A Relational Study on Artificial Intelligence methods for Identification of Malaria parasites: A Review

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ABSTRACT: Malaria is a severe and contagious disease worldwide. The disease is transmitted through *Anopheles* mosquitoes, specifically females. The World Health Organization's (WHO) report unveiled that there were 0.228 billion cases and around 567,000 deaths due to malaria in 2018. In 2022, cases rose to 0.249 billion, deaths rose to around 608,000. Detection of malaria parasites at preliminary stages can reduce the mortality rates. The two supremely used traditional methods of malaria testing are RDTs and light microscopy. However, the traditional methods are tedious, prone to errors, rely on manual labor, and require specialized pathologists. Automated systems using image processing, deep learning, and machine learning can be devised for the rapid and efficient diagnosis of the disease. This work describes the comprehensive study of several already existing computer-aided diagnostic approaches and models in this area aiming to pave the way for enhanced and accelerated malaria identification in the upcoming years.

Keywords: Malaria, Light Microscopy, RDTs, ML, SVM, Image Processing, VGG, Deep Learning, CNN, DTGCN, Xception, R-CNN, Snapshot Ensemble

1 INTRODUCTION

A pernicious disease known as Malaria is mostly found in tropical and subtropical countries. The highest transmission is in Africa which lies south of the Sahara and in parts of Oceania [15].

The primary carrier of malaria is the Anopheles mosquitoes, specifically females. When they feed on the blood of an infected person, they ingest the *Plasmodium* parasite into their body. When the infected female mosquito bites another person to feed on blood, it transmits the malaria parasites into the bloodstream, causing the person to become infected with malaria. This transmission cycle continues and promotes the propagation of the disease. Hence, malaria is a significant global health concern, where Anopheles mosquitoes thrive.

The five species of the Plasmodium parasite that leads to the disease called Malaria in humans are: *Plasmodium falciparum, Plasmodium vivax, Plasmodium ovale, Plasmodium knowlesi, and Plasmodium malaria*.

Plasmodium vivax and *Plasmodium falciparum* are the ones who pose the greatest threat. *P. falciparum* is the most widespread and deadliest malarial parasite worldwide and the one which is rising in power is the *P. vivax* malarial parasite [15].

The two common traditional methods of malaria detection are light microscopy and RDTs. In these manual methods, the drop of an individual’s blood is spread out on the testing slide by a laboratory expert to examine it under a microscope. Both are cost-effective methods but are time-consuming, error-prone, and require expert microscopists who have proficiency in reading the slides.

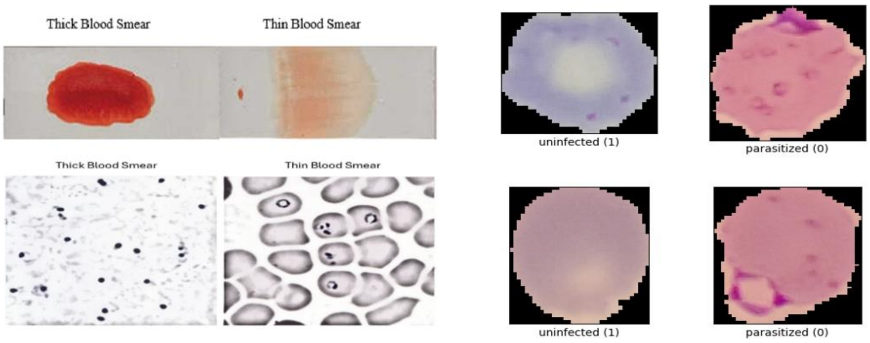

Figure 1. Blood film images and microscopic images from sample dataset

So, to curb the problems of the traditional manual methods of malaria detection, to fasten the diagnosis, to reduce the burden of the microscopists, and for the detection of the disease in its preliminary stages automated systems are required.

The graph in (Fig. 2) depicts the number of malaria cases and associated deaths globally from 2018 to 2022.

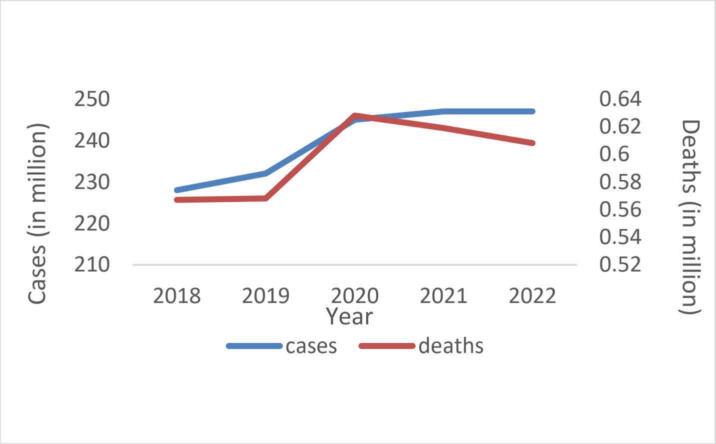

Figure 2. Trend of malaria cases and deaths from 2018 to 2022

2 DISCUSSION

The field of malaria detection has observed a significant amount of research in the past years, particularly focused on automating diagnostic processes. The literature survey performed in this paper shows that the malaria detection process can be made flexible and quick by automating it through computer-based systems.

The dataset is the collection of images, taken from the microscope, in the form of blood films (i.e. thin, thick). The entire process is shown in (Fig. 3).

The literature review presented in this paper is synthesized in Table 2, offering a comprehensive overview.

3 EVALUATING TECHNIQUES

The following are the techniques used for evaluating the performance of the models:

$$Accuracy = \frac{tpr+tnr}{tpr+tnr+fpr+fnr}, Precision = \frac{tpr}{tpr+fpr}, Recall = \frac{tpr}{tpr+fnr}, F1 = \frac{2*Precision*Recall}{Precision+Recall} = \frac{2*tpr}{2*tpr+fpr+fnr}, Specificity = \frac{tnr}{fpr+tnr}$$

The variables are: True Positive (tpr), True Negative (tnr), False Positive (fpr), False Negative (fnr).

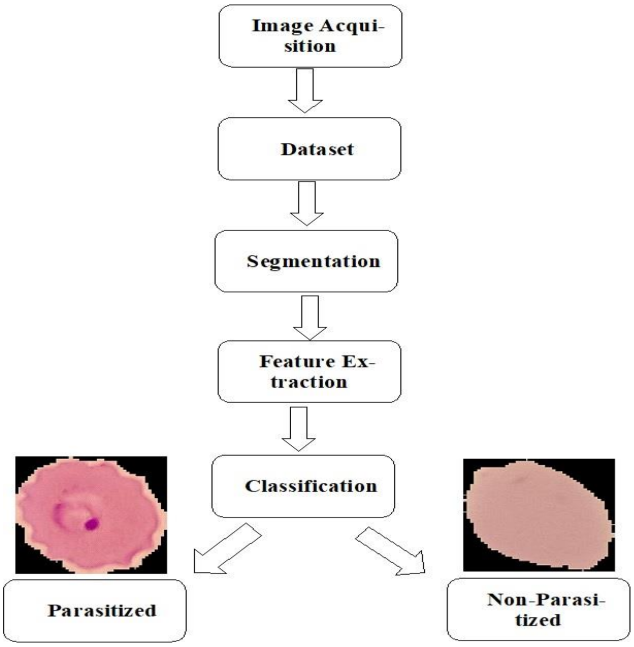

Figure 3. Classification Diagram

Table 1. Performance Evaluation based on Different Methodologies

Sr No	Author	Methodology	F-Score	Precision	Sensitivity/ Recall	Specificity	Accuracy
1	Saurav Mishra [14]	EfficientNet Transfer Learning	97.97%	97.97%	98.00%	98.00%	97.77%
		EfficientNet Snapshot Ensemble	99.37%	99.52%	99.00%	99.00%	99.37%
2	Vijayalakshmi A et al. [5]	VGG16-SVM	87.05%	84.47%	98.80%	88.81%	85.00%
		VGG19-SVM	91.66%	89.95%	93.44%	92.92%	93.00%
3	Yuhang Dong et al. [16]	GoogLeNet	97.66%	98.05%	97.29%	98.69%	98.13%
4	Sumit Kumar [12]	CNN - 2 layers	--	--	97.06%	98.50%	95.40%
5	Saiprasath G et al. [7]	Random Forest	64.50%	77.50%	55.30%	--	--
		AdaBoost	61.10%	72.90%	52.60%	--	--
6	Amal H. Alharbi [3]	SVM	93.97%	--	93.90%	--	--
7	Mehedi Masud et al. [10]	CLR-triangular2 (CNN using Cyclic SGD)	97.00%	97.00%	97.00%	--	97.30%
8	Rajesh Mayya et al. [11]	MobileNet2	95.00%	95.00%	95.00%	--	96.60%
9	Ashit Kumar Dutta et al. [4]	BMODTL-BMPC (Training/Testing - 90:10)	99.04%	99.05%	99.05%	99.05%	99.04%

10	Aliyu Abubakar et al. [1]	VGG16-SVM	94.91%	94.26%	95.57%	--	94.88%
11	Amin Alqudah et al. [2]	CNN (64x64)	98.84%	98.90%	98.79%	98.90%	98.85%
12	Christonson Berin Jones et al. [6]	CNN-SVM	93.75%	97.00%	89.36%	97.00%	94.00%
13	Sen Li et al. [13]	DTGCN (CNN, transfer graph building, UGCN)	98.30%	98.50%	98.30%	--	98.30%

Table 2. Literature Survey

Sr No	Author	Year	Objective	Methods Used	Outcomes
1	Saurav Mishra [14]	2021	Analyzing blood smears through a microscope istime-consuming.	Transfer Learning, Snapshot Ensemble model	Develop a system that helps in the precise and prompt detection of malaria to achieve a malaria-free environment.
2	Vijayalakshmi A et al. [5]	2019	Malaria, being contagious, needs to be identified at its preliminary stages.	VGG, SVM	The integration of VGG19-SVM outperformed CNNmodels.
3	Yuhang Dong et al. [16]	2017	Resources like specialized pathologists are unavailable in underdeveloped areas.	LeNet, AlexNet, GoogLeNet, SVM	Deep convolutional neural networks have attained better accuracy compared to the SVM method and require minimal input from human experts.
4	Sumit Kumar et al. [12]	2023	Counting parasitic red blood cells manually is both error-prone and long-drawn-out.	CNN	Even with a 2-layer CNN, accurate malaria detection can be performed.
5	Saiprasath G et al. [7]	2019	Less number of trained experts and resources.	Various machine learning algorithms.	The suggested methodology identifies malaria infection through captured microscopic images without expert intervention.
6	WHO Malaria Report [15]	2023	Detection of malaria using image processing is time-consuming process.	RDTs and Light microscopy	An expanded vector control toolbox is being developed.
7	Amal H. Alharbi et al. [3]	2022	Counting the blood cells manually is time-consuming.	XG-Boost, SVM, Neural networks	The enhanced accuracy of DL models shape them useful for decision-making purposes.
8	Mehedi Masud et al. [10]	2020	Traditional methods are tedious and prone to human errors.	CNN, SGD	CNN can efficaciously and precisely aid in real-time malaria detection from input images.
9	Rajesh Mayya et al. [11]	2022	The conventional microscopy technique uses the most typical	CNN, Various pre trained learning approach	Inception-V3 and MobileNetV2 models have better accuracy.

			comprehension method for observing malaria-infected cells during screening.		
10	Ashit Kumar Dutta et al. [4]	2022	The clinical setting for the diagnosis of malaria is time-consuming.	Gaussian Filtering, Graph Cuts Segmentation, Barnacles mating optimizer algorithm	The BMODTL-BMPC method overtops alternative recent methods.
11	Aliyu Abubakar et al. [1]	2021	Rise in the count of cases but an insufficiency of diagnostic facilities.	Various Deep Convolutional Networks	Extensive evaluations are provided regarding precision, recall, accuracy, and computational time.
12	Amin Alqudah et al. [2]	2020	Malaria poses a risk to over 40% of the world's population.	CNN	To categorize the segmented RBCs into the classes of infected and uninfected, an advanced model based on CNN + transfer learning was used.
13	Muhammad Imran Razzak [9]	2015	The complexity of blood cells creates challenges in both segmentation and morphological analysis.	ANN, BPNN Rao's method and bounding box	Automated malarial parasite examination and categorization
14	Christonson Berin Jones et al. [6]	2022	Difficulty in malaria detection due to the deficient technology and equipment.	CNN, SVM	The suggested scheme is precise, helpful, and reliable for parasite detection.
15	Sen Li et al. [13]	2021	In the traditional method, distinguishing multiple growth stages remains a challenge.	DTGCN Unsupervised learning	The suggested approach demonstrated superior effectiveness when compared to various state-of-the-art methods.

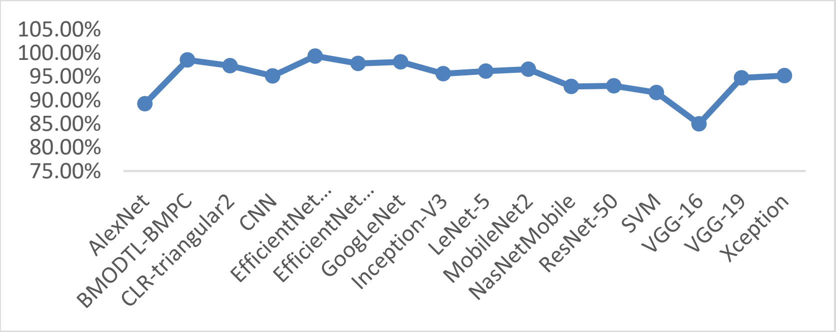

Figure 4. Graphical Representation of Table 1 based on Accuracy

4 CONCLUSION

The conclusion derived after reading various papers during the literature survey is that malaria poses a significant threat to human life if ignored. It must be diagnosed at its beginning stages. The traditional and manual methods are iterative, deviation-prone, and require well-equipped and well-trained experts to read the blood slides. As a result, there's a pressing need to automate the malaria detection process.

It has been found that the DL-based models have outperformed the ML-based models. EfficientNet Snapshot Ensemble [13], CNN [11], and Xception [8] have attained the utmost accuracy rate.

Various models based on ML and DL are compared to give clear and wholesome insight to future researchers for the advancement of the ongoing models in this field.

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