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Research Article

A Study into the Detection of Malaria using Artificial Intelligence

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ABSTRACT

Malaria is among the most frequent mosquito-borne infections and a major public health issue across the globe. Currently, the conventional method for diagnosing malaria is a microscopic study of a stained blood film. Artificial Neural Networks (ANN) might be used to diagnose sickness in red blood cells, according to researchers. For this aim, characteristics / variables are generated from data collected from digital holographic pictures of blood cells and fed into an artificial neural network (ANN), which identifies the cell is infected or not. The current research concentrates on the use of artificial intelligence to identify malaria.

Keywords: *Malaria, Artificial Neural Networks (ANN), Artificial Intelligence (AI), Deep Learning (DI), Convolutional Neural Networks (CNNs) Malaria Diagnosis*

INTRODUCTION

Malaria is a mosquito-borne, fatal illness induced by Plasmodium parasites. Infected female Anopheles mosquitoes spread the parasites via bites. Whereas researchers will not go into detail about the disease, there are 5 different kinds of malaria. Malaria is clearly common around the globe, especially in tropical areas. The nature and mortality of this illness are the driving forces behind this effort. If an infected mosquito bites you, parasites transported by the insect may enter your bloodstream and start damaging oxygen-carrying RBCs. The primary signs of malaria are similar to those of the flu or a virus, with you becoming ill within a few days or even weeks of being bitten by a mosquito (Zulfikar et al., 2017). On the other hand, these dangerous parasites will slumber in the human system for nearly a year without causing any issues! As a result, delaying the proper treatment might lead to problems and even death. As a result, early and accurate malaria screening and diagnosis will save people.

Though the malaria virus does not acquire the form of a mutant mosquito, it certainly has the appearance of one. In certain regions of the globe, the fatal illness has assumed epidemic, possibly endemic levels, killing an estimated 400,000 individuals each year. It's almost non-existent in other parts of the planet. Some locations are just more susceptible to disease outbreaks than others; some conditions render a region more prone to be infected with malaria.

- Poverty levels are high.
- Accessibility to adequate healthcare is limited.
- Uncertainty in politics
- The occurrence of disease-carrying vectors

With this confluence of issues, researchers must bear the following in mind while constructing the framework:

- There might be a power outage due to a lack of a stable power supply.
- The computing power of battery-powered gadgets is lower.
- It's possible that you won't be able to connect to the Internet.
- Malaria Diagnosis Using Traditional Methods

- Malaria identification and detection may be accomplished using a variety of procedures and assays.

A few examples are thick and thin blood smear exams, polymerase chain reaction (PCR), and quick diagnostic procedures (RDT). researchers won't go into all of the ways, but the fact is that conventional tests are often employed as an alternative, especially when high-quality microscopy facilities are unavailable (Poostchi et al., 2018). The best-known approach for diagnosing malaria is a microscopic analysis of blood. A patient's blood is put on a glass slide and dyed with a differentiating chemical to help identify parasites in RBCs.

DL (Deep Learning) models, or CNNs (Convolutional Neural Networks), have been very successful in a broad range of computer vision applications. While we presume you already know something about CNNs, if you don't, you may learn more about them by reading this article. Briefly, Convolution and pooling layers are important layers in a CNN model, as seen in the diagram below.

CNN can develop filters as well as extract information automatically. Previously, parameters like size, colour, and cell shape had to be manually input into machine learning algorithms. CNN will significantly reduce prediction time while replicating physician precision. From our information, Convolutional Neural Networks discovers hierarchical connections (Rajaraman et al., 2018). As a result, kids are ready to comprehend various features of pictures. The first convolution level, for instance, will learn tiny and local structures like corners and edges, whereas the second convolution layer will learn broader structures depending on the first layers' information, and so forth. Rajaraman published fascinating research titled "Pre-trained CNNs as feature extractors for enhanced parasite identification in thin blood smear pictures." It discusses six pre-trained models using the data from the previous study. can identify malaria with a 94.9 percent efficiency when compared to non-infected samples

MALARIA DETECTION

Malaria is a treatable condition with medications on the market, including ones that may assist tourists visiting malaria-prone areas to avoid contracting the sickness. Furthermore, there is currently no viable malaria vaccine, despite ongoing research and field investigations in this area. Malaria is a quickly growing illness after it has been infected, with a high chance of evolving into acute, including cerebral malaria with neurologic indications in P. falciparum infections (Alom et al., 2019). As a result, it's critical to get a malaria diagnosis as soon as possible. Although malaria may be detected in a variety of methods, existing malaria diagnostic tests might be improved by lowering costs, boosting specificity, and making them easier to use. We have dedicated two sub - sections to light microscopy as well as RDTs, which seem to be still the two most frequently employed diagnostic tools in these places since automated malaria detection for resource-poor contexts is the core theme of our study. Other approaches for malaria detection are briefly discussed as well; however, they are perhaps less adapted to the circumstances in distant malaria areas.

The key to diagnosing malaria is identifying the presence of parasites. Identification of parasite species, the presence of possibly complex infections, and the monitoring of P. falciparum parasite stage progression in connection to illness severity are all crucial (Elmahmudi & Ugail, 2020). Counting parasites to determine parasitemia levels is vital for diagnosing infection and estimating its severity, but it also enables patient care by evaluating therapeutic effectiveness and possible drug tolerance.

2.1 Light microscopy

Light microscopy of blood films is the present gold-standard approach for malaria detection in the field. Microscopy continues to be the most common screening technique, particularly in resource-poor countries, despite the availability and popularity of alternative kinds of detection in recent times, particularly Rapid diagnostic tests. Every parasite species may be identified using microscopy. It may calculate parasitemia levels, clear a patient after an effective therapy, and track medication resistance. It is also less costly and more commonly accessible than other approaches (Elmahmudi & Ugail, 2018). The long training necessary for a microscopist to become a skilled malaria slide reader, the high expense of training and hiring, retaining expertise, as well as the significant amount of manual work needed are the primary drawbacks.

A droplet of the patient's blood is placed on a glass plate, which will then be submerged in a staining liquid to make parasites more apparent using a typical light microscope, generally with a 100 oil objective, to detect malaria under a microscope. Thick as well as thin blood smears are the most common forms of blood smears used to diagnose malaria. The existence of parasites in a sample of blood is detected using a thick smear (Jilani et al., 2019). Thick smears are more sensitive to parasite identification than thin smears, with an 11-fold increase.5 However, thin smears, which are created by dispersing a sample of blood on a glass plate, have other benefits. They make it easier for the examiner to detect malaria species and parasite phases. A skilled microscopist spends 15–30 minutes microscopically examining a single drop of a blood sample, comprising quantitative parasite diagnosis as well as species confirmation. Hundreds or even thousands of blood samples are physically screened for malaria annually, implying a significant financial investment in malaria detection.

2.2 Rapid diagnostic tests

The fundamental benefit of microscopic malaria detection is its low direct cost, which makes it ideal for resource-poor areas. Considering the limited funds normally present in malaria-prone locations, any current diagnostic techniques, as well as any novel techniques, must demonstrate that they can offer the same simplicity of use and price point as microscopy. RDTs are perhaps the sole and most significant competitor in this regard. They take 10–15 minutes to process and diagnose proof of malaria parasites (Abubakar, 2020). Their identification responsiveness is lower than manual microscopy but comparable, and they don't require any special machinery or training. Even though Rapid Direct Tests are presently more costly than microscopy in elevated areas, it is a reasonable question if these tests will soon be able to replace microscopy. According to World Health Organization, more nations utilise microscopy than Rapid Direct Tests at the moment of writing. In remote places where microscopy is not accessible, RDTs are more often employed (Abubakar et al., 2020). RDTs were used to perform around 47percent of malaria examinations in malaria-endemic countries across the globe. On the other hand, rapid tests do not negate the requirement for malaria microscopy. Rapid tests have a significant drawback in that the findings are not quantifiable. As a result, microscopy and Rapid tests complement each other rather than replacing one another at the current moment.

2.3 Some other tests

Malaria can be diagnosed using a variety of methods. The cost per test, the technique's specificity, sensitivity, the duration per test, and the user's needed skill level are all significant considerations. In addition, counting the number of infected RBCs is useful as a prognostic indicator.

- ***Polymerase chain reaction (PCR)***

Classical microscopic analysis of stained peripheral blood smears has demonstrated lower specificity and sensitivity than Polymerase chain reaction, a molecular approach. In fact, it is thought to be the most reliable of all the tests. It can distinguish between parasite species and detect extremely low parasite quantities in the blood. Nevertheless, Polymerase chain reaction is a time-consuming, high-cost technique that requires experienced personnel to process for many hours (Abubakar & Ugail, 2019). As per Tangpukdee, Polymerase chain reaction is not widely used in underdeveloped nations due to the difficulty of the tests and a lack of funding to run them properly and on a regular basis. The Polymerase chain reaction approach needs quality assurance and equipment upkeep; henceforth, it could not be beneficial for malaria detection in remote rural areas or even in distinctive clinical investigative contexts.

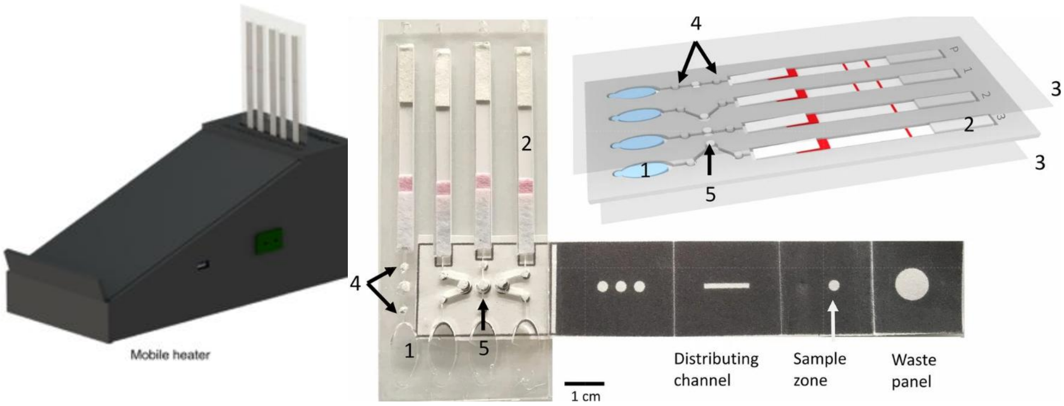
- ***Fluorescent microscopy***

Quantitative buffy coat is a fluorescence microscopy-based laboratory test for detecting malaria or even other blood parasite infections. Under UV light, parasites are visible thanks to a fluorescent pigment. This test, as per Adeoye and Nga, is more precise than a traditional thick smear. Profitably accessible portable fluorescence microscopes with fluorescent reagent for parasite labelling are now accessible (Abubakar et al., 2020). Even though the quantitative buffy coat approach is straightforward, dependable, and user-friendly, it necessitates specialist equipment, is more expensive than ordinary light microscopy, and therefore is ineffective at distinguishing parasite types and populations.

Flow cytometry is a technique for measuring the number of cells in a sample. This technology uses a laser to count and identify cells, allowing thousands of cells to be profiled every second. Flow cytometry has the advantage of automating parasitemia counts; however, it has limited sensitivity. Flow cytometry is less suited as a diagnostic method in the field whenever a clear response is needed for treatment choices. Nevertheless, industrialised nations may be used in the therapeutic environment for reliable parasite counts, such as during medication treatment follow-up.

DIAGNOSTIC SYSTEM

A smart phone-based heater for isothermal DNA amplification, a microfluidic paper chip for DNA testing, a blockchain structure, as well as an Artificial Intelligence element for decision assistance are the main elements of our diagnostic solution.



(a) (b) (c)

Figure 1: Diagnostic of a system

a) The completed instrument, which shows the phone that was used to provide control, manage assay settings, give the opportunity interact with the cloud, interpret information, and offer geotagging option. The diagnostic chip, which has been put into the heating component, can be seen (Ugail et al., 2019). The entire gadget, such as the mobile, is lightweight and can be handled in one palm, allowing diagnostics to be provided almost anywhere.

b) The gadget and its accompanying circuit in an open section view. (i)) circuit elements, such as a micro controller, heater control system, power supply unit, (ii) the equipment's casing and main part, (iii) A thermal monitoring port on the outside, and (iv) the “aluminium band”, which receives the investigative instrument and conducts heating for the nucleic acid multiplication test.

c) A microfluidic circuit with chambers for the "LAMP reaction," lateral flow strips for information, and a QR code for provenance are all part of the plastic cartridge. The dashed lines indicate the control and test lines, which define the cropped region for AI evaluation.

A thermocouple was used to check the temperatures felt and administered, and several target temperatures were used to test the heater's efficiency. At 40, 65, 75, and 90 degrees Celsius, the discrepancies between the actual and goal temperatures were all under 0.5 degrees Celsius (SD) (Singh et al., 2020). In the unavailability of a main supply power source, a 10,000-mAh battery pack might be utilised to give more than the phone's 9-hour battery life

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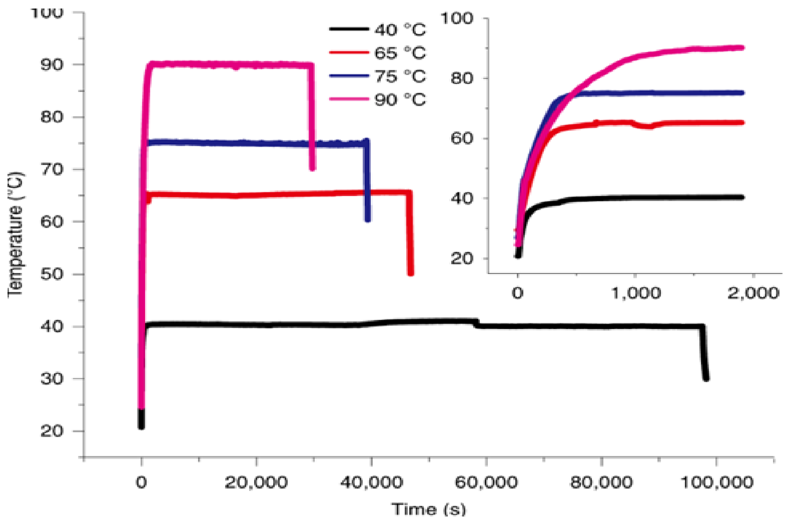

Figure 2 : Evaluation of mobile heaters

The temperature was measured at 90 degrees Celsius (purple), 75 degrees Celsius (blue), 65 degrees Celsius (red), and 40 degrees Celsius (black). Whenever the battery power was depleted, the temperature dropped. The phone's battery life was determined by whether or not additional functions were utilised. The phone's battery life might be prolonged, if necessary, by using a hand-held battery pack. Magnification on the temperature "ramping" up, displaying the efficacy of the proportionate, integral, as well as derivative algorithm control. Heating to 65 °C required 10 minutes (600 seconds), allowing for a one-hour LAMP experiment.

While uploading diagnostic tests to the cloud for long-term storage and information origin, the efficiency of a blockchain network may impact the user experience, particularly latency as well as maximum capacity (Hassan et al., 2020). The assessment was focused on these two primary functionalities of the blockchain system, and it was compared to the Hyperledger Caliper 0.2.0 standard. "An Ubuntu 18.04 virtual system with 4 GB RAM and a four-core CPU served as the test environment. The test was conducted using a Caliper 2-organization-1-peer model, and it involved 12 rounds with varying quantities of transactions and transmit rates".

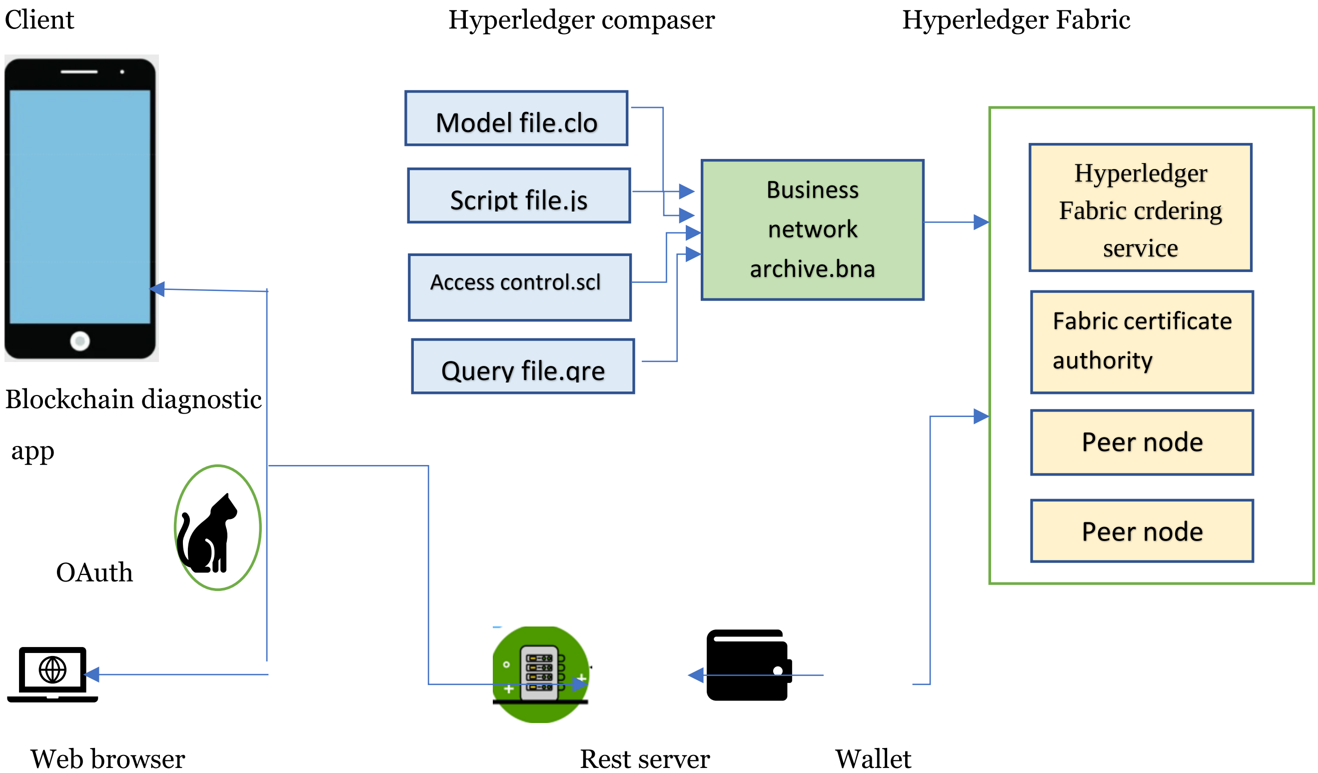

Figure 3: The blockchain network's infrastructure development

The script file, model file, user access file, as well as query file were all packaged into a "business network archive (BNA)" file and distributed to a Fabric Runtime. The blockchain network may be accessed by an internet browser on a regular laptop/ desktop or via a smartphone application. The authentication service was supplied through OAuth 2.0.

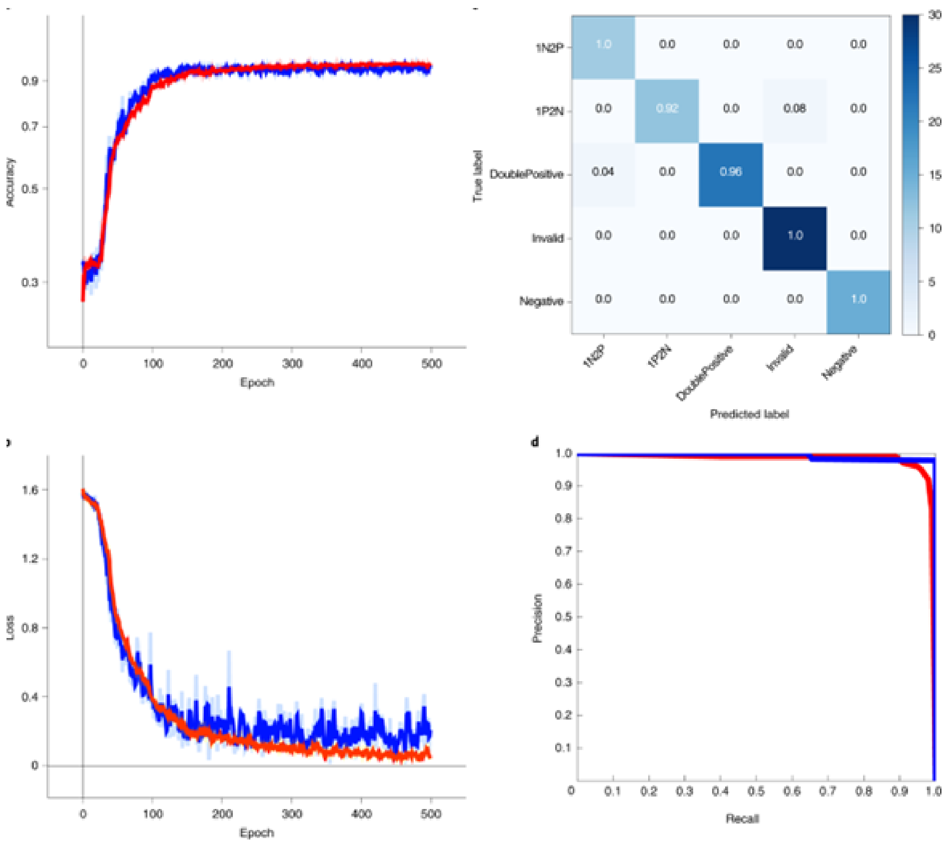

Fig. 5: Artificial Intelligence performance.

b) During the Artificial Intelligence training phase during epochs, accurateness (between 0–1) and loss the training dataset is represented by the red trace, while the blue trace represents the validation dataset.

c) The CNN model's test results confusion matrix, which represents the determined selection as well as the real label of each test picture. The number on every grid of the matrix signifies the relative accuracy of forecasts in that instance, the quantity of images sorted into each category is shown by the background colour of each grid.

d) Precision–recall curve shows for our "CNN (blue) as well as the SSD ResNet50 (red)" to make comparisons their prediction ability, with recollection evaluated as True Positive / (True Positive + False Negative) and accuracy assessed as True Positive/ (True Positive + False Positive), the outcome is termed a positive case if the level of confidence of a forecast overdoes a certain threshold; otherwise, it is called a negative case (Craja et al., 2020). The result is real if the forecast meets the performance is based on the input; otherwise, it is false. The CNN with "ResNet50 curves" has a region under the curve of 0.983 and 0.973, respectively.

In an investigative setting, any incorrect categorization has relatively modest consequences if detected quickly, since the test is given at the time of upkeep and can easily be repetitive. Only slight delays and negligible cost increases result from such an occurrence. Mislabeling of double-positive tests, for example, in which a sick individual has a "P. falciparum infection" but no "positive Pan test," would lead the operator to do the test regardless of the patient's outcome (Oblé & Bontempi, 2019). As long as the test findings are quickly available and the healthcare practitioners are alerted via the decision-making tool, Every test repetition will not cause a treatment delay of more than one hour. As a result, in neither case does the system's credibility suffer.

Especially contrasted to formerly shown techniques in decision - making, our CNN system is likely to produce results that can be trusted quickly and precisely. It also utilizes smartphone edge computing, which does not rely on cloud connection, rendering it more appropriate for usage in remote areas and naturally more safe. The

Artificial Intelligence output is interpreted to offer a prompt that assists practitioners in determining which care route, therapy, or response is appropriate for each outcome in all potential scenarios (Liang et al., 2016). There is no additional inference needed by the healthcare professional to evaluate potential misclassified likelihoods or mistakes, ensuring high interpretability with no requirement for clarity in the algorithm's choice, and thus supplying aspects that translate to accountable, dependable, and trustworthy (ART) fundamentals.

Our technique improves reliability to 97.83 percent when contrasted to the latest advancements in malaria cloud-based diagnostics. It's also worth noting that using AI decision support frameworks enables the learning to be refined over time, resulting in even better decision support options. This might be useful for novel tests that don't have the same precision as “laboratory-based training sets”. The usage of blockchain know-how in this scenario also assures that photographs and findings may be utilised for future practice while adhering to strict privacy limitations.

To illustrate the flexibility of the block chain technology functionality in allowing multiple The structure was changed to identify each personal DNA-based lateral flow outcome, and artificial intelligence-based methods were to be introduced to the framework, allocate one of 3 classifications (favourable if two lines are discovered, false if only one peruses, incorrect if none are prevalent), and afterward merge such results to unveil an as a whole readout, supplying a decision - making support quick for the positive examination as info.

By contrasting an SSD ResNet50 neural net to acquire clinical testing outcomes with our CNN model, the platform's capacity to handle multiple Artificial intelligence systems was proven. Both performed well when it came to making diagnostic predictions (Rajaraman et al., 2019). When it comes to analysing diagnostic results, the SSD ResNet50 as well as our CNN architecture offer various benefits. The CNN is both simpler and quicker, however the “SSD ResNet50” may give additional data, like the strip outcome. The accuracy curves for our CNN network as well as the SSD ResNet (Guz, 2012; Moses et al., 2022; Porwal et al., 2024; Min et al., 2024; Cho, 2024; Berrada & Herrou, 2023; Rolla, 2023).

In a rural environment, 40 school students were subjected to a total of Forty tests. The model only mislabelled one test, which was a test in which the standard solution was mislabelled as negative (Sriporn et al., 2020). The framework classified correctly 11 tests as invalid when experimental results were harmed.

We anticipate these difficulties to be considerably minimised in forthcoming maneuver generations, when mass production procedures like moulding may be employed. This 'invalid' test result demonstrates that our decision-making assistance system is capable of detecting such issues and informing the user whether the test has to be repeated (Russakovsky et al., 2015). This is simple to implement in practise at the time of care, adding to an increase in 'confidence' in the innovation by assessing the effectiveness of the examination and discriminating between failure versus effective containers, thereby increasing the decision of model's interpretability.

CONCLUSION

Malaria diagnosis is difficult in and of itself, as well as the accessibility of qualified professionals throughout the world is also a major challenge. Researchers looked at simple open-source Artificial Intelligence algorithms that can offer researchers state-of-the-art accuracy in diagnosing malaria, allowing Artificial Intelligence to be used for social benefit. They strongly advise everyone to read the publications and research papers referenced in this essay; without them, researcher would not have been able to envision and write this piece. Let's hope that open-source Artificial Intelligence capabilities become more widely used in healthcare, making it more affordable and accessible to everyone across the globe. The work shows that the ML technique is a viable tool for clinical information systems by providing working prototype techniques for classifying UM and SM from nMI. In the future, machine learning techniques might be included in medical decision systems to detect early febrile sickness and track responsiveness to acute SM therapy, especially in endemic areas.

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Declaration of Conflicts of Interests

Authors declare that they have no conflict of interest.

Availability of data and materials

Not Applicable

Use of Artificial Intelligence

Not applicable

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

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