Recognition of malaria parasites using images of red blood cells

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Abstract : Malaria is a serious disease in the world and may lead to death if not treated. It is an infection caused by a single-celled parasite that penetrates the bloodstream through the bite of mosquitoes. Malaria is diagnosed in several ways, including direct detection by a doctor and microscopic diagnosis by examining blood smears from red blood cells infected with parasites, in addition to the rapid diagnostic test, and these methods are ineffective because of the difference the accuracy of the diagnosis and also its low results in the diagnosis, so it was necessary to use modern technologies to recognize malaria effectively. In this paper, malaria was recognized by classifying images of infected and uninfected blood cells using the fine-tuning a pre-trained Convolutional Neural Network as a model for artificial intelligence. The results of the proposed model were compared with the method of microscopy and rapid diagnosis, and the experimental results showed that the proposed model for the identification of malaria diseases achieved high accuracy and efficiency in terms of performance measures: Accuracy, Sensitivity, Specificity, Precision, F1 score, and Matthews correlation coefficient, where the results were (98.30%, 96.99%, 97.75%, 97.73%, 97.36%, and 94.75%) respectively.

Keywords: Convolutional Neural Network, microscopic diagnosis, Rapid Diagnostic Test, Deep learning.

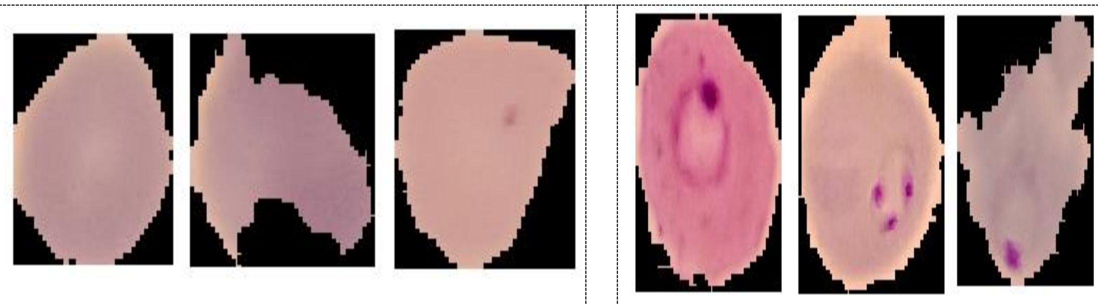
1. Introduction

Malaria is a serious and deadly disease and is transmitted by the bite of a female Anopheles mosquito to a person who is not infected with parasites called Plasmodium, which leads to an increase in temperature accompanied by shivering, which may lead to death. Malaria spreads in hot and warm regions, where about 500 million people are infected at most every year, and the death rate reaches 2.7 million deaths annually [1-2], according to the World Health Organization report, 435,000 deaths in 2017 [3]. Recently, Yemen has witnessed a sharp deterioration at the humanitarian and health level due to the war, and this has led to the suspension of most hospitals and the displacement of medical staff.

Malaria has spread widely in Yemen, and thousands of civilians have died as a result of malaria, and there are no accurate statistics on the number of deaths due to the absence of a health statistics unit. Malaria can be prevented, controlled and treated more effectively if a more accurate and efficient diagnostic method is available. There are methods that use the diagnosis of malaria, such as microscopy, but it is ineffective and has low efficiency and depends on the experience of the microscope specialist, as well as the Rapid Diagnostic Tests (RDT) method, which works on a large scale, but is more expensive and provides less information than microscopy. It was necessary to use modern technologies such as artificial intelligence to identify malaria because of their effectiveness and high efficiency and deal with large data. Artificial intelligence has important uses in the field of biomedicine [4] and in the field of medical diagnosis [5, 6, 7, 8, 9, 10, 11, 12]. There are studies [13], [14] and [15] that used machine learning techniques to recognize malaria, as well as recent studies that used deep learning techniques such as a CNN، which achieved high accuracy and efficiency.

In this paper, a deep learning model approach was used to recognize malaria disease by images of erythrocytes that were divided into images of malaria-infected and non-malaria-infected red cells as in Figure 1.

Fine-tuning a pre-trained CNN has been applied as a deep learning approach model where it can be trained on big data and its internal structure can be changed and also has the ability to process red blood cell images, extract their characteristics, classify and then recognize them with high efficiency and accuracy.



a) Normal **b) Malaria**

Figure 1. Red blood cells infected with malaria and non-infected

This paper is arranged as follows: the related works are listed in the second section, while the methodology used to recognize malaria is described in the third section. The fourth section presented the implemented results, and finally the research conclusions were presented.

2. Related works

We present an overview of literature that relates to work presented here. Reference [16] proposed a method for recognizing malaria using the SVM support vector machine algorithm via microscopic images of malaria that were classified into contaminated and non-contaminated. Dong et al. [17] proposed a convolutional neural network for image feature extraction and a LENET-5 network for image recognition of contaminated malaria. In reference [18], a fuzzy logic method was proposed for malaria identification, which achieved high accuracy. A study [19] proposed a convolutional neural network as a model for artificial intelligence to recognize malaria, and it achieved high accuracy. Reference [20] suggested ANN and BN methods for recognizing malaria for people living in the Brazilian Amazon. In reference [21] the Naïve-Bayesian method was used to classify malaria as a probabilistic method. Reference [22] suggested the Adaptive Neurological Inference System (ANFIS) method for recognizing malaria diseases, where the accuracy of identification reached 98%. Reference [23] proposed a fuzzy expert system to recognize malaria, which has high accuracy, but has the problem of not being able to recognize cerebral malaria. References [24] and [25] suggested machine learning methods (Bayesian learning, support vector machines, logistic regression, and the nearest neighbor algorithm) to recognize malaria by image analysis and classification. Reference [26] proposed a method for recognizing malaria images using thresholding as a pre-processing images before classifying them using the Fuzzy C-Mean algorithm. References [27] and [28] suggested a pre-trained Convolutional Neural Network to automatically extract characteristics from malaria images and then classify them. Reference [29] proposed a CNN pre-trained on the ImageNet large dataset to classify malaria images based on preset weights and achieve high classification accuracy. Reference [30] compared SVM and convolutional neural network algorithms for image recognition of malaria. They found that CNN achieved a high accuracy of 95% while SVM achieved 92%. Reference [31] suggested two algorithms CNN and AlexNet for recognizing malaria and found that CNN achieved an accuracy of 97.37% higher than AlexNet.

3. Methods

In this section, we will show the methods used to detect malaria and the proposed method using artificial intelligence.

3.1 The doctor's examination of the patient

The diagnosis of malaria is made based on the symptoms that the patient suffers from, such as: fever, chills, nausea, vomiting, and headache, but these symptoms may be similar to other diseases such as influenza and viral infections, so the accuracy of the diagnosis is very weak. In some cases, it initially indicates the presence of a disease in the person and the need to follow up his condition to find out the cause of these symptoms. This method is the least expensive, but it can be the first method that the patient resorts to when noticing these symptoms.

3.2 Microscopic examination method

Microscopy is one of the traditional ways to identify malaria parasites light microscopy. The examination is done under a microscope, by taking a sample of the patient's blood, and the sample is examined under a microscope and dyed with a certain dye to give the parasites a distinctive appearance and identify them.

The method of microscopy is simple and familiar in most laboratories and occurs relatively quickly within a few hours and gives information about the presence or absence of infection, as well as the type of parasites and the number of infected blood cells, so it provides a valuable information. While its disadvantages lie in the difference in the accuracy of the diagnosis from one laboratory to another due to the difference in the accuracy of the microscope and reagents and the experience of the laboratory technician. And often, low levels of parasites are not easily detected and therefore an incorrect negative result is given. Only a skilled lab technician can detect these low levels.

Blood can be prepared in two ways for malaria microscopy: a thick blood smear and a thin blood smear. A thick blood smear is a drop of blood (about 6-10 ml) drop on a clean, dry glass slide. Thick blood smears are very useful in detecting the presence of parasites, as they examine a larger sample of blood. (There are often a few parasites in the blood at the time of the test.) During 10-60 minutes of staining in this aqueous medium, the erythrocytes fade away due to osmotic swelling, leaving the leukocytes and parasites if present largely (but not completely) intact. Thick smears are mainly used to detect infection and to estimate parasites in the blood (sensitivity is 11 times greater than that of a thin smear). A thin blood smear is a drop of blood that spreads across a large area of a slide. Thin blood smears help doctors detect the types of malaria that cause infection and determine the amount of parasites in the blood by evaluating the size of infected RBCs compared to uninfected RBCs. A thin blood smear is less sensitive than a thick blood smear especially when there are low parasitemia levels.

In order to obtain better results in microscopic diagnosis, we believe that strict training of laboratory technicians, evaluation of their continuous performance, and adoption of standardized protocols for preparing slides is necessary.

3.3 Rapid Diagnostic Test

Malaria Rapid Diagnostic Tests are an alternative to microscopy of malaria sometimes called Malaria Rapid Diagnostic Devices (MRDDS) and work to detect specific malaria antigens in a person's blood. The test process is done by placing the patient’s blood sample on the sample pad on the test card with some reagents, as the test card contains specific ranges that determine whether the patient is infected with one of the types of malaria or not, the results are based on the presence or absence of a colored line on the test strips Available in 5-20 minutes, depending on the product. RDTs have an advantage over microscopy in that they require less training for their correct use, as opposed to microscopy, which requires laboratory expertise for diagnosis. As for the disadvantages of RDT diagnosis, the results depend on the quality of the product, and therefore the best products are not always available in the market, and this makes the results unreliable. In addition, the appearance of faint lines on the test strips leads to different interpretations of the results by laboratory technicians, and therefore the results may be positive or negative. Also, a quick reading of the results does not give accurate results and it is better to wait for a longer period according to the examination instructions.

3.3 Proposed method for recognizing malaria

In this part, we will show how to recognize malaria from images of red blood cells. The proposed method for recognizing malaria is described in the following steps: data collection, pre-processing of red blood cell images, and finally using the fine-tuning a pre-trained Convolutional Neural Network algorithm which classify the extracted features and recognize the malaria disease as shown in Figure 2.

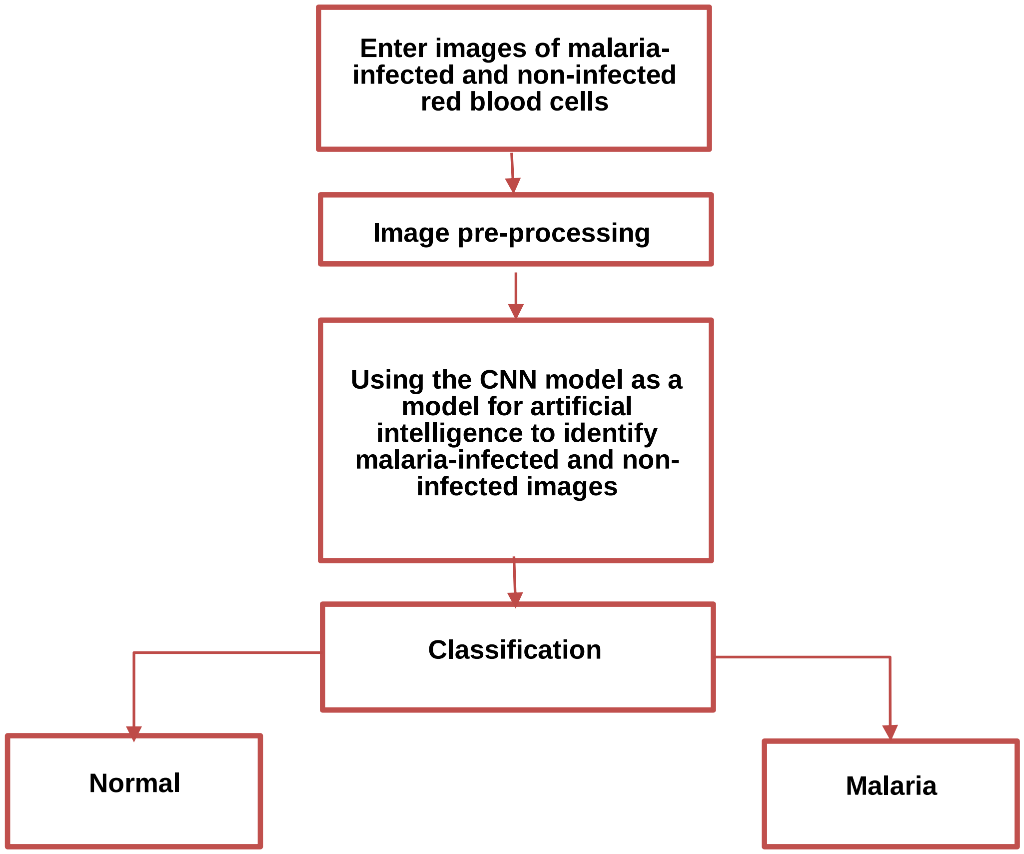


Figure 2. The proposed model to recognize malaria.

A. Data collection

The dataset of erythrocyte images was collected from Chittagong Medical College Hospital, Bangladesh and consisted of 27,562 RBCs and divided into malaria-infected and uninfected cells.

B. Data pre-processing

All erythrocyte images in the dataset were fixed to 64 x 64 x 3 pixels in the training and testing phases to fit the input layer of the CNN.

C. Training Phase: In this phase, the dataset of malaria and non-malaria erythrocytes are divided into 70% for the training phase and 30% for the testing phase. After the training process, the final weights of the network are saved that will be used in the testing phase.

D. Testing Phase*:* In this phase, the images were resized to the same size that was done in the training phase, and then the final weights obtained in the training phase were used for testing.

- Deep learning Model

A convolutional neural network is a deep learning network as a model for artificial intelligence that contains a deep architecture consisting of input, hidden, and output layers. CNN layers are multi-layered and have local connections that are variable weights as shown in figure 3.

CNN has many applications, especially in the field of image recognition with high accuracy, as it extracts the important features of images automatically without the need to use feature extraction algorithms such as machine learning algorithms, then the features are categorized and finally the images are classified. It has the ability to deal with a large data set, as it achieves high accuracy, but it takes a longer time to train.

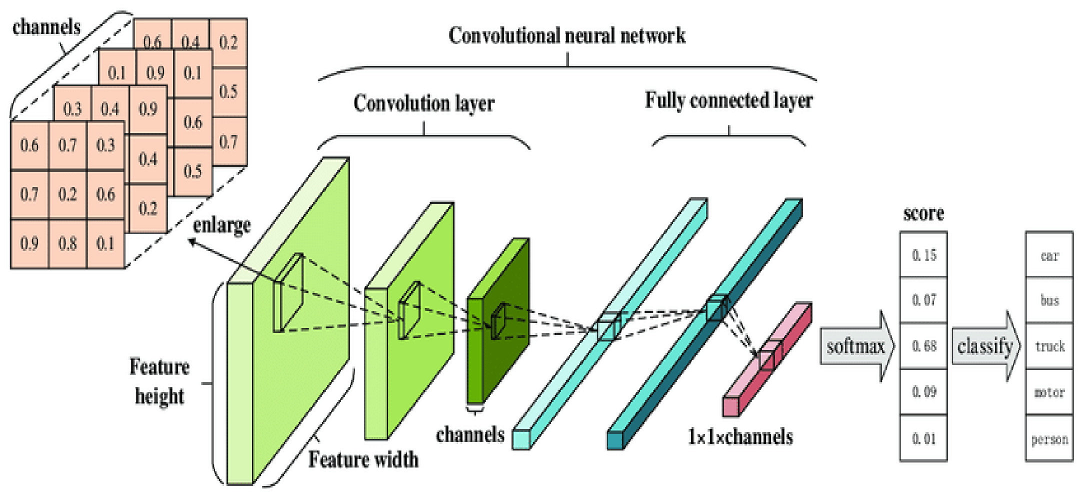


Figure 3. The architecture of a convolutional neural network

4. Results

According to 29 studies between 2001 and 2020 analyzed using Review Manager Midas (Stata) and Meta-disc, the sensitivity and specificity of studies comparing RDT with microscopy ranged from 79%-100% to 80%-100%, respectively [32]. While the results obtained from implementing the proposed method using pre-trained CNN are much better than RDT and microscopy. Where the data set that was dealt with in this method is very large and consists of 27,562 images of red blood cells divided into malaria-infected and uninfected cells compared to the small number of samples using RDT and microscopy. We divided the data set into two parts, 70% for training and 30% data for testing. Results obtained from the fine-tuning of the pre-trained CNN are given in Table 1 and Figure 4. To assess the recognition performance of images of malaria- and non-malaria-infected erythrocytes, the following were used: accuracy, sensitivity, specificity, accuracy, F1_score and Mathews correlation coefficient.

Table 1. The performance of the proposed models.

Metric Measure\Classifier	Fine-tuning a pre-trained CNN model
Accuracy	**98.30%**
Sensitivity	96.99%
Specificity	96.99%
Precision	97.73%
F1_score	97.36%
Matthews Correlation Coefficient	94.75%

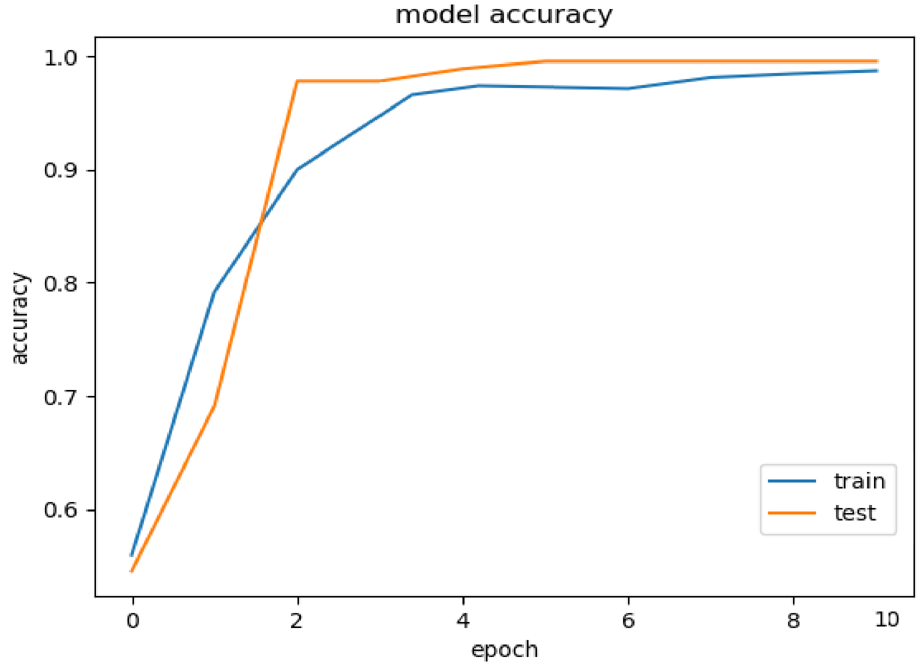


Figure 4. Training and testing accuracy of Fine-tuning a pre-trained CNN model.

The above figure shows the accuracy curve of training and testing with 10 number of epochs and 128 batch sizes. The results show that the fine-tuning of the pre-trained CNN model has superior performance and a high accuracy of 98.30%.

5. Conclusions

This paper aims to recognize malaria using modern techniques, where traditional methods such as RDT and microscopy showed lower and different accuracy and instability in the results. And that was important to suggest the use of modern methods such as artificial intelligence to obtain a higher accuracy and stability in the results. A pre-trained CNN fine-tuning was chosen as an artificial intelligence model for malaria recognition and trained on a data set of 27,562 images, where these images were divided into 70% for training and 30% for testing. We found that the convolutional neural network model clearly gives a high accuracy of 98.25%, and the experimental results showed the effectiveness of the proposed method. In future work, we suggest using artificial intelligence and machine learning and selecting models for networks with higher efficiency to obtain better results.

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