bar with tabs: 'Verified' (selected), 'Pending', and 'Blacklisted'. A table follows, with columns: Name, Email, Role, Sex, and Actions. One row is shown: Daniel Santiago Brandt, brandon02@example.org, Encoder, Female, with an 'Open' button in the Actions column. The table has a light gray border.

Figure 4.31: List of Verified Accounts

This screenshot shows the same DengueDash application interface as Figure 4.31, but the 'Pending' tab is selected in the navigation bar. The main content area displays a table with columns: Name, Email, Sex, Created At, and Actions. One row is listed: John David Doe, testereee@example.gov.ph, Male, 2025-05-15, with 'Approve' and 'Delete' buttons in the Actions column. The table has a light gray border.

Figure 4.32: List of Pending Accounts

The screenshot shows the DengueDash application interface. On the left is a sidebar with a logo, the title "DengueDash", and a "Modules" section containing "Accounts" (selected), "Manage Accounts", "Analytics", and "Data Tables". At the bottom of the sidebar is a user profile card for "Saint Paul's Hospital" with the email "saintpaul@gmail.com". The main content area has a header "User Profile" and a sub-header "View and manage user details". It displays the following user information:

Name	Charles Larson Griffin	Email	bakerwendy@example.org
Sex	Female	Role	Encoder
Hospital (DRU)	Saint Paul's Hospital		

Below this are timestamped log entries for "Created At" (May 5 2025 at 04:47:12), "Updated At" (May 15 2025 at 05:56:45), and "Last Login" (May 15 2025 at 16:53:47). At the bottom are two buttons: "Promote to Admin" and "Delete User".

Figure 4.33: Account Details

The screenshot shows the DengueDash application interface. The sidebar is identical to Figure 4.33. The main content area has a header "Manage Accounts" and a sub-header "View and manage registered and pending accounts". Below this is a table with three columns: "Email", "Date Added", and "Actions". A single row is present for the email "testereee@example.gov.ph", with the date added as "2025-05-15" and an "Unban" button in the "Actions" column.

Figure 4.34: List of Blacklisted Accounts

1098 **Managing DRUs**

1099 Unlike the registration of encoder accounts, the creation of Disease Reporting
 1100 Units can only be done within the web application, and the user performing the
 1101 creation must be an administrator of a surveillance unit. Figure 4.35 presents the
 1102 fields the admin user must fill out, and once completed, the new entry will show
 1103 as being managed by that unit, as shown in Figure 4.36. Figure 4.37, on the other
 1104 hand, shows the details provided in the registration form as well as its creation
 1105 details. There is also an option to delete the DRU, and when invoked, all the
 1106 accounts being managed by it, and the cases reported under those accounts will
 1107 be soft-deleted.

The screenshot shows the 'DengueDash' web application interface. On the left is a sidebar with 'Modules' listed: Accounts, DRU (selected), Analytics, and Data Tables. The main content area has a header 'Dru > Add' and a title 'Register Disease Reporting Unit'. It says 'Add a new Disease Reporting Unit to the surveillance system.' Below this are several input fields:

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

At the bottom is a large black 'Register DRU' button.

Figure 4.35: Disease Reporting Unit Registration

DengueDash

Modules

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

CN Iloilo City Epidemiol... iloilocesu@gmail.com

Manage Disease Reporting Units

View and manage Disease Reporting Units

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

Figure 4.36: List of Disease Reporting Units

DengueDash

Modules

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

CN Iloilo City Epidemiol... iloilocesu@gmail.com

Disease Reporting Unit Profile

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	
Created At May 5 2025 at 04:47:11	Updated At May 5 2025 at 04:47:11

Delete DRU

Figure 4.37: Disease Reporting Unit details

4.6 User Testing

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

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

¹¹²² Chapter 5

¹¹²³ Conclusion

¹¹²⁴ The development of DengueWatch marks a transformative leap forward in public
¹¹²⁵ health technology, providing Iloilo City with a centralized system to combat one
¹¹²⁶ of the most persistent mosquito-borne diseases. Previously, data was recorded
¹¹²⁷ manually on paper, making tracking and analysis slow and error-prone. Dengue-
¹¹²⁸ Watch digitizes this process, enabling faster, more accurate monitoring. More
¹¹²⁹ than an academic project, DengueWatch serves as a practical solution aimed at
¹¹³⁰ shifting the approach from reactive outbreak response to proactive prevention. By
¹¹³¹ combining deep learning models with real-time climate data integration, the sys-
¹¹³² tem achieves a level of accuracy and usability that makes it viable for real-world
¹¹³³ deployment.

¹¹³⁴ At the heart of DengueWatch is a Long Short-Term Memory (LSTM) neural
¹¹³⁵ network, which outperformed traditional forecasting models such as ARIMA and
¹¹³⁶ Kalman Filter. The LSTM model achieved a Root Mean Square Error (RMSE) of
¹¹³⁷ 20.15, followed by the hybrid KF-LSTM model with an RMSE of 25.56, demon-

strating a substantial improvement in predictive capability. Consequently, the LSTM model was selected for integration into the DengueWatch system. It can be said that retraining depends solely on the user's discretion, however, ideally, the model should be retrained whenever new data is added to ensure it can adapt to emerging trends.

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

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

¹¹⁵⁴ Chapter 6

¹¹⁵⁵ References

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¹²⁴¹ **Appendix A**

¹²⁴² **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

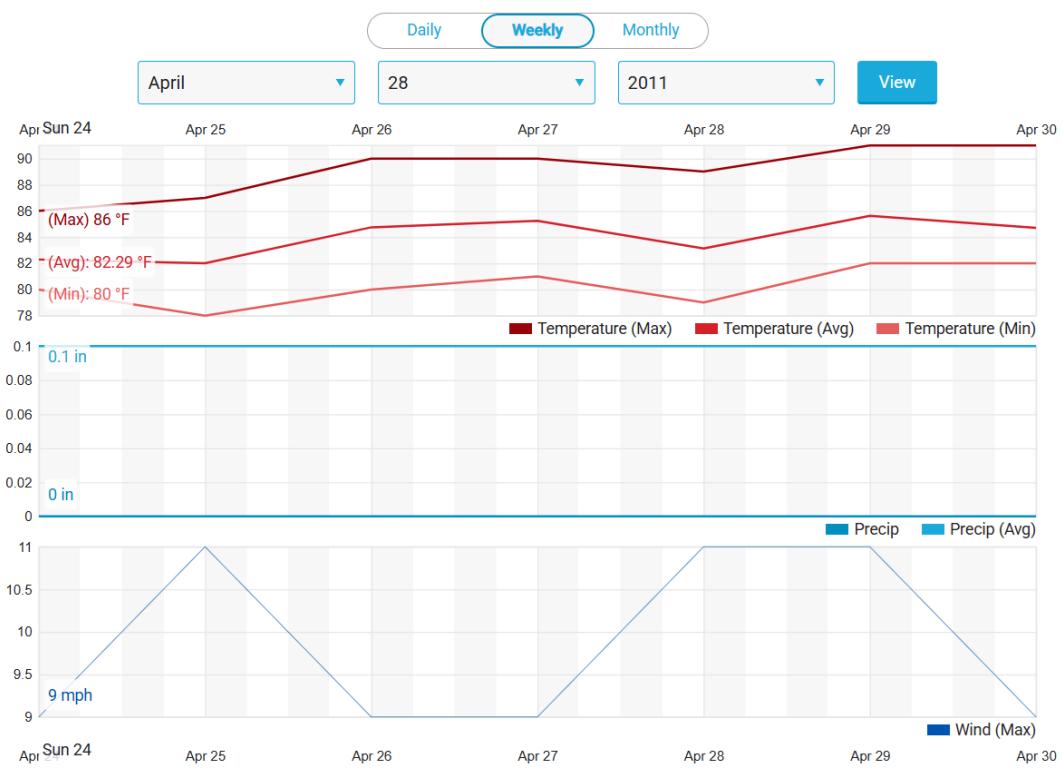


Figure A.2: Snippet of Weather Data Collection

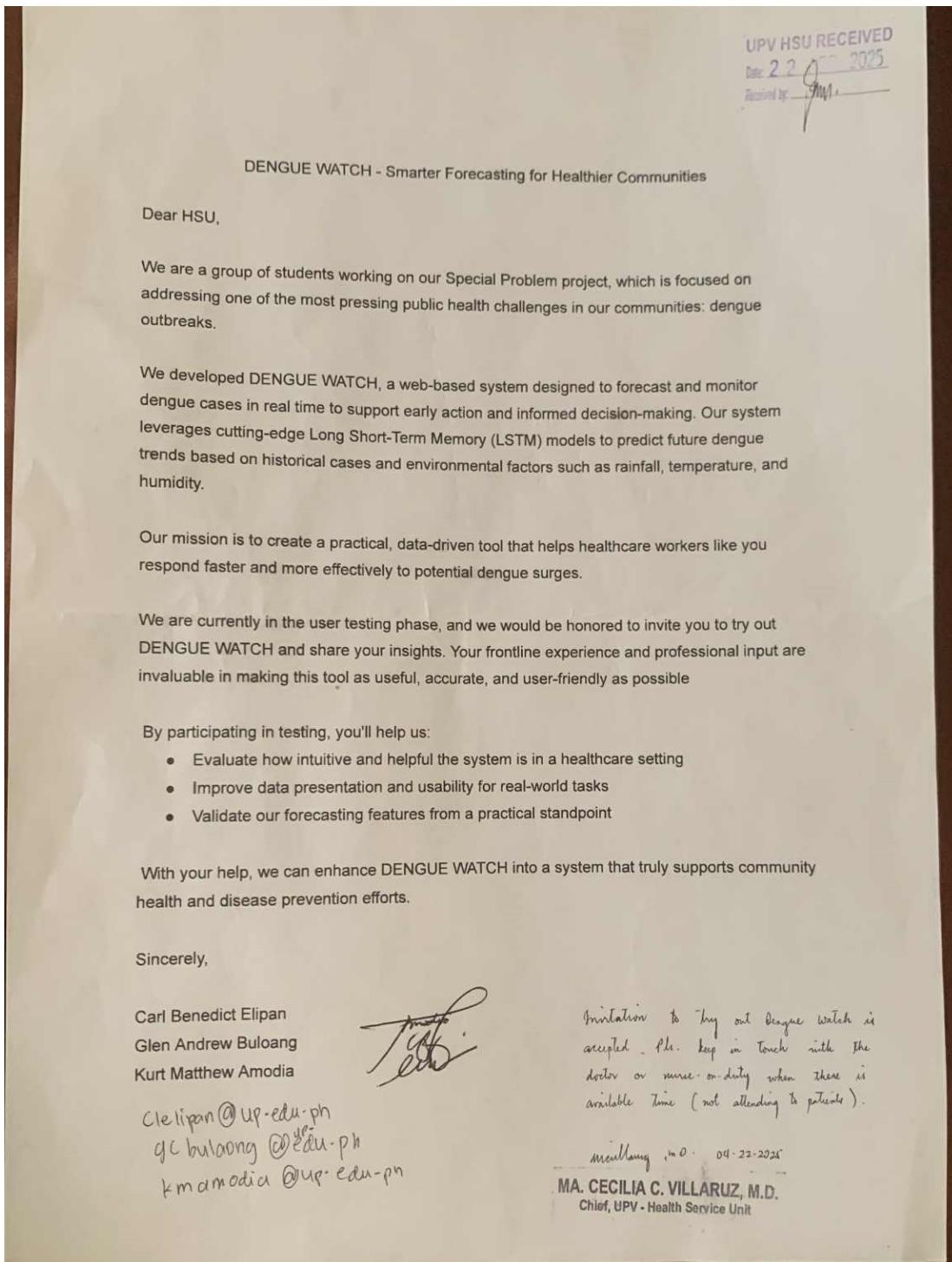


Figure A.3: Letter of Approval for User Testing in UPV HSU

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