

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

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

16 Francis D. DIMZON
17 Adviser

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Abstract

Dengue fever remains a significant public health concern in the Philippines, with cases rising dramatically in recent years. Nationwide outbreaks have placed immense strain on healthcare systems, underscoring the need for innovative approaches to surveillance and response. In Iloilo City, this national trend was reflected in a significant surge, with the Iloilo Provincial Health Office reporting 4,585 cases and 10 fatalities as of August 10, 2023—a 319% increase from the previous year’s 1,095 cases and one death. This research focused on developing a centralized system for monitoring and forecasting dengue trends in Iloilo City, incorporating graphical visualizations such as heatmaps, trends, and historical graphs. The study explored the application of artificial intelligence (AI) in dengue prediction, utilizing deep learning models. The performance of the Long Short-Term Memory (LSTM) model was compared with traditional statistical methods, including non-seasonal and seasonal Autoregressive Integrated Moving Average (ARIMA) models and the Kalman Filter. Evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE) were used to identify the most effective model for integration into the system. Forecasting was based on climate variables such as temperature, rainfall, relative humidity, and previous monthly case counts. The LSTM model emerged as the best performer with an RMSE of 16.15, demonstrating its suitability for time-series predictions, while the Kalman Filter showed the poorest performance with an RMSE of 38.40. By integrating predictive analytics with real-time data visualization, the proposed system aims to support public health agencies, such as the Department of Health (DOH), by providing actionable insights for proactive intervention strategies. This AI-driven solution enhances traditional outbreak reporting systems by enabling timely, data-informed decisions to mitigate the impact of dengue in the region.

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

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Chapter 1

Introduction

1.1 Overview

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

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

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

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

180 **1.2 Problem Statement**

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

193 **1.3 Research Objectives**

194 **1.3.1 General Objective**

195 This study aims to develop an AI-based dengue forecasting and monitoring system
196 for Iloilo City and Province. The researchers will train and compare multiple deep
197 learning models to predict dengue case trends based on climate data and historical
198 dengue cases to help public health officials in possible dengue case outbreaks.

199 **1.3.2 Specific Objectives**

200 Specifically, this study aims to:

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

215 1.4 Scope and Limitations of the Research

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

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

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

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

241 1.5 Significance of the Research

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

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

265 awareness campaigns and community engagement initiatives, empowering
266 residents with knowledge and preventative measures to protect themselves
267 and reduce the spread of dengue.

Chapter 2

Review of Related Literature

2.1 Dengue

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

2.2 Outbreak Definition

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

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

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

304 **2.3 Existing System: RabDash DC**

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

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

321 2.4 Deep Learning

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

335 2.5 Kalman Filter

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

351 Our study will compare ARIMA, seasonal ARIMA, Kalman Filter, and LSTM
352 models using our own collected dengue case data along with weather data to
353 identify the most effective model for real-time forecasting.

2.6 Weather Data

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

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

2.7 Chapter Summary

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

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

Chapter 3

Research Methodology

This chapter lists and discusses the specific steps and activities that will be performed to accomplish the project. The discussion covers the activities from pre-proposal to Final SP Writing.

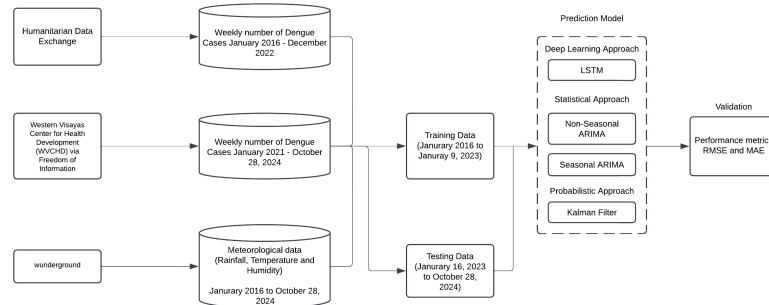


Figure 3.1: Workflow for forecasting the number of weekly dengue cases

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

3.1 Research Activities

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

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

Data Fields

- **Time.** Represents the specific year and week corresponding to each entry in the dataset.
- **Rainfall.** Denotes the observed average rainfall, measured in millimeters, for a specific week.
- **Humidity.** Refers to the observed average relative humidity, expressed as a percentage, for a specific week.
- **Max Temperature.** Represents the observed maximum temperature, measured in degrees Celsius, for a specific week.
- **Average Temperature.** Represents the observed average temperature, measured in degrees Celsius, for a specific week.

- 430 • **Min Temperature.** Represents the observed minimum temperature, mea-
431 sured in degrees Celsius, for a specific week.
- 432 • **Wind.** Represents the observed wind speed, measured in miles per hour
433 (mph), for a specific week.
- 434 • **Cases.** Refers to the number of reported dengue cases during a specific
435 week.

436 Data Integration and Preprocessing

437 The dengue case data was integrated with the weather data to create a com-
438 prehensive dataset, aligning the data based on corresponding timeframes. The
439 dataset underwent a cleaning process to address any missing values, outliers, and
440 inconsistencies to ensure its accuracy and reliability. To ensure that all features
441 and the target variable were on the same scale, a MinMaxScaler was applied to
442 normalize both the input features (climate data) and the target variable (dengue
443 cases).

444 Exploratory Data Analysis (EDA)

- 445 • Analyzed trends, seasonality, and correlations between dengue cases and
446 weather factors.
- 447 • Created visualizations like time series plots and scatterplots to highlight
448 relationships and patterns in the data.

449 Outbreak Detection

450 To detect outbreaks, we computed the outbreak threshold value of dengue cases
451 using the formula,

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

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

453 3.1.2 Develop and Evaluate Deep Learning Models for 454 Dengue Case Forecasting

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

460 Data Preprocessing

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

467 LSTM Model

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

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

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

483 **LSTM units:**

- 484 • min value: 32
- 485 • max value: 128
- 486 • step: 16
- 487 • sampling: linear

488 **Learning Rate:**

- 489 • min value: 0.0001
- 490 • max value: 0.01
- 491 • step: None
- 492 • sampling: log

493 The tuner was instantiated with:

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

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

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

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

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

518 **ARIMA**

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

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

- 526 • Autoregressive order (p): 0 to 3
- 527 • Differencing order (d): 0 to 2
- 528 • Moving average order (q): 0 to 3

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

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

540 Seasonal ARIMA (SARIMA)

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

559 Kalman Filter:

- 560 • Input Variables: The target variable (Cases) was modeled using three re-
561 gressors: rainfall, max temperature, and humidity.
- 562 • Training and Testing Split: The dataset was split into 80% training and
563 20% testing to evaluate model performance.
- 564 • Observation Matrix: The Kalman Filter requires an observation matrix,
565 which was constructed by adding an intercept (column of ones) to the re-
566 gressors.

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

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

580 **3.1.3 Integrate the Predictive Model into a Web-Based** 581 **Data Analytics Dashboard**

582 **Dashboard Design and Development**

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

587 **Model Integration and Deployment**

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

590 **3.1.4 System Development Framework**

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

597 **Design and Development**

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

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

611 Testing and Integration

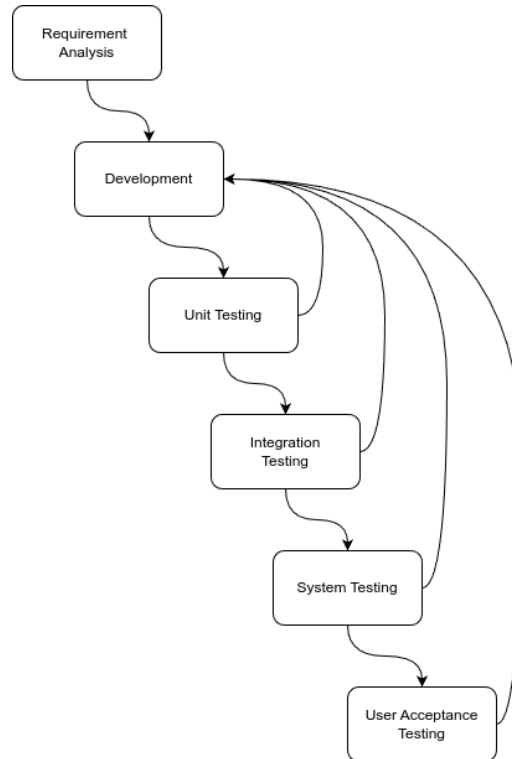


Figure 3.2: Testing Process for DengueWatch

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

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

627 **3.2 Development Tools**

628 **3.2.1 Software**

629 **Github**

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

635 **Visual Studio Code**

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

640 **Django**

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

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

649 **Next.js**

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

656 **Postman**

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

662 **3.2.2 Hardware**

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

666 **3.2.3 Packages**

667 **Django REST Framework**

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

672 Leaflet

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

679 Chart.js

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

687 Tailwind CSS

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

696 Shadcn

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

702 **Zod**

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

707 3.3 Application Requirements

708 3.3.1 Backend Requirements

709 Database Structure Design

710 Determining how data flows and how it would be structured is crucial in creating
711 the system as it defines how extendible and flexible it would be for future features
712 and updates. Thus, creating a comprehensive map of data ensures proper nor-
713 malization that eliminates data redundancy and improves data integrity. Figure
714 3.3 depicts the designed database schema that showcases the relationship between
715 the application's entities.

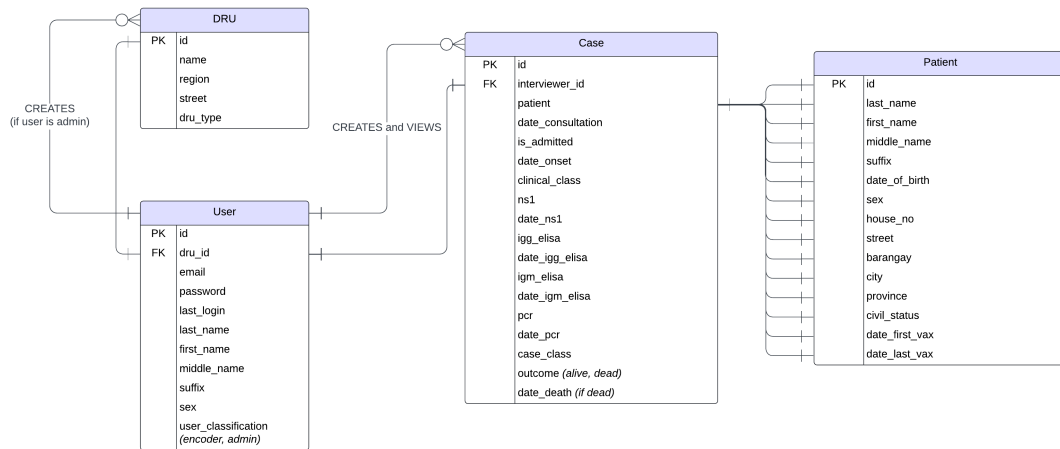


Figure 3.3: Entity-Relationship Database Schema Hybrid Diagram for DengueDash Database Structure

716 3.3.2 User Interface Requirements

717 Admin Interface

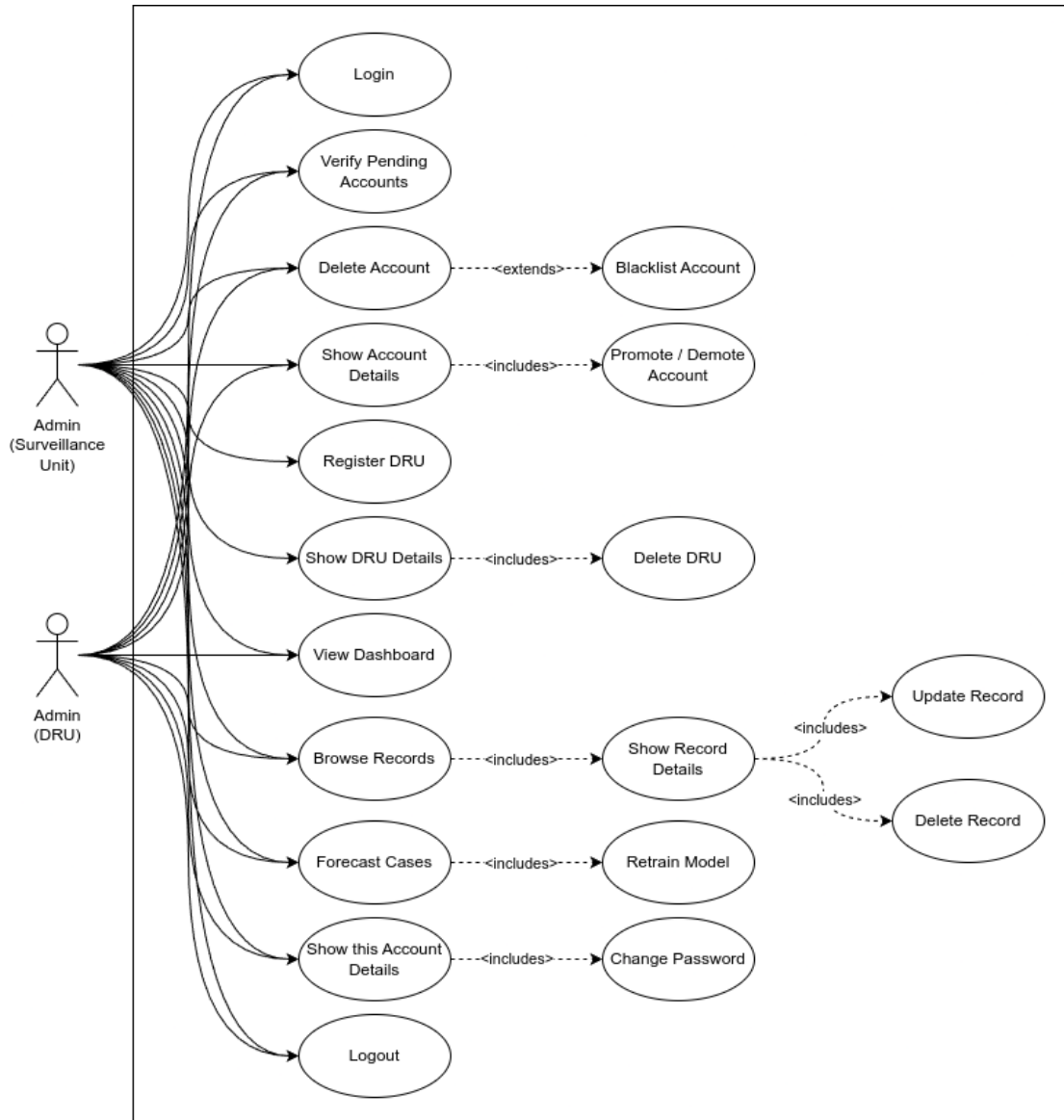


Figure 3.4: Use Case Diagram for Admins

718 Figure 3.4 shows the actions of an admin for a specific Disease Reporting Unit
 719 (DRU) and an admin for a specific Surveillance Unit can take in the application.
 720 Both of them include the management of accounts, browsing records, and fore-
 721 casting and retraining all the consolidated data under their supervision. Most

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

728 Encoder Interface

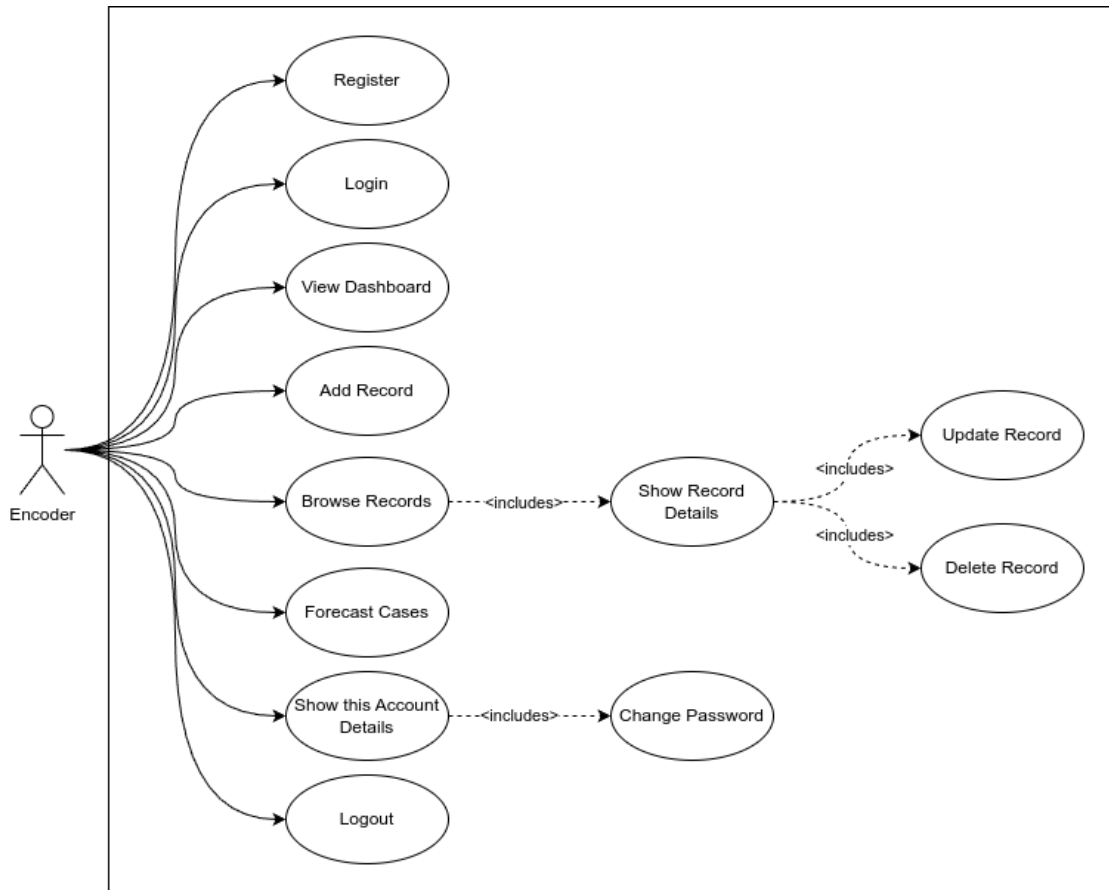


Figure 3.5: Use Case Diagram for Encoder

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

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

736 **3.3.3 Security and Validation Requirements**

737 **Password Encryption**

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

746 **Authentication**

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

752 **Data Validation**

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

761 3.4 Calendar of Activities

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

Table 3.1: Timetable of Activities for 2024

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

Table 3.2: Timetable of Activities for 2025

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

Chapter 4

Results and Discussion/System Prototype

4.1 Data Gathering

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

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

```
data.head()
```

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

Figure 4.1: Snippet of the Combined Dataset

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

dtypes: datetime64[ns](1), float64(6), int64(1)
memory usage: 45.1 KB

Figure 4.2: Data Contents

782 4.2 Exploratory Data Analysis

783 From the summary above, the dataset consists of 720 weekly records with 8
784 columns:

- 785 • **Time.** Weekly timestamps (e.g. "2011-w1")
- 786 • **Rainfall.** Weekly average rainfall (mm)
- 787 • **MaxTemperature, AverageTemperature, MinTemperature.** Weekly
788 temperature data (C)
- 789 • **Wind.** Wind speed (m/s)
- 790 • **Humidity.** Weekly average humidity (%)
- 791 • **Cases.** Reported dengue cases

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

Figure 4.3: Dataset Statistics

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

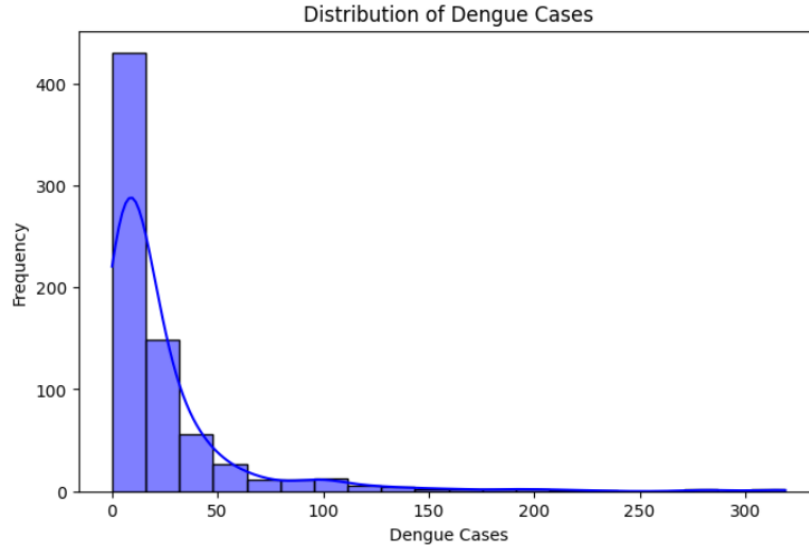


Figure 4.4: Distribution of Dengue Cases

In figure 4.4, a histogram of dengue cases shows a right-skewed distribution, indicating that most weeks experience low case counts, while a few weeks record outbreaks.

To further analyze the distribution, dengue cases were categorized into different intervals (Figure 4.5): 0-5 cases, 6-15 cases, 16-30 cases, 31-100 cases and 101+

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

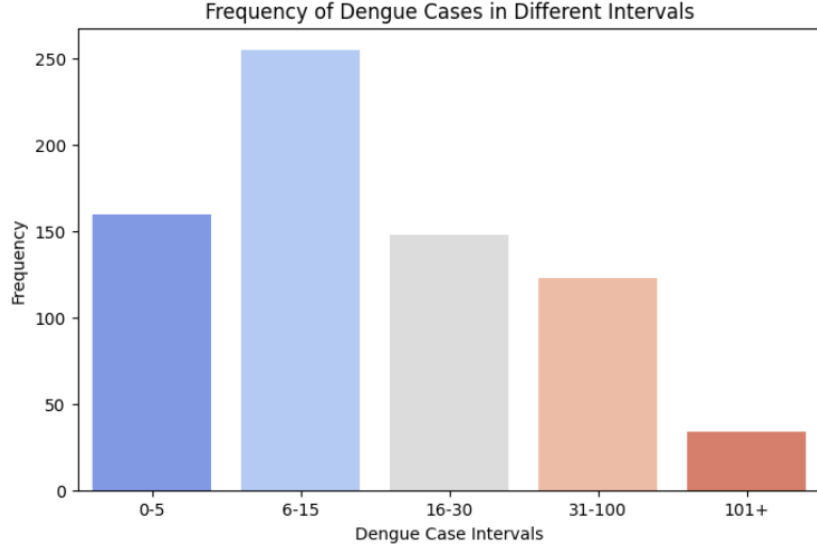


Figure 4.5: Frequency of Dengue Cases in Different Intervals

806

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

813 Figure 4.7 shows the ranking of correlation coefficients between dengue cases
 814 and selected features, including rainfall, humidity, maximum temperature, aver-
 815 age temperature, minimum temperature, and wind speed. Among these, rainfall
 816 exhibits the highest positive correlation with dengue cases (correlation coefficient
 817 0.13), indicating that increased rainfall may contribute to higher cases counts.
 818 This aligns with existing studies suggesting that stagnant water from heavy rain-
 819 fall creates breeding grounds for mosquitos. It is followed by humidity (0.10),
 820 suggesting that higher humidity levels may enhance mosquito reproduction, lead-
 821 ing to more dengue cases. Temperature has a weak to moderate positive corre-
 822 lation with dengue cases, with maximum temperature (0.09) showing a stronger
 823 relationship than average and minimum temperature.

824 Figure 4.8 shows the ranking of correlation coefficients between dengue cases
 825 and selected features, with the addition of lagged effects. The analysis reveals no

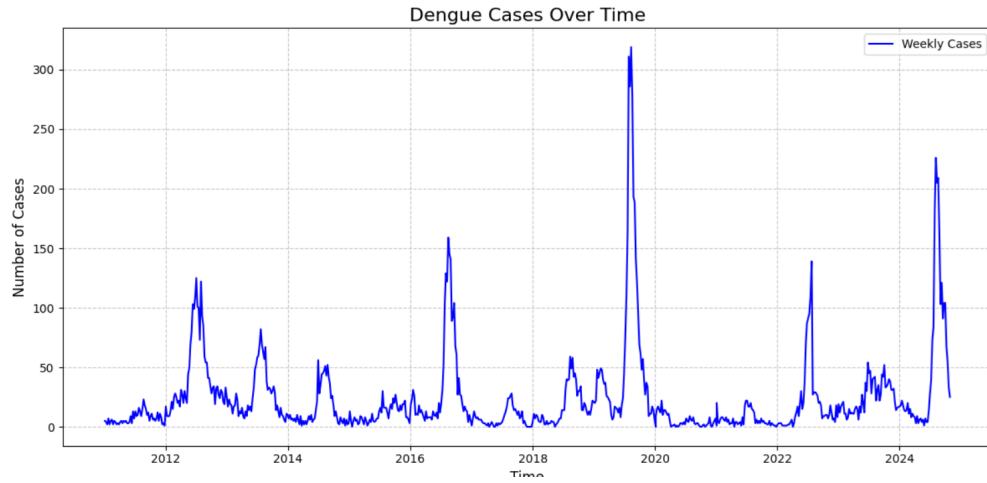


Figure 4.6: Trend of Dengue Cases

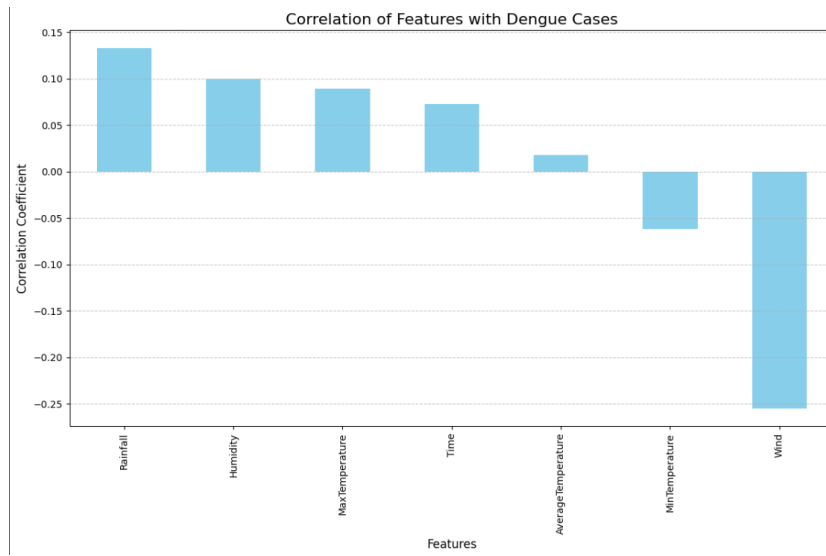


Figure 4.7: Ranking of Correlations

improvement in correlation when lagged variables are compared to direct observations. This suggests that the observed values of rainfall, humidity, and maximum temperature remain the most significant predictors for dengue case forecasting. Overall, the exploratory data analysis highlights the significance of rainfall, humidity, and max temperature variables in dengue case forecasting.

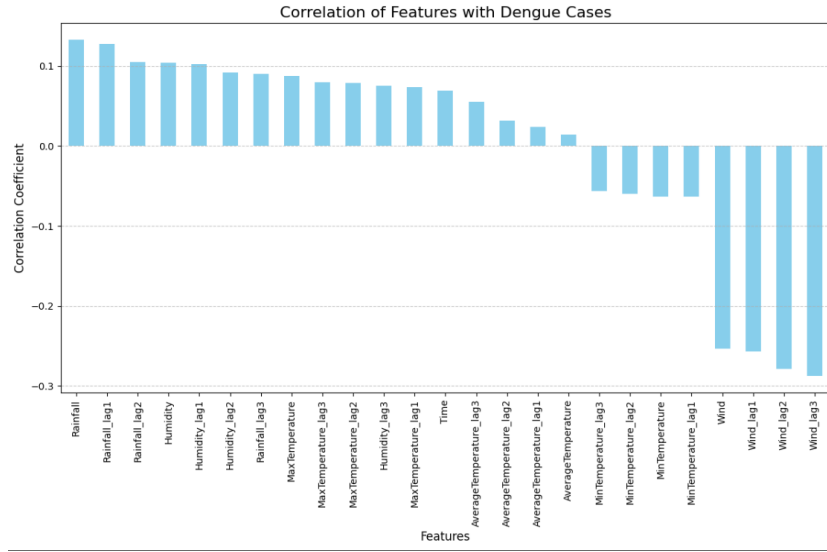


Figure 4.8: Ranking of Correlations (with lagged effects)

4.3 Outbreak Detection

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

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

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

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

$$= 98.03407 \quad (4.4)$$

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

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

840 4.4 Model Training Results

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

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

Table 4.1: Comparison of different models for dengue prediction

849 4.4.1 LSTM Model

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

Window Size	MSE	RMSE	MAE	R ²
5	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

854

855 The results indicate that a window size of 5 weeks provides the most accurate
 856 predictions, as evidenced by the lowest MSE and RMSE values. Furthermore, the
 857 R² score of 0.83 indicates that 83% of the variability in the target variable (cases)
 858 is explained by the independent variables (the inputs) in the model, making it a
 859 reliable configuration overall.

860 Figure 4.9 illustrates the model's performance in predicting dengue cases for
 861 each fold using a window size of 5. As shown in the plot, the training set progres-

862 sively increases with each fold, mimicking a real-world scenario where more data
 863 becomes available over time for dengue prediction. Figure 4.10 demonstrates that
 864 the predicted cases closely follow the trend of the actual cases, indicating that the
 865 LSTM model successfully captures the underlying patterns in the data. It is also
 866 evident that as the fold number increases and the training set grows, the accuracy
 867 of the predictions on the test set improves. Despite the test data being unseen,
 868 the model exhibits a strong ability to generalize, suggesting it effectively leverages
 869 past observations to predict future trends.

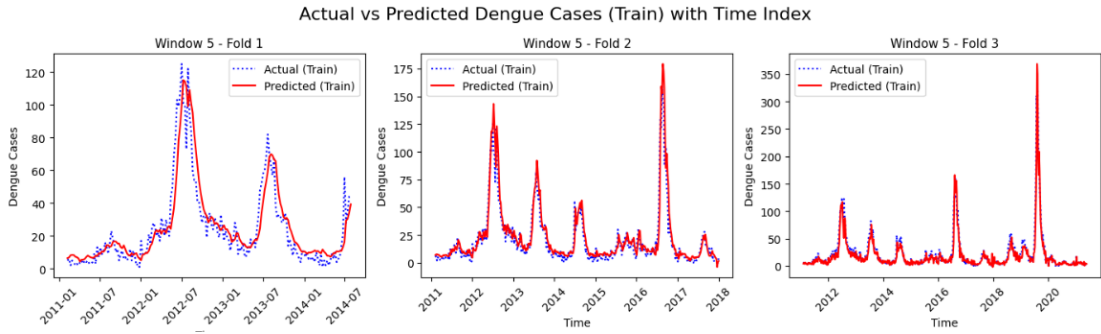


Figure 4.9: Training Folds - Window Size 5

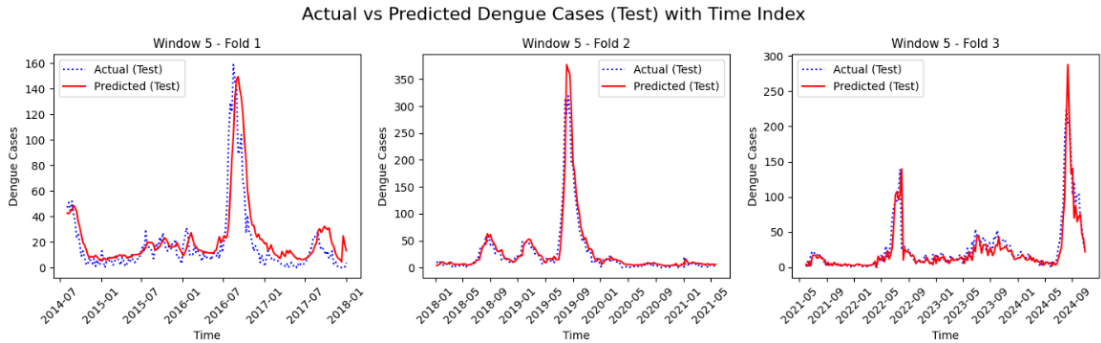


Figure 4.10: Testing Folds - Window Size 5

870 4.4.2 ARIMA Model

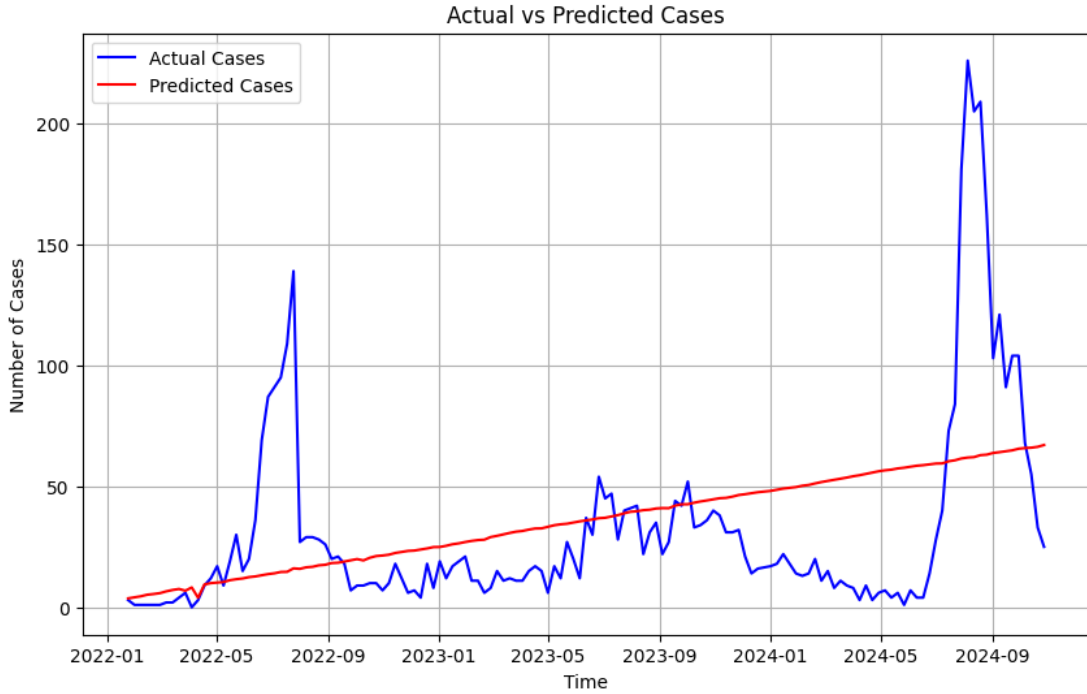


Figure 4.11: ARIMA Prediction Results for Test Set

871 The ARIMA model was developed to capture non-seasonal trends in the data.
 872 To determine the best model configuration, grid search was used to explore vari-
 873 ous combinations of ARIMA parameters, ultimately selecting **ARIMA(1, 2, 2)**.
 874 The model was iteratively refined over **400 iterations** to ensure convergence to
 875 an optimal solution. Figure 4.11 illustrates the comparison between actual and
 876 predicted dengue cases in the test set. As shown in the plot, the ARIMA model
 877 struggled to capture the non-linear characteristics and abrupt spikes in the data.
 878 Consequently, it failed to accurately reflect the fluctuations and outbreak patterns
 879 seen in the actual case counts.

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

- 882 • **MSE (Mean Squared Error):** 1521.48
- 883 • **RMSE (Root Mean Squared Error):** 39.01
- 884 • **MAE (Mean Absolute Error):** 25.80

4.4.3 Seasonal ARIMA (SARIMA) Model

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

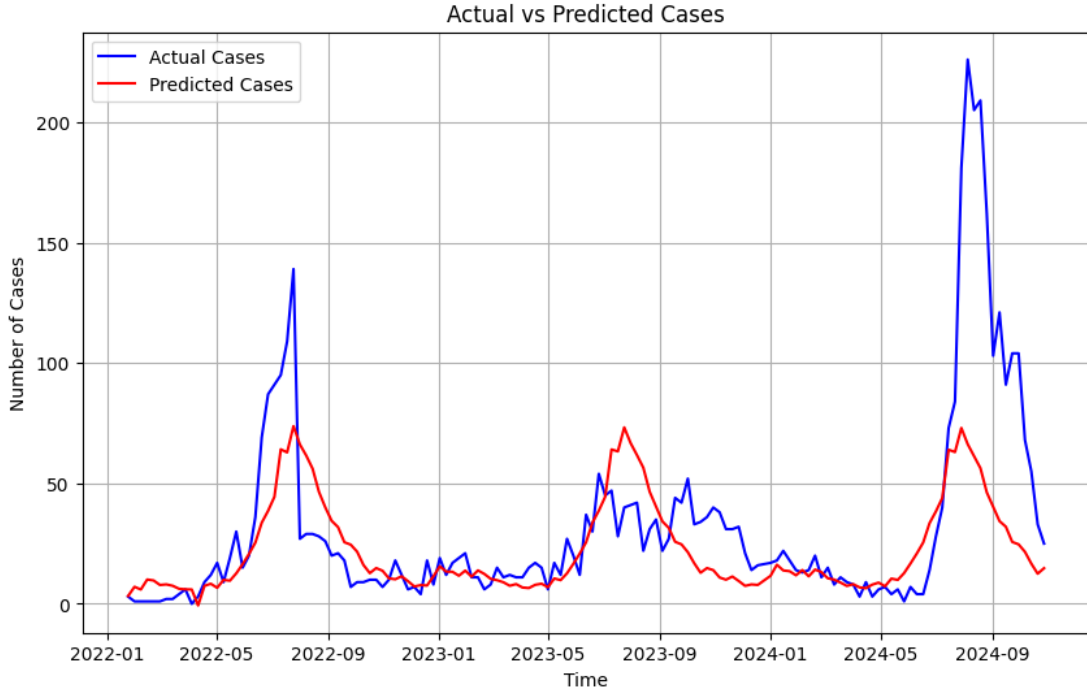


Figure 4.12: Seasonal ARIMA Prediction Results for Test Set

This model incorporates seasonal parameters, which were tuned using grid search to find the best configuration: **SARIMA(2, 0, 2)(0, 1, 1)[52]**. As with ARIMA, **400 iterations** were applied to ensure a robust fit. As shown in Figure 4.12, the SARIMA model demonstrates a notable improvement in performance. Unlike its non-seasonal counterpart, it effectively captures the general trend and aligns more closely with the peaks observed in the actual dengue cases, indicating its ability to model seasonal dynamics.

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

- **MSE:** 1109.69
- **RMSE:** 33.31

900

- **MAE: 18.09**

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

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After training the model, the SARIMA model was validated using the same Time Series Cross-Validation strategy employed in the LSTM model. Table 4.3 presents the performance metrics for each fold, as well as the average metrics across all folds. The average RMSE and MAE values were close to those obtained during the initial training phase, indicating that the SARIMA model performed consistently across different time segments.

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

Table 4.3: Comparison of SARIMA performance for each fold

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4.4.4 Kalman Filter Model

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Figure 4.13 shows the comparison between the actual dengue cases and the predicted values on the test set. As illustrated in the plot, the Kalman Filter model demonstrates a moderate ability to follow the general trend of the actual data. While it effectively captures some rising and falling patterns, it still struggles to accurately replicate the sharp peaks and extreme values found in the real case counts. This limitation is particularly noticeable during the large spikes in 2022 and 2024. The model's performance was evaluated using standard regression metrics. The results are as follows:

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

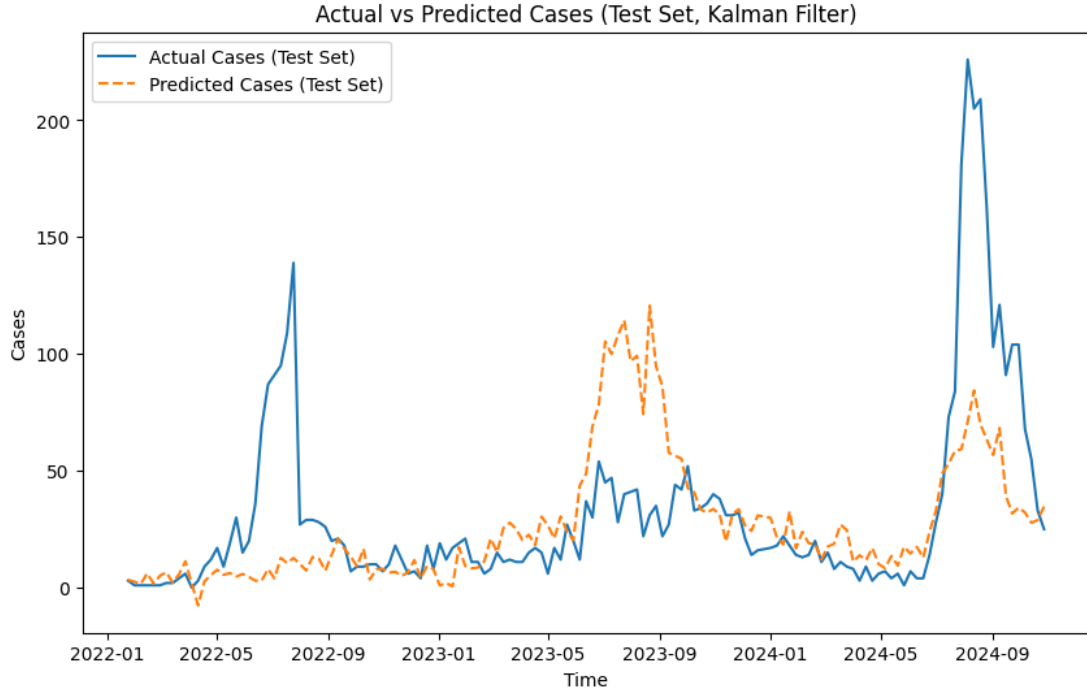


Figure 4.13: Kalman Filter Prediction Results for Test Set

920 The Kalman Filter was then combined with the LSTM model in order to see
 921 improvements in its predictions. Table 4.4 shows the metrics across three folds
 922 using the same Time Series Cross Validation Strategy employed in the previous
 923 models to see how it performed on different time segments.

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

Table 4.4: Comparison of KF-LSTM performance for each fold

924 2

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

928 4.5 System Prototype

929 4.5.1 Home Page

930 The Home Page is intended for all visitors of the web application. The Analytics
 931 Dashboard, which displays relevant statistics for dengue cases at a certain year
 932 and location, is the primary component highlighted, as seen in Figure 4.14. This
 933 component includes a combo chart that graphs the number of dengue cases and
 934 deaths per week in a specific year, a choropleth map that tracks the number of
 935 dengue cases per location, and various bar charts that indicate the top locations
 936 affected by dengue.

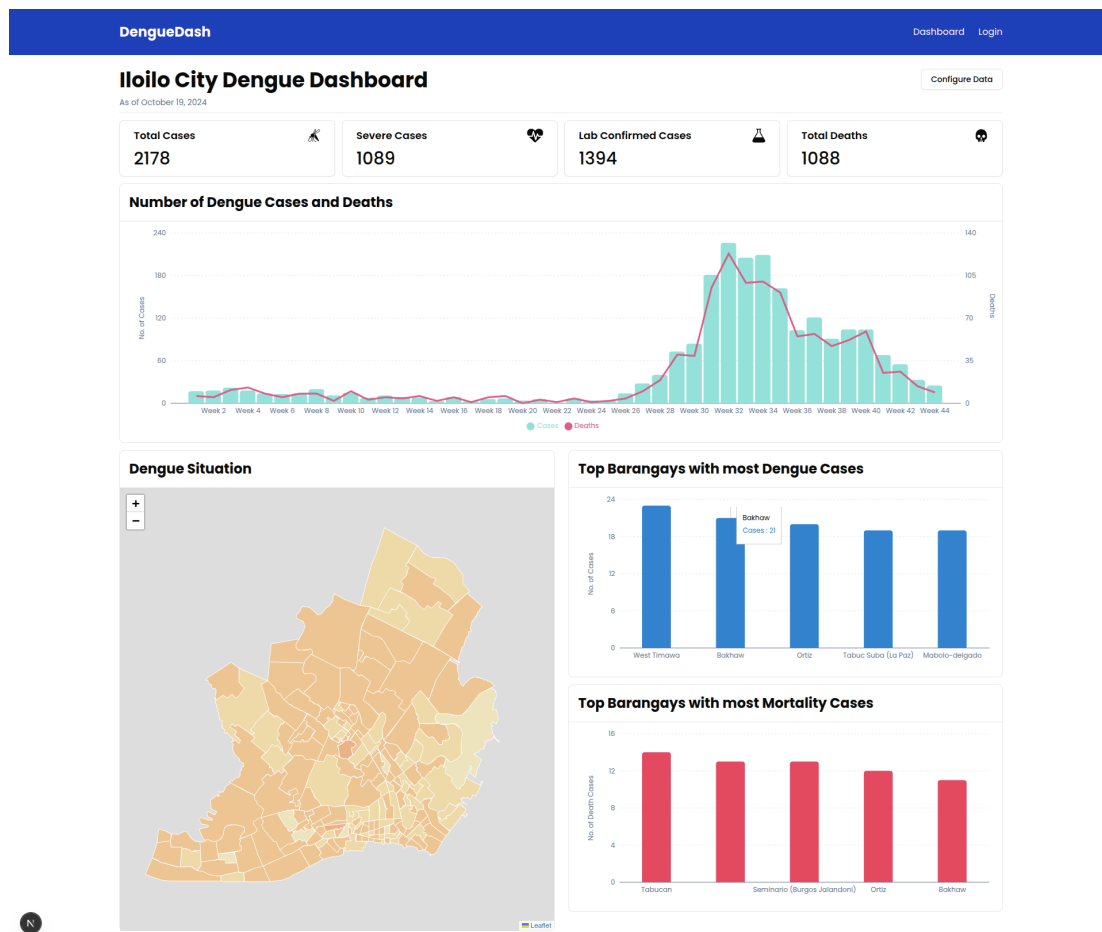


Figure 4.14: Home Page

4.5.2 User Registration, Login, and Authentication

The registration page, as shown in Figure 4.15, serves as a gateway to access the authenticated pages of the web application. Only prospected 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, the user can log in to the system through the page shown in Figure 4.16. After entering the correct credentials, which consist of an email and password, the system uses HTTP-only cookies containing JSON Web Tokens (JWT) to prevent vulnerability to Cross-site Scripting (XSS) attacks. It will then proceed to the appropriate page the type of user belongs to.

DengueDash [Dashboard](#) [Login](#)

Sign Up

Create your account to get started

First Name <input type="text" value="John"/>	Middle Name (optional) <input type="text" value="David"/>
Last Name <input type="text" value="Doe"/>	Sex <input type="text" value="Select gender"/>
Email <input type="text" value="john@example.com"/>	Region <input type="text" value="Select region"/>
Surveillance Unit <input type="text" value="Select surveillance unit"/>	DRU <input type="text" value="Select DRU"/>
Password <input type="password"/>	Confirm Password <input type="password"/>

Must be at least 8 characters long

[Create Account](#)

[Already have an account? Sign in](#)

Figure 4.15: Sign Up Page

Figure 4.16: Login Page

949 4.5.3 Encoder Interface

950 Case Report Form

951 Figures 4.17 and 4.18 show the digitized counterpart of the form obtained from the
 952 Iloilo Provincial Epidemiology and Surveillance Unit. As the system aims to sup-
 953 port expandability for future features, some fields were modified to accommodate
 954 more detailed input. It is worth noting that all of the included fields adhere to the
 955 latest Philippine Integrated Disease and Surveillance Response (PIDSRS) Dengue
 956 Forms, which the referenced form was based on. By doing this, if implemented
 957 on a national scale, the transition between targeted users will be easier. More-
 958 over, the case form includes the patient’s basic information, dengue vaccination
 959 status, consultation details, laboratory results, and the outcome. On the other
 960 hand, encoders can also create case records using a ”bulk upload” feature that
 961 makes use of a formatted CSV file template. As shown in Figure 4.19, an encoder
 962 can download the template using the ”Download Template” button, and insert
 963 multiple records inside the file, then upload it by clicking the ”Click to upload”
 964 button. The web application automatically checks the file for data inconsistencies
 965 and validation.

DengueDash

Modules

Analytics

Forms

Case Report Form

Data Tables

Settings

Elizabeth Thomas Ra...

zewis@example.com

Building Your Application > Data Fetching

Case Report Form

Bulk Upload

Personal Information

Clinical Status

Personal Detail

First Name

Middle Name

Last Name

Suffix

Sex

Civil Status

Date of Birth

Address

Region

Province

City

Barangay

Street

House No.

Vaccination

Date of First Vaccination

Date of Last Vaccination

Next

Figure 4.17: First Part of Case Report Form

DengueDash

Modules

Analytics

Forms

Case Report Form

Data Tables

Settings

Building Your Application > Data Fetching

Case Report Form

Bulk Upload

Personal Information

Clinical Status

Consultation

Date Admitted/Consulted/Seen

Pick a date

Is Admitted?

Select

Date Onset of illness

Pick a date

Clinical Classification

Select

Laboratory Results

NS1

Pending Result

Date done (NS1)

Pick a date

IgG ELISA

Pending Result

Date done (IgG ELISA)

Pick a date

IgM ELISA

Pending Result

Date done (IgM ELISA)

Pick a date

PCR

Pending Result

Date done (PCR)

Pick a date

Outcome

Case Classification

Select

Outcome

Select

Date of Death

Pick a date

Previous

Submit

Elizabeth Thomas Ro...

zewis@example.com

Figure 4.18: Second Part of Case Report Form

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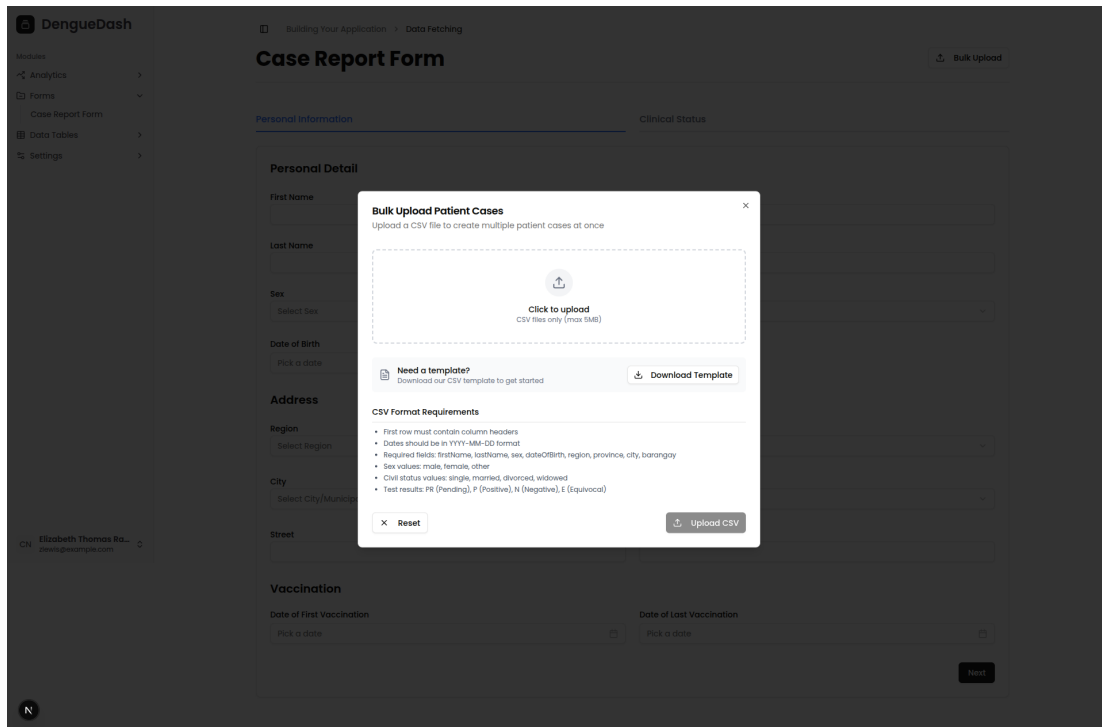



Figure 4.19: Bulk Upload of Cases using CSV

966 Browsing, Update, and Deletion of Records

967 Once the data generated from the case report form or the bulk upload is vali-
 968 dated, it will be assigned as a new case and can be accessed through the Dengue
 969 Reports page, as shown in Figure 4.20. The said page displays basic information
 970 about the patient related to a specific case, including their name, address, date
 971 of consultation, and clinical and case classifications. It is also worth noting that
 972 it only shows cases the user is permitted to view. For example, in a local Disease
 973 Reporting Unit (DRU) setting, the user can only access records that belong to
 974 the same DRU. On the other hand, in a consolidated surveillance unit such as a
 975 regional, provincial, or city quarter, its users can view all the records from all the
 976 DRUs that report to them. Moving forward, Figure 4.21 shows the detailed case
 977 report of the patient on a particular consultation date.

DengueDash

Modules

Accounts

DRU

Analytics

Data Tables

Dengue Reports

Settings

Ilolo City Epedemiol...

ilolocruz@gmail.com

Dengue Reports

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

< Previous

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2137

Next >

Figure 4.20: Dengue Reports

Modules

- Accounts >
- DRU >
- Analytics >
- Data Tables >
- Dengue Reports >
- Settings >

Ilalo City Epidemiol...
ilalocase@gmail.com

Building Your Application > Data Fetching

Personal Information

Full Name
Medina, Michael Paige

Sex
Male

Full Address
995 Monique Spur, Tacas, ILOILO CITY (Capital), Ilalo

Date of Birth
October 11, 1935

Civil Status
Widowed

Vaccination Status

First Dose
April 26, 2023

Last Dose
May 31, 2020

Case Record #25017089

Date of Consultation
November 1, 2024

Date Onset of Illness
October 23, 2024

Patient Admitted?
No

Clinical Classification
With warning signs

Laboratory Results

NSI Negative	Date Done October 27, 2024
IgG Elisa Equivocal	Date Done October 30, 2024
IgM Elisa Pending Result	Date Done N/A
PCR Pending Result	Date Done N/A

Outcome

Case Classification
Probable

Date of Death
October 31, 2024

Outcome
Dead

Interviewer

Interviewer
Daniels, Lisa Long

DRU
Molo District Health Center

Update Case

Delete Case

Figure 4.21: Detailed Case Report

978 To update the case, the user can click the "Update Case" button, where a
 979 dialog will appear, and the updateable fields will be shown. It is worth noting
 980 that in this case, only fields under Laboratory Results and Outcome are included
 981 since they are the only ones that are time-based, where the result may change in
 982 the future. After updating, a prompt will show up confirming the action of the
 983 user. Moving forward, to delete a case record, the user must click the "Delete
 984 Case" button, and a prompt verifying the action will appear. After confirming,
 985 the case will be deleted permanently.

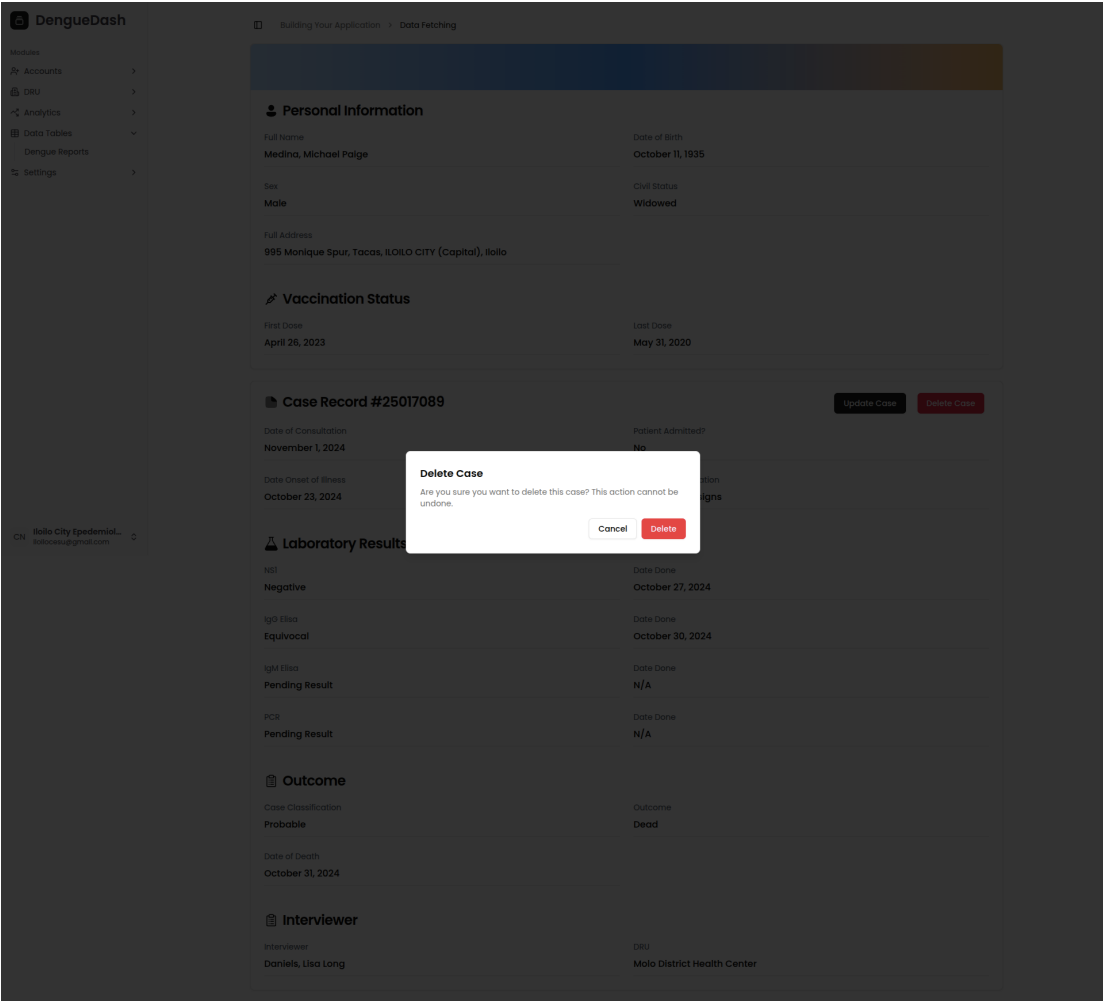


Figure 4.23: Delete Report Alert Dialog

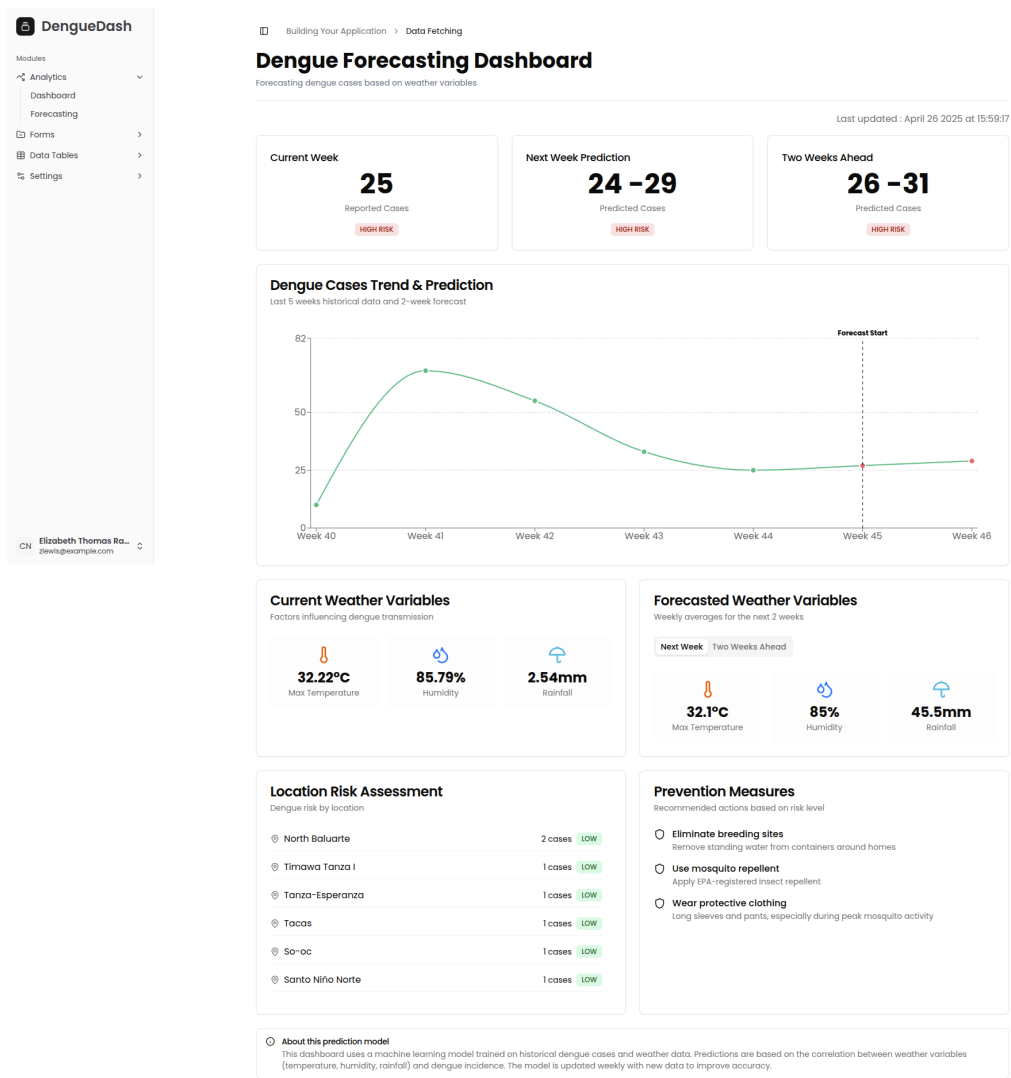


Figure 4.24: Forecasting Page

987 **4.5.4 Admin Interface**

988 **Retraining**

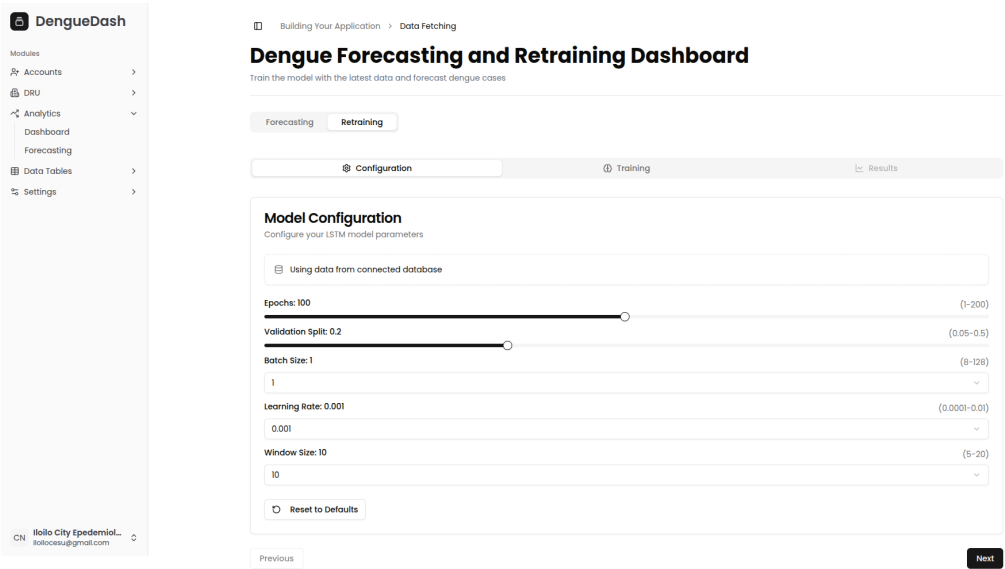


Figure 4.25: Retraining Configurations

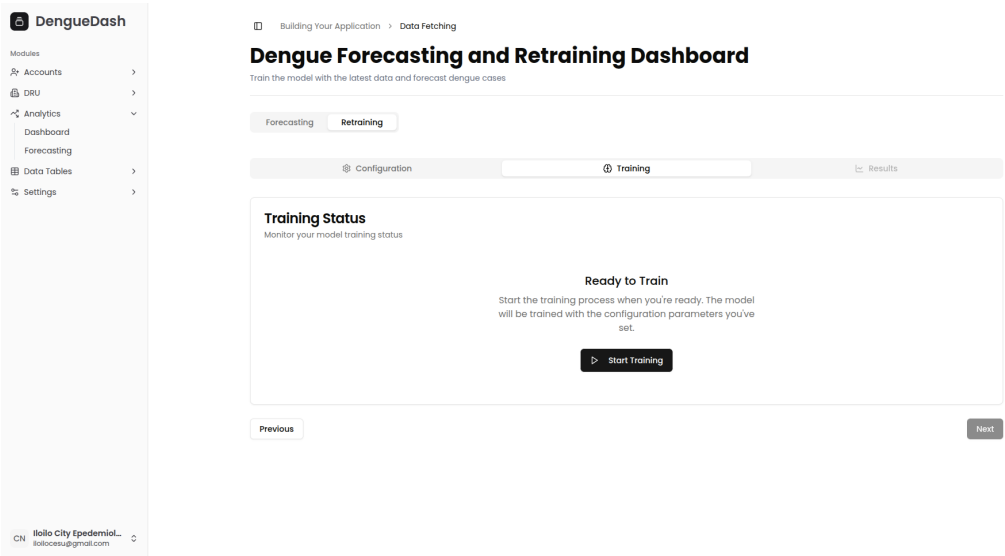


Figure 4.26: Start Retraining

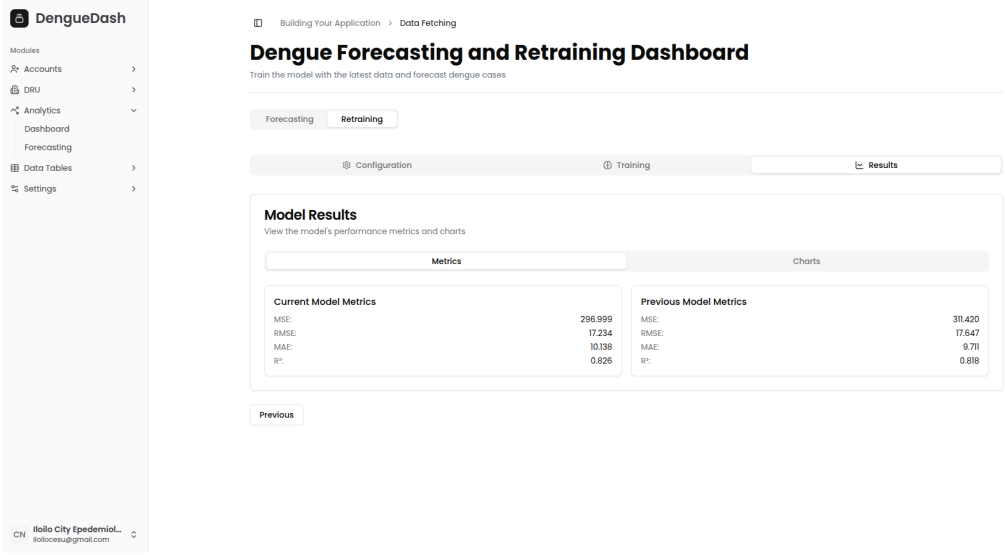


Figure 4.27: Retraining Results

989 **Managing Accounts**

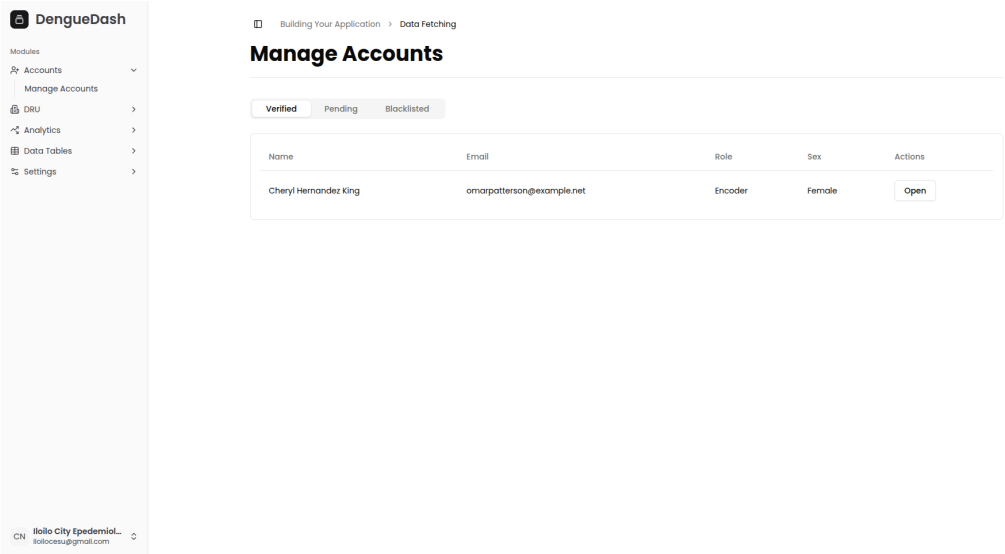
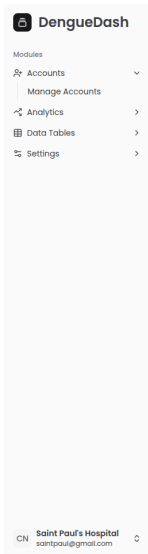


Figure 4.28: List of Verified Accounts

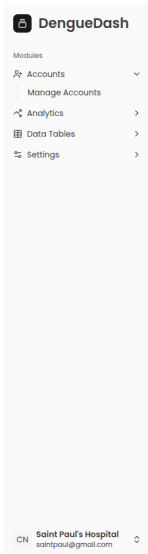


Manage Accounts

Verified Pending Blacklisted

Name	Email	Sex	Created At	Actions
John David Doe	testereeee@example.gov.ph	Male	2025-04-26	<button>Approve</button> <button>Delete</button>

Figure 4.29: List of Pending Accounts



User Profile

View and manage user details

Name	John David Doe			Email	testereeee@example.gov.ph
Sex	Male			Role	Encoder
Hospital (DRU)	Saint Paul's Hospital				
Created At	April 26 2025 at 16:19:07		Updated At	April 26 2025 at 16:21:16	
			Last Login	N/A	
<button>Promote to Admin</button>			<button>Delete User</button>		

Figure 4.30: Account Details

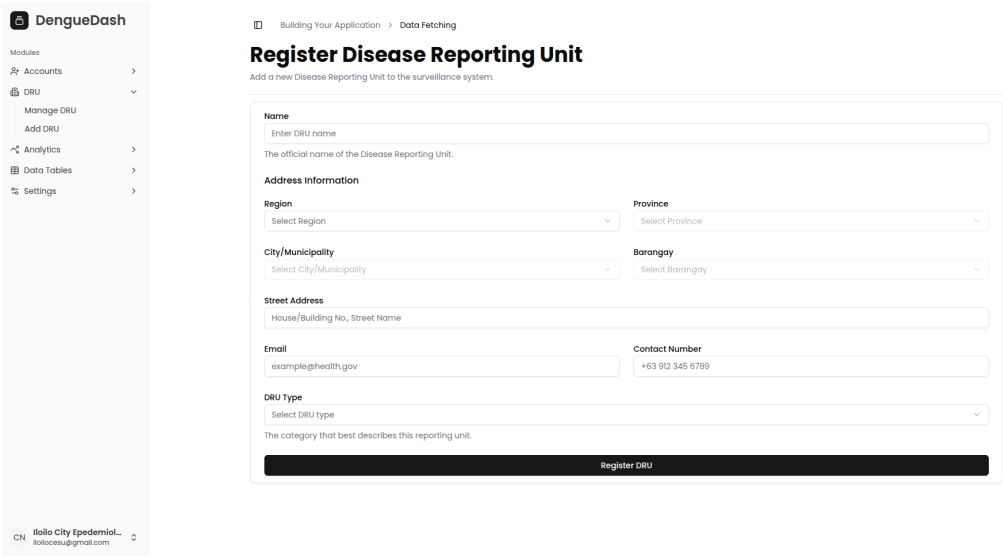


Figure 4.31: DRU Registration

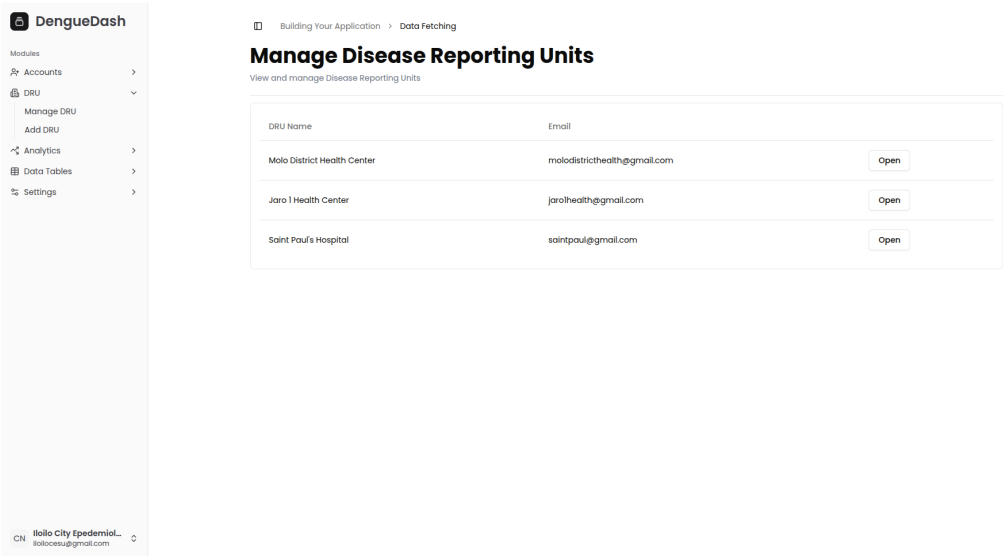


Figure 4.32: List of DRUs

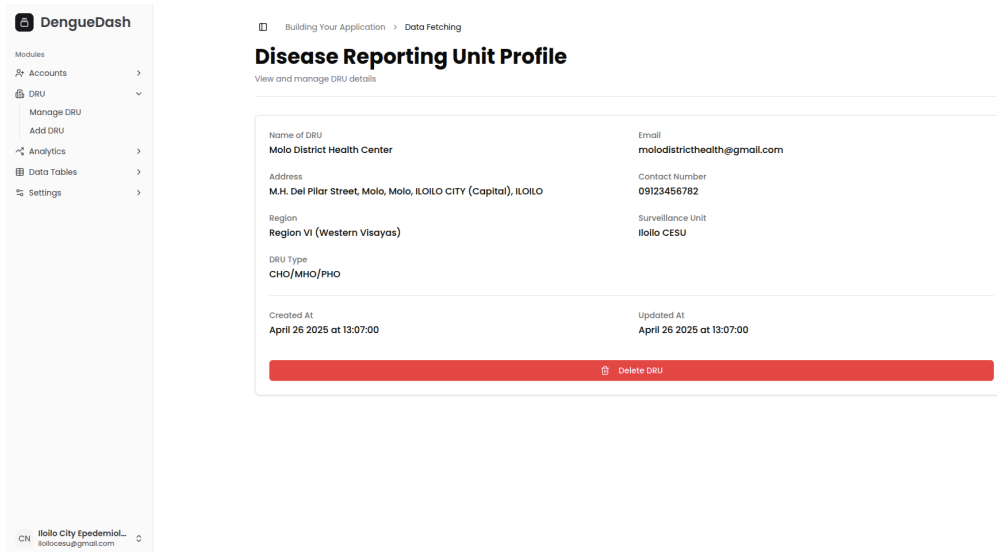


Figure 4.33: DRU details

991 4.6 User Testing

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

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

Table 4.5: Computed System Usability Scores per Participant

998 The average System Usability Scale (SUS) score across systems is typically
 999 68 (Babich, 2015). In this testing, the system achieved an average SUS score
 1000 of 88.5, indicating a highly positive user experience. This score suggests that
 1001 participants found the system not only enjoyable to use but also intuitive enough

1002 to recommend to others. Furthermore, it demonstrates that the system is suitable
1003 for real-world applications without presenting significant complexity for first-time
1004 users.

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1091 **Appendix A**

1092 **Appendix Title**

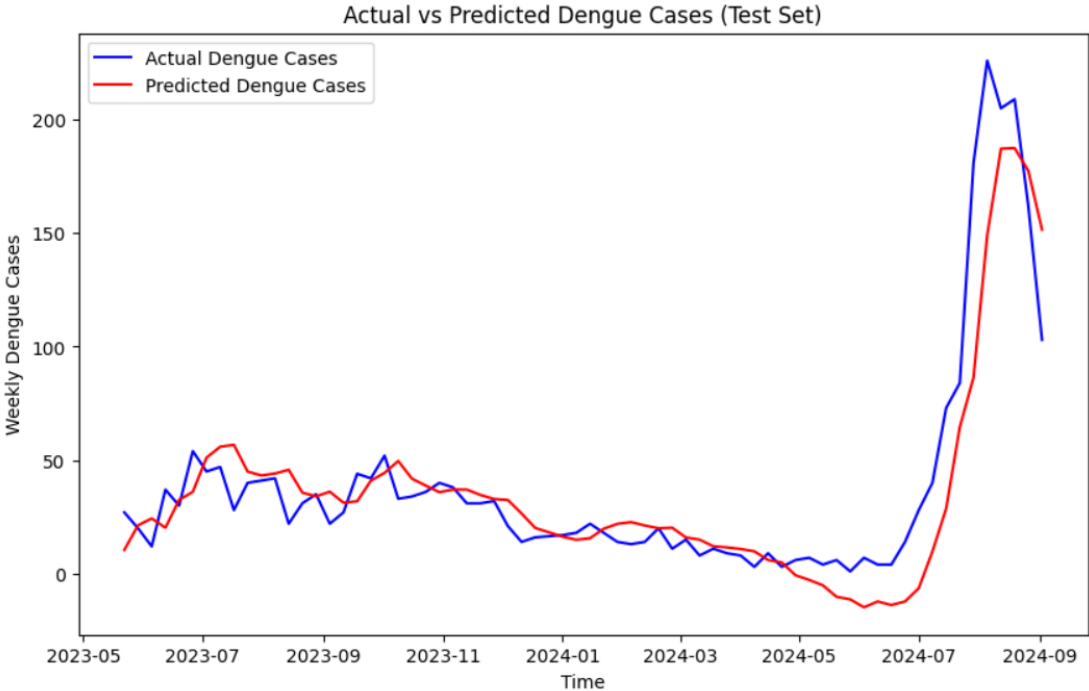


Figure A.1: LSTM Prediction Results for Test Set

1093 **Appendix B**

1094 **Resource Persons**

1095 **Mr. Firstname1 Lastname1**

1096 Role1

1097 Affiliation1

1098 emailaddr1@domain.com

1099 **Ms. Firstname2 Lastname2**

1100 Role2

1101 Affiliation2

1102 emailaddr2@domain.net

1103