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Design and implementation of an IoT-OL trap for community-based dengue early warning system

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Key words: Internet of things, *Aedes aegypti*, Orvicidal-larvicidal trap

Abstract

Surveillance of mosquito populations is central to successful vector intervention and disease control. Conventional surveillance techniques of manual egg counts and field-based assessments are cumbersome, slow, and hard to scale for real-time monitoring applications. To overcome these limitations, the paper introduces the design, implementation, and deployment of an Internet of Things (IoT)-Based Orvicidal-Larvidal (OL) trap and Community Dengue Early Warning System (C-DEWS) to facilitate the automated detection, enumeration, and monitoring of *Aedes aegypti* eggs in Cauayan City, Isabela. A Raspberry Pi equipped with micro-camera lenses captures the images and in determining the object of interest. The Convolution Neural Network (CNN) associated with the device achieves an outstanding 99.5% success rate for detecting and counting *Aedes aegypti* eggs, ensuring a reliable system. In addition, all key indicators, such as environmental factors, sanitary practices, *Aedes aegypti* egg distribution per location, and integration of dengue cases from the City Health Office (CHO) determine and monitor the dengue outbreak. This work shows how smart mosquito surveillance systems emerge from integrating data and multiple networks with cloud management frameworks.

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Introduction

The Philippine government, with different health organizations, carried out campaigns in *Aedes aegypti* surveillance using Orvicidal Larvicidal traps, also known as the OL-Trap, as part of a broader strategy to enhance vector control efforts and surveillance of dengue's endemic nature (Balingit *et al.*, 2020). Data collected in these traps are significant in explaining the dynamics of mosquito populations (Salazar and Gimutao, 2018). This method shows remarkable advantages, yet challenges remain, such as the manual counting of mosquito eggs being inadequate in the face of rapidly expanding mosquito populations, time-consuming (Naranjo-Alcazar *et al.*, 2024), and if not properly maintained, these traps can become breeding sites themselves (Malarvizhi *et al.*, 2023). Another approach also focuses on monitoring their immature stages in aquatic locations, including riverbanks, lake edges, and rice fields. Nevertheless, diversity of mosquito habitats and the labor-intensive process of physical sampling present significant challenges to effective monitoring (Sakata *et al.*, 2022). Citizen Science initiatives for public mosquito species reporting public participation has likewise improved mosquito surveillance operation especially in supporting health authorities, however it is vital to ensure that the result of this program translate into meaningful public health improvements (Sakata *et al.*, 2022; Walther and Kampen, 2017). Given these circumstances, developing a predictive system that would automate the ongoing campaign to contain and prevent the outbreak of dengue disease becomes an essential solution (Salam *et al.*, 2021).

The advancements of the Internet of Things (IoT) have created opportunities since its application in varied fields, including agriculture (Prema and Belinda, 2019), climate studies (Ojo *et al.*, 2024) and urban planning (Bellini *et al.*, 2022), where data contributes greatly to decision-making (Qureshi, 2018; Mardiani *et al.*, 2024). More so, integrating neural networks allows IoT devices to gain more functionality, thus offering better services (Yao *et al.*, 2019). IoT systems exhibit exceptional performance through continuous operation and immediate insight delivery which allows them to resolve complex problems requiring accuracy and speed (Mardiani *et al.*, 2024). Real-time data collection and data analysis emerge as promising mechanisms to improve mosquito surveillance (Gumiran *et al.*, 2023; Gumiran *et al.*, 2022; Isa *et al.*, 2019). For instance, IoT served as an early warning and rapid response to monitor environmental parameters and vector populations using networked devices (Aldosery *et al.*, 2022). In addition, IoT-based applications were also used to determine the dengue virus infection chains and prevent infections through cloud computing and fog computing paradigms (Manoharan *et al.*, 2023; Vijayakumar *et al.*, 2019). While these results are promising, the adoption and implementation of proposed IoT-based early warning systems within local communities remain limited. With this, it is important to understand the details about environmental factors influencing its survival and breeding (Aldosery *et al.*, 2022), sanitation practices aimed to control mosquitoes (Tambo *et al.*, 2019), and total egg counts in different locations to follow the dengue case trend.

The major contributions of this work are (1) developing and implementing a scalable IoT-enabled OL trap for autonomous monitoring of mosquitoes, (2) employing a Convolutional Neural Network as a classifier for *Aedes aegypti* egg, and (3) deployment Community Dengue Early Warning System (C-DEWS) to engage the community and support localized dengue management efforts.

Materials and methods

System requirements

This study presents the designing, developing, and implementing a system aimed at improving the monitoring and control of *Aedes aegypti* eggs to reduce dengue outbreaks through IoT OL-Trap. The system requirements were rigorously defined to ensure effectiveness in operation and to derive valuable insight for local health authorities to make informed decisions.

For this to be achieved, the system must be capable of receiving data over a long period without affecting its functional sustainability. A substantial volume of collected data is necessary to provide accurate results of patterns and trends. In addition, weather stations will need to monitor environmental variables, such as temperature, rainfall, and humidity.

Moreover, the hardware components like Raspberry Pi and the camera modules need a robust-enclosure arrangement to keep them away from extreme temperature, water and human interference.

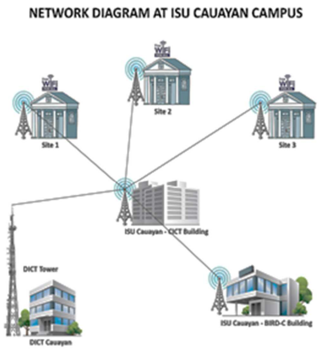


Fig. 1. Network topology

The IoT-OL trap must maintain steady access to a stable internet connection to transmit data to the server for thorough analytical processing. A representation of the network topology is shown in Fig. 1. The network's central hub is located at the Isabela State University (ISU) Cauayan CCSICT Building. The data from the barangays (i.e. village) is systematically aggregated and transmitted to the server housed in the ISU- Business Intelligence Research and Development Center (BIRD-C) to process incoming data and execute analytics while maintaining secure storage.

Convolutional neural network on detection and counting Aedes aegypti

The Philippine Nuclear Research Institute (PNRI) provided the datasets utilized for training. The datasets underwent adaptive thresholding as an image preprocessing technique to ensure the eggs' visibility for detection. Adaptive thresholding is among the main approaches for isolating objects from background while maintaining fine details (Desiani *et al.*, 2022; Akbaba and Polat, 2022). After training, the model successfully classified the eggs from *Aedes aegypti* to non-*Aedes*, with 99.5% classification accuracy (Fajardo, 2023).

Hardware design

The micro-computer serves as a central component responsible for handling and controlling the data captured (Liu *et al.*, 2023). This device combines a Raspberry Pi 4 with an RPI-HQ-12. 3MP-V1 high camera, with a 300X microscope lens capable of taking clear images of *Aedes aegypti* eggs. LED illumination is used to provide uniform and bright lighting, improving the overall image quality. It also includes custom acrylic glass support for sturdiness and to ensure that the OL trap is correctly aligned with the camera lens of the microscope. The device setup is shown in Fig. 2, and the IoT-OL trap design with a protective enclosure is shown in Fig. 3.

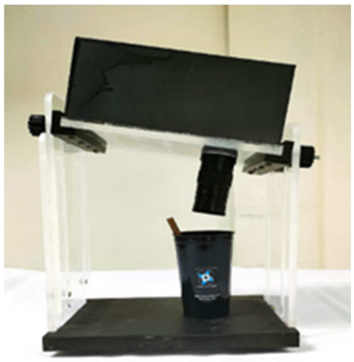


Fig. 2. Acrylic stand

Fig. 3. Box enclosure

The Power Beam radio antenna facilitates the long-range, reliable data transmission of the deployed IoT-OL Trap to the central server, operating within the 5 GHz frequency band (5150–5875 MHz) and achieves TCP/IP throughput rates beyond 450 Mbps.

The environmental factors affecting mosquito activity are continuously monitored with the help of weather stations situated at Isabela State University—Cauayan Campus and Barangay San Fermin, Barangay Cabaruan and Barangay Distric 2. This assists the system to identify patterns which might contribute to dengue spread.

The Department of Information and Communications Technology (DICT) in Cauayan City, Isabela, provides the backbone of the network's infrastructure to this complex architecture.

The DICT Tower and its support facilities maintain available connectivity between devices, users, and servers. Thus, this stable connectivity provides the basis for the system's ability to stream live from the Ovitraps to allow remote monitoring.

Software design

The research team strategically deployed the IoT-OL trap on locations based on the dengue hotspot map provided by the Local Government Unit (LGU) of Cauayan City, Isabela City Health Office. The process of Raspberry Pi is programmed to capture the captured images of *Aedes aegypti* from the ovitrap every 4 hours. Besides, each of the Raspberry Pi is set up to upload the data into the corresponding folder associated with its MAC address ensuring that data from each device is organized and stored separately, thus making real-time index computation possible. The LED is activated before the camera captures an image, and afterward, it turns off. After the input image travels through the model, a detection function conducts inference operations. Ultimately, the system analyzes the captured image and determines the quantity of eggs laid. Data transmission occurs between the device and server through HTTP/HTTPS protocol connection. Based on the information collected from the OL-trap, the system generates the image of the mosquito, the total number of eggs detected, the timestamp of image capture and the Raspberry Pi's unique ID.

Upon transmission, the system uses this data to run analytics, creates a historical dataset from the mosquito egg counts, and correlates it to the environmental factors collected. This is also to be used for mapping purposes. The system triggers notification alerts to health officials on both mobile applications and web interfaces when egg counts hit specified thresholds.

The app also provides convenient access to historical and trend data. Furthermore, users can also visualize real-time data, view mosquito data, and monitor environmental factors with the help of the web dashboard centralizing all principal information. The interactive dashboard uses maps to show areas where mosquito breeding sites are, aiding decision-making for local health authorities.

Results and discussion

In this work, the research team developed the IoT-OL trap and Community Dengue Early Warning System (C-DEWS) that proved to be successful based on the pilot deployment at Cauayan City, Isabela. With this, we have identified the following results:

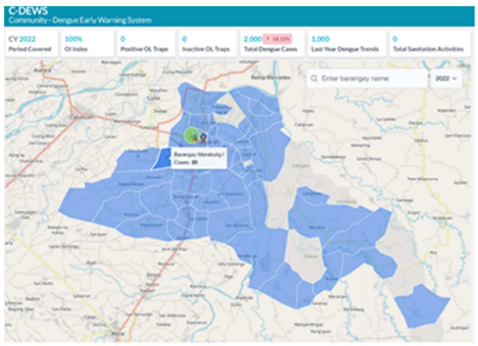


Fig. 4. C-DEWS visualization map

The map shown in Fig. 4 illustrates the distribution of dengue causes in each barangay from 2015 to 2022. Based on this visualization map, several of the barangays still consistent in experiencing high incidences while other areas appeared to be less affected.

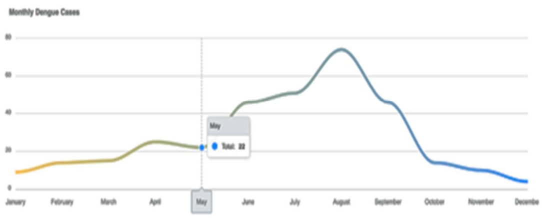
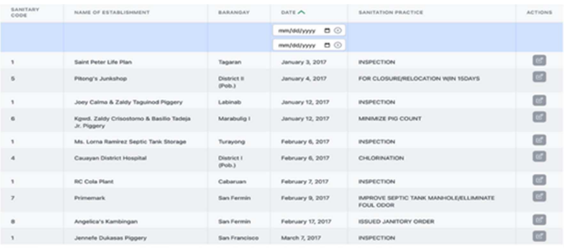


Fig. 5. Dengue case trend

Fig. 5 represents the patterns and trends of dengue cases. The number of cases starts around April and May and continues to climb, peaking around August. The number of cases begins to decline in October towards the end of the year. The research team also examined the sanitation practices from numerous establishments throughout various barangays and linked it to observed dengue case data. Fig. 6 demonstrates the activities done in preventing dengue outbreak.



SANITARY CODE	NAME OF ESTABLISHMENT	BARANGAY	DATE	SANITATION PRACTICE	ACTIONS
			mm/dd/yyyy mm/dd/yyyy		
1	Saint Peter Life Plan	Tagaran	January 3, 2017	INSPECTION	
5	Pitong's Junkshop	District II (Pob.)	January 4, 2017	FOR CLOSURE/RELOCATION W/IN 15DAYS	
1	Joey Calma & Zaldy Taguinod Piggery	Labinab	January 12, 2017	INSPECTION	
6	Kgwd. Zaldy Crisostomo & Basilio Tadeja Jr. Piggery	Marabulig I	January 12, 2017	MINIMIZE PIG COUNT	
1	Ms. Lorna Ramirez Septic Tank Storage	Turayong	February 6, 2017	INSPECTION	
4	Cauayan District Hospital	District I (Pob.)	February 6, 2017	CHLORINATION	
1	RC Cola Plant	Cabaruan	February 7, 2017	INSPECTION	
7	Primemark	San Fermin	February 9, 2017	IMPROVE SEPTIC TANK MANHOLE/ELLIMINATE FOUL ODOR	
8	Angelica's Kambingan	San Fermin	February 17, 2017	ISSUED JANITORY ORDER	
1	Jennefe Dukasas Piggery	San Francisco	March 7, 2017	INSPECTION	

Fig. 6. Sanitation practices

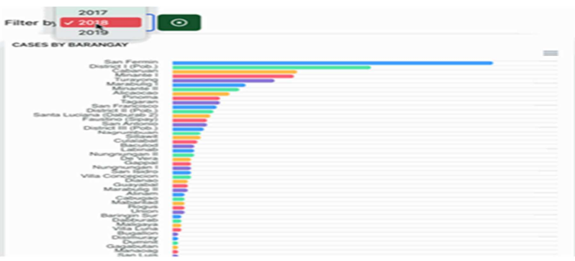


Fig. 7. Cases per barangay

The visual presentation shown in Fig. 7 highlights where dengue infections appear in each barangay. The case classification chart depicted in Fig. 8 shows the information about confirmed, suspected, and probable cases with most being under current investigation. The data shows cases with warning signs that need to be monitored before they become severe.

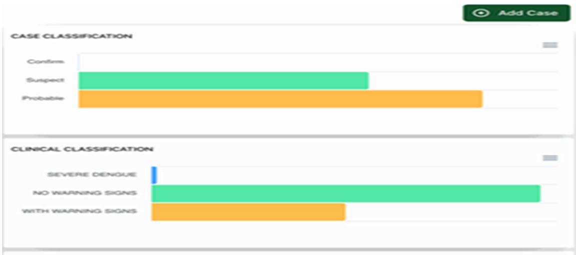


Fig. 8. Case and clinical classifications

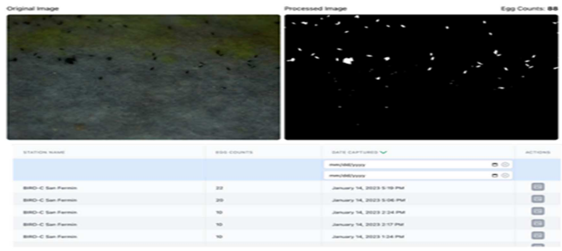


Fig. 9. Captured and preprocessed images using CNN

As mentioned earlier, Convolutional Neural Network was used in detecting and counting *Aedes aegypti* eggs. The captured images shown in Fig. 9 were directly received from the IoT-OL traps. The left side presents the raw image or its original state, while the right side showcases the preprocessing techniques, revealing the egg's distinct characteristics.

Conclusion

In this study, a Community Dengue Early Warning System (C-DEWS) was successfully designed and implemented. The Convolutional Neural Network created for the IoT-OL Trap was utilized to make the operation of this system smarter and more reliable. The hardware and the software design were explained to describe the data transmission to C-DEWS. The results obtained were rendered to identify the environmental factors that affect mosquito activity, the sanitation practices to prevent its outbreak, and the total number of eggs counted in each site to understand patterns in dengue cases.

The study was carried out to assess the system's effectiveness in detecting *Aedes aegypti* egg.

Exploring different algorithms to enhance the microcomputer's performance and system optimization designed to decrease latency and minimize energy usage stands as essential recommendations for long-term deployments.

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