American Journal of Data Science and Artificial Intelligence (AJDSAI)

ISSN: 3069-3632 (ONLINE)

VOLUME 2 ISSUE 2 (2026)

PUBLISHED BY

E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Data Science and Artificial Intelligence (AJDSAI)

Volume 2 Issue 2, Year 2026
ISSN: 3069-3632 (Online)
DOI: https://doi.org/10.54536/ajdsai.v2i2.7696
https://journals.e-palli.com/home/index.php/ajdsai

DenGuess: Design and Development of a Machine Learning Web-Based Application for Dengue Outbreak Prediction in City of Koronadal Using Random Forest Model Classifier

Arabela Czarina Saga[1], Mickhaela Belle Acob[1], Joleigh Ancheta[1], Junesheil Fryle Durana[1], Leona Jean Fuscablo[1], Jaylord Villaruel[1], Mia Joy Inocencio[1*], Carlos Gaygay Jr.[1]

Article Information

Received: March 02, 2026

Accepted: May 08, 2026

Published: September 21, 2026

Keywords

Health, Prediction, Prevention, Random Forest ,Technology

ABSTRACT

Dengue outbreaks remain a major public health problem in Koronadal City with limited technology for monitoring the disease. Health workers are often challenged in accessing and preventing outbreaks due to the lack of available tools. While Random Forest models have been shown to be useful for predicting dengue, their practical application remains still limited. In this study, the researchers developed a machine learning web application to predict dengue outbreaks for five (5) selected barangays in Koronadal weekly, using the epidemiological and meteorological data from 2020 to 2025. The model's performance was measured using a) real-time simulation accuracy, b) precision, c) recall, and d) F1-scores, and the website was evaluated using the user interface and user experience. The findings demonstrate that the model provides balanced and satisfactory predictions, and the website scores high on all criteria, confirming the usability and reliability of the website. This system provides timely forecast information to support the decision-making process, create more awareness among the community and increase preparedness in the city. Researchers suggest further systematizing the UI and UX of the website and to integrate the system into the city's public health infrastructure to improve data collection, validation, and engagement within the community.

INTRODUCTION

Globally, dengue fever has emerged as a major vector-borne disease that affected over 100 countries, with estimated 390 million infections annually, posing a major threat to public health systems, particularly in tropical regions (World Health Organization, 2025). This disease still remained to be a major health problem here in the Philippines, especially in rapidly growing cities like Koronadal. As dengue continued to be that big of an issue, advancements in tools and ways to combat disease monitoring and prediction were being utilized. Generally, machine learning techniques have attracted more attention among these approaches because of their ability to improve accuracy by combining real-time climate, epidemiological, and mobility data. However, in the Philippines, where dengue was known to be recurrent and remained endemic, technologies like these were not yet widely known or deployed in real-time public health tools.

Several global and local studies have proven the effectiveness of machine learning, specifically Random Forest (RF). Random Forest models were shown to be highly effective in predicting dengue outbreaks, especially in tropical regions like the Philippines. A study showed that RF with environmental data from Mindanao managed to achieve prediction accuracies exceeding 85% (Velasco *et al.*, 2022). Their work also highlighted important climatic factors, such as rainfall and temperature, which played a major role in dengue outbreaks. Another study in CALABARZON proved that Random Forest had the best performance among all six machine learning models, showing its effectiveness in capturing the influence of the weather pattern that is a major factor in dengue outbreaks (Castro *et al.*, nd). A study conducted by Francisco *et al.* demonstrated that the RF model achieved high performance, with an accuracy exceeding 80% in predicting dengue outbreaks (Francisco *et al.*, 2021). Additionally, studies in Baguio City proved that RF model showed a strong performance in predicting dengue outbreaks by using environmental data and meteorological data (Addawe *et al.*, 2024). In some studies, RF models had achieved competitive classification accuracy, exceeding 80%, confirming the importance of the climate factors combined with dengue cases in predicting dengue outbreaks (Omadlao *et al.*, 2022). Overall, local studies confirmed the effectiveness of RF models in predicting dengue outbreaks within the Philippines.

In Guangdong, China, hybrid RF models that integrated meteorological data have reached an accuracy of 96.17%, outperforming other algorithms Wang *et al.*, 2020). Another study in Colombia also used an RF model that was able to forecast weekly dengue cases with mean absolute errors as low as 9.32 for one-week-ahead predictions, demonstrating robustness in large-scale applications (Martinez-Gramage *et al.*, 2020). Furthermore, a comparative study in Peru reported that RF models achieved 84.94% accuracy and 92.88% sensitivity in dengue classification, reflecting high diagnostic precision (Exebio-Chepe *et al.*, 2024). More recently, Ren and Xu demonstrated RF strength in geospatial prediction in China, achieving over 80%

[1] Notre Dame of Marbel University – Integrated Basic Education Department Senior High School, Philippines
[*] Corresponding author's e-mail: miajoyinocencio@gmail.com

accuracy in risk rankings, correlations above 0.86 with actual dengue clusters, and nearly 90% clusters occurring in dengue prediction (Ren & Xu, 2024). Similarly, the RF model was seen to perform accurately in classifying dengue cases in Southeast Asia. According to Fang et al, the model reportedly had sensitivity and specificity rates over 88%, which further indicates the potential of RF as a powerful tool in decision-making (Fang et al, 2024). It is no secret that the RF model has a great potential in detecting and classifying dengue cases, and could be applied effectively for localized dengue monitoring, risk assessment, and early clinical diagnosis in tropical environments.

Despite having demonstrated effectiveness in predicting dengue outbreaks around the world, the RF model still faces a significant lack of implementation for the general public. Most studies primarily focus on optimization as well as data analysis within specific regions, leaving the actual application of the model often overlooked. Hence, resulting in a significant limitation in the implementation of RF models as an accessible and user-friendly tool. The lack of these applications may significantly contribute to the lack of community preparedness, hinder LGU operations, and delay the creation of informed health decisions. This study aims to solve this problem through the design and development of an accessible, user-friendly website that integrates the RF Machine Learning model in order to provide timely dengue outbreaks predictions in the City of Koronadal, which can provide early warning signals and possible precautionary measures that will help reduce outbreak frequencies and enhance community preparedness.

Specifically, this study 1) designed a dengue outbreak prediction framework using local epidemiological and environmental data; 2) developed a machine learning web-based application on the RF model; and 3) conducted a performance evaluation on the RF Model in terms of a) accuracy, b) precision, c) recall, and d) F1-score; (4) evaluated the websites' a) User Interface and b) User Experience. These objectives made way for the RF models to support SDG 3 (Good Health and Well-being) for faster and more precise ways to detect possible dengue outbreaks. Not only that but the application also contributed to SDG 9 (Industry, Innovation, and Infrastructure) by using artificial intelligence and climate data to improve healthcare systems. Through this model, the community's health response will become stronger, with a reduced spread of dengue, and development of technological advancements that create a healthier and more innovative future.

MATERIALS AND METHODS

Materials

This study used laptop and cellphone for programming and coding to develop the website, as well the epidemiological and meteorological data from the City of Koronadal that served as the training data for the RF Model. The Python programming language was the main tool for building the model. Visual Studio Code (VSC) for writing, editing, testing and debugging the code. Firebase was also used for handling the system's backend and to handle web-based functions and data management. Sci-kit Learn also provides necessary tools that are needed for data analysis. Lastly, Vercel was used for the hosting and publishing of the website, enabling users to access them online

Research Design

This study used Design and Development (D&D) with a machine learning classification to predict dengue outbreaks in Koronadal City. This design referred to a context-aware, iterative process where a model or tool was created, tested in real-world settings, assessed, and improved over several cycles to make it useful and efficient in addressing public health issues (Tinoca *et al.*, 2022). The developed predictive model that forecasted dengue outbreaks in selected barangays in the city which had high dengue cases and a large population, provided the data that were needed for the study. According to previous study, integrating epidemiological and environmental data into predictive models helped identify patterns signaling potential outbreaks (Addawe *et al.*, 2024). This study was conducted from September 2025 to December 2025, covering phases of data collection, model development, and final evaluation of the website.

Procedure

Identification of Data Sources

Before collecting the data, the researchers first submitted a permit to the officials to obtain permission for the data gathering. Epidemiological data consisting of weekly reported dengue cases from 5 barangays in Koronadal, City, namely, Sto. Niño, General Paulino Santos, Santa Cruz, Zone II, and Morales covering the years 2020 to 2025, were collected from the Department of Health (DOH). Environmental data, including temperature, rainfall, and humidity, were sourced from public databases like the Department of Science and Technology (DOST) and the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). The lagged meteorological data helped capture the effects of mosquito development, thereby improving the accuracy of predicting dengue outbreaks using RF models (Carvajal *et al.*, 2018). Combining all these features was an important factor that contributed to predicting dengue outbreaks (Addawe *et al.*, 2024). The researchers also identified five (5) barangays in the city with the most dengue cases and have a large population to serve as pilot sites for model validation, data collection, and community risk communication. Data to model dengue cases were measured on a weekly time scale, and analyzed into monthly values to make a comparison and visualization of the results.

The ML classifiers input data consisted of dengue case data, weather-related data and time-related data as they were needed to enable the model to acquire patterns in predicting future dengue outbreaks. These inputs were composed of the average numbers of dengue cases (Ave) to represent general tendencies during the past months, lagged values of dengue cases (Lag) to represent time variables, and meteorological factors (MF) which affect the breeding of mosquitos. Moreover, the number of cases (C) is used currently and monthly cases of dengue cases. The inclusion of was made to consider the current situation and seasonal differences. All input to the ML classification model was as a time sensitive numerical tuple which was run with the help of the scikit-learn library.

Design of the Machine Learning Application Software

Figure 1 shows the workflow for the detection of outbreak and non-outbreak periods of dengue in barangay using Machine learning software. The design integrated a machine learning-based website that used the Random Forest algorithm as its main classifier, processing combined epidemiological and meteorological data for dengue outbreak prediction. The web interface design follows health information system principles which focus on user-friendly operation, minimal data entry, transparent feedback, and simple navigation (Omadlao *et al.*, 2022). The system delivers an AI-based outbreak risk assessment system to Koronadal City health workers enabling immediate preventive action deployment.

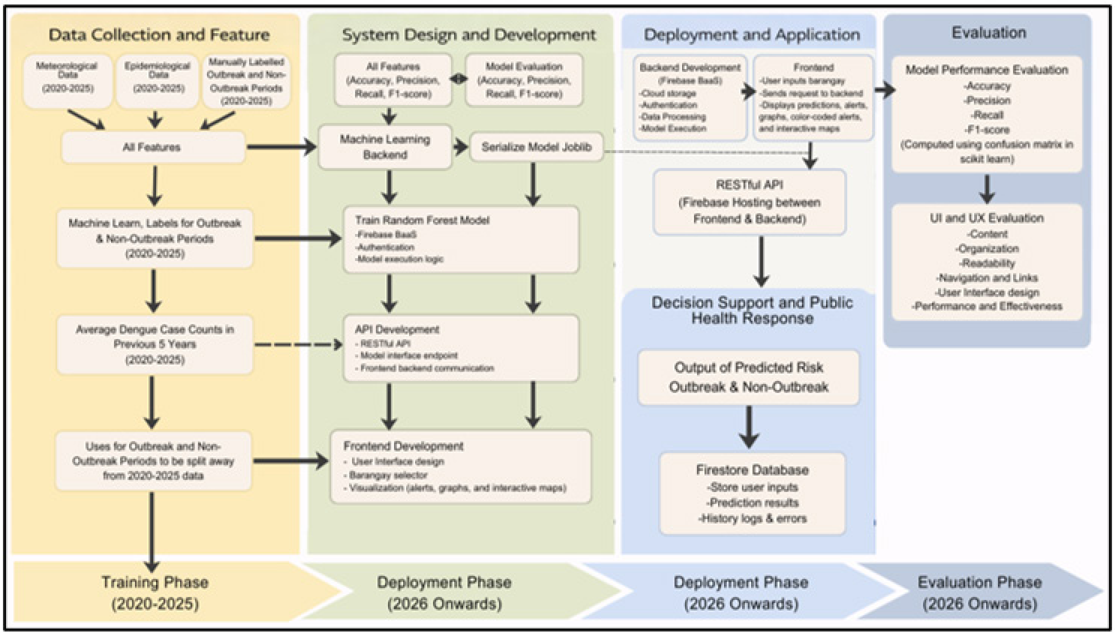

Figure 1: Workflow for the detection of outbreak and non-outbreak periods of dengue using Machine Learning Application

Model Development Using Random Forest Classifier

Model Training in the RF Model

The Random Forest model was trained through Sci-kit-learn by using dengue case records from 2020 to 2025 together with monthly weather data from the PAGASA. The missing temperature and rainfall data received mean imputation treatment but mode imputation was used for barangay names and outbreak labels were generated through historical limit method which used five-year average data (Runge-Ranzinger *et al.*, 2014). Outbreaks were labeled "1" when dengue cases surpassed the five-year average for that time frame and "0" otherwise. The dataset was split by number of sets, with >85% used for training, 15% for testing and validation (Olana *et al.*, 2010). The model underwent five-cross validation to ensure the reliability of the model. The final model, implemented in Python using Scikit-learn was selected from cross-validation combined with test results then deployed to classify outbreak and non-outbreak cases through the preprocessing pipeline. The Random Forest model was trained to forecast the risk of dengue outbreak on a weekly basis and thereafter the result of weekly forecasts was collected into monthly results by summing up the weekly result.

Model Evaluation

The performance of the Random Forest model was evaluated using accuracy, precision, recall, and F1 score, which determined the model's performance in creating predictions for outbreak and non-outbreak periods within the City of Koronadal and was computed on weekly classification outputs. Through a confusion matrix generated in Sci-kit learn library, actual outbreak data was placed in the first column, meanwhile predicted results were placed in the second. The confusion matrix was selected to assess the accuracy of the model in predicting the correct actual outbreaks when actual outbreak occurs and a false alarm when actual outbreak did not occur. True positives are periods of an outbreak that have been correctly identified by the model (actual = 1, predicted = 1), whereas the True negatives are those that are non-outbreak periods, which have been correctly identified by the model (actual = 0, predicted = 0). False positives are the periods between the outbreaks that are falsely alleged to be outbreaks by the model (actual = 0, predicted = 1), and False negatives are periods of the outbreak that the model has overlooked to identify (actual = 1, predicted = 0).

Model Evaluation Metrics

These values were determined by comparing the model's predictions with the actual testing data regarding the actual outbreaks. The best model configuration was selected based on the balance between precision and recall, with higher priority given to maximizing recall to avoid missing outbreaks while maintaining an acceptable precision ranging from 0.85-0.90. The alignment of monthly trends was evaluated separately by aggregating the weekly predictions to assess how well the model captured overall outbreak patterns over time.

Table 1: Model Evaluation Metrics Used for Random Forest Classification

Metrics	Formula	Description
Accuracy	$\frac{(TP + TN)}{(TP + TN + FP + FN)}$	Accuracy tells how correct the model is overall, showing the proportion of total predictions, both outbreaks and non-outbreaks, that was correctly classified.
Precision	$\frac{TP}{(TP + FP)}$	Precision showed how reliable the model is when predicting outbreak. With high precision, there are fewer false positives because the majority of the outbreak predictions will be accurate.
Recall	$\frac{TP}{(TP + FN)}$	Recall measured the ability of the model to detect real outbreaks from the data. Higher recall means the model detected most of real outbreak, resulting fewer missed outbreaks.
F1- Score	$\frac{2\ (Precision \times Recall)}{(Precision + Recall)}$	The Fl-score combined precision and recall into a single value. It gave a balance between avoiding false alarms (precision) and not missing real outbreaks (recall). A higher Fl score indicates that the model performed well in both aspects.

Application Design and Development

Application Design

The researchers initially coded the training information into the Random Forest (RF) model to facilitate pattern learning to make predictions. Once the model was optimized, the trained model was stored as a Joblib file, and could then be deployed without having to retrain it. The RF model was also developed into a web application, with Firebase, a cloud storage developer, authentication, and data processing provider. The frontend enables users to key in data that is processed in real time and it includes the barangays chosen or the case details and generate predictions. Firestore is used to store user inputs, prediction results, and system logs to monitor and analyze them and give real-time alerts, depending on user preferences. New data is used to retrain the model to remain accurate and reliable, so that the website can effectively predict multiple outbreaks on a large scale and with minimal reliability.

User Interface and User Experience Design

The website's user interface (UI) and user experience (UX) were designed for simplicity, accessibility, and functionality, allowing users to navigate easily and get timely dengue risk results. The system supports three user categories: a) admins, b) health officials, and c) the general public. Health officials may encode dengue case reports, admins validate data accuracy before uploading it to the server, and public users access real-time risk maps through the dashboard. All input data are stored in Firebase, which connects to the Random Forest (RF) model for prediction. The system outputs barangay risk levels, forecasted dengue cases, and warning alerts, displayed together with safety protocols and emergency hotlines for quick access to healthcare services. The admin dashboard enables data monitoring, validation, and system updates, ensuring reliability and up-to-date predictions. Visual outputs include a color-coded map marking low (green), moderate (yellow), and high (red) risk areas. Overall, the website integrates data collection, prediction, and visualization to support efficient dengue prevention, and public awareness.

Testing and Performance Evaluation

The assessment utilized a five-point Likert scale to evaluate a website's user interface and experience. In pre-implementation, qualified experts in digital health and technology assessed the app and provided feedback on its features. In selecting the expert, the researchers considered the following; a) must be an IT specialist; b) have experience in public health information; c) have a Bachelor's degree in Information Technology, Computer Science, and Public Health. The system was also evaluated by Barangay Officials enabling them to have suggestions and improvements. After assessing their ratings, all the suggestions and recommendations were implemented to the website then post-implementation was conducted to the Science and Information Technology experts.

Table 2: Rating Scale of the Evaluators' Assessment of the Website (Pimentel, 2010)

Rating Scale	Range	Description	Interpretation
5	4.21 - 5.00	Strongly Agree	Excellent Quality
4	3.41 - 4.20	Agree	Good Quality
3	2.61 - 3.40	Neutral	Fair Quality
2	1.81 - 2.60	Disagree	Poor Quality
1	1.00 - 1.80	Strongly Disagree	Very Poor Quality

Data Analysis

The study analyzed data on the website's user interface and user experience in predicting dengue outbreaks, using user responses and system outputs. Likert-scale responses were summed using the Weighted Mean into a single value to measure the overall user agreement, Standard Deviation to provide a measure of response variability and reliability, the descriptive statistics and a rating scale interpreted the usability and system effectiveness (Pimentel, 2010), and Cronbach Alpha was used to determine the internal consistency of questionnaire items (Cronbach, 1951). A confusion matrix was also used to evaluate the Random Forest model's performance which compared actual dengue outbreak labels with model predictions to identify true and false positives and negatives, providing a clear assessment of the system's predictive ability.

Ethical Consideration

Prior to the preparation of the study, the researchers completed all necessary documents such as consent forms and evaluation forms. First, a letter of request was addressed to the school principal to obtain permission to conduct the study. After the letter of request was granted, formal letters were sent to the appropriate authorities for further approval. Data collection only proceeded once all required approvals had been granted. All collected data was only used for academic purposes. The researchers followed the Data Privacy Act of 2012 by ensuring the protection of all the personal information, especially the participant's identity, and was kept under strict confidentiality and used only for the declared purpose.20 The researcher upheld ethical standards maintaining respect and transparency throughout the process.

RESULTS AND DISCUSSION

Dengue Outbreak Prediction Framework

Figure 4 shows the dengue outbreak prediction framework of the DenGuess system, illustrating how data from health workers and public users are integrated to support early outbreak detection. Improved dengue outbreak forecasts at the barangay level are supported by the use of an integrated data-driven system, which facilitates timely identification of risks and informed decision making. Its nature lies in the flexibility and reliability of the Random Forest model, which can capture complex relationships among several interrelated factors such as the data sources that include reported dengue cases, climate variables, and user-submitted symptoms, and are hence well-suited for dynamic public health data. The data are uploaded and managed by the admins and health workers on a monthly basis; this data is preprocessed and analyzed to generate predicted risk levels, which are then stored in a Firestore database and displayed on a public dashboard for weekly risk viewing, symptom reporting, and access to dengue prevention information (Carvajal *et al.*, 2018).

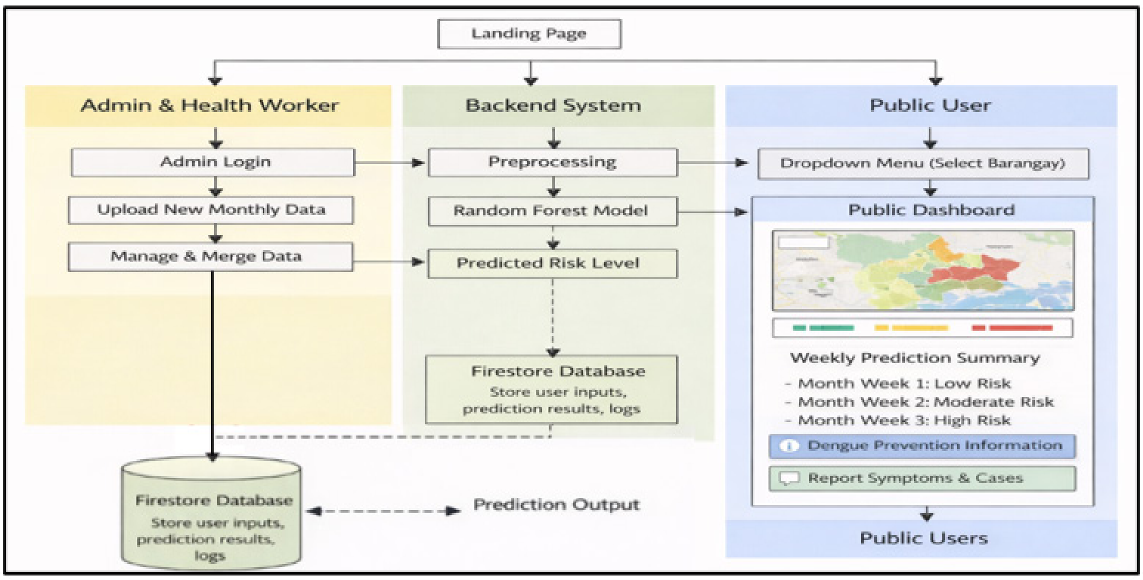

Figure 2: Dengue Outbreak Prediction Framework

Machine Learning Web-based Application

Figures 5 highlight the key features of the application that support dengue prediction and decision-making. To demonstrate practical implementation, the developed DenGuess system was deployed online and can be accessed at https://denguess.vercel. The Landing Page

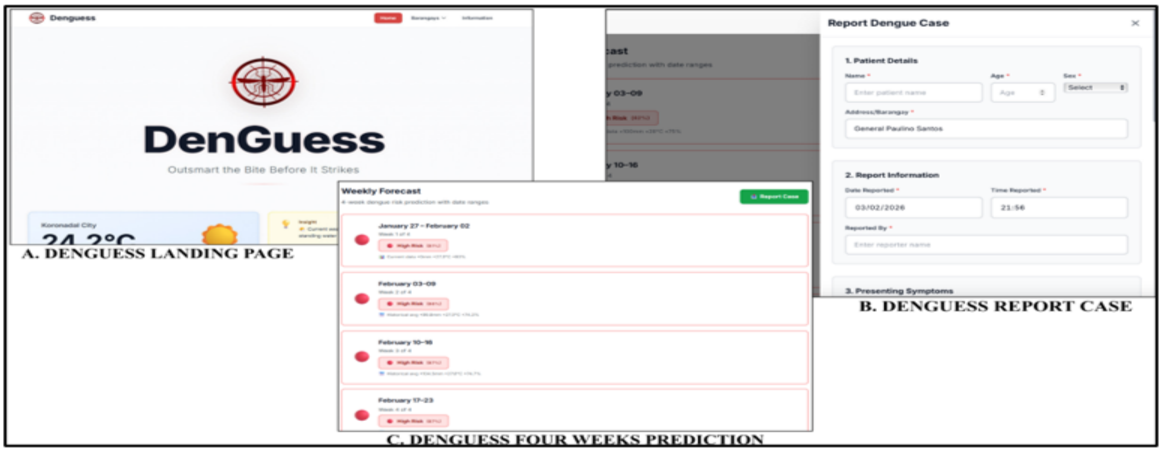

Figure 3: DenGuess Web-Based Application

acts as the central hub, giving users quick access to forecasts and reporting tools. The dengue prediction interface presents barangay-level risk forecasts through maps and weekly summaries, helping users anticipate outbreaks and plan preventive actions. Users such as the health workers can also submit dengue cases or symptom reports directly through the platform, enabling real-time community monitoring and providing immediate access to essential dengue information for timely responses. In order to trigger timely interventions, outbreak alerts are highly important to mobilize vector control and to prime or reorganize healthcare delivery services in preparation for a surge in suspected cases (Runge-Ranzinger *et al.*, 2014). Several papers have proved that meteorological data and record of previous cases are the best indicators for dengue outbreaks. Common methods used in designing early warning systems including outbreak detection are statistical and machine learning methods (Addawe *et al.*, 2024).

Random Forest Evaluation

Table 2 summarizes the classification performance of the RF Model used for dengue outbreak prediction. Figure 5 presents temporal trend validation across all barangay

Table 2: Performance Metrics of RF Model

Metrics	Training	Testing	Validated Data
Accuracy	98.06%	97.14%	82.26%
Precision	97.64%	100.00%	100.00%
Recall	100.00%	96.43%	95.58%
F1- Score	98.80%	98.18%	89.60%

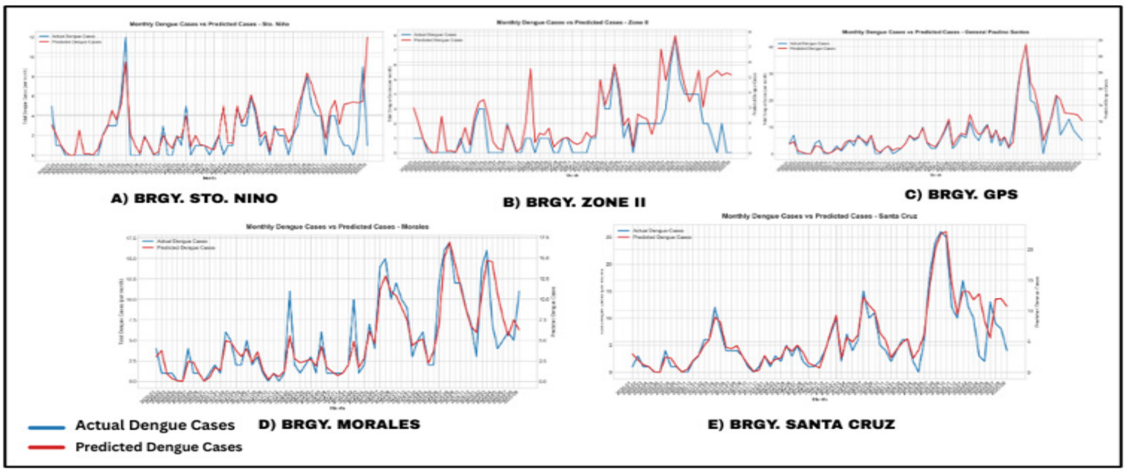

Figure 4: Actual vs. Aggregated Weekly Predicted Monthly Dengue Cases Across All Barangay.
Note. This figure demonstrates temporal trend validation, not real-time weekly prediction performance

suggests that important temporal patterns, such as seasonal peaks and outbreak phases, are well represented in the model, but the focus is on trend-level prediction, rather than on precise prediction of cases, which is an imperative of early warning and dengue preparedness and that trend-based dengue prediction is a common theme of other studies on this subject (Ramadona *et al.*, 2016).

Website's User Interface and User Experience Evaluation

Table 3 evaluates the website's user interface in terms of the content and design, comparing pre-implementation and post-implementation phases to determine improvements after system enhancement. The website's user interface was evaluated in areas spanning from its content readability, accessibility and organization, to its design. The website showed substantial improvement after the necessary adjustments were implemented, notably for its accessibility, convenience, and lack of distracting elements which all garnered a perfect post-implementation mean. The website's user interface garnered an overall post-implementation mean of 4.28±0.062, meaning it is of excellent quality. It was seen that removing jargon and simplifying content in layman's terms significantly increased user comprehension, which allowed for the interpretation of complex machine learning outputs easier for the general public (Tractinsky *et al.*, 2000).

Table 3: Evaluation of Website's User Interface

		Evaluation (Mean ± SD) (n= 42)			
No.	**Indicator**	**Pre-implementation**	**Interpretation**	**Post-implementation**	**Interpretation**
1.	The material and topic of the website are interesting and always updated.	4.22±0.87	Excellent	4.33±0.52	Excellent
2.	It is easy to access the website's content.	4.22±0.80	Excellent	5.00±0.00	Excellent
3.	The website displays information or content.	4.25±0.87	Excellent	4.50±0.55	Excellent
4.	The website's content is easy to read and it is available on the website.	4.25±0.81	Excellent	4.67±0.52	Excellent
5.	The language used in the website is convenient.	4.19±0.79	Good	5.00±0.00	Excellent
6.	The website's content can be recognized through scroll left and right when reading.	4.17±0.88	Good	4.50±0.84	Excellent
7.	The website's design and interface are attractive and are pleasing to look at.	4.31±0.62	Excellent	4.17±0.98	Good
8.	The used website color is discreet.	4.17±0.97	Good	4.67±0.52	Excellent
9.	It does not contain disturbing features like scrolling or blinking text and repeated animation.	4.14±0.83	Good	4.67±0.82	Excellent
10.	It has consistent website views.	4.29±0.89	Excellent	4.83±0.41	Excellent
11.	The website does not have too many contents of web advertisements.	4.33±0.72	Excellent	5.00±0.00	Excellent
12.	The website's design generates interest and it is easy to learn how to use it.	4.28±0.78	Excellent	4.33±0.52	Excellent
	Overall Post-Implementation Mean			4.28	Excellent

However, the user design and aesthetic mean has decreased post-implementation, meaning that despite having an interesting and is user-friendly design, its aesthetics need to be further improved. The website's design is not something to look over as studies have found that users are more likely to turn to the Internet before consulting an actual professional (Alduraywish *et al.*, 2020). It was also seen that users deem the websites are more functional and reliable when the interface appears to be more pleasing to the eyes rather than jam-packed. This not only shows how the internet affects user's decision making, (Mahmoodabadi *et al.*, 2025) but also shows the potential risk of misinterpreting or disregarding even the most accurate predictive results (Okura *et al.*, 2020; Nontapet *et al.*, 2022). This alone justifies the need to enhance these parameters, as it would evidently bring significant improvements in how public health information systems are used in the community, as well as in user adherence and comprehension, serving as a gateway to creating actionable plans that support in making timely interventions possible.

Table 4 illustrates the evaluation of a website's user experience in terms of navigation and performance, which shows measurable improvements in clarity and ease of movements across the system after implementation. The post-implementation results show that the website's UX received an overall "Excellent Quality" rating because the links were clearer, the menus were better organized, and the paths were easier to follow. The highest scores were seen in link clarity and system maintenance with a score of 4.83±0.51, showing that users could move around the website easily with little confusion. Meanwhile, other areas like system direction and the handling of new browser windows scored relatively lower, with a mean of 4.00±1.10, leaving room for enhancements in the future.

Table 4: Evaluation of Website's User Experience

		Evaluation (Mean ± SD) (n= 42)			
No.	**Indicator**	**Pre-implementation**	**Interpretation**	**Post-implementation**	**Interpretation**
13.	Directions for the precision of existence of the website are observable.	4.36±0.54	Excellent	4.50±0.55	Excellent
14.	Links and instructions to facilitate search of desired context exist.	4.11±0.67	Good	4.83±0.41	Excellent
15.	Browsing the website with existing links or the back button on the browser is convenient.	4.06±0.67	Good	4.83±0.51	Excellent
16.	The website has been well-maintained and always updated.	4.11±0.76	Good	4.83±0.41	Excellent
17.	New windows browsers when browsing the website can be used.	4.19±0.75	Good	4.50±0.84	Excellent
18.	Links and menus by standard are in place and easy to recognize.	4.03±0.91	Good	4.67±0.52	Excellent
19.	Speed to download files and access one page to another page on the website.	4.17±0.66	Good	4.50±0.84	Excellent
20.	There is ease of distinguishing links that have not been or have been visited.	4.09±0.74	Good	4.00±1.10	Good
21.	There is ease of access in the website at anytime and anywhere.	4.17±0.82	Good	4.83±0.41	Excellent
22.	The website provides responding to expectations for all actions performed.	4.12±0.74	Good	4.17±0.41	Good
23.	The website is efficient and friendly for all people to use.	4.29±0.75	Excellent	4.33±0.63	Excellent
24.	There are clear and useful images when we don't know how to process the action.	4.14±0.91	Good	4.67±0.82	Excellent
	Overall Post-Implementation Mean			4.22	Excellent

This signifies that these improvements are substantial in improving how health workers and citizens could quickly access outbreak risk predictions, risk maps, and case reporting features (World Health Organization, 2018) while some features, such as system directions and opening new windows, still need improvement, the higher post-implementation scores confirm that the changes greatly improved the website's usability and access to information for both users and local health offices (Nielsen, 1994). The system also received very high satisfaction ratings for navigation and accessibility, showing that real-time simulations and color-coded risk maps were easy to understand and helpful in real-life public health situations (Ribeiro *et al.*, 2016). By presenting complex machine learning results in a simple and visual way, the system allowed users to understand predictions quickly and make better health decisions, showing that using machine learning tools in the Philippine healthcare setting is possible because most users had little difficulty using the system (Department of Health, 2022).

CONCLUSION

This study designed a dengue outbreak prediction framework using local epidemiological and environmental data; developed a machine learning web-based application on the RF model; and conducted a performance assessment on the RF Model in terms of accuracy of real time simulation, precision, recall, and F1-score; evaluated the website's content, organization, readability, navigation and links, user interface design, performance and effectiveness in predicting dengue outbreaks. The system showed moderate predictive capabilities in terms of accuracy of real-time simulation, precision, recall, and F1-score, which proves its usefulness in the detection of dengue outbreak intervals, reducing the number of false alarms, and not letting the factual outbreaks slip. Through combining effective predictive modeling with an effective interaction interface, the study suggests that the system can deliver timely risk data, improve community awareness, and improve population health preparedness in the City of Koronadal. Overall, combining machine learning with practical web-based tools is an effective solution for improving the detection, prevention, and control of dengue outbreaks in the early stages.

Recommendations

This study recommends using DenGuess as a vital component of the City of Koronadal's public health infrastructure. 1) It must coordinate with local health offices and barangay units to respond to the outbreak and report data on time, while also requesting the government to help fund the on-site costs and maintenance. 2) To maintain predictive accuracy, it is suggested to continuously retrain the Random Forest model using the latest epidemiological data and variables, including human mobility and population density. 3) It could encourage community participation by training health workers and residents, 4) expanding the system to neighboring municipalities, 5) risk identification at the barangay level, and 6) building an offline mobile application to make the system more inclusive.

REFERENCES

Addawe, J. C., Juayong, R. A. B., & Caro, J. D. L. (2024). Prediction of outbreak periods of dengue in Baguio City, Philippines using machine learning classification models. *In Atlantis Highlights in Computer Sciences* (pp. 380–394). Atlantis Press. https://doi.org/10.2991/978-94-6463-388-7_23

Alduraywish, S. A., Altamimi, L. A., Aldhuwayhi, R. A., AlZamil, L. R., Alzeghayer, L. Y., Alsaleh, F. S., Alsayari, A. J., Alaqeel, M. K., & Alotaibi, N. K. (2020). Sources of health information and their impacts on medical knowledge perception among the Saudi Arabian population: Cross-sectional study. *Journal of Medical Internet Research, 22*(3), e14414. https://doi.org/10.2196/14414

Carvajal, T. M., Viacrusis, K. M., Hernandez, L. F. T., Ho, H. T., Amalin, D. M., & Watanabe, K. (2018). Machine learning methods reveal the temporal pattern of dengue incidence using meteorological factors in metropolitan Manila, Philippines. *BMC Infectious Diseases, 18*(1), 183. https://doi.org/10.1186/s12879-018-3066-0

Castro, I. K. G., Elquiero, N. E. M., & Fradejas, J. D. (n.d.). *Assessing machine learning methods in predicting dengue incidence using climatic factors in Region* IV-A (CALABARZON), Philippines. Animo Repository. https://animorepository.dlsu.edu.ph/etdb_bio/27

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334. https://doi.org/10.1007/BF02310555

Department of Health (Philippines). (2022). *National eHealth strategy and framework 2022–2027*. Department of Health.

Exebio-Chepe, Y. V., Bravo-Ruiz, J. A., & Tuesta-Montesa, V. A. (2024). Comparison of machine learning algorithms for dengue virus (DENV) classification. *Journal of Applied Research and Technology, 22*(5), 729–745. https://doi.org/10.22201/icat.24486736e.2024.22.5.2422

Fang, W., Ren, K., Liu, T., Shang, J., Jia, S., Jiang, X., & Zhang, J. (2024). Evaluation of random forest-based input variable selection methods. *Scientific Reports, 14*(1), 31578. https://doi.org/10.1038/s41598-024-81502-y

Francisco, M. E., Carvajal, T. M., Ryo, M., Nukazawa, K., Amalin, D. M., & Watanabe, K. (2021). Dengue disease dynamics are modulated by the combined influences of precipitation and landscape: A machine learning-based approach. *Science of the Total Environment, 792*, 148406. https://doi.org/10.1016/j.scitotenv.2021.148406

Lake, I. R., Colón-González, F. J., Barker, G. C., Morbey, R. A., Smith, G. E., & Elliot, A. J. (2019). Machine learning to refine decision making within syndromic surveillance. *BMC Public Health, 19*(1), 559. https://doi.org/10.1186/s12889-019-6899-0

Mahmoodabadi, A., Dehghan, H., Kimiafar, K., Karami, M., Mousavi Baigi, S. F., & Mehrabadi, M. F. (2025). Usability evaluation methods for hospital information systems. *BMC Health Services Research, 25*, 1540. https://doi.org/10.1186/s12913-025-13745-y

Martínez-Gramage, J., Albiach, J. P., Moltó, I. N., Amer-Cuenca, J. J., Moreno, V. H., & Segura-Ortí, E. (2020). A random forest framework to improve injury prevention strategies in team sports. *Sensors, 20*(21), 6388. https://doi.org/10.3390/s20216388

Nielsen, J. (1994). *Usability engineering*. Morgan Kaufmann.

Nontapet, O., Jaroenpool, J., Maneerattanasa, S., Thongchan, S., Ponprasert, C., Khammaneechan, P., Chansang, C., & Tozan, Y. (2022). Predicting dengue risk villages using machine learning and geographical information systems in Thailand. *International Journal of Environmental Research and Public Health, 19*(19), 11989. https://doi.org/10.3390/ijerph191911989

Okuhara, T., Ishikawa, H., Ueno, H., Okada, H., Kato, M., & Kiuchi, T. (2020). Readability comparison of pro- and anti-smoking health information and its impact on self-efficacy for smoking cessation. *Health Psychology Open, 7*(1), 2055102920915585. https://doi.org/10.1177/2055102920915585

Olana, K. O. A., Poprom, N., Siewchaisakul, P., Punyapornwithaya, V., & Thongprachum, A. (2025). Spatial distribution and dengue forecasting in the Philippines. *Transboundary and Emerging Diseases, 2025*, 9987654. https://doi.org/10.1155/2025/9987654

Omadlao, Z. R. D., Cabrales, J. M. A., Cristobal, S. C. M., Dee, M. V. A., Tadeo, J. R. V., Marigmen, J. L. D. C., & Pajarillo, R. R. (2022). Machine learning-based dengue forecasting system for Irisan, Baguio City. *AIP Conference Proceedings, 2472*, 040019. https://doi.org/10.1063/5.0092785

Pimentel, M. (2010). An evidence-based treatment algorithm for IBS based on a bacterial/SIBO hypothesis: Part 2. *The American Journal of Gastroenterology, 105*(6), 1227–1230. https://doi.org/10.1038/ajg.2010.131

Ramadona, A. L., Lazuardi, L., Hii, Y. L., Holmner, Å., Kusnanto, H., & Rocklöv, J. (2016). Prediction of dengue outbreaks based on disease surveillance and meteorological data. *PLOS ONE, 11*(3), e0152688. https://doi.org/10.1371/journal.pone.0152688

Ren, H., & Xu, N. (2024). Forecasting dengue fever epidemics in China using time series analysis and machine learning methods. *Infectious Diseases of Poverty, 13*(1), 50. https://doi.org/10.1186/s40249-024-01198-2

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. *In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144). Association for Computing Machinery. https://doi.org/10.1145/2939672.2939778

Runge-Ranzinger, S., McCall, P. J., Kroeger, A., & Horstick, O. (2014). Dengue disease surveillance: An updated systematic literature review. *Tropical Medicine & International Health, 19*(9), 1116–1160. https://doi.org/10.1111/tmi.12333

Sy, P., Navera, C., Tan, K., & Nicolas, F. (2021). *Data privacy protection in research involving human participants*. Figshare. https://doi.org/10.6084/m9.figshare.14479353.v4

Tinoca, L., Piedade, J., Santos, S., Pedro, A., & Gomes, S. (2022). Design-based research in education: Methodological insights and practical implications. *Education Sciences, 12*(6), 410. https://doi.org/10.3390/educsci12060410

Tractinsky, N., Shoval-Katz, A., & Ikar, D. (2000). What is beautiful is usable. *Interacting with Computers, 13*(2), 127–145. https://doi.org/10.1016/S0953-5438(00)00031-X

Velasco, R. F., Lippe, M., Tamayo, F., Mfuni, T., Sales-Come, R., Mangabat, C., Schneider, T., & Günter, S. (2022). Forest mapping in tropical landscapes. *Remote Sensing of Environment, 274*, 112997. https://doi.org/10.1016/j.rse.2022.112997

Wang, J., Yu, H., Hua, Q., Jing, S., Liu, Z., Peng, X., Cao, C., & Luo, Y. (2020). Random forest model in the prediction of COVID-19 severity. *PeerJ, 8*, e9945. https://doi.org/10.7717/peerj.9945

World Health Organization. (2018). *Early warning, alert and response systems for public health emergencies*. World Health Organization.

World Health Organization. (2025, August 21). *Dengue and severe dengue*. https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue