

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

4           A Special Problem  
5           Presented to  
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**Approval Sheet**

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The Division of Physical Sciences and Mathematics, College of Arts and  
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certifies that this is the approved version of the following special problem:

22

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

23

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31                              **Declaration**

32        We, Kurt Matthew A. Amodia, Glen Andrew C. Bulaong, and Carl Benedict  
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34        is the record of work carried out by us. Any significant borrowings have been  
35        properly acknowledged and referred.

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## Dedication

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

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

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

49

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## Abstract

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

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

# **91      Contents**

<b>92      1    Introduction</b>	<b>1</b>
93        1.1   Overview of the Current State of Technology . . . . .	1
94        1.2   Problem Statement . . . . .	3
95        1.3   Research Objectives . . . . .	4
96            1.3.1   General Objective . . . . .	4
97            1.3.2   Specific Objectives . . . . .	4
98        1.4   Scope and Limitations of the Research . . . . .	5
99        1.5   Significance of the Research . . . . .	6
<b>100     2    Review of Related Literature</b>	<b>9</b>
101        2.1   Dengue . . . . .	9
102        2.2   Outbreak Definition . . . . .	10

103	2.3 Existing System: RabDash DC . . . . .	11
104	2.4 Deep Learning . . . . .	11
105	2.5 Kalman Filter . . . . .	12
106	2.6 Weather Data . . . . .	13
107	2.7 Chapter Summary . . . . .	14
108	<b>3 Research Methodology</b>	<b>15</b>
109	3.1 Research Activities . . . . .	16
110	3.1.1 Gather Dengue Data and Climate Data to Create a Com-	
111	plete Dataset for Forecasting . . . . .	16
112	3.1.2 Develop and Evaluate Deep Learning Models for Dengue	
113	Case Forecasting . . . . .	19
114	3.1.3 Integrate the Predictive Model into a Web-Based Data An-	
115	alytics Dashboard . . . . .	25
116	3.1.4 System Development Framework . . . . .	25
117	3.2 Development Tools . . . . .	28
118	3.2.1 Software . . . . .	28
119	3.2.2 Hardware . . . . .	30
120	3.2.3 Packages . . . . .	30

## CONTENTS ix

121	3.3 Application Requirements . . . . .	32
122	3.3.1 Backend Requirements . . . . .	32
123	3.3.2 User Interface Requirements . . . . .	34
124	3.3.3 Security and Validation Requirements . . . . .	37
125	<b>4 Results and Discussion/System Prototype</b>	<b>39</b>
126	4.1 Data Gathering . . . . .	39
127	4.2 Exploratory Data Analysis . . . . .	40
128	4.3 Outbreak Detection . . . . .	46
129	4.4 Model Training Results . . . . .	47
130	4.4.1 LSTM Model . . . . .	48
131	4.4.2 ARIMA Model . . . . .	50
132	4.4.3 Seasonal ARIMA (SARIMA) Model . . . . .	51
133	4.4.4 Kalman Filter Model . . . . .	53
134	4.5 Model Simulation . . . . .	55
135	4.6 System Prototype . . . . .	56
136	4.6.1 Home Page . . . . .	56
137	4.6.2 User Registration, Login, and Authentication . . . . .	57

138	4.6.3 Encoder Interface . . . . .	59
139	4.6.4 Admin Interface . . . . .	68
140	4.7 User Testing . . . . .	75
141	<b>5 Conclusion</b>	<b>77</b>
142	<b>6 References</b>	<b>81</b>
143	<b>A Data Collection Snippets</b>	<b>85</b>

# <sup>144</sup> List of Figures

<sup>145</sup>	3.1 Workflow for forecasting the number of weekly dengue cases . . . . .	15
<sup>146</sup>	3.2 Testing Process for DengueWatch . . . . .	27
<sup>147</sup>	3.3 Entity-Relationship Database Schema Hybrid Diagram for DengueDash	
<sup>148</sup>	Database Structure . . . . .	33
<sup>149</sup>	3.4 Use Case Diagram for Admins . . . . .	34
<sup>150</sup>	3.5 Use Case Diagram for Encoder . . . . .	36
<sup>151</sup>	4.1 Snippet of the Combined Dataset . . . . .	40
<sup>152</sup>	4.2 Data Contents . . . . .	41
<sup>153</sup>	4.3 Dataset Statistics . . . . .	41
<sup>154</sup>	4.4 Trend of Dengue Cases . . . . .	42
<sup>155</sup>	4.5 Ranking of Correlations . . . . .	43
<sup>156</sup>	4.6 Pre-Transform Feature Distributions . . . . .	44

157	4.7 Scatterplots . . . . .	44
158	4.8 Post-Transform Feature Distributions . . . . .	45
159	4.9 Transformed Distributions: Scatterplots . . . . .	45
160	4.10 Ranking of Correlations with New Distributions . . . . .	46
161	4.11 Training Folds - Window Size 5 . . . . .	49
162	4.12 Testing Folds - Window Size 5 . . . . .	50
163	4.13 ARIMA Prediction Results for Test Set . . . . .	51
164	4.14 Seasonal ARIMA Prediction Results for Test Set . . . . .	52
165	4.15 Kalman Filter Prediction Results for Test Set . . . . .	54
166	4.16 Predicted vs Actual Dengue Cases 2025 . . . . .	56
167	4.17 Home Page . . . . .	57
168	4.18 Sign Up Page . . . . .	58
169	4.19 Login Page . . . . .	59
170	4.20 First Part of Case Report Form . . . . .	60
171	4.21 Second Part of Case Report Form . . . . .	61
172	4.22 Bulk Upload of Cases using CSV . . . . .	62
173	4.23 Dengue Reports . . . . .	63

*LIST OF FIGURES*

xiii

174	4.24 Detailed Case Report . . . . .	64
175	4.25 Update Report Dialog . . . . .	65
176	4.26 Delete Report Alert Dialog . . . . .	66
177	4.27 Forecasting Page . . . . .	68
178	4.28 Retraining Configurations . . . . .	69
179	4.29 Start Retraining . . . . .	70
180	4.30 Retraining Results . . . . .	70
181	4.31 List of Verified Accounts . . . . .	71
182	4.32 List of Pending Accounts . . . . .	72
183	4.33 Account Details . . . . .	72
184	4.34 Disease Reporting Unit Registration . . . . .	73
185	4.35 List of Disease Reporting Units . . . . .	74
186	4.36 Disease Reporting Unit details . . . . .	74
187	A.1 Snippet of Consolidated Data . . . . .	85
188	A.2 Snippet of Weather Data Collection . . . . .	86
189	A.3 Letter of Approval for User Testing in UPV HSU . . . . .	87
190	A.4 System Usability Score Questionnaire . . . . .	88



# <sup>191</sup> List of Tables

<sup>192</sup>	4.1 Comparison of different models for dengue prediction . . . . .	48
<sup>193</sup>	4.2 Comparison of Window Sizes . . . . .	48
<sup>194</sup>	4.3 Time-Series Cross Validation Results: Comparison of Window Sizes	49
<sup>195</sup>	4.4 Comparison of SARIMA performance for each fold . . . . .	53
<sup>196</sup>	4.5 Comparison of KF-LSTM performance for each fold . . . . .	55
<sup>197</sup>	4.6 Computed System Usability Scores per Participant . . . . .	75

<sup>198</sup> **Chapter 1**

<sup>199</sup> **Introduction**

<sup>200</sup> **1.1 Overview of the Current State of Technology**

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

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

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

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

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

<sup>235</sup> **1.2 Problem Statement**

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

<sup>255</sup> **1.3 Research Objectives**

<sup>256</sup> **1.3.1 General Objective**

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

<sup>262</sup> **1.3.2 Specific Objectives**

<sup>263</sup> Specifically, this study aims to:

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

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

## 276 1.4 Scope and Limitations of the Research

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

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

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

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

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

## <sup>302</sup> 1.5 Significance of the Research

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

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

## *1.5. SIGNIFICANCE OF THE RESEARCH*

7

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

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

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



# <sup>329</sup> Chapter 2

## <sup>330</sup> Review of Related Literature

### <sup>331</sup> 2.1 Dengue

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

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

## <sup>349</sup> 2.2 Outbreak Definition

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

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

<sup>365</sup> **2.3 Existing System: RabDash DC**

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

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

<sup>382</sup> **2.4 Deep Learning**

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

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

## 396 2.5 Kalman Filter

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

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

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

## 415 2.6 Weather Data

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

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

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

## <sup>433</sup> 2.7 Chapter Summary

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

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

# <sup>448</sup> Chapter 3

## <sup>449</sup> Research Methodology

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

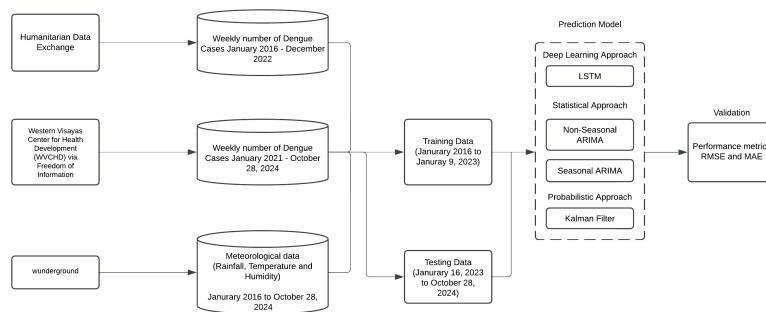


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

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

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

460 **3.1 Research Activities**

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

463 **Acquisition of Dengue Case Data**

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

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

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

479

480 **Data Fields**

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

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

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

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

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

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

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

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

**497 Data Integration and Preprocessing**

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

**505 Exploratory Data Analysis (EDA)**

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

**510 Outbreak Detection**

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

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

513 where  $\mu$  is the historical mean and  $\sigma$  is the standard deviation.

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

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

521 **Data Preprocessing**

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

528 **LSTM Model**

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

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

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

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

544 LSTM units:

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

## 549 Learning Rate:

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

554        The tuner was instantiated with:

- 555        • **max trials = 10:** Limiting the search to 10 different configurations
- 556        • **executions per trial = 3:** Running each configuration thrice to reduce variance
- 558        • **validation split = 0.2:** Reserving 20% of the training data for validation

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

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

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

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

579 **ARIMA**

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

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

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

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

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

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

### 601 Seasonal ARIMA (SARIMA)

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

620 **Kalman Filter:**

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

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

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

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

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

643 **Dashboard Design and Development**

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

648 **Model Integration and Deployment**

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

651 **3.1.4 System Development Framework**

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

**658 Design and Development**

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

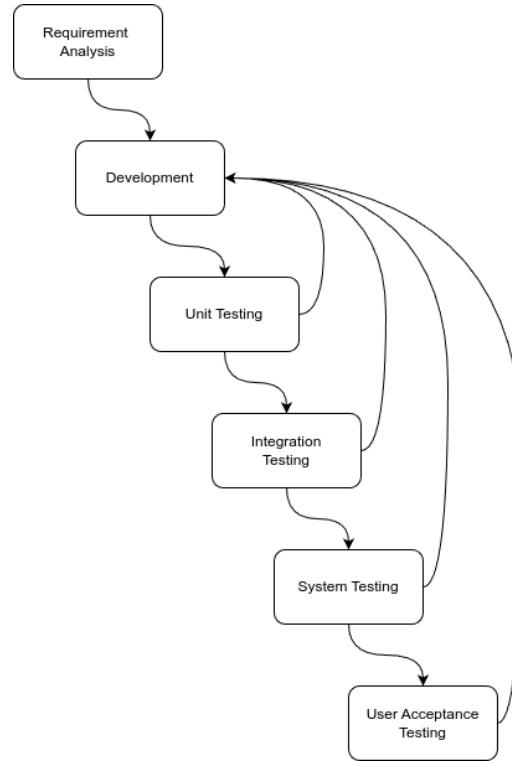
672 **Testing and Integration**

Figure 3.2: Testing Process for DengueWatch

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

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

## 3.2 Development Tools

### 3.2.1 Software

#### Github

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

#### Visual Studio Code

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

**701 Django**

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

**710 Next.js**

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

**717 Postman**

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

<sup>722</sup> Postman? Postman API Platform, n.d.).

### <sup>723</sup> 3.2.2 Hardware

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

### <sup>727</sup> 3.2.3 Packages

#### <sup>728</sup> Django REST Framework

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

#### <sup>733</sup> Leaflet

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

**740 Chart.js**

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

**748 Tailwind CSS**

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

**757 Shadcn**

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

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

<sup>763</sup> **Zod**

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

<sup>768</sup> **3.3 Application Requirements**

<sup>769</sup> **3.3.1 Backend Requirements**

<sup>770</sup> **Database Structure Design**

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

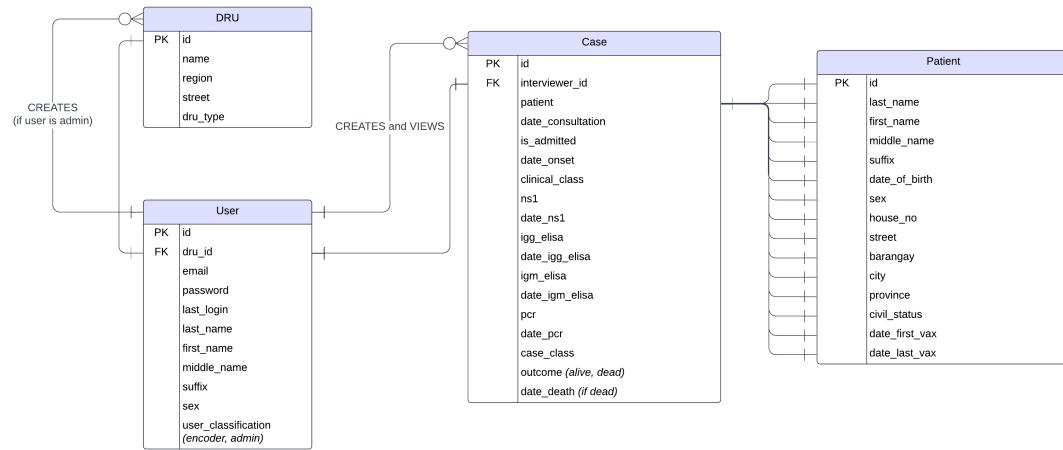


Figure 3.3: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

### <sup>777</sup> 3.3.2 User Interface Requirements

#### <sup>778</sup> Admin Interface

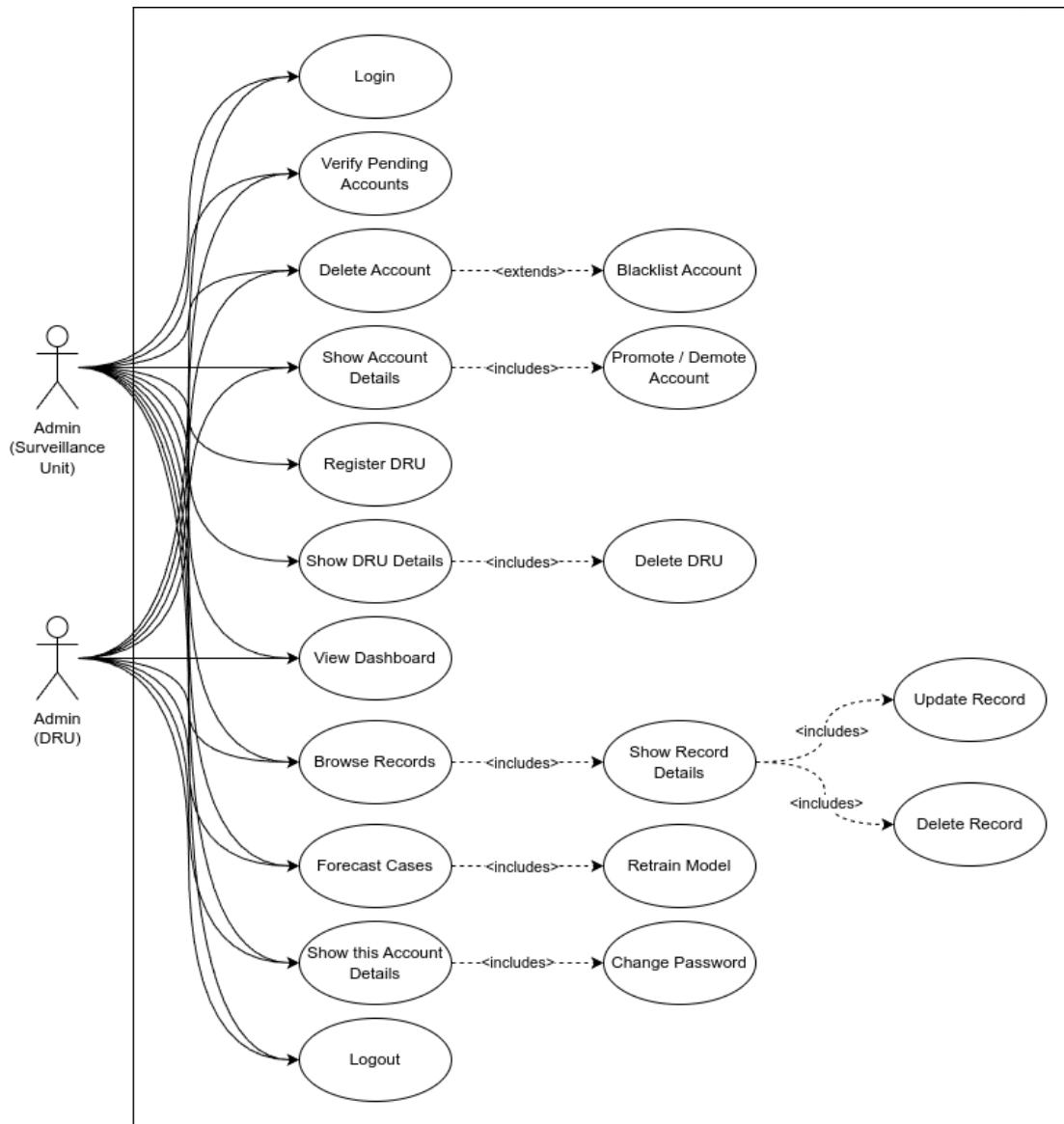


Figure 3.4: Use Case Diagram for Admins

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

<sup>789</sup> **Encoder Interface**

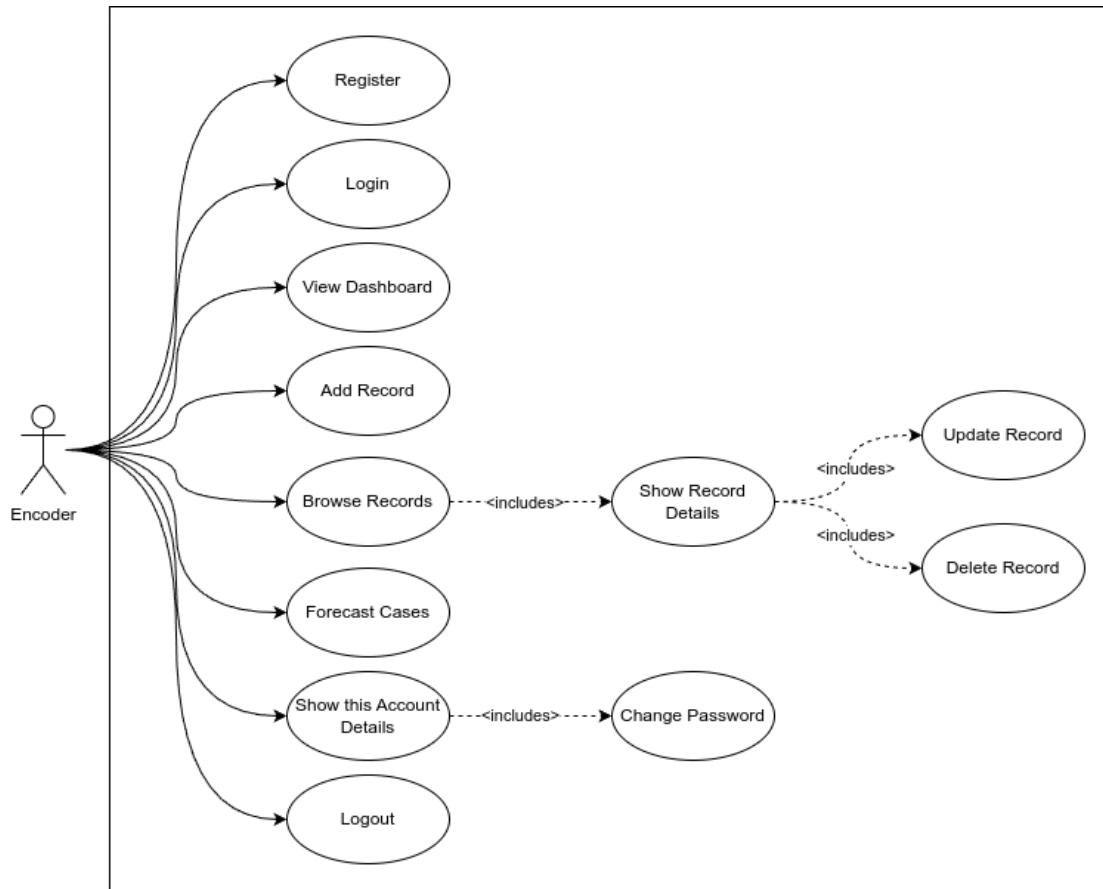


Figure 3.5: Use Case Diagram for Encoder

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

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

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

**807 Authentication**

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

**813 Data Validation**

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

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

822 **Chapter 4**

823 **Results and Discussion/System**

824 **Prototype**

825 **4.1 Data Gathering**

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

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

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

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

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

Figure 4.1: Snippet of the Combined Dataset

## 840 4.2 Exploratory Data Analysis

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

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

#	Column	Non-Null Count	Dtype
0	Time	720 non-null	datetime64[ns]
1	Rainfall	720 non-null	float64
2	MaxTemperature	720 non-null	float64
3	AverageTemperature	720 non-null	float64
4	MinTemperature	720 non-null	float64
5	Wind	720 non-null	float64
6	Humidity	720 non-null	float64
7	Cases	720 non-null	int64
dtypes: datetime64[ns](1), float64(6), int64(1)			
memory usage: 45.1 KB			

Figure 4.2: Data Contents

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

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

	Time	Rainfall	MaxTemperature	AverageTemperature	MinTemperature	Wind	Humidity	Cases
<b>count</b>	720	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000
<b>mean</b>	2017-12-02 11:22:00	13.957499	32.191142	28.110319	25.038472	6.172417	81.609442	23.744444
<b>min</b>	2011-01-03 00:00:00	0.000000	-14.600000	24.494444	12.222222	1.910000	73.185714	0.000000
<b>25%</b>	2014-06-21 06:00:00	1.270000	31.666667	27.504167	25.000000	4.117500	79.885713	5.000000
<b>50%</b>	2017-12-07 12:00:00	4.318000	32.222222	28.161111	25.000000	5.725000	81.771429	12.000000
<b>75%</b>	2021-05-11 18:00:00	10.414000	32.777778	28.751389	25.555556	7.860000	83.503571	26.000000
<b>max</b>	2024-10-28 00:00:00	445.008000	58.333333	30.916667	32.222222	19.200000	89.571429	319.000000
<b>std</b>	NaN	35.448846	2.616379	0.999800	1.291659	2.446703	2.831674	37.144813

Figure 4.3: Dataset Statistics

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

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

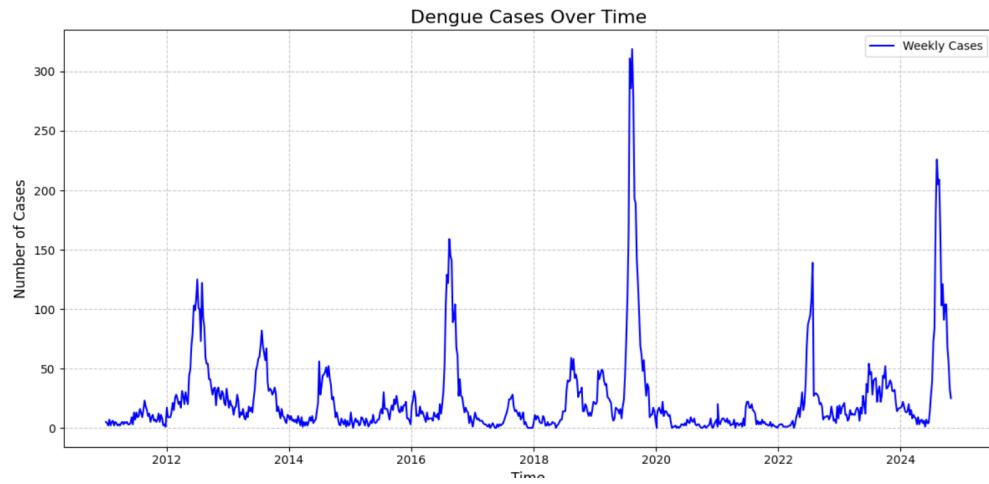


Figure 4.4: Trend of Dengue Cases

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

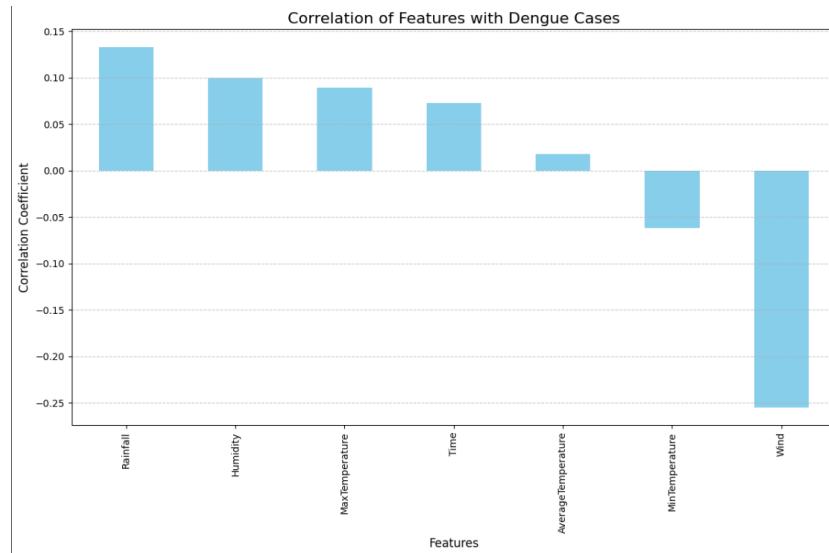


Figure 4.5: Ranking of Correlations

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

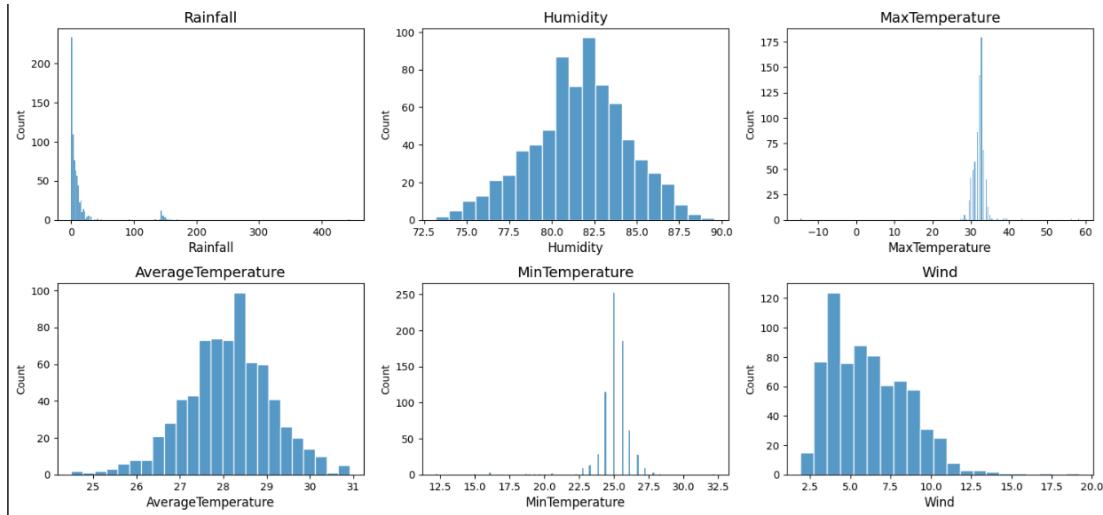


Figure 4.6: Pre-Transform Feature Distributions

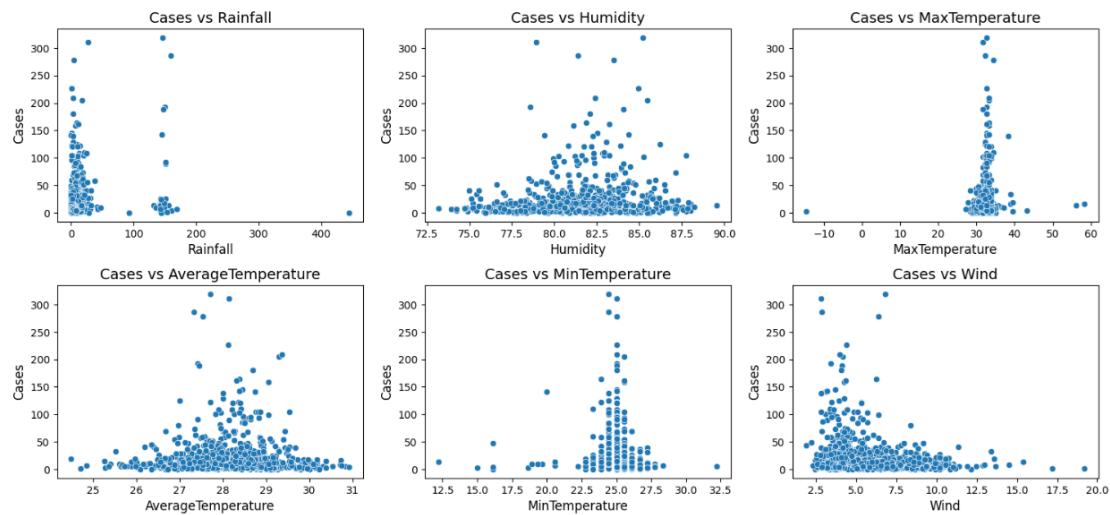


Figure 4.7: Scatterplots

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

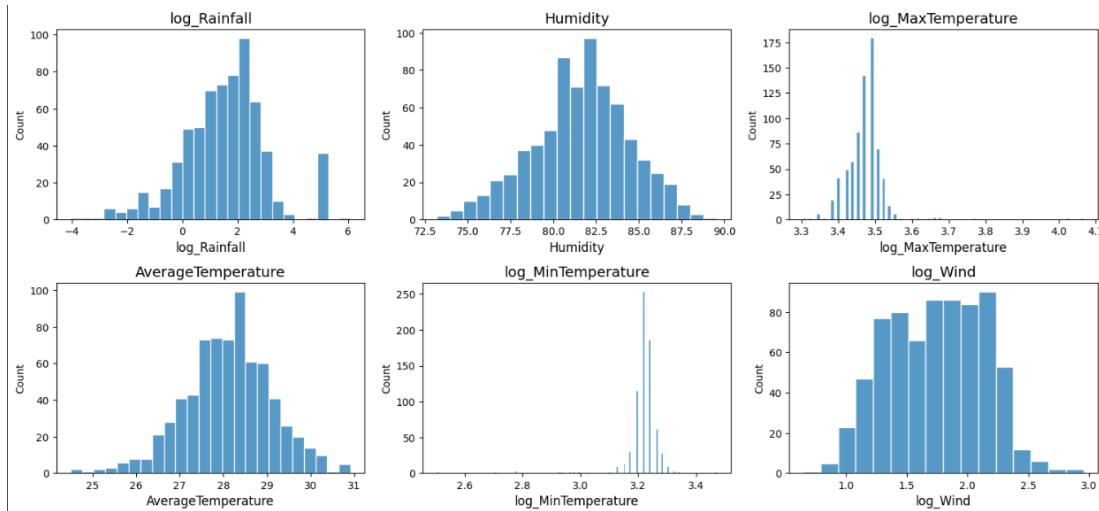


Figure 4.8: Post-Transform Feature Distributions

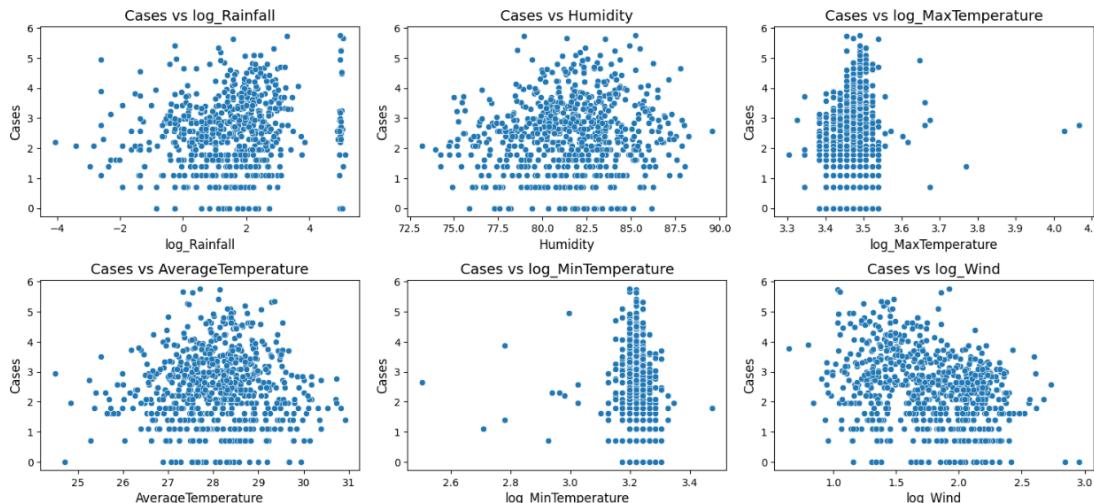


Figure 4.9: Transformed Distributions: Scatterplots

886 Figure 4.10 presents the recomputed correlation coefficients between dengue

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

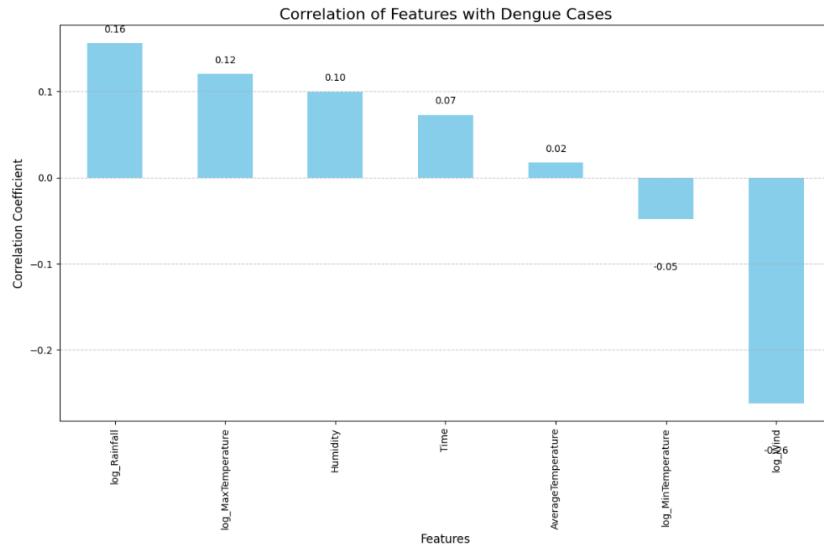


Figure 4.10: Ranking of Correlations with New Distributions

### 4.3 Outbreak Detection

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

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

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

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

$$= 98.03407 \quad (4.4)$$

897 where  $\mu$  is the historical mean and  $\sigma$  is the standard deviation.

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

## 903 4.4 Model Training Results

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

Method	LSTM	Seasonal ARIMA	ARIMA	Kalman Filter	KF-LSTM
Testing MSE	285.54	1261.20	1521.48	1474.82	785.35
Testing RMSE	16.90	34.45	39.00	38.40	25.56
Testing MAE	9.45	18.73	25.80	22.33	14.55
Best Parameters	Window Size: 5 Learning Rate: 0.01 Units: 64	(2,0,2)(0,1,1)	(1,2,2)	Observation Covariance: 10.0 Transition Covariance: 0.1 × Identity	Same as LSTM

Table 4.1: Comparison of different models for dengue prediction

#### 912 4.4.1 LSTM Model

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

Window Size	MSE	RMSE	MAE	R <sup>2</sup>
5	<b>285.54</b>	<b>16.90</b>	<b>9.45</b>	<b>0.83</b>
10	<b>334.63</b>	<b>18.29</b>	<b>9.85</b>	<b>0.80</b>
20	<b>294.85</b>	<b>17.17</b>	<b>9.35</b>	<b>0.83</b>

Table 4.2: Comparison of Window Sizes

917

918 The results indicate that a window size of 5 weeks provides the most accurate  
 919 predictions, as evidenced by the lowest MSE and RMSE values. Furthermore, the  
 920 R<sup>2</sup> score of 0.83 indicates that 83% of the variability in the target variable (cases)  
 921 is explained by the independent variables (the inputs) in the model, making it a  
 922 reliable configuration overall.

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

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

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

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

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

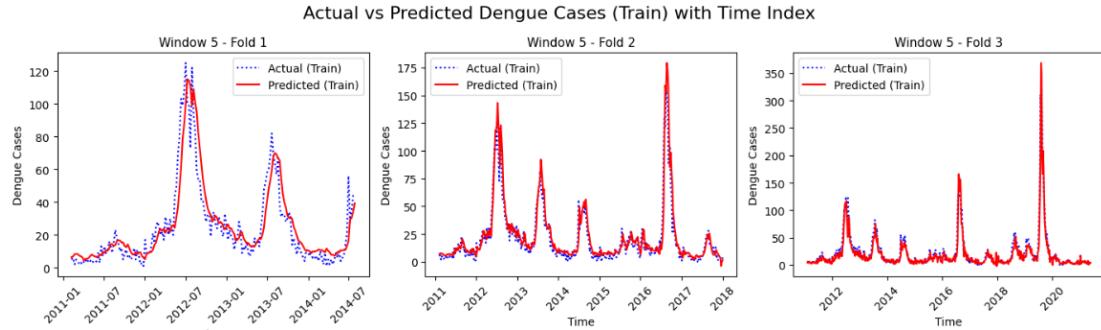


Figure 4.11: Training Folds - Window Size 5

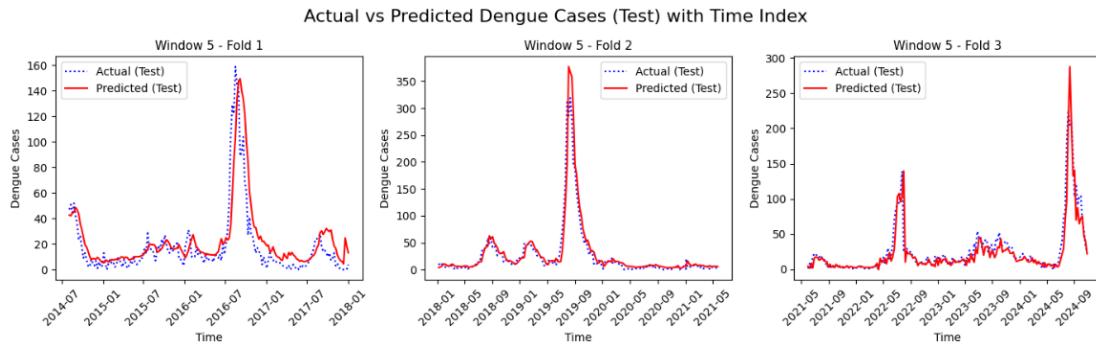


Figure 4.12: Testing Folds - Window Size 5

#### 936 4.4.2 ARIMA Model

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

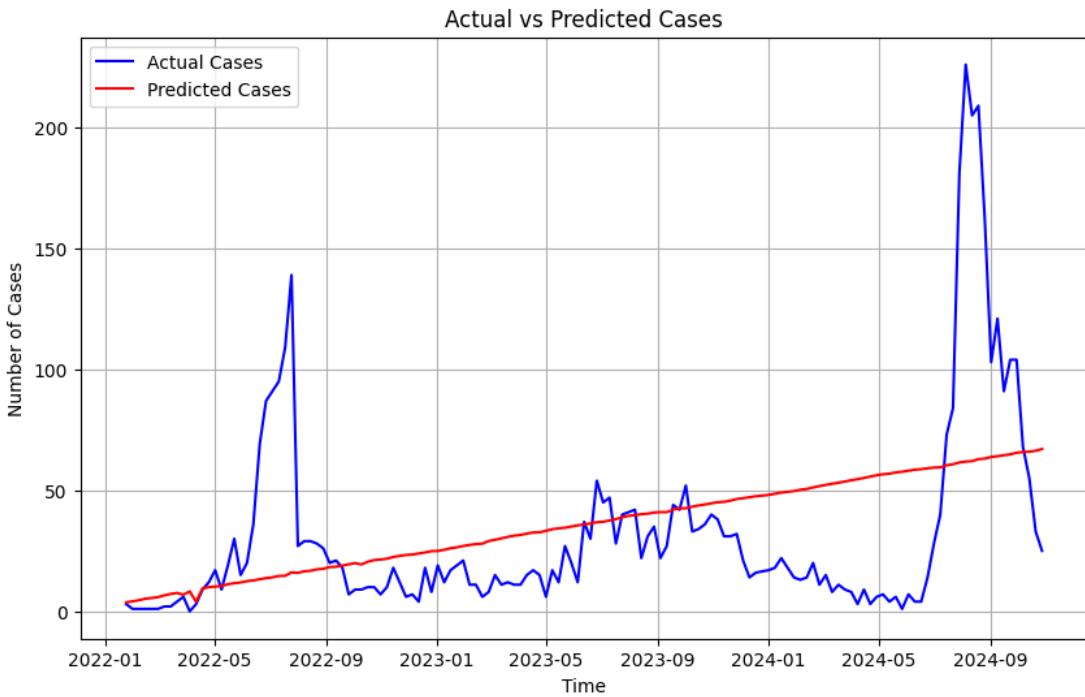


Figure 4.13: ARIMA Prediction Results for Test Set

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

948        • **MSE (Mean Squared Error):** 1521.48

949        • **RMSE (Root Mean Squared Error):** 39.01

950        • **MAE (Mean Absolute Error):** 25.80

#### 951        4.4.3 Seasonal ARIMA (SARIMA) Model

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

954 data.

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

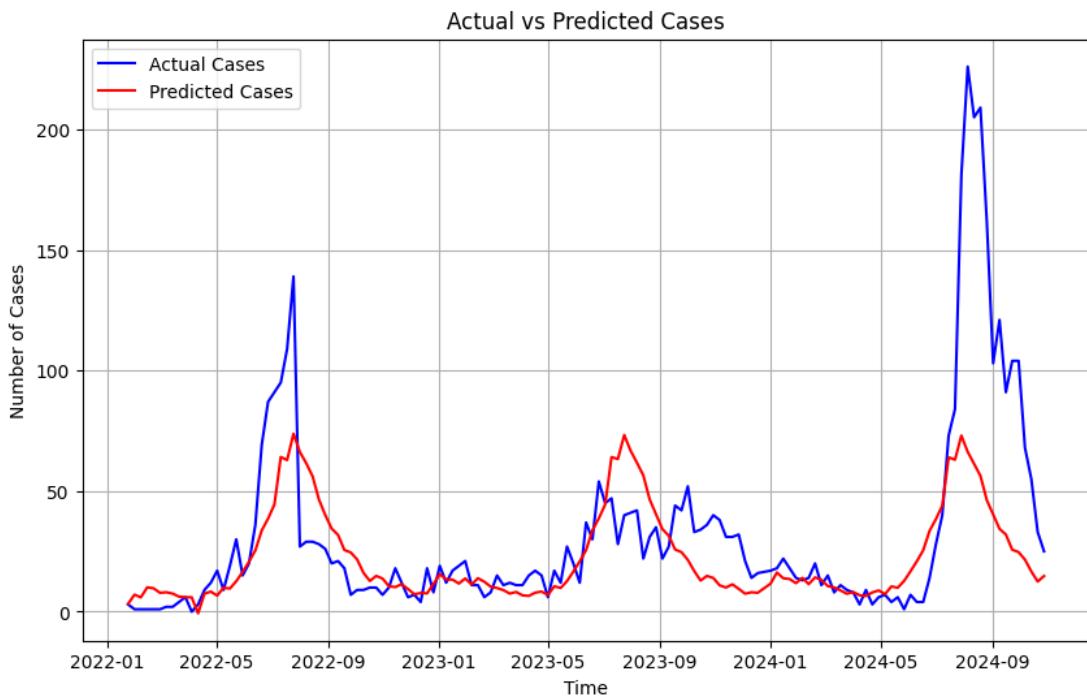


Figure 4.14: Seasonal ARIMA Prediction Results for Test Set

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

964 • **MSE:** 1109.69

965 • **RMSE:** 33.31

966 • **MAE:** 18.09

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

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

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

Table 4.4: Comparison of SARIMA performance for each fold

#### 977 4.4.4 Kalman Filter Model

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

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

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

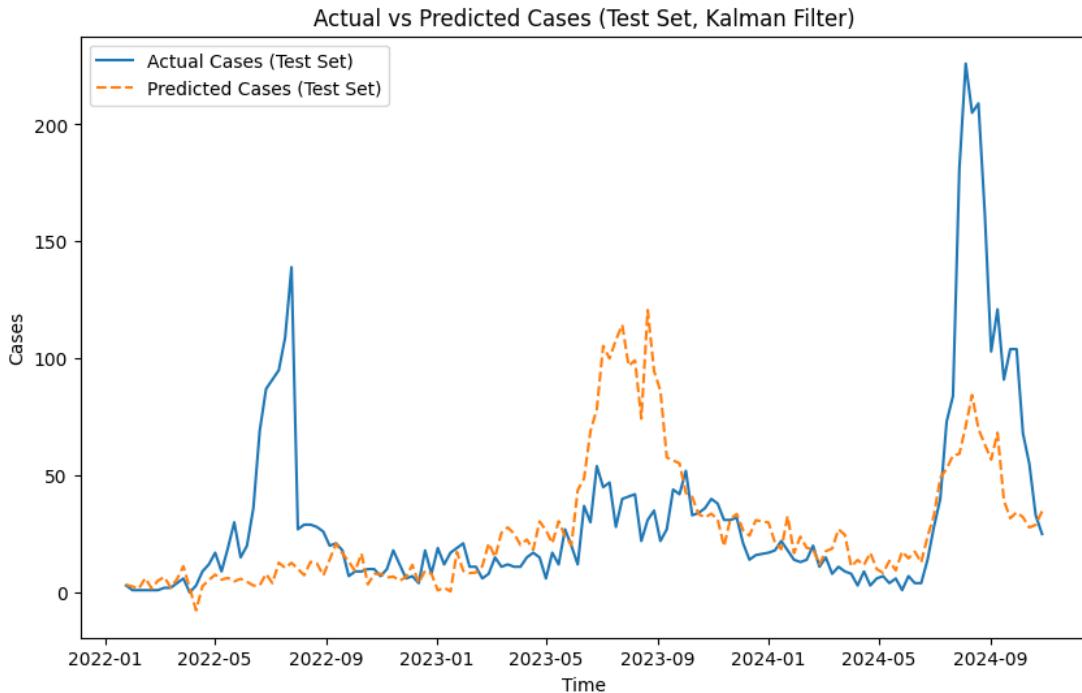


Figure 4.15: Kalman Filter Prediction Results for Test Set

986 The Kalman Filter was then combined with the LSTM model in order to see  
 987 improvements in its predictions. Table 4.5 shows the metrics across three folds  
 988 using the same Time Series Cross Validation Strategy employed in the previous  
 989 models to see how it performed on different time segments.

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

Table 4.5: Comparison of KF-LSTM performance for each fold

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

## 993 4.5 Model Simulation

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

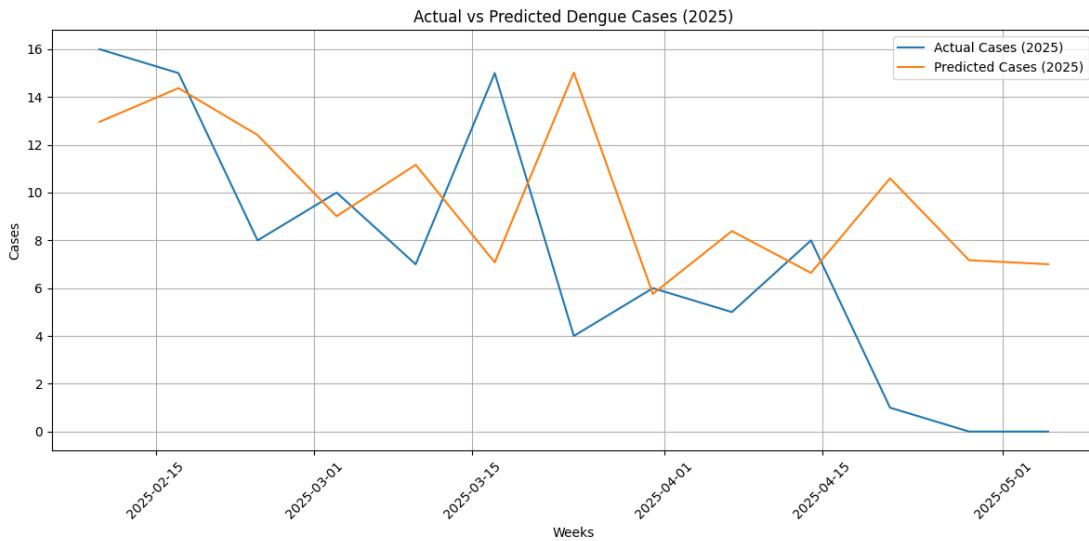


Figure 4.16: Predicted vs Actual Dengue Cases 2025

## 1003 4.6 System Prototype

### 1004 4.6.1 Home Page

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

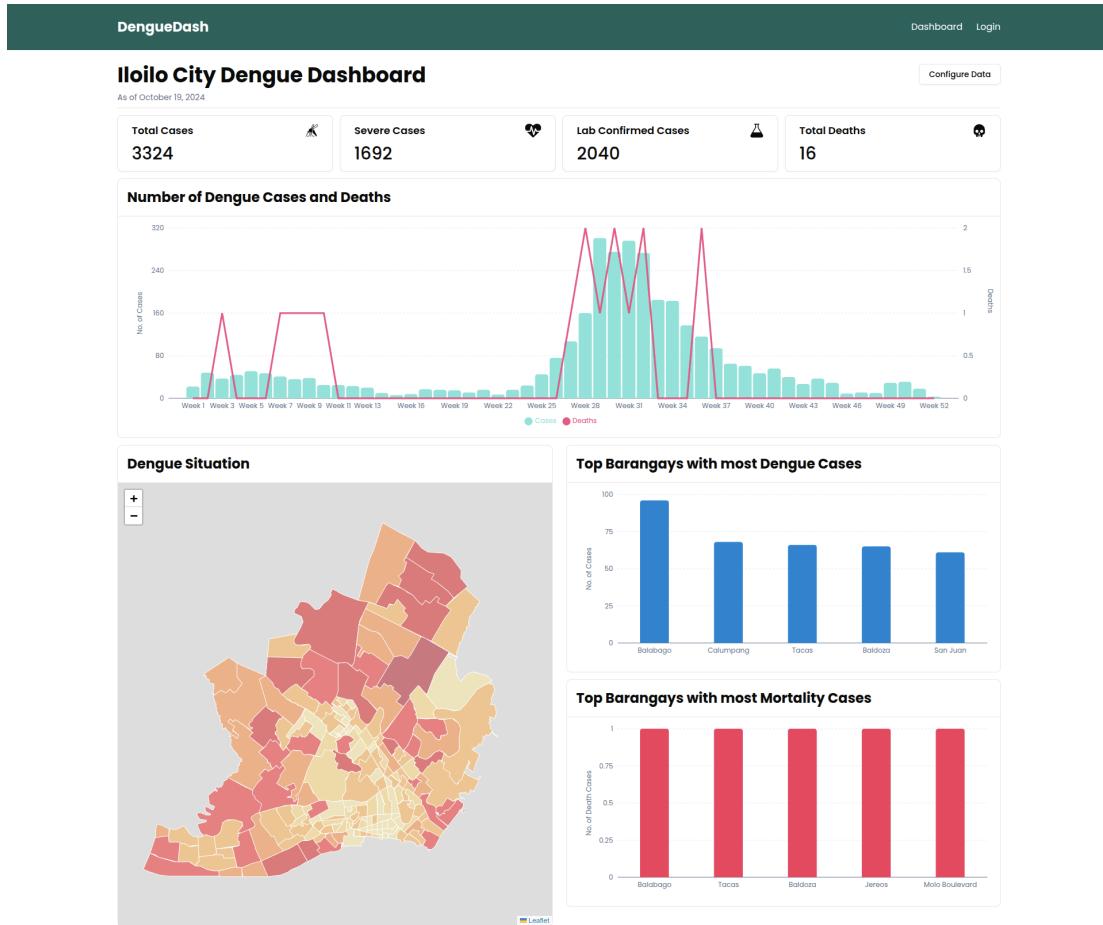


Figure 4.17: Home Page

### 4.6.2 User Registration, Login, and Authentication

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

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

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

Figure 4.18: Sign Up Page

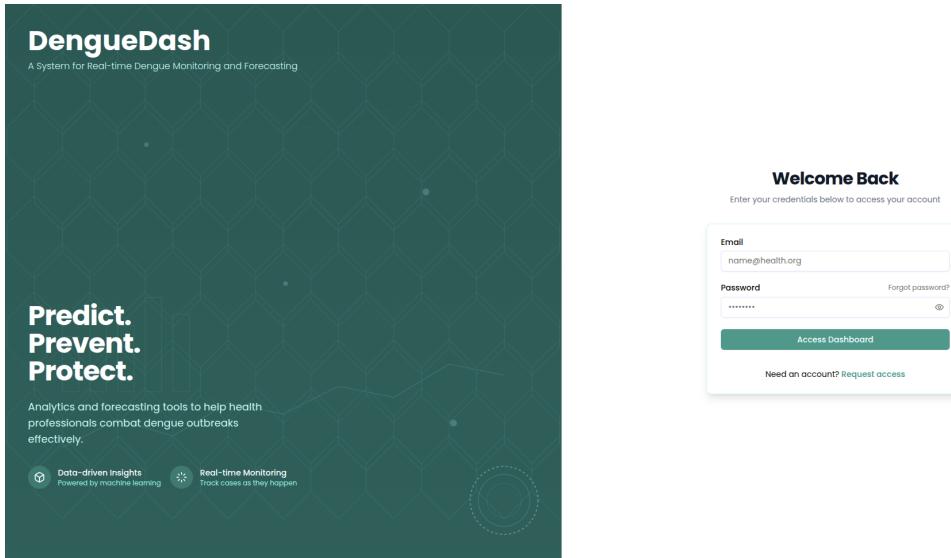


Figure 4.19: Login Page

### 1024 4.6.3 Encoder Interface

#### 1025 Case Report Form

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

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

The screenshot shows the 'Case Report Form' page within the 'DengueDash' application. The left sidebar displays the navigation menu with 'Case Report Form' selected under 'Forms'. The main content area is titled 'Case Report Form' and contains three sections: 'Personal Information', 'Address', and 'Vaccination'. The 'Personal Information' section includes fields for First Name, Middle Name, Last Name, Suffix, Sex (dropdown), Civil Status (dropdown), and Date of Birth (date picker). The 'Address' section includes fields for Region (dropdown), Province (dropdown), City (dropdown), Barangay (dropdown), Street, and House No. The 'Vaccination' section includes fields for Date of First Vaccination (date picker) and Date of Last Vaccination (date picker). A 'Bulk Upload' button is located at the top right of the form area. A user profile is visible on the far left.

Figure 4.20: First Part of Case Report Form

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

Figure 4.21: Second Part of Case Report Form

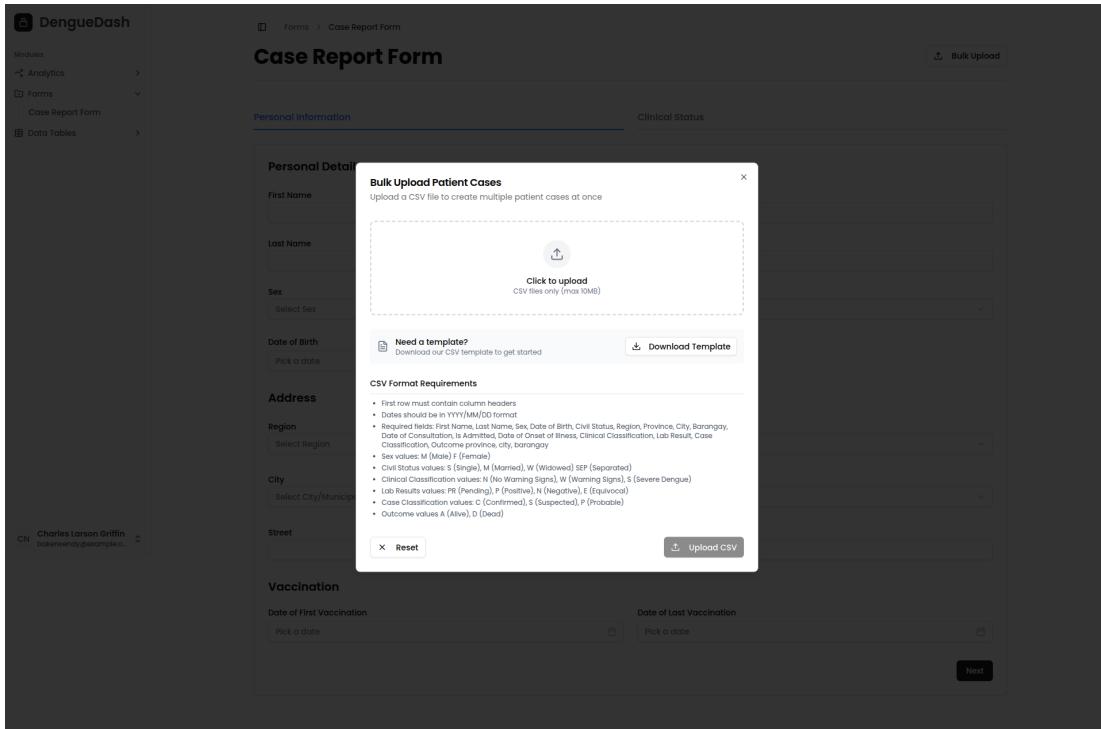


Figure 4.22: Bulk Upload of Cases using CSV

#### **1041 Browsing, Update, and Deletion of Records**

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

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



The screenshot displays the DengueDash application interface. On the left, a sidebar menu lists 'Analytics', 'Forms', 'Data Tables' (which is expanded), and 'Dengue Reports'. The main content area is titled 'Dengue Reports' and shows a table of patient cases. The table has columns for Case ID, Name, Barangay, City, Date Consulted, Clinical Classification, Case Classification, and Action (with an 'Open' button). There are 8 rows of data. At the bottom of the table, there are navigation links for 'Previous', 'Next', and page numbers 1 through 689.

Case ID	Name	Barangay	City	Date Consulted	Clinical Classification	Case Classification	Action
25016448	Doe, John David	Bulak Sur	BATAD	2025-04-30	With warning signs	Probable	<button>Open</button>
25016363	Garcia, Amanda Jennifer	Nabitosan	ILOILO CITY (Capital)	2024-09-22	With warning signs	Confirmed	<button>Open</button>
25016368	Mendez, Jacqueline Tita	Jalandoni-Wilson	ILOILO CITY (Capital)	2024-09-22	Severe dengue	Confirmed	<button>Open</button>
25016369	Lee, Laura Michelle	PHHC Block 22 NHA	ILOILO CITY (Capital)	2024-09-22	With warning signs	Confirmed	<button>Open</button>
25016372	Wood, Cindy Jaime	East Timawa	ILOILO CITY (Capital)	2024-09-22	With warning signs	Confirmed	<button>Open</button>
25016373	Keith, Trevor Katrina	Ortiz	ILOILO CITY (Capital)	2024-09-22	With warning signs	Confirmed	<button>Open</button>
25016378	Leon, Jorge Deborah	Hipodromo	ILOILO CITY (Capital)	2024-09-22	With warning signs	Confirmed	<button>Open</button>
25016371	Warner, Joshua Kristen	Kauswagan	ILOILO CITY (Capital)	2024-09-21	Severe dengue	Confirmed	<button>Open</button>

< Previous 1 2 3 ... 689 Next >

CN Charles Larson Griffin  
bakerwendy@example.o...

Figure 4.23: Dengue Reports

The screenshot shows the DengueDash application interface. On the left, a sidebar lists modules: Analytics, Forms, Data Tables, and Dengue Reports. The main area displays a "Personal Information" section for a patient named Doe, John David, born April 29, 2025, male, married, residing at 1231 Ice Ice Baby, Bulak Sur, BATAD, ILOILO. Below this is a "Vaccination Status" section showing first and last doses on May 7, 2025, and May 13, 2025 respectively. The central part of the screen is titled "Case Record #25016448". It includes fields for Date of Consultation (April 30, 2025), Patient Admitted? (No), Date Onset of Illness (April 29, 2025), Clinical Classification (With warning signs), and a "Case Classification" field set to Probable. The "Laboratory Results" section lists pending results for NS1, IgG Elisa, IgM Elisa, and PCR. The "Outcome" section shows the outcome as Dead. At the bottom, the "Interviewer" section lists Griffin, Charles Larson, as the interviewer, with Saint Paul's Hospital listed as the DRU. Buttons for "Update Case" and "Delete Case" are located in the top right corner of the main content area.

Figure 4.24: Detailed Case Report

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

1060 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 (selected), and Dengue Reports. The main area shows a 'Personal Information' section with fields for Full Name (Doe, John David), Date of Birth (May 15, 2025), Sex (Female), and Civil Status (Single). Below this is a 'Case Record' section with fields for First Dose (May 15, 2025) and Date of Consultation (May 15, 2025). A 'Laboratory Results' section contains dropdowns for NS1 (Pending Result, Date Done N/A), IgG Elisa (Pending Result, Date Done N/A), IgM Elisa (Pending Result, Date Done N/A), and PCR (Pending Result, Date Done N/A). An 'Outcome' section has an Outcome dropdown set to 'Alive'. At the bottom right of the dialog are 'Cancel' and 'Save Changes' buttons. The status bar at the bottom right says 'N/A'.

Figure 4.25: Update Report Dialog

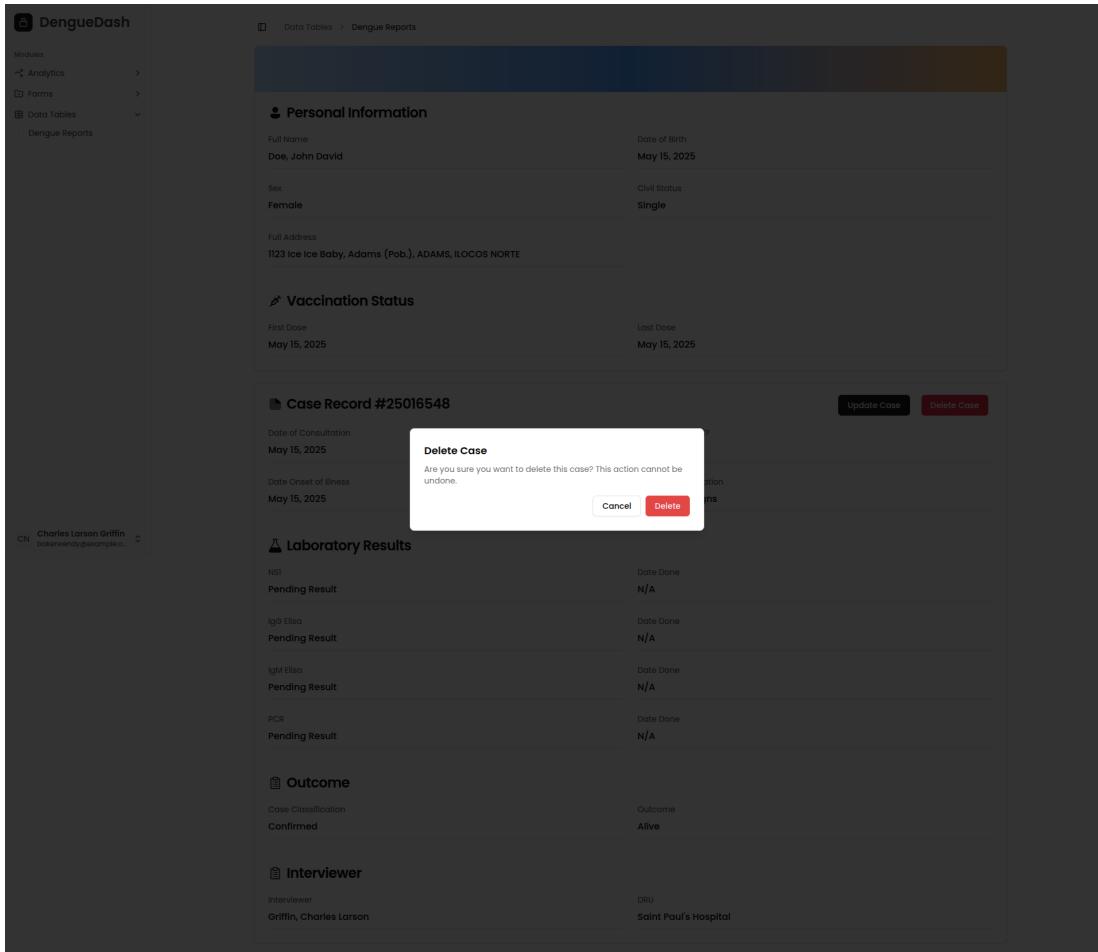


Figure 4.26: Delete Report Alert Dialog

## 1061 Forecasting

1062 The piece de resistance of the web application's feature is the Forecasting Page.  
 1063 This is where users can forecast dengue cases for the next following weeks. To  
 1064 predict, the application utilizes the exported LSTM model in a Keras format  
 1065 derived from training the consolidated data from the database. It requires the  
 1066 recent weekly dengue cases and weather variable data (temperature, humidity, and  
 1067 rainfall) based on the window size. This allows the web application to display a line

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

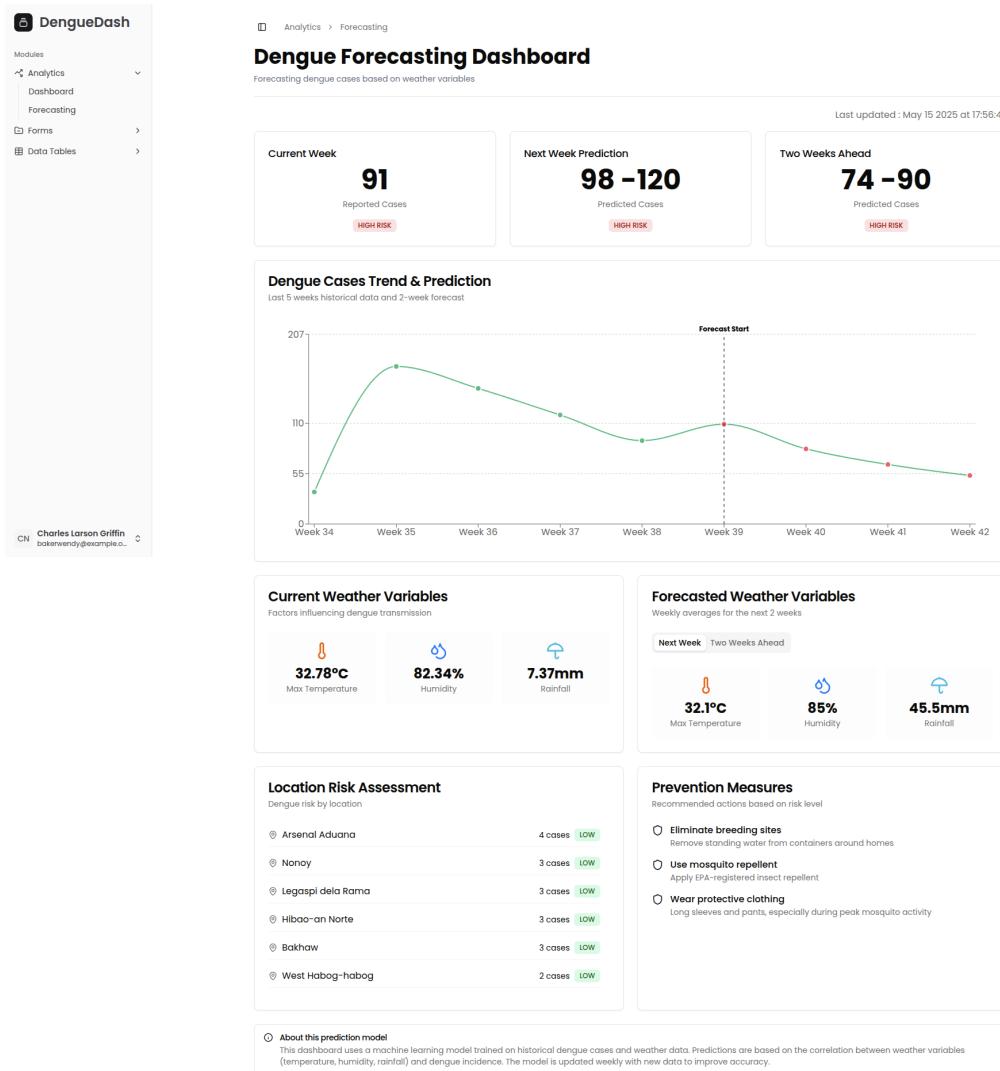


Figure 4.27: Forecasting Page

#### 1078 4.6.4 Admin Interface

#### 1079 Retraining

1080 With LSTM being the best-performing model among the models used in forecast-  
1081 ing dengue cases, it is the model chosen to power the prediction and retraining

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

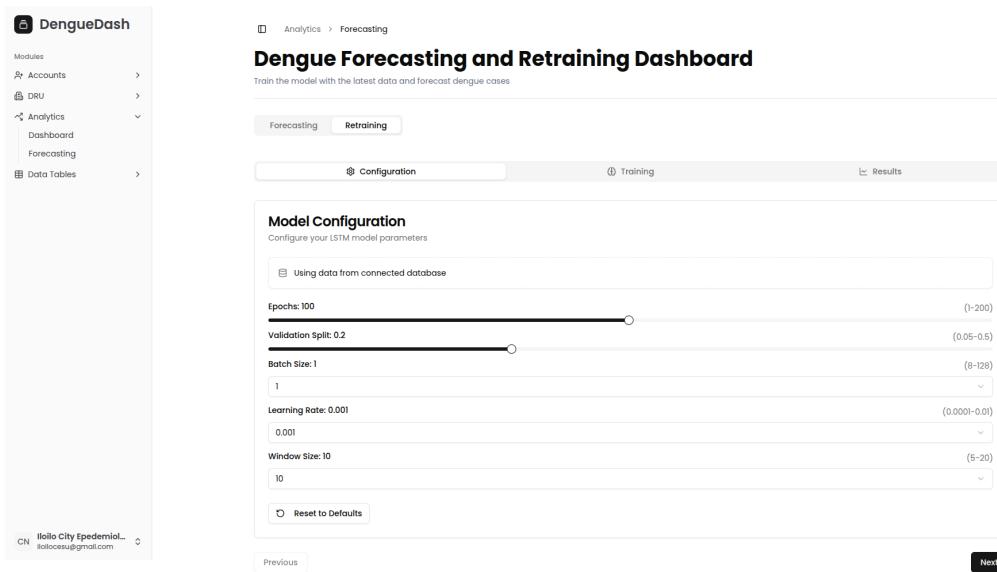


Figure 4.28: Retraining Configurations

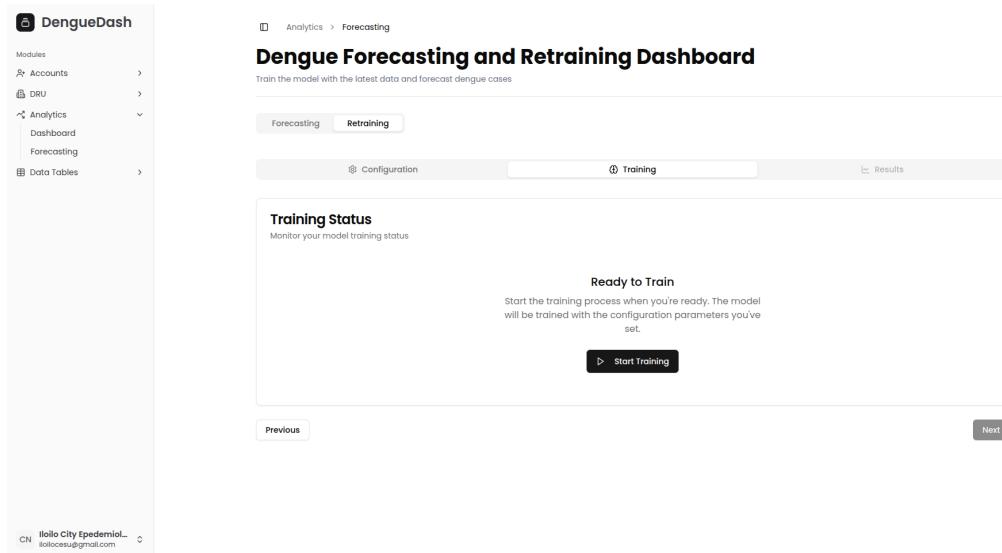


Figure 4.29: Start Retraining

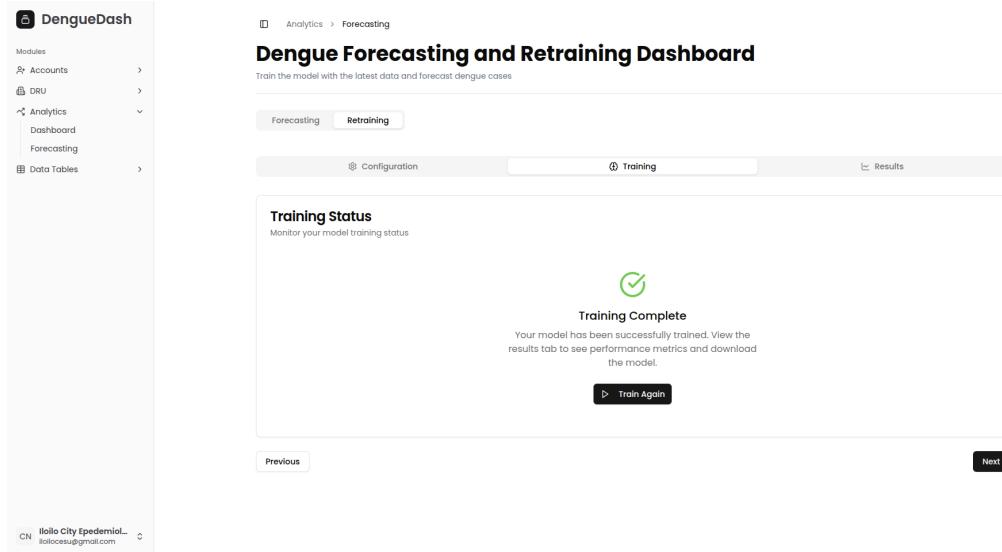


Figure 4.30: Retraining Results

1092 **Managing Accounts**

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

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

Figure 4.31: List of Verified Accounts

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

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

Below the sidebar, the user information is displayed: CN Saint Paul's Hospital, saintpaul@gmail.com.

The main content area is titled "Manage Accounts" and has a subtitle "View and manage registered and pending accounts". It includes a breadcrumb navigation: Accounts > Manage. Below this, there are three tabs: "Verified", "Pending" (which is selected), and "Blacklisted". A table lists account details:

Name	Email	Sex	Created At	Actions
John David Doe	testereee@example.gov.ph	Male	2025-05-16	<button>Approve</button> <button>Delete</button>

Figure 4.32: List of Pending Accounts

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

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

Below the sidebar, the user information is displayed: CN Saint Paul's Hospital, saintpaul@gmail.com.

The main content area is titled "User Profile" and has a subtitle "View and manage user details". It includes a breadcrumb navigation: Accounts > Manage. A table displays user details:

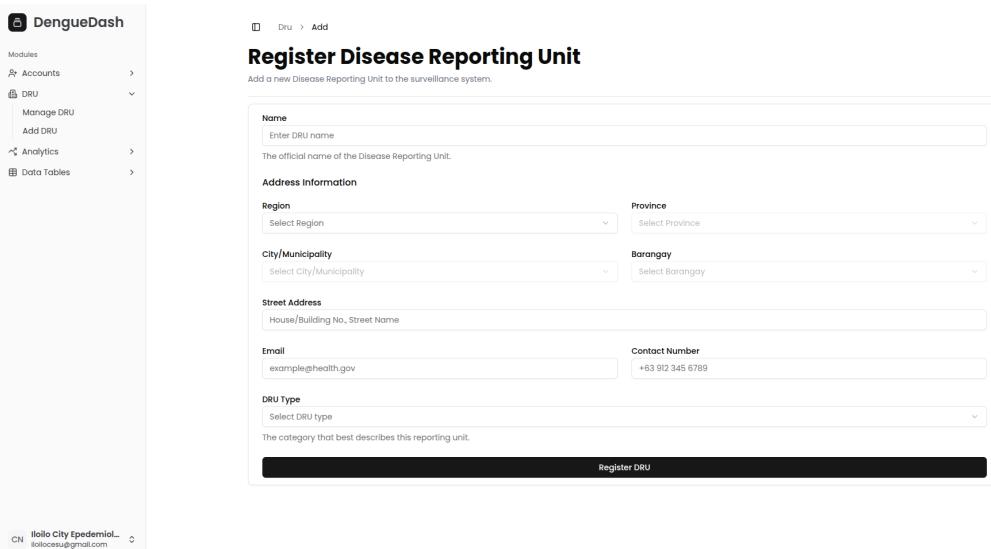
Name Charles Larson Griffin	Email bakerwendy@example.org
Sex Female	Role Encoder
Hospital (ORU) Saint Paul's Hospital	
Created At May 5 2025 at 04:47:12	Updated At May 15 2025 at 05:55:45
	Last Login May 15 2025 at 16:53:47

At the bottom of the profile card, there are two buttons: "Promote to Admin" and "Delete User".

Figure 4.33: Account Details

## 1105 Managing DRUs

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



The screenshot displays the DengueDash web application interface. On the left, a sidebar menu lists 'Modules' including 'Accounts', 'DRU' (selected), 'Analytics', and 'Data Tables'. The main content area is titled 'Register Disease Reporting Unit' with the sub-instruction 'Add a new Disease Reporting Unit to the surveillance system.' Below the title are several input fields:

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

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

Figure 4.34: Disease Reporting Unit Registration

The screenshot shows the DengueDash application interface. On the left is a sidebar with navigation links: Modules, Accounts, DRU (selected), Analytics, and Data Tables. The main content area has a header "Manage Disease Reporting Units" and a sub-header "View and manage Disease Reporting Units". It displays a table with four rows of DRU information:

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

At the bottom left of the main area, there is a user profile placeholder: CN Iloilo City Epidemiol... iloilocesu@gmail.com.

Figure 4.35: List of Disease Reporting Units

The screenshot shows the DengueDash application interface. On the left is a sidebar with navigation links: Modules, Accounts, DRU (selected), Analytics, and Data Tables. The main content area has a header "Disease Reporting Unit Profile" and a sub-header "View and manage DRU details". It displays a table with detailed information about the Molo District Health Center:

Name of DRU Molo District Health Center	Email moldistricthealth@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 area, there is a red button with the text "Delete DRU".

At the bottom left of the main area, there is a user profile placeholder: CN Iloilo City Epidemiol... iloilocesu@gmail.com.

Figure 4.36: Disease Reporting Unit details

**4.7 User Testing**

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

Participant	Usability Score
1	95.0
2	90.0
3	85.0
4	87.5
5	85.0
<b>Average</b>	<b>88.5</b>

Table 4.6: Computed System Usability Scores per Participant

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



# <sup>1129</sup> Chapter 5

## <sup>1130</sup> Conclusion

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

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

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

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

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

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

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

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



# <sup>1172</sup> Chapter 6

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1254 **Appendix A**

1255 **Data Collection Snippets**

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

Figure A.1: Snippet of Consolidated Data

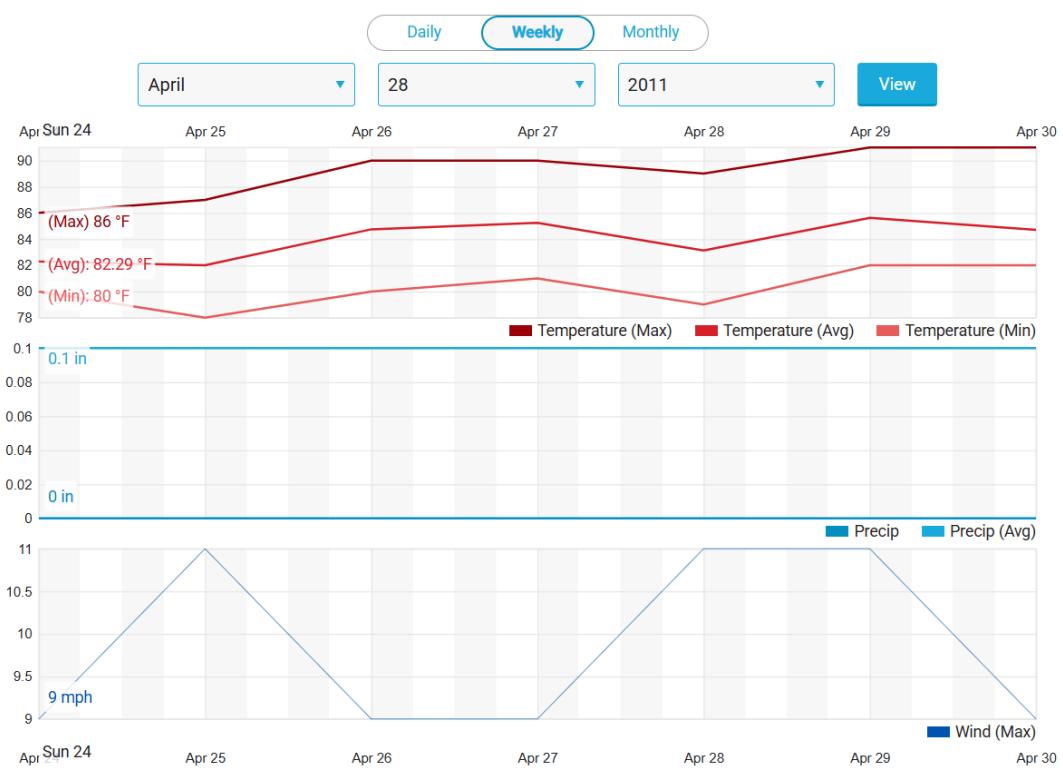


Figure A.2: Snippet of Weather Data Collection

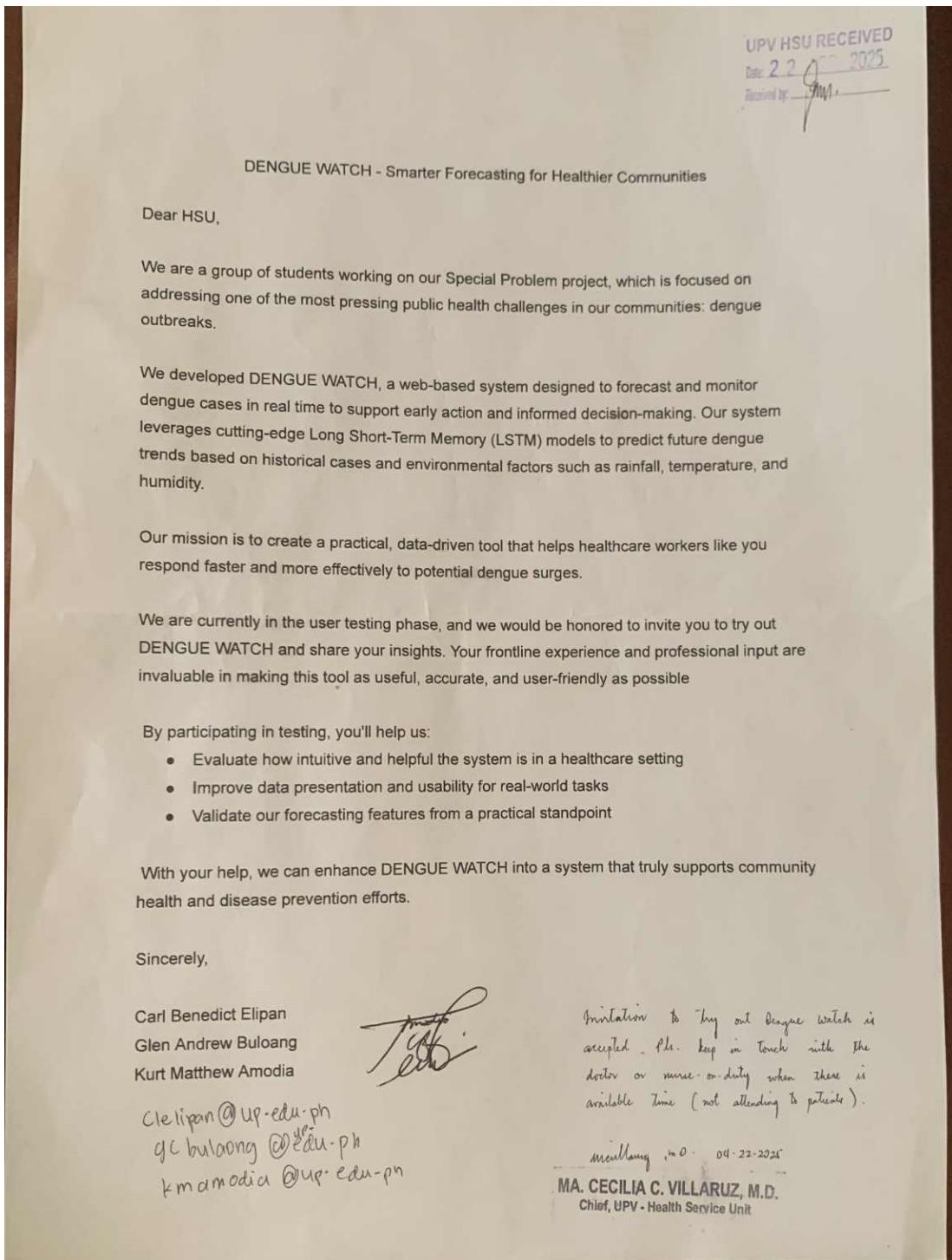


Figure A.3: Letter of Approval for User Testing in UPV HSU

Please enter your participant number: 2

**System Usability Scale (SUS)**

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

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

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

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

Please provide important comments about the website:

Figure A.4: System Usability Score Questionnaire