

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

<sup>4</sup> A Special Problem Proposal  
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## Abstract

20 Dengue fever remains a significant public health concern in the Philippines, with  
21 cases rising dramatically in recent years. Nationwide outbreaks have placed im-  
22 mense strain on healthcare systems, underscoring the need for innovative ap-  
23 proaches to surveillance and response. In Iloilo City, this national trend was  
24 reflected in a significant surge, with the Iloilo Provincial Health Office reporting  
25 4,585 cases and 10 fatalities as of August 10, 2023—a 319% increase from the pre-  
26 vious year’s 1,095 cases and one death. This study developed a centralized system  
27 for monitoring and modernizing data management of dengue cases in public health  
28 institutions, making it more efficient and acceptable. Using data gathered from  
29 the Iloilo Provincial Health Office and online sources, several deep learning mod-  
30 els were trained to predict dengue cases, utilizing weather variables and historical  
31 case data as inputs. These models included Long Short-Term Memory (LSTM),  
32 ARIMA, Seasonal ARIMA, Kalman Filter (KF), and a hybrid KF-LSTM model.  
33 The models underwent time series cross-validation strategies to mimic real-world  
34 conditions as closely as possible and were evaluated using metrics such as Mean  
35 Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute  
36 Error (MAE). The LSTM model demonstrated the best performance with the  
37 lowest RMSE of 16.90, followed by the hybrid KF-LSTM model at 25.56. The  
38 LSTM model was then integrated into the system to provide forecasting features  
39 that could support health institutions by offering actionable insights for proactive  
40 intervention strategies.

**Keywords:** ARIMA, artificial intelligence, dengue prediction, LSTM,  
Kalman Filter, deep learning, climate variables, public  
health, outbreak mitigation

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<sup>154</sup> **Chapter 1**

<sup>155</sup> **Introduction**

<sup>156</sup> **1.1 Overview**

<sup>157</sup> From 2020 to 2022, dengue cases declined due to reduced surveillance during the  
<sup>158</sup> COVID-19 pandemic (WHO, 2023), but cases surged in 2023 as restrictions were  
<sup>159</sup> lifted. This year saw an increase in dengue outbreaks worldwide, with over five mil-  
<sup>160</sup> lion cases and more than 5,000 deaths reported in over 80 countries (Bosano, 2023).  
<sup>161</sup> Dengue is endemic in the Philippines, leading to longer and more widespread sea-  
<sup>162</sup> sonal outbreaks. Globally, dengue infections have increased significantly, posing  
<sup>163</sup> a major public health challenge. The World Health Organization reported a ten-  
<sup>164</sup> fold rise in cases between 2000 and 2019, with a peak in 2019 when the disease  
<sup>165</sup> spread across 129 countries (WHO, 2024).

<sup>166</sup> Iloilo City and Province are intensifying efforts to curb the rising dengue cases  
<sup>167</sup> (Lena, 2024). As of August 10, 2023, the Iloilo Provincial Health Office recorded  
<sup>168</sup> 4,585 cases and 10 deaths, a 319% increase from last year's 1,095 cases and one  
<sup>169</sup> death. Governor Arthur Defensor Jr. confirmed that the province has reached the  
<sup>170</sup> dengue outbreak threshold based on Department of Health (DOH). Local govern-  
<sup>171</sup> ment units (LGUs) have been informed, and the province's disaster management  
<sup>172</sup> office is on blue alert, indicating disaster mode. (Perla, 2024)

<sup>173</sup> In Iloilo City, 649 dengue cases were recorded this year 2024, with two deaths.  
<sup>174</sup> Cases cluster in 40 out of 180 barangays, meaning multiple cases are being reported  
<sup>175</sup> in these areas over several weeks. The city's health officer, Dr. Roland Jay  
<sup>176</sup> Fortuna, reported high utilization of non-COVID-19 hospital beds, reaching over  
<sup>177</sup> 76%, prompting concerns about hospital capacity.

178 This study explores the monitoring and forecasting of dengue outbreaks by an-  
179 alyzing key factors such as temperature, relative humidity, and historical dengue  
180 cases, using different models. The findings aim to provide an advanced, AI-driven  
181 alternative for dengue prevention and control, targeting agencies like the Depart-  
182 ment of Health (DOH). By aligning with the national AI Roadmap, particularly  
183 in Iloilo City, this research aspires to improve outbreak responses through cutting-  
184 edge technology rather than traditional reporting methods.

## 185 **1.2 Problem Statement**

186 Dengue remains a critical public health challenge worldwide, with cases increasing  
187 due to the easing of COVID-19 restrictions and heightened global mobility. While  
188 a temporary decline in cases was observed during the pandemic (2020–2022) due  
189 to reduced surveillance efforts, 2023 marked a resurgence, with over five million  
190 cases and more than 5,000 deaths reported across 80 countries. In dengue-endemic  
191 regions like the Philippines, the threat is particularly severe. In Iloilo City and  
192 Province, dengue cases rose by 319% as of August 2023, overwhelming local health-  
193 care systems. This surge strained resources, with over 76% of non-COVID-19 hos-  
194 pital beds occupied by dengue patients, highlighting the urgent need for effective  
195 predictive tools. The lack of a reliable system to monitor and forecast dengue  
196 outbreaks contributes to delayed interventions, exacerbating public health risks  
197 and healthcare burdens in the region.

## 198 **1.3 Research Objectives**

### 199 **1.3.1 General Objective**

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

### 205 **1.3.2 Specific Objectives**

206 Specifically, this study aims to:

- 207 1. Gather dengue data from the Iloilo Provincial Health Office and climate data  
208 (including temperature, rainfall, wind, and humidity) from online sources.  
209 Combine and aggregate these data into a unified dataset to facilitate com-  
210 prehensive dengue case forecasting.
- 211 2. Evaluate deep learning models for predicting dengue cases using metrics  
212 such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE),  
213 and Mean Squared Error (MSE). Compare the performance of these models  
214 to determine the most accurate forecasting approach.
- 215 3. Develop a web-based analytics dashboard that integrates a predictive model  
216 and provides data management system for dengue cases in Iloilo City and  
217 the Province.
- 218 4. Assess the usability and effectiveness of the analytics dashboard through  
219 structured feedback and surveys involving health professionals and policy-  
220 makers.

221 **1.4 Scope and Limitations of the Research**

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

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

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

<sup>241</sup> identify risk areas. However, its usability depends on feedback from stakeholders,  
<sup>242</sup> which may vary based on their familiarity with analytics tools. Moreover, exter-  
<sup>243</sup> nal factors such as limited internet connectivity or device availability in remote  
<sup>244</sup> areas may affect the system's adoption and effectiveness. While the dashboard  
<sup>245</sup> provides valuable insights, it cannot incorporate all factors influencing dengue  
<sup>246</sup> transmission, emphasizing the need for ongoing validation and refinement.

## <sup>247</sup> 1.5 Significance of the Research

<sup>248</sup> This study's development of an AI-based dengue forecasting and monitoring sys-  
<sup>249</sup> tem has wide-reaching significance for various stakeholders in Iloilo City:

- <sup>250</sup> • Public Health Agencies: Organizations like the Department of Health (DOH)  
<sup>251</sup> and local health units in Iloilo City and Province stand to benefit greatly  
<sup>252</sup> from the system. With dengue predictions, we can help these agencies opti-  
<sup>253</sup> mize their response strategies and implement targeted prevention measures  
<sup>254</sup> in high-risk areas before cases escalate.
- <sup>255</sup> • Local Government Units (LGUs): LGUs can use the system to support  
<sup>256</sup> their disaster management and health initiatives by proactively addressing  
<sup>257</sup> dengue outbreaks. The predictive insights allow for more efficient planning  
<sup>258</sup> and resource deployment in barangays and communities most vulnerable to  
<sup>259</sup> outbreaks, improving overall public health outcomes.
- <sup>260</sup> • Healthcare Facilities: Hospitals and clinics, which currently face high bed  
<sup>261</sup> occupancy rates during dengue season will benefit from early outbreak fore-  
<sup>262</sup> casts that can help in managing patient inflow and ensuring adequate hos-  
<sup>263</sup> pital capacity.
- <sup>264</sup> • Researchers and Policymakers: This AI-driven approach contributes valua-  
<sup>265</sup> ble insights for researchers studying infectious disease patterns and policy-  
<sup>266</sup> makers focused on strengthening the national AI Roadmap. The system's  
<sup>267</sup> data can support broader initiatives for sustainable health infrastructure  
<sup>268</sup> and inform policy decisions on resource allocation for dengue control.
- <sup>269</sup> • Community Members: By reducing the frequency and severity of outbreaks,  
<sup>270</sup> this study ultimately benefits the community at large. This allows for timely

<sup>271</sup> awareness campaigns and community engagement initiatives, empowering  
<sup>272</sup> residents with knowledge and preventative measures to protect themselves  
<sup>273</sup> and reduce the spread of dengue.

<sup>274</sup> **Chapter 2**

<sup>275</sup> **Review of Related Literature**

<sup>276</sup> **2.1 Dengue**

<sup>277</sup> Dengue disease is a tropical and subtropical mosquito-borne viral illness and is a  
<sup>278</sup> major health concern in the Philippines (Bravo, Roque, Brett, Dizon, & L'Azou,  
<sup>279</sup> 2014). The majority of individuals with dengue experience no symptoms. Fever is  
<sup>280</sup> the most common symptom, typically 4 to 7 days after being bitten by an infected  
<sup>281</sup> mosquito (Zhou & Malani, 2024). In recent years, the trend of dengue cases in  
<sup>282</sup> the Philippines has shown notable fluctuations, with periodic outbreaks occur-  
<sup>283</sup> ring every 3 to 5 years, often influenced by climatic and environmental changes.  
<sup>284</sup> According to the Department of Health (DOH), the number of reported cases  
<sup>285</sup> has steadily increased over the past decades, attributed to urbanization, popula-  
<sup>286</sup> tion growth, and inadequate vector control measures (World Health Organization  
<sup>287</sup> (WHO), 2018). Moreover, studies suggest that El Niño and La Niña events have  
<sup>288</sup> significant effects on dengue incidence, with warmer temperatures and increased  
<sup>289</sup> rainfall providing favorable breeding conditions for mosquitoes (Watts, Burke,  
<sup>290</sup> Harrison, Whitmire, & Nisalak, 2020). The study of Carvajal et. al. highlights  
<sup>291</sup> the temporal pattern of dengue cases in Metropolitan Manila and emphasizes the  
<sup>292</sup> significance of relative humidity as a key meteorological factor, alongside rainfall  
<sup>293</sup> and temperature, in influencing this pattern (Carvajal et al., 2018).

<sup>294</sup> **2.2 Outbreak Definition**

<sup>295</sup> The definition of an outbreak is a critical factor in disease surveillance, as it  
<sup>296</sup> determines the threshold at which an unusual increase in cases is considered a

297 public health concern. Studies suggest that outbreak thresholds should be context-  
298 specific, given the variability in transmission dynamics across different locations  
299 (Runge-Ranzinger et al., 2016). Outbreak definitions defined using the Endemic  
300 Channel often base thresholds on 2 standard deviations (SD) above the mean  
301 number of historic dengue cases. Other studies (Hemisphere, 2015) also used an  
302 alert threshold of a 5-year mean plus 2 standard deviations. A study by (Brady,  
303 Smith, Scott, & Hay, 2015) discussed that definitions of dengue outbreaks differ  
304 significantly across regions and time, making them inconsistent and incomparable.

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

### 310 **2.3 Existing System: RabDash DC**

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

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

## <sup>327</sup> 2.4 Deep Learning

<sup>328</sup> The study of (Ligue & Ligue, 2022) highlights how data-driven models can help  
<sup>329</sup> predict dengue outbreaks. The authors compared traditional statistical meth-  
<sup>330</sup> ods, such as non-seasonal and seasonal autoregressive integrated moving average  
<sup>331</sup> (ARIMA), and traditional feed-forward network approach using a multilayer per-  
<sup>332</sup> ceptron (MLP) model with a deep learning approach using the long short-term  
<sup>333</sup> memory (LSTM) architecture in their prediction model. They found that the  
<sup>334</sup> LSTM model performs better in terms of accuracy. The LSTM model achieved a  
<sup>335</sup> much lower root mean square error (RMSE) compared to both MLP and ARIMA  
<sup>336</sup> models, proving its ability to capture complex patterns in time-series data (Ligue  
<sup>337</sup> & Ligue, 2022). This superior performance is attributed to LSTM's capacity  
<sup>338</sup> to capture complex, time-dependent relationships within the data, such as those  
<sup>339</sup> between temperature, rainfall, humidity, and mosquito populations, all of which  
<sup>340</sup> contribute to dengue incidence (Ligue & Ligue, 2022).

## <sup>341</sup> 2.5 Kalman Filter

<sup>342</sup> The Kalman Filter is another powerful tool for time-series forecasting that can be  
<sup>343</sup> integrated into our analysis. It provides a recursive solution to estimating the state  
<sup>344</sup> of a linear dynamic system from a series of noisy measurements. Its application  
<sup>345</sup> in epidemiological modeling can enhance prediction accuracy by accounting for  
<sup>346</sup> uncertainties in the data(Li et al., 2022). Studies have shown that Kalman filters  
<sup>347</sup> are effective in predicting infectious disease outbreaks by refining estimates based  
<sup>348</sup> on observed data. A study published in Frontiers in Physics utilized the Kalman  
<sup>349</sup> filter to predict COVID-19 deaths in Ceará, Brazil. They found that the Kalman  
<sup>350</sup> filter effectively tracked the progression of deaths and cases, providing critical in-  
<sup>351</sup> sights for public health decision-making (Ahmadini et al., 2021). Another research  
<sup>352</sup> article in PLOS ONE focused on tracking the effective reproduction number ( $R_t$ )  
<sup>353</sup> of COVID-19 using a Kalman filter. This method estimated the growth rate of  
<sup>354</sup> new infections from noisy data, demonstrating that the Kalman filter could main-  
<sup>355</sup> tain accurate estimates even when case reporting was inconsistent(Arroyo-Marioli,  
<sup>356</sup> Bullano, Kucinskas, & Rondón-Moreno, 2021).

<sup>357</sup> Our study will compare ARIMA, seasonal ARIMA, Kalman Filter, and LSTM  
<sup>358</sup> models using our own collected dengue case data along with weather data to  
<sup>359</sup> identify the most effective model for real-time forecasting.

## 360 2.6 Weather Data

361 The relationship between weather patterns and mosquito-borne diseases is inher-  
362 ently nonlinear, meaning that fluctuations in disease cases do not respond propor-  
363 tionally to changes in climate variables(Colón-González, Fezzi, Lake, & Hunter,  
364 2013) Weather data, such as minimum temperature and accumulated rainfall, are  
365 strongly linked to dengue case fluctuations, with effects observed after several  
366 weeks due to mosquito breeding and virus incubation cycles. Integrating these  
367 lagged weather effects into predictive models can improve early warning systems  
368 for dengue control(Cheong, Burkart, Leitão, & Lakes, 2013). A study also suggests  
369 that weather-based forecasting models using variables like mean temperature and  
370 cumulative rainfall can provide early warnings of dengue outbreaks with high sen-  
371 sitivity and specificity, enabling predictions up to 16 weeks in advance(Hii, Zhu,  
372 Ng, Ng, & Rocklöv, 2012).

373 We will utilize weather data, including variables such as temperature, rainfall,  
374 and humidity, as inputs for our dengue forecasting model. Given the strong, non-  
375 linear relationship between climate patterns and dengue incidence, these weather  
376 variables, along with their lagged effects, are essential for enhancing prediction  
377 accuracy and providing timely early warnings for dengue outbreaks.

## 378 2.7 Chapter Summary

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

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

<sup>393</sup>

# Chapter 3

<sup>394</sup>

## Research Methodology

<sup>395</sup> This chapter lists and discusses the specific steps and activities that will be per-  
<sup>396</sup> formed to accomplish the project. The discussion covers the activities from pre-  
<sup>397</sup> proposal to Final SP Writing.

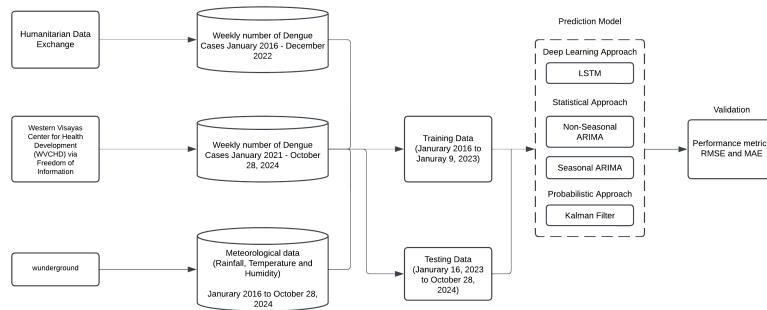


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

<sup>398</sup> This summarizes the workflow for forecasting the number of weekly dengue  
<sup>399</sup> cases. This workflow focuses on using statistical, deep learning, and probabilistic  
<sup>400</sup> models to forecast the number of reported dengue cases. The approach involves  
<sup>401</sup> deploying several models for prediction, including ARIMA and Seasonal ARIMA  
<sup>402</sup> as statistical approaches, LSTM as a deep learning approach, and the Kalman  
<sup>403</sup> Filter as a probabilistic approach. These methods are compared with each other  
<sup>404</sup> to determine the most accurate model.

405 **3.1 Research Activities**

406 **3.1.1 Gather Dengue Data and Climate Data to Create a  
407 Complete Dataset for Forecasting**

408 **Acquisition of Dengue Case Data**

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

418 Moreover, using a weekly interval provided more data points for training the  
419 models compared to a monthly format. This is particularly critical in time series  
420 modeling, where larger datasets help improve the robustness of the model and its  
421 ability to generalize to new data. Also, the collection of weather data was done  
422 by utilizing web scraping techniques to extract weekly weather data (e.g., rainfall,  
423 temperature, and humidity) from Weather Underground ([wunderground.com](http://wunderground.com)).

424  
425 **Data Fields**

- 426     • **Time.** Represents the specific year and week corresponding to each entry  
427       in the dataset.
- 428     • **Rainfall.** Denotes the observed average rainfall, measured in millimeters,  
429       for a specific week.
- 430     • **Humidity.** Refers to the observed average relative humidity, expressed as  
431       a percentage, for a specific week.
- 432     • **Max Temperature.** Represents the observed maximum temperature, mea-  
433       sured in degrees Celsius, for a specific week.
- 434     • **Average Temperature.** Represents the observed average temperature,  
435       measured in degrees Celsius, for a specific week.

- 436     • **Min Temperature.** Represents the observed minimum temperature, mea-  
437       sured in degrees Celsius, for a specific week.
- 438     • **Wind.** Represents the observed wind speed, measured in miles per hour  
439       (mph), for a specific week.
- 440     • **Cases.** Refers to the number of reported dengue cases during a specific  
441       week.

442   **Data Integration and Preprocessing**

443   The dengue case data was integrated with the weather data to create a com-  
444   prehensive dataset, aligning the data based on corresponding timeframes. The  
445   dataset undergoed a cleaning process to address any missing values, outliers, and  
446   inconsistencies to ensure its accuracy and reliability. To ensure that all features  
447   and the target variable were on the same scale, a MinMaxScaler was applied to  
448   normalize both the input features (climate data) and the target variable (dengue  
449   cases).

450   **Exploratory Data Analysis (EDA)**

- 451     • Analyzed trends, seasonality, and correlations between dengue cases and  
452       weather factors.
- 453     • Created visualizations like time series plots and scatterplots to highlight  
454       relationships and patterns in the data.

455   **Outbreak Detection**

456   To detect outbreaks, we computed the outbreak threshold value of dengue cases  
457   using the formula,

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

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

459    **3.1.2 Develop and Evaluate Deep Learning Models for**  
460    **Dengue Case Forecasting**

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

466    **Data Preprocessing**

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

473    **LSTM Model**

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

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

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

489        **LSTM units:**

- 490            • min value: 32
- 491            • max value: 128
- 492            • step: 16
- 493            • sampling: linear

494        **Learning Rate:**

- 495            • min value: 0.0001
- 496            • max value: 0.01
- 497            • step: None
- 498            • sampling: log

499        The tuner was instanstiated with:

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

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

512        To validate the effectiveness of the model, cross-validation was implemented.  
513        However, standard k-fold cross-validation randomly shuffles the data, which isn't  
514        suitable for time series since the order of observations is important. To address  
515        this, a time series-specific cross-validation strategy was used with TimeSeriesS-  
516        plit from the scikit-learn library. This method creates multiple train-test splits

517 where each training set expands over time and each test set follows sequentially.  
518 This approach preserves the temporal structure of the data while helping reduce  
519 overfitting by validating the model across different time segments.

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

524 **ARIMA**

525 The ARIMA model was utilized to forecast weekly dengue cases, leveraging histori-  
526 cal weather data—including rainfall, maximum temperature, and humidity—as  
527 exogenous variables alongside historical dengue case counts as the primary depen-  
528 dent variable. The dataset was partitioned into training (80%) and testing (20%)  
529 sets while maintaining temporal consistency.

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

- 532 • Autoregressive order ( $p$ ): 0 to 3  
533 • Differencing order ( $d$ ): 0 to 2  
534 • Moving average order ( $q$ ): 0 to 3

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

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

546 **Seasonal ARIMA (SARIMA)**

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

565 **Kalman Filter:**

- 566     • Input Variables: The target variable (Cases) was modeled using three re-  
567       gressors: rainfall, max temperature, and humidity.
- 568     • Training and Testing Split: The dataset was split into 80% training and  
569       20% testing to evaluate model performance.
- 570     • Observation Matrix: The Kalman Filter requires an observation matrix,  
571       which was constructed by adding an intercept (column of ones) to the re-  
572       gressors.

573     The Kalman Filter's Expectation-Maximization (EM) method was employed  
574     for training, iteratively estimating model parameters over 10 iterations. After  
575     training, the smoothing method was used to compute the refined state estimates  
576     across the training data. Observation matrices for the test data were constructed  
577     in the same manner as for the training set, ensuring compatibility with the learned  
578     model parameters. On the test data, the Kalman Filter applied these parameters  
579     to predict and correct the estimated dengue cases, providing more stable and  
580     accurate forecasts compared to direct regression models. Additionally, a hybrid

581 Kalman Filter–LSTM (KF-LSTM) model was developed to combine the strengths  
582 of both approaches. In this setup, the LSTM model was first used to predict  
583 dengue cases based on historical data and weather features. The Kalman Filter  
584 was then applied as a post-processing step to the LSTM predictions, smoothing  
585 out noise and correcting potential errors.

586 **3.1.3 Integrate the Predictive Model into a Web-Based**  
587 **Data Analytics Dashboard**

588 **Dashboard Design and Development**

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

593 **Model Integration and Deployment**

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

596 **3.1.4 System Development Framework**

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

603 **Design and Development**

604 After brainstorming and researching the most appropriate type of application to  
605 accommodate both the prospected users and the proposed solutions, the team  
606 has decided to proceed with a web application. Given the time constraints and  
607 available resources, it has been decided that the said means is the most pragmatic

608 and practical move. The next step is to select modern and stable frameworks  
609 that align with the fundamental ideas learned by the researchers in the university.  
610 The template obtained from WVCHD and Iloilo Provincial Epidemiology and  
611 Surveillance Unit was meticulously analyzed to create use cases and develop a  
612 preliminary well-structured database that adheres to the requirements needed  
613 to produce a quality application. The said use cases serve as the basis of general  
614 features. Part by part, these are converted into code, and with the help of selected  
615 libraries and packages, it resulted in the desired outcome that may still modified  
616 and extended to achieve scalability.

## 617 Testing and Integration

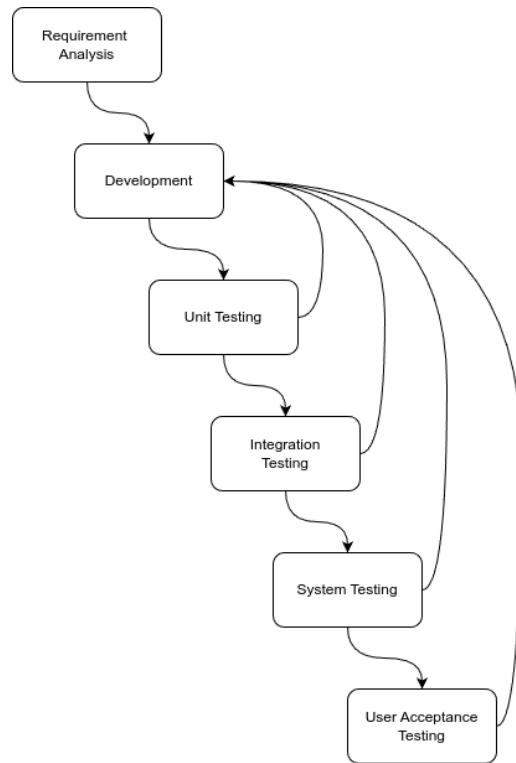


Figure 3.2: Testing Process for DengueWatch

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

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

## 633 **3.2 Development Tools**

### 634 **3.2.1 Software**

#### 635 **Github**

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

#### 641 **Visual Studio Code**

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

#### 646 **Django**

647 Django is a free and open-sourced Python-based web framework that offers an  
648 abstraction to develop and maintain a secure web application. As this research  
649 aims to create a well-developed and maintainable application, it is in the best  
650 interest to follow an architectural pattern that developers and contributors in the

651 future can understand. Since Django adheres to Model-View-Template (MVT)  
652 that promotes a clean codebase by separating data models, business logic, and  
653 presentation layers, it became the primary candidate for the application's back-  
654 bone.

### 655 **Next.js**

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

### 662 **Postman**

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

### 668 **3.2.2 Hardware**

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

### 672 **3.2.3 Packages**

#### 673 **Django REST Framework**

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

678 **Leaflet**

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

685 **Chart.js**

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

693 **Tailwind CSS**

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

702 **Shadcn**

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

708 **Zod**

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

713 **3.3 Application Requirements**

714 **3.3.1 Backend Requirements**

715 **Database Structure Design**

716 Determining how data flows and how it would be structured is crucial in creating  
717 the system as it defines how extendible and flexible it would be for future features  
718 and updates. Thus, creating a comprehensive map of data ensures proper nor-  
719 malization that eliminates data redundancy and improves data integrity. Figure  
720 3.3 depicts the designed database schema that showcases the relationship between  
721 the application's entities.

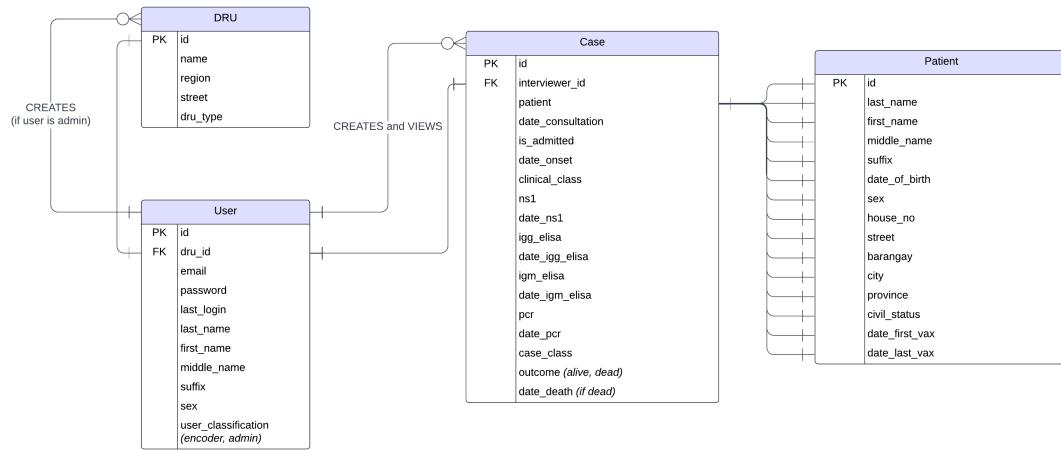


Figure 3.3: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

### <sup>722</sup> 3.3.2 User Interface Requirements

#### <sup>723</sup> Admin Interface

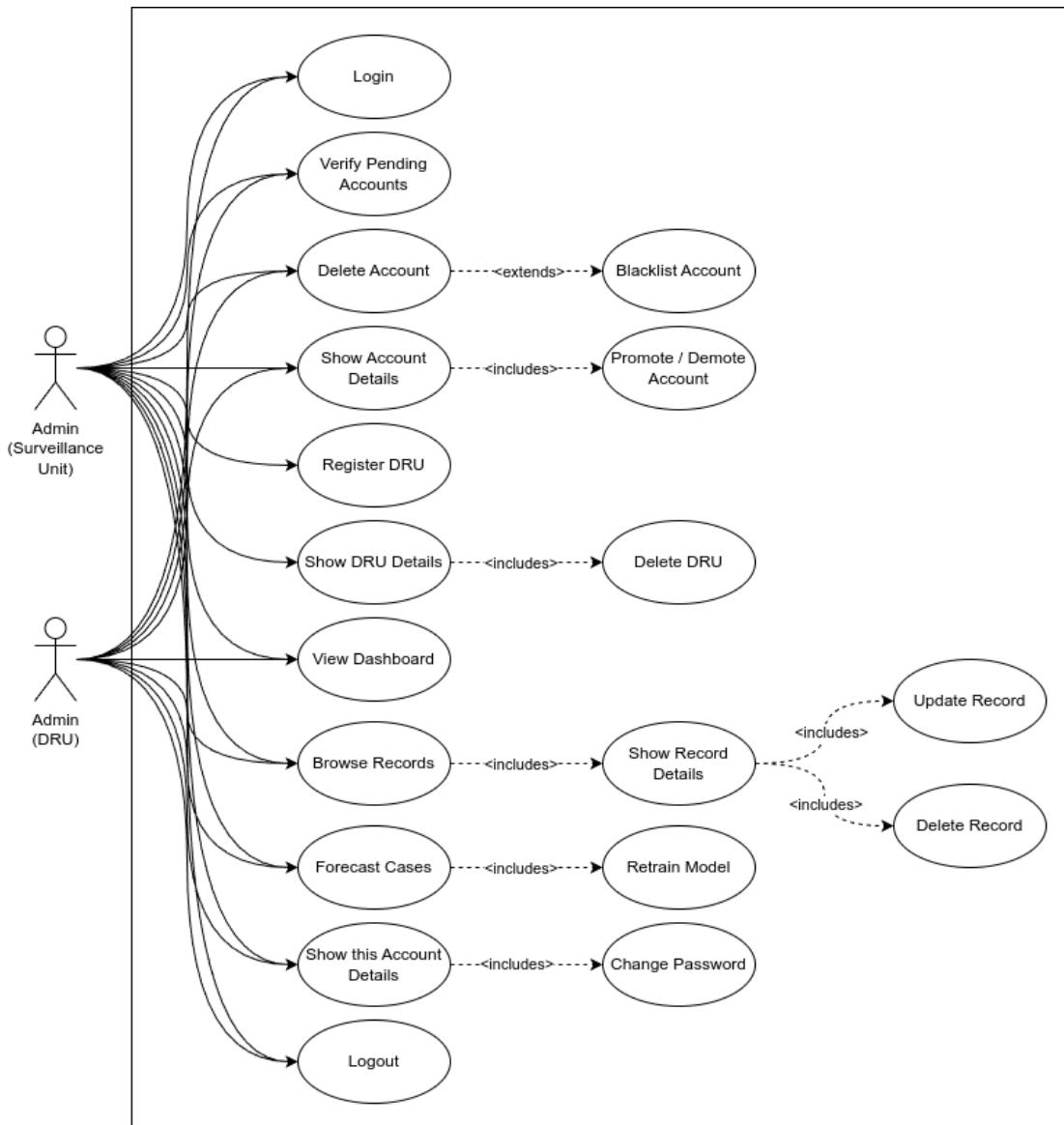


Figure 3.4: Use Case Diagram for Admins

<sup>724</sup> Figure 3.4 shows the actions of an admin for a specific Disease Reporting Unit (DRU) and an admin for a specific Surveillance Unit can take in the application.  
<sup>725</sup> Both of them include the management of accounts, browsing records, and fore-  
<sup>726</sup> casting and retraining all the consolidated data under their supervision. Most  
<sup>727</sup>

728 importantly, these users must verify the encoders who register under their ju-  
729 risdiction before allowing their account to access the application in the name of  
730 safeguarding the integrity of the data. The only advantage of the latter type of ad-  
731 ministrator is that it has a one-step higher authorization as it manages the DRUs.  
732 In addition, only the authorized surveillance unit administrator can register and  
733 create a DRU to uphold transparency and accountability.

### 734 Encoder Interface

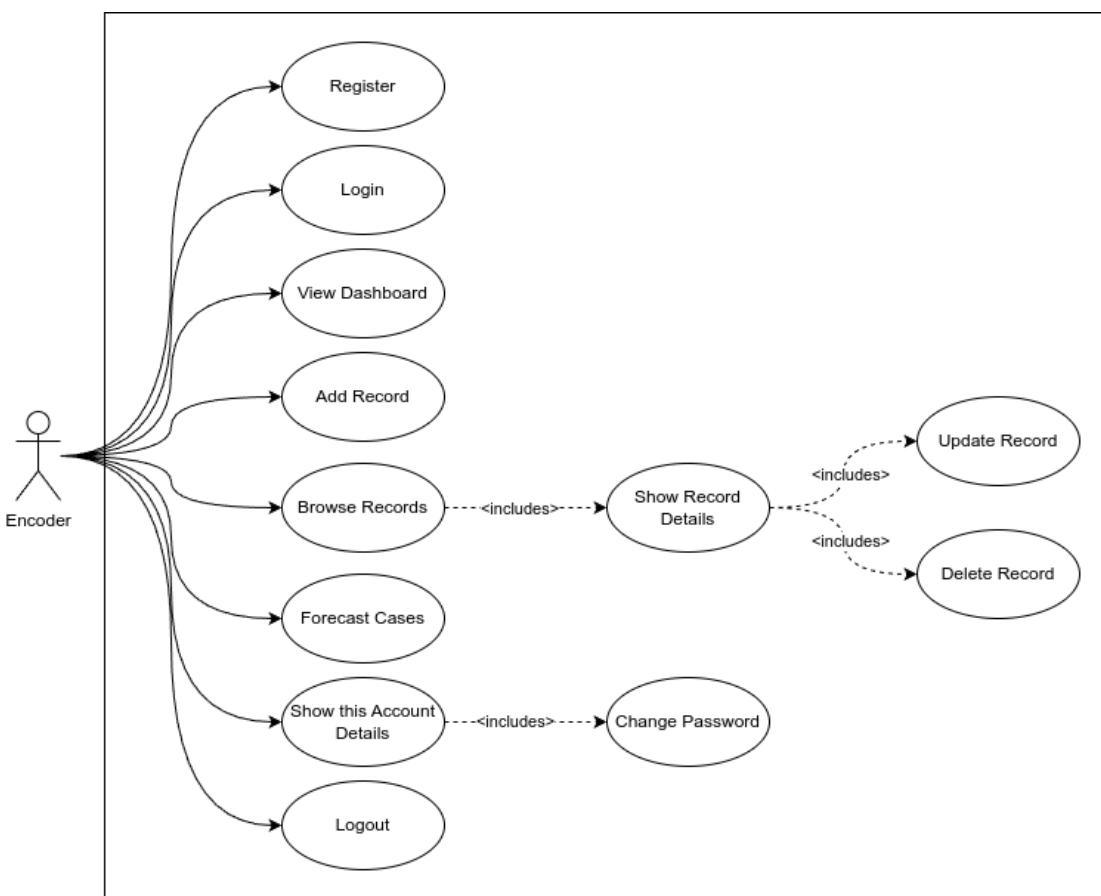


Figure 3.5: Use Case Diagram for Encoder

735 Figure 3.5, on the other hand, illustrates the use cases for the system's primary  
736 users. These users can register but must wait for further verification to access the  
737 application. Similar to the previous interfaces, encoders can browse and manage  
738 records, as well as forecast the consolidated cases under a specific surveillance or  
739 disease reporting unit, but they are not allowed to retrain the model. Lastly, they

740 are the only type of user that can file and create dengue cases by filling out a form  
741 with the required details.

### 742 3.3.3 Security and Validation Requirements

#### 743 Password Encryption

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

#### 752 Authentication

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

#### 758 Data Validation

759 Both the backend and frontend should validate the input from the user to preserve  
760 data integrity. Thus, Zod is implemented in the latter to help catch invalid inputs  
761 from the user. By doing this, the user can only send proper requests to the server  
762 which streamlines the total workflow. On the other hand, Django has also a built-  
763 in validator that checks the data type and ensures that the input matches the  
764 expected format on the server side. These validation processes ensure that only  
765 valid and properly formatted data is accepted, which reduces the risk of errors  
766 and ensures consistency across the web application.

## 767 3.4 Calendar of Activities

768 A Gantt chart showing the schedule of the activities is included below. Each  
769 bullet represents approximately one week of activity.

Table 3.1: Timetable of Activities for 2024

Activities	Aug	Sept	Oct	Nov	Dec
Project Initiation and Team Formation	••				
Literature Review and Data Gathering	••	••••			
Data Cleaning and Feature Selection		••		•	•
Creating System Dashboard		••	••••	•	
Analysis and Interpretation of Results			•		•
Documentation	••	••••	••••	••••	••••

Table 3.2: Timetable of Activities for 2025

Activities	Jan	Feb	Mar	Apr	May
Create Admin Dashboard	•	•••			
Integrate the Best Model to the System	•	••••			
Extend Features to Accommodate a National Setting		•	••		
User Testing			••	•	
Documentation	••	••••	••••	••••	••••

770 **Chapter 4**

771 **Results and Discussion/System  
772 Prototype**

773 **4.1 Data Gathering**

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

- 779 1. Dengue Case Data: The primary source of historical dengue cases came  
780 from the Humanitarian Data Exchange and the Western Visayas Center for  
781 Health Development (WVCHD). The dataset, accessed through Freedom of  
782 Information (FOI) requests, provided robust case numbers for the Western  
783 Visayas region. The systematic collection of these data points was essential  
784 for establishing a reliable baseline for model training and evaluation.
- 785 2. Weather Data: Weekly weather data was obtained by web scraping from  
786 Weather Underground, allowing access to rainfall, temperature, wind, and  
787 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

#	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

## 788 4.2 Exploratory Data Analysis

789 From the summary above, the dataset consists of 720 weekly records with 8  
 790 columns:

- 791 • **Time.** Weekly timestamps (e.g. "2011-w1")
- 792 • **Rainfall.** Weekly average rainfall (mm)
- 793 • **MaxTemperature, AverageTemperature, MinTemperature.** Weekly  
 794 temperature data (C)
- 795 • **Wind.** Wind speed (m/s)
- 796 • **Humidity.** Weekly average humidity (%)
- 797 • **Cases.** Reported dengue cases

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

Figure 4.3: Dataset Statistics

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

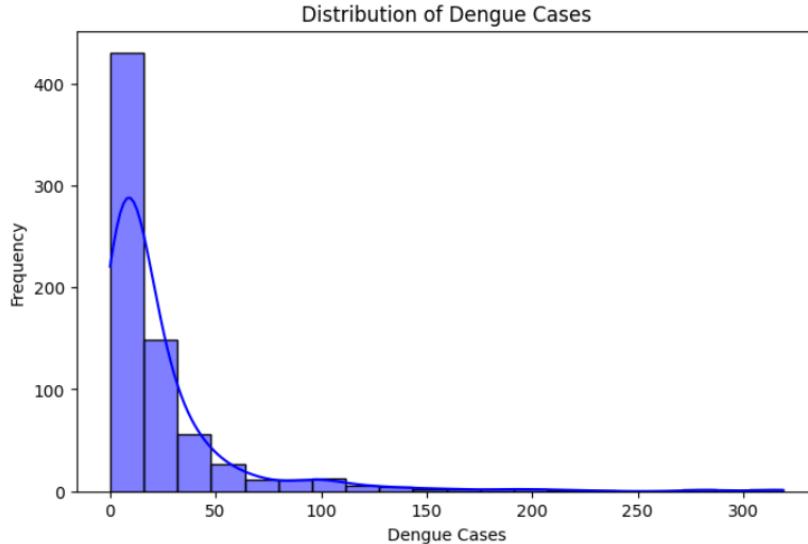


Figure 4.4: Distribution of Dengue Cases

805 In figure 4.4, a histogram of dengue cases shows a right-skewed distribution,  
 806 indicating that most weeks experience low case counts, while a few weeks record  
 807 outbreaks.  
 808 To further analyze the distribution, dengue cases were categorized into different  
 809 intervals (Figure 4.5): 0-5 cases, 6-15 cases, 16-30 cases, 31-100 cases and 101+

810 cases. The majority of weeks falls within the 0-5 cases and 6-15 cases categories,  
811 indicating that most weeks have low dengue cases. Meanwhile, weeks with 101+  
cases are rare, suggesting that extreme outbreaks are not frequent.

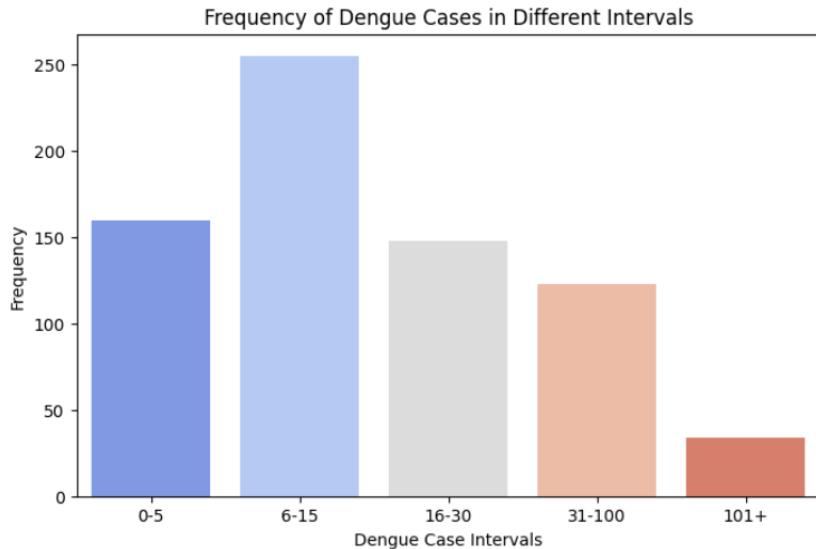


Figure 4.5: Frequency of Dengue Cases in Different Intervals

812  
813 Figure 4.6 illustrates the trend of weekly dengue cases over time. The data  
814 reveals periodic spikes in the number of cases, suggesting a seasonal pattern in  
815 dengue cases. Notably, peak cases are observed during certain periods approx-  
816 imately 3 years, potentially aligning with specific climatic conditions such as  
817 increased rainfall or temperature changes. This underscores the importance of  
818 incorporating climate variables into the forecasting model.

819 Figure 4.7 shows the ranking of correlation coefficients between dengue cases  
820 and selected features, including rainfall, humidity, maximum temperature, aver-  
821 age temperature, minimum temperature, and wind speed. Among these, rainfall  
822 exhibits the highest positive correlation with dengue cases (correlation coefficient  
823 0.13), indicating that increased rainfall may contribute to higher cases counts.  
824 This aligns with existing studies suggesting that stagnant water from heavy rain-  
825 fall creates breeding grounds for mosquitos. It is followed by humidity ( 0.10),  
826 suggesting that higher humidity levels may enhance mosquito reproduction, lead-  
827 ing to more dengue cases. Temperature has a weak to moderate positive corre-  
828 lation with dengue cases, with maximum temperature (0.09) showing a stronger  
829 relationship than average and minimum temperature.

830 Figure 4.8 shows the distributions of each feature while Figure 4.9 shows scat-  
831 terplots of each feature against the number of cases. The distributions of Rainfall,

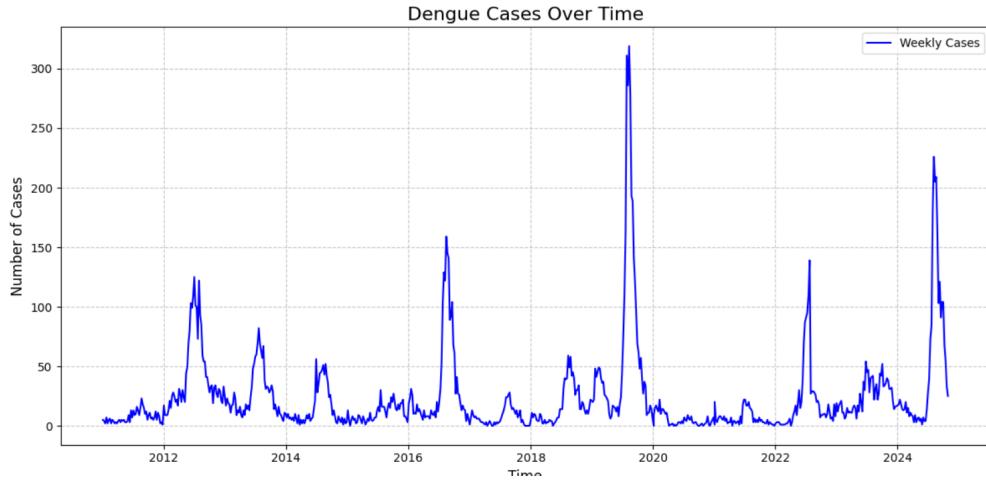


Figure 4.6: Trend of Dengue Cases

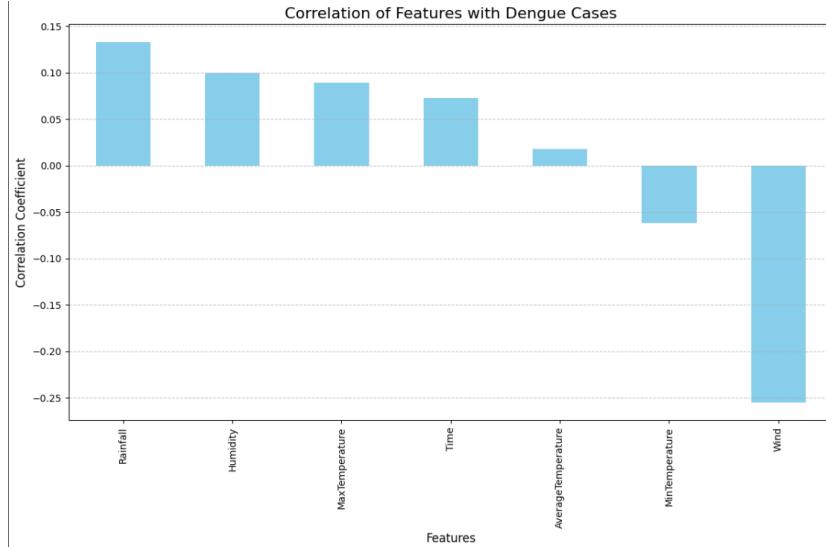


Figure 4.7: Ranking of Correlations

832 Max Temperature, Min Temperature, and Wind appear skewed, which is common  
 833 for many real-world variables. This skewness can distort correlation estimates, as  
 834 Pearson correlation assume linear relationships and are more reliable when vari-  
 835 ables follow a symmetric or approximately normal distribution (Bobbitt, 2021).  
 836 Applying a log transformation can help normalize these distributions, improve  
 837 linearity, and thus lead to more meaningful and accurate correlation analysis.

838 After applying a log transformation, Figure 4.10 shows the new distributions  
 839 for the previously skewed distributions, while Figure 4.11 shows the new scatter-  
 840 plots of each feature against the number of cases. Now, all distributions exhibit a

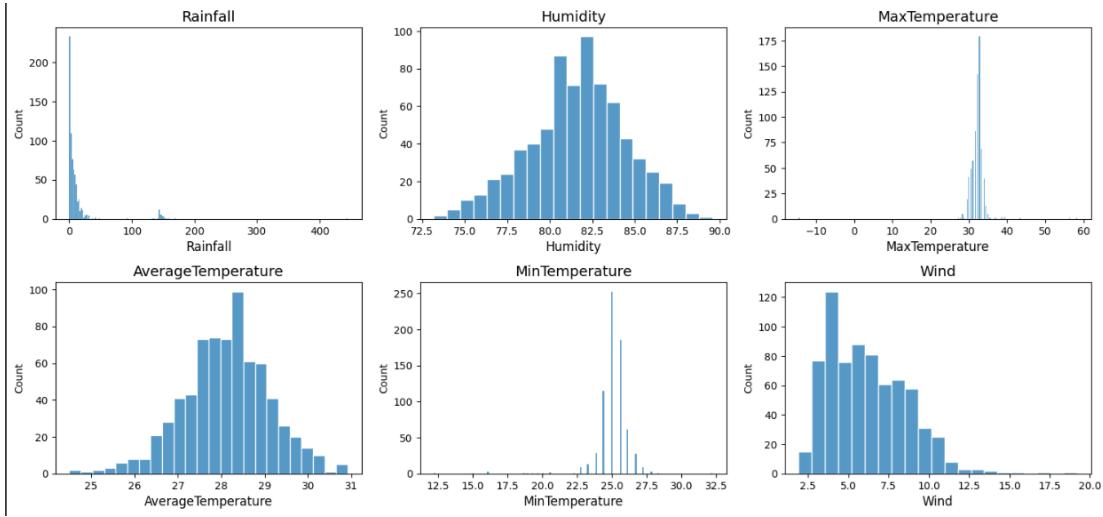


Figure 4.8: Pre-Transform Feature Distributions

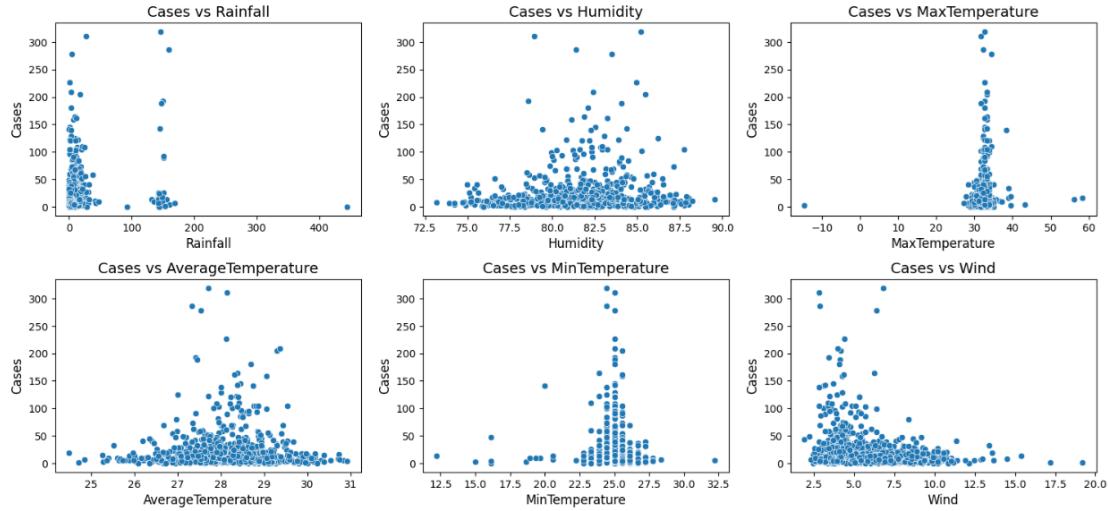


Figure 4.9: Scatterplots

841 somewhat normal distribution which is ideal for computing linear computations  
 842 such as Pearson's correlation.

843 Figure 4.12 presents the recomputed correlation coefficients between dengue  
 844 cases and the log-transformed weather features. Rainfall shows the strongest cor-  
 845 relation at 0.16, followed by Max Temperature at 0.12, and Humidity at 0.10.  
 846 While other features are included, their correlation values are very small and not  
 847 considered meaningful. Although the individual correlations are weak, they pro-  
 848 vide valuable signals that, when combined in a multivariate model, may contribute  
 849 meaningfully to predictive performance., As a result, Rainfall, Max Temperature,

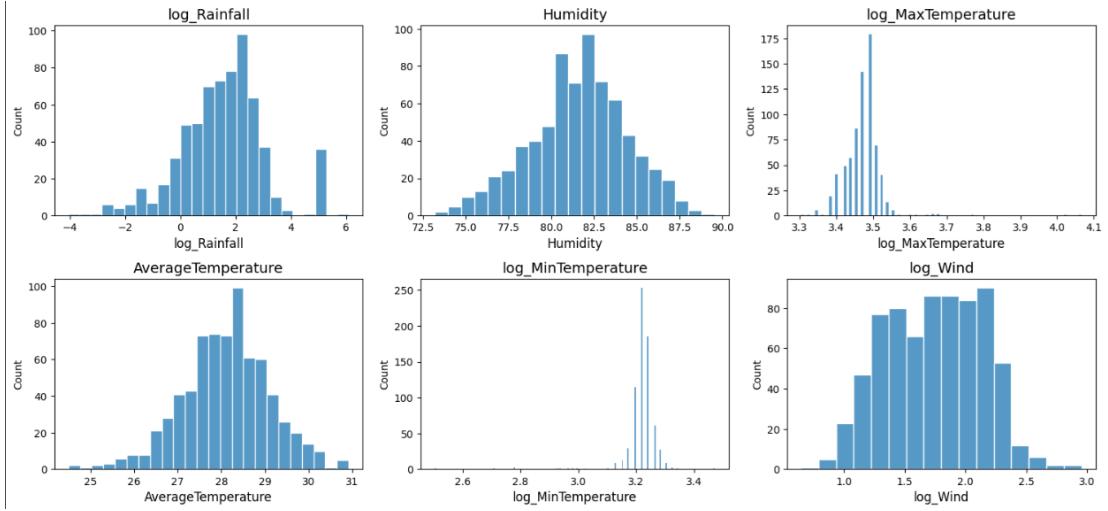


Figure 4.10: Post-Transform Feature Distributions

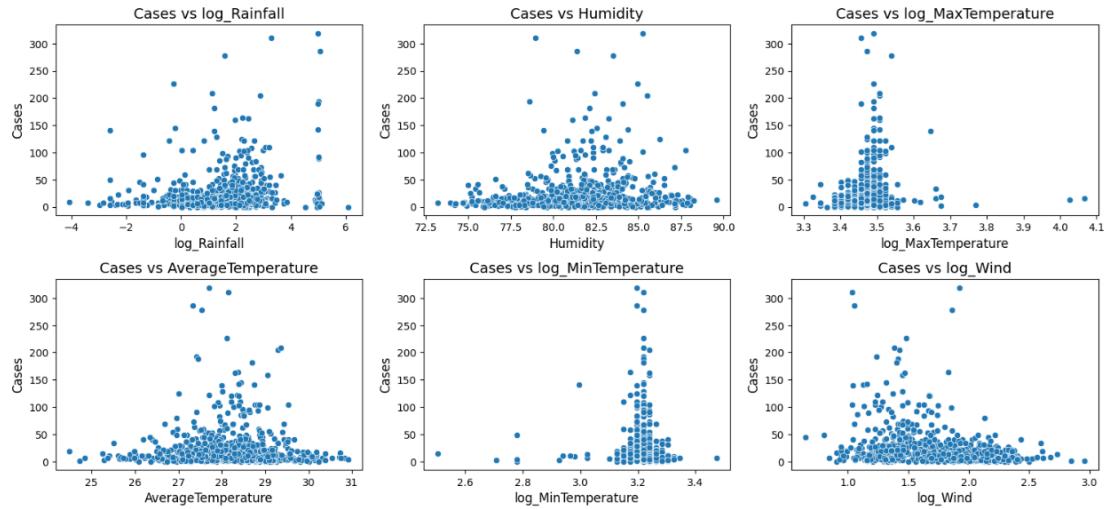


Figure 4.11: Transformed Distributions: Scatterplots

850 and Humidity are selected as the key features for model training.

### 851 4.3 Outbreak Detection

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

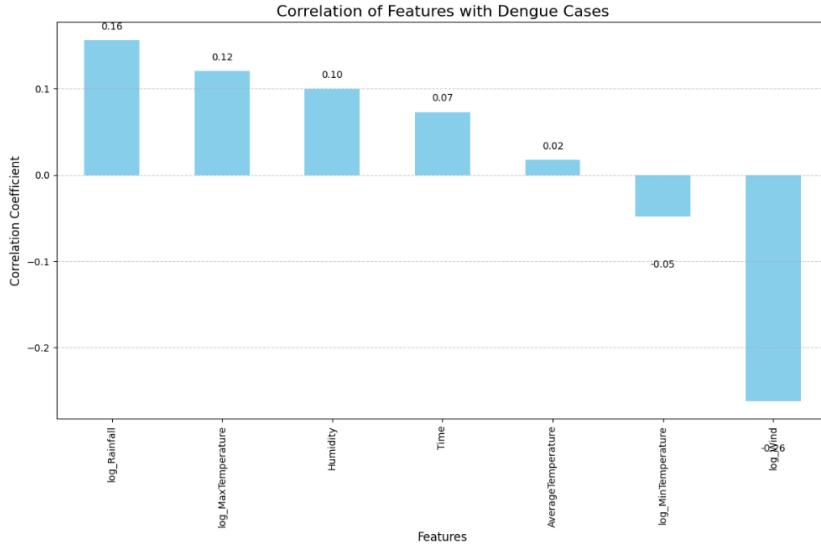


Figure 4.12: Ranking of Correlations with New Distributions

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

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

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

$$= 98.03407 \quad (4.4)$$

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

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

## 860 4.4 Model Training Results

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

866 the models performed differently on testing data. LSTM outperformed the other  
 867 models with the lowest RMSE, MSE, and MAE while the other three models had  
 868 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: $0.1 \times \text{Identity}$	Same as LSTM

Table 4.1: Comparison of different models for dengue prediction

#### 869 4.4.1 LSTM Model

870 The LSTM model was tuned for the following parameters: learning rate and units.  
 871 The hyperparameter tuning was conducted for each window size, finding the best  
 872 parameters for each window size. Further evaluating which window size is most  
 873 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	285.54	16.90	9.45	0.83
10	334.63	18.29	9.85	0.80
20	294.85	17.17	9.35	0.83

Table 4.2: Comparison of Window Sizes

874  
 875 The results indicate that a window size of 5 weeks provides the most accurate  
 876 predictions, as evidenced by the lowest MSE and RMSE values. Furthermore, the  
 877 R<sup>2</sup> score of 0.83 indicates that 83% of the variability in the target variable (cases)  
 878 is explained by the independent variables (the inputs) in the model, making it a  
 879 reliable configuration overall.

880 Figure 4.13 illustrates the model's performance in predicting dengue cases  
 881 for each fold using a window size of 5. As shown in the plot, the training set  
 882 progressively increases with each fold, mimicking a real-world scenario where more  
 883 data becomes available over time for dengue prediction. Figure 4.14 demonstrates  
 884 that the predicted cases closely follow the trend of the actual cases, indicating  
 885 that the LSTM model successfully captures the underlying patterns in the data.  
 886 It is also evident that as the fold number increases and the training set grows, the  
 887 accuracy of the predictions on the test set improves. Despite the test data being

888 unseen, the model exhibits a strong ability to generalize, suggesting it effectively  
 889 leverages past observations to predict future trends.

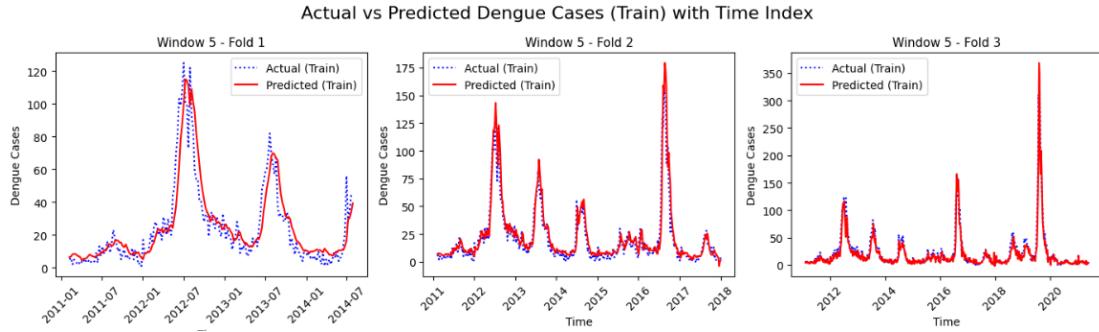


Figure 4.13: Training Folds - Window Size 5

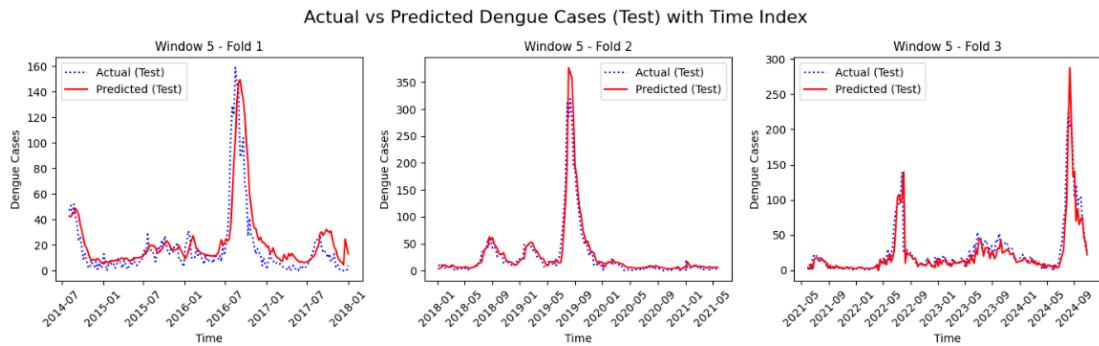


Figure 4.14: Testing Folds - Window Size 5

890 **4.4.2 ARIMA Model**

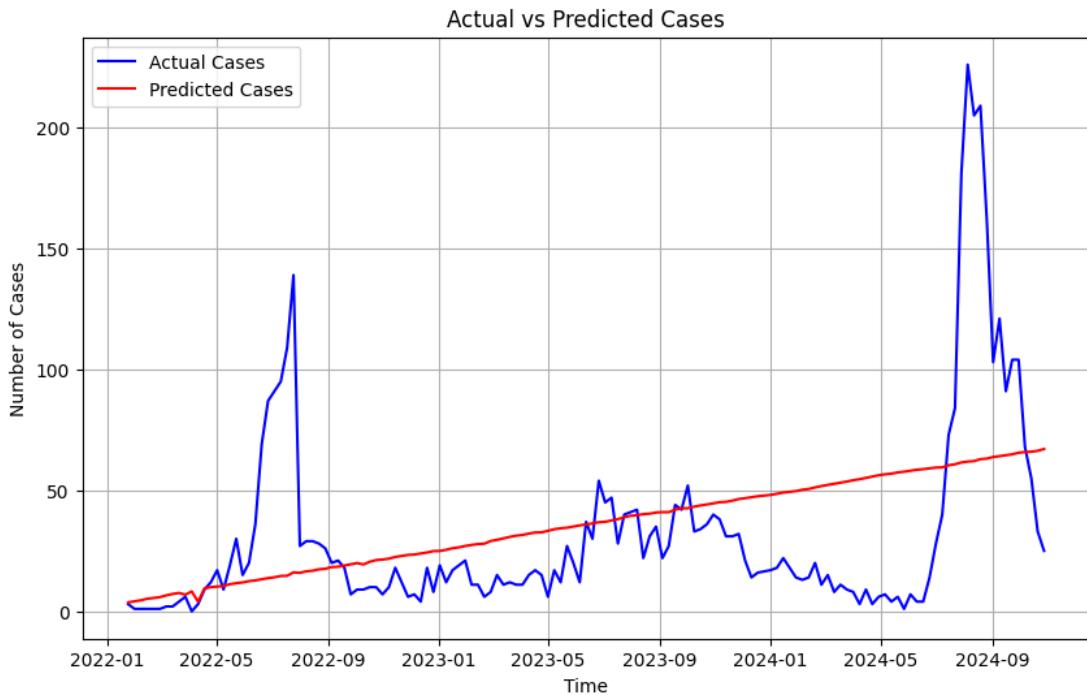


Figure 4.15: ARIMA Prediction Results for Test Set

891 The ARIMA model was developed to capture non-seasonal trends in the data.  
892 To determine the best model configuration, grid search was used to explore vari-  
893 ous combinations of ARIMA parameters, ultimately selecting **ARIMA(1, 2, 2)**.  
894 The model was iteratively refined over **400 iterations** to ensure convergence to  
895 an optimal solution. Figure 4.15 illustrates the comparison between actual and  
896 predicted dengue cases in the test set. As shown in the plot, the ARIMA model  
897 struggled to capture the non-linear characteristics and abrupt spikes in the data.  
898 Consequently, it failed to accurately reflect the fluctuations and outbreak patterns  
899 seen in the actual case counts.

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

- 902 • **MSE (Mean Squared Error):** 1521.48  
903 • **RMSE (Root Mean Squared Error):** 39.01  
904 • **MAE (Mean Absolute Error):** 25.80

### 905 4.4.3 Seasonal ARIMA (SARIMA) Model

906 To address the limitations of the ARIMA model, a Seasonal ARIMA (SARIMA)  
907 model was developed to capture both non-seasonal and seasonal variations in the  
908 data.

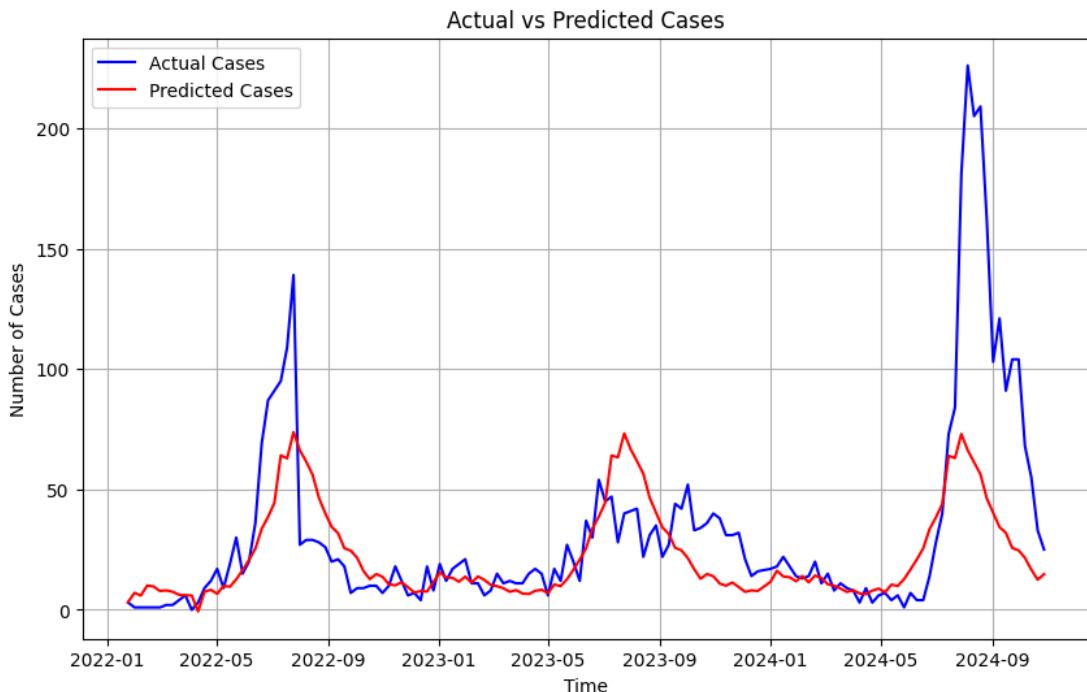


Figure 4.16: Seasonal ARIMA Prediction Results for Test Set

909 This model incorporates seasonal parameters, which were tuned using grid  
910 search to find the best configuration: **SARIMA(2, 0, 2)(0, 1, 1)[52]**. As with  
911 ARIMA, **400 iterations** were applied to ensure a robust fit. As shown in Figure  
912 4.16, the SARIMA model demonstrates a notable improvement in performance.  
913 Unlike its non-seasonal counterpart, it effectively captures the general trend and  
914 aligns more closely with the peaks observed in the actual dengue cases, indicating  
915 its ability to model seasonal dynamics.

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

- 918 • **MSE:** 1109.69
- 919 • **RMSE:** 33.31

920 • MAE: 18.09

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

925 After training the model, the SARIMA model was validated using the same  
926 Time Series Cross-Validation strategy employed in the LSTM model. Table 4.3  
927 presents the performance metrics for each fold, as well as the average metrics  
928 across all folds. The average RMSE and MAE values were close to those obtained  
929 during the initial training phase, indicating that the SARIMA model performed  
930 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 4.3: Comparison of SARIMA performance for each fold

#### 931 4.4.4 Kalman Filter Model

932 Figure 4.17 shows the comparison between the actual dengue cases and the pre-  
933 dicted values on the test set. As illustrated in the plot, the Kalman Filter model  
934 demonstrates a moderate ability to follow the general trend of the actual data.  
935 While it effectively captures some rising and falling patterns, it still struggles to  
936 accurately replicate the sharp peaks and extreme values found in the real case  
937 counts. This limitation is particularly noticeable during the large spikes in 2022  
938 and 2024. The model's performance was evaluated using standard regression met-  
939 rics. The results are as follows:

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

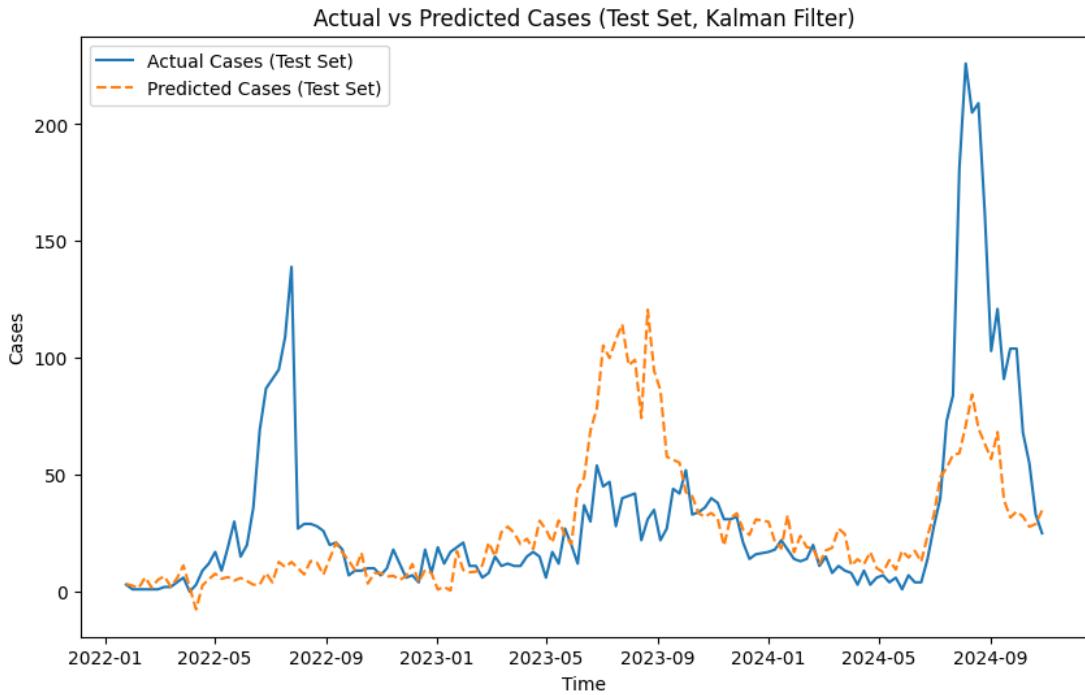


Figure 4.17: Kalman Filter Prediction Results for Test Set

940        The Kalman Filter was then combined with the LSTM model in order to see  
 941        improvements in its predictions. Table 4.4 shows the metrics across three folds  
 942        using the same Time Series Cross Validation Strategy employed in the previous  
 943        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 4.4: Comparison of KF-LSTM performance for each fold

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

## 947 4.5 Model Simulation

948 To evaluate the LSTM model's real-world forecasting ability, a simulation was  
949 conducted to predict dengue cases for the year 2025. The model was trained  
950 exclusively on data from 2011 to 2024, using both dengue cases and weather vari-  
951 ables. Importantly, the actual dengue case values for 2025 were never included  
952 during training. Instead, only the weather variables collected for 2025 were input  
953 into the model to generate predictions for that year. After prediction, the fore-  
954 casted dengue cases for 2025 were compared against the true observed cases to  
955 assess the model's accuracy. Figure 4.18 shows that the predicted values closely  
956 follow the trend, although it may overestimate the dengue cases in some weeks.

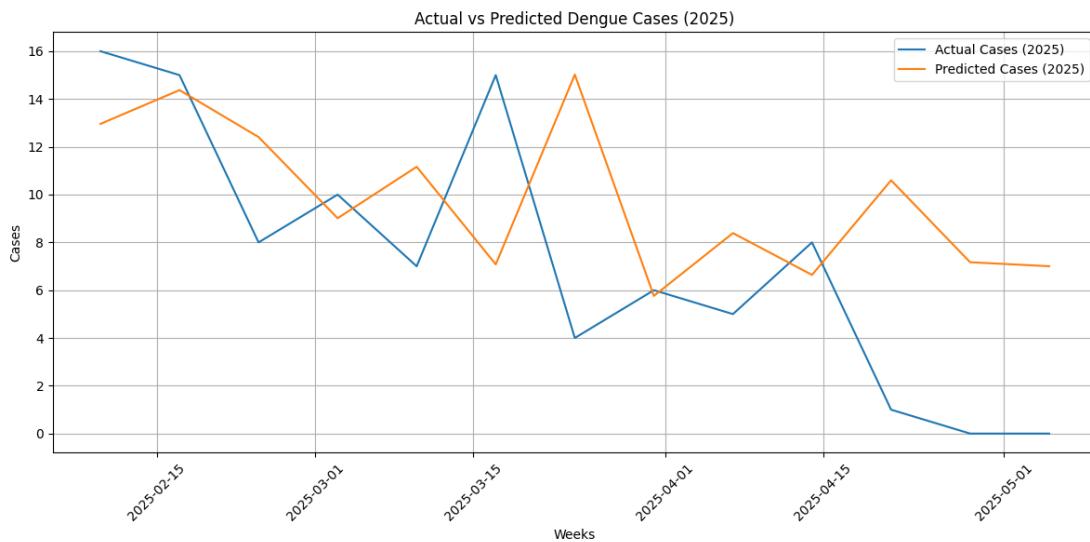


Figure 4.18: Predicted vs Actual Dengue Cases 2025

## 957 4.6 System Prototype

### 958 4.6.1 Home Page

959 The Home Page is intended for all visitors of the web application. The Analytics  
960 Dashboard, which displays relevant statistics for dengue cases at a certain year  
961 and location, is the primary component highlighted, as seen in Figure 4.19. This  
962 component includes a combo chart that graphs the number of dengue cases and  
963 deaths per week in a specific year, a choropleth map that tracks the number of

964 dengue cases per location, and various bar charts that indicate the top locations  
 965 affected by dengue.

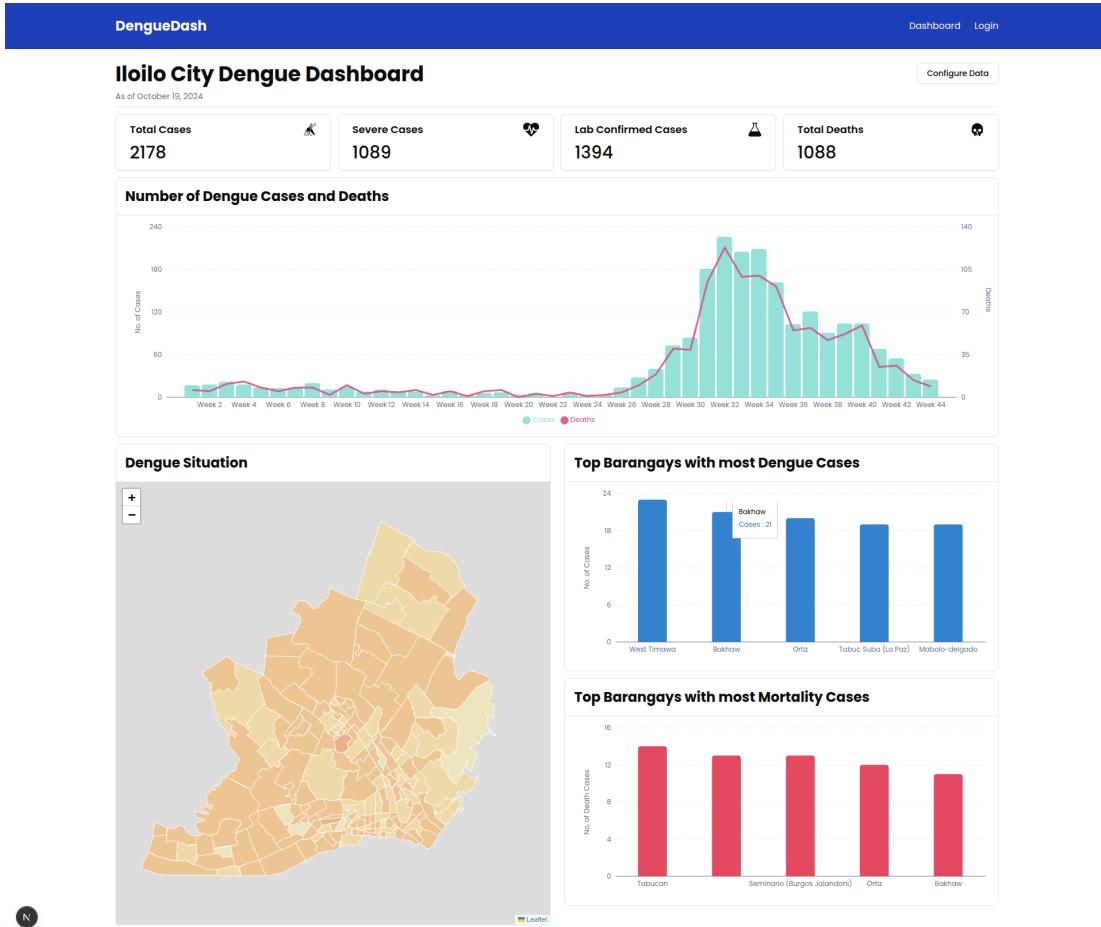


Figure 4.19: Home Page

#### 966 4.6.2 User Registration, Login, and Authentication

967 The registration page, as shown in Figure 4.20, serves as a gateway to access the  
 968 authenticated pages of the web application. Only prospected encoders can create  
 969 an account since administrator accounts are only made by existing administrator  
 970 accounts to protect the data's integrity in production. After registering, the  
 971 "encoder account" cannot access the authorized pages yet as it needs to be veri-  
 972 fied first by an administrator managing the unit the user entered. Once verified,  
 973 the user can log in to the system through the page shown in Figure 4.21. Af-  
 974 ter entering the correct credentials, which consist of an email and password, the

975 system uses HTTP-only cookies containing JSON Web Tokens (JWT) to prevent  
976 vulnerability to Cross-site Scripting (XSS) attacks. It will then proceed to the  
977 appropriate page the type of user belongs to.

The screenshot shows the 'Sign Up' page of the DengueDash application. At the top, there is a blue header bar with the text 'DengueDash' on the left and 'Dashboard Login' on the right. Below the header, the page title 'Sign Up' is centered, with the sub-instruction 'Create your account to get started' underneath it. The form consists of 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'. At the bottom of the form is a large black button labeled 'Create Account'. Below this button, there is a link 'Already have an account? Sign in'.

Figure 4.20: Sign Up Page

The screenshot shows the 'Welcome back!' page of the DengueDash application. At the top, there is a blue header bar with the text 'DengueDash' on the left and 'Dashboard Login' on the right. The main content area has a white background with a central box titled 'Welcome back!'. Inside this box, there are two input fields: 'Email' (with placeholder text 'Enter your email') and 'Password' (with placeholder text 'Enter your password'). Below these fields are two small checkboxes: 'Remember me' and 'Forgot password?'. At the bottom of the box is a large green button labeled 'Continue'.

Figure 4.21: Login Page

### 978 4.6.3 Encoder Interface

#### 979 Case Report Form

980 Figures 4.22 and 4.23 show the digitized counterpart of the form obtained from the  
981 Iloilo Provincial Epidemiology and Surveillance Unit. As the system aims to sup-  
982 port expandability for future features, some fields were modified to accommodate  
983 more detailed input. It is worth noting that all of the included fields adhere to the  
984 latest Philippine Integrated Disease and Surveillance Response (PIDS) Dengue  
985 Forms, which the referenced form was based on. By doing this, if implemented  
986 on a national scale, the transition between targeted users will be easier. More-  
987 over, the case form includes the patient's basic information, dengue vaccination  
988 status, consultation details, laboratory results, and the outcome. On the other  
989 hand, encoders can also create case records using a "bulk upload" feature that  
990 makes use of a formatted CSV file template. As shown in Figure 4.24, an encoder  
991 can download the template using the "Download Template" button, and insert  
992 multiple records inside the file, then upload it by clicking the "Click to upload"  
993 button. The web application automatically checks the file for data inconsis-  
994 tencies and validation.

The screenshot shows the 'Case Report Form' page within the 'DengueDash' application. The left sidebar contains a navigation menu with 'Analytics', 'Forms' (selected), 'Data Tables', and 'Settings'. A user profile at the bottom left shows 'CN Elizabeth Thomas Ra...' and an email address. The main content area has a header 'Case Report Form' with a 'Bulk Upload' button. Below are three tabs: 'Personal Information' (selected), 'Clinical Status', and 'Vaccination'. The 'Personal Information' tab contains sections for 'Personal Detail' (with fields for First Name, Middle Name, Last Name, Suffix, Sex, and Date of Birth), 'Address' (Region, Province, City, Barangay, Street, and House No.), and 'Vaccination' (Date of First Vaccination and Date of Last Vaccination). A 'Next' button is at the bottom right.

Figure 4.22: First Part of Case Report Form

The screenshot shows the second part of a 'Case Report Form' within the DengueDash application. The left sidebar contains a navigation menu with 'Case Report Form' selected. The main area has a header 'Case Report Form' and a 'Bulk Upload' button. It is divided into sections: 'Personal Information' (which is currently active, indicated by a blue underline) and 'Clinical Status'. The 'Clinical Status' section is further divided into 'Consultation' and 'Laboratory Results'.

**Consultation**

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

**Laboratory Results**

Test	Status	Date done
NS1	Pending Result	Pick a date
IgG ELISA	Pending Result	Pick a date
IgM ELISA	Pending Result	Pick a date
PCR	Pending Result	Pick a date

**Outcome**

Case Classification	Outcome
Select	Select

Date of Death: Pick a date

Buttons at the bottom include 'Previous' and 'Submit'.

Figure 4.23: Second Part of Case Report Form

The screenshot shows the DengueDash application interface. On the left, there's a sidebar with 'Case Report Form' selected under 'Forms'. The main area is titled 'Case Report Form' and has tabs for 'Personal Information' and 'Clinical Status'. A 'Bulk Upload' button is in the top right. A modal window titled 'Bulk Upload Patient Cases' is open in the center. It contains a file upload input with a placeholder 'Click to upload' and a note 'CSV files only (max 5MB)'. Below the input are 'Need a template?' and 'Download Template' buttons. Underneath is a 'CSV Format Requirements' section with a bulleted list of rules. At the bottom of the modal are 'Reset' and 'Upload CSV' buttons.

Figure 4.24: Bulk Upload of Cases using CSV

## 995 Browsing, Update, and Deletion of Records

996 Once the data generated from the case report form or the bulk upload is vali-  
 997 dated, it will be assigned as a new case and can be accessed through the Dengue  
 998 Reports page, as shown in Figure 4.25. The said page displays basic information  
 999 about the patient related to a specific case, including their name, address, date  
 1000 of consultation, and clinical and case classifications. It is also worth noting that  
 1001 it only shows cases the user is permitted to view. For example, in a local Disease  
 1002 Reporting Unit (DRU) setting, the user can only access records that belong to  
 1003 the same DRU. On the other hand, in a consolidated surveillance unit such as a  
 1004 regional, provincial, or city quarter, its users can view all the records from all the  
 1005 DRUs that report to them. Moving forward, Figure 4.26 shows the detailed case  
 1006 report of the patient on a particular consultation date.

**Dengue Reports**

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

< Previous 1 2 ... 2137 Next >

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

Figure 4.25: Dengue Reports

The screenshot shows the DengueDash application interface. On the left is a sidebar with a navigation tree under 'Modules': Accounts, DRU, Analytics, Data Tables (selected), Dengue Reports, and Settings. The main area has a header 'Building Your Application > Data Fetching'. Below is a card-based view of a case record:

- Personal Information**: Full Name - Medina, Michael Paige, Date of Birth - October 11, 1935, Sex - Male, Civil Status - Widowed, Full Address - 995 Monique Spur, Tacas, ILOILO CITY (Capital), Iloilo.
- Vaccination Status**: First Dose - April 26, 2023, Last Dose - May 31, 2020.
- Case Record #25017089**: Date of Consultation - November 1, 2024, Patient Admitted? - No, Date Onset of Illness - October 23, 2024, Clinical Classification - With warning signs.
- Laboratory Results**: NS1 - Negative, Date Done - October 27, 2024; IgG Elisa - Equivocal, Date Done - October 30, 2024; IgM Elisa - Pending Result, Date Done - N/A; PCR - Pending Result, Date Done - N/A.
- Outcome**: Case Classification - Probable, Outcome - Dead, Date of Death - October 31, 2024.
- Interviewer**: Interviewer - Daniels, Lisa Long, DRU - Molo District Health Center.

Buttons at the top right of the card area include 'Update Case' (black) and 'Delete Case' (red).

Figure 4.26: Detailed Case Report

1007 To update the case, the user can click the "Update Case" button, where a  
 1008 dialog will appear, and the updateable fields will be shown. It is worth noting  
 1009 that in this case, only fields under Laboratory Results and Outcome are included  
 1010 since they are the only ones that are time-based, where the result may change in  
 1011 the future. After updating, a prompt will show confirming the action of the user.  
 1012 Moving forward, to delete a case record, the user must click the "Delete Case"  
 1013 button, and a prompt verifying the action will appear. After confirming, the case  
 1014 will be deleted permanently.

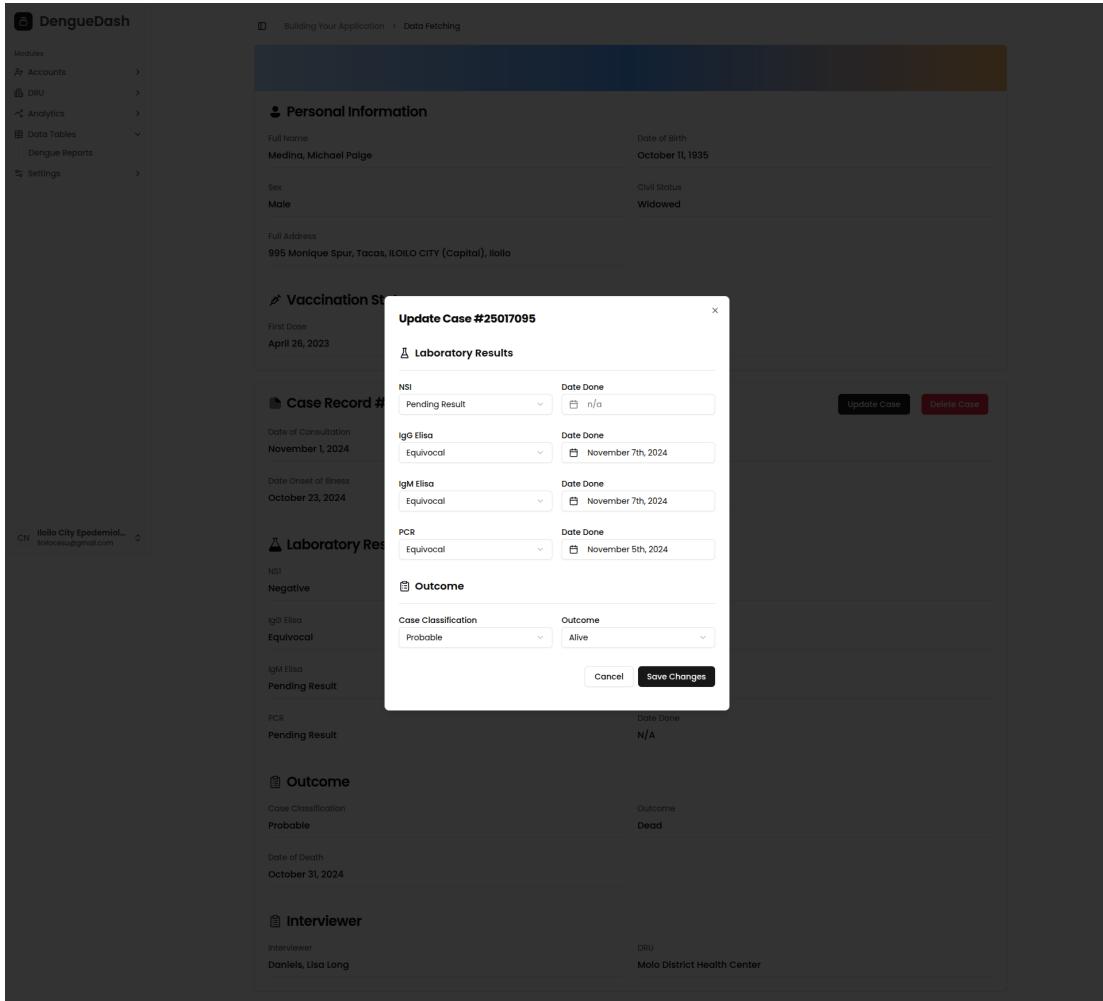


Figure 4.27: Update Report Dialog

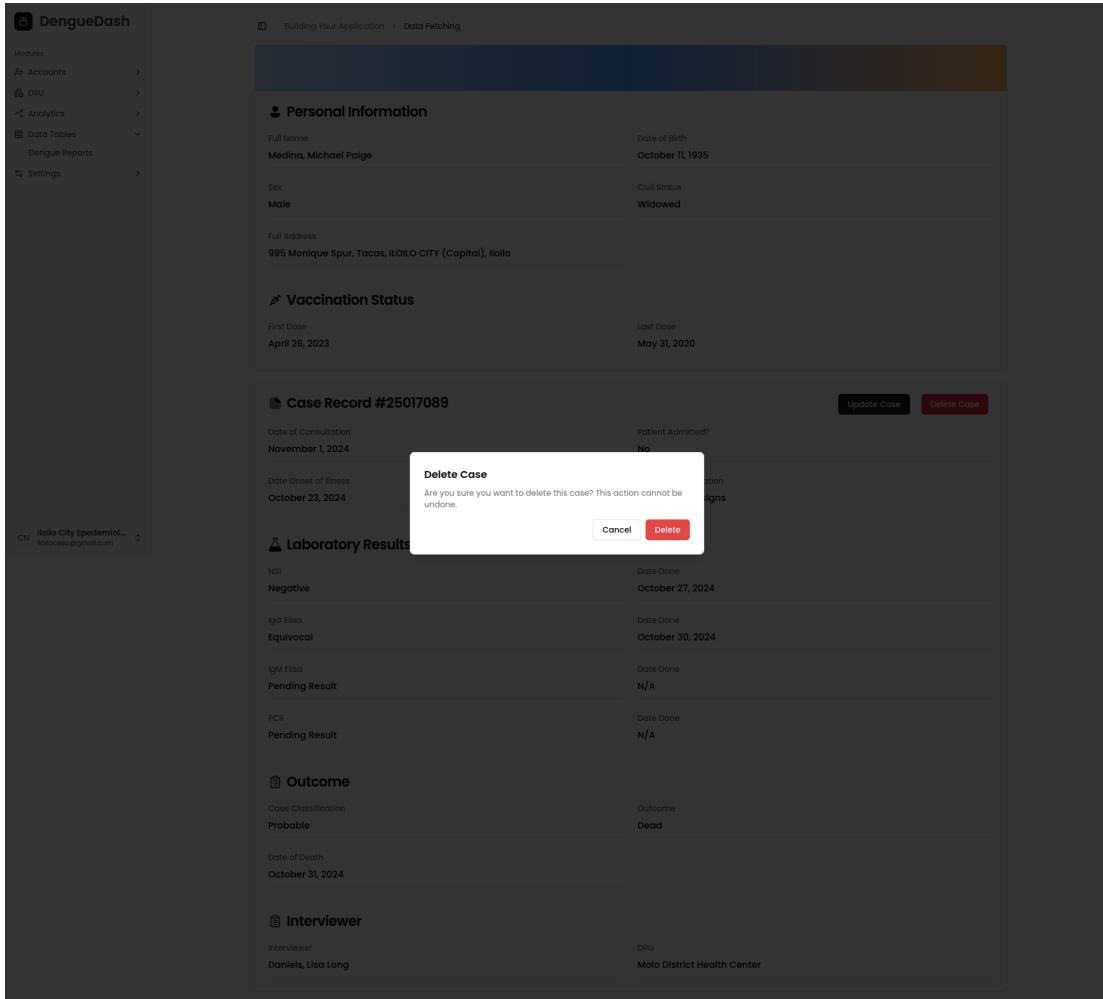


Figure 4.28: Delete Report Alert Dialog

## 1015    Forecasting

1016    The piece de resistance of the web application's feature is the Forecasting Page.  
 1017    This is where users can forecast dengue cases for the next following weeks. To  
 1018    predict, the application utilizes the exported LSTM model in a Keras format  
 1019    derived from training the consolidated data from the database. It requires the  
 1020    recent weekly dengue cases and weather variable data (temperature, humidity, and  
 1021    rainfall) based on the window size. This allows the web application to display a line  
 1022    chart with the anticipated number of dengue cases over the following four weeks.  
 1023    Moving forward, the Forecasting page, as shown in Figure 4.29, introduces a user-  
 1024    friendly interface that shows the current cases for the week and the predictions for  
 1025    the next two weeks with a range of 90 percent to 110 percent confidence interval

1026 that is presented in a simple but organized manner. There is also a line chart  
 1027 that shows the number of cases from the last 5 weeks plus the forecasted weekly  
 1028 cases. In addition, the current weather data for a specific week is also shown, as  
 1029 well as the forecasted weather data fetched from the OpenWeather API. Lastly,  
 1030 locations where dengue cases have been reported for the current week are listed  
 1031 in the Location Risk Assessment component.

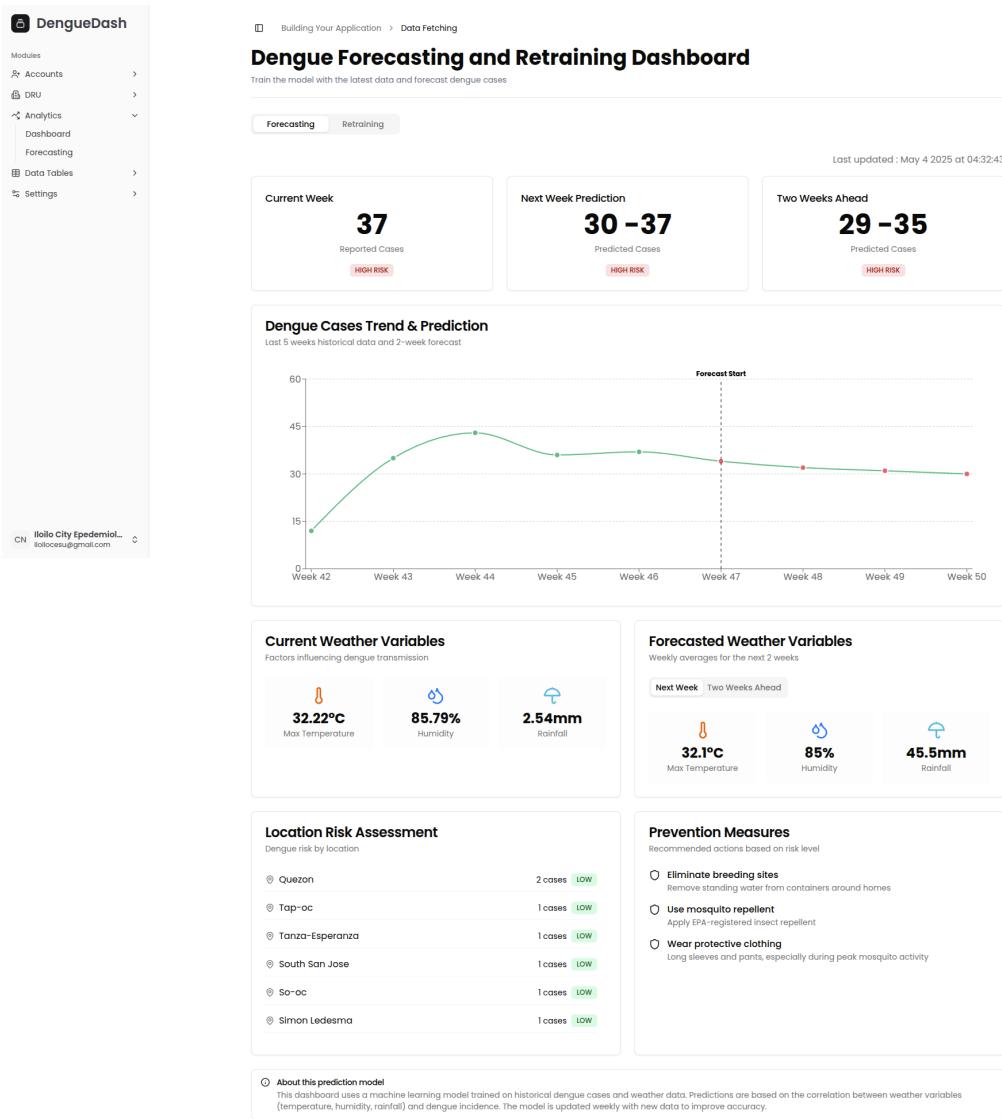


Figure 4.29: Forecasting Page

## 1032 4.6.4 Admin Interface

### 1033 Retraining

1034 With LSTM being the best-performing model among the models used in forecast-  
1035 ing dengue cases, it is the model chosen to power the prediction and retraining  
1036 of the consolidated data within the web application. Since the retraining process  
1037 consumes a lot of processing power and requires a more advanced understanding  
1038 of how it works, it was decided that the said feature should only be available  
1039 to admin users. Furthermore, the retraining component in the Forecasting page  
1040 includes three additional components that include the configuration of LSTM pa-  
1041 rameters (Figure 4.30), the actual retraining of the consolidated data from the  
1042 database (Figure 4.31), and the results of the retraining that shows the current  
1043 and previous model metrics depending on the parameters entered (Figure 4.32).  
1044 It is also worth noting that when trained, the model used a seeded number to  
1045 promote reproducibility.

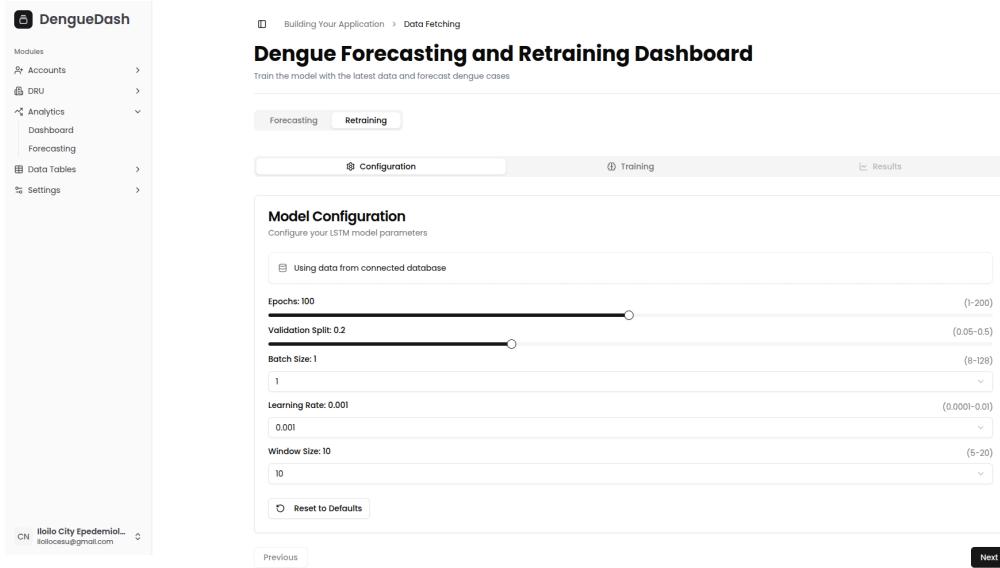


Figure 4.30: Retraining Configurations

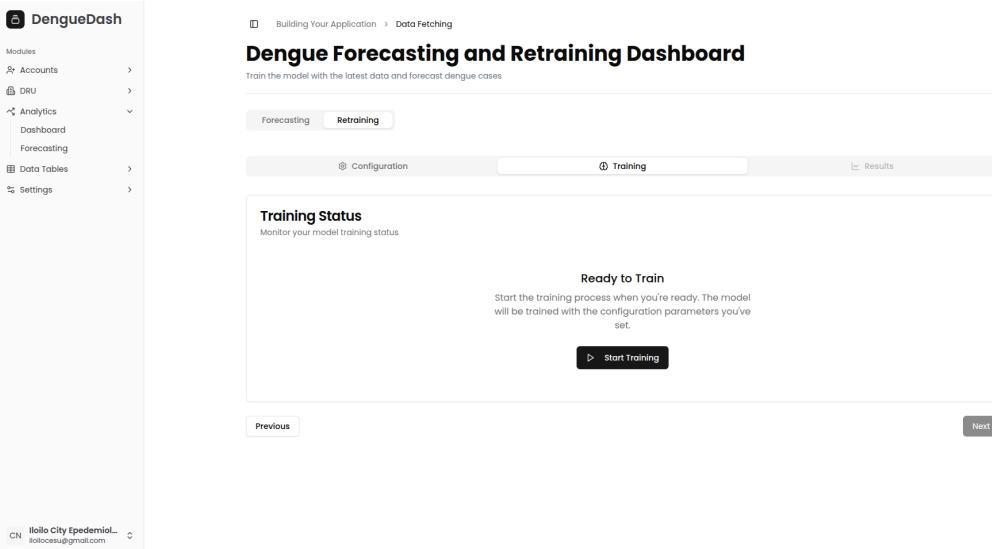


Figure 4.31: Start Retraining

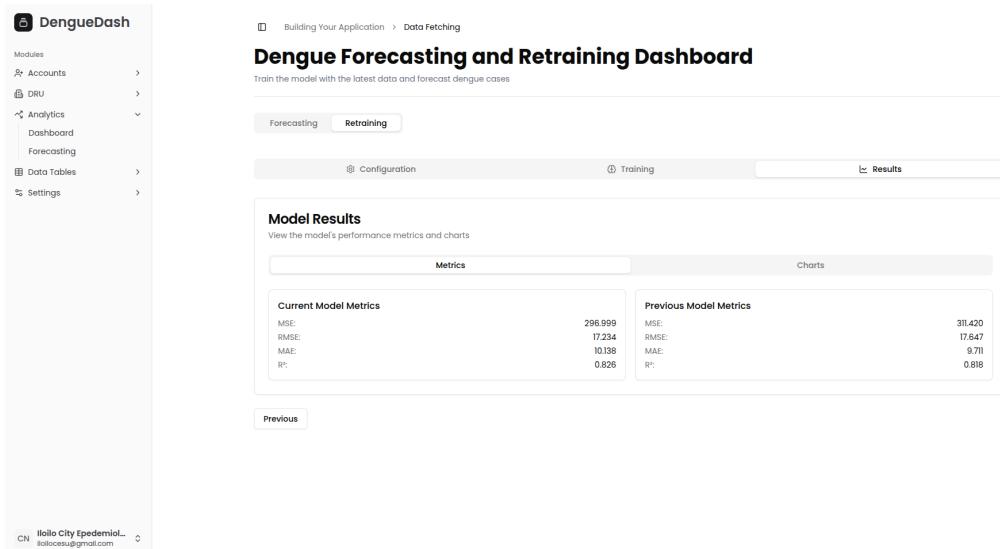


Figure 4.32: Retraining Results

## 1046 Managing Accounts

1047 Proper management of accounts is important to protect the integrity and confi-  
1048 dentiality of data. Thus, it is crucial for administrators to track their users and  
1049 control the flow of information. As discussed in the user registration of encoders,  
1050 admin users from a specific DRU or surveillance have the power to grant them ac-  
1051 cess to the web application. Figure 4.34 illustrates the interface for this scenario,  
1052 as the admins can approve or reject their applications. Once approved, these users  
1053 can access the features given to encoders and may be promoted to have admin-  
1054 istrative access, as shown in Figure 4.35. When deleting an account, the user's  
1055 email will be blacklisted and illegible to use when creating another account, and  
1056 all the cases reported by this user will be soft-deleted. The same figure also shows  
1057 the expanded details of the user, which include personal information and brief  
1058 activity details within the system.

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

- Modules
  - Accounts (selected)
  - DRU
  - Analytics
  - Data Tables
  - Settings

The main content area is titled "Manage Accounts". At the top, there are three buttons: "Verified" (highlighted), "Pending", and "Blacklisted". Below these buttons is a table with the following data:

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

At the bottom left of the main content area, there is a small footer element:

CN iloilo City Epidemiol...

Figure 4.33: List of Verified Accounts

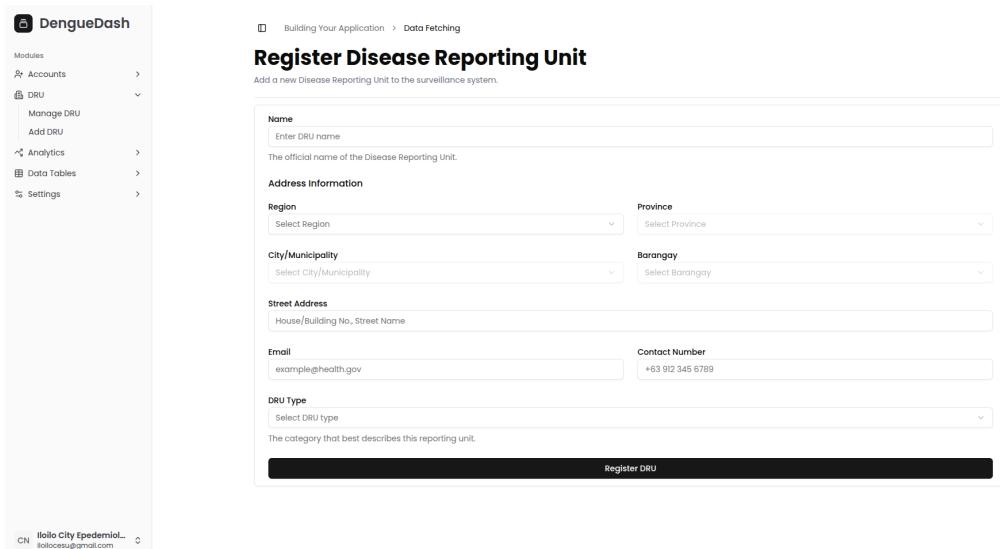
Figure 4.34: List of Pending Accounts

Figure 4.35: Account Details

## 1059 Managing DRUs

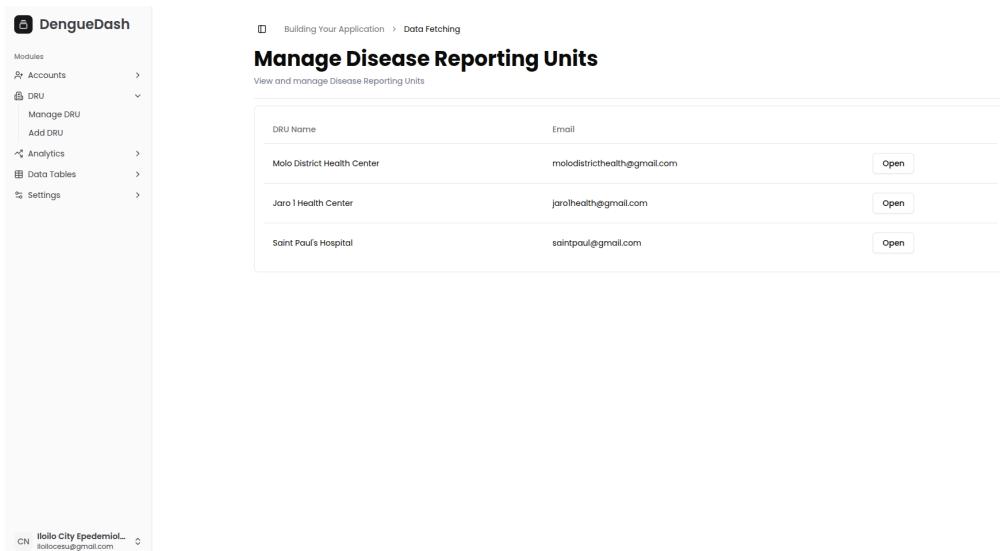
- 1060 Unlike the registration of encoder accounts, the creation of Disease Reporting  
 1061 Units can only be done within the web application, and the user performing the  
 1062 creation must be an administrator of a surveillance unit. Figure 4.36 presents the

1063 fields the admin user must fill out, and once completed, the new entry will show  
 1064 as being managed by that unit, as shown in Figure 4.37. Figure 4.38, on the other  
 1065 hand, shows the details provided in the registration form as well as its creation  
 1066 details. There is also an option to delete the DRU, and when invoked, all the  
 1067 accounts being managed by it, and the cases reported under those accounts will  
 1068 be soft-deleted.



The screenshot shows the 'Register Disease Reporting Unit' page. The left sidebar has a 'DRU' section with 'Manage DRU' and 'Add DRU' options. The main form has fields for 'Name' (with placeholder 'Enter DRU name'), 'Address Information' (Region dropdown, Province dropdown), 'City/Municipality' (dropdown), 'Barangay' (dropdown), 'Street Address' (placeholder 'House/Building No, Street Name'), 'Email' (example@example.gov), 'Contact Number' (+63 912 345 6789), 'DRU Type' (dropdown), and a 'Register DRU' button.

Figure 4.36: DRU Registration



The screenshot shows the 'Manage Disease Reporting Units' page. The left sidebar has a 'DRU' section with 'Manage DRU' and 'Add DRU' options. The main table lists three DRUs: 'Molo District Health Center' (Email: molodistricthealth@gmail.com, 'Open' button), 'Jaro I Health Center' (Email: jarohealth@gmail.com, 'Open' button), and 'Saint Paul's Hospital' (Email: saintpaul@gmail.com, 'Open' button).

Figure 4.37: List of DRUs

Figure 4.38: DRU details

## 1069 4.7 User Testing

1070 To evaluate the usability of the system, the System Usability Scale (SUS) was  
 1071 utilized. SUS is a Likert-scale-based questionnaire comprising 10 items that are  
 1072 critical to assessing system usability. A total of five participants completed the sur-  
 1073vey. Their responses were processed following the step-by-step calculation method  
 1074 adopted from (Babich, 2015). The resulting usability scores for each participant  
 1075 are shown in Table 4.5.

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 4.5: Computed System Usability Scores per Participant

1076 The average System Usability Scale (SUS) score across systems is typically  
 1077 68 (Babich, 2015). In this testing, the system achieved an average SUS score  
 1078 of 88.5, indicating a highly positive user experience. This score suggests that  
 1079 participants found the system not only enjoyable to use but also intuitive enough

1080 to recommend to others. Furthermore, it demonstrates that the system is suitable  
1081 for real-world applications without presenting significant complexity for first-time  
1082 users.

1083 **Chapter 5**

1084 **Conclusion**

1085 **Revolutionizing Dengue Surveillance: The Rise of AI-Driven Forecasting**  
1086

1087 The development of DengueWatch marks a transformative leap forward in pub-  
1088 lic health technology, providing Iloilo City with a centralized system to combat  
1089 one of the most persistent mosquito-borne diseases. Previously, data was recorded  
1090 manually on paper, making tracking and analysis slow and error-prone. Dengue-  
1091 Watch digitizes this process, enabling faster, more accurate monitoring. More  
1092 than an academic project, DengueWatch serves as a practical solution aimed at  
1093 shifting the approach from reactive outbreak response to proactive prevention. By  
1094 combining deep learning models with real-time climate data integration, the sys-  
1095 tem achieves a level of accuracy and usability that makes it viable for real-world  
1096 deployment.

1097 At the heart of DengueWatch is a Long Short-Term Memory (LSTM) neu-  
1098 ral network, which outperformed traditional forecasting models such as ARIMA  
1099 and Kalman Filter. The LSTM model achieved a Root Mean Square Error  
1100 (RMSE) of 16.30, compared to 39.00 and 38.40 for ARIMA and Kalman, respec-  
1101 tively—demonstrating a substantial improvement in predictive capability. This  
1102 advantage stems from the LSTM’s ability to capture long-term dependencies and  
1103 model nonlinear relationships between environmental factors and disease patterns.

1104 The analysis also revealed that climate indicators, particularly rainfall and  
1105 humidity, play a significant role in dengue outbreaks, typically leading to a surge  
1106 in cases three to five weeks after anomalies are detected. By incorporating these  
1107 lagged effects, DengueWatch achieved an explanatory power of 83% ( $R^2 = 0.83$ ),  
1108 offering a game-changing advantage for early intervention and resource allocation.

1109        Usability testing further underscored DengueWatch's readiness for real-world  
1110 deployment. The system achieved an average System Usability Scale (SUS) score  
1111 of 88.5, significantly above the industry benchmark of 68. This indicates that  
1112 users found the system intuitive, efficient, and suitable for operational use in  
1113 public health contexts. Key features such as a user-friendly dashboard, a two-week  
1114 forecasting window aligned with mosquito life cycles, and automated outbreak  
1115 alerts ensure that the system supports timely, effective responses.

1116        Beyond its immediate application in Iloilo City, the framework behind Dengue-  
1117 Watch holds the potential for broader impact. With minor adaptations, it can  
1118 be scaled nationally through integration with Department of Health surveillance  
1119 systems.

1120        DengueWatch exemplifies how deep learning can bridge the gap between data  
1121 science and life-saving interventions. It empowers health workers to act preemp-  
1122 tively, policymakers to allocate resources strategically, and communities to en-  
1123 gage in early preventive measures. As climate change accelerates the spread of  
1124 vector-borne diseases, systems like DengueWatch will become indispensable in  
1125 safeguarding public health. This system not only demonstrates the power of AI  
1126 in epidemiological forecasting but also lays the foundation for a smarter, more  
1127 resilient approach to combating infectious diseases in the years ahead.

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<sup>1217</sup> **Appendix A**

<sup>1218</sup> **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

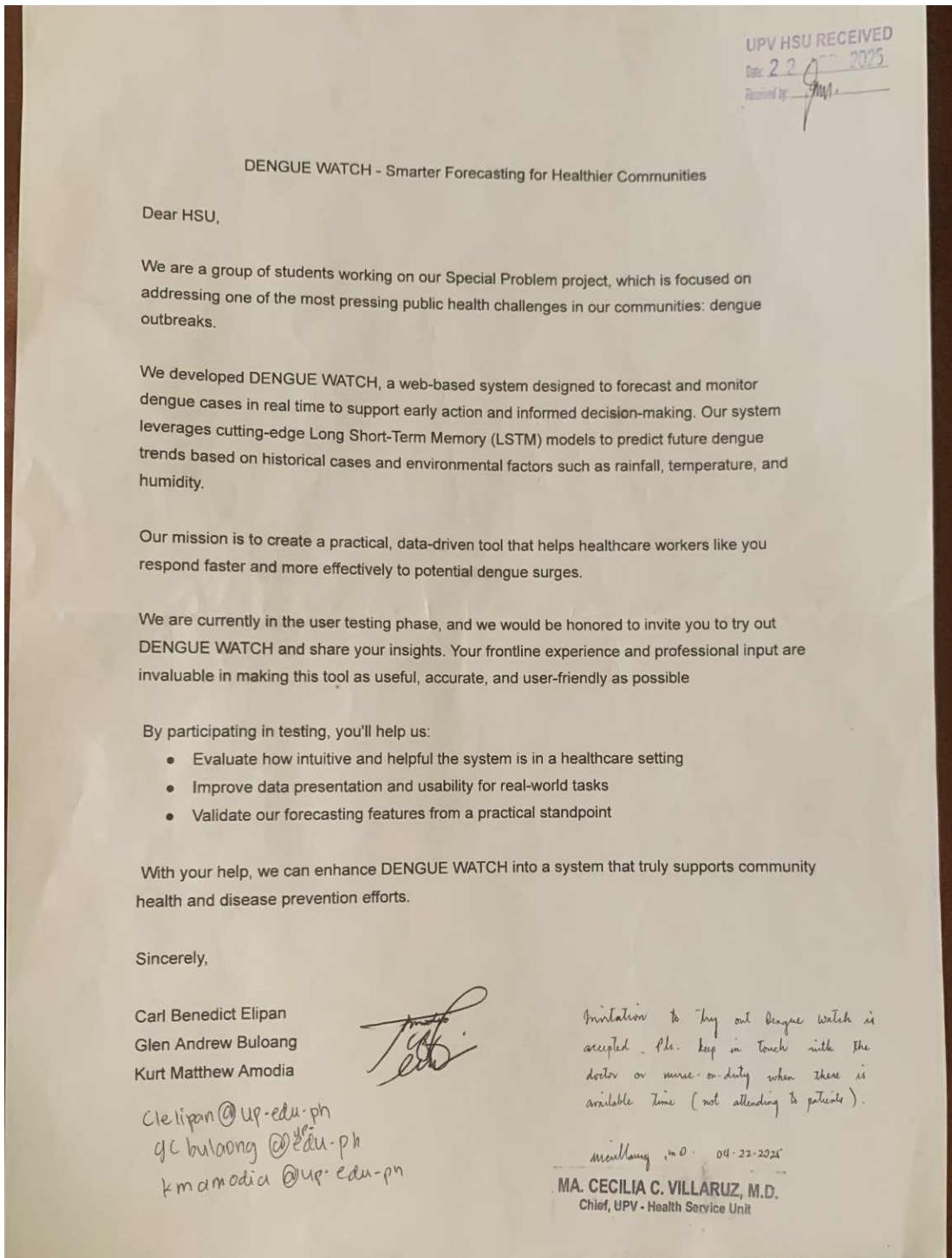


Figure A.3: Letter of Approval for User Testing in UPV HSU

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

<sub>1219</sub> **Appendix B**

<sub>1220</sub> **Resource Persons**

<sub>1221</sub> **Mr. Firstname1 Lastname1**

<sub>1222</sub> Role1

<sub>1223</sub> Affiliation1

<sub>1224</sub> emailaddr1@domain.com

<sub>1225</sub> **Ms. Firstname2 Lastname2**

<sub>1226</sub> Role2

<sub>1227</sub> Affiliation2

<sub>1228</sub> emailaddr2@domain.net

<sub>1229</sub> ....