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MACHINE LEARNING APPROACH FOR CLASSIFICATION OF MALARIA DISEASE

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ABSTRACT
Malaria disease, a parasitic disease health problem, occurs due to damaging of red blood cells in the blood. It is difficult to identify in a clinical set-up. Various methods have been found to predict or diagnosing the malaria disease. Malaria Diagnosis is normally done by visual microscopy. It is time consuming and offers low accuracy due to operator's tiredness. So it is required to design a system which is able to take photos of blood smears using motorized sophisticated microscope. The image processing task is launched after gathering enough samples for microscopy. The outcome is then placed before the doctor for the final decision. It is observed that machine learning techniques have wider applicability for critical diagnosis of malaria which in turn helps the clinicians for diagnosing the disease. This paper utilizes the machine learning approach for classification malaria disease.

KEYWORDS: Anopheles Mosquito, Parasites. Nucleus and Cytoplasm.

INTRODUCTION
An infected female Anopheles mosquito spreads the malaria parasite. These night mosquitoes after biting human being sporozites and enters into the human blood and it affects the liver first and then the matured sporozites are burst and formed as mezosites which affect RBC - Red Blood Cells. These mezosites are called Parasites. Nucleus & cytoplasm of Parasite are used in preliminary basis for the classification of a parasite to non-parasite. It is estimated that, malaria deaths have been decreased by 60% population growth world-widedue to advanced testing procedure.[1] There are many clinical methods which can be used for malaria diagnosis which are peripheral blood smear (PBS), quantitative buffy coat (QBC), rapid diagnosis test (RDT), Polymerase Chain Reaction (PCR), and Third Harmonic Generation (THG).[2-3] PBS has limitations of human resistance and time requirement. The automated system can overcome these limitations. Proper segmentation of red blood cells (RBC), obtained from blood images, from the background separation can help to achieve high accuracy in detecting the presence of plasmodium and helps in classification of life cycle stages of the malaria parasite. Table 1 shows the features of four types of malaria Parasites. Plasmodium Falciparum has incubation duration of 6-14 days only. In India only Plasmodium Falciparum, Plasmodium Vivax attacks the humans due to bad food habits.[4-6] This causes death in malaria disease. The Life cycle of parasite is shown in figure 1.

Table. 1: Characteristics of Malaria Parasites.

Parasite	Characteristics		
	Incubation Period	**Fever Period**	**RBC Affect**
P.Falciparum	6-14 days	48 hrs.	All
P. Vivax	12-17 days	48 hrs.	Reticulocytes
P. Malaria	13-40 days	72 hrs.	Matured RBC
P. Ovale	9-18 days	50 hrs.	Reticulocytes

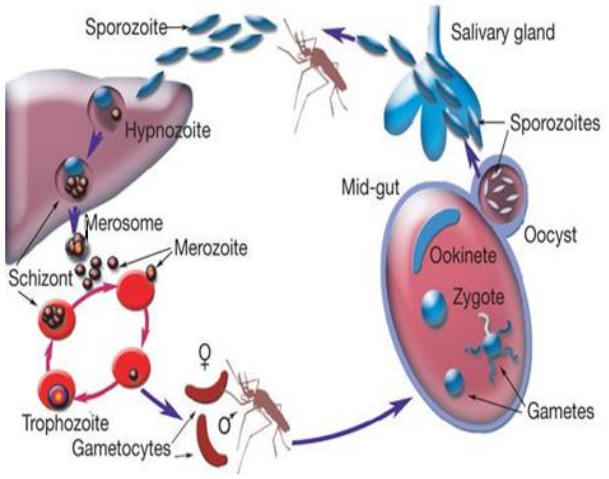

Figure. 1. Malaria Parasite Life Cycle.

The life cycle stages of malaria parasite above show three different stages- trophozoites, schizocytes, and gametocytes.[7] Each is featured by shape, size, and texture. For identification of disease all the features are important in image processing. These are the keys to differentiate and diagnose the parasite stages.

Literature Review

A morphological approach to cell segmentation is more efficient than the watershed algorithm.[8] The parasites' classification was still based on morphological operators although many systems use computer-aided diagnosis of malaria. All of them try to process and analyse malaria-infected peripheral blood cells images. Recent approaches addressed the problem of malaria diagnosis in remote areas, or improving significantly both the detection and the classification performances.[9]

In a machine learning technique, Rough Set used on training set for generation a classification model for malaria diagnosis for different malaria cases and therapy was provided accordingly. A Fuzzy Expert System for the management of malaria was developed by some researchers.[10] The Application of Machine Learning Techniques using computer technology is used to reduce the number of mortality and reduce the waiting time to see the specialist on malaria.[11]

Malaria diagnosing method is needed to collect the blood samples to identify malaria disease. Thick blood films and Thin Blood films are used for detection of malaria parasite density and features of malaria parasites. Magnetic bead based simultaneous ELISA & Sequential detection (SCSD) was proposed by researchers for detection of malaria biomarkers – pLDH and PfHRPII.[12] Some researchers analyzed the Digital Holographic Interferometric Microscopic (DHM) image for detection of infected erythrocytes using Artificial Neural Networks technology.[13] Others predicted the status of malaria patients based on Rule based classification.[14] Researchers also developed a Disease free equilibrium model with Halanay inequalities for discrete time dynamic system of Neural Networks for diagnosing malaria disease.[15] Some researchers determined the gametocyte stage of malaria parasite using Self-Knowledge Model (SKM) and Dual-Knowledge Model (DKM).[16] Other researchers investigated a method for detection of malaria parasite P Falciparum using Rapid diagnostic test by Nested PCR methods.[17]

Researchers also developed method for detection of malaria parasite using Adaptive histogram, Threshold segmentation and K-means clustering techniques.[18-19] Others examined the Classification of Plasmodium Vivax parasite using image processing and KNN techniques.[20] A method for detection of effected erythrocytes based on Adaptive median filter, edge enhancement and Fuzzy C-Means clustering techniques.[21] Some researchers investigated and estimated parasite density leading to the detection of Malaria using Adaptive threshold and Connected Component Analysis.[22]

Proposed Method: The method of detection of malaria parasite is the image recognition, the image classification and parasitemia estimation. The method is shown in Figure 3. In computer-aided diagnosis initial steps for image processing are pre-processing, segmentation, and feature extraction. Next the image classification and detection of infected red blood cells are done. The stages of Malaria Parasites are given in figure 4.

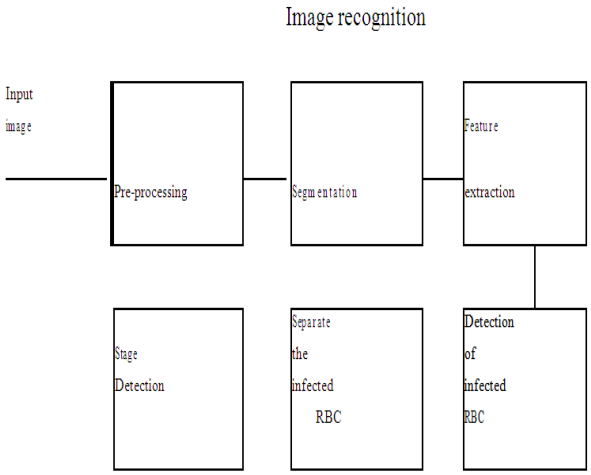

Figure. 3: Image classification and parasitemia estimation.

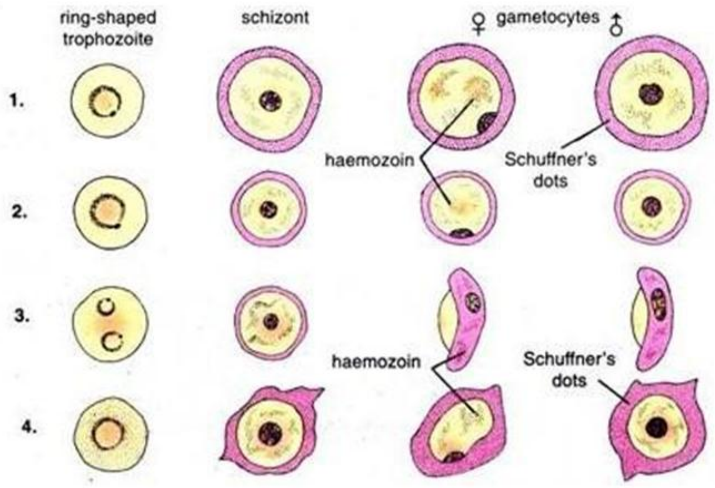

Figure. 4 Malaria Parasites stages - 1. Plasmodium Vivax 2. Plasmodium Malariae 3. Plasmodium Falciparum 4. Plasmodium Ovale.

Based on the patterns, parasites can be categorized as presented in Table 2.

Table. 2: Malaria Parasite Detection on Pattern Based.

Parasite	Rings	Tropozoites	Schizonts	Gametocytes
P. Falciparum	One or two Small Chromatin Dots	Amoeboid Shape	8 – 24 small merozoites	Crescent shaped
P. Vivax	Chromatin size 2.5µm	Large no of chromatin dots	16-24 merozoites &Size in RBC is 9-10 µm	Round or Oval shape& size is almost the RBC
P. Malaria	Chromatin size 6.5-7 µm	Large no of chromatin dots	6-12 merozoites	Round shape& size is almost the RBC
P. Ovale	Chromatin size 6.2 µm	Large no of chromatin dots with size 2.5 µm	6 -14 merozoites	Round or Oval shape& size is almost the RBC

RESULT ANALYSIS

First a data set is created from different hospitals in Kolkata consisting of both types of samples parasitic and nonparasitic blood samples. 50 images are used for training stages and the remaining 50 images for testing stage were used. Schizont, trophozoite, and gametocyte are three different stages of malaria from the blood smears. Statistical features are studied in this research. There is a growth of granular spotting, that is, the growth of cytoplasm known as matured trophozoites. These cytoplasm dots create a particular texturewhich differentiates it from other two stages more prominently. Texture features are also included in the feature extraction list. The different values for all seven features are given to the SVM for training the stages. The images used are labelled according to the stages name as the trophozoites are named as T1,T2,T3,..., and so forth, while schizonts are named as S1,S2,S3,..., and so forth, and gametocytes are named as G1,G2,G3,..., and so forth. The values of features are as shown in Tables 3, 4, and 5 for each stage I, II, III, respectively.

Table. 3: The values obtained while training dataset for stage I.

Image number	Stage I: trophozoites						
	Statistical features					Texture based features	
	Mean	Variance	Skewness	Kurtosis	Contrast	Energy	Correlation
T1	0.950	0.006	−2.052	−25.114	0.059	0.843	0.859
T2	0.951	0.007	−3.339	−38.326	0.053	0.868	0.906
T3	0.961	0.006	−5.414	−68.288	0.054	0.938	0.894
T4	0.937	0.013	−2.647	−22.71	0.092	0.792	0.918
T5	0.946	0.013	−3.281	−28.756	0.097	0.846	0.913

Table. 4: The values obtained while training dataset for stage II.

Image number	Stage II: schizonts						
		Statistical features				Texture based features	
	Mean	Variance	Skewness	Kurtosis	Contrast	Energy	Correlation
S1	0.961	0.004	−1.055	−15.137	0.0269	0.766	0.885
S2	0.772	0.107	−0.308	−0.940	0.397	0.203	0.937
S3	0.812	0.085	−0.449	−1.539	0.377	0.272	0.929
S4	0.785	0.100	−0.359	−1.133	0.381	0.228	0.938
S5	0.621	0.230	0.015	0.0317	1.144	0.106	0.885

Table. 5: The values obtained while training dataset for stage III.

Image number	Stage III: gametocytes						
		Statistical features				Texture based features	
	Mean	Variance	Skewness	Kurtosis	Contrast	Energy	Correlation
G1	0.835	0.055	−0.194	−0.825	0.242	0.267	0.915
G2	0.974	0.001	−1.758	−41.813	0.008	0.926	0.887
G3	0.830	0.056	−0.157	−0.661	0.188	0.256	0.933
G4	0.897	0.043	−1.347	−6.491	0.201	0.544	0.942
G5	0.945	0.013	−2.679	−22.707	0.203	0.753	0.823

Based on the classification results obtained in the proposed work, the quality of the result is to be decided by calculating Sensitivity, Accuracy and Specificity. The results are shown in Table 6 for manual and proposed method using SVM. All the images used for testing were labelled as Ts-1,Ts-2,Ts-3,..., and so forth, where Ts stands for testing sample and the number of sample followed by this.

Table. 6: Calculations of total RBC, infected RBC, and the TP, TN, FP, and FN values considering all the seven features.

Image number	Total RBC count		Infected RBC count						
	Manual	Algorithm	Manual	Algorithm	TP	TN	FP	FN	Elapsed time
Ts-1	28	29	4	5	4	24	1	0	33.94
Ts-2	11	10	1	1	1	10	0	0	21.96
Ts-3	30	33	3	3	3	27	0	0	34.19
Ts-4	14	15	1	1	1	14	0	0	23.97
Ts-5	10	10	4	4	4	6	0	0	21.57
Ts-6	10	10	3	3	3	7	0	0	20.82
Ts-7	11	11	3	4	3	8	1	0	21.00
Ts-8	7	7	1	1	1	6	0	0	17.15
Ts-9	12	11	3	3	3	8	0	0	20.72
Ts-10	12	12	1	2	1	11	1	0	21.36
Ts-11	22	25	3	4	3	23	1	0	30.84
Ts-12	22	25	3	5	2	23	1	1	30.69
Ts-13	8	10	5	5	5	5	0	0	19.69
Ts-14	15	16	3	3	3	13	0	0	23.95
Ts-15	36	37	1	1	1	36	0	0	31.83
Total	248	261	39	45	38	221	5	1	24.91

Support Vector Machine classifier considers all three stages of malaria parasite as shown in Figure 5. The three images in (a) are of third stage as gametocytes while (b) consists of second stage, that is, the schizonts, and (c) consists of the first stage trophozoites image samples which are used for training purpose. Some of the testing samples are shown in Figure 6 where in (a) there are first-stage sample images, that is, trophozoites, and (b) consists of second-stage sample images, that is, schizonts, and lastly (c) consists of all the third-stage parasite samples, that is, gametocytes.

CONCLUSION

like statistical and textural based have increased the diagnosis accuracy of the presented system. As the number of people infected by malaria in tropical region is high, special prevention is needed of early diagnosis of malaria parasite. The automated diagnosis of malaria parasite in blood images is presented in this paper. The features.

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