

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

4 A Special Problem
5 Presented to
6 the Faculty of the Division of Physical Sciences and Mathematics
7 College of Arts and Sciences
8 University of the Philippines Visayas
9 Miag-ao, Iloilo

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

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

16 Francis DIMZON, Ph.D.
17 Adviser

18 June 2025

19

Approval Sheet

20

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

22

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

23

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

25

26

Approved by:

Name

Signature

Date

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

27

Ara Abigail E. Ambita _____
(Panel Member)

Kent Christian A. Castor _____
(Division Chair)

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

31 **Declaration**

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

Name	Signature	Date
Kurt Matthew A. Amodia (Student)	_____	_____
Glen Andrew C. Bulaong (Student)	_____	_____
Carl Benedict L. Elipan (Student)	_____	_____

Dedication

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

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

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

49

Acknowledgment

50 This research would not have been possible without the support and guidance
51 of several individuals and institutions.

52 First and foremost, we express our deepest gratitude to our adviser, Dr. Francis
53 Dimzon, for his invaluable insights, unwavering support, and commitment to
54 our project. His guidance was instrumental in shaping the direction of our re-
55 search.

56 We also extend our sincere thanks to the Iloilo Provincial Health Office and
57 the Iloilo Epidemiological Unit, for accomodating our inquiries and sharing vital
58 data and insights. Their cooperation played a crucial role in the success of the
59 research.

60 Our appreciation also goes to the UPV Health Services Unit, especially the
61 doctors and nurses who participated in our user testing. Your thoughtful feedback
62 provided essential perspectives that greatly contributed to the relevance of our
63 research.

64 Finally, we are greatly thankful to God Almighty, for granting us the strength,
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

⁸⁴ **Contents**

⁸⁵	1	Introduction	1
⁸⁶		1.1 Overview of the Current State of Technology	1
⁸⁷		1.2 Problem Statement	3
⁸⁸		1.3 Research Objectives	4
⁸⁹		1.3.1 General Objective	4
⁹⁰		1.3.2 Specific Objectives	4
⁹¹		1.4 Scope and Limitations of the Research	5
⁹²		1.5 Significance of the Research	6
⁹³	2	Review of Related Literature	9
⁹⁴		2.1 Dengue	9
⁹⁵		2.2 Outbreak Definition	10

96	2.3 Existing System: RabDash DC	10
97	2.4 Deep Learning	11
98	2.5 Kalman Filter	12
99	2.6 Weather Data	13
100	2.7 Chapter Summary	14
101	3 Research Methodology	15
102	3.1 Research Activities	16
103	3.1.1 Dengue and Climate Data Collection	16
104	3.1.2 Develop and Evaluate Deep Learning Models for Dengue	
105	Case Forecasting	19
106	3.1.3 Integrate the Predictive Model into a Web-Based Data An-	
107	alytics Dashboard	25
108	3.1.4 System Development Framework	26
109	3.2 Development Tools	28
110	3.2.1 Software	28
111	3.2.2 Hardware	30
112	3.2.3 Packages	30
113	3.3 Application Requirements	33

CONTENTS

ix

114	3.3.1 Backend Requirements	33
115	3.3.2 User Interface Requirements	34
116	3.3.3 Security and Validation Requirements	37
117	4 Results and Discussion	39
118	4.1 Data Gathering	39
119	4.2 Exploratory Data Analysis	40
120	4.3 Outbreak Detection	45
121	4.4 Model Training Results	45
122	4.4.1 LSTM Model	47
123	4.4.2 ARIMA Model	49
124	4.4.3 Seasonal ARIMA (SARIMA) Model	50
125	4.4.4 Kalman Filter Model	52
126	4.5 Model Simulation	54
127	4.6 System Prototype	56
128	4.6.1 Home Page	56
129	4.6.2 User Registration, Login, and Authentication	57
130	4.6.3 Encoder Interface	59

131	4.6.4 Admin Interface	68
132	4.7 User Testing	74
133	5 Conclusion	77
134	6 References	79
135	A Data Collection Snippets	83

¹³⁶ List of Figures

137	3.1 Workflow for forecasting the number of weekly dengue cases	16
138	3.2 Testing Process for DengueWatch	27
139	3.3 Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure	33
140		
141	3.4 Use Case Diagram for Admins	34
142	3.5 Use Case Diagram for Encoder	36
143		
144	4.1 Trend of Dengue Cases	42
145	4.2 Rainfall and Dengue Cases Over Time	42
146	4.3 Kernel Density Estimate Plots of Meteorological Features	44
147	4.4 Training Folds - Window Size 5	48
148	4.5 Testing Folds - Window Size 5	49
149	4.6 ARIMA Prediction Results for Test Set	50

149	4.7 Seasonal ARIMA Prediction Results for Test Set	51
150	4.8 Kalman Filter Prediction Results for Test Set	53
151	4.9 Predicted vs Actual Dengue Cases 2025	55
152	4.10 Home Page	56
153	4.11 Personal Information Tab of Sign Up Page	57
154	4.12 Verification Tab of Sign Up Page	58
155	4.13 Login Page	58
156	4.14 First Part of Case Report Form	60
157	4.15 Second Part of Case Report Form	60
158	4.16 Bulk Upload of Cases using CSV	61
159	4.17 Dengue Reports	62
160	4.18 Detailed Case Report	63
161	4.19 Update Report Dialog	64
162	4.20 Delete Report Alert Dialog	65
163	4.21 Forecasting Page	67
164	4.22 Retraining Configurations	68
165	4.23 Start Retraining	69

LIST OF FIGURES

xiii

166	4.24 Retraining Results	69
167	4.25 List of Verified Accounts	70
168	4.26 List of Pending Accounts	71
169	4.27 Account Details	71
170	4.28 List of Blacklisted Accounts	72
171	4.29 Disease Reporting Unit Registration	73
172	4.30 List of Disease Reporting Units	73
173	4.31 Disease Reporting Unit details	74
174	A.1 Snippet of Consolidated Data	83
175	A.2 Snippet of Weather Data Collection	84
176	A.3 Letter of Approval for User Testing in UPV HSU	85
177	A.4 System Usability Score Questionnaire	86

List of Tables

178	3.1 Hyperparameter Tuning: Search Space and Tuner Configuration	20
180	4.1 Snippet of the combined dataset	40
181	4.2 Data Schema: Column Names, Non-Null Counts, and Data Types	41
182	4.3 Descriptive Statistics of the Combined Dataset	41
183	4.4 Comparison of different models for dengue prediction	46
184	4.5 Comparison of Window Sizes	47
185	4.6 Time-Series Cross Validation Results: Comparison of Window Sizes	48
186	4.7 Comparison of SARIMA performance for each fold	52
187	4.8 Comparison of KF-LSTM performance for each fold	54
188	4.9 Computed System Usability Scores per Participant	75

¹⁸⁹ **Chapter 1**

¹⁹⁰ **Introduction**

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

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

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

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

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

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

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

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

²²⁶ **1.2 Problem Statement**

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

²⁴⁶ **1.3 Research Objectives**

²⁴⁷ **1.3.1 General Objective**

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

²⁵³ **1.3.2 Specific Objectives**

²⁵⁴ Specifically, this study aims to:

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

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

267 1.4 Scope and Limitations of the Research

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

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

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

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

293 1.5 Significance of the Research

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

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

1.5. SIGNIFICANCE OF THE RESEARCH

7

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

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

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

³²⁰ Chapter 2

³²¹ Review of Related Literature

³²² 2.1 Dengue

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

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

³⁴¹ 2.2 Outbreak Definition

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

³⁵² 2.3 Existing System: RabDash DC

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

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

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

369 2.4 Deep Learning

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

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

³⁸³ 2.5 Kalman Filter

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

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

402 2.6 Weather Data

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

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

420 2.7 Chapter Summary

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

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

⁴³⁵ Chapter 3

⁴³⁶ Research Methodology

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

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

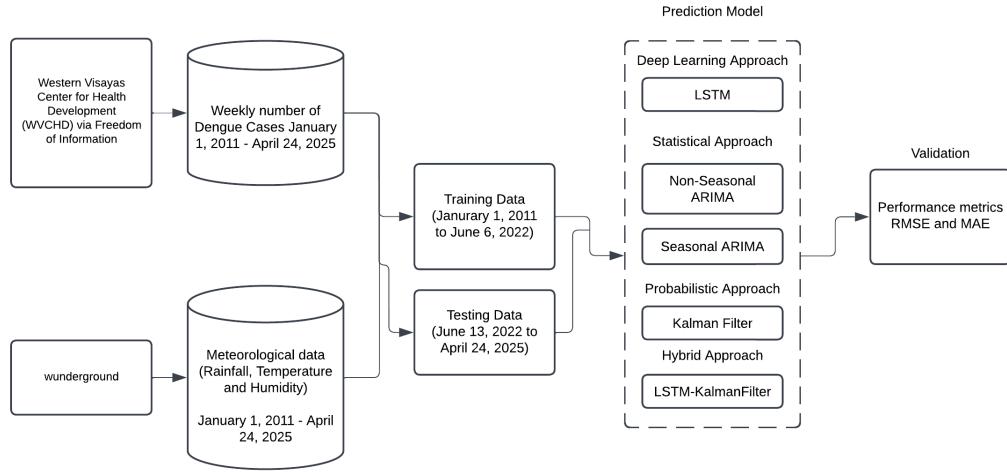


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

⁴⁴⁷ 3.1 Research Activities

⁴⁴⁸ 3.1.1 Dengue and Climate Data Collection

⁴⁴⁹ Acquisition of Dengue Case Data

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

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

465

466 **Data Fields**

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

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

483 **Data Integration and Preprocessing**

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

491 **Exploratory Data Analysis (EDA)**

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

497 **Outbreak Detection**

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

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

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

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

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

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

511 **Data Preprocessing**

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

⁵¹⁸ **LSTM Model**

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

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

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

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

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

Table 3.1: Hyperparameter Tuning: Search Space and Tuner Configuration

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

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

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

555 ARIMA

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

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

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

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

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

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

577 Seasonal ARIMA (SARIMA)

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

596 Kalman Filter:

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

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

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

617 **Model Simulation:**

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

622 dengue cases for the period from February 2025 to May 2025. Listing 3.1 shows
 623 a code snippet of the model training.

Listing 3.1: Code Snippet for Model Training

```

624     # Fit on train set
625
626     history = model.fit(
627         X_train, y_train,
628         epochs=100,
629         batch_size=1,
630         validation_split=0.2,
631         callbacks=[early_stop],
632         verbose=1
633     )
634
635     # Predict on 2025
636
637     y_pred_test = model.predict(X_test, verbose=0)

```

636 3.1.3 Integrate the Predictive Model into a Web-Based 637 Data Analytics Dashboard

638 Dashboard Design and Development

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

643 Model Integration and Deployment

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

646 3.1.4 System Development Framework

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

653 Design and Development

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

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

667 **Testing and Integration**

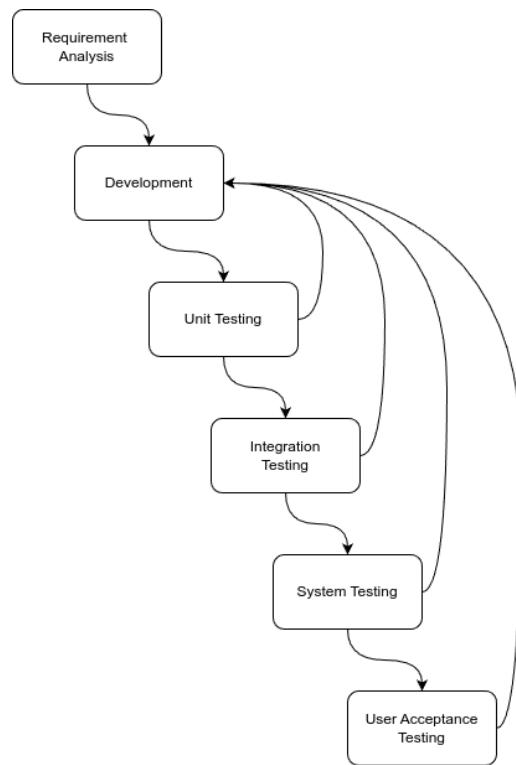


Figure 3.2: Testing Process for DengueWatch

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

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

683 **3.2 Development Tools**

684 **3.2.1 Software**

685 **Github**

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

691 Visual Studio Code

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

696 Django

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

705 Next.js

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

712 Postman

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

718 3.2.2 Hardware

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

722 3.2.3 Packages**723 Django REST Framework**

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

728 Leaflet

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

735 Chart.js

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

743 Tailwind CSS

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

⁷⁴⁹ *sites without ever leaving your HTML.*, n.d.). Given the limited timeline for this
⁷⁵⁰ project, using this framework is a wise choice due to its stability and popularity
⁷⁵¹ among developers.

⁷⁵² **Shadcn**

⁷⁵³ Shadcn offers a collection of open-source UI boilerplate components that can be
⁷⁵⁴ directly copied and pasted into one's project. With the flexibility of the provided
⁷⁵⁵ components, Shadcn allows developers to have full control over customization and
⁷⁵⁶ styling. Since this is built on top of Tailwind CSS and Radix UI, it is supported
⁷⁵⁷ by most modern frontend frameworks, including Next.js (Shadcn, n.d.).

⁷⁵⁸ **Zod**

⁷⁵⁹ Data validation is integral in this web application since it will handle crucial data
⁷⁶⁰ that will be used for analytical inferences and observations. Since Zod is primarily
⁷⁶¹ used for validating and parsing data, it ensures proper communication between
⁷⁶² the client and the server (Zod, n.d.).

⁷⁶³ **3.3 Application Requirements**

⁷⁶⁴ **3.3.1 Backend Requirements**

⁷⁶⁵ **Database Structure Design**

⁷⁶⁶ Determining how data flows and how it would be structured is crucial in creating
⁷⁶⁷ the system as it defines how extendible and flexible it would be for future features
⁷⁶⁸ and updates. Thus, creating a comprehensive map of data ensures proper nor-
⁷⁶⁹ malization that eliminates data redundancy and improves data integrity. Figure
⁷⁷⁰ 3.3 depicts the designed database schema that showcases the relationship between
⁷⁷¹ the application's entities.

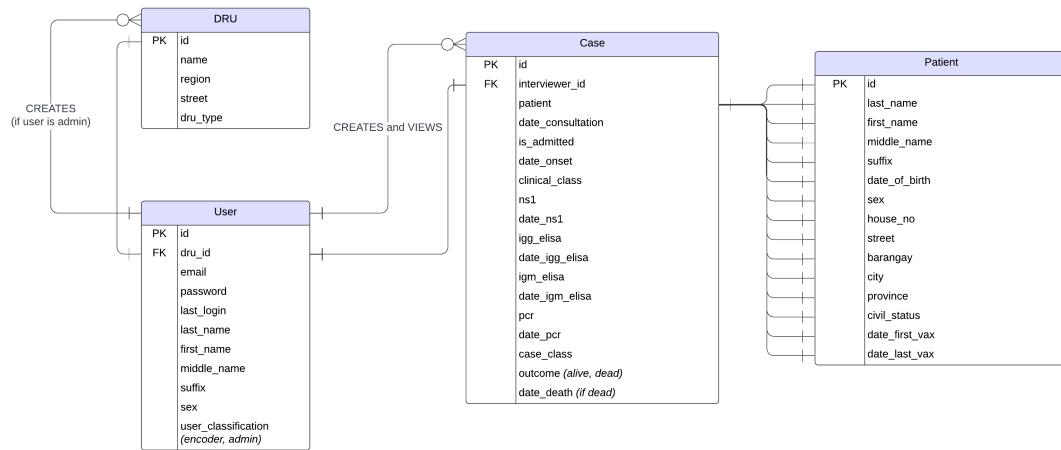


Figure 3.3: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

⁷⁷² 3.3.2 User Interface Requirements

⁷⁷³ Admin Interface

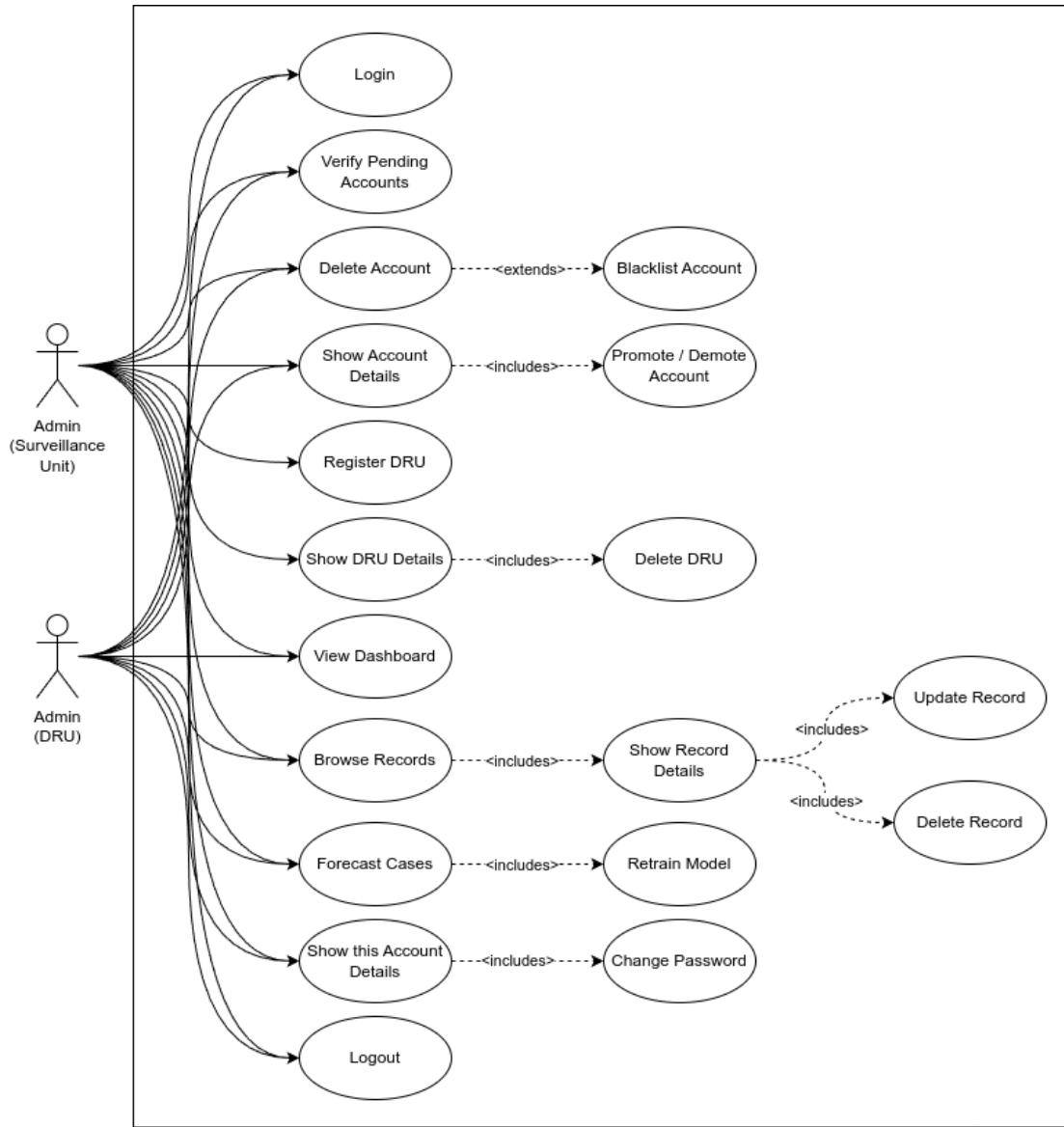


Figure 3.4: Use Case Diagram for Admins

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

⁷⁸⁴ **Encoder Interface**

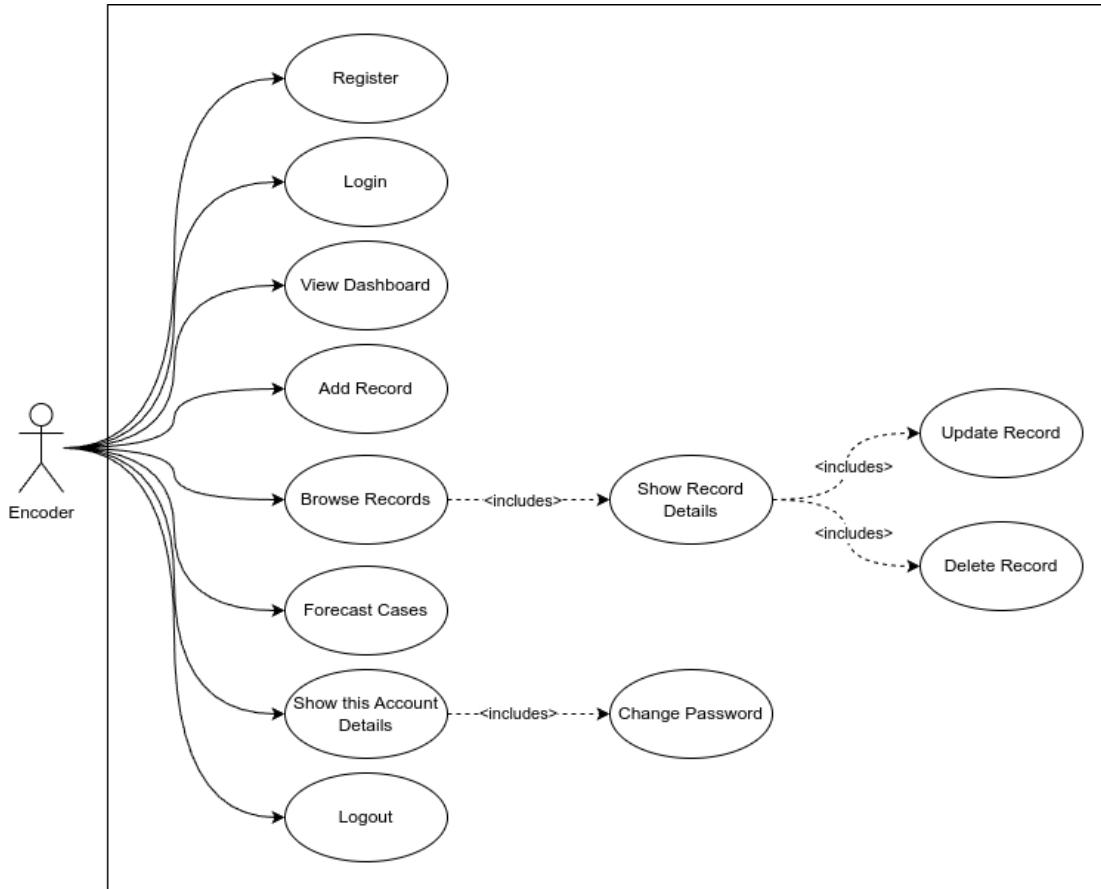


Figure 3.5: Use Case Diagram for Encoder

⁷⁸⁵ Figure 3.5, on the other hand, illustrates the use cases for the system's primary
⁷⁸⁶ users. These users can register but must wait for further verification to access the
⁷⁸⁷ application. Similar to the previous interfaces, encoders can browse and manage
⁷⁸⁸ records, as well as forecast the consolidated cases under a specific surveillance or
⁷⁸⁹ disease reporting unit, but they are not allowed to retrain the model. Lastly, they
⁷⁹⁰ are the only type of user that can file and create dengue cases by filling out a form
⁷⁹¹ with the required details.

792 3.3.3 Security and Validation Requirements**793 Password Encryption**

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

802 Authentication

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

808 Data Validation

809 Both the backend and frontend should validate the input from the user to preserve
810 data integrity. Thus, Zod is implemented in the latter to help catch invalid inputs
811 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.

⁸¹⁷ **Chapter 4**

⁸¹⁸ **Results and Discussion**

⁸¹⁹ **4.1 Data Gathering**

⁸²⁰ The data for dengue case prediction was gathered from a variety of reliable sources,
⁸²¹ enabling a comprehensive dataset spanning from January 2011 to October 2024.
⁸²² This dataset includes 720 rows of data, each containing weekly records of dengue
⁸²³ cases along with corresponding meteorological variables, such as rainfall, temper-
⁸²⁴ ature, and humidity.

⁸²⁵ 1. Dengue Case Data: The primary source of historical dengue cases came
⁸²⁶ from the Humanitarian Data Exchange and the Western Visayas Center for
⁸²⁷ Health Development (WVCHD). The dataset, accessed through Freedom of
⁸²⁸ Information (FOI) requests, provided robust case numbers for the Western
⁸²⁹ Visayas region. The systematic collection of these data points was essential
⁸³⁰ for establishing a reliable baseline for model training and evaluation.

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

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

Table 4.1: Snippet of the combined dataset

834 4.2 Exploratory Data Analysis

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

- 836 • **Time.** Weekly timestamps (e.g. “2011-w1”)
- 837 • **Rainfall.** Weekly average rainfall (mm)
- 838 • **MaxTemperature, AverageTemperature, MinTemperature.** Weekly
 839 temperature data ($^{\circ}\text{C}$)
- 840 • **Wind.** Wind speed (m/s)
- 841 • **Humidity.** Weekly average humidity (%)
- 842 • **Cases.** Reported dengue cases

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

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

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

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

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

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

Table 4.3: Descriptive Statistics of the Combined Dataset

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

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

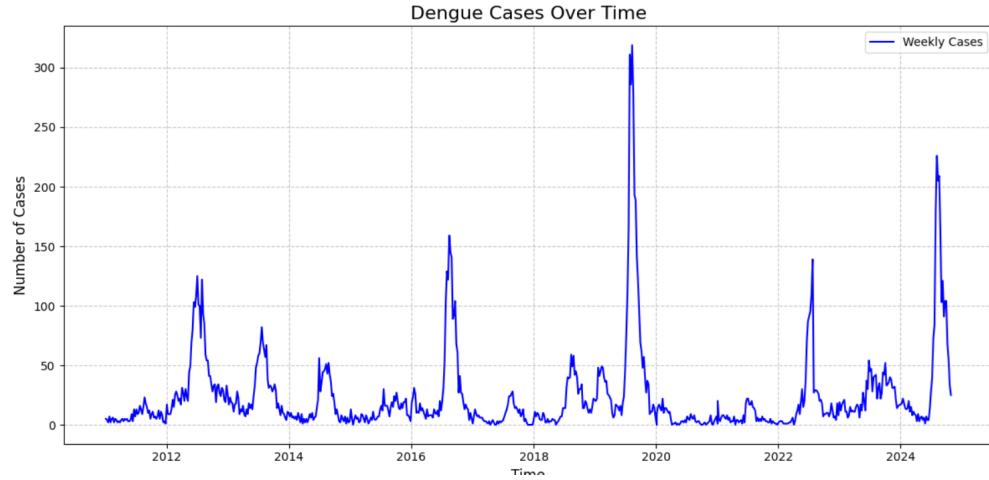


Figure 4.1: Trend of Dengue Cases

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

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

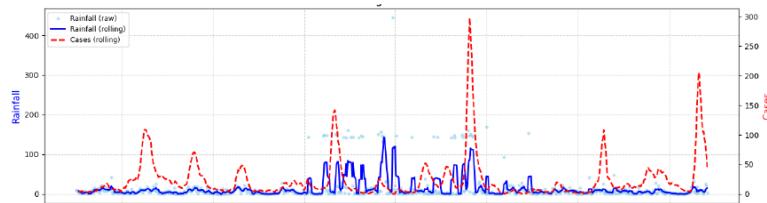


Figure 4.2: Rainfall and Dengue Cases Over Time

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

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

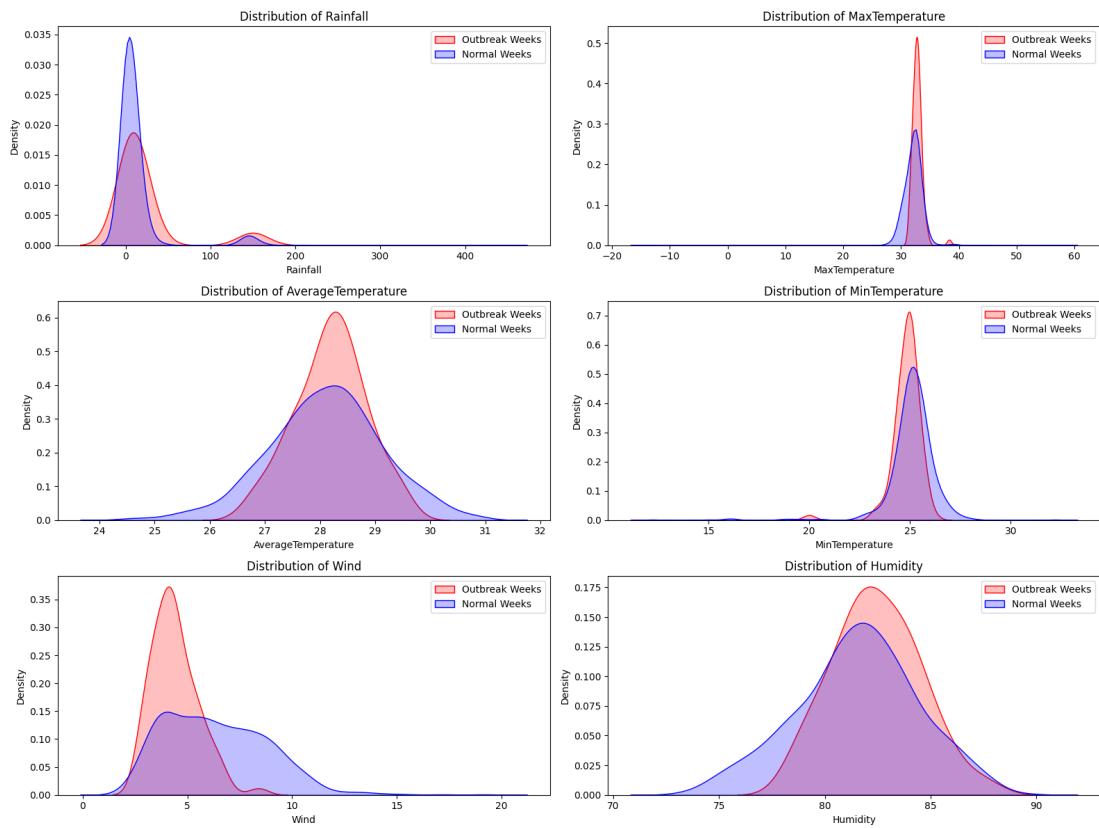


Figure 4.3: Kernel Density Estimate Plots of Meteorological Features

884 4.3 Outbreak Detection

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

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

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

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

$$= 98.03407 \quad (4.4)$$

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

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

892 4.4 Model Training Results

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

897 of the models using these metrics.

- 898 • **MSE** represents the average of the squared differences between predicted
- 899 and actual values. It penalizes larger errors more heavily.
- 900 • **RMSE**, the square root of MSE, provides a more interpretable value in the
- 901 same units as the target (i.e., number of dengue cases).
- 902 • **MAE** calculates the average magnitude of the errors without considering
- 903 their direction, giving a more straightforward understanding of the average
- 904 prediction error.

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

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

Table 4.4: Comparison of different models for dengue prediction

907 As shown in Table 4.4, the LSTM model consistently achieved the lowest MSE
908 (406.03), RMSE (20.15), and MAE (12.61) among all evaluated models. This
909 suggests that, on average, the LSTM’s predictions were about 12 to 20 cases away
910 from the actual values, which is a strong indication of reliability for practical use
911 in public health decision-making.

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

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

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

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

923 4.4.1 LSTM Model

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

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

Table 4.5: Comparison of Window Sizes

928

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

933 reliable configuration overall.

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

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

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

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

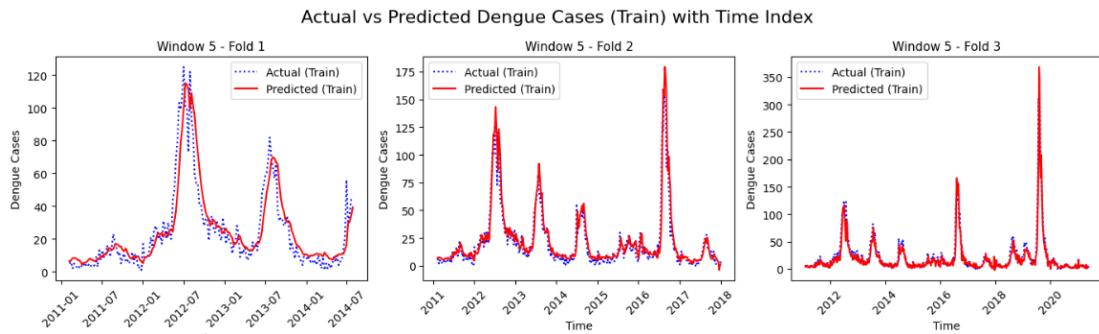


Figure 4.4: Training Folds - Window Size 5

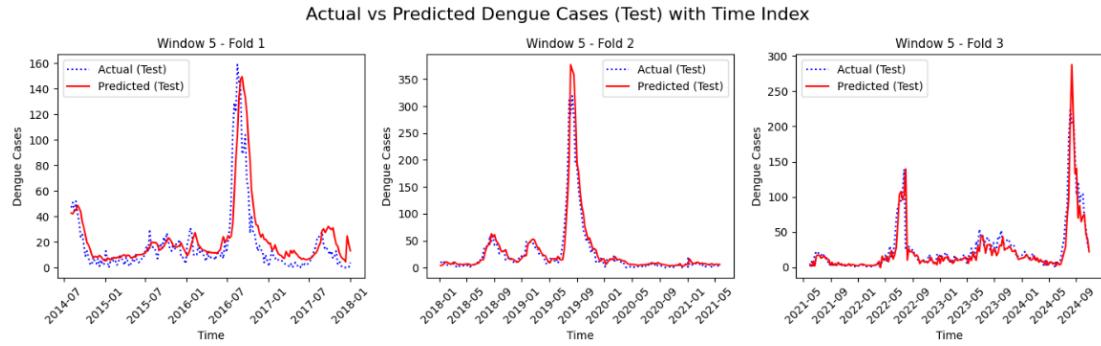


Figure 4.5: Testing Folds - Window Size 5

947 4.4.2 ARIMA Model

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

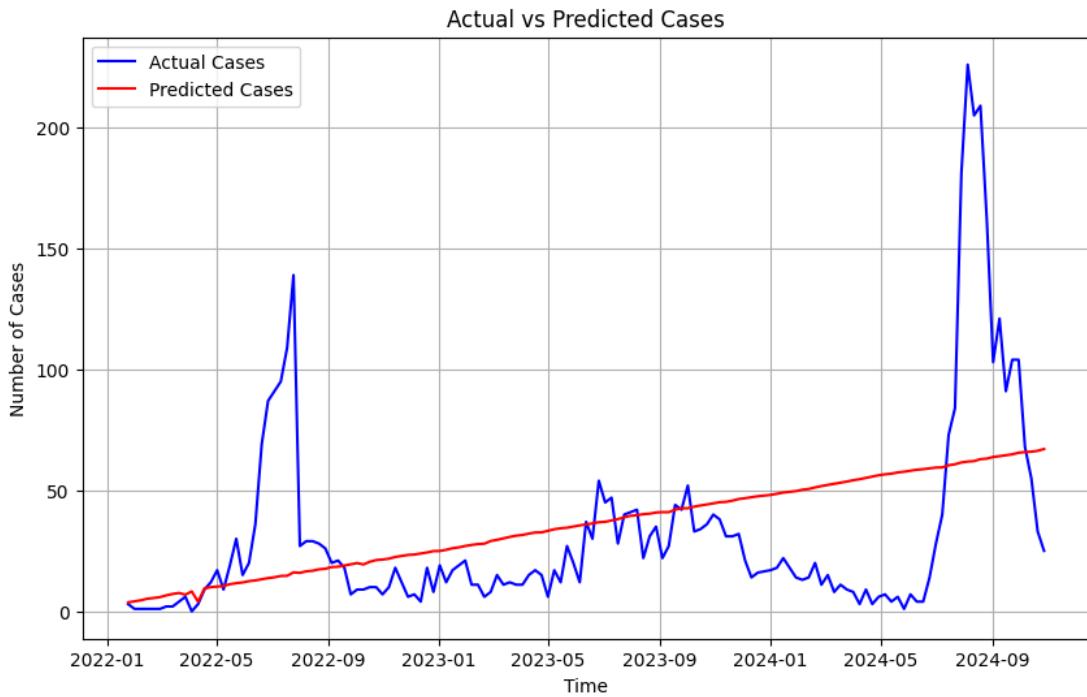


Figure 4.6: ARIMA Prediction Results for Test Set

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

- 959 • **MSE (Mean Squared Error):** 1521.48
- 960 • **RMSE (Root Mean Squared Error):** 39.01
- 961 • **MAE (Mean Absolute Error):** 25.80

962 4.4.3 Seasonal ARIMA (SARIMA) Model

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

965 data.

966 This model incorporates seasonal parameters, which were tuned using grid
 967 search to find the best configuration: **SARIMA(2, 0, 2)(0, 1, 1)[52]**. As with
 968 ARIMA, **400 iterations** were applied to ensure a robust fit. As shown in Figure
 969 4.7, the SARIMA model demonstrates a notable improvement in performance.
 970 Unlike its non-seasonal counterpart, it effectively captures the general trend and
 971 aligns more closely with the peaks observed in the actual dengue cases, indicating
 972 its ability to model seasonal dynamics.

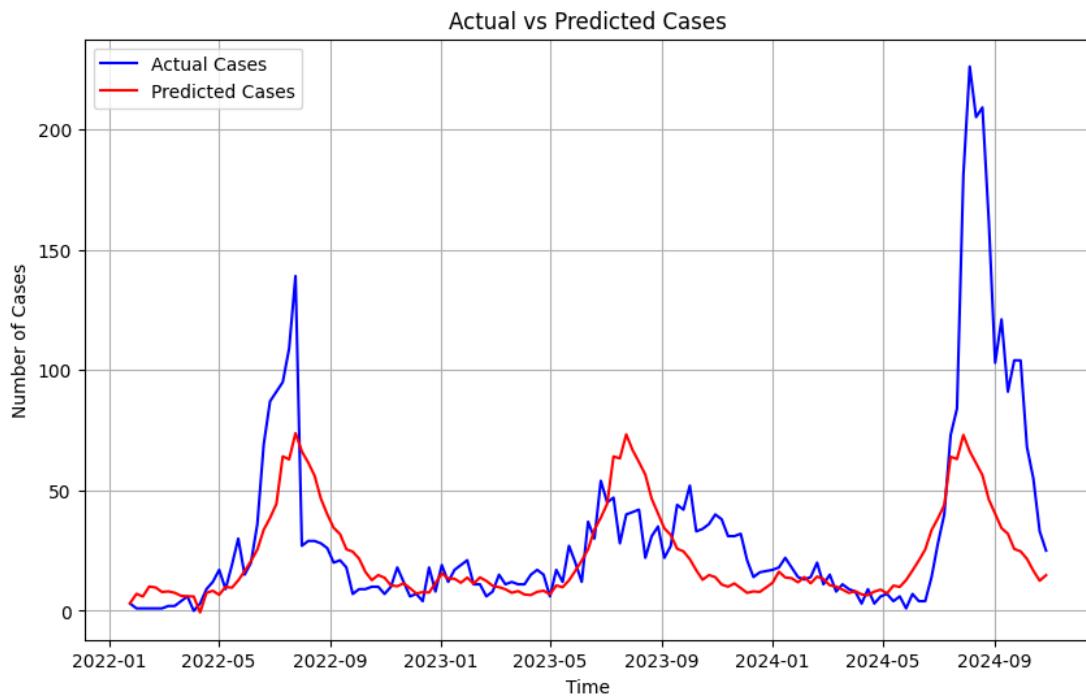


Figure 4.7: Seasonal ARIMA Prediction Results for Test Set

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

975 • **MSE:** 1109.69

976 • **RMSE:** 33.31

977 • **MAE:** 18.09

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

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

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

Table 4.7: Comparison of SARIMA performance for each fold

988 4.4.4 Kalman Filter Model

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

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

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

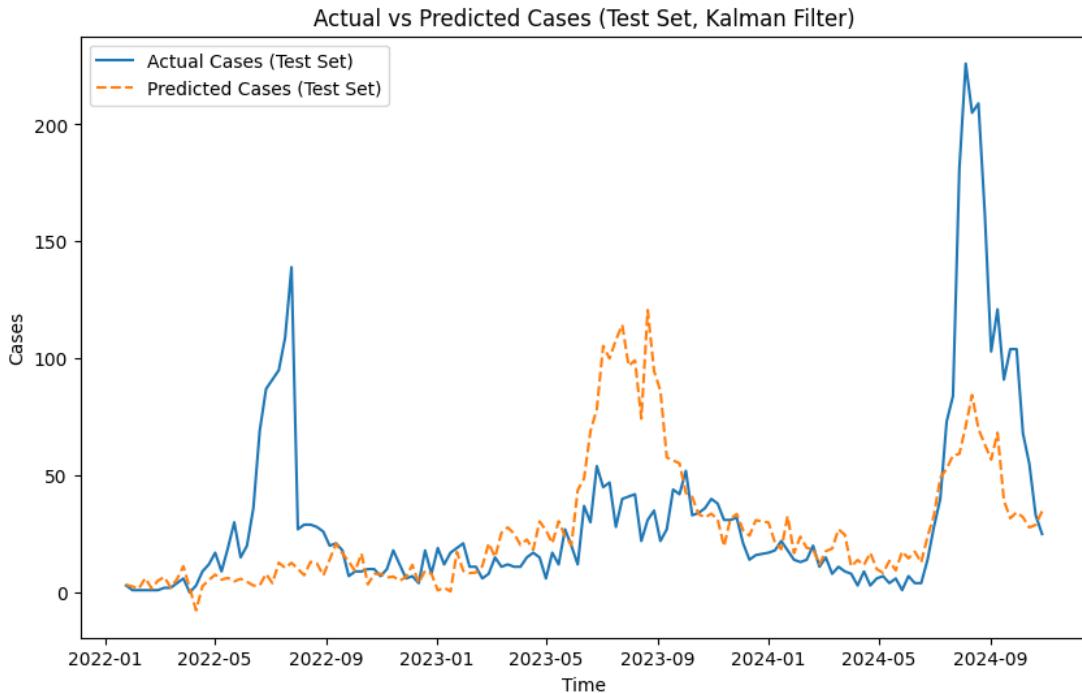


Figure 4.8: Kalman Filter Prediction Results for Test Set

997 The Kalman Filter was then combined with the LSTM model in order to see
 998 improvements in its predictions. Table 4.8 shows the metrics across three folds
 999 using the same Time Series Cross Validation Strategy employed in the previous
 1000 models to see how it performed on different time segments.

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

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

1001 As can be seen in the table above, the performance of the hybrid model demon-
 1002 strated improvements in all metrics as compared to just using the Kalman Filter
 1003 alone.

1004 4.5 Model Simulation

1005 To evaluate the LSTM model’s real-world forecasting ability, a simulation was
 1006 conducted to predict dengue cases for the year 2025. The model was retrained
 1007 exclusively, using the parameters found from the initial training, on data from 2011
 1008 to January 2025, using both dengue cases and weather variables. Importantly, the
 1009 actual dengue case values for 2025 were never included during training. Instead,
 1010 only the weather variables collected for 2025 were input into the model to generate
 1011 predictions for that year. After prediction, the forecasted dengue cases for 2025
 1012 were compared against the true observed cases to assess the model’s accuracy.
 1013 Figure 4.9 shows that the predicted values closely follow the trend, although it
 1014 may overestimate the dengue cases in some weeks.

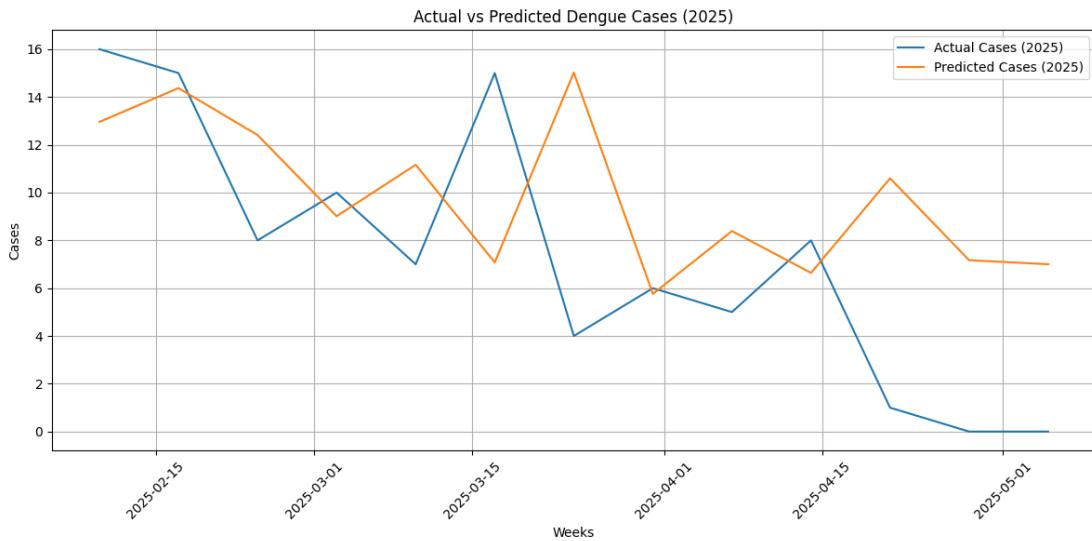


Figure 4.9: Predicted vs Actual Dengue Cases 2025

1015 Retraining the model is essential to ensure it remains accurate and responsive
 1016 to the evolving trends of dengue case patterns over time. Ideally, the model should
 1017 be updated whenever new data becomes available to capture recent dynamics.
 1018 However, given the computational cost associated with retraining, a more practical
 1019 approach is to update the model on a monthly basis. This allows the incorporation
 1020 of approximately four weeks' worth of new data, providing a meaningful update
 1021 to the model's predictive capabilities without excessive resource consumption.
 1022 Furthermore, this schedule aligns with the typical data release cycle of provincial
 1023 health offices, which, based on the researchers' experience, usually occurs monthly.
 1024 This balance between accuracy and efficiency ensures that the model remains both
 1025 up-to-date and manageable in real-world deployment.

1026 **4.6 System Prototype**

1027 **4.6.1 Home Page**

1028 The Home Page is intended for all visitors to the web application. The Analytics
1029 Dashboard, which displays relevant statistics for dengue cases at a certain time
1030 and location, is the primary component highlighted, as seen in Figure 4.10. This
1031 component includes a combo chart that graphs the number of dengue cases and
1032 deaths per week in a specific year, a choropleth map that tracks the number of
1033 dengue cases per barangay in a location, and various bar charts that indicate the
1034 top constituent places affected by dengue.

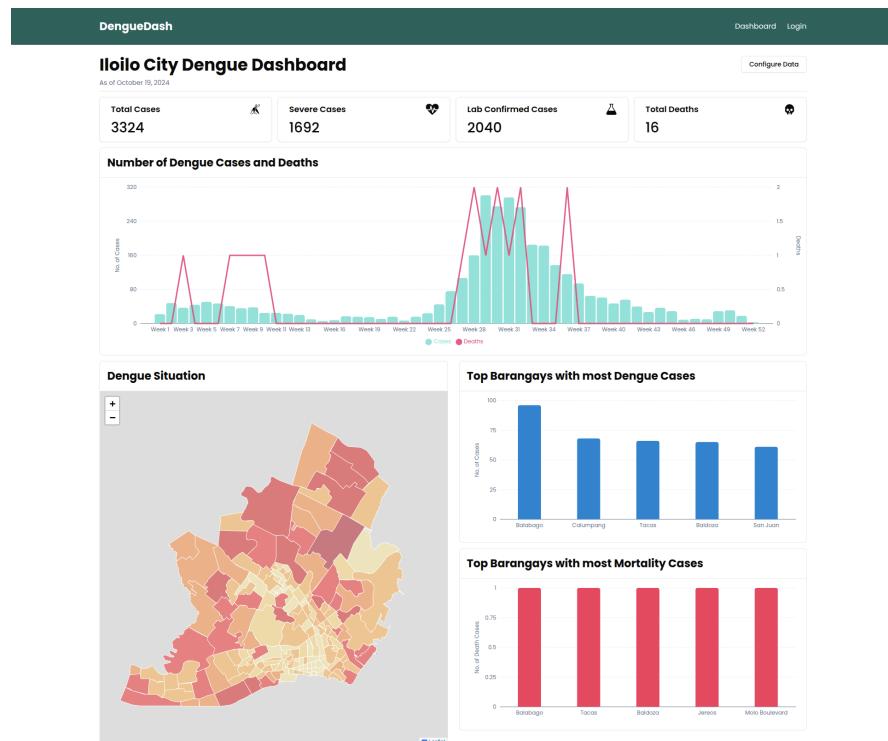
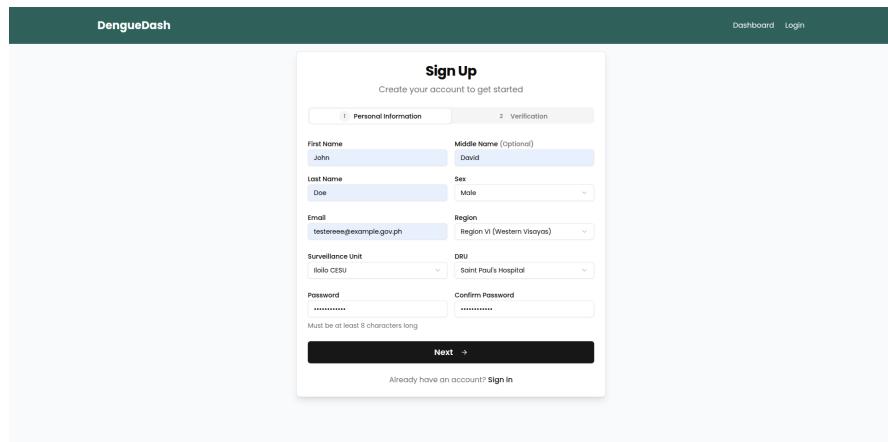


Figure 4.10: Home Page

1035 **4.6.2 User Registration, Login, and Authentication**

1036 The registration page, as shown in 4.11 and 4.12, serves as a gateway to access
 1037 the authenticated pages of the web application. Only prospective encoders can
 1038 register an account, as administrator accounts are created by existing administra-
 1039 tor accounts to protect the integrity of the data in production. After registering,
 1040 the "encoder account" cannot access the authorized pages yet as it needs to be
 1041 verified first by an administrator managing the unit the user entered. Because
 1042 of this, proper identification (user's picture and employee identification card) is
 1043 mandatory to help the admins verify the identity of the registrant. Once verified,
 1044 the user can log in to the system through the page shown in Figure 4.13. Af-
 1045 ter entering the correct credentials, which consist of an email and password, the
 1046 system uses HTTP-only cookies containing JSON Web Tokens (JWT) to prevent
 1047 vulnerability to Cross-site Scripting (XSS) attacks. It will then proceed to the
 1048 appropriate page for the type of user it belongs to. Logging out, on the other
 1049 hand, will remove both the access and refresh tokens from the browser and will
 1050 blacklist the latter token to make it unusable for security purposes.



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

Figure 4.11: Personal Information Tab of Sign Up Page

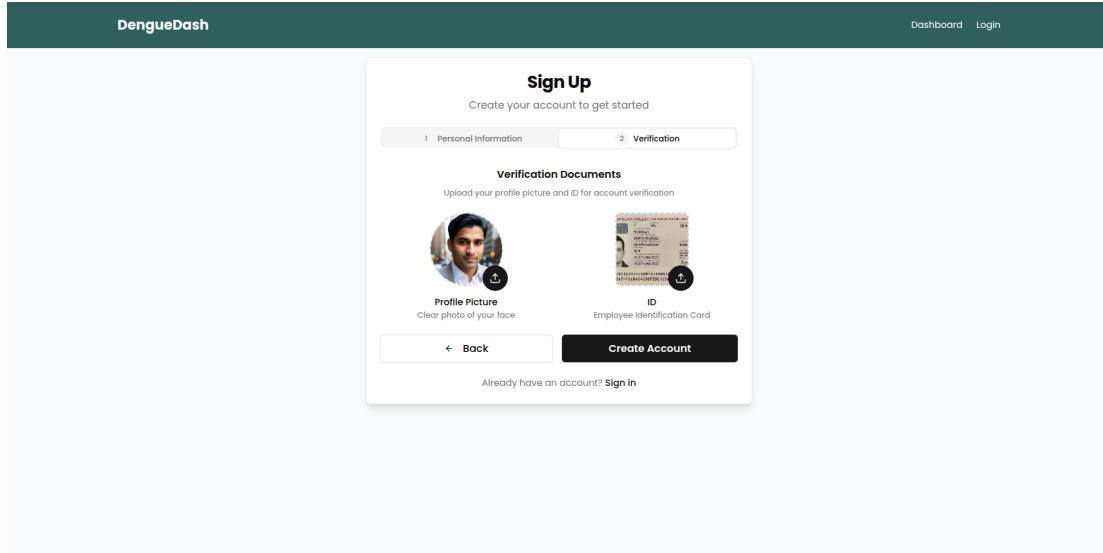


Figure 4.12: Verification Tab of Sign Up Page

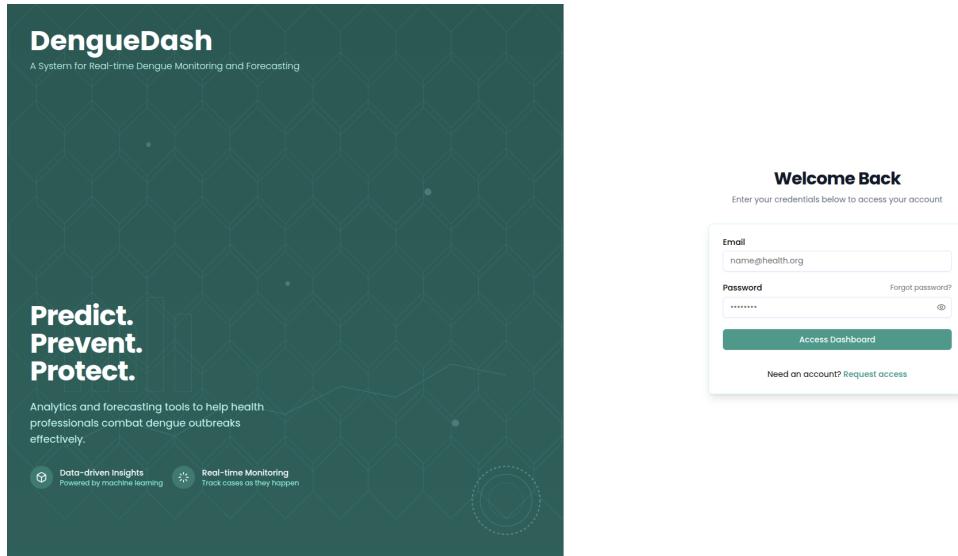


Figure 4.13: Login Page

1051 4.6.3 Encoder Interface**1052 Case Report Form**

1053 Figures 4.14 and 4.15 show the digitized counterpart of the form obtained from the
1054 Iloilo Provincial Epidemiology and Surveillance Unit. As the system aims to sup-
1055 port expandability for future features, some fields were modified to accommodate
1056 more detailed input. It is worth noting that all of the included fields adhere to the
1057 latest Philippine Integrated Disease and Surveillance Response (PIDS) Dengue
1058 Forms, which the referenced form was based on. By doing this, if implemented
1059 on a national scale, the transition between targeted users will be easier. More-
1060 over, the case form includes the patient's basic information, dengue vaccination
1061 status, consultation details, laboratory results, and the outcome. On the other
1062 hand, encoders can also create case records using a "bulk upload" feature that
1063 makes use of a formatted CSV file template. As shown in Figure 4.16, an encoder
1064 can download the template using the "Download Template" button, and insert
1065 multiple records inside the file, then upload it by clicking the "Click to upload"
1066 button. The web application automatically checks the file for data inconsis-
1067 tencies and validation.

CHAPTER 4. RESULTS AND DISCUSSION

DengueDash

Modules

- Analytics
- Forms
 - Case Report Form
- Data Tables

Forms > Case Report Form

Case Report Form

Personal Information

Clinical Status

Personal Detail

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

Date of Birth

Pick a date

Address

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

Vaccination

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

Next

Figure 4.14: First Part of Case Report Form

DengueDash

Modules

- Analytics
- Forms
 - Case Report Form
- Data Tables

Forms > Case Report Form

Case Report Form

Personal Information

Clinical Status

Consultation

Date Admitted/Consulted/Seen	Is Admitted?
Pick a date	Select
Date Onset of illness	Clinical Classification
Pick a date	Select

Laboratory Results

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

Outcome

Case Classification	Outcome
Select	Select

Date of Death

Pick a date

Previous

Submit

Figure 4.15: Second Part of Case Report Form

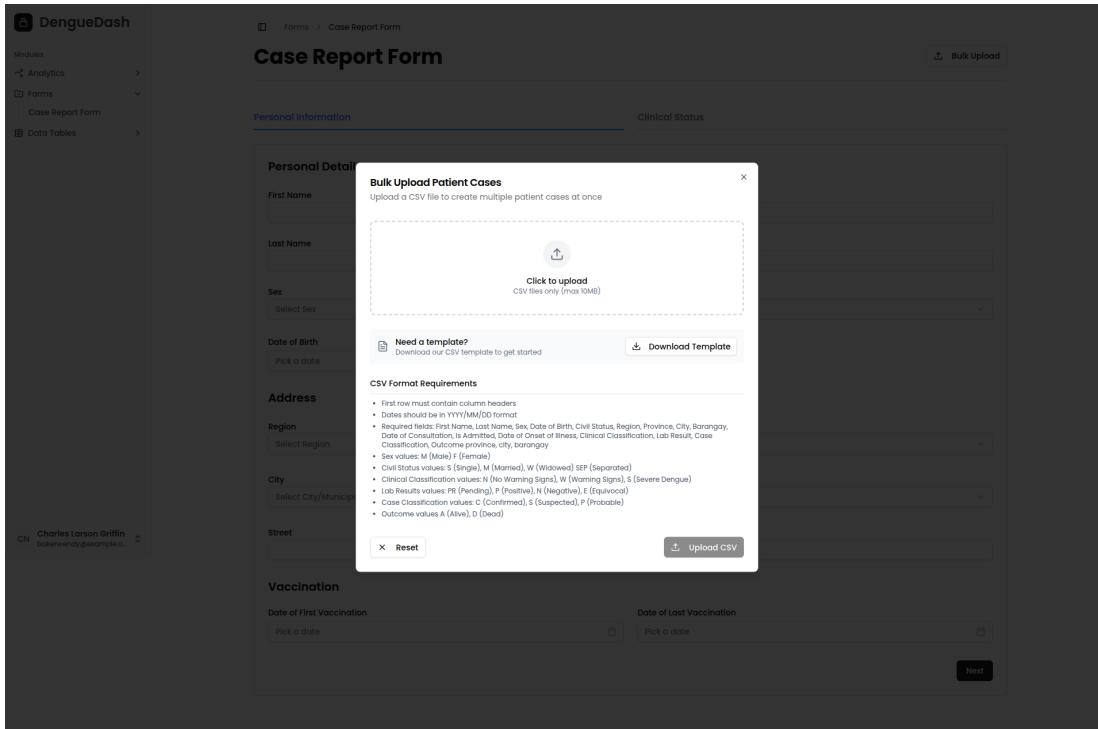


Figure 4.16: Bulk Upload of Cases using CSV

1068 Browsing, Update, and Deletion of Records

1069 Once the data generated from the case report form or the bulk upload is vali-
 1070 dated, it will be assigned as a new case and can be accessed through the Dengue
 1071 Reports page, as shown in Figure 4.17. The said page displays basic information
 1072 about the patient related to a specific case, including their name, address, date
 1073 of consultation, and clinical and case classifications. It is also worth noting that
 1074 it only shows cases that the user is permitted to view. For example, in a local
 1075 Disease Reporting Unit (DRU) setting, the user can only access records that be-
 1076 long to the same DRU. Additionally, users can search for cases by name, location,
 1077 date of consultation, or classifications associated with the specific query, making

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

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

< Previous 1 2 ... 712 Next >

CN Robert Welch Johns... [marijames@example.org](#)

Figure 4.17: Dengue Reports

The screenshot shows the DengueDash application interface. On the left is a sidebar with 'DengueDash' logo and navigation links: Modules (Analytics, Forms, Data Tables, Dengue Reports), and a user profile for Charles Larson Griffin (CN: Charles Larson Griffin, Email: bakerwendy@example.com). The main content area is titled 'Data Tables > Dengue Reports'. It displays a detailed case record for Case Record #25016448.

Personal Information:

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

Vaccination Status:

- First Dose: May 7, 2025
- Last Dose: May 13, 2025

Case Record #25016448:

- Date of Consultation: April 30, 2025
- Patient Admitted?: No
- Date Onset of Illness: April 29, 2025
- Clinical Classification: With warning signs

Laboratory Results:

Test	Status	Date Done
NS1	Pending Result	N/A
IgG Elisa	Pending Result	N/A
IgM Elisa	Pending Result	N/A
PCR	Pending Result	N/A

Outcome:

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

Interviewer:

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

Figure 4.18: Detailed Case Report

1083 To update the case, the user can click the "Update Case" button, where a
 1084 dialog will appear, and the updateable fields will be shown. It is worth noting
 1085 that in this case, only fields under Laboratory Results and Outcome are included
 1086 since they are the only ones that are time-based, where the result may change
 1087 in the future. After updating, a prompt will show confirming the user's action.
 1088 Moving forward, to delete a case record, the user must click the "Delete Case"
 1089 button, and a prompt verifying the action will appear. After confirming, the case

1090 will be deleted permanently.

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

Figure 4.19: Update Report Dialog

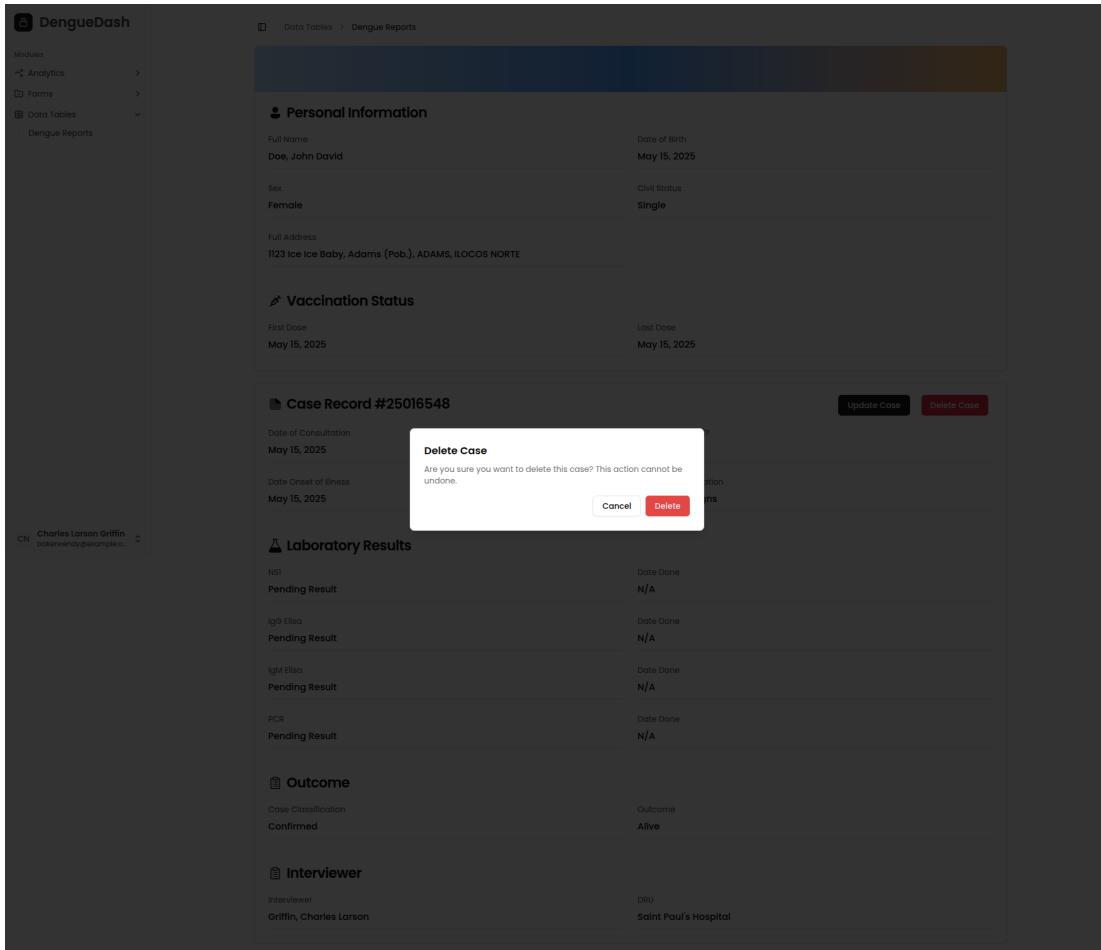


Figure 4.20: Delete Report Alert Dialog

1091 Forecasting

1092 The piece de resistance of the web application's feature is the Forecasting Page.
 1093 This is where users can forecast dengue cases for the next few weeks. To predict,
 1094 the application utilizes the exported LSTM model in a Keras format derived from
 1095 training the consolidated data from the database. The said file stores the model's
 1096 architecture and the learned parameters, which include the weights and biases
 1097 to predict cases without training the data again. Furthermore, it requires the

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

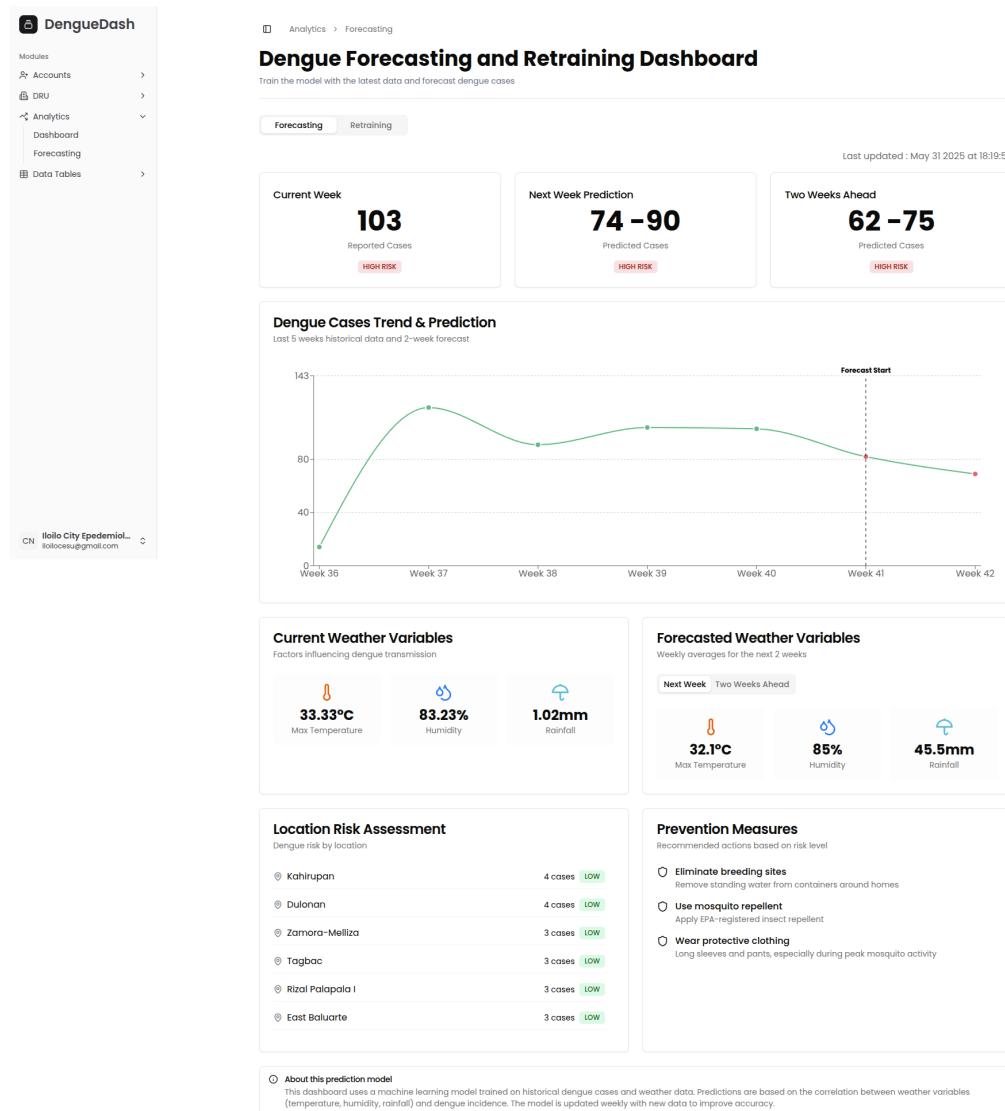


Figure 4.21: Forecasting Page

1112 4.6.4 Admin Interface

1113 Retraining

1114 With LSTM being the best-performing model among the models used in forecast-
1115 ing dengue cases, it is the model chosen to power the prediction and retraining
1116 of the consolidated data within the web application. Since the retraining process
1117 consumes a lot of processing power and requires a more advanced understanding
1118 of how it works, it was decided that the said feature should only be available to
1119 admin users of surveillance units. Furthermore, the retraining component in the
1120 Forecasting page includes three additional components that include the configura-
1121 tion of LSTM parameters (Figure 4.22), the actual retraining of the consolidated
1122 data from the database (Figure 4.23), and the results of the retraining that shows
1123 the current and previous model metrics depending on the parameters entered
1124 (Figure 4.24). It is also worth noting that when training, the model used a seeded
1125 number to promote reproducibility.

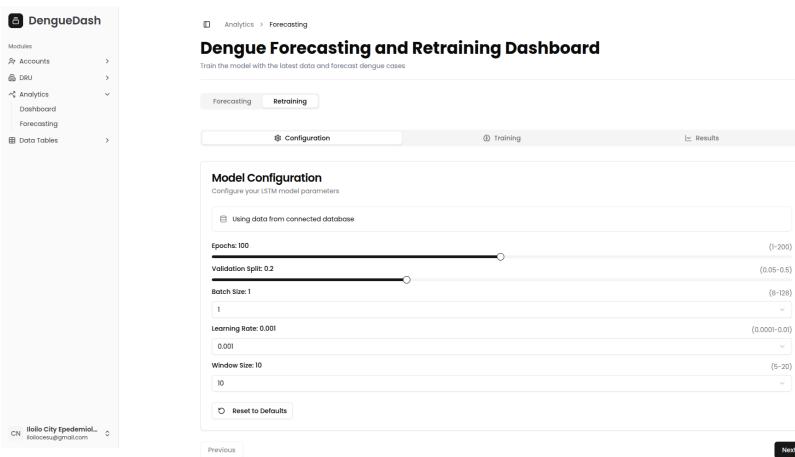


Figure 4.22: Retraining Configurations

4.6. SYSTEM PROTOTYPE

69

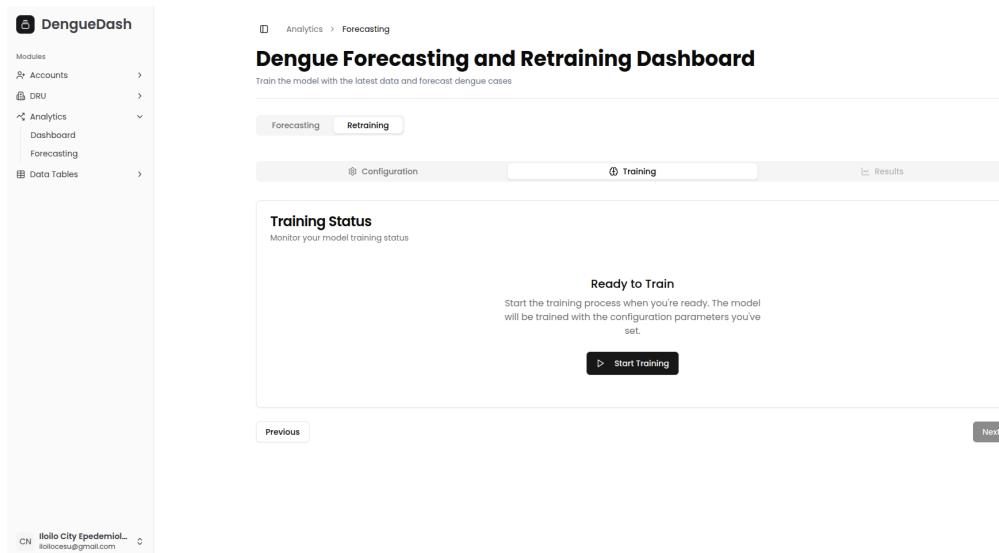


Figure 4.23: Start Retraining

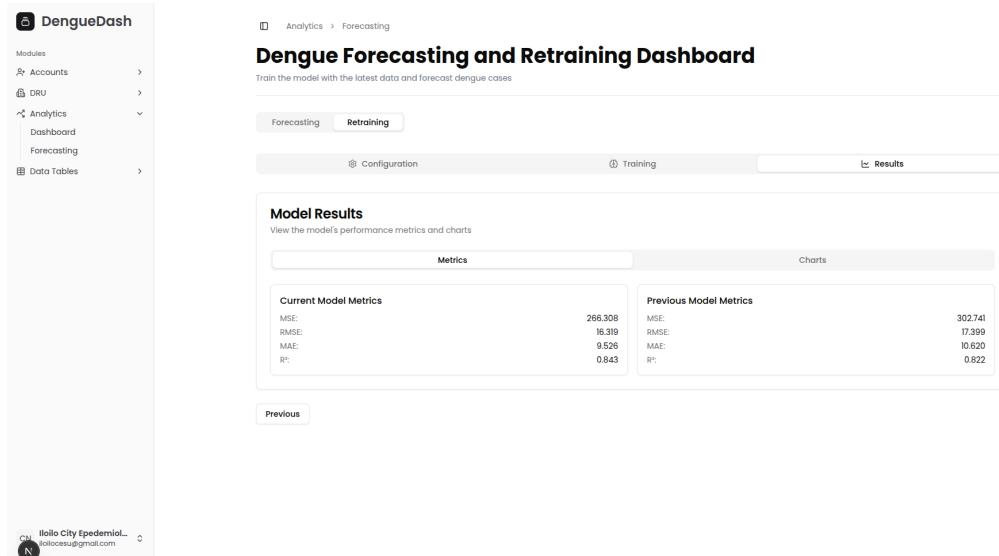


Figure 4.24: Retraining Results

1126 **Managing Accounts**

1127 Proper management of accounts is important to protect the integrity and confi-
1128 dentiality of data. Thus, it is crucial for administrators to track their users and
1129 control the flow of information. As discussed in the user registration of encoders,
1130 admin users from a specific DRU or surveillance unit have the power to grant
1131 them access to the web application. Figure 4.26 illustrates the interface for this
1132 scenario, as the admins can approve or reject their applications. Once approved,
1133 these users can access the features given to encoders and may be promoted to
1134 have administrative access, as shown in Figure 4.27. The same figure also shows
1135 the expanded details of the user, which include personal information and brief
1136 activity details within the system. When deleting an account, the user’s email
1137 will be blacklisted and illegible to use when creating another account, and all the
1138 cases reported by this user will be soft-deleted. However, the blacklist status can
1139 be reverted by clicking the ”Unban” button, which would make the user of the
1140 email able to register to the web application again as shown in Figure 4.28.

Name	Email	Role	Sex	Actions
Daniel Santiago Brandt	brandon02@example.org	Encoder	Female	<button>Open</button>

Figure 4.25: List of Verified Accounts

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: "CN: Saint Paul's Hospital" and "saintpaul@gmail.com". The main content area has a header "Manage Accounts" with a sub-header "View and manage registered and pending accounts". Below this is a navigation bar with tabs: "Verified" (disabled), "Pending" (selected), and "Blacklisted". A table lists one account: "John David Doe" with email "testereee@example.gov.ph", sex "Male", and created at "2025-05-16". To the right of the table are "Approve" and "Delete" buttons.

Figure 4.26: List of Pending Accounts

The screenshot shows the DengueDash application interface. The sidebar and user profile are identical to Figure 4.26. The main content area has a header "User Profile" with a sub-header "View and manage user details". It displays a user profile for "Charles Larson Griffin" with the following details: Name "Charles Larson Griffin", Email "bakerwendy@example.org", Sex "Female", Role "Encoder", and Hospital "(ORU) Saint Paul's Hospital". Below this are timestamped log entries: "Created At May 5 2025 at 04:47:12", "Updated At May 15 2025 at 05:55:45", and "Last Login May 15 2025 at 16:53:47". At the bottom are two buttons: "Promote to Admin" (disabled) and "Delete User".

Figure 4.27: Account Details

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

Figure 4.28: List of Blacklisted Accounts

1141 Managing DRUs

1142 Unlike the registration of encoder accounts, the creation of Disease Reporting
 1143 Units can only be done within the web application, and the user performing the
 1144 creation must be an administrator of a surveillance unit. Figure 4.29 presents the
 1145 fields the admin user must fill out, and once completed, the new entry will show
 1146 as being managed by that unit, as shown in Figure 4.30. Figure 4.31, on the other
 1147 hand, shows the details provided in the registration form as well as its creation
 1148 details. There is also an option to delete the DRU, and when invoked, all the
 1149 accounts being managed by it, and the cases reported under those accounts will
 1150 be soft-deleted.

DengueDash

Modules

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

CN iloilo City Epidemiol... [ilolocesu@gmail.com](#)

Register Disease Reporting Unit

Add a new Disease Reporting Unit to the surveillance system.

Name
Enter DRU name
The official name of the Disease Reporting Unit.

Address Information

Region	Province
Select Region	Select Province
City/Municipality	Barangay
Select City/Municipality	Select Barangay

Street Address
House/Building No., Street Name

Email
example@health.gov

Contact Number
+63 912 345 6789

DRU Type
Select DRU type
The category that best describes this reporting unit.

Register DRU

Figure 4.29: Disease Reporting Unit Registration

DengueDash

Modules

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

CN iloilo City Epidemiol... [ilolocesu@gmail.com](#)

Manage Disease Reporting Units

View and manage Disease Reporting Units

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

Figure 4.30: List of Disease Reporting Units

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

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

At the bottom right of the main content area is a red button labeled "Delete DRU".

Figure 4.31: Disease Reporting Unit details

1151 4.7 User Testing

1152 To evaluate the usability of the system, the System Usability Scale (SUS) was
1153 utilized. SUS is a Likert-scale-based questionnaire comprising 10 items that are
1154 critical to assessing system usability. A total of five participants completed the sur-
1155vey. Their responses were processed following the step-by-step calculation method
1156 adopted from (Babich, n.d.). The resulting usability scores for each participant
1157 are shown in Table 4.9.

1158 The average System Usability Scale (SUS) score across systems is typically
1159 68 (Babich, n.d.). In this testing, the system achieved an average SUS score
1160 of 88.5, indicating a highly positive user experience. This score suggests that
1161 participants found the system not only enjoyable to use but also intuitive enough

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

Table 4.9: Computed System Usability Scores per Participant

₁₁₆₂ to recommend to others. Furthermore, it demonstrates that the system is suitable
₁₁₆₃ for real-world applications without presenting significant complexity for first-time
₁₁₆₄ users.

¹¹⁶⁵ Chapter 5

¹¹⁶⁶ Conclusion

¹¹⁶⁷ The development of DengueWatch marks a transformative leap forward in public
¹¹⁶⁸ health technology, providing Iloilo City with a centralized system to combat one
¹¹⁶⁹ of the most persistent mosquito-borne diseases. Previously, data was recorded
¹¹⁷⁰ manually on paper, making tracking and analysis slow and error-prone. Dengue-
¹¹⁷¹ Watch digitizes this process, enabling faster, more accurate monitoring. More
¹¹⁷² than an academic project, DengueWatch serves as a practical solution aimed at
¹¹⁷³ shifting the approach from reactive outbreak response to proactive prevention. By
¹¹⁷⁴ combining deep learning models with real-time climate data integration, the sys-
¹¹⁷⁵ tem achieves a level of accuracy and usability that makes it viable for real-world
¹¹⁷⁶ deployment.

¹¹⁷⁷ At the heart of DengueWatch is a Long Short-Term Memory (LSTM) neural
¹¹⁷⁸ network, which outperformed traditional forecasting models such as ARIMA and
¹¹⁷⁹ Kalman Filter. The LSTM model achieved a Root Mean Square Error (RMSE) of
¹¹⁸⁰ 20.15, followed by the hybrid KF-LSTM model with an RMSE of 25.56, demon-

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

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

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

₁₁₉₈ **Chapter 6**

₁₁₉₉ **References**

- ₁₂₀₀ About GitHub and Git - GitHub Docs. (n.d.). Retrieved from
₁₂₀₁ <https://docs.github.com/en/get-started/start-your-journey/about-github-and-git>
- ₁₂₀₂ Ahmadini, A. A. H., Naeem, M., Aamir, M., Dewan, R., Alshqaq, S. S. A., & Mashwani, W. K. (2021). Analysis and Forecast of the Number of Deaths, Recovered Cases, and Confirmed Cases from COVID-19 for the Top Four Affected Countries Using Kalman Filter. *Frontiers in Physics*, *9*, 629320.
- ₁₂₀₃ Arroyo-Marioli, F., Bullano, F., Kucinskas, S., & Rondón-Moreno, C. (2021). Tracking R of COVID-19: A New Real-Time Estimation Using the Kalman Filter. *PLOS ONE*, *16*(1), e0244474.
- ₁₂₀₄ Babich, N. (n.d.). *How to Use the System Usability Scale (SUS) to Evaluate the Usability of Your Website, year=2015*. Usability Geek. Retrieved from <https://usabilitygeek.com/how-to-use-the-system-usability-scale-sus-to-evaluate-the-usability-of-your-website/> (Accessed: 2025-04-26)

- 1215 Bosano, R. (2023). *WHO: PH Most Affected by Dengue in Western Pacific*.
1216 Retrieved Use the date of access, from [https://news.abs-cbn.com/](https://news.abs-cbn.com/spotlight/12/22/23/who-ph-most-affected-by-dengue-in-western)
1217 [spotlight/12/22/23/who-ph-most-affected-by-dengue-in-western](#)
1218 [-pacific](#)
- 1219 Brady, O. J., Smith, D. L., Scott, T. W., & Hay, S. I. (2015). Dengue Disease
1220 Outbreak Definitions Are Implicitly Variable. *Epidemics*, 11, 92–102.
- 1221 Bravo, L., Roque, V. G., Brett, J., Dizon, R., & L’Azou, M. (2014). Epidemiology
1222 of Dengue Disease in the Philippines (2000–2011): A Systematic Literature
1223 Review. *PLOS Neglected Tropical Diseases*, 8(11), e3027.
- 1224 Carvajal, T. M., Viacrucis, K. M., Hernandez, L. F. T., Ho, H. T., Amalin, D. M.,
1225 & Watanabe, K. (2018). Machine Learning Methods Reveal the Temporal
1226 Pattern of Dengue Incidence Using Meteorological Factors in Metropolitan
1227 Manila, Philippines. *BMC Infectious Diseases*, 18, 1–15.
- 1228 *Chart.js*. (n.d.). Retrieved from <https://www.chartjs.org/>
- 1229 Cheong, Y. L., Burkart, K., Leitão, P. J., & Lakes, T. (2013). Assessing Weather
1230 Effects on Dengue Disease in Malaysia. *International Journal of Environmental
1231 Research and Public Health*, 10(12), 6319–6334.
- 1232 Christie, T. (n.d.). *Home - Django REST framework*. Retrieved from <https://www.djangoproject-rest-framework.org/>
- 1233
- 1234 Colón-González, F. J., Fezzi, C., Lake, I. R., & Hunter, P. R. (2013). The
1235 Effects of Weather and Climate Change on Dengue. *PLOS Neglected Tropical
1236 Diseases*, 7(11), e2503.
- 1237 Hemisphere, N. (2015). Update on the Dengue Situation in the Western Pacific
1238 Region. *Update*.
- 1239 Hii, Y. L., Zhu, H., Ng, N., Ng, L. C., & Rocklöv, J. (2012). Forecast of Dengue
1240 Incidence Using Temperature and Rainfall. *PLOS Neglected Tropical Dis-*

- 1241 *eases*, 6(11), e1908.
- 1242 Joel, C. (2021, 10). *6 reasons to use Tailwind over traditional CSS*. Retrieved
1243 from <https://dev.to/charliejoel/6-reasons-to-use-tailwind-over-traditional-css-1nc3>
- 1244
- 1245 Leaflet — an open-source JavaScript library for interactive maps. (n.d.). Retrieved
1246 from <https://leafletjs.com/>
- 1247 Li, X., Feng, S., Hou, N., Li, H., Zhang, S., Jian, Z., & Zi, Q. (2022). Applications
1248 of Kalman Filtering in Time Series Prediction. In *International conference*
1249 on *intelligent robotics and applications* (pp. 520–531).
- 1250 Ligue, K. D. B., & Ligue, K. J. B. (2022). Deep Learning Approach to Forecasting
1251 Dengue Cases in Davao City Using Long Short-Term Memory (LSTM).
1252 *Philippine Journal of Science*, 151(3).
- 1253 Perla. (2024). *Iloilo Beef Up Efforts Amid Hike in Dengue Cases*. Retrieved Use
1254 the date of access, from <https://www.pna.gov.ph/articles/1231208>
- 1255 RabDashDC. (2024). *RabDash DC*. Retrieved Use the date of access, from
1256 <https://rabdash.com>
- 1257 Runge-Ranzinger, S., Kroeger, A., Olliaro, P., McCall, P. J., Sánchez Tejeda, G.,
1258 Lloyd, L. S., . . . Coelho, G. (2016). Dengue Contingency Planning: From
1259 Research to Policy and Practice. *PLOS Neglected Tropical Diseases*, 10(9),
1260 e0004916.
- 1261 Shadcn. (n.d.). *Introduction*. Retrieved from <https://ui.shadcn.com/docs>
- 1262 *Tailwind CSS - Rapidly build modern websites without ever leaving your HTML*.
1263 (n.d.). Retrieved from <https://tailwindcss.com/>
- 1264 Watts, David M and Burke, Donald S and Harrison, Bruce A and Whitmire, Ralph
1265 E and Nisalak, Ananda. (2020). Effect of temperature on the transmission
1266 of dengue virus by **aedes aegypti**. *The American Journal of Tropical*

- 1267 *Medicine and Hygiene*, 36(1), 143–152.
- 1268 *What is Postman? Postman API Platform*. (n.d.). Retrieved from <https://www.postman.com/product/what-is-postman/>
- 1269
- 1270 *Why Visual Studio Code?* (2021, 11). Retrieved from <https://code.visualstudio.com/docs/editor/whyvscode>
- 1271
- 1272 World Health Organization (WHO). (2018). Dengue and severe dengue in the Philippines. *WHO Dengue Factsheet*. (Available at: <https://www.who.int>)
- 1273
- 1274
- 1275 Zhou, S., & Malani, P. (2024). What Is Dengue? *JAMA*, 332(10), 850–850.
- 1276 Zod. (n.d.). *TypeScript-First Schema Validation with Static Type Inference*. Retrieved from <https://zod.dev/?id=introduction> (Accessed: 2025-04-
- 1277
- 1278 26)

¹²⁷⁹ **Appendix A**

¹²⁸⁰ **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

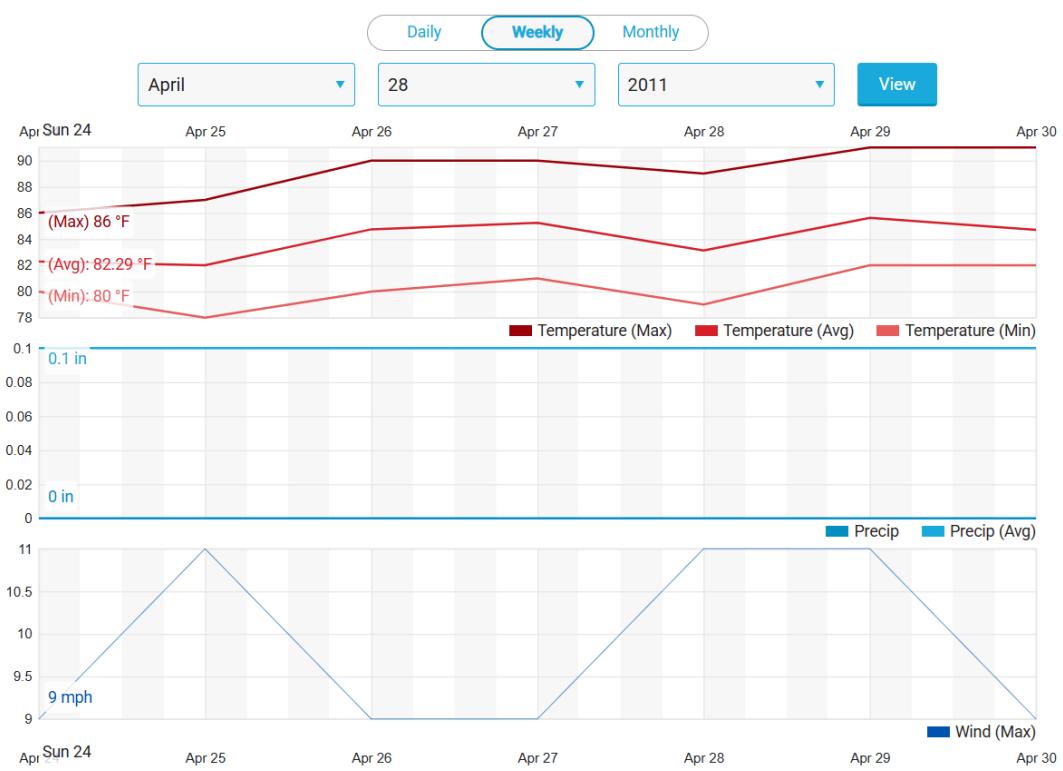


Figure A.2: Snippet of Weather Data Collection

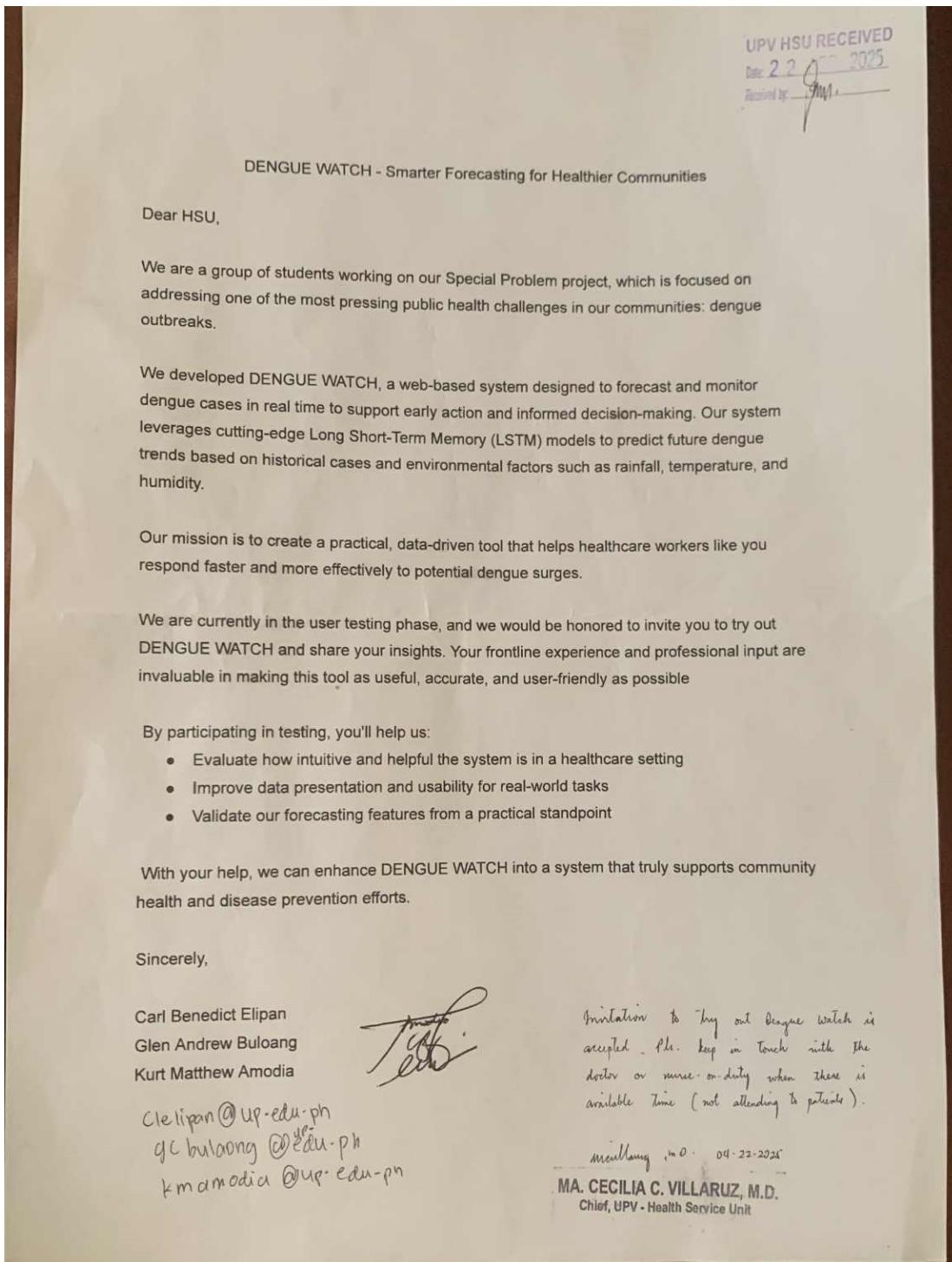


Figure A.3: Letter of Approval for User Testing in UPV HSU

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