Deep Convolutional Neural Network Model for Optical Microscopic Automated Diagnosis of *Plasmodium Falciparum* Parasites in Sub-Saharan Africa.

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Abstract

Deep learning techniques are prevalent in the medical discipline due to their high level of accuracy in disease diagnosis. One such disease is malaria caused by Plasmodium falciparum and transmitted by the female anopheles mosquito. According to the World Health Organisation (WHO), millions of people are infected annually, leading to inevitable deaths in the infected population. Statistical records show that early detection of malaria parasites could prevent deaths and Deep Convolutional Neural Network (CNN) has proved helpful in the early detection of malarial parasites. The human fault is identified to be a major cause of inaccurate diagnostics in the traditional microscopy malaria diagnosis method. Therefore, the method would be more reliable if human expert dependency is restricted or eliminated, and thus, the motivation of this paper. This study presents the application of a Deep Convolutional Neural Network (CNN) to locally generated, low-cost, portable optical microscopic blood films of thin blood smears for automation of P. falciparum parasite detection in the red blood cells. We propose to source automated microscopy blood films (acquired with a digital camera or smartphone) from both private and public clinical parasitology laboratories within Nigeria. We would use the primary data to train our proposed model to be able to predict and classify these blood as infected or uninfected. The work is at the stage of data collection and we hope to commence the research soon. The proposed model is expected to show that early detection of the malaria parasite has the potential to improve patient's survival through the application of deep CNN and as well reduce the involvement of trained human experts in the malaria diagnosis process. Hence, the computational approach to malaria diagnosis helps eliminate the limitations of traditional approaches.

Keywords: Deep Convolutional Neural Network, *Plasmodium parasite, Diagnosis,* Optical microscopy, Digital blood images.

1. Introduction

Malaria is a life threatening disease caused by plasmodium parasites that is transmitted to humans through the bites of infected female Anopheles mosquitoes in the form of sporozoites [1]. According to the WHO, there are five species of plasmodium parasites, including *Plasmodium falciparum, P. vivax, P. ovale, P. malaria, and P. knowlesi [2]*. *Plasmodium falciparum* is the most severe strain form of the disease, and millions of people are infected annually, with a greater number of the infected population having a high risk of inevitable

death, especially in the tropical zones of the world [3]. More of both morbidity and mortality occurs in sub-Saharan Africa, accounting for over 90% on both cases [4]. Children under 5 years of age are observed to be regular victims of the disease [5].

Medical diagnosis is a complex medical step involving patient history, personal examinations, and testing which allows for a more comprehensive understanding of patient ailments [6]. Popular diagnostic approaches include machine learning, nucleic acid sequence-based amplification, urine malaria tests, and saliva-based test for Plasmodium *p*rotein detection [7]. The standard practice in malaria diagnosis is a schematic examination of a blood smear under microscopy for the presence of the malaria parasite in the human red blood cells [8]. The approach is time-consuming, highly tedious, and also difficult to maintain consistency. Studies have shown that there is lack of poor facilities and insufficient competent Parasitologists, especially in malaria-endemic regions like tropical Africa, giving rise to wrong results and improper medical attention [9]. Available information shows that human error has been discovered as the key cause of inaccurate results in the traditional microscopic malaria diagnostics methods [10]. Most deaths in the tropical zones where high death rates have been reported are due to misdiagnosis resulting in wrong treatment [11]. Malaria diagnostic results are most preferred if human expert intervention is eradicated or maximally alleviated in the diagnostic process; hence, the motivation for this research. The research aims to apply Deep Convolutional Neural Network (CNN) to locally generated, low-cost, portable optical microscopic blood films for automation of *P. falciparum* parasite detection in the red blood cells.

Early diagnosis improves a patient's survival [12]. If a disease is properly diagnosed, it paves way for effective medication and cure, thereby guaranteeing the safety of patients [13]. Machine learning (ML) has proved helpful in the early detection of malarial parasites. Recent research has adopted ML to provide computer systems with the ability to learn automatically using several learning algorithms. Computing and enhancement in technology have identified ML as one of the approaches for a quick malaria test by training computers to make decisions without human intervention [14]. A machine learning approach can be used to revolutionize these clinical parasitology laboratories. Here, the blood test results are converted to a machine learning dataset, which can be used to train appropriate machine learning models to test for the presence of malaria parasites in the red blood cells.

Existing literature shows that CNN and its variants (deep learning) are the most commonly used ML techniques in optical microscopy malaria diagnosis, with a high prediction accuracy of 99.23% [15]. This is the basis for the choice of adopting Deep CNN model in the research and this is prevalent in the medical profession due to its high level of accuracy in disease diagnosis, including *P. falciparum* [15].

Deep learning is a subgroup and the latest trend in machine learning [16] that is suited for feature (lines, gradients, contours, and shapes) extraction from a structured array of data, such as images [17].

ML is an Artificial Intelligence (AI) technique that automatically learns and improves from experience [18]. ML is an AI technique that automatically emulates human intelligence behaviour and learns and improves from experience [18]. AI is defined as the technology that uses computer knowledge to represent intelligent behaviour with insignificant human intervention.

The prevalence of the malaria disease and the availability of some technology tools in Africa have made the collection of large datasets available through a repeated malaria blood test in our medical laboratories. This makes the analysis of the blood images possible with the use of the CNN.

Image analysis on microscopic blood films using CNN has the potential to improve early detection of the malaria parasite and achieve high efficiency and accuracy in identifying and classifying malaria parasites in blood smears. The computational approach to malaria diagnosis has the capacity to eliminate the limitations of the traditional approaches.

2. Light Microscopy with Stained Blood Smears

Light microscopy with stained blood smears is one of the available traditional diagnostic methods. Parasite identification through light microscopy inspection of blood smears is currently the recommended method for diagnosing malaria accurately. The standard microscopic procedure, as recommended by the WHO, consists of the following steps [19].

1. **Preparation of blood films:** A sample of the patient's peripheral blood is acquired, usually from the finger. The blood is applied to a microscopic slide, and a thick- or thin film is prepared. Thick films consist of multiple layers of blood cells, while thin films are spread out such that only one layer of erythrocytes is present.

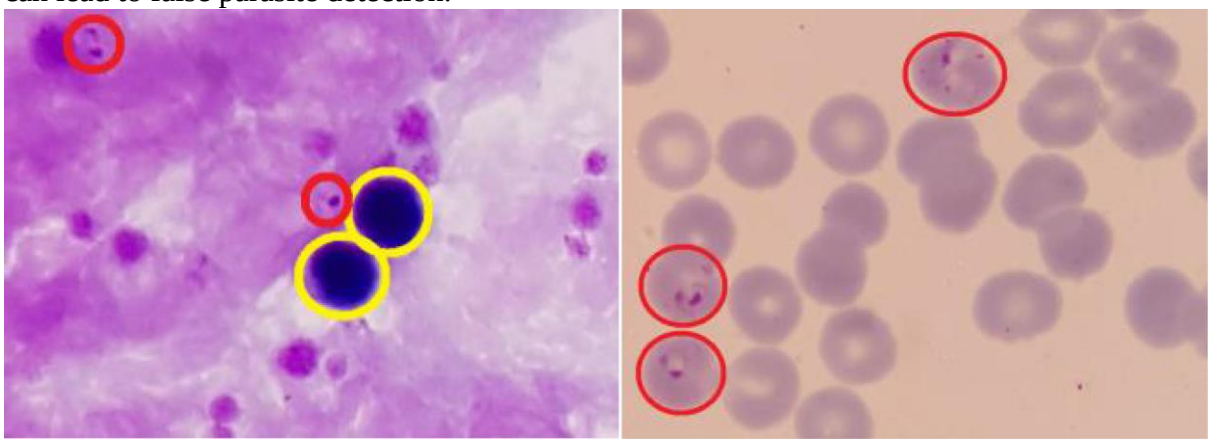
2. **Staining:** To allow for distinction of the blood cells and parasites, a stain is applied. Microscopy slides are most commonly stained with a Giemsa stain, but other Romanowsky stains such as Field's and Leishman stains can also be used. Field's stain has the advantage of very short staining time, but a slightly lower sensitivity is achieved when this stain is used. Leishman staining takes half as long as Giemsa staining, and leads to the same diagnostic accuracy, but the solution is less stable [19].

3. **Examination with light microscope:** The microscopic slides are examined with a 100x oil immersion objective. For thick films, at least 100 Field of View (FOV) should be examined before a negative diagnosis is reached, while for thin films, the minimum is 800 FOV.

4. **Data interpretation:** In thick smears the parasite density is determined in parasites per μL of blood, by determining the number of parasites × 8000, divided by the number of white blood cells. In thin smears the number of infected and non-infected red blood cells is tallied, and parasitaemia is expressed as percentage of total cells infected. The species and stage of the parasites is also identified.

This study will investigate automatic malaria parasite detection and counting in digital images of thin blood smears to be acquired with a digital camera. The advantage of thick smears is that a larger amount of blood can be inspected in one Field of View (FOV), so a high sensitivity can be reached in less time. However, when parasite density is high, it can be difficult to distinguish individual parasites, so thin smears are used. A thick blood smear is used to detect the presence of malaria parasites in a drop of blood. It allows more efficient detection of parasites than a thin blood smear, with about 11 times higher sensitivity [20][21]. A thin blood smear results from spreading a drop of blood across a glass slide, and is typically used to differentiate parasite species and development stages. Thick and thin blood smears, as shown

in Figure1, require different processing methods for parasite detection. In thin blood smears, both white blood cells (WBCs) and red blood cells (RBCs) are clearly visible. A typical step for automatic parasite detection in thin smears is to first segment RBCs and then classify each segmented RBC as infected or uninfected [20]. In thick blood smears, however, only WBCs and the nuclei of RBCs are visible as shown in Figure 2. 1. Therefore, parasites need to be detected directly, and a typical step is to first preselect parasite candidates and then classify the candidates as either actual parasites or background noise. This can be challenging because the nuclei of WBCs and various non-parasite components can absorb stain, creating artifacts that can lead to false parasite detection.



a) Thick blood smear b) Thin blood smear

Figure 1: Examples of thick and thin blood smears. Red circles are parasites and yellow circles are white blood cells [20].

Research Plan on How to Address the Research Question

The first step is to source local optical microscopic blood film datasets from both private and public clinical parasitology laboratories available within my country.

The second step is to prepare the dataset in the form it should be used to train appropriate ML models (CNN) to automate plasmodium falciparum detection in red blood cells.

The third step is to train the model for prediction and classification of infected and uninfected thin film optical microscopic blood films.

Summarily, most algorithms proposed in literature are focussed on the classification of thin-smear Giemsa stained images, acquired through the procedure described in section 3.1. They aim to automatically count all uninfected and parasitised erythrocytes, and often follow the following steps to do so:

1) Preprocessing the blood smear image
2) Segmenting the erythrocytes from the background
3) Extracting parasite features
4) Mathematically dividing the erythrocytes into classes.

This approach is schematically depicted in figure 2. Examples of techniques used for each step are given below.

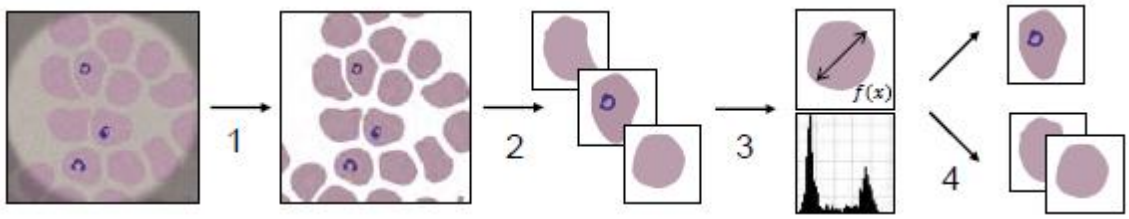


Figure 2: Schematic representation of the basic image analysis pipeline followed by most (traditional) automated malaria diagnosis algorithms, the numbers underneath the arrows refer to the four operations in this pipeline; **1)** preprocessing, **2)** segmentation, **3)** feature extraction and **4)** classification [19].

The novelty of this research is that the researchers want to build the model with blood film sourced from our local clinical parasitology laboratory (primary data) that should be able to address the indigenous problems in malaria diagnosis here in Nigeria.

I expect that participating in the 2023 Indaba program will give me better exposure to effectively carry out the proposed research.

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