

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

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12       Bachelor of Science in Computer Science by

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## Approval Sheet

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

23

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

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31                          **Declaration**

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

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## Dedication

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

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

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

49

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## Abstract

67        Dengue fever remains a significant public health concern in the Philippines, with  
68        cases rising dramatically in recent years. Iloilo City experienced a surge in cases, with  
69        4,585 reported cases and 10 deaths as of August 10, 2023, a 319% increase from the  
70        previous year's 1,095 cases and one death. This rise overwhelmed local healthcare facil-  
71        ities, with over 76% of non-COVID-19 hospital beds occupied by dengue patients. The  
72        lack of a reliable monitoring and forecasting system delayed interventions, worsening  
73        the public health burden. To address this, the study developed a centralized system to  
74        modernize data management and monitoring of dengue cases in public health institu-  
75        tions. Using data from the Iloilo Provincial Health Office and online sources, several  
76        deep learning models were trained to forecast dengue cases on weather variables and  
77        historical data. Models tested included LSTM, ARIMA, Seasonal ARIMA, Kalman Fil-  
78        ter (KF), and a hybrid KF-LSTM, evaluated with time series cross-validation and error  
79        metrics like MSE, RMSE, and MAE. The LSTM model performed best, achieving the  
80        lowest RMSE of 16.90, followed by the hybrid KF-LSTM with 25.56. The LSTM model  
81        was integrated into the system, providing forecasting capabilities to support proactive  
82        interventions and better resource planning in health institutions.

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

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<sup>190</sup> **Chapter 1**

<sup>191</sup> **Introduction**

<sup>192</sup> **1.1 Overview of the Current State of Technology**

<sup>193</sup> Dengue cases surged globally in 2023 and continued to rise in 2025, with over  
<sup>194</sup> five million cases and more than 5,000 deaths across 80 countries (Bosano, 2023).

<sup>195</sup> The World Health Organization reported a ten-fold increase in cases from 2000  
<sup>196</sup> to 2019, peaking in 2019 with the disease affecting 129 countries (WHO, 2024).

<sup>197</sup> In the Philippines, dengue remains endemic, leading to prolonged and widespread  
<sup>198</sup> outbreaks.

<sup>199</sup> In Iloilo, dengue cases escalated dramatically. By August 2023, the provincial  
<sup>200</sup> health office reported 4,585 cases and 10 deaths, marking a 319% increase from  
<sup>201</sup> the previous year (Perla, 2024). Iloilo has reached the outbreak threshold, and  
<sup>202</sup> local authorities are on blue alert. In Iloilo City, 649 cases were recorded in 2024,  
<sup>203</sup> with two deaths. Hospital capacity is strained, with non-COVID-19 hospital bed

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

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

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

<sup>227</sup> **1.2 Problem Statement**

<sup>228</sup> Dengue remains a critical public health challenge worldwide, with cases increasing  
<sup>229</sup> due to the easing of COVID-19 restrictions and heightened global mobility. While  
<sup>230</sup> a temporary decline in cases was observed during the pandemic (2020–2022) due  
<sup>231</sup> to reduced surveillance efforts, 2023 marked a resurgence, with over five million  
<sup>232</sup> cases and more than 5,000 deaths reported across 80 countries (Bosano, 2023).  
<sup>233</sup> In Iloilo City and Province, dengue cases rose by 319% as of August 2023, over-  
<sup>234</sup> whelming local healthcare systems. This surge strained resources, with over 76%  
<sup>235</sup> of non-COVID-19 hospital beds occupied by dengue patients (Perla, 2024), high-  
<sup>236</sup> lighting the urgent need for effective monitoring and predictive tools. Despite  
<sup>237</sup> all these studies, there remains a significant gap in the development of publicly  
<sup>238</sup> accessible systems that apply these predictive models in real-world settings. Most  
<sup>239</sup> existing studies remain confined to academic or theoretical contexts, with little  
<sup>240</sup> translation into practical tools for local communities and public health authorities.  
<sup>241</sup> In particular, there is a lack of research focused specifically on dengue prediction  
<sup>242</sup> and surveillance in Iloilo. While deep learning models have shown high accuracy  
<sup>243</sup> in other regions, their application in the local context of Iloilo is minimal. The  
<sup>244</sup> lack of a reliable system to monitor and forecast dengue outbreaks contributes to  
<sup>245</sup> delayed interventions, exacerbating public health risks and healthcare burdens in  
<sup>246</sup> the region.

<sup>247</sup> **1.3 Research Objectives**

<sup>248</sup> **1.3.1 General Objective**

<sup>249</sup> This study aims to develop a centralized monitoring and analytics system for  
<sup>250</sup> dengue cases in Iloilo City and Province with data management and forecasting  
<sup>251</sup> capabilities. The researchers will train and compare multiple deep learning models  
<sup>252</sup> to predict dengue case trends based on climate data and historical dengue cases  
<sup>253</sup> to help public health officials in possible dengue case outbreaks.

<sup>254</sup> **1.3.2 Specific Objectives**

<sup>255</sup> Specifically, this study aims to:

- <sup>256</sup> 1. gather dengue data from the Iloilo Provincial Health Office and climate data  
<sup>257</sup> (including temperature, rainfall, wind, and humidity) from online sources,  
<sup>258</sup> and combine and aggregate these into a unified dataset to facilitate compre-  
<sup>259</sup> hensive dengue case forecasting;
- <sup>260</sup> 2. train and evaluate deep learning models for predicting dengue cases using  
<sup>261</sup> metrics such as Mean Absolute Error (MAE), Root Mean Squared Error  
<sup>262</sup> (RMSE), and Mean Squared Error (MSE), and determine the most accurate  
<sup>263</sup> forecasting approach; and
- <sup>264</sup> 3. develop a web-based analytics dashboard that integrates the predictive model,  
<sup>265</sup> provides a data management system for dengue cases in Iloilo City and the

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

## 268 1.4 Scope and Limitations of the Research

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

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

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

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

## 294 1.5 Significance of the Research

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

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

## *1.5. SIGNIFICANCE OF THE RESEARCH*

7

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

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

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



# <sup>321</sup> Chapter 2

## <sup>322</sup> Review of Related Literature

### <sup>323</sup> 2.1 Dengue

<sup>324</sup> Dengue disease is a tropical and subtropical mosquito-borne viral illness and is a  
<sup>325</sup> major health concern in the Philippines (Bravo, Roque, Brett, Dizon, & L'Azou,  
<sup>326</sup> 2014). The majority of individuals with dengue experience no symptoms. Fever is  
<sup>327</sup> the most common symptom, typically 4 to 7 days after being bitten by an infected  
<sup>328</sup> mosquito (Zhou & Malani, 2024). In recent years, the trend of dengue cases in  
<sup>329</sup> the Philippines has shown notable fluctuations, with periodic outbreaks occur-  
<sup>330</sup> ring every 3 to 5 years, often influenced by climatic and environmental changes.  
<sup>331</sup> According to the Department of Health (DOH), the number of reported cases  
<sup>332</sup> has steadily increased over the past decades, attributed to urbanization, popula-  
<sup>333</sup> tion growth, and inadequate vector control measures (World Health Organization  
<sup>334</sup> (WHO), 2018). Moreover, studies suggest that El Niño and La Niña events have  
<sup>335</sup> significant effects on dengue incidence, with warmer temperatures and increased

<sup>336</sup> rainfall providing favorable breeding conditions for mosquitoes (Watts, David M  
<sup>337</sup> and Burke, Donald S and Harrison, Bruce A and Whitmire, Ralph E and Nisalak,  
<sup>338</sup> Ananda, 2020). The study of Carvajal et. al. highlights the temporal pattern of  
<sup>339</sup> dengue cases in Metropolitan Manila and emphasizes the significance of relative  
<sup>340</sup> humidity as a key meteorological factor, alongside rainfall and temperature, in  
<sup>341</sup> influencing this pattern (Carvajal et al., 2018).

## <sup>342</sup> 2.2 Outbreak Definition

<sup>343</sup> The definition of an outbreak is a critical factor in disease surveillance, as it  
<sup>344</sup> determines the threshold at which an unusual increase in cases is considered a  
<sup>345</sup> public health concern. Studies suggest that outbreak thresholds should be context-  
<sup>346</sup> specific, given the variability in transmission dynamics across different locations  
<sup>347</sup> (Runge-Ranzinger et al., 2016). Outbreak definitions defined using the Endemic  
<sup>348</sup> Channel often base thresholds on 2 standard deviations (SD) above the mean  
<sup>349</sup> number of historic dengue cases. Other studies (Hemisphere, 2015) also used an  
<sup>350</sup> alert threshold of a 5-year mean plus 2 standard deviations. A study by (Brady,  
<sup>351</sup> Smith, Scott, & Hay, 2015) discussed that definitions of dengue outbreaks differ  
<sup>352</sup> significantly across regions and time, making them inconsistent and incomparable.

## <sup>353</sup> 2.3 Existing System: RabDash DC

<sup>354</sup> RabDash, developed by the University of the Philippines Mindanao, is a web-  
<sup>355</sup> based dashboard for rabies data analytics. It combines predictive modeling with

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

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

## 370 2.4 Deep Learning

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

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

## 384 2.5 Kalman Filter

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

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

## 403 2.6 Weather Data

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

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

## 421 2.7 Chapter Summary

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

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

<sup>436</sup> **Chapter 3**

<sup>437</sup> **Research Methodology**

<sup>438</sup> This chapter lists and discusses the specific steps and activities that were per-  
<sup>439</sup> formed to accomplish the project. The discussion covers the activities from pre-  
<sup>440</sup> proposal to Final SP Writing.

<sup>441</sup> Figure 3.1 summarizes the workflow for forecasting the number of weekly  
<sup>442</sup> dengue cases. This workflow focuses on using statistical, deep learning, and prob-  
<sup>443</sup> abilistic models to forecast the number of reported dengue cases. The approach  
<sup>444</sup> involves deploying several models for prediction, including ARIMA and Seasonal  
<sup>445</sup> ARIMA as statistical approaches, LSTM as a deep learning approach, and the  
<sup>446</sup> Kalman Filter as a probabilistic approach. These methods are compared with  
<sup>447</sup> each other to determine the most accurate model.

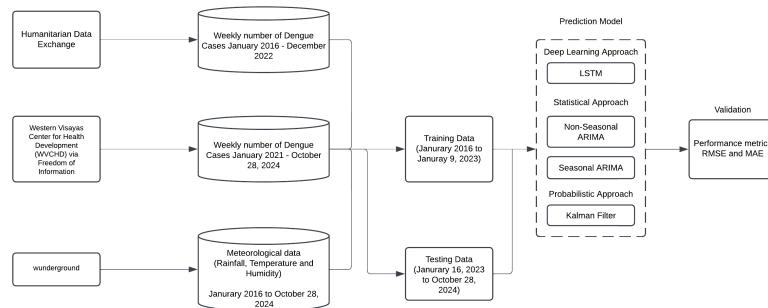


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

## 448 3.1 Research Activities

### **449 3.1.1 Dengue and Climate Data Collection**

## 450 Acquisition of Dengue Case Data

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

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

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

466

467 **Data Fields**

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

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

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

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

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

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

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

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

**484 Data Integration and Preprocessing**

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

**492 Exploratory Data Analysis (EDA)**

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

**498 3.1.2 Develop and Evaluate Deep Learning Models for  
499 Dengue Case Forecasting**

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

504 for preparing and training the model are outlined below.

505 **Data Preprocessing**

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

512 **LSTM Model**

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

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

520 To prepare the data for LSTM, a sliding window approach was utilized. Se-  
521 quences of weeks of normalized features were constructed as input, while the  
522 dengue case count for the subsequent week was set as the target variable. This  
523 approach ensured that the model leveraged temporal dependencies in the data for

524 forecasting. To enhance the performance of the LSTM model in predicting dengue  
525 cases, Bayesian Optimization was employed using the Keras Tuner library. The  
526 tuning process aimed to minimize the validation loss (mean squared error) by  
527 adjusting key model hyper-parameters. The search space is summarized below:

528 **LSTM units:**

- 529     ● min value: 32  
530     ● max value: 128  
531     ● step: 16  
532     ● sampling: linear

533 **Learning Rate:**

- 534     ● min value: 0.0001  
535     ● max value: 0.01  
536     ● step: None  
537     ● sampling: log

538 The tuner was instantiated with:

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

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

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

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

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

**563 ARIMA**

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

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

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

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

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

**585 Seasonal ARIMA (SARIMA)**

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

**604 Kalman Filter:**

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

608        20% testing to evaluate model performance.

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

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

625        **Model Simulation:**

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

631 **3.1.3 Integrate the Predictive Model into a Web-Based**  
632 **Data Analytics Dashboard**

633 **Dashboard Design and Development**

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

638 **Model Integration and Deployment**

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

641 **3.1.4 System Development Framework**

642 The Agile Model is the birthchild of both iterative and incremental approaches

643 in Software Engineering. It aims to be flexible and effective at the same time by

644 being adaptable to change. It's also important to note that small teams looking

645 to construct and develop projects quickly can benefit from this kind of method-

646 ology. As the Agile Method focuses on continuous testing, quality assurance is a

647 guarantee since bugs and errors are quickly identified and patched.

**648 Design and Development**

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

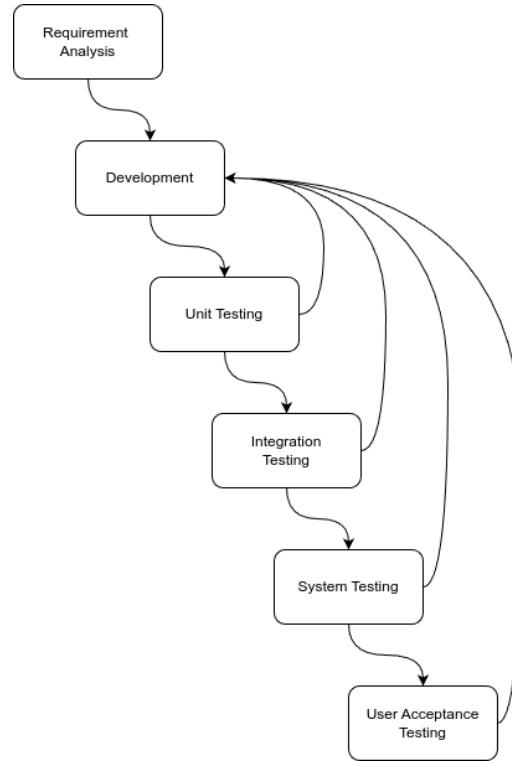
662 **Testing and Integration**

Figure 3.2: Testing Process for DengueWatch

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

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

## 3.2 Development Tools

### 3.2.1 Software

#### Github

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

#### Visual Studio Code

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

**691 Django**

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

**700 Next.js**

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

**707 Postman**

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

<sup>712</sup> Postman? Postman API Platform, n.d.).

### <sup>713</sup> 3.2.2 Hardware

<sup>714</sup> The web application was developed on laptop computers with minimum specifications of an 11th-generation Intel i5 CPU and 16 gigabytes of RAM. Furthermore,  
<sup>715</sup> an RTX 3060 mobile GPU was also utilized to retrain the integrated model locally.  
<sup>716</sup>

### <sup>717</sup> 3.2.3 Packages

#### <sup>718</sup> Django REST Framework

<sup>719</sup> Django Rest Framework (DRF) is a third-party package for Django that provides a  
<sup>720</sup> comprehensive suite of features to simplify the development of robust and scalable  
<sup>721</sup> Web APIs (Christie, n.d.). These services include Serialization, Authentication  
<sup>722</sup> and Permissions, Viewsets and Routers, and a Browsable API .

#### <sup>723</sup> Leaflet

<sup>724</sup> One of the features of the web application is the ability to map the number  
<sup>725</sup> of cases using a Choropleth Map. Leaflet is the only free, open-sourced, and  
<sup>726</sup> most importantly, stable JavaScript package that can do the job. With its ultra-  
<sup>727</sup> lightweight size, it offers a comprehensive set of features that does not trade  
<sup>728</sup> off performance and usability (*Leaflet — an open-source JavaScript library for*  
<sup>729</sup> *interactive maps*, n.d.).

**730 Chart.js**

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

**738 Tailwind CSS**

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

**747 Shadcn**

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

<sup>751</sup> styling. Since this is built on top of Tailwind CSS and Radix UI, it is supported  
<sup>752</sup> by most modern frontend frameworks, including Next.js (Shadcn, n.d.).

<sup>753</sup> **Zod**

<sup>754</sup> Data validation is integral in this web application since it will handle crucial data  
<sup>755</sup> that will be used for analytical inferences and observations. Since Zod is primarily  
<sup>756</sup> used for validating and parsing data, it ensures proper communication between  
<sup>757</sup> the client and the server (Zod, n.d.).

<sup>758</sup> **3.3 Application Requirements**

<sup>759</sup> **3.3.1 Backend Requirements**

<sup>760</sup> **Database Structure Design**

<sup>761</sup> Determining how data flows and how it would be structured is crucial in creating  
<sup>762</sup> the system as it defines how extendible and flexible it would be for future features  
<sup>763</sup> and updates. Thus, creating a comprehensive map of data ensures proper nor-  
<sup>764</sup> malization that eliminates data redundancy and improves data integrity. Figure  
<sup>765</sup> 3.3 depicts the designed database schema that showcases the relationship between  
<sup>766</sup> the application's entities.

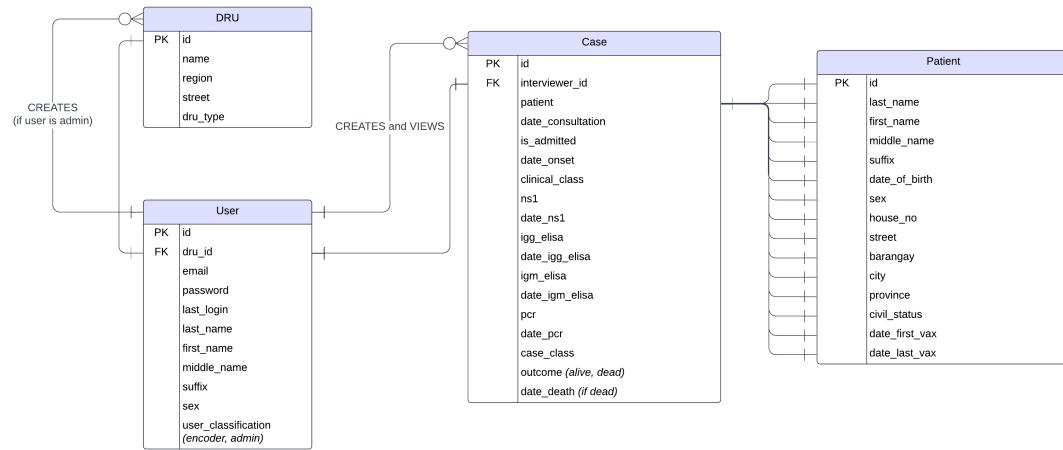


Figure 3.3: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

<sup>767</sup> **3.3.2 User Interface Requirements**

<sup>768</sup> **Admin Interface**

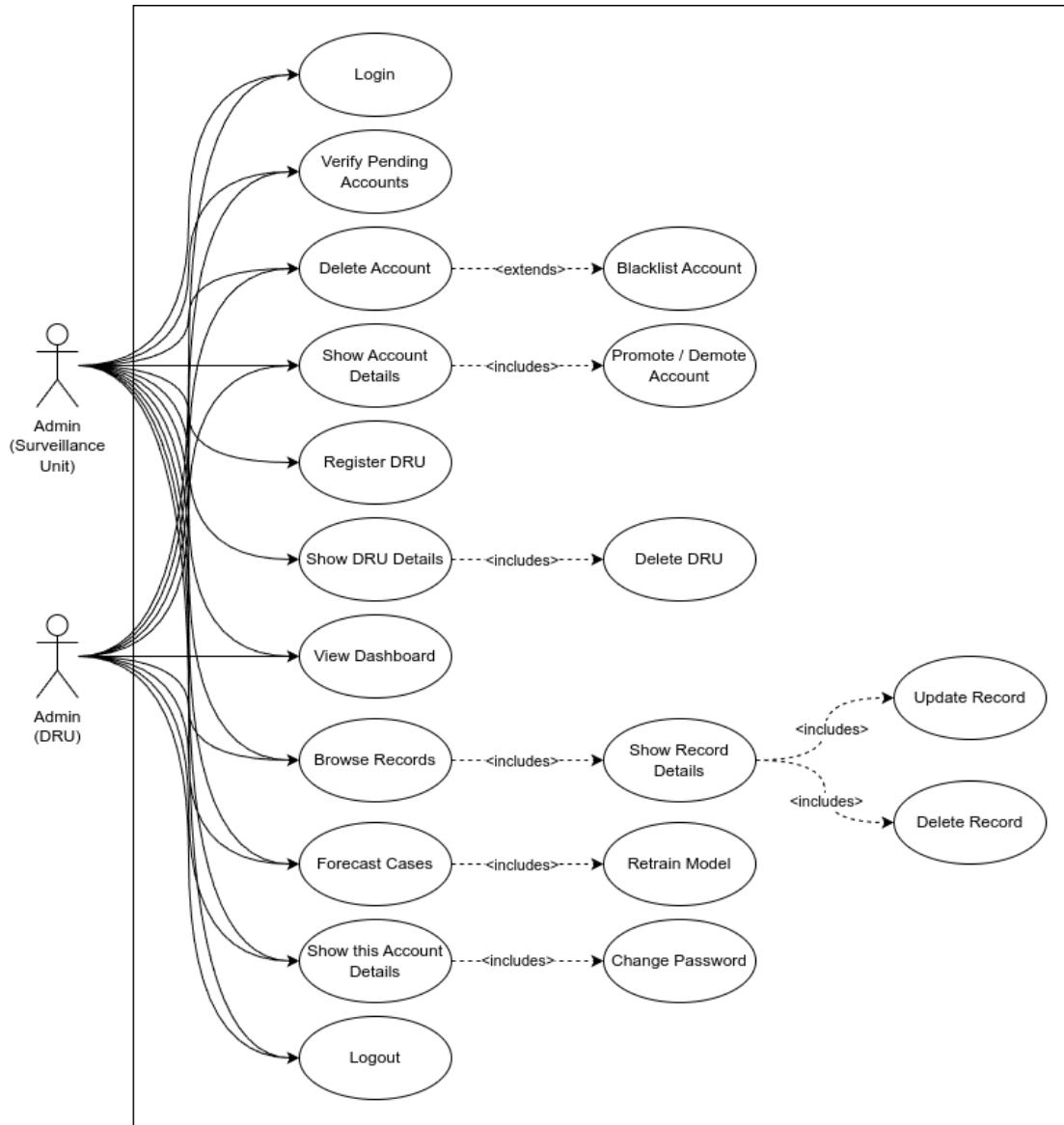


Figure 3.4: Use Case Diagram for Admins

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

<sup>779</sup> **Encoder Interface**

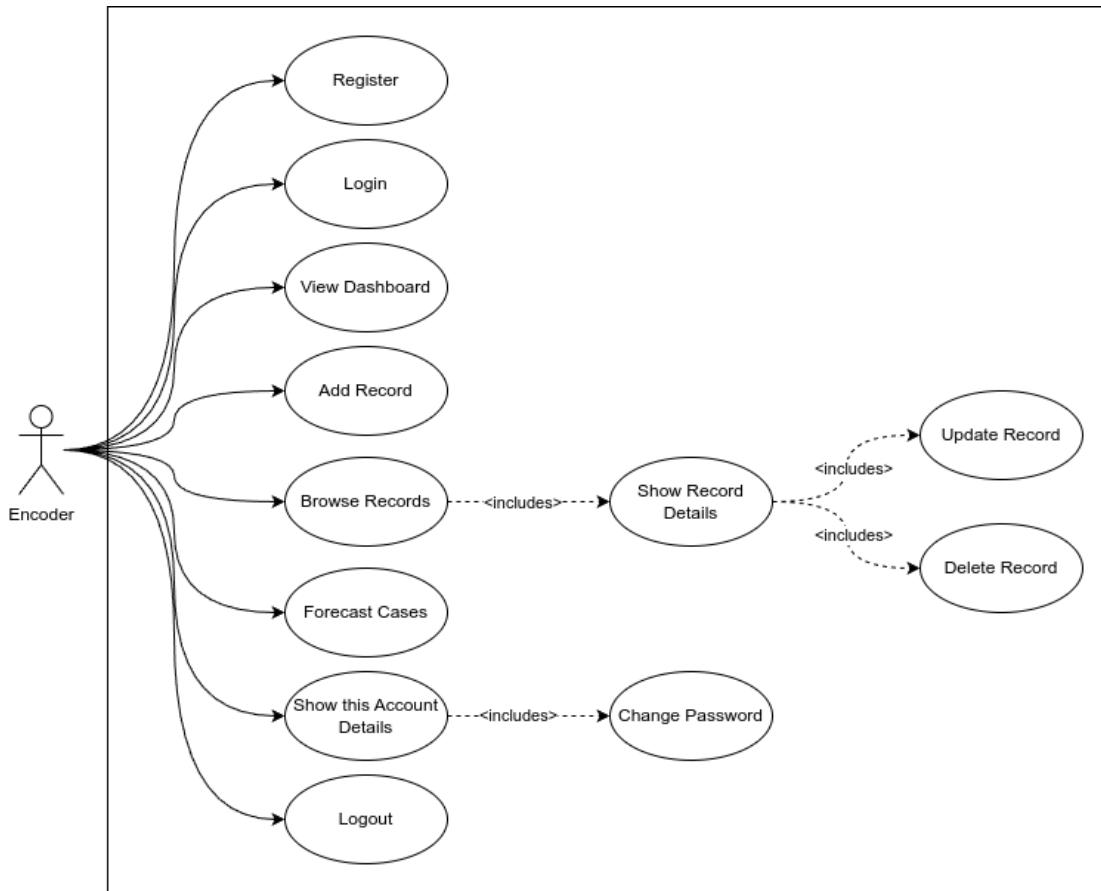


Figure 3.5: Use Case Diagram for Encoder

<sup>780</sup> Figure 3.5, on the other hand, illustrates the use cases for the system's primary  
<sup>781</sup> users. These users can register but must wait for further verification to access the  
<sup>782</sup> application. Similar to the previous interfaces, encoders can browse and manage  
<sup>783</sup> records, as well as forecast the consolidated cases under a specific surveillance or  
<sup>784</sup> disease reporting unit, but they are not allowed to retrain the model. Lastly, they  
<sup>785</sup> are the only type of user that can file and create dengue cases by filling out a form  
<sup>786</sup> with the required details.

**787 3.3.3 Security and Validation Requirements****788 Password Encryption**

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

**797 Authentication**

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

**803 Data Validation**

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

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

812 **Chapter 4**

813 **Results and Discussion**

814 **4.1 Data Gathering**

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

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

826     2. Weather Data: Weekly weather data was obtained by web scraping from  
 827     Weather Underground, allowing access to rainfall, temperature, wind, and  
 828     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	23.8888900	11.39	86.242857	5
1	2011-01-10	8.587143	30.000000	26.705556	24.444444	7.32	88.028571	4
2	2011-01-17	5.338571	30.000000	26.616667	25.000000	7.55	84.028571	2
3	2011-01-24	5.410000	30.555556	26.483333	20.555556	10.67	80.971429	7
4	2011-01-31	2.914286	28.333333	25.283333	18.650000	11.01	74.885714	2

Figure 4.1: Snippet of the Combined Dataset

## 829 4.2 Exploratory Data Analysis

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

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

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

Figure 4.2: Data Contents

838 From the statistics in Figure 4.3, the number of cases ranges from 0 to 319.  
 839 The average number of dengue cases per week is 23.74, with a median of 12 cases  
 840 and a standard deviation of 37.14. The distribution is highly skewed, with some  
 841 weeks experiencing significant number of cases (up to 319 cases). Rainfall shows  
 842 a wide variation (0 to 445mm), while temperature remains relatively stable, with  
 843 an average of 28.1 degree celsius. Humidity levels ranges from 73% to 89% with  
 844 a mean of 81.6%.

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

Figure 4.3: Summary Statistics for the Aggregated Dataset

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

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

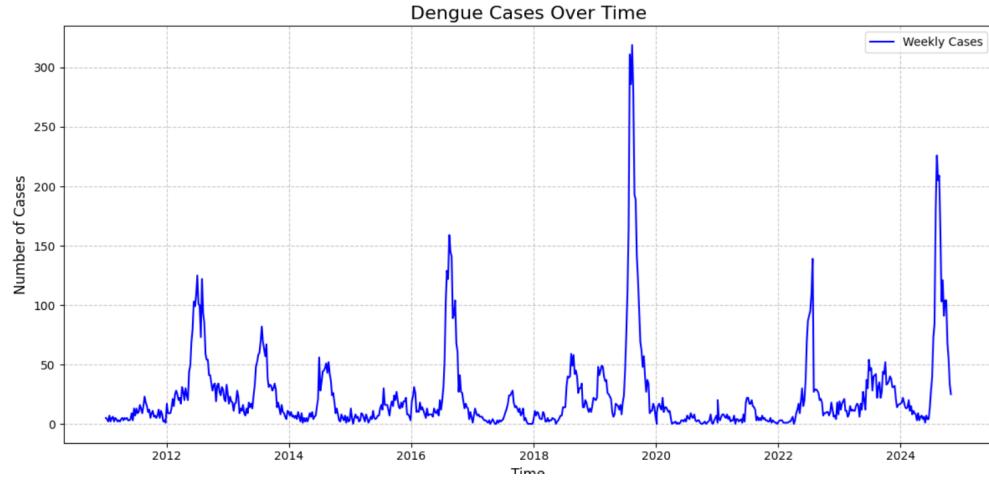


Figure 4.4: Trend of Dengue Cases

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

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

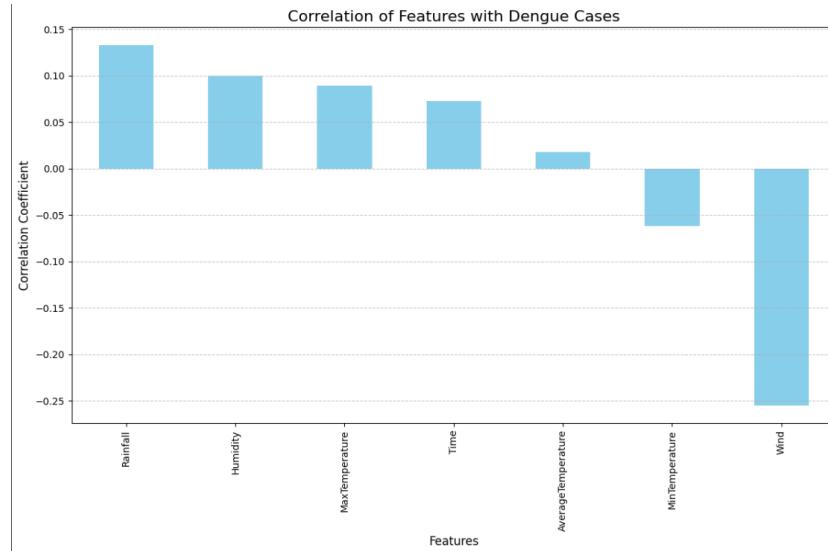


Figure 4.5: Ranking of Correlations

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

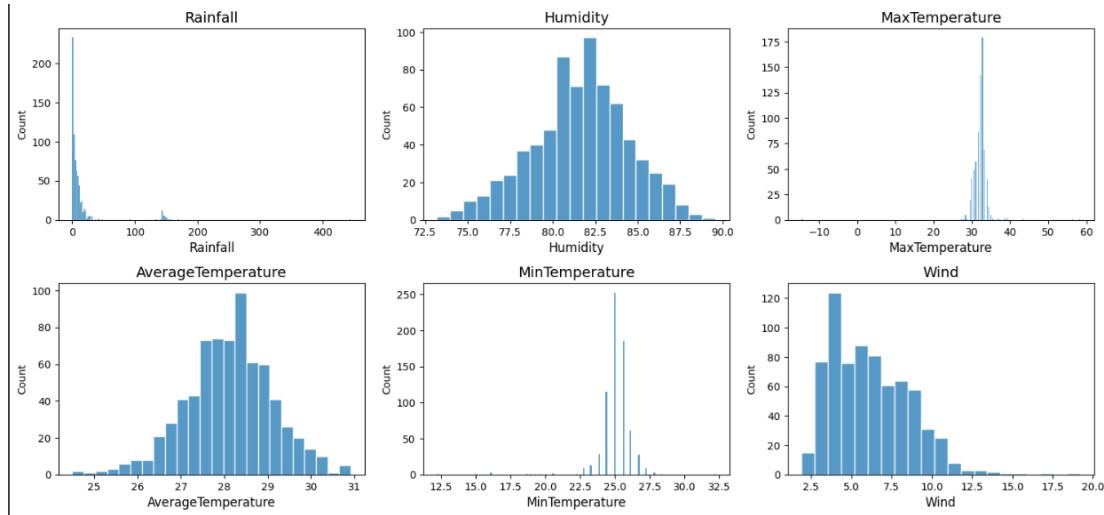


Figure 4.6: Pre-Transform Feature Distributions

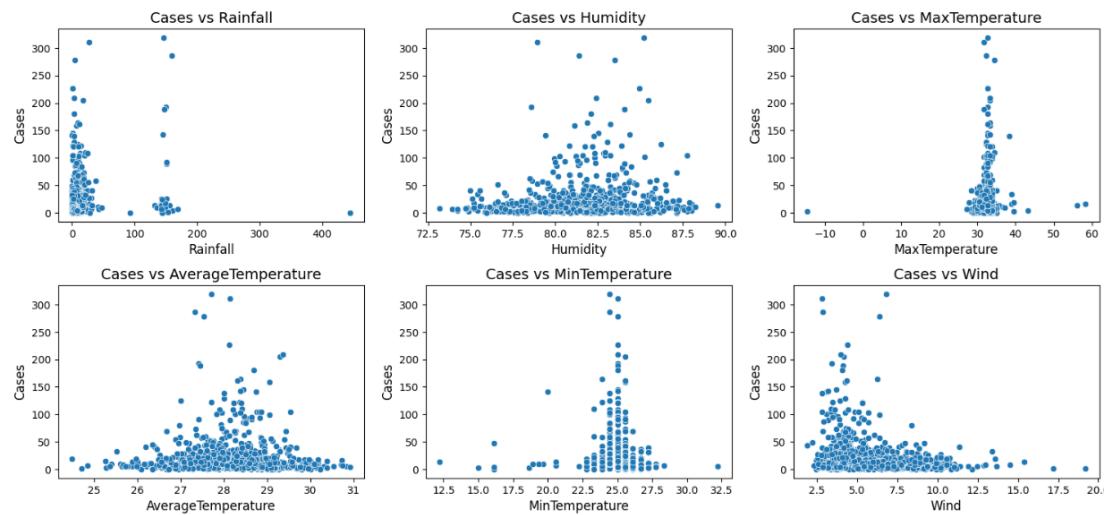


Figure 4.7: Pre-Transform Scatterplots

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

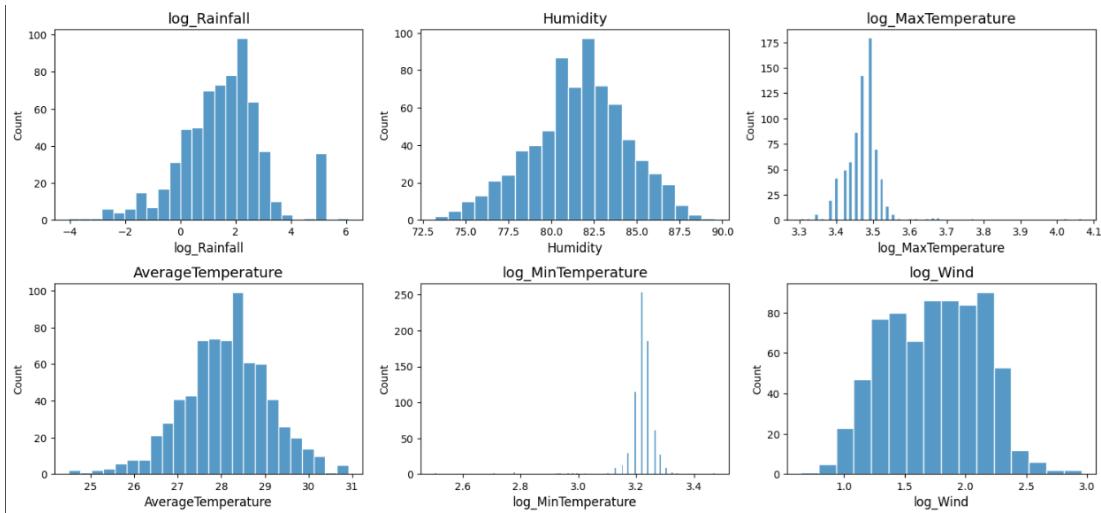


Figure 4.8: Post-Transform Feature Distributions

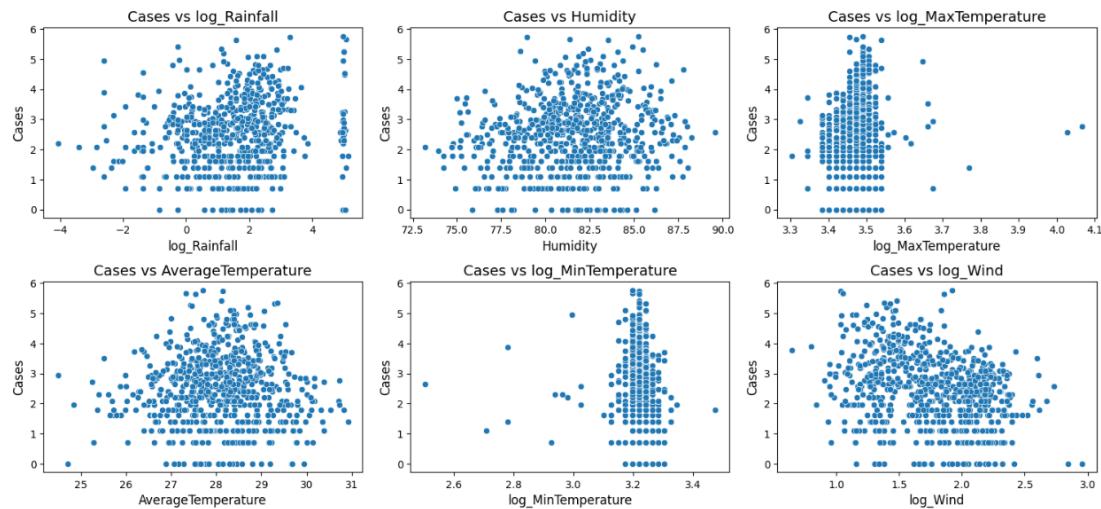


Figure 4.9: Transformed Distributions: Scatterplots

876 Figure 4.10 presents the recomputed correlation coefficients between dengue

cases and the log-transformed weather features. Rainfall shows the strongest correlation at 0.16, followed by Max Temperature at 0.12, and Humidity at 0.10. While other features are included, their correlation values are very small. Although the individual correlations are weak, they provide valuable signals that, when combined in a multivariate model, may contribute meaningfully to predictive performance., As a result, Rainfall, Max Temperature, and Humidity are selected as the key features for model training.

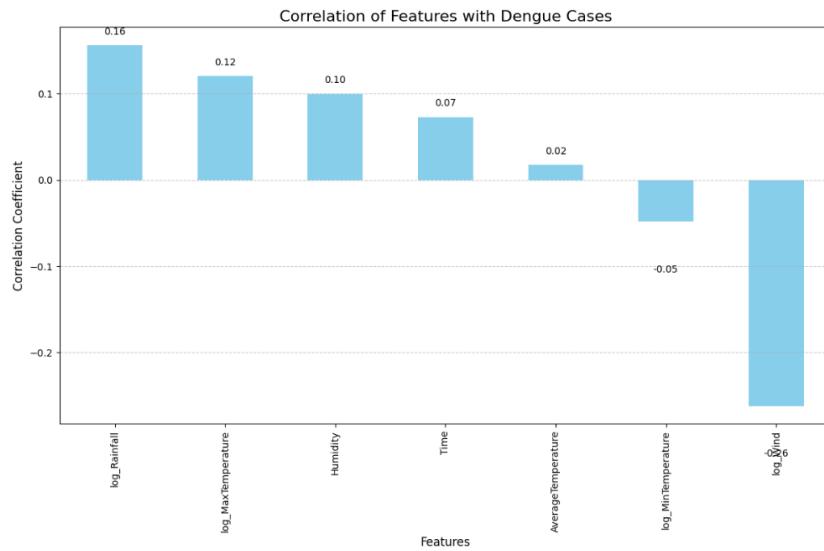


Figure 4.10: Ranking of Correlations with New Distributions

### 4.3 Model Training Results

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

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

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

Table 4.1: Comparison of different models for dengue prediction

### 893 4.3.1 LSTM Model

894 The LSTM model was tuned for the following parameters: learning rate and units.  
 895 The hyperparameter tuning was conducted for each window size, finding the best  
 896 parameters for each window size. Further evaluating which window size is most  
 897 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

898  
 899 The results indicate that a window size of 5 weeks provides the most accurate  
 900 predictions, as evidenced by the lowest MSE and RMSE values. Furthermore, the  
 901 R<sup>2</sup> score of 0.83 indicates that 83% of the variability in the target variable (cases)  
 902 is explained by the independent variables (the inputs) in the model, making it a  
 903 reliable configuration overall.

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

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

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

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

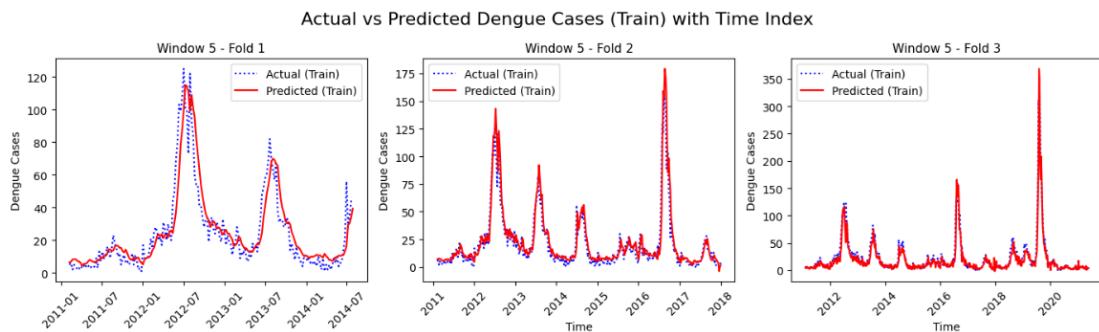


Figure 4.11: Training Folds - Window Size 5

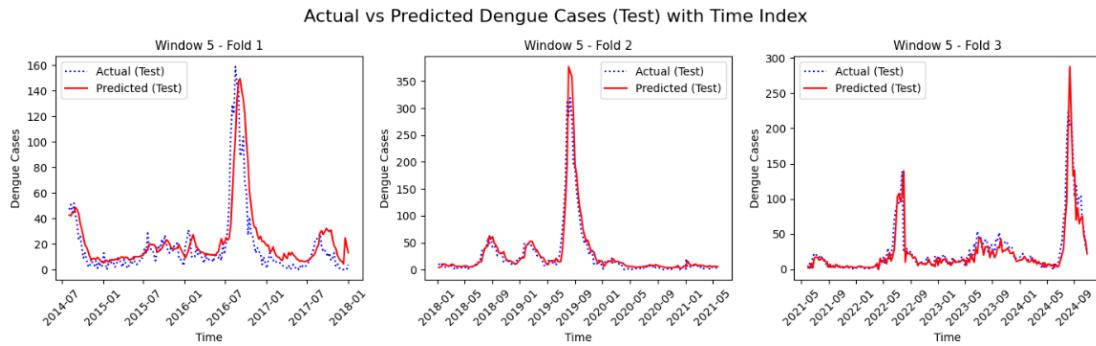


Figure 4.12: Testing Folds - Window Size 5

### 917 4.3.2 ARIMA Model

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

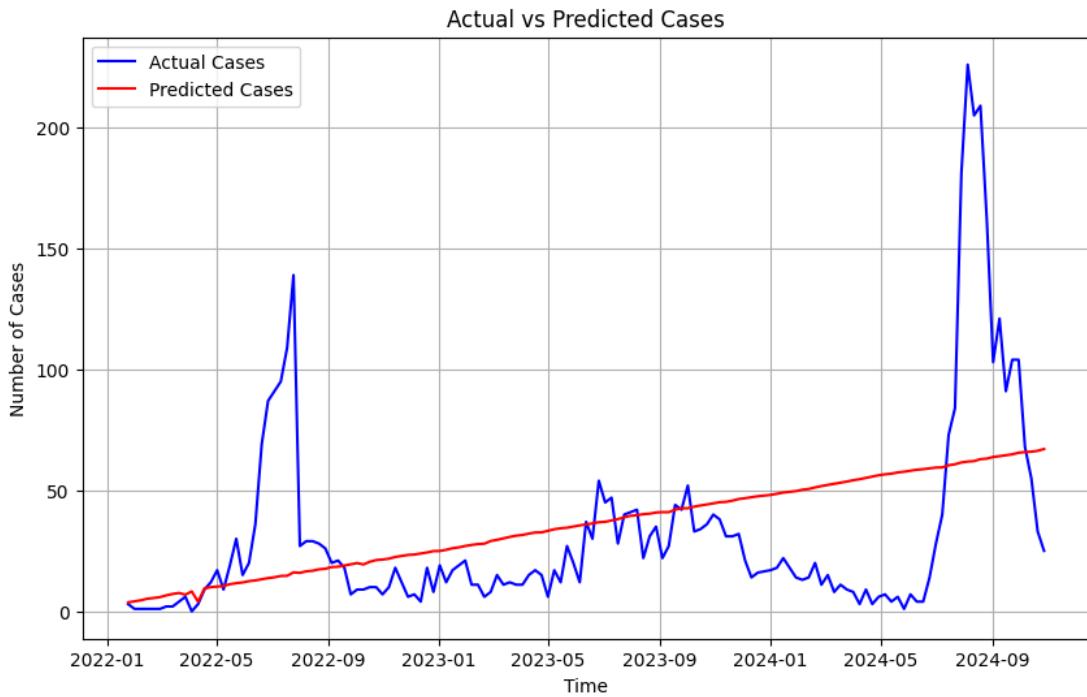


Figure 4.13: ARIMA Prediction Results for Test Set

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

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

### 932        4.3.3 Seasonal ARIMA (SARIMA) Model

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

935 data.

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

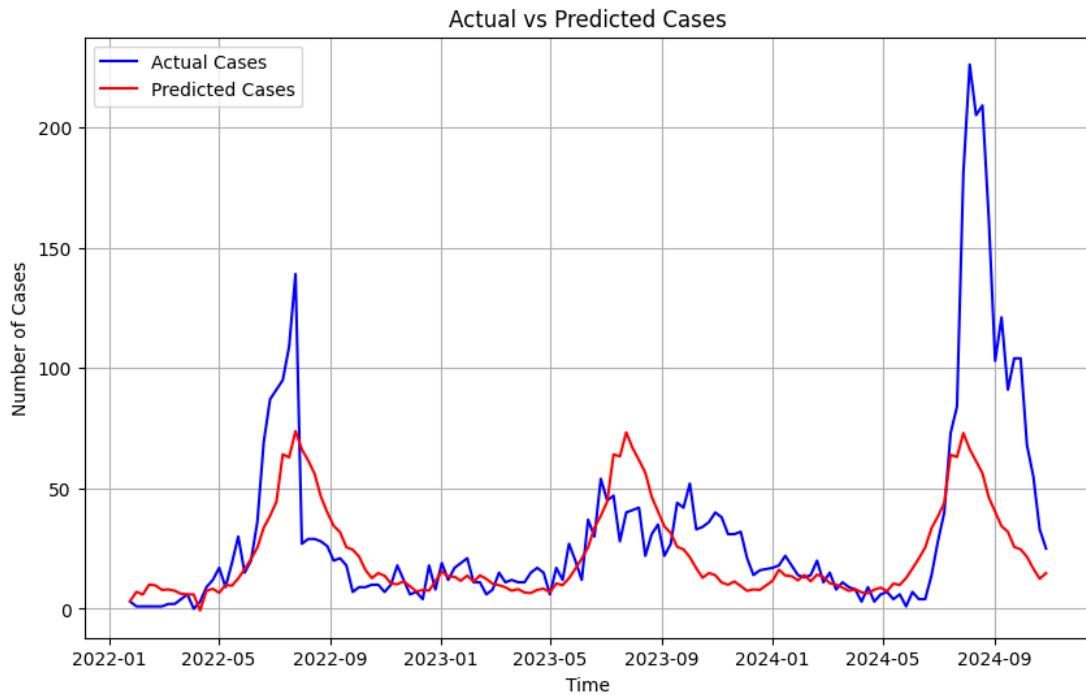


Figure 4.14: Seasonal ARIMA Prediction Results for Test Set

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

945        • **MSE:** 1109.69

946        • **RMSE:** 33.31

947        • **MAE:** 18.09

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

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

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

Table 4.4: Comparison of SARIMA performance for each fold

#### 958    4.3.4   Kalman Filter Model

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

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

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

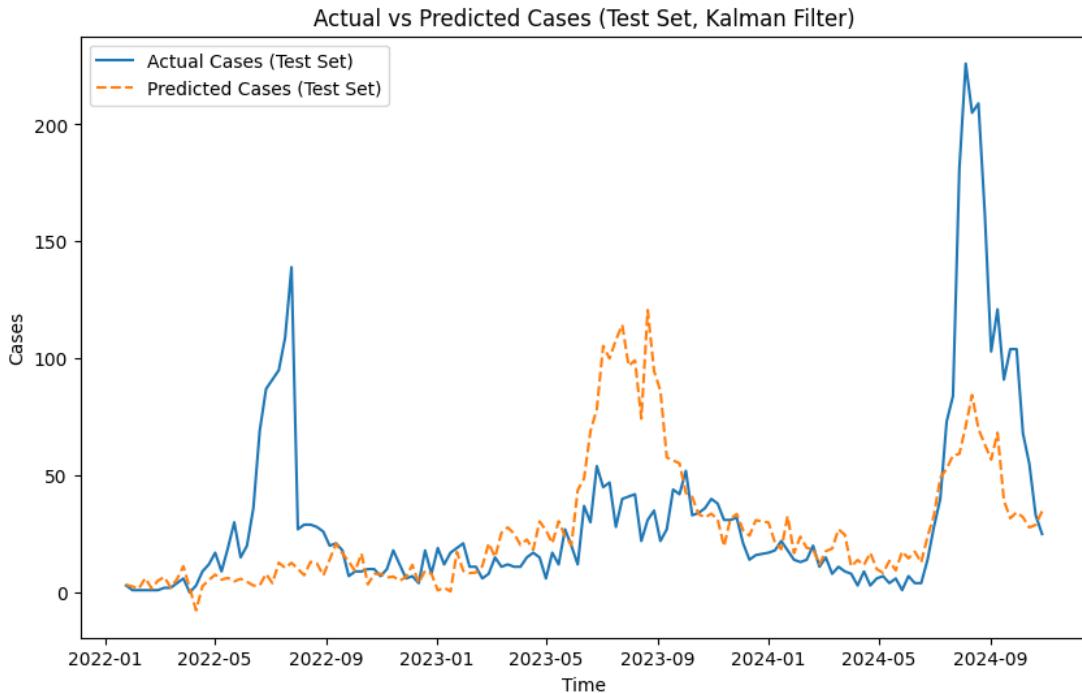


Figure 4.15: Kalman Filter Prediction Results for Test Set

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

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

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

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

## 974 4.4 Model Simulation

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

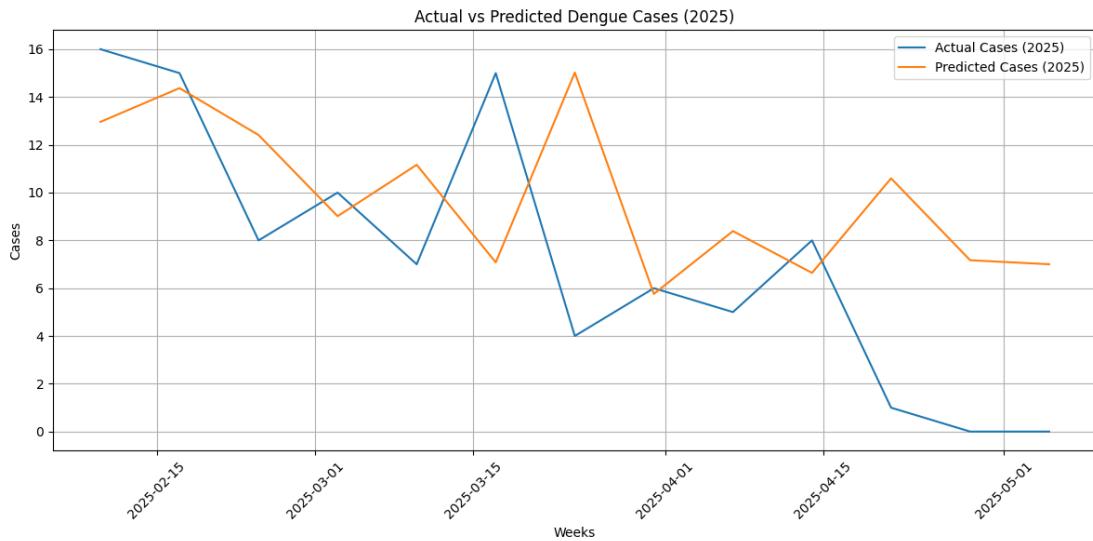


Figure 4.16: Predicted vs Actual Dengue Cases 2025

## 985 4.5 System Prototype

### 986 4.5.1 Home Page

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

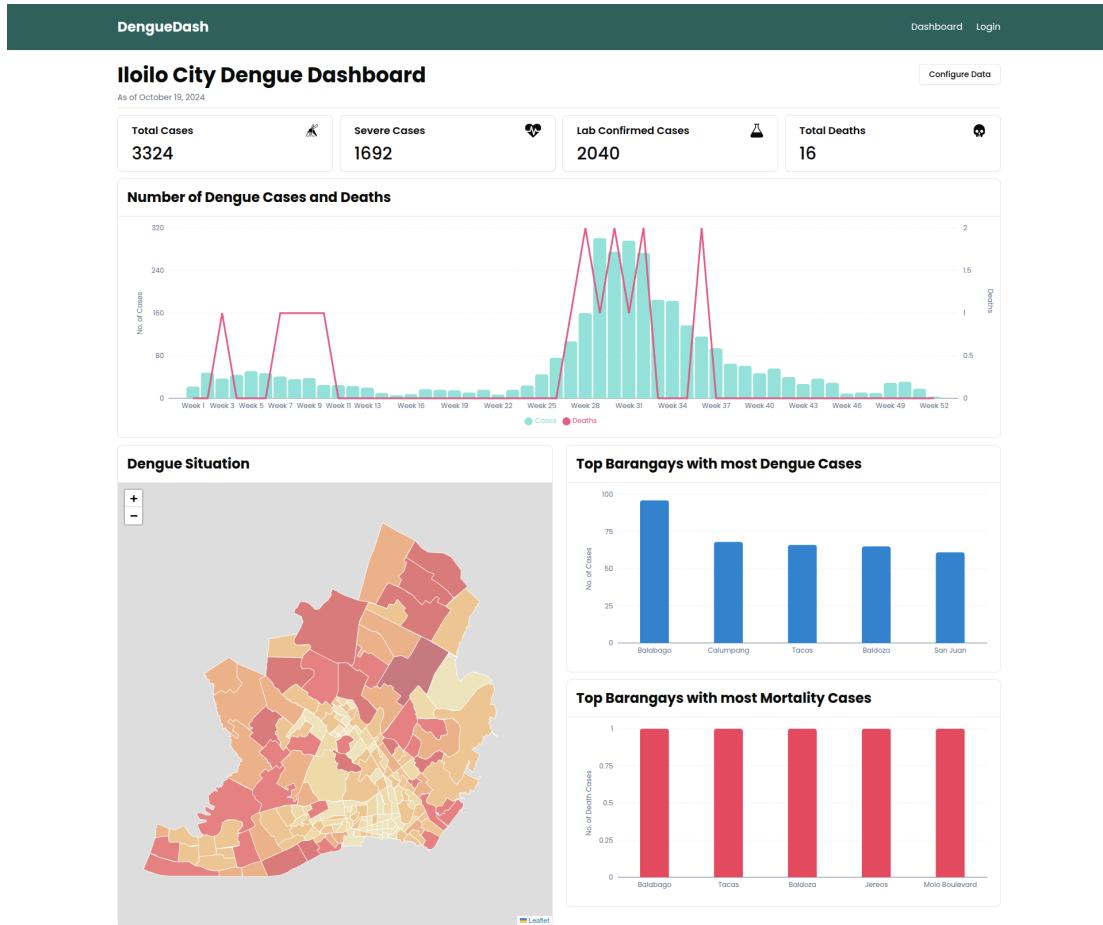


Figure 4.17: Home Page

#### 4.5.2 User Registration, Login, and Authentication

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

1001 the user can log in to the system through the page shown in Figure 4.19. After  
1002 entering the correct credentials, which consist of an email and password, the  
1003 system uses HTTP-only cookies containing JSON Web Tokens (JWT) to prevent  
1004 vulnerability to Cross-site Scripting (XSS) attacks. It will then proceed to the  
1005 appropriate page for the type of user it belongs to. Logging out on the other  
1006 hand, will remove both the access and refresh tokens from the browser, and will  
1007 blacklist the latter token to make it unusable for security purposes.

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

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

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

Figure 4.18: Sign Up Page

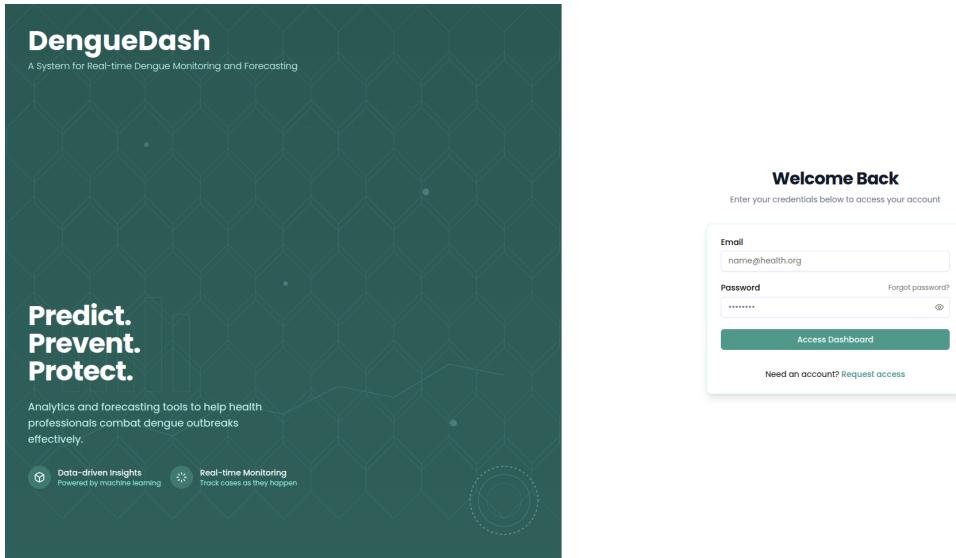


Figure 4.19: Login Page

### 1008 4.5.3 Encoder Interface

#### 1009 Case Report Form

1010 Figures 4.20 and 4.21 show the digitized counterpart of the form obtained from the  
1011 Iloilo Provincial Epidemiology and Surveillance Unit. As the system aims to sup-  
1012 port expandability for future features, some fields were modified to accommodate  
1013 more detailed input. It is worth noting that all of the included fields adhere to the  
1014 latest Philippine Integrated Disease and Surveillance Response (PIDS) Dengue  
1015 Forms, which the referenced form was based on. By doing this, if implemented  
1016 on a national scale, the transition between targeted users will be easier. More-  
1017 over, the case form includes the patient's basic information, dengue vaccination  
1018 status, consultation details, laboratory results, and the outcome. On the other  
1019 hand, encoders can also create case records using a "bulk upload" feature that

1020 makes use of a formatted CSV file template. As shown in Figure 4.22, an encoder  
1021 can download the template using the "Download Template" button, and insert  
1022 multiple records inside the file, then upload it by clicking the "Click to upload"  
1023 button. The web application automatically checks the file for data inconsistencies  
1024 and validation.

The screenshot shows the 'Case Report Form' page within the 'DengueDash' application. The left sidebar displays navigation links for 'Analytics', 'Forms' (selected), and 'Data Tables'. The main content area is titled 'Case Report Form' and contains three tabs: 'Personal Information' (selected), 'Clinical Status', and 'Vaccination'. The 'Personal Information' tab includes sections for 'Personal Detail' (with fields for First Name, Middle Name, Last Name, Suffix, Sex, Date of Birth, and Civil Status), 'Address' (with fields for Region, Province, City, Barangay, Street, and House No.), and 'Vaccination' (with fields for Date of First Vaccination and Date of Last Vaccination). A 'Bulk Upload' button is located at the top right of the form area. On the far left, a user profile is visible: CN Charles Larson Griffin, bakerwendy@example.com.

Figure 4.20: First Part of Case Report Form

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

Figure 4.21: Second Part of Case Report Form

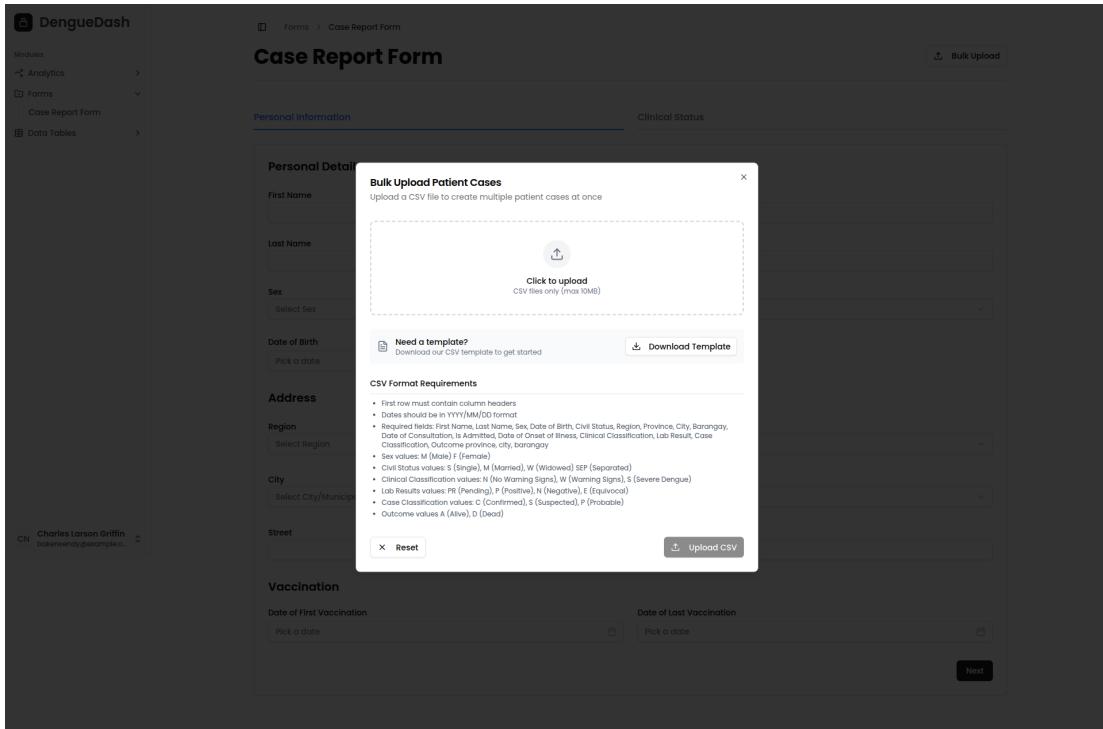


Figure 4.22: Bulk Upload of Cases using CSV

### 1025 Browsing, Update, and Deletion of Records

1026 Once the data generated from the case report form or the bulk upload is validated,  
 1027 it will be assigned as a new case and can be accessed through the Dengue Reports  
 1028 page, as shown in Figure 4.23. The said page displays basic information about  
 1029 the patient related to a specific case, including their name, address, date of con-  
 1030 sultation, and clinical and case classifications. It is also worth noting that it only  
 1031 shows cases that the user is permitted to view. For example, in a local Disease  
 1032 Reporting Unit (DRU) setting, the user can only access records that belong to  
 1033 the same DRU. On the other hand, in a consolidated surveillance unit such as a  
 1034 regional, provincial, or city quarter, its users can view all the records from all the

1035 DRUs that report to them. In addition, the user can also search for a case using  
 1036 the name, location, date of consultation, or classifications that are associated with  
 1037 the specific query, making it easier to find pertinent information quickly and effi-  
 1038 ciently. Moving forward, Figure 4.24 shows the detailed case report of the patient  
 1039 on a particular consultation date.

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

< Previous 1 2 ... 712 Next >

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

Figure 4.23: Dengue Reports

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

**Personal Information:**

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

**Vaccination Status:**

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

**Case Record #25016448:**

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

**Laboratory Results:**

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

**Outcome:**

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

**Interviewer:**

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

Figure 4.24: Detailed Case Report

1040 To update the case, the user can click the "Update Case" button, where a  
 1041 dialog will appear, and the updateable fields will be shown. It is worth noting  
 1042 that in this case, only fields under Laboratory Results and Outcome are included  
 1043 since they are the only ones that are time-based, where the result may change  
 1044 in the future. After updating, a prompt will show confirming the user's action.  
 1045 Moving forward, to delete a case record, the user must click the "Delete Case"  
 1046 button, and a prompt verifying the action will appear. After confirming, the case

1047 will be deleted permanently.

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

Figure 4.25: Update Report Dialog

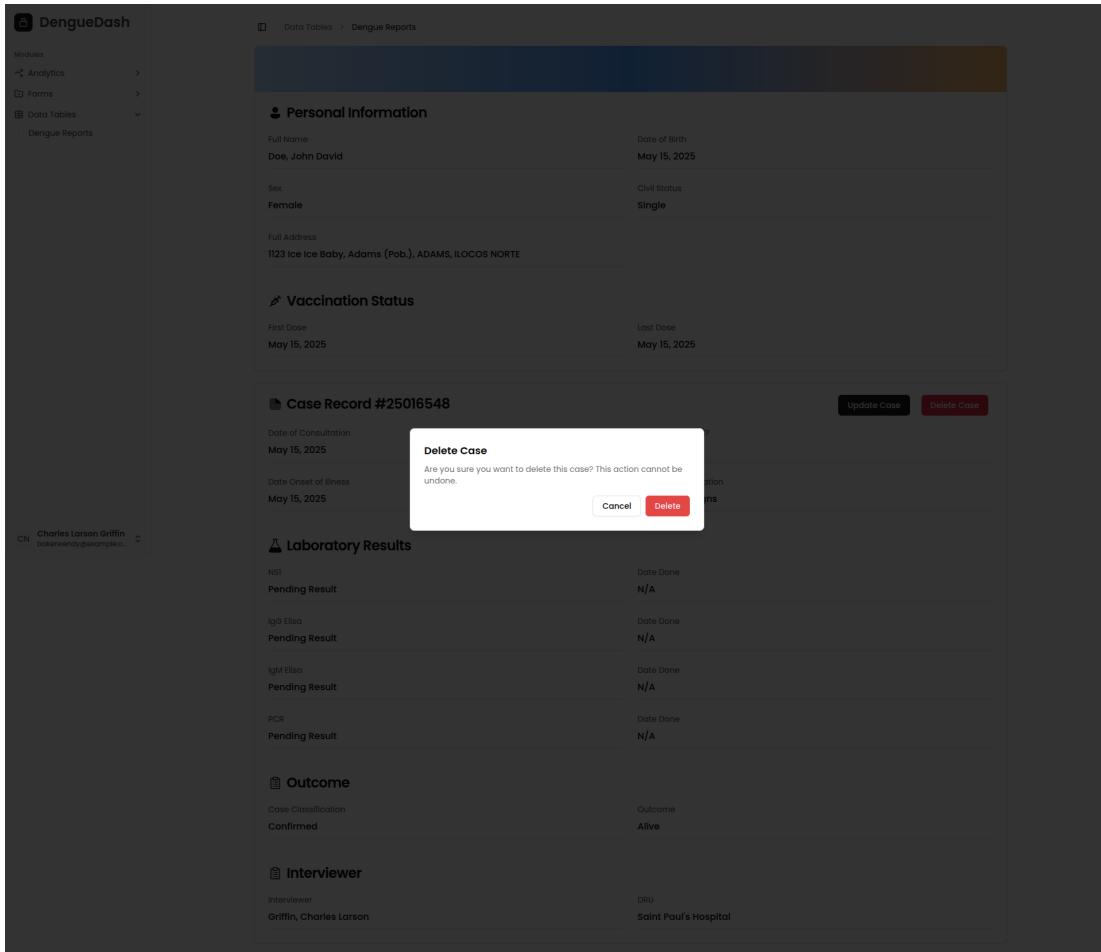


Figure 4.26: Delete Report Alert Dialog

1048 **Forecasting**

1049 The piece de resistance of the web application's feature is the Forecasting Page.  
 1050 This is where users can forecast dengue cases for the next few weeks. To predict,  
 1051 the application utilizes the exported LSTM model in a Keras format derived from  
 1052 training the consolidated data from the database. The said file stores the model's  
 1053 architecture and the learned parameters, which include the weights and biases, so  
 1054 that it can predict cases without training the data again. Furthermore, it requires

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

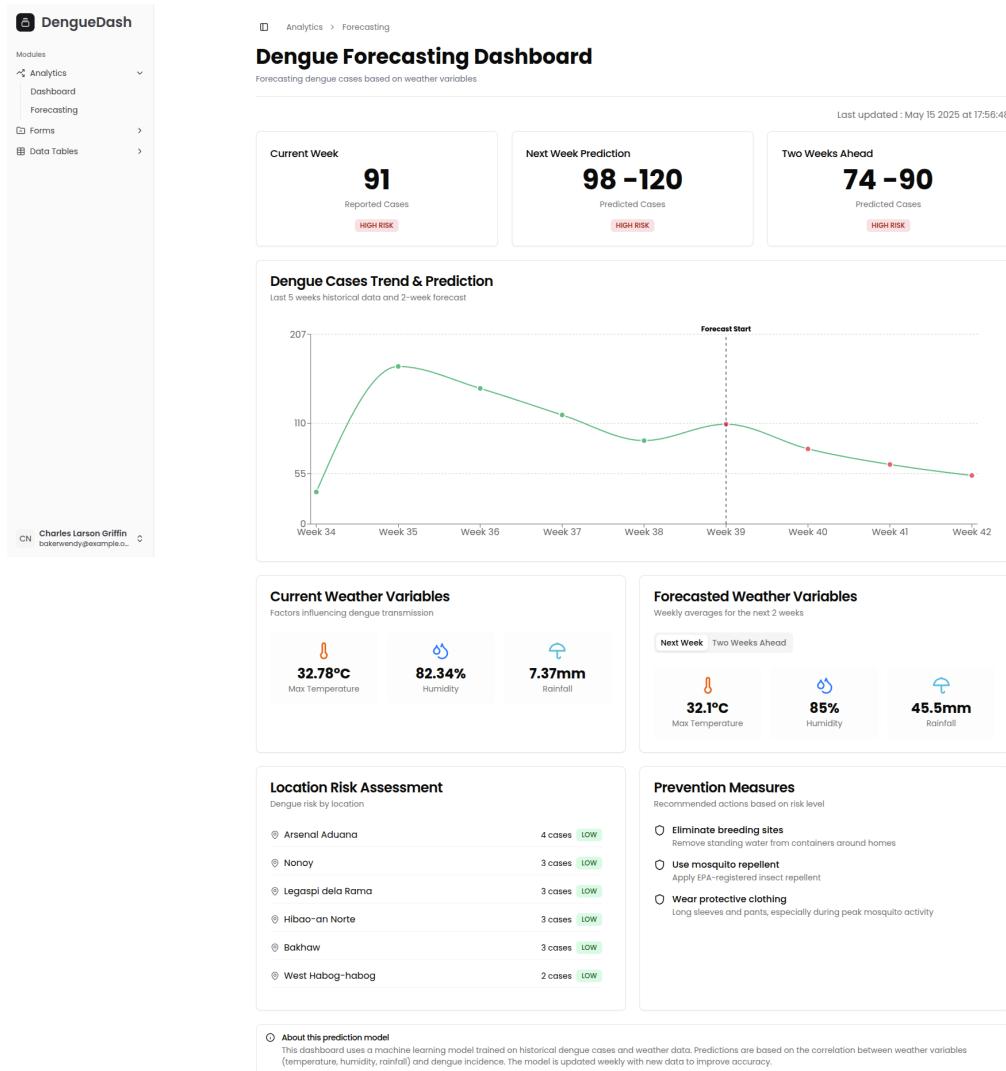


Figure 4.27: Forecasting Page

#### 1067 4.5.4 Admin Interface

#### 1068 Retraining

1069 With LSTM being the best-performing model among the models used in forecast-  
 1070 ing dengue cases, it is the model chosen to power the prediction and retraining

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

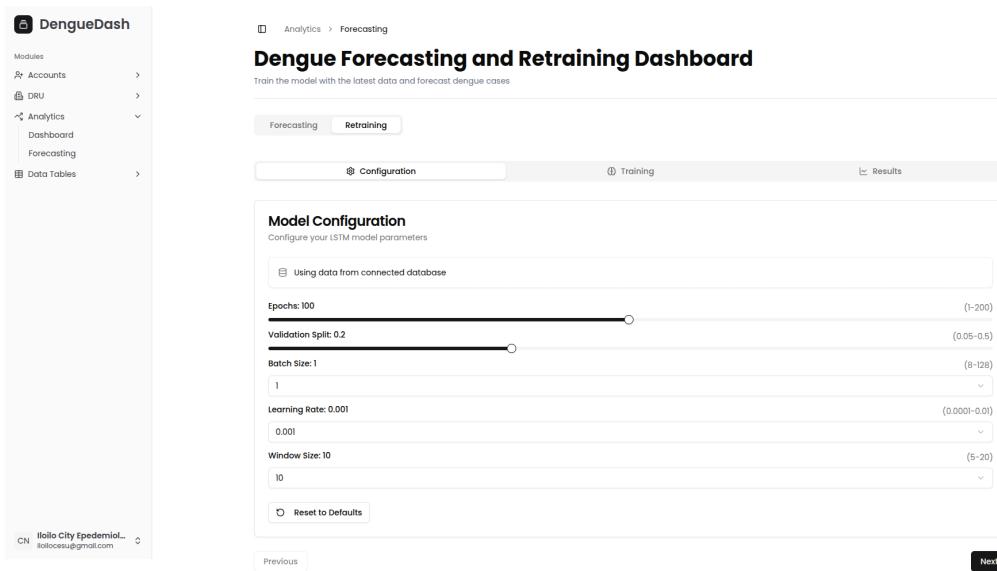


Figure 4.28: Retraining Configurations

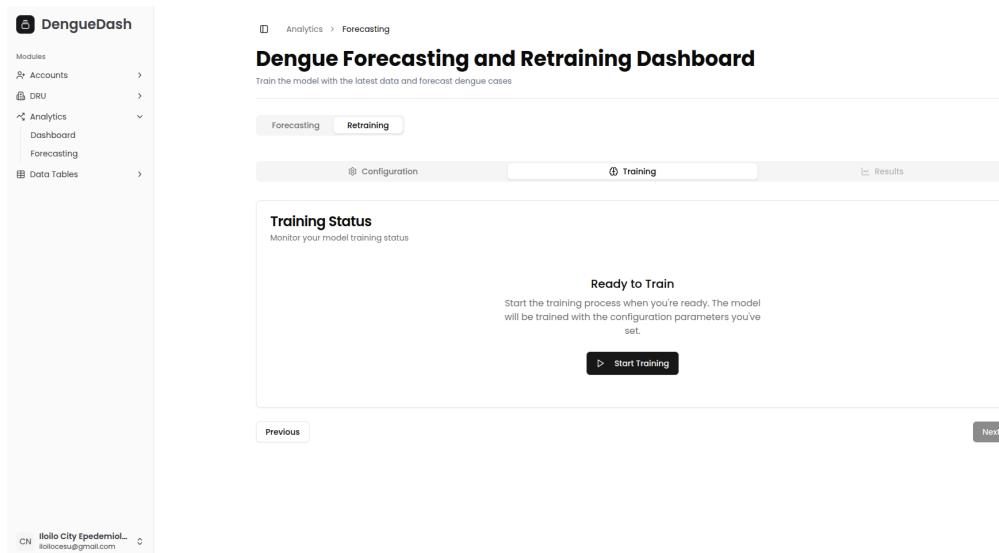


Figure 4.29: Start Retraining

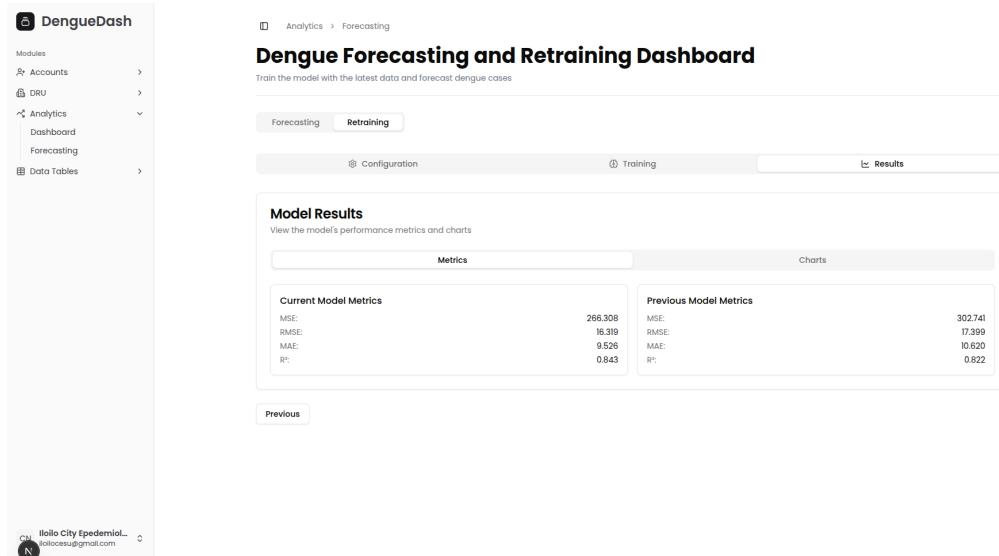


Figure 4.30: Retraining Results

**1081 Managing Accounts**

1082 Proper management of accounts is important to protect the integrity and confi-  
1083 dentiality of data. Thus, it is crucial for administrators to track their users and  
1084 control the flow of information. As discussed in the user registration of encoders,  
1085 admin users from a specific DRU or surveillance unit have the power to grant  
1086 them access to the web application. Figure 4.32 illustrates the interface for this  
1087 scenario, as the admins can approve or reject their applications. Once approved,  
1088 these users can access the features given to encoders and may be promoted to  
1089 have administrative access, as shown in Figure 4.33. The same figure also shows  
1090 the expanded details of the user, which include personal information and brief  
1091 activity details within the system. When deleting an account, the user’s email  
1092 will be blacklisted and illegible to use when creating another account, and all the  
1093 cases reported by this user will be soft-deleted. However, the blacklist status can  
1094 be reverted by clicking the ”Unban” button, which would make the user of the  
1095 email be able to register to the web application again as shown in Figure 4.34.

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

Figure 4.31: List of Verified Accounts

The screenshot shows the DengueDash application interface. The sidebar is identical to Figure 4.31, with 'Modules' and 'Accounts' selected. At the bottom of the sidebar, it says 'CN Saint Paul's Hospital' and 'saintpaul@gmail.com'. The main content area has a header 'Accounts > Manage' and 'Manage Accounts'. It says 'View and manage registered and pending accounts'. Below this is a navigation bar with tabs: 'Verified', 'Pending' (selected), and 'Blacklisted'. A table follows, with columns: Name, Email, Sex, Created At, and Actions. One row is shown: John David Doe, testereee@example.gov.ph, Male, 2025-05-15, with 'Approve' and 'Delete' buttons in the Actions column. The table has a light gray border.

Figure 4.32: List of Pending Accounts

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

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

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

Figure 4.33: Account Details

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

Figure 4.34: List of Blacklisted Accounts

## 1096 Managing DRUs

1097 Unlike the registration of encoder accounts, the creation of Disease Reporting  
 1098 Units can only be done within the web application, and the user performing the  
 1099 creation must be an administrator of a surveillance unit. Figure 4.35 presents the  
 1100 fields the admin user must fill out, and once completed, the new entry will show  
 1101 as being managed by that unit, as shown in Figure 4.36. Figure 4.37, on the other  
 1102 hand, shows the details provided in the registration form as well as its creation  
 1103 details. There is also an option to delete the DRU, and when invoked, all the  
 1104 accounts being managed by it, and the cases reported under those accounts will  
 1105 be soft-deleted.

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

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

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

Figure 4.35: Disease Reporting Unit Registration

**DengueDash**

Modules

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

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

**Manage Disease Reporting Units**

View and manage Disease Reporting Units

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

Figure 4.36: List of Disease Reporting Units

**DengueDash**

Modules

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

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

**Disease Reporting Unit Profile**

View and manage DRU details

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

**Delete DRU**

Figure 4.37: Disease Reporting Unit details

**4.6 User Testing**

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

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

Table 4.6: Computed System Usability Scores per Participant

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



<sub>1120</sub> **Chapter 5**

<sub>1121</sub> **Conclusion**

<sub>1122</sub> The development of DengueWatch marks a transformative leap forward in public  
<sub>1123</sub> health technology, providing Iloilo City with a centralized system to combat one  
<sub>1124</sub> of the most persistent mosquito-borne diseases. Previously, data was recorded  
<sub>1125</sub> manually on paper, making tracking and analysis slow and error-prone. Dengue-  
<sub>1126</sub> Watch digitizes this process, enabling faster, more accurate monitoring. More  
<sub>1127</sub> than an academic project, DengueWatch serves as a practical solution aimed at  
<sub>1128</sub> shifting the approach from reactive outbreak response to proactive prevention. By  
<sub>1129</sub> combining deep learning models with real-time climate data integration, the sys-  
<sub>1130</sub> tem achieves a level of accuracy and usability that makes it viable for real-world  
<sub>1131</sub> deployment.

<sub>1132</sub> At the heart of DengueWatch is a Long Short-Term Memory (LSTM) neural  
<sub>1133</sub> network, which outperformed traditional forecasting models such as ARIMA and  
<sub>1134</sub> Kalman Filter. The LSTM model achieved a Root Mean Square Error (RMSE) of  
<sub>1135</sub> 16.90, followed by the hybrid KF-LSTM model with an RMSE of 25.56, demon-

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

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

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

# <sup>1152</sup> Chapter 6

## <sup>1153</sup> References

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<sup>1239</sup> **Appendix A**

<sup>1240</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

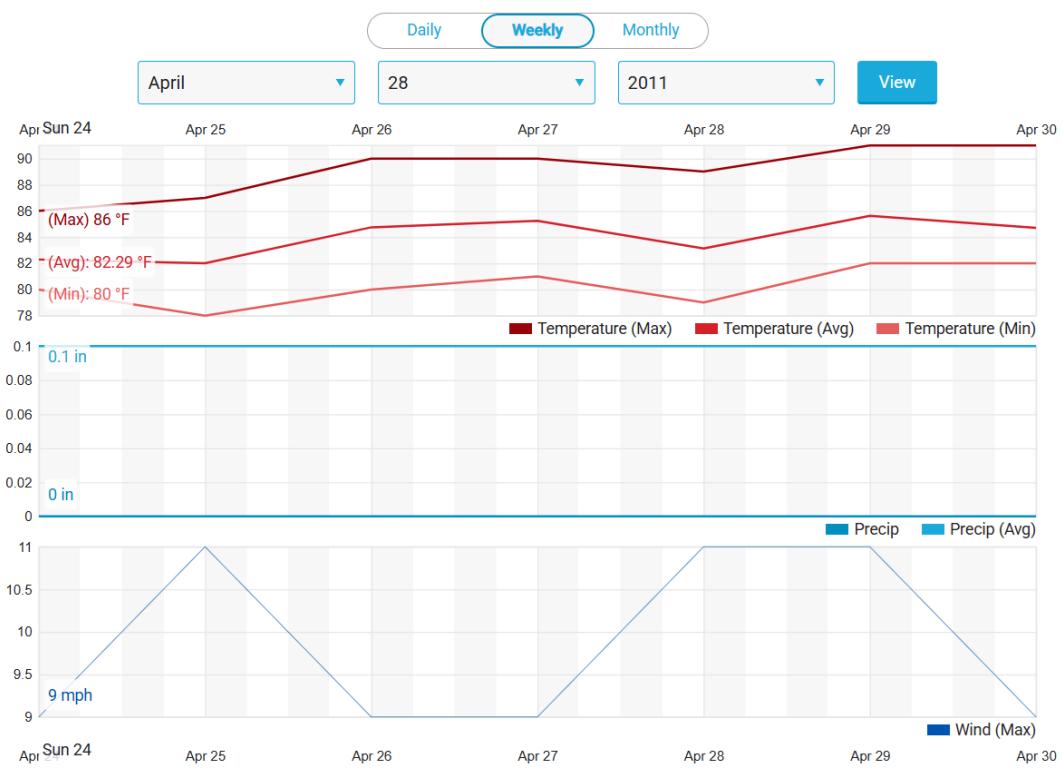


Figure A.2: Snippet of Weather Data Collection

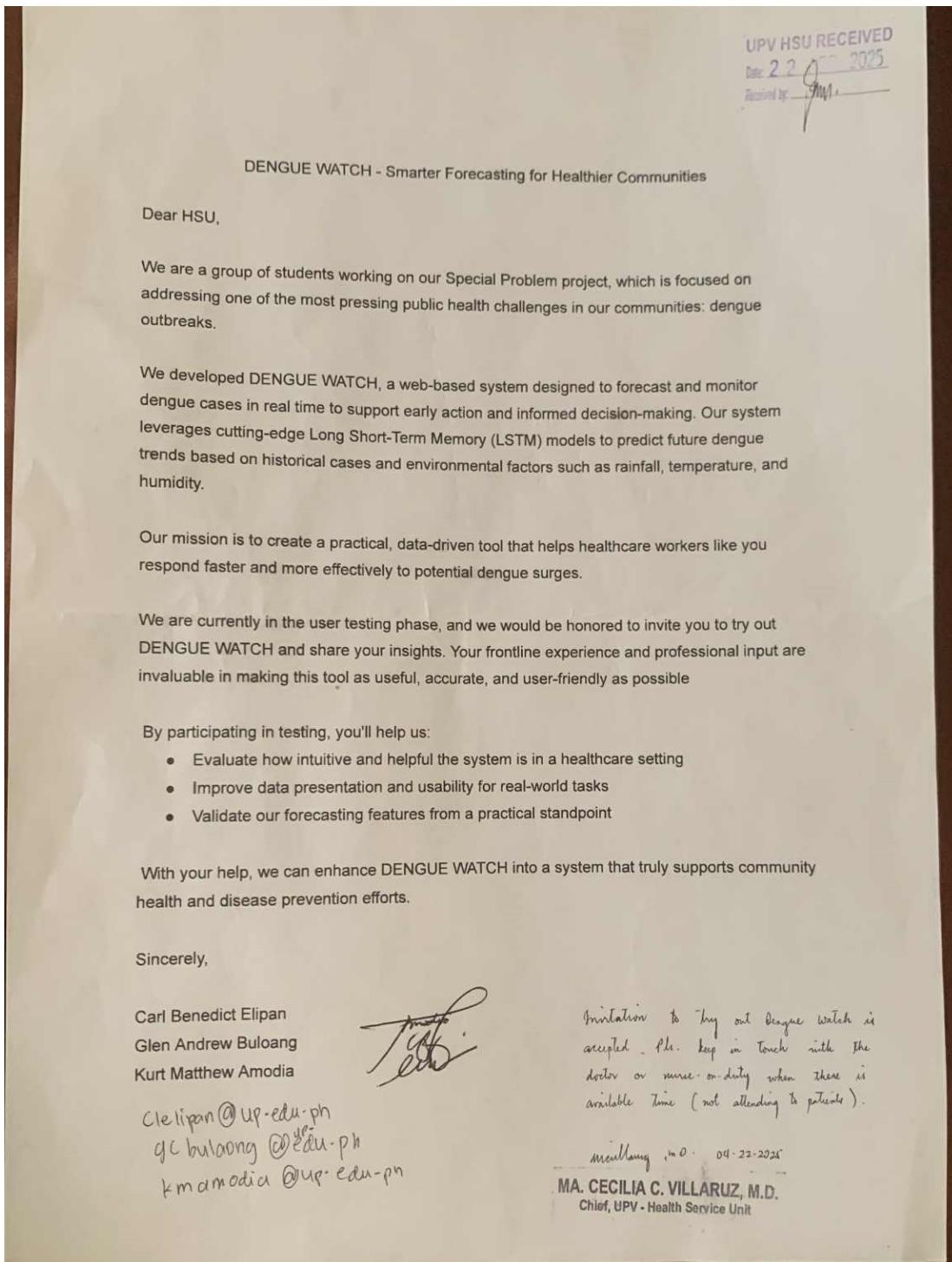


Figure A.3: Letter of Approval for User Testing in UPV HSU

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