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Detecting Malaria Cells with Plasmo-D Expert System Developed on Android and Computer Vision

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ABSTRACT

Malaria is a mosquito-borne disease that has been responsible for numerous deaths in humans for decades, caused by a single bite from an Anopheles mosquito. For proper treatment, the affected person needs to undergo a series of tests. Currently, separating infected and uninfected cells is done manually, which is time-consuming overall. However, this article presents a developed expert system called Plasmodium Detector (Plasmo-D), which leverages computer vision to detect malaria-infected cells using image recognition. Plasmo-D was built as an Android application, featuring an information menu, splash screen, and classification screen, along with an image recognition system that utilized computer vision. Data sourcing of 27,528 cell images was obtained from the Data Library of the United States National Library of Medicine. Training was conducted using Microsoft Azure, and the application was deployed to Android using Java programming language and an Android XML (Extensible Markup Language) user interface, along with TensorFlow Lite. Five iterations were conducted, and the parameters studied included cell images, backgrounds, visual style, size, type, lighting, and camera angle. High accuracy (up to 99.8%) in classifying parasitized, uninfected, and irrelevant images ('not a cell').

1. INTRODUCTION

Malaria is a life-threatening disease caused by plasmodium, a disease-causing organism that is transmitted to humans through the bites of infected female anopheles mosquitoes. This phenomenon occurs regularly and is prevalent across both cities and rural areas. The recent report by [1] states that more than 67 million cases of Malaria in Nigeria account for 27 percent of the global malaria burden and 31 percent of global deaths, and 38 percent of global deaths in children under the age of five, respectively. This statistic applies to some third-world countries where unclear bushes, standing water, and poor health infrastructure are prevalent. A malaria test is necessary to confirm the presence of Plasmodium in the bloodstream of the affected patient after some symptoms have been noticed. Prevention measures for mosquito bites included the use of pre-treated bed nets, spraying of insecticides, and fast-acting medicines. The most common method for detecting Plasmodium is the Malaria Rapid Diagnostic Test (MRDT). It is widely and expensively available at clinics for the earlier detection of malaria. Malaria is responsible for death in many third-world countries due to a lack of standard laboratories for earlier detection, a shortage of trained medical personnel, and low awareness of the risk associated with malaria caused by mosquitoes [2]. In addition, more than 214 million cases are recorded globally, with 400,000 deaths. Types of plasmodium are Plasmodium vivax, Plasmodium malariae, Plasmodium ovale, Plasmodium Knowlesi, and Plasmodium falciparum. Plasmodium falciparum and Plasmodium vivax are the two species, with Plasmodium falciparum being the most dominant and persistent. In the sub-Saharan part of Africa alone, Plasmodium falciparum accounted for 99% of the estimated malaria cases in 2016, while P. Vivax is predominantly reported in America, Southeast Asia, and the Eastern Mediterranean [2]. One report published by the Centers for Disease Control and Prevention in the United States states that millions of blood films are examined yearly. This enormous work is done manually to count malaria cell. Based on this backdrop, this article presents Plasmo-D expert systems for malaria cell detection using computer vision and an image recognition model.

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1.1 Global burden of malaria

Over 200 million malaria cases were registered each year globally, and 400,000 people lost their lives [3]. Africa has the highest malaria transmission, followed by Oceania, Asia, and South America, according to the WHO [4]. This may be unrelated to the areas surrounding malaria. This leads to higher dropout rates among students, requires 2 to 3 weeks for proper treatments, and affects parental functionality when infected. Adults are not spared when infected by malaria, infected ones failed to care for their families when infected by malaria. Overall, the malaria epidemic disrupts the economy of affected countries, thereby leading to a drop in their Gross Domestic Product (GDP). More than 90% of malaria cases occur in Africa, as 41% of the world's population resides in areas where cases of malaria (Table 1) are prevalent [4].

Table 1. Cases of malaria

Malaria cases	Causes	Effect/treatment	References
1960 malaria cases	Marsh fever is associated with swampy areas, standing water, and unclear bushes. Eradicate malaria with spraying.	Sickness in children leads to out- of-school absences, parents being unable to play their role when infected, the use of insecticide home sprays, and the use of treated mosquitoes.	[4]
Malaria in Africa. swamp drainage, unclear bushes, standing water	Bites by pathogenic anopheles' mosquitoes	bednet, traditional methods, bark of cinchona trees(quine), insecticides, home spray, use of treated mosquito net, use of malaria medicine (chloroquine and Artemisins)	[4]

1.2 Methods of detecting malaria-infected cells

The methods used to detect malaria-infected cells were the Polymerase Chain Reaction (PCR) and Rapid Diagnostic Tests (RDTs). The two are specialized methods implemented when high-quality microscopy services are unavailable. The World Health Organization (WHO) has approved the blood smear method as the standard diagnostic method for malaria. According to the WHO protocol, the diagnosis involved an intensive examination of the blood smear using a 100X magnification lens, handled by a trained laboratory technician. Manually counting the number of red blood cells from the 5,000-parasitic cells could be devastating. Blood smear can be divided into two [5] types. The thick blood smears help detect the presence of parasites, while thin blood smears help identify the species of the parasite that causes the infection, in line with the WHO. The accuracy of diagnosis depends mainly on human expertise, with some variability.

1.3 Techniques for image recognition and malaria-infected cells detection

One of the techniques for detecting infected and uninfected red blood cells is the thin smears, or identifying parasite species using the thick smears. Some methods for malaria diagnosis are shown in Table 2.

Table 2. Classification methods for malaria diagnosis

Blood smear	Classification type	Classification methodology
Thin blood smear	Unsupervised	K-means clustering
		Quaternion Fourier transform (QFT)
	Supervised	Naïve Bayes tree, Decision tree, Euclidean distance classifier, K-nearest neighbors' classifier thresholding, Support Vector Machine, Bayesian classifier, Annular ring ratio method, Logistic regression tree, Linear programming, Template matching, Ada-boost, Nearest mean classifier, Normalized cross-correlation, Linear discriminant, Crowd-source games, Fuzzy interface system, Deep Learning. Neural network
Thick blood smear	Unsupervised	K-means clustering
	Supervised	Naïve Bayes tree, thresholding, Support vector machine. Neural network, Randomized Tree Classifier, Genetic algorithm, K-means clustering

1.4 Studies using mobile diagnostics and image recognition

Smartphones are becoming a powerful computing device in the medical industry. Their built-in camera, when used along with a small magnifying device, is capable of diagnosing diseases such as malaria. For instance, Breslauer [6] developed a mobile phone-mounted light microscope and demonstrated its medical capabilities for imaging falciparum-infected plasmodia and sickle red blood cells in LED-infected bright-field and Mycobacterium tuberculosis sputum samples. Resolution in all cases surpassed the need to detect the morphology of blood cells and microorganisms. Digitized images were utilized to demonstrate automated Bacillus counting using image analysis technology for tuberculosis samples.

In their work, [7] developed a cost-effective cell phone-based device capable of transmitting polarized light for imaging the malaria pigment known as hemozoin, a material used by blood parasites for digestion and disposal. The technique of image processing and evaluation using controlled identification has been presented [8] to determine the existence of *Plasmodium falciparum trophozoites* and white blood cells in Giemsa-stained dense blood smears. The automated detection of trophozoites using a support vector machine achieved a tolerance level of 80.5% and a precision of 93.8%. And a combination of elements in symmetry, color, and texture. On the other hand, white blood cell detection achieved a sensitivity of 98.2% and a specificity of 72.1%. However, [9] developed a 3D-printable adapter attached to a smartphone and a microscope. It was reported that although all images were taken with a dedicated microscope camera for their experiments, they provided pixel resolution better than that of their phone camera. They proposed a method for the automated analysis of dense blood smears, involving the measurement of morphological and moment characteristics, and an ensemble tree classifier based on these characteristics to distinguish between parasite-containing abnormal patches and regular patches. The quality recorded under the operating characteristic curve of the receiver was 97%. The handheld Android phone software systems are capable of diagnosing malaria from thin film photographs of Giemsa-stained blood [10].

Some scholars [11]-[19] have revealed that, although imaging is a complex morphological procedure, it is capable of detecting red and white blood cells and recognizing infected cell parasites. The software produced different life cycles of parasites and determined the rate of parasitemia. In the same vein, [20] opined that remote aid can compensate for in regions where advanced health care is found inadequate for diagnosing vector-borne diseases. This article, therefore, concentrated on the analysis of images and the identification portion of a program designed to reduce the risk of misdiagnosing less common diseases, such as malaria, by healthcare professionals. The clinical output of a computer for automatic rapid diagnostic test analysis, utilizing smartphone technology and software for image analysis, has been tested [21]. The device's diagnostic quality was equivalent to that of a rapid diagnostic test in visual perception, with no glaring variation for *Plasmodium falciparum* and *Plasmodium vivax*. Besides reporting cases in near real-time and facilitating quality control, providing structured, automated analysis of rapid diagnostic tests in remote areas will significantly benefit the wide-ranging introduction of accelerated, therapeutic malaria-based diagnostic services. Meanwhile, [22] demonstrated a rapid diagnostic test reader platform based on cell phones that can work with specific immune chromatographic assays and similar tests on lateral flow devices. A network of 6 levels of deep belief in the identification of malaria parasites in peripheral blood smears has been suggested [23]. They achieved 96.4% precision in the function of randomizing a dataset of 4,100 cells with train/test splits. It is clear that malaria is a global problem; cases in third-world countries are significant, with a lack of standard kits for malaria diagnosis and a shortage of medical personnel. The development of an expert system called Plasmodium Detector(Plasmo-D) would leverage computer vision to detect malaria-infected cells, making image recognition of greater importance.

2. METHOD

The development of Plasmo-D expert system followed standard procedures [24]-[32]. Relevant research studies [33]-[49] were thoroughly reviewed with some of their steps on data collection, data splitting, training and cross validation were adopted for the current work. Random splitting was used to divide the datasets into training and validation sets, and validation was conducted through 5-fold cross-validation. Moreover, an alternative way to define the performance of the algorithm is through a confusion matrix, a table used to evaluate the performance of a classification algorithm.

2.1. Collection of cell images

Twenty-seven thousand five hundred and eight (27,000) digital images of cells infected and uninfected with malaria were sourced online from the National Library of Medicine, United States. The photos were open- sourced through Kaggle for academic research and were verified by the World Health Organization (WHO). Cell images (Figure 1 and Figure 2) were resampled to sizes of 100 x 100, 224 x 224, 227 x 227, and 299 x 299 pixels to suit the input requirements of computer vision and machine learning algorithms, thereby

facilitating quick convergence. The rationale for choosing the resolution was that it determined the level of detail contained in the cell images, particularly the number of pixels within them. Therefore, the higher the resolution and the richer the pixel count, the more detail and definition it reveals. The model was trained and tested on a Windows-based system with an Intel Core i5-5IOU processor on Microsoft Azure, utilizing Azure Cognitive Services to train and enhance image recognition models. The number of cells for each fold is shown in Table 3.

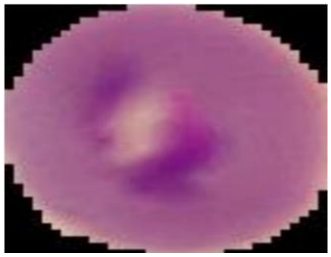

Figure 1. Cell images infected

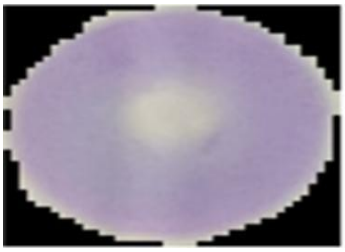

Figure 2. Cell images uninfected

2.2. Collection of cell images

Pre-processing of images removed noise and other unwanted artifacts using the Azure Vision Application Programming Interface (API). Cell images were scaled down to meet the standard image formats Joint Photographic Experts Group (JPG), Portable Network Graphic (PNG), or (BITMAP)(BMP) that were not greater than 6 MB in size (4MB for prediction images) and less than 256 pixels on the shortest edge. The Custom Vision Service was equipped to scale up for images shorter than automatically. Labeling or tagging of cell images was achieved through sectioning cells into two major classes, the INFECTED (images of cells infected with malaria) and UNINFECTED (images of cells not infected with malaria), and a third control group, NOT A CELL IMAGE(NACI). 50 photos of people randomly taken with Samsung Galaxy A8(2018) camera (16 MP) served as control. This class did not contain cell images but pictures of other objects or entities that are not cells. The tag given to this class is “NOT A CELL IMAGE”. The performance of the image recognition model was improved by creating a new class to remove anomalies. The first step was data training, followed by uploading the cell images for training after they were tagged. The training process involved cell images serving as raw data, input for the computer vision algorithm. The classifier used all the input data to create a model, which in turn identified the visual qualities of each cell tag. Labelling on the cell images was performed by the Custom Vision Service using a machine learning algorithm. Figure 3 was a screenshot of the steps, which was checked on the same image. The algorithm was trained on the data and its accuracy was tested. In Stage 2, the Computer Vision Application Programming Interface (API) utilized the output result from Stage 1 as input, training the image recognition system and developing an Android application that integrated the model. The model was then exported using the TensorFlow Lite extension. In stage 3, the Android Application Development was implemented using the Java programming language, connected to a developed user interface. This worked with a mobile device running the Android operating system. The materials used for PLASMO-D development were enumerated in Table 4. Overall, five iterations were conducted.

Table 3. Number of cell images for the parasitized and the uninfected

Folds	Parasitized	Uninfected
1	2756	2757
2	2758	2758
3	2776	2762
4	2832	2760
5	2657	2742
Total	13779	13779

Table 4. Materials for the construction of PLASMO-D.

Item	Quantity	Purpose
image cells	27,558	For training/ evaluating the developed Plasmo-D expert system
Microsoft Azure	N/A	The platform on which the model was trained and developed utilized Microsoft Azure services, employing the Custom Vision API to process the images.
Java programming language:	N/A	Responsible for model deployment and building of the Android application, implementation of different logics for testing the Android application, as well as linking the user interface objects or entities of the application with the functional part of the program.
Extensible Markup Language (XML):	N/A	For designing the front-end part of the Android application or the User Interface design of the application with Extensible Markup Language(XML). XML was a meta-language to create personalized XML, especially for viewing online documents.
Android Studio integrated development environment (ide):	N/A	For integration of the image recognition model into the Android application.
TensorFlow lite:	N/A	To export the image recognition model from the Microsoft Azure platform on the Custom Vision training environment as a readable format for use in android studio.

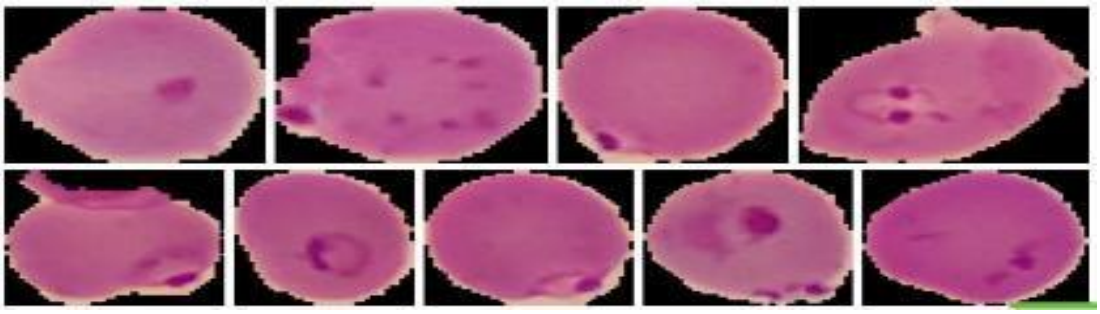

Figure 3. Cell images after the training processes

2.3. The development of the android application

The image recognition model and the development of the Android application software followed standard engineering design software development life cycle procedures [50] (Figure 4). This included the problem definition: the problem of designing and creating an Android application that interacts with a database, utilizing the image recognition model, and provides output (infected, uninfected, or not a call image) was defined. Problem analysis: The problem of designing and creating an Android application was analyzed using paper sketches to assign different activities within the application process, to come up with an appropriate solution. Application design development: This involves creating mock-up sketches or prototypes of view groups and layout types for generating views for the screen activities selected from the results obtained in the previous step. The flowchart of the Plasmo-D working process is shown in Figure 7. Coding and documentation were carried out using XML and Java programming languages, and testing and debugging were also performed. One at a time, the prescribed solution was tested, checked for bugs, and debugged and Maintenance of the development was the last stage.

2.4. OPERATION OF PLASMO-D EXPERT SYSTEM

The developed android application was named Plasmo-D, a shortened form of "PLASMODIUM DETECTOR" with Plasmo stand for PLASMODIUM and D for DETECTOR respectively. First, Plasmo-D starts working when the Android mobile phone is connected to a conventional light microscope. Scanned images using the enabled phone camera and displayed them after diagnosis. Second, the application's splash screen navigated to the classification or detection menu, and classification of images, along with detection, commenced after the "COMMENCE DETECTION" button was released.

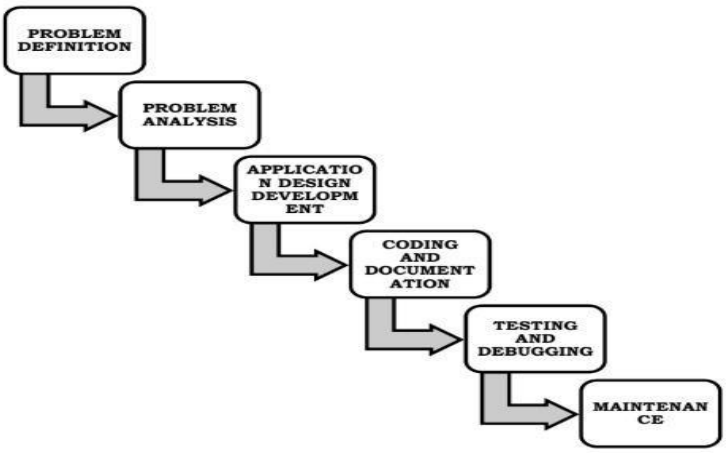

Figure 4. Flowchart of Plasmo-D development

2.5. The android application development at stage 3

The model was exported through the TensorFlow Lite extension from Azure Custom Vision for easy importing into Android Studio for Android application development. The camera function, texture view, and classifier were initiated after the images were scanned. The model then worked on the image's appearance, and the classification of these images was made. An Android application (PLASMO-D) was developed for classifying infected cells with malaria and uninfected cells, along with the application icon and its display in the app drawer.

3. RESULTS AND DISCUSSION

The results of the cell's image processing and training processes using the image recognition model are provided in Table 5. Figure 5 and figure 6 show images of cells infected with the malaria parasite Plasmodium falciparum and those not infected. The testing process indicated that the developed Plasmo-D expert systems, which run on Android applications, allowed users to scan images and view the results of their diagnoses, quickly displaying whether they were infected with malaria or not.

3.1. Image processing at stage 1

The result generated at stage 1 was stored in the Azure Custom Vision cloud, which included scaled-down and fitted images for use and training by the Azure services API. It was observed that there were variations in the size of the processed images compared to the original image files and sizes; however, no noticeable distortion in appearance to the human eyes was observed.

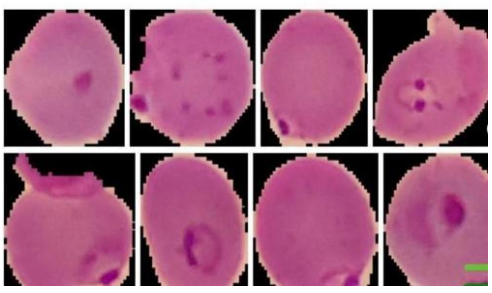

Figure 5. The processed images

Figure 6. Trained images in the training environment

3.2. First iteration 1

Plasmo-D achieved a performance evaluation of 98.3% after completing the first training on cell images using the image recognition model, as shown in Figure 8. Furthermore, 95% precision was recorded, and for recall, it was 95%, while the percentages for uninfected cells were 98.5% and 97%. This was after the model had been trained with five hundred (500) images of malaria-infected and uninfected cells. This finding indicated that the model can differentiate between infected and uninfected individuals.

Table 5. Precision and recall data from training with PLASMO-D

Training	Cell images	No cell images	Infected images PE	uninfected images PE	Not a cell
First	500	None	98.5%	97%.	
Second	1066	None	(1066) 98.6%.	(850)98.6%.	
Third 3 hours	1066	605	99.7%.	99.7%.	(605) 99.7%.
Fourth(3 hours)	1066	605	99.8%	99.8%	
Fifth	1066	605	99.8%	99.8%	

3.3. Iteration 2

In this iteration, the number of infected cells with malaria was approximately double that used in the first training. A total of 1066 images of infected cells with malaria were used for this training, and 850 photos of uninfected cells were used, resulting in a ratio of 1.25:1 of infected to uninfected cells. This was done to assess how the image recognition system or model could be further improved. With a slight change in the ratio of training images, the model's performance has improved considerably to 98.6%, as shown in Figure 9.

3.4. Third iteration 3

For the third training (Figure 10), the number of cell images was maintained, but a new class of images was introduced, which includes only non-cell pictures of different types. A total of 605 non-cell photos were introduced to form the third classification label of “NOT A CELL IMAGE”. This time, the model was trained for a more extended period with a budget of 3 hours. After the third training, the image recognition model is seen to have improved so well in performance to 99.7%.

3.5. The fourth and fifth iterations

For the fourth iteration, there was no significant change in the number of images used for training and the training parameters. The model was only trained for an additional 3 hours to determine if any further improvement was possible. After the fourth training session, which lasted an extra 3 hours, the image recognition system's model improved significantly, achieving an overall performance of 99.8% and 98% for precision and recall, respectively. Another training session was conducted on the model to determine if any further improvements could be achieved. However, at this point, the model's performance, precision, and recall actually decreased. Since there was no improvement in the model after the fifth training, the state of the model after the fourth training, with a performance of 99.8%, was then exported for use in the development of the Android application.

3.6. Training of cell images with computer vision

Visuals representing metrics of the model along with their performances showing percentages of recall, precision value, (AP) as well as image counts for the data sets- infected, on-infected cells, and the not-a-cell were described in Figure 8-Figure 12, respectively. The recall was an indication of all the positives, whereas precision was the number of true positives divided by the total number of optimistic predictions. However, it was observed that the AP, which was obtained by finding the area under the precision- recall curve for iterations 3, 4, 5, were very close values of 99.7%, 99.8%, and 99.2%, respectively. This might not be unconnected to the accuracy of the Plasmo-D in predicting the data sets.

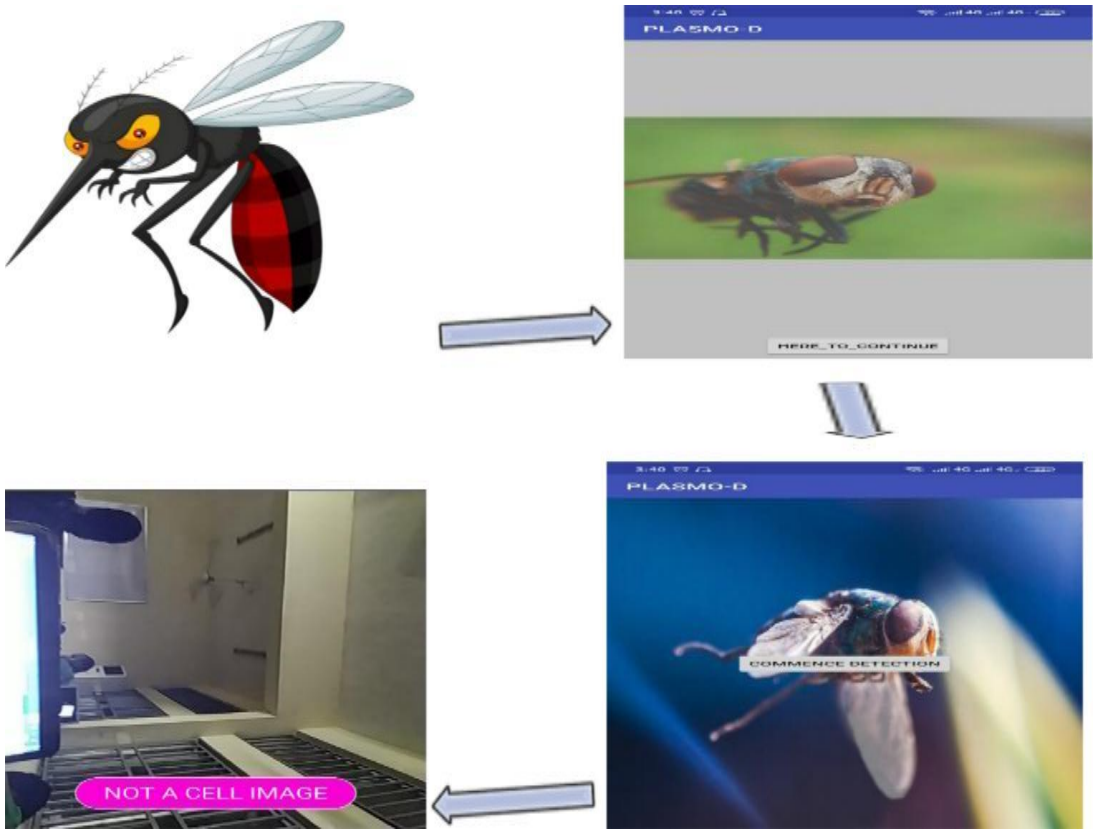

Figure 7. Image of the Android Studio platform for Android application development

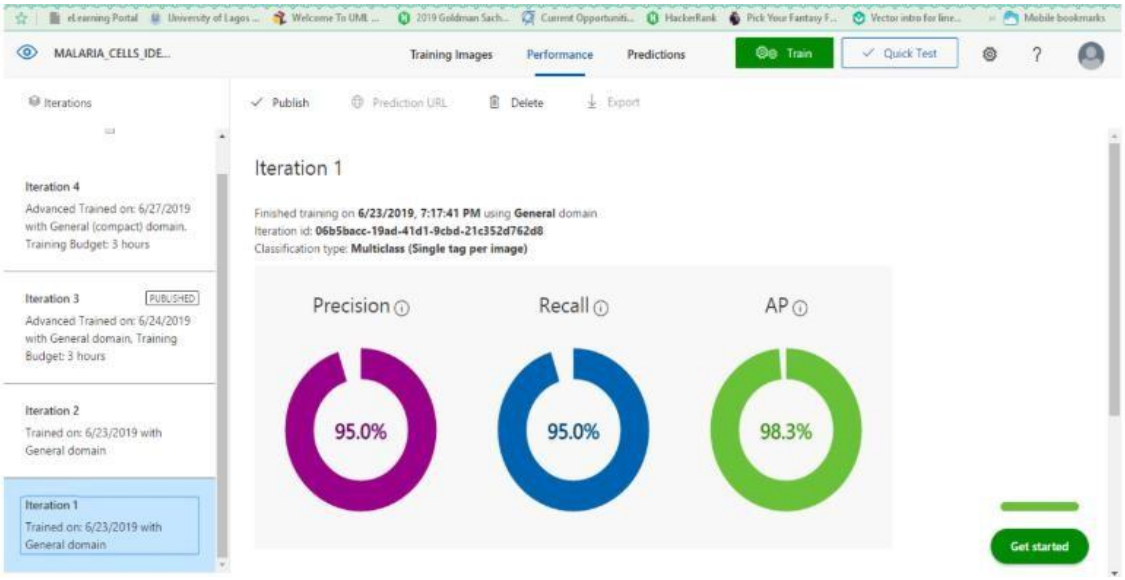

Figure 8. First training performance result of the model

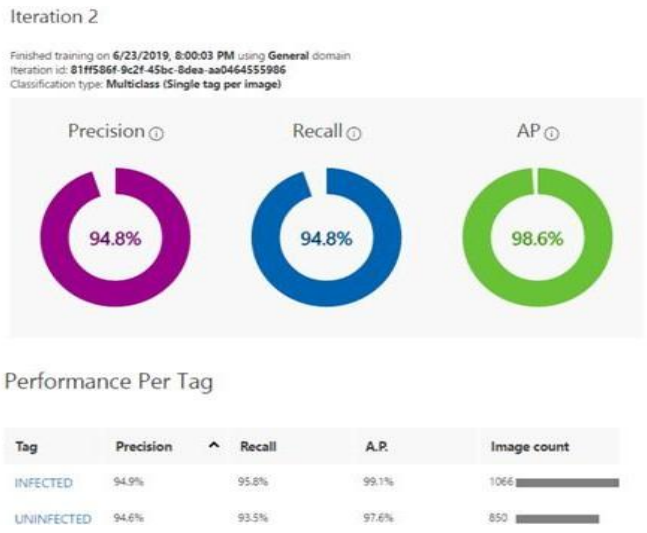

Figure 9. Second training performance result of the model

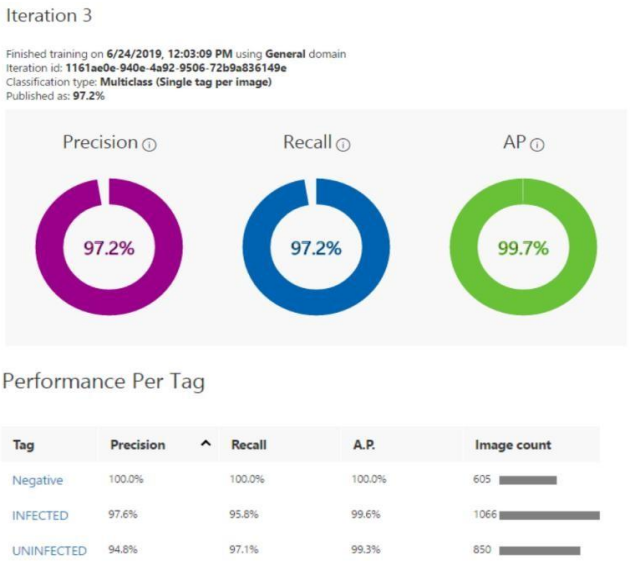

Figure 10. Third training performance result of the model

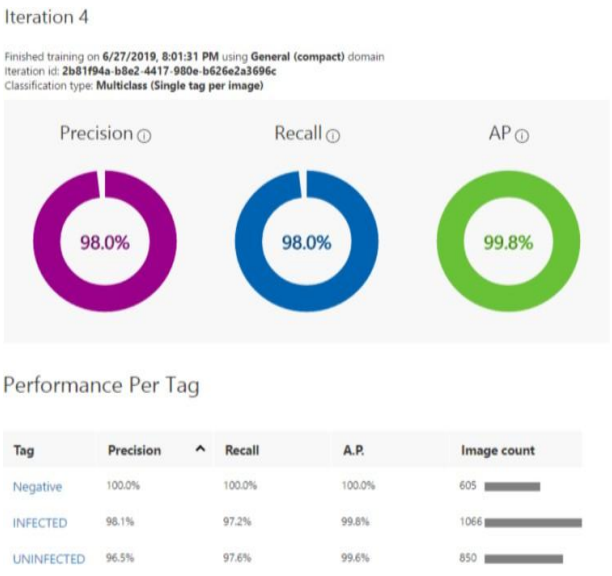

Figure 11. Fourth training performance result of the model

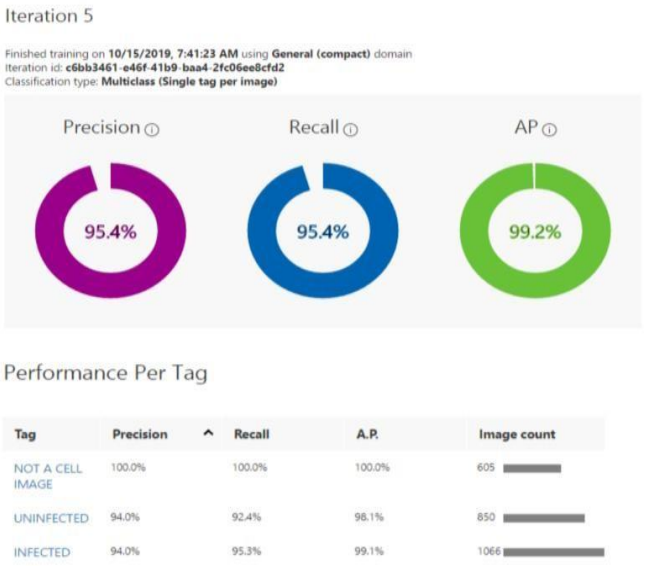

Figure 12. Fifth training performance result of the model

3.7. Benefits of plasmo-d over existing detection system

Plasmo-D was faster because it was using computer vision for image recognition. This operation, which was similar to using lenses that were far superior to human eyes due to their computing power, was for identification. Additionally, based on the tests conducted, Plasmo-D has an efficiency above 95% in identifying infected, non-infected, or non-cell images. However, one precaution is that the Android device must be stable; otherwise, it may not be in a stable position during use, which affects prediction. This might not be unconnected to the series of caches and processes running in the background. Plasmo- D has a 100% attribute of being able to identify non-cell images because the time and stability required to achieve this were less and quite smooth. On the other hand, Plasmo-D would not run on Android devices whose software development kit (SDK) version for Android was below level 21, which corresponds to the Android Lollipop stage. This was not surprising because the deployment of the artificial intelligence model was only supported on devices with the Android operating system version 5.0, also known as Android Lollipop, and above. Plasmo-D applications run smoothly on up to 70% of the Android devices available, including those newly manufactured, as they were developed to adapt to the latest operating system through a Google Maven library. Maven is used for Java-based projects, specifically for downloading dependencies, libraries, or Java Archive (JAR) files added to its software development kit extension during development. In terms of usability, Plasmo-D is user-friendly because it operates offline, a feature uncommon among other detection systems, and does not require internet access for image classification or detection. Installation required no special skill, and the software is available at https://devpost.com/software/plasmo-d. Nevertheless, to run the application on an Android device, it needed to be granted root access to utilize the device's camera and require 70 megabytes (MB) of space for smooth operation. Moreover, Android devices with operating systems that support the Plasmo-D application should have at least 1 Gigabyte (GB) of Random Access Memory (RAM) to function correctly. Finally, if Plasmo-D is optimized, its performance would improve.

4. CONCLUSION AND LIMITATION

The detection of malaria-infected cells can be accelerated using AI-driven malaria diagnosis, such as Plasmo-D. It was developed with the aid of computer vision and image recognition, an Android-based application that predicted whether erythrocytes were infected with malaria parasites or not. Plasmo-D was a novel application that could process and train a large number of cell images simultaneously, particularly in malaria-prone areas. During testing, it recorded performance up to 99.8% after five iterations. This demonstrated the power of the artificial intelligence model for classifying malaria cells. Moreover, it could be a valuable technology for the medical and scientific fields if optimized. However, human-centered usability testing is recommended for software improvement to provide actionable insights into creating a better user experience. Plasmo-D system represents a significant advancement in AI-driven malaria diagnosis, combining high accuracy with practical deployment via mobile technology.

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