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MORALITY BEFORE KNOWLEDGE

Advancements in diagnostic approaches for malaria and dengue fever cases in Indonesia and Nigeria

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ABSTRACT
Background: This review aims to compare diagnostic advancements for malaria and dengue fever in Indonesia and Nigeria, highlighting the implementation of AI-based technologies and electrochemical biosensors. Both diseases are endemic in these tropical countries and present overlapping clinical symptoms, making laboratory-based confirmation methods such as RT-PCR and serological assays critical for accurate diagnosis. **Methods**: A structured literature review was conducted using Scopus, PubMed, and IEEE Xplore databases, focusing on peer-reviewed studies published between 2015 and 2024 that reported diagnostic performance and field applicability of the technologies. This scientific review synthesizes existing literature on infection mechanisms, conventional diagnostic methods (microscopy, RDT, ELISA, PCR), and state-of-the-art sensing technologies, including the AI-based malaria detection system (AIDMAN: YOLOv5 + Transformer + CNN) and electrochemical biosensors for dengue. **Findings:** The AI approach for malaria achieved high accuracy (patch-level 98.62% AUC 99.92%; image-level 97% AUC 98.84%). Dengue NS1 electrochemical biosensors reached a detection limit of $\sim 10^{-12}$ g/mL with excellent sensitivity and reproducibility, suitable for point-of-care use. **Conclusion**: Integrating sensing technologies from rapid tests to AI-driven microscopy and biosensors enables faster, more accurate diagnosis, improving patient management in resource-limited settings. **Novelty/Originality of this article:** This is the first comprehensive review that bridges cross-country (Indonesia and Nigeria) and cross-technology (AI and biosensor) approaches, offering valuable insight into sustainable diagnostic innovation for tropical infectious diseases.

KEYWORDS: malaria; dengue fever; diagnostics; RT-PCR; RDT; AI; biosensor; Indonesia; Nigeria.

1. Introduction

This review aims to compare diagnostic advancements for malaria and dengue fever in Indonesia and Nigeria, focusing on novel AI-based and biosensor technologies to improve detection accuracy and applicability in low-resource settings. Malaria and dengue fever are two endemic diseases that continue to impose a public health burden in many tropical countries, including Indonesia and Nigeria. Despite differences in geography and health systems, both countries face similar challenges in early detection and disease management. Malaria, transmitted by *Anopheles* mosquitoes, and dengue, spread by *Aedes* mosquitoes,

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share overlapping clinical symptoms such as fever, headache, muscle and joint pain, rash, and conjunctivitis, complicating differential diagnosis.

According to WHO data (2023), Indonesia reported over 600,000 confirmed malaria cases, while Nigeria accounted for approximately 27% of global malaria deaths. Meanwhile, dengue fever has shown a nearly 300% increase in reported cases over the last two decades in both countries, with periodic outbreaks and expanding geographic distribution. These trends highlight an urgent need for improved diagnostic tools that are fast, accurate, and adaptable to low-resource settings. Conventional diagnostic approaches, including light microscopy, rapid diagnostic tests (RDT), ELISA, and PCR remain the gold standards but are limited by infrastructure, time requirements, and trained personnel. The emergence of new technologies such as artificial intelligence (AI) for automated microscopy and electrochemical biosensors offers promising solutions, particularly in rural or resource-constrained areas.

Despite the increasing availability of diagnostic tools, their accuracy, applicability, and affordability in field settings remain insufficiently explored, especially in comparative contexts across developing countries. Moreover, few studies have critically examined how such technologies perform and integrate into national health systems. This review aims to examine and compare the development, diagnostic performance, and practical applicability of AI-based tools for malaria and biosensor-based systems for dengue in Indonesia and Nigeria. The discussion is guided by the following questions: what diagnostic tools are currently available for malaria and dengue in Indonesia and Nigeria; how do AI and biosensor-based technologies compare in terms of accuracy, cost, and field readiness; and what are the implementation challenges and future opportunities for diagnostic innovation in tropical health systems.

In Nigeria, *Plasmodium falciparum* is the most commonly encountered species and responsible for the majority of malaria cases. Studies and reports from the National Malaria Elimination Program (NMEP) and peer-reviewed research indicate that *P. falciparum* accounts for over 96% of malaria cases (Djaafara et al., 2025; Opute et al., 2022). Other species such as *Plasmodium malariae* and *Plasmodium ovale* are also present but in much smaller proportions (Djaafara et al., 2025). Interestingly, there have been rare reports of *Plasmodium vivax* infections in Duffy-negative individuals (Djaafara et al., 2025). In Indonesia, both *P. falciparum* and *P. vivax* are major causes of malaria, although their prevalence varies by region. For example, in Papua, *P. falciparum* is more dominant, whereas in other areas *P. vivax* is more commonly the cause of malaria (Ajogbasile et al., 2021). National malaria control programs and studies conducted from 2015 to 2025 show that while *P. falciparum* remains the primary concern, *P. vivax* also poses a significant challenge (Ajogbasile et al., 2021).

Malaria vector species in Indonesia includes several Anopheles mosquitoes whose distribution varies by region. Anopheles sundaicus is common in coastal areas such as Java and Sumatra (Oboh et al., 2018; Opute et al., 2022). Anopheles maculatus is prevalent in hilly regions and rice-field areas (Ajogbasile et al., 2021). Anopheles barbirostris is found in both rice paddies and forested habitats (Oboh et al., 2018). Anopheles balabacensis is present in forested regions (Oboh et al., 2018). The primary malaria vectors in Nigeria are Anopheles gambiae, the most dominant species, widespread across various ecological zones (Djaafara et al., 2025); Anopheles funestus, common in humid, rural environments (Djaafara et al., 2025); and Anopheles arabiensis, found in drier regions and noted for its adaptability (Djaafara et al., 2025).

Dengue fever is also a major public health challenge in both Indonesia and Nigeria. There are four dengue virus serotypes (DENV-1, DENV-2, DENV-3, and DENV-4), and the dominant serotype often shifts over time (Raafat et al., 2019). In Indonesia, DENV-1 is the most easily transmitted serotype, even in areas with no prior dengue history. DENV-2 and DENV-3 are known to be the most virulent and are often responsible for severe dengue outbreaks; these two serotypes have caused the most frequent dengue epidemics in Southeast Asia. In Nigeria, the pattern is somewhat different: DENV-2 is the most common serotype, particularly in southern regions (WHO, 2016, 2019). DENV-1 is also present and

historically significant, while DENV-3 and DENV-4 are detected but occur rarely (Syafruddinid et al., 2020; WHO, 2016).

The primary dengue vector species in Indonesia is *Aedes aegypti*, which is widespread throughout the country (Aryati et al., 2020). *Aedes albopictus* is also found, especially in rural and peri-urban areas (Aryati et al., 2020). In Nigeria, the main vector species are the same: *Aedes aegypti* predominates in urban areas, and *Aedes albopictus* is commonly found in peri-urban and rural settings (Animasaun et al., 2025). Currently, conventional methods are generally used for diagnosing malaria and dengue fever. The first and gold-standard diagnostic method for malaria is light microscopy, due to its high accuracy (Fitri et al., 2022). With a light microscope, one can directly visualize *Plasmodium* parasites in the blood, determine the species (e.g., *P. falciparum*, *P. vivax*), identify developmental stages, and estimate parasite density. This method offers both high sensitivity for clinical malaria and comprehensive clinical information: not only confirming infection but also grading its severity (parasite density), thereby guiding treatment choice and monitoring. Light microscopy achieves sensitivity above 95% and specificity above 90% in detecting malaria.

When microscopy is unavailable or impractical especially in remote setting, Rapid Diagnostic Tests (RDTs) are widely employed as a quick immunodiagnostic tool (Fitri et al., 2022). RDTs are inexpensive, easy to use, and deliver results rapidly, making them ideal for field deployment. Their sensitivity ranges from 85% to 94.8%, with specificity above 95%. However, field studies in Cameroon and Nigeria have reported lower accuracy, likely due to technical issues, operator variability, or local epidemiological factors (Fitri et al., 2022). Early dengue diagnosis relies primarily on serological assays involving IgM and IgG detection, Hemagglutination Inhibition (HI), NS1 antigen tests, and Plaque Reduction Neutralization Tests (PRNT) (Kabir et al., 2021). IgM/IgG serology: Anti-dengue IgM appears approximately 5 days after symptom onset and persists for 2–3 months, making it useful for detecting acute infection. IgG indicates past or secondary infection but may cross-react with other flaviviruses. An IgM/IgG ratio >1.32 suggests primary infection, whereas <1.32 indicates secondary infection (Kabir et al., 2021).

Table 1. Diagnostic methods for malaria and dengue fever over time in Nigeria

Period	Diagnostic method	Disease	Application	Reference
1970s	Microscopy	Malaria	Garki Project; rural settings	Trenholme et al., 1974
1980s	Microscopy	Malaria	Primary healthcare facilities; national control efforts	NMCP History
1990	Microscopy	Malaria	Therapeutic drug trials for chloroquine efficacy	Mochly-Rosen et al., 1990
2000s	Rapid Diagnostic Tests (RDTs)	Malaria	Malaria case management in health facilities, especially rural areas	Nallamothu et al., 2005
2010s	RDTs + PCR (for surveillance)	Malaria	Malaria indicator surveys, drug resistance studies	NMEP Reports; NCDC Reports (2017, 2019)
2015–present	PCR + RDT	Malaria	Public health sector, Integrated Community Case Management (iCCM)	Hodnebrog et al., 2020
2019	Trioplex PCR, RDTs	Dengue	Introduced at National Reference Lab for differential diagnosis (e.g. Lassa, Zika)	NCDC Report 2019
2020s	National RDTs + PCR (research/labs)	Malaria, Dengue	Routine health services, outbreak investigations	NCDC Strategic Plan 2020–2024

NMCP: National Malaria Control Program
NCDC: Nigeria Centre for Disease Control and Prevention

Hemagglutination Inhibition (HI): Can distinguish primary from secondary infection but has low sensitivity for early detection. NS1 antigen test: NS1 ELISA (e.g., InBios® NS1 ELISA, the only FDA-approved kit) offers the highest sensitivity (95.9%) and excellent accuracy across all serotypes especially DENV-4 (Kabir et al., 2021). Rapid NS1 tests suit low-resource settings but are less sensitive than ELISA. Plaque Reduction Neutralization Test (PRNT): Considered the gold standard for confirming dengue infection and evaluating vaccine-induced immunity. However, it is time-consuming, technically complex, and lacks a unified global protocol (Kabir et al., 2021). In practice, combining multiple methods serology (IgM, IgG, IgM/IgG ratio), NS1 antigen detection, and PRNT is often necessary for accurate dengue diagnosis, given the limited sensitivity and potential cross-reactivity of serological assays.

The diagnostic methods for malaria used by both Indonesia and Nigeria are generally the same, namely RDT (Rapid Diagnostic Test) and microscopy. Meanwhile, the diagnostic methods for dengue fever used in both countries include RDT and Hemagglutination Inhibition (HI) using an ELISA reader. The timeline presented in Tables 1 and 2 indicates that the use of PCR in both countries began after 2010.

Table 2. Diagnostic methods for dengue fever over time in Indonesia

Year	Diagnostic method	Disease	Application	Reference
1999	ELISA	Dengue	Seroprevalence studies	Perlmann et al., 2000
2000s	PCR	Dengue	Urban hospitals	Aryati et al., 2013
2015–present	PCR + RDT	Dengue	Urban hospitals, outbreak investigations	Babin et al., 2021

This scientific review summarizes existing literature to explore the infection mechanisms of malaria and dengue fever, and outlines the available methods for diagnosing both diseases. By drawing on ongoing research into diagnostic tools, this study aims to contribute to a comprehensive understanding and the development of more advanced diagnostic technologies.

2. Methods

This study is designed as a narrative review, synthesizing and critically analyzing existing literature on malaria and dengue diagnostic approaches, particularly in the context of Indonesia and Nigeria. The methodology used in this paper is based on sensing techniques, which include two approaches: a microscopy-based sensor for malaria diagnostics and a biosensor for dengue fever detection. For malaria diagnostics, this paper utilizes sensing methods involving Artificial Intelligence (AI), which are still under active development. Meanwhile, advancements in early detection methods for dengue fever are explored through biosensor technology.

2.1 Malaria diagnostics using AI

In malaria diagnostics using AI, this paper refers to AIDMAN (Artificial Intelligence-Based Object Detection System for Malaria Diagnosis) as the main reference, as it represents one of the most comprehensive and clinically applicable deep learning studies to date. The methodology used in AIDMAN is outlined as follows:

2.1.1 Data collection and processing

The referenced study by Liu et al. (2023) used the SmartMalariaNET dataset for training. A total of 1,822 thin blood smear images were collected from 140 patients at clinical health facilities, specifically the Sierra Leone–China Friendship Hospital and Rokupa

Government Hospital, both located in Freetown, Sierra Leone. The images were captured using smartphone cameras through microscope lenses, reflecting real-world, resource-limited conditions. All images were segmented into small patches using bounding boxes generated by YOLOv5. Each patch was annotated by three microscopy experts based on the presence or absence of *Plasmodium* infection. These labeled data were used for training and evaluating the classification model (Liu et al., 2023).

2.1.2 Cell detection using YOLOv5

YOLOv5 (You Only Look Once version 5) is a single-stage object detection algorithm that processes the entire image in one pass to detect multiple objects simultaneously. Compared to two-stage detectors like Faster R-CNN, YOLOv5 is faster and sufficiently accurate, making it ideal for real-time medical applications (Liu et al., 2023). Its primary role in this methodology is to detect and locate red blood cells (erythrocytes) in the thin smear images captured by smartphones. YOLOv5 generates bounding boxes around detected cells and crops them into image patches for further classification. It can detect intact and overlapping cells while ignoring irrelevant background regions or staining artifacts (Liu et al., 2023).

2.1.3 Cell classification using AAM (Attentional aligner model)

The extracted patches are then classified using a Transformer-based model known as AAM (Attentional Aligner Model). AAM is a deep learning model specifically designed to classify cells in medical images, particularly to identify *Plasmodium*-infected cells. It employs an attention mechanism to learn visual features that distinguish infected from uninfected cells. AAM integrates a multi-scale feature extractor, a local context aligner, and a multi-head attention mechanism to recognize unique characteristics of malaria parasites (Liu et al., 2023). The multi-scale feature extractor is a component that extracts features from images at various levels of detail (scales). Its function within the AAM model is to analyze blood cell images from small to large scales. At a small scale, it can detect fine details such as the dark nucleus of the parasite. At a medium scale, it can identify the purple ring structure of *Plasmodium*. At a large scale, it captures the overall shape of the cell (Liu et al., 2023).

The local context aligner is a component that adjusts and aligns local information from different scales using a Transformer. The functions of the local context aligner in AAM (Liu et al., 2023) are to integrate information from different scales to avoid conflicts, to help differentiate between actual parasites and noise (such as stains or lighting artifacts), and to use pixel positioning to understand the spatial location of features. The multi-head attention mechanism is part of the Transformer that allows the model to focus on multiple important regions of the image simultaneously. The functions of multi-head attention in AAM (Liu et al., 2023) are to give special "attention" to areas of the image most likely to indicate infection, to analyze information from multiple perspectives in parallel, and to reduce the influence of irrelevant elements and enhance significant ones.

2.1.4 Image-level diagnosis using CNN and clinical validation

To reduce false positives caused by uninfected cells that resemble infected ones, a Convolutional Neural Network (CNN) is used for whole-image diagnosis. The CNN receives a heatmap composed of the top 25 patches (with the highest infection probability scores) previously classified by AAM. These patches are reconstructed into a mosaic image that the CNN uses to determine whether the image contains *Plasmodium* parasites (Liu et al., 2023). To evaluate the real-world effectiveness of AIDMAN, clinical validation was conducted using new blood smear images from 64 patients. AIDMAN's diagnostic results were then compared with expert microscopic diagnoses and Rapid Diagnostic Tests (RDTs).

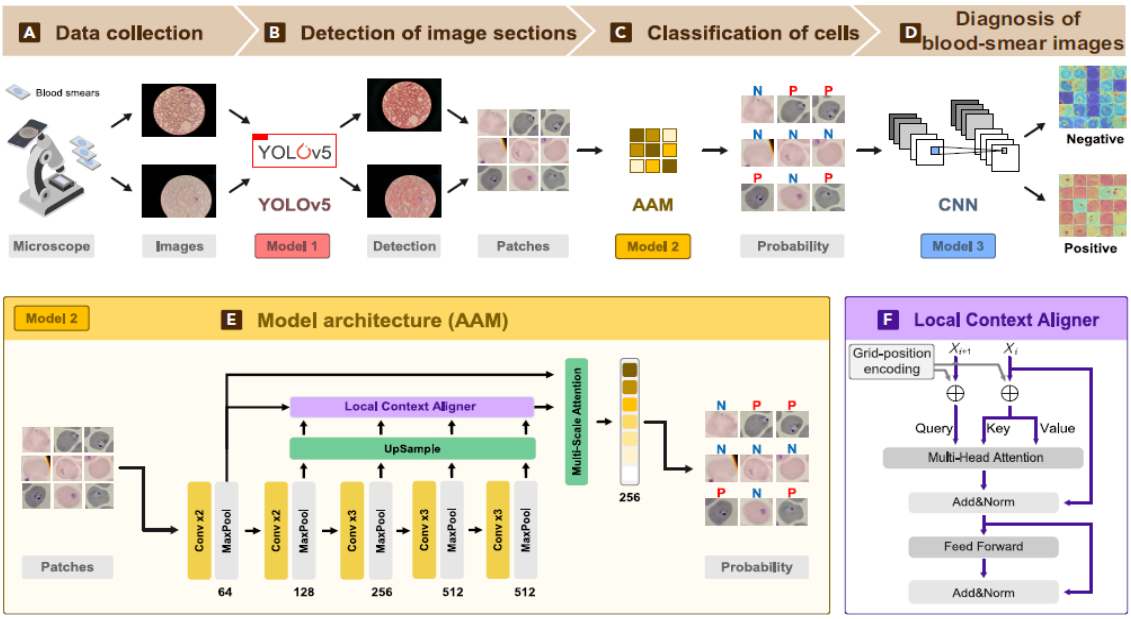

Fig. 1. Methodology used by AIDMAN in this study (Liu et al., 2023)

2.2 Biosensor methods for dengue fever

Sensor-based technology methods have been widely developed with various advantages. Sensors that incorporate biological components such as antibodies or DNA are called biosensors. In their development, there are various biosensor reading methods, such as electrochemical, optical, or magnetic. Electrochemical biosensors detect signal changes caused by the interaction between biological molecules and the sensor surface (Figueroa-Miranda et al., 2021; Nate et al., 2022; Singh et al., 2019; Yang et al., 2015).

In the development of biosensor technology, there are several main components in its working principle, namely the target, recognition element, transduction element, and working electrode. The target is the element that represents the final objective of the biosensor reading or measurement. The recognition element is the component that specifically binds to the target. The transduction element is the component that converts the biochemical interaction between the target and the recognition element on the biosensor surface into a signal that can be analyzed and measured. This transduction element is also referred to as the reading method; for example, in the case of an electrochemical biosensor, the signal will be in the form of an electronic signal. The working electrode is the biosensor surface where the recognition element is embedded and where the electrochemical reaction between the target and the recognition element takes place.

3. Results and Discussion

3.1 Malaria diagnosis using AI

In the study by Liu et al. (2023), a large dataset for cell classification was obtained, consisting of 5,654 image patches taken from 1,822 thin blood smear images. The dataset for blood smear image diagnosis using CNN for overall classification based on heatmaps from patches comprised 496 images.

Table 3. Dataset for patch and CNN image classification

Dataset	Patch classification	CNN image classification
Training	3,393	297
Validation	1,131	99
Testing	1,130	100

(Liu et al., 2023)

The study results show that a tiered approach starting with data collection, followed by detection using YOLOv5, classification using AAM, and blood smear image diagnosis using CNN achieves very high accuracy, both at the cell level and the overall blood smear image level. In the cell detection stage, YOLOv5 was able to recognize and locate red blood cells with an average accuracy of 90.8% (Liu et al., 2023). This indicates good performance even under image conditions with visual disturbances or noise, such as overlapping cells and uneven staining. For patch classification, AAM showed significant accuracy results, reaching 98.62%, with an AUC (Area Under Curve) value of 99.92% (Liu et al., 2023). An AUC close to 1 means that patch classification using AAM has high quality. This demonstrates that the combination of the feature extractor, local context aligner, and multi-head attention in AAM can effectively distinguish between infected and non-infected cells, even with image artifacts or lighting effects.

However, since most patches in a blood smear image are negative, directly applying AAM to the entire image results in a high false-positive rate (Liu et al., 2023). Therefore, adding CNN for final diagnosis at the image level strengthens the system and successfully reduces these errors. CNN uses a heatmap (based on color) compiled from the 25 patches with the highest scores and achieves a diagnostic accuracy of 97% with an AUC of 98.84%, demonstrating the model's ability to handle diagnosis on whole smear images (Liu et al., 2023).

Based on the comparison of accuracy using different malaria diagnostic methods, AIDMAN achieved an accuracy of 98.44% when compared to microscopy, which is considered the gold standard for malaria diagnosis. This validation demonstrates that the AIDMAN system is reliable and can be used as an alternative diagnostic tool, especially in areas with limited resources, both in terms of human personnel and equipment. Overall, the integration of YOLOv5, AAM, and CNN in AIDMAN not only provides an accurate solution for malaria diagnosis but also offers practicality and time efficiency, as it is capable of processing a single image in approximately 1 second. This makes AIDMAN highly feasible as a diagnostic support tool in field settings. Clinical validation of the AIDMAN system conducted by Liu et al. (2023) involved 64 new patient samples not included in the training dataset. The results were compared with microscopic examination by three highly experienced experts and also with RDT (Rapid Diagnostic Test) results.

Table 4. Comparison of accuracy using different malaria diagnostic methods

Detection method		Number of patients		Total	Accuracy (%)
		Positive	Negative		
Microscopic testing	Positive	34	0	34	100
	Negative	0	30	30	
RDT	Positive	32	1	33	95.31
	Negative	2	29	31	
AIDMAN	Positive	33	0	33	98.44
	Negative	1	30	31	

(Liu et al., 2023)

3.2 Biosensor development for early detection of dengue fever

The measurement of anti-dengue IgG and/or IgM antibodies using antibody-capture ELISA is the most commonly used method for confirming a dengue fever diagnosis. ELISA is relatively easier to perform compared to other diagnostic techniques; however, it requires laboratory equipment and trained personnel (Soh et al., 2016). In addition, antibody titer does not rise immediately; thus IgM ELISA has <50% sensitivity for at least 4 days after symptom onset in primary infections. As a result, IgM ELISA is less useful for clinical management and is mainly supportive in confirming a diagnosis (Hunsperger et al., 2016). The use of electrochemical systems in biosensor development offers a more user-friendly detection approach, as biosensors can be applied in the field and require only a very small sample volume (~50 μL) (Palomar et al., 2020).

This study leverages the latest advances in nanofabrication to develop an efficient biosensor protocol applicable for detecting a wide range of biomolecules. Palomar et al. (2020) developed a biosensor for NS1 detection using gold electrodes as an early detection method for dengue fever. After the optimization stage, the developed biosensor showed excellent reproducibility and sensitivity compared to other detection tool development reports in the literature (Nawaz et al., 2018; Palomar et al., 2020; Santos et al., 2018; Silva et al., 2015). The Limit of Detection (LOD) achieved in the study by Palomar et al. (2020) reached 1 × 10^−12 g/mL. Differential Pulse Voltammetry (DPV), used as the detection technique, enabled measurement of targets at very low concentrations due to its high sensitivity. Based on this low LOD, the biosensor developed in the study shows strong potential for early detection of dengue virus infections.

3.2.1 Stability and selectivity testing of dengue

Selectivity testing in the study was carried out by evaluating the biosensor against a variety of non-specific targets. Gold electrodes modified with dengue antibodies were tested against solutions of bovine serum albumin, urease, cysteine, rabies antibodies (IgG), and dengue-specific toxins. Based on these tests, the biosensor did not show any significant response to non-specific targets. Stability testing was also performed on the biosensor, which is a critical parameter in electrochemical systems, as it validates the obtained results and eliminates the possibility of false positives caused by sensor instability. The biosensor in this study maintained a stable signal even after more than 10 consecutive measurements, thus confirming that the response was due to DENV-NS1 detection.

3.2.2 Detection of dengue toxins in human serum

The study then proceeded to test the biosensor using human serum. Three different concentrations of dengue virus in human serum (0.01, 1, and 100 ng/mL) were tested across several electrodes. The results showed consistent and comparable outcomes. According to the literature, the required NS1 concentration in human serum for dengue detection ranges from 0.001 to 2 µg/mL (Wasik et al., 2018). This finding demonstrates the potential of the biosensor for detecting dengue toxins in real samples. The biosensor-based detection method is very simple and fast, making it ideal as a point-of-care device (Palomar et al., 2020).

3.3 Comparison between technologies

AI-based malaria diagnosis systems (such as AIDMAN) and electrochemical biosensors for dengue each offer distinct advantages. AI enables fast and automated classification of blood images, making it highly suitable for resource-limited settings since it only requires a microscope and a smartphone. On the other hand, biosensors provide rapid detection based on serum samples without the need for image analysis or model training. The combination of these approaches holds great potential for integrated application in infectious disease surveillance systems in tropical countries.

Moreover, when compared with other studies in the literature, AIDMAN shows superior performance in several aspects of malaria detection. This highlights the system's advantage over other existing research-based approaches.

Table 5. Advantages of the AIDMAN system compared to other AI-based systems

Aspect	Study					
	Liu et al. (2023)	Saba et al. (2024)	Kareem et al. (2025)	Akyirem et al. (2024)	Abdul et al. (2022)	Musa et al. (2023)
Data type	Thin blood smear, smartphone camera	Thick blood smear	Digital slide dataset	RGB blood image	Thick blood smear	Thick blood smear

Main objective	Whole-image diagnosis (image-level)	Parasite species detection	Automated web-based detection	Infected cell classification	Lightweight model	Object detection
AI method	YOLOv5 + Transformer + CNN	Classification CNN	VGG16 (deep CNN)	CNN + Transfer Learning	Lightweight CNN	CNN + YOLO
Accuracy	Image-level: 97%, AUC: 98.84%	Cell classification: 99.5%	97%	96.9%	~96%	~98% (dataset-dependent)
Clinical validation	Yes (64 real patient samples)	No	No	No	No	No
Real implementation	Smartphone-compatible	Lab-only	Website-based	Not yet implemented	Potential for embedded use	No mobile application
Species detection	No (only positive/negative)	Yes	No	No	No	No
AI interpretability	Yes (top-25 patch heatmap)	No	No	No	No	No
Key strengths	Comprehensive system, heatmap, clinical validation, field-ready	High patch-level accuracy, species detection	Easy to use (web-based)	Adaptive and lightweight	Suitable for low-resource devices	Fast YOLO-based detection
Limitations	Does not detect species, only thin smears	No clinical validation, no image-level diagnosis	Requires internet (no offline mode)	Not tested in real-time	No heatmap available	Not tested on smartphones

3.4 Limitations and future directions

This study is a narrative review that focuses on two main technological approaches. Due to resource constraints, not all diagnostic technologies are comprehensively discussed, such as LAMP (Loop-Mediated Isothermal Amplification) (Notomi et al., 2000) or CRISPR-based biosensing (Nguyen et al., 2020). Moreover, although AIDMAN and NS1 biosensors demonstrate high performance, their real-world application remains limited by infrastructure, initial costs, and training requirements. Further research is recommended to explore the integration of these technologies into unified detection systems, as well as to conduct cost-benefit evaluations in various local contexts in Indonesia and Nigeria.

4. Conclusions

The performance of the AI system for malaria is very high, both at the patch classification level and the whole image diagnosis level, with a patch classification accuracy of 98.62%, AUC: 99.92%, and a smear image diagnosis accuracy of 97%, AUC: 98.84%. This system has been proven to have great potential for implementation in resource-limited areas, especially in Africa, as it does not require complex laboratory infrastructure or a large number of experts. Electrochemical biosensor technology can achieve a very low limit of detection, making it ideal for the early detection of dengue fever.

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References
Abdul, R., Shah, S. Y., Khalid, S., & Nazir, T. (2022). Lightweight CNN for malaria detection in low-resource settings. *Computers in Biology and Medicine, 145*, 105406. https://doi.org/10.1016/j.compbiomed.2022.105406

Ajogbasile, F. V., Kayode, A. T., Oluniyi, P. E., Akano, K. O., Uwanibe, J. N., Adegboyega, B. B., ... & Happi, C. T. (2021). Genetic diversity and population structure of Plasmodium falciparum in Nigeria: insights from microsatellite loci analysis. *Malaria Journal*, *20*(1), 236. https://doi.org/10.1186/s12936-021-03734-x

Akyirem, S., Gyan, E. T., & Owusu, M. (2024). Improving malaria parasite detection with 2D CNN and transfer learning. *South Eastern European Journal of Public Health*. https://doi.org/10.11576/seejph-xxxx

Animasaun, O. S., Shaibu, J. O., Akomolafe, B. K., Animasaun, O. P., Niyang, P. A. M., Olugbade, O. T., ... & Audu, R. A. (2025). Enhancing surveillance for dengue fever in Oyo State,

Nigeria–a one health approach. *One Health Outlook*, *7*(1), 5. https://doi.org/10.1186/s42522-024-00121-9

Aryati, A., Trimarsanto, H., Yohan, B., Wardhani, P., Fahri, S., & Sasmono, R. T. (2013). Performance of commercial dengue NS1 ELISA and molecular analysis of NS1 gene of dengue viruses obtained during surveillance in Indonesia. *BMC Infectious Diseases, 13*, 611. https://doi.org/10.1186/1471-2334-13-611

Aryati, A., Wrahatnala, B. J., Yohan, B., Fanny, M., Hakim, F. K. N., Sunari, E. P., Zuroidah, N., Wardhani, P., Santoso, M. S., Husada, D., Rohman, A., Tarmizi, S. N., Sievers, J. T. O., & Tedjo Sasmono, R. (2020). Dengue virus serotype 4 is responsible for the outbreak of dengue in East Java City of Jember, Indonesia. *Viruses*, *12*(9), 1–20. https://doi.org/10.3390/v12090913

Babin, B. M., Fernandez-Cuervo, G., Sheng, J., Green, O., Ordoñez, A. A., Turner, M. L., Keller, L. J., Jain, S. K., Shabat, D., & Bogyo, M. (2021). Chemiluminescent protease probe for rapid, sensitive, and inexpensive detection of live *Mycobacterium tuberculosis*. *ACS Central Science, 7*(5), 803–814. https://doi.org/10.1021/acscentsci.0c01345

Djaafara, B. A., Sherrard-Smith, E., Churcher, T. S., Fajariyani, S. B., Prameswari, H. D., Herdiana, H., Puspadewi, R. T., Lestari, K. D., Elyazar, I. R. F., & Walker, P. G. T. (2025). Spatiotemporal heterogeneity in malaria transmission across Indonesia: analysis of routine surveillance data 2010–2019. *BMC Medicine*, *23*(1). https://doi.org/10.1186/s12916-025-03902-9

Figueroa-Miranda, G., Chen, S., Neis, M., Zhou, L., Zhang, Y., Lo, Y., ... & Mayer, D. (2021). Multi-target electrochemical malaria aptasensor on flexible multielectrode arrays for detection in malaria parasite blood samples. *Sensors and Actuators B: Chemical*, *349*, 130812. https://doi.org/10.1016/j.snb.2021.130812

Fitri, L. E., Widaningrum, T., Endharti, A. T., Prabowo, M. H., Winaris, N., & Nugraha, R. Y. B. (2022). Malaria diagnostic update: From conventional to advanced method. *Journal of Clinical Laboratory Analysis, 36*(4), e24314. https://doi.org/10.1002/jcla.24314

Hodnebrog, Ø., Aamaas, B., Fuglestvedt, J. S., Marston, G., Myhre, G., Nielsen, C. J., Sandstad, M., Shine, K. P., & Wallington, T. J. (2020). Updated global warming potentials and radiative efficiencies of halocarbons and other weak atmospheric absorbers. *Reviews of Geophysics, 58*(3), e2019RG000691. https://doi.org/10.1029/2019RG000691

Hunsperger, E. A., Muñoz-Jordán, J., Beltran, M., Colón, C., Carrión, J., Vazquez, J., … & Margolis, H. S. (2016). Performance of dengue diagnostic tests in a single-specimen diagnostic algorithm. *The Journal of Infectious Diseases, 214*(6), 836–844. https://doi.org/10.1093/infdis/jiw103

Kabir, M. A., Zilouchian, H., Younas, M. A., & Asghar, W. (2021). Dengue detection: Advances in diagnostic tools from conventional technology to point of care. *Biosensors, 11*(7), 206. https://doi.org/10.3390/bios11070206

Kareem, S. A., Jamiu, M. A., & Yusuf, R. A. (2025). AutoMalariaNet: Automated malaria parasite detection using VGG16 model in a web-based interface. *American Journal of Neural Networks and Applications, 11*(1), 7–14. https://doi.org/10.1234/ajnna.2025.011007

Liu, W., Zhang, Y., Zhang, D., Zhao, Y., Fang, J., Peng, Y., … & Zhou, J. (2023). AIDMAN: An AI-based object detection system for malaria diagnosis from smartphone thin-blood-smear images. *Patterns, 4*(10), 100806. https://doi.org/10.1016/j.patter.2023.100806

Mochly-Rosen, D., Henrich, C. J., Cheever, L., Khaner, H., & Simpson, P. C. (1990). A protein kinase C isozyme is translocated to cytoskeletal elements on activation. *Cell Regulation, 1*(9), 693–706. https://doi.org/10.1091/mbc.1.9.693

Musa, T. A., Bello, R. S., & Adeoye, A. (2023). Real-time malaria parasite detection using YOLO and CNN: An object detection approach. *Informatics in Medicine Unlocked, 40*, 101176. https://doi.org/10.1016/j.imu.2023.101176

Nallamothu, B. K., Saint, M., Saint, S., & Mukherjee, D. (2005). Clinical problem-solving. Double jeopardy. *New England Journal of Medicine, 353*(1), 75–80. https://doi.org/10.1056/NEJMcps050117

Nate, Z., Gill, A. A. S., Chauhan, R., & Karpoormath, R. (2022). Recent progress in

electrochemical sensors for detection and quantification of malaria. *Analytical Biochemistry, 643*, 114592. https://doi.org/10.1016/j.ab.2022.114592

Nawaz, M. H., Hayat, A., Catanante, G., Latif, U., & Marty, J. L. (2018). Development of a portable and disposable NS1 based electrochemical immunosensor for early diagnosis of dengue virus. *Analytica Chimica Acta, 1026*, 1–7. https://doi.org/10.1016/j.aca.2018.04.032

Nguyen, L. T., Smith, B. M., Jain, P. K. (2020). CRISPR-Cas-based diagnostics: Molecular assays for infectious diseases. *Nature Reviews Microbiology, 18*(11), 718–732. https://doi.org/10.1038/s41579-020-00406-x

Notomi, T., Okayama, H., Masubuchi, H., Yonekawa, T., Watanabe, K., Amino, N., & Hase, T. (2000). Loop-mediated isothermal amplification of DNA. *Nucleic Acids Research, 28*(12), e63. https://doi.org/10.1093/nar/28.12.e63

Oboh, M. A., Badiane, A. S., Ntadom, G., Ndiaye, Y. D., Diongue, K., Diallo, M. A., & Ndiaye, D. (2018). Molecular identification of Plasmodium species responsible for malaria reveals Plasmodium vivax isolates in Duffy negative individuals from southwestern Nigeria. *Malaria Journal*, *17*(1), 1–12. https://doi.org/10.1186/s12936-018-2588-7

Opute, A. O., Akinkunmi, J. A., Funsho, A. O., Obaniyi, A. K., & Anifowoshe, A. T. (2022). Genetic diversity of Plasmodium falciparum isolates in Nigeria. A review. *Egyptian Journal of Medical Human Genetics*, *23*(1). https://doi.org/10.1186/s43042-022-00340-7

Palomar, Q., Xu, X., Gondran, C., … & Barthelemy, J. (2020). Voltammetric sensing of recombinant viral dengue virus 2 NS1 based on Au nanoparticle–decorated multiwalled carbon nanotube composites. *Microchimica Acta, 187*, 363. https://doi.org/10.1007/s00604-020-04339-y

Perlmann, P., Perlmann, H., Looareesuwan, S., Krudsood, S., Kano, S., Matsumoto, Y., Brittenham, G., Troye-Blomberg, M., & Aikawa, M. (2000). Contrasting functions of IgG and IgE antimalarial antibodies in uncomplicated and severe *Plasmodium falciparum* malaria. *The American Journal of Tropical Medicine and Hygiene, 62*(3), 373–377. https://doi.org/10.4269/ajtmh.2000.62.373

Raafat, N., Blacksell, S. D., & Maude, R. J. (2019). A review of dengue diagnostics and implications for surveillance and control. *Transactions of The Royal Society of Tropical Medicine and Hygiene, 113*(11), 653–660. https://doi.org/10.1093/trstmh/trz068

Saba, Z., Imran, M., Khan, M. A., Rauf, H. T., Rehman, A., & Bukhari, S. A. C. (2024). Deep learning-based detection of Plasmodium species using thick blood smear images. *Computers in Biology and Medicine, 169*, 107647. https://doi.org/10.1016/j.compbiomed.2024.107647

Santos, A., Bueno, P. R., & Davis, J. J. (2018). A dual marker label free electrochemical assay for Flavivirus dengue diagnosis. *Biosensors & Bioelectronics, 100*, 519–525. https://doi.org/10.1016/j.bios.2017.09.014

Silva, M. M. S., Dias, A. C. M. S., Silva, B. V. M., Gomes-Filho, S. L. R., Kubota, L. T., Goulart, M. O. F., & Dutra, R. F. (2015). Electrochemical detection of dengue virus NS1 protein with a poly(allylamine)/carbon nanotube layered immunoelectrode. *Journal of Chemical Technology & Biotechnology, 90*(1), 194–200. https://doi.org/10.1002/jctb.4305

Singh, N. K., Tungon, P., Estrella, P., & Goswami, P. D. (2019). Development of an aptamer-based field effect transistor biosensor for quantitative detection of Plasmodium falciparum glutamate dehydrogenase in serum samples. *Biosensors and Bioelectronics, 123*, 30–35. https://doi.org/10.1038/nindia.2018.149

Soh, L. T., Squires, R. C., Tan, L. K., Pok, K. Y., Yang, H., Liew, C., … & Konings, F. (2016). External quality assessment of dengue and chikungunya diagnostics in the Asia Pacific region, 2015. *Western Pacific Surveillance and Response Journal*, 7(2), 26–34. https://doi.org/10.5365/WPSAR.2016.7.1.002

Syafruddinid, D., Lestari, Y. E., Permana, D. H., Asih, P. B. S., Laurent, B. S., Zubaidah, S., Rozi, I. E., Kosasih, S., Shinta, Sukowati, S., Hakim, L., Haryanto, E., Mangunwardoyo, W., Bangs, M. J., & Lobo, N. F. (2020). Anopheles sundaicus complex and the presence of anopheles epiroticus in Indonesia. *PLoS Neglected Tropical Diseases*, *14*(7), 1–16. https://doi.org/10.1371/journal.pntd.0008385

Trenholme, G. M., Williams, R. L., Patterson, E. C., Frischer, H., Carson, P. E., & Rieckmann, K. H. (1974). A method for the determination of amodiaquine. *Bulletin of the World Health Organization, 51*(4), 431–434. https://apps.who.int/iris/handle/10665/65703

Wasik, D., Mulchandani, A., & Yates, M. V. (2018). Salivary detection of dengue virus NS1 protein with a label-free immunosensor for early dengue diagnosis. *Sensors, 18*(8), 2641. https://doi.org/10.3390/s18082641

WHO. (2016). *Entomological surveillance for Aedes spp. in the context of Zika virus. Interim guidance for entomologists*. World Health Organization. https://apps.who.int/iris/handle/10665/204624

WHO. (2019). *List of WHO prequalification vector control products*. World Health Organization. https://www.who.int/pq-vector-control/prequalified-lists/LOPrequalifiedProducts20190411

WHO. (2023). *World malaria report 2023*. World Health Organization. https://www.who.int/publications/i/item/9789240076680

Yang, Q., Pedreira-Rincon, J., Balerdi-Sarasola, L., Baptista-Pires, L., Munoz, J., Camprubi-Ferrer, D., Idili, A., & Parolo, C. (2015). An aptamer-based electrochemical sensor for the quantification of the malaria biomarker lactate dehydrogenase. *Biosensors and Bioelectronics, 274*, 117152. https://doi.org/10.1016/j.bios.2025.117152

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