

A Review on Evaluation of Algorithms for Malaria Disease Diagnosis

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Abstract

Plasmodium falciparum-caused malaria is life-threatening and continues to be a global concern. According to the World Health Organization's (WHO) report, this disease affects hundreds of millions of people annually. There were approximately 247 million cases of malaria reported in 2022. Female anopheles mosquitoes, which bite between dusk and dawn, carry this disease. Additionally, they are referred to as "night-biting" mosquitoes. The rapid diagnostic test (RDT), clinical diagnosis, polymerase chain reaction (PCR), and microscopic diagnosis are some of the methods used to identify malaria. The capabilities of the available human determine the efficacy of conventional diagnostic techniques like PCR and clinical testing.

Keywords: Malaria • Plasmodium falciparum • Algorithm

Introduction

The other two methods, RDT and microscopic diagnosis, are used because they are effective malaria diagnosis methods and contribute the most to malaria control today. Because there is no need for experts, the RDT method of diagnosis is remarkably effective. Because there are no shortcomings like in RDT, the microscopic systems require skilled microscopists and are regarded as an efficient method of diagnosis. Automatic microscopic, or the use of microscopic blood smear images for malaria detection, can be a useful diagnostic tool because it can segment and classify infected cells. For the visual recognition challenge, a modified Convolution network was created. For the MNIST dataset, Rectified-Correlations on a Sphere (RECOS) have been proposed by CNN and AlexNet for a multilayer system. Because more data is needed to improve prediction accuracy, the European Bioinformatics Institute focused on the data by expanding the bandwidth and computational infrastructure.

Description

M.Z. Alom conducted a survey of deep learning approaches in 2018. In that survey, they talked about advanced methods for training models and other generative models. The GoogleNet model performs better than CNN for the application of autonomous driving. Common prediction and classification models include Bayesian, linear regression with Relu, and Support Vector Machine generalized models. The CNN model accurately predicted the outbreak of malaria in 2019. CNN was utilized in mobile applications to predict malaria disease in other studies. Using CNN, Yuhang Dong developed a model to automatically learn the features needed to diagnose malaria. Semantic segmentation is the process of extracting specific details for classification from any image dataset. CNNs are useful for determining picture classes. Very few

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studies have used deep learning to distinguish types with cryptic morphological variation. Deep learning algorithms known as convolutional neural networks (CNNs) are effective at extracting features from an organized array of data, such as photographs. Patterns like lines, gradients, contours, and geometries are examples of these features. CNN and other neural networks have the advantage of being able to recognize features in raw image datasets. CNN, in contrast to typical machine learning algorithms that extract some features and feed them into the training algorithm, automatically extracts the necessary features. A compact CNN model made for mobile machine learning deployment is called Mobile Net V2. The goal of the MobileNet concept is to make the most of memory and computational power.

However, there is a dearth of research on classification using methods like image processing, machine learning, and computer vision, which provide malaria disease detection with accurate and efficient computation. This contribution to malaria parasite detection will have a significant impact on the development of a highly accurate automated system for the foreseeable future. The following are our main contributions Based on deep learning methods like CNN, MobileNetV2, and ResNet50, a new framework for diagnosing malaria is proposed. Utilization of hyper parameters and fine-tuning to improve overall classification performance in order to distinguish between malaria-infected and uninfected cell images. In order to determine the proposed framework's dependability and practicality, various performance metrics are validated. Because it uses the CNN model, an automated model that is based on the CNN is extremely effective for diagnosis. Jungle fever is a serious sickness that keeps on causing worry all over the planet. In this paper, the three deep learning models CNN, MobileNetV2, and ResNet50 were compared. Using blood smear images, this study examines the efficacy of new deep-learning methods for malaria identification using an experimental design [1-5].

Malaria is a serious disease that still has people all over the world worried. This paper compared three deep learning models: ResNet50, CNN MobileNetV2, and others. Using blood smear images, this study examines the efficacy of new deep-learning methods for malaria identification using an experimental design. Using the training data, we inferred the deep learning architectures using models after training. In all of the models that were taken into consideration, we utilized 25 epochs, where an epoch is a complete transit of the learning data through the machine learning (ML) algorithm. A crucial hyper parameter of the process is its epoch number. The number of epochs, or full passes, through the algorithm's training or learning phase is specified by the entire training dataset. The above figures are related to loss and accuracy in terms of training and testing for the CNN model, MobileNetV2, and ResNet50, respectively, according to some of the observations made from the results. After comparing all of the graphs, it can be seen that the validation accuracy of the ResNet is higher than that of the other models being considered, and that

the training accuracy of the MobileNetV2 model is higher than that of the CNN and ResNet50 models. It is evident that the ResNet50 has a lower training error than other models. Additionally, the CNN model's significant reduction in training and validation error can be seen from above. We can conclude from the accuracy and error that ResNet50 is superior to CNN and MobileNetV2 due to its higher accuracy and lower error.

Conclusion

In terms of malaria disease detection, we compare CNN, MobileNetV2, and ResNet50, three deep learning methods, in this paper. The developed models were compared, and the winner was chosen as the winner. The conclusion that environmental factors play a significant role in facilitation is possible. The presence and transmission of malaria. ResNet50 outperformed all other models and produced superior malaria disease detection results. Statistical metrics like precision, recall, the f1-score, the roc curve, and others were calculated to confirm the findings. When compared to the previous research, it is possible to draw the conclusion that the results presented in this study are the most recent advancements. For better outcomes, the work can be extended to investigate additional deep learning methods and image processing pre-processing methods.

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Conflict of Interest

No potential conflict of interest was reported by the authors.

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