UAV-Based, AI-powered detection and heat mapping of potential mosquito breeding sites using YOLOv8

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Abstract. Mosquito-borne diseases, particularly dengue, remain a major public health challenge in tropical regions such as the Philippines. In 2024, dengue cases increased sharply nationwide, with the Davao Region reporting over 9,000 cases and rising mortality. Conventional mosquito control methods are often labor-intensive, costly, and difficult to sustain, especially in underserved communities. This study proposes an automated, real-time mosquito breeding site detection system integrating unmanned aerial vehicles (UAVs) with artificial intelligence-based image analysis and spatial heat mapping. A DJI Air 3 drone conducts aerial surveillance, while an OKdo Jetson Nano microcontroller runs dual YOLOv8 models: YOLOv8n for object detection and YOLOv8seg for water segmentation, optimized using NVIDIA TensorRT. The system detects potential breeding containers such as buckets, tires, and stagnant water, and generates heat maps to classify risk levels across barangays in Caraga, Davao Oriental. Field tests over 72 flights showed inference times of 56.1–114.8 ms and frame rates of 13.21–15 FPS. The model achieved 93.20% accuracy with high recall, precision, and F1 scores. Regression analysis indicated a strong correlation ($R^2 = 0.937$) between detected breeding sites and dengue cases, confirming predictive validity and supporting its use for targeted public health interventions.

1 Introduction

Mosquito-borne diseases continue to pose serious global health risks, with dengue fever among the most rapidly spreading infections. In the Philippines, more than 269,000 dengue cases were recorded by late 2024 [1], placing enormous strain on healthcare systems. Conventional control strategies such as eliminating standing water and applying insecticides remain effective but are resource-intensive and unsustainable in low-income or remote communities. Advances in artificial intelligence (AI) and unmanned aerial vehicles (UAVs) have created new opportunities for automated surveillance and early outbreak prevention. Modern object detection algorithms like YOLOv8 achieve high-speed, high-accuracy performance [2], making them ideal for environmental monitoring.

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However, most previous studies have focused only on image classification without integrating spatial heat mapping or correlating detections with actual dengue data.

This study introduces a UAV-based AI system that uses dual YOLOv8 models on an NVIDIA Jetson Nano to detect potential mosquito breeding sites in real time. The system identifies containers and stagnant water from aerial footage and generates heatmaps that visualize the concentration and severity of breeding zones. By correlating detection outputs with dengue case data from Caraga, Davao Oriental, this research demonstrates how UAV-assisted analytics can inform data-driven dengue prevention efforts.

2 Related Studies

Vector-borne diseases remain among the leading causes of global morbidity and mortality [3]. Dengue alone causes about 96 million symptomatic cases annually [4], with substantial socioeconomic costs estimated in the billions of dollars. In the Philippines, dengue has persisted as a recurring epidemic with significant financial and public health burdens [5].

Traditional vector control relies on environmental sanitation, larvicidal treatment, and biological agents such as Bacillus thuringiensis israelensis [6]. However, these interventions face challenges of insecticide resistance and ecological risks. Integrated approaches that combine environmental management, technology-driven surveillance, and predictive analytics have gained attention.

UAVs have been increasingly used for large-scale environmental surveillance because of their high-resolution imaging and flexibility [7]. Earlier detection systems using basic classifiers such as HOG or SSD achieved limited success [8], while YOLO-based deep learning models have since demonstrated high precision even in complex outdoor conditions [9]. YOLOv8, in particular, enhances both speed and segmentation accuracy [10].

Deploying these models on edge AI devices such as the NVIDIA Jetson Nano allows real-time inference in field operations [11]. Previous works have proven its reliability for lightweight, low-power detection tasks [12]. However, few have combined object detection, water segmentation, and geospatial heat mapping in one portable framework, which this study aims to achieve.

3 Methodology

3.1 Research Setting and Data Collection

The system was tested in seven barangays of Caraga, Davao Oriental: Lamiawan, Manorigao, Palma Gil, Poblacion, Santa Fe, San Jose, and San Luis. These locations were selected based on high dengue incidence and compliance with UAV flight regulations [13]. Model training and validation data were collected in Brgy. Mandug, Davao City using a DJI Air 3 drone equipped with a 48 MP camera. Flights were conducted at 6 ± 2 meters altitude to balance detection accuracy and field coverage.

Captured imagery was transmitted to an OKdo Jetson Nano microcontroller for on-site processing and storage.

3.2 System Development and Architecture

Two YOLOv8 models were employed: YOLOv8n for object detection (bottles, buckets, plastic containers, tires, pots, and cans) and YOLOv8-seg for stagnant water segmentation. Both were converted to TensorRT engine files to optimize inference speed.

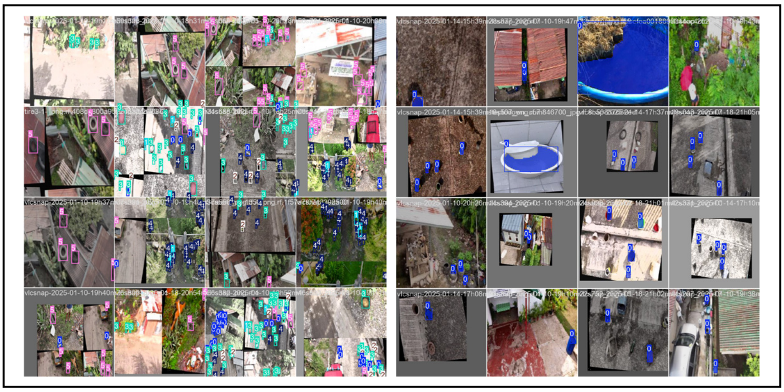

Fig. 1. Sample annotated training images for object detection and water segmentation.

The system follows a streamlined workflow. UAVs capture aerial footage, the Jetson Nano performs onboard detection and segmentation, and the detections are automatically aggregated into heatmaps that indicate breeding risk levels.

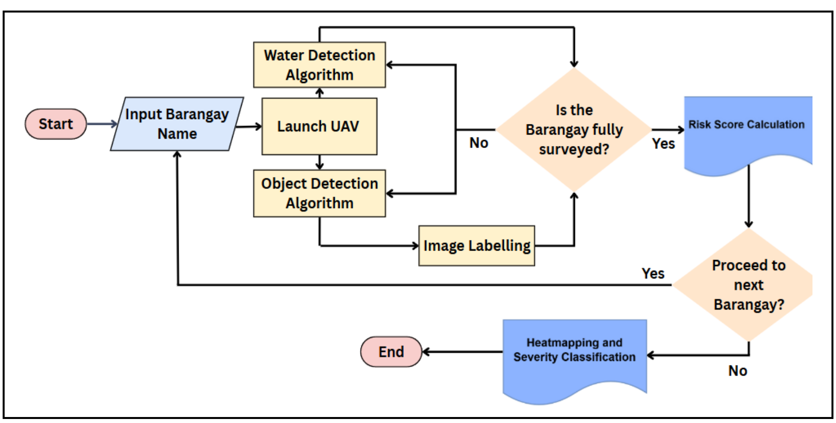

Fig. 2. Workflow of the UAV-assisted detection and heat mapping system.

On the other hand, the system architecture, shown in Figure 3, depicts the integration of UAV imaging, edge computing, and visualization components that enable end-to-end detection and risk mapping.

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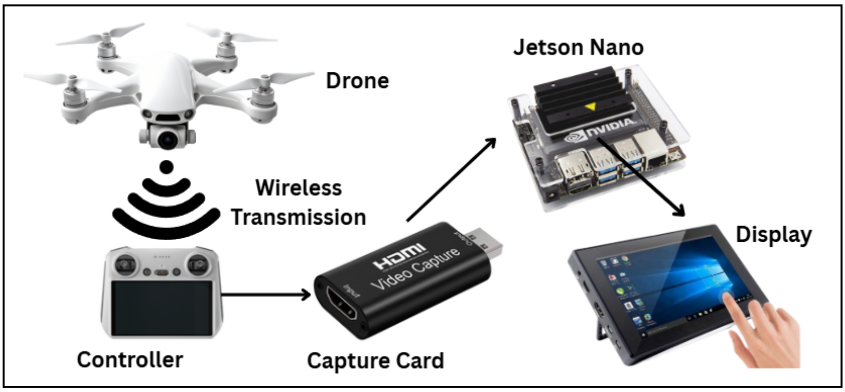

Fig. 3. Overall system architecture for UAV-based mosquito breeding site detection and heat mapping.

3.3 Evaluation Procedures

System efficiency was evaluated in 72 UAV flight tests. Metrics measured included preprocessing, inference, and postprocessing delays, as well as frame rate. Classification performance was determined using precision, recall, F1-score, and overall accuracy derived from a confusion matrix. Predictive validity was analyzed through linear regression and ANOVA to assess the relationship between detected breeding sites and dengue case data.

4 Results and Discussions

4.1 Model Training and Detection Performance

Training datasets were annotated in Roboflow and augmented for robustness. YOLOv8n achieved an mAP@0.5 of 0.805, while YOLOv8-seg recorded 0.798. The highest detection scores were observed for plastic containers (0.913) and cans (0.914), confirming strong performance for container recognition.

4.2 Processing Efficiency

The system exhibited stable real-time performance during field testing. Preprocessing averaged 2.2 to 9.1 ms, inference 56.1 to 114.8 ms, and postprocessing 5.5 to 7.6 ms, maintaining 13 to 15 FPS. TensorRT optimization on the Jetson Nano minimized delays and enabled continuous UAV operation with efficient energy use, confirming its readiness for real-world deployment.

4.3 Detection Accuracy

Overall detection accuracy reached 93.2 percent, reflecting strong classification and segmentation capability across all object types. Detection remained consistent for tires, pots, and buckets, while bottles showed slightly lower accuracy due to reflective surfaces

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and smaller image scale. Even with these limitations, the models maintained dependable results under varied outdoor conditions.

Table 1. Precision, recall, and F1-score per object class

Class	True Positive	False Positive	False Negative	Precision	Recall	F1-Score
Bottle	119	14	21	89.47%	85.00%	87.18%
Bucket	156	13	12	92.31%	92.86%	92.58%
Plastic Container	194	11	9	94.63%	95.57%	95.10%
Tire	153	7	7	95.62%	95.62%	95.62%
Pot	181	10	7	94.76%	96.28%	95.51%
Can	121	10	8	92.37%	93.80%	93.08%
Water	145	13	14	91.77%	91.19%	91.48%

4.4 Correlation with Dengue Cases

Furthermore, regression analysis revealed a strong positive correlation ($R^2 = 0.937$) between detected containers and dengue cases, indicating high predictive validity, while ANOVA confirmed statistical significance ($F = 74.47$, $p < 0.001$).

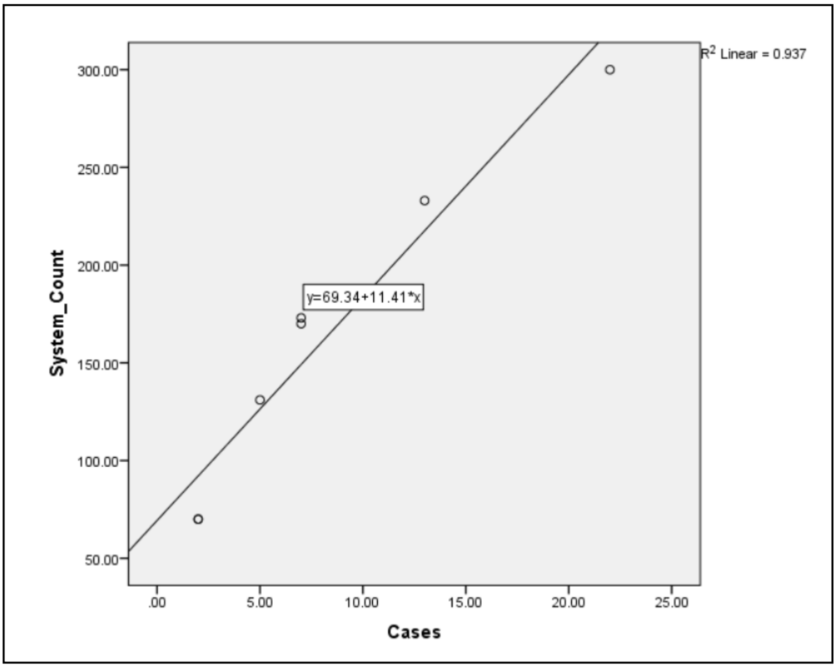

Fig. 4. Scatterplot of dengue cases versus breeding site counts

4.5 System Usability and Field Performance

Hardware testing confirmed reliable operation and portability. The Jetson Nano, integrated with the DJI Air 3 drone, maintained stable performance with low power consumption. The setup included a lightweight acrylic enclosure, cooling fan, and a 7-inch display for real-time visualization as shown in Figure 5.

Fig. 5. Hardware setup including drone, microcontroller, and display unit.

Field deployment across the seven barangays demonstrated effective detection in varied environmental conditions. The generated heatmaps clearly identified high-risk areas, allowing local health authorities to focus control measures where needed.

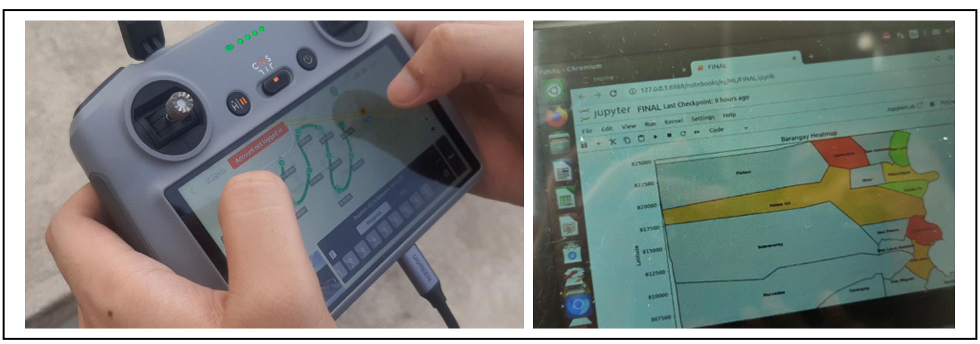

Fig. 6. Sample field deployment and generated heatmap.

Compared with prior UAV–AI frameworks [9], [10], [12], the proposed system achieved similar or higher accuracy while relying solely on edge processing, making it practical for remote and resource-limited applications.

5 Conclusion

This study confirmed the feasibility of integrating UAV imaging and edge AI for automated mosquito breeding site detection and risk mapping. The dual YOLOv8 models, optimized on a Jetson Nano, enabled real-time processing with 93.2 percent detection accuracy. Statistical validation revealed a strong correlation (R^2 = 0.937) between detected containers and dengue cases, highlighting the system's predictive reliability. The UAV–AI framework provides a cost-effective, scalable, and data-driven solution for dengue surveillance and can significantly enhance evidence-based decision-making in public health. Future work may improve detection of smaller or partially hidden objects and integrate automated UAV flight path planning for wider coverage.

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References

1. World Health Organization: WHO, Dengue and severe dengue, (2024). https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue
2. A. Amarasinghe et al., A Machine Learning Approach for Identifying Mosquito Breeding Sites via Drone Images, in SenSys '17: Proceedings of the 15th ACM Conference on Embedded Network Sensor Systems, 1–2 (2017). doi:10.1145/3131672.3136986
3. T. M. Penhollow, L. Torres, Impact of mosquito-borne diseases on global public health. Int. Phys. Med. Rehabil. J. **6**, 19–20 (2021). doi:10.15406/ipmrj.2021.06.00273
4. K. Marczell et al., The macroeconomic impact of a dengue outbreak: Case studies from Thailand and Brazil. PLoS Negl. Trop. Dis. **18**, e0012201 (2024). doi:10.1371/journal.pntd.0012201
5. F. E. Edillo et al., Economic cost and burden of dengue in the Philippines. Am. J. Trop. Med. Hyg. **92**, 360–366 (2014). doi:10.4269/ajtmh.14-0139
6. Y.-J. Huang, S. Higgs, D. Vanlandingham, Biological control strategies for mosquito vectors of arboviruses. Insects. **8**, 21 (2017). doi:10.3390/insects8010021
7. F. Mechan, Z. Bartonicek, D. Malone, R. S. Lees, Unmanned aerial vehicles for surveillance and control of vectors of malaria and other vector-borne diseases. Malar. J. **22**, 23–34 (2023). doi:10.1186/s12936-022-04179-3
8. J. Datta et al., Recognising Mosquito Breeding Zones Applying Machine Learning Over UAV Images: A Comparative Study between Dense Urban Area Urban Slum Area, in Routledge eBooks, (2023). doi:10.4324/9781003356233-13
9. K. Yu et al., Using UAV images and deep learning in investigating potential breeding sites of *Aedes albopictus*. Acta Trop. **255**, 107234 (2024). doi:10.1016/j.actatropica.2024.107234
10. R. Sapkota, D. Ahmed, M. Karkee, Comparing YOLOv8 and Mask R-CNN for instance segmentation in complex orchard environments. Artif. Intell. Agric. **13**, 84–99 (2024). doi:10.1016/j.aiia.2024.07.001
11. S. Valladares et al., Performance Evaluation of the Nvidia Jetson Nano Through a Real-Time Machine Learning Application, in Intelligent Human Systems Integration. Advances in Intelligent Systems and Computing. **1322**, 343–349 (2021). doi:10.1007/978-3-030-68017-6_51
12. T.-N. Doan, T.-H. Phan, A Novel Smart System with Jetson Nano for Remote Insect Monitoring. Int. J. Adv. Comput. Sci. Appl. **15**, (2024). doi:10.14569/ijacsa.2024.0150798

https://doi.org/10.1051/e3sconf/202668805002

13. Drone Laws in the Philippines. UAV Coach (2021). https://uavcoach.com/drone-laws-in-philippines/