

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

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

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

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18 November 6, 2024

Abstract

20 In response to a marked rise in dengue cases, Iloilo City and Province are en-
21 hancing control measures. As of August 10, 2023, the Iloilo Provincial Health
22 Office reported 4,585 cases and 10 fatalities, reflecting a 319% increase from last
23 year's 1,095 cases and one death. This research includes the development of a cen-
24 tralized system for monitoring and forecasting dengue trends in the Iloilo region.
25 This study explores the application of artificial intelligence (AI) for dengue pre-
26 diction, using a deep learning approach with Long Short-Term Memory (LSTM)
27 networks. The LSTM model is compared with traditional statistical methods,
28 including non-seasonal and seasonal Autoregressive Integrated Moving Average
29 (ARIMA) models and the Kalman Filter for state estimation algorithm in noisy
30 data conditions. Forecasting was based on climate variables such as temperature,
31 rainfall, relative humidity, and previous monthly case counts, with performance
32 evaluated using Root Mean Square Error (RMSE). The LSTM model achieved
33 the highest accuracy, demonstrating its capacity to capture nonlinear patterns
34 and effectively integrate long-term historical data for enhanced prediction. This
35 research, aimed at supporting public health agencies like the Department of Health
36 (DOH), advocates for AI-driven solutions that improve outbreak response beyond
37 traditional reporting systems.

Keywords: ARIMA, artificial intelligence, dengue prediction, LSTM,
38 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, 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 (Organization, 2024) reported a ten-fold rise in cases between 2000 and 2019, with a peak in 2019 when the disease spread across 129 countries.

Iloilo City and Province are intensifying efforts to curb the rising dengue cases. 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) criteria, and a formal declaration is pending. Local government units (LGUs) have been informed, and the province's disaster management office is on blue alert, indicating disaster mode. (Lena, 2024)

In Iloilo City, 649 dengue cases were recorded during the same period, 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.

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

96 1.2 Problem Statement

97 The problem being addressed here is that dengue cases remain a critical public
98 health issue worldwide, with rising cases attributed to the easing of COVID-19
99 restrictions and increased global mobility. From 2020 to 2022, dengue cases saw
100 a temporary decline due to reduced surveillance efforts amidst the pandemic.
101 However, 2023 witnessed a significant resurgence, with over five million cases and
102 more than 5,000 deaths reported across 80 countries, indicating the continued
103 vulnerability of dengue-endemic regions like the Philippines. In Iloilo City and
104 Province, dengue cases surged dramatically by 319% as of August 2023, with
105 local health systems struggling to manage the influx. High hospitalization rates
106 due to dengue, with over 76% of non-COVID-19 hospital beds occupied, have
107 raised concerns about healthcare capacity and the need for enhanced predictive
108 measures.

109 1.3 Research Objectives

110 1.3.1 General Objective

111 This study aims to develop an AI-based dengue forecasting and monitoring system
112 for Iloilo City and Province. The system will use Long Short-Term Memory
113 (LSTM) to predict dengue case trends based on climate data and historical dengue
114 cases to help public health officials in possible dengue case outbreaks.

115 1.3.2 Specific Objectives

116 Specifically, this study aims to develop a system that can:

- 117 1. Predict weekly dengue cases using climate variables such as temperature,
118 rainfall, and relative humidity, along with historical dengue case data.
- 119 2. Compare the performance of LSTM-based deep learning models with tradi-
120 tional forecasting methods, including ARIMA and the mathematical model
121 Kalman Filtering.
- 122 3. Generate automated alerts for local government units (LGUs) and public
123 health agencies to enhance preparedness and resource allocation.
- 124 4. Provide a user-friendly interface that displays forecasted dengue trends and
125 outbreak hotspots for better decision-making by public health stakeholders.

126 1.4 Scope and Limitations of the Research

127 This study aimed to develop an AI-based dengue forecasting and monitoring sys-
128 tem specifically designed for Iloilo City. The system focuses on two major features:
129 dengue case prediction and risk area identification. The dengue case prediction
130 feature utilizes climate variables—such as temperature, rainfall, and relative hu-
131 midity—along with historical dengue case data to forecast monthly dengue cases.
132 The results will be displayed in a user-friendly interface, providing public health
133 officials with actionable insights to enhance outbreak management and resource
134 allocation. However, this study has several limitations. The accuracy of the
135 dengue case predictions heavily relies on the quality and completeness of the input
136 data. Inconsistent or incomplete historical data may lead to reduced prediction
137 accuracy. Additionally, the model’s performance may fluctuate based on varia-
138 tions in climate patterns, which are not always predictable. The model utilizes
139 advanced machine learning techniques, but it cannot account for all factors influ-
140 encing dengue transmissions, such as socio-economic conditions or public health
141 interventions, which may further impact case dynamics. Finally, the dataset used
142 for training the predictive models has not undergone peer review but has been
143 validated by local public health experts to ensure its relevance and accuracy for
144 the study’s context. As a result, the findings should be interpreted with caution,
145 and ongoing validation and adjustments may be necessary to enhance the model’s
146 robustness and applicability in real-world settings.

1.5 Significance of the Research

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

- **Public Health Agencies:** Organizations like the Department of Health (DOH) and local health units in Iloilo City and Province stand to benefit greatly from the system. With dengue predictions, we can help these agencies optimize their response strategies and implement targeted prevention measures in high-risk areas before cases escalate.
- **Local Government Units (LGUs):** LGUs can use the system to support their disaster management and health initiatives by proactively addressing dengue outbreaks. The predictive insights allow for more efficient planning and resource deployment in barangays and communities most vulnerable to outbreaks, improving overall public health outcomes.
- **Healthcare Facilities:** Hospitals and clinics, which currently face high bed occupancy rates during dengue season will benefit from early outbreak forecasts that can help in managing patient inflow and ensuring adequate hospital capacity.
- **Researchers and Policymakers:** This AI-driven approach contributes valuable insights for researchers studying infectious disease patterns and policymakers focused on strengthening the national AI Roadmap. The system's data can support broader initiatives for sustainable health infrastructure and inform policy decisions on resource allocation for dengue control.
- **Community Members:** By reducing the frequency and severity of outbreaks, this study ultimately benefits the community at large. This allows for timely awareness campaigns and community engagement initiatives, empowering residents with knowledge and preventative measures to protect themselves and reduce the spread of dengue.

Chapter 2

Review of Related Literature

2.1 Existing System: RabDash DC

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

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

2.2 Deep Learning

The study of Kim Dianne Ligue and Kristine Joy Ligue highlights how data-driven models can help predict dengue outbreaks. The authors compared traditional

196 statistical methods, such as non-seasonal and seasonal autoregressive integrated
197 moving average (ARIMA), and traditional feed-forward network approach using a
198 multilayer perceptron (MLP) model with a deep learning approach using the long
199 short-term memory (LSTM) architecture in their prediction model. They find
200 that the LSTM model performs better in terms of accuracy. The LSTM model
201 achieved a much lower root mean square error (RMSE) compared to both MLP
202 and ARIMA models, proving its ability to capture complex patterns in time-series
203 data (Ligue & Ligue, 2022). This superior performance is attributed to LSTM's
204 capacity to capture complex, time-dependent relationships within the data, such
205 as those between temperature, rainfall, humidity, and mosquito populations, all
206 of which contribute to dengue incidence (Ligue & Ligue, 2022).

207 2.3 Kalman Filter

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

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

226 2.4 Weather Data

227 The relationship between weather patterns and mosquito-borne diseases is inher-
228 ently nonlinear, meaning that fluctuations in disease cases do not respond propor-

tionally 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, non-linear 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.

2.5 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.

Study	Method	Weather Variables	Forecasting Model	Region	Key Findings	Gaps Identified
Endrassak DC	Centralized System with Ventilation and Forecasting	N/A	LSHM	Davao City, Mindanao, Philippines	Real-time tracking and prediction for rainy outbreaks	Lack of design-specific application
Liou et al. (2022)	Comparative Study for forecasting design case	Temperature, Rainfall, Humidity	LSHM, ARIMA, MLP	Mindanao, Philippines	LSHM outperforms traditional models for design forecasting	Limited focus on weather effects and indoor aspects
Akman et al. (2021)	Kolman Filter	N/A	Kolman Filter	COVID-19 in Brazil	Kolman filter accurately tracked infection rates despite data inconsistencies	Application limited to COVID-19 requires adaptation for design
Abdullah et al. (2021)	Kolman Filter	N/A	Kolman Filter	COVID-19 worldwide	Successfully tracked IR values in fluctuating infection data	Lack of application for various known disease like design
He et al. (2013)	Multivariate model	Mean Temperature, Cumulative Rainfall	Polynomial regression, ROC curve	Singapore	30-week forecast potential with high sensitivity and specificity	Regional limitations for forecast applicability

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.

3.1 Research Activities

Research activities include inquiry, survey, research, brainstorming, canvassing, consultation, review, interview, observe, experiment, design, test, document, etc. Be sure that for each method, process, or algorithm used, there is a justification why that method was chosen. The methodology also includes the following information:

- who is responsible for the task
- the resource person to be contacted
- what will be done
- when and how long will the activity be done
- where will it be done
- why should the activity be done

DO NOT FORGET to cite your references.

277 3.2 Calendar of Activities

278 A Gantt chart showing the schedule of the activities should be included as a table.
 279 For example:

280 Table 3.1 shows a Gantt chart of the activities. Each bullet represents approx-
 281 imately one week worth of activity.

Table 3.1: Timetable of Activities

Activities (2009)	Jan	Feb	Mar	Apr	May	Jun	Jul
Study on Prerequisite Knowledge			●●	●●●●			
Review of Existing Racing Strategies	●●	●●●●	●●●●	●●●●			
Identification of Best Features				●●●●	●●		
Development of Racing Strategies				●●	●●●●	●●	
Simulation of Racing Strategies				●●	●●●●	●●●	
Analysis and Interpretation of the Results					●●●●	●●●●	●
Documentation	●●	●●●●	●●●●	●●●●	●●●●	●●●●	●●

282 Chapter 4

283 Preliminary Results/System 284 Prototype

285 This chapter presents the preliminary results or the system prototype of your SP.
286 Include screenshots, tables, or graphs and provide the discussion of results.

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³²⁰ **Appendix A**

³²¹ **Appendix Title**

322 **Appendix B**

323 **Resource Persons**

324 **Mr. Firstname1 Lastname1**

325 Role1

326 Affiliation1

327 emailaddr1@domain.com

328 **Ms. Firstname2 Lastname2**

329 Role2

330 Affiliation2

331 emailaddr2@domain.net

332