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Malaria Infected Erythrocyte Classification Based on the Histogram Features using Microscopic Images of Thin Blood Smear

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Abstract

Objectives: This paper aims to develop a system for malaria infected erythrocyte classification based on the histogram feature set. **Method:** The method consist of pre-processing, segmentation, feature extraction based on the histogram of different color channels, feature selection and malaria infected erythrocyte classification using Artificial Neural Networks (ANN), Support Vector Machine (SVM), k-Nearest Neighbor (k-NN) and Naive Bayes. **Findings:** The experimental analysis of all the classifiers with the different combinations of features has been carried out on clinical database. Based on the experimental results it may be concluded that ANN provides the higher classification rate in comparison to other classifiers which provides an overall accuracy of 96.32% and F-score of 85.32% respectively. **Applications:** The proposed system may be used for the automatic recognition of the malaria infected erythrocytes in the thin blood smears.

Keywords: Erythrocyte, Histogram Features, Malaria, Microscopic Image, Thin Blood Smears

1. Introduction

Malaria is a serious mosquito-borne infectious disease claimed by World Health Organization, caused by *Plasmodium* species[1]. Different type of *Plasmodium* species are *Plasmodium falciparum*, *Plasmodium vivax*, *Plasmodium malariae*, *Plasmodium Ovale*. This malaria parasite shows a complex life cycle including an insect vector and a vertebrate host. These malaria species are further classified into three life-cycle stages i.e. trophozoite, schizont and gametocyte. Malaria commonly occurs in Asia and Sub Africa region which is responsible for the death of the millions of people per year[1].

In India, the present situation of malaria is described as a malaria endemic country which is commonly reported with both *Plasmodium vivax* and *Plasmodium falciparum*[2]. In malaria, the parasites are host inside the erythrocytes and the morphological features of the erythrocyte changes. The various stages of the malaria parasite exhibit functional and morphological changes in infected erythrocytes[3]. In the beginning, clinical expert diagnoses the presence of malaria parasites with the microscopic examination of blood smears i.e. thin smear and thick smear. In the thin smear microscopic examination, the morphological feature of the erythrocyte is analyzed to detect the presence of parasite.

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However, blood smear microscopic examination done by a clinical expert is a very slow process and accuracy of the species identification depends on the skill of the expert[4].

Various literature studies suggesting a computerized detection of malaria based on digital image processing techniques using the microscopic image of blood smear[5]. Microscopic image analysis as well as medical imaging plays a *significant role* in the diagnosis of different diseases i.e. oral cancer, breast cancer, cervical cancer, skin cancer, muscle fiber segmentation, bacterial classification and MRI segmentation, etc[6,7]. There are various literature studies which used the features of the erythrocyte such as morphology, intensity histogram, color histogram and textural to detect the infected erythrocyte[8–12]. A system based on morphological approach has been proposed for detecting and classifying malaria parasites[9]. Color histogram based malaria diagnosis has also been proposed[10]. The features such as local area granulometry, colour histogram and shape measurement have been used to develop an automatic system for identification of malaria parasites in thin blood film smears[11]. Infected erythrocyte (*Plasmodium falciparum*) quantification and classification in thin blood smear has also been proposed which have utilized the histogram feature set (saturation level histogram, colour histogram, tamura texture histogram, gray scale histogram and sobel histogram)[12]. Automatic diagnosis of malaria has also been proposed with different features such as shape features, intensity feature and textural feature[13]. Quantitative characterization of *Plasmodium* vivax in infected erythrocytes based on textural feature has been discussed[14]. Proposed a color and statistical features based normal and infected erythrocyte classification using binary SVM classifier[15]. Feed forward back propagation neural network based diagnostic system has also been discussed to detect the malaria in thin smear with geometric feature, color feature and gray-level textures feature[16]. An automatic *Plasmodium* parasites detection and classification based on morphological as well as histogram features in thin blood smear images has been proposed[17]. An algorithm for automatic diagnosis of malaria in thin blood smears has also been discussed, based on classifiers such as SVM, Naive Bayes, k-NN with color, texture and geometry feature of the erythrocyte[18–22]. From the various studies, it came to know that the researchers have used the combination of the different features to classify the erythrocytes. As some of the infectious stage does not affect the geometrical feature of the erythrocyte, the classification of erythrocyte with geometrical features becomes non effective. The important issue of this research work is the proper classification of the erythrocytes. In this paper, we focus on the histogram features of the different color channel, which can successfully classify the infected and non-infected erythrocyte in the thin blood smear.

The contributions of this paper are as follows:

a. The histogram feature set for the different color channel to classify the infected and normal erythrocyte has been proposed.
b. The proposed feature set consists of the histogram of the absolute difference between red channel and green channel of the RGB image, chrominance histogram along with the green channel histogram and saturation level histogram.
c. The optimal set of feature has been selected by evaluating the different feature combinations for each classifier.
d. The classification performance of the classifiers such as Naive Bayes, k-NN, SVM and ANN with the different feature combination has also been analyzed.
e. The comparative analysis of the different feature sets has also been performed using different classifiers i.e. Naive Bayes, k-NN, SVM and ANN.

The content of the paper is arranged as follows. The overview of the proposed system is described in Section 2. In Section 3, the analysis of the experimental results obtained from different classifiers with different feature set, the optimal feature selection of each classifier and performance comparison between our systems with the previous methods is presented. Section 4 explains the conclusion and future scope of the research work.

2. Proposed Method

2.1 Overview

The overview of the proposed method is shown in Figure 1. It consists of four main steps: pre-processing, segmentation, feature extraction, feature selection and classification. The pre-processing phase consists of illumination correction and noise removal. The main aim of this step is to

normalize the images and to remove the unwanted noise present in the microscopic images of the thin blood smear. The filtered image obtained from the pre-processing step is used in the next step for segmenting erythrocyte from the background. Further, the feature extraction step extracts the suitable features to classify the normal and infected erythrocyte. Finally, classification is carried out using different classifiers such as k-NN, SVM, ANN and Naive Bayes. The detail explanation of each step of the proposed model is given in the next sections.

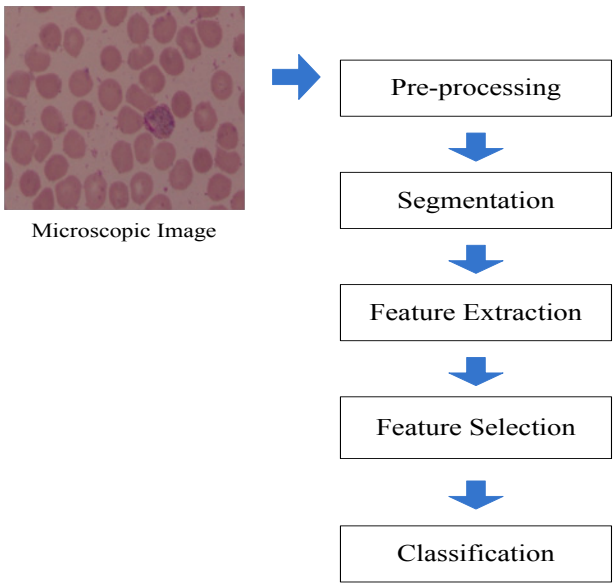


Figure 1. Block diagram of the proposed infected erythrocyte classification method.

2.2 Microscopic Image Database

The microscopic image of thin blood smear has been used for the analysis of the proposed system, to classify the infected and non-infected erythrocyte. The clinical database of the microscopic images has been collected from the registered pathological clinic of Cachar district, Assam, India. The detail on the collected database is shown below in the Table 1.

Table 1. Detail of microscopic image database

S. No.	Data-base	Staining	Size (Pixels)	Re-solution	Total eryth-rocytes
1	Clinical database	Leishman	1500x1000	100X	870

2.3 Pre-Processing

The different light sources in camera and staining variability of blood smear causes illumination problem with the thin blood smear images. In order to overcome this issue, the adapted gray world normalization is used[23]. The illumination corrected image is further undergone through median filtering process to enhance the quality of the microscopic images used for further processing as shown in Figure 2. The median filtering process is done with a window size of 5×5.

2.4 Segmentation

After pre-processing the images, the region of interest, i.e. erythrocyte needs to be extracted for the further analysis. Here, the erythrocytes are segmented from the complicated background using the global thresholding technique[24]. The segmented region of interest contained the entire stained component as well as the clump erythrocyte. The unwanted stained components are separated from the erythrocyte by morphological filtering process. Further, the morphological filtered binary image is undergone through marker controlled watershed with the regional minima of the H- transform image as an internal marker, to segment the clump erythrocyte into a single erythrocyte[25,26]. In Figure 3, the final segmentation result of the erythrocytes into

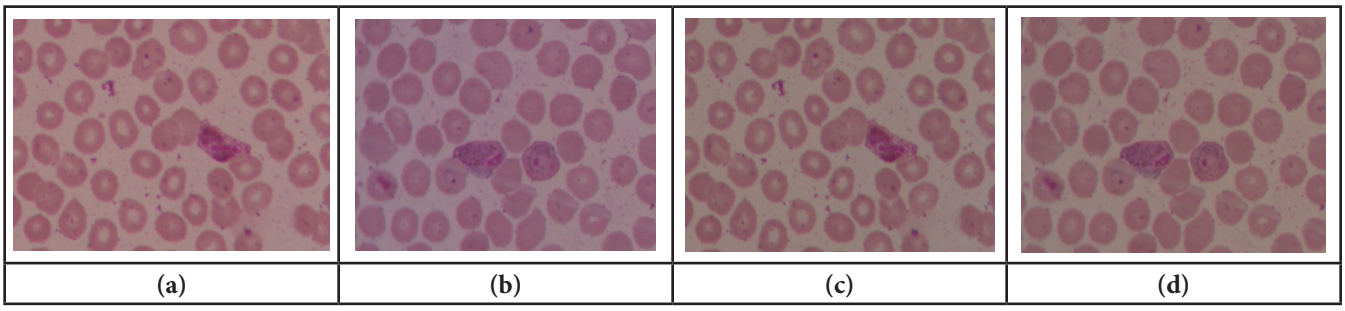
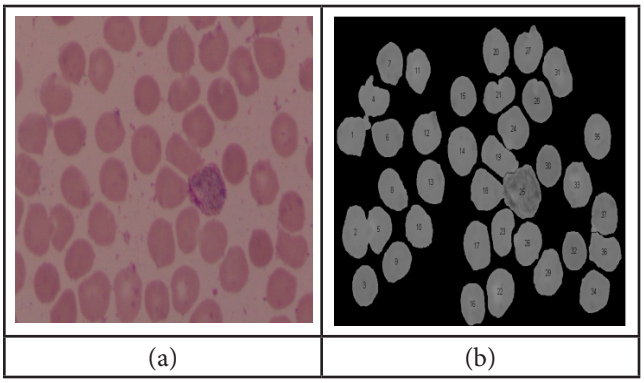


Figure 2. (a-b) Original microscopic image (c-d) Illumination corrected image.

individual is shown, which will be used further for feature extraction.



(a) (b)

Figure 3. Segmentation result (a) Original image (b) Segmented erythrocytes.

2.5 Feature Extraction

The feature of erythrocyte segmented in previous step needs to be extracted to classify the normal and infected erythrocytes. To enhance the performance of the classification of normal and infected erythrocyte, the histogram properties of different color channel have been considered. It consists of chrominance channel histogram, R-G histogram, green channel histogram and saturation level histogram. In Table 2, the details of the color channel histogram is listed.

Table 2. Feature set of the proposed system

Feature set	Feature
f1	Green channel histogram
f2	Saturation level histogram
f3	Chrominance channel histogram
f4	R-G histogram

Green channel histogram: It represents the intensity distribution of the green channel of the Red, Green and Blue (RGB) image.

Saturation level histogram: In the Hue, Saturation, and Value (HSV) color space, the basic color in the pixel is represented by hue, the colorfulness related to its brightness is defined by saturation and value represents the luminance color. The saturation level histogram is the histogram of the saturation channel of the HSV color space in which the malaria parasites are clearly visible.

Chrominance (Cb) channel histogram: In YCbCr color space, luminance information is represented by component (Y), and the two color-difference components (Cb and Cr) represent chrominance. Here, chrominance (Cb) channel histogram represents the histogram of the blue-difference chroma component[27].

R-G histogram: It is the histogram of the absolute difference between red channel and green channel of the RGB image[28].

To generate the feature vectors, the basic descriptor of the histogram properties such as mean, variance, skewness, kurtosis, median, mode, 10^{th} percentile, 90^{th} percentile, entropy have been used. In summary, an erythrocyte image is represented by 36 dimensional features which characterize the 4 histograms; each histogram is represented by 9 dimensional features.

Mean is the average intensity level in the region of the erythrocyte, which is given as

$$\mu = \sum_{n=1}^{N} np(n) \tag{1}$$

The measure of the dispersion of intensity represents the variance:

$$\sigma^2 = \sum_{n=1}^{N} (n-\mu)^2 p(n) \tag{2}$$

Skewness gives the measure of histogram symmetry:

$$\mu_3 = \frac{1}{\sigma^3} \sum_{n=1}^{N} (n-\mu)^3 p(n) \tag{3}$$

Kurtosis measures the tail of the histogram:

$$\mu_4 = \frac{1}{\sigma^4} \sum_{n=1}^{N} (n-\mu)^4 p(n) - 3 \tag{4}$$

Entropy of the histogram is given as:

$$E = -\sum_{n=1}^{N} p(n) \log_2 p(n) \tag{5}$$

Where $h(n)$ gives the frequency of pixel intensity value $n(n = 1, \ldots\ldots\ldots\ldots N)$ in the erythrocyte's histogram h and $p(n) = \frac{h(n)}{A}$ represents the probability function which is computed from the histogram of the erythrocytes area $A = \sum_{n} h(n)$.

2.6 Feature Selection

In this section, the feature selection procedure is discussed to select the best set of feature for erythrocytes

classification. Feature selection is the most crucial step in image analysis. Here, the features such as saturation level histogram, green channel histogram, chrominance channel histogram and R-G histogram are considered and the different combination of features is tested to select the best features set which gives the high accuracy for classification of infected and non-infected erythrocytes.

2.7 Classification

For the classification of the erythrocyte, the performance of four different classifiers such as k-NN, SVM, ANN and Naive Bayes is analyzed.

2.7.1 k-NN Based Classification

The k Nearest Neighbor (k-NN) is a non-parametric classification model[29–31]. In k-NN classification, majority voting of its neighbor is used for classification of an object. The object is allocated to the class having most common among its k nearest neighbors. The feature vectors and its corresponding class levels are stored during the training stage. A test vector is classified by assigning the label that occurs commonly among the k training samples nearest to the query data. Euclidean distance is commonly used distance metric in k-NN classification. The most important task in this context is the proper selection of k value.

2.7.2 SVM Based Classification

SVM is a machine learning process for classifying the input data into different classes[32–36]. SVM can perform both the linear as well as non-linear classification. For a given training dataset of n points of the form

$$\left(\vec{x}_1, y_1\right),.....,\left(\vec{x}_n, y_n\right) \tag{6}$$

Where $\vec{y}_i \in \{0,1\}$ indicates the class levels of the training data $\vec{x}_i$ belongs. $\vec{x}_i$ Represents the P-dimensional feature vector. Class label 0 represents the normal erythrocyte and class label 1 indicates infected erythrocyte. The main aim of SVM model is creating of a hyper-plane that separates the different sets of data given by:

$$\langle W, x\rangle + b = 0 \tag{7}$$

The classification function can be represented as:

$$f(x) = \phi(x).w + b = \sum_{i=1}^{l} y_i a_i \phi(x).\phi(x_i) + b \tag{8}$$

Where, unknown $\hat{x}$ depends on the dot product.

2.7.3 ANN Based Classification

An ANN is defined as an information processing system with certain performance characteristics inspired by biological neural networks[37–43]. Due to their ability to learn non-parametric relationships between input and output of the system, ANNs have been used for pattern classification. Here, multilayered ANN has been used for the erythrocytes classification. The designed network consists of three layers i.e. input layer, tan sigmoid hidden layer and output layer. The features of both the normal and infected erythrocytes are supply into the network in input layer, tan-sigmoid hidden layer carry out the steps to obtain the desirable output and nodes of output layer correspond to erythrocyte.

2.7.4 Naive Bayes Based Classification

Naive Bayes classifier is a data classifier technique based on Bayes' Theorem[44]. It is assumed that the value of a particular set of feature is independent of any other value of the feature where class variable is given. This method calculates the probability distribution's parameter by assuming that the predictors are conditionally independent of the given class. The posterior probability of test data belonging to each class is computed in the prediction step. According to the largest posterior probability, the method classifies the test data into their respective classes.

3. Results and Discussion

The experimental analysis of the results is carried out in this section. In this proposed technique, the classification of normal and infected erythrocyte is carried out using the histogram feature set. The proposed feature set consists of the histogram of different color channel such as saturation channel, green channel, chrominance channel, the absolute difference between red channel and green channel. From the proposed feature set, the optimal feature set is selected for each classifier by evaluating the different combinations of the features. The performance analysis of the different classifiers has been carried out using metrics such as

sensitivity, specificity, accuracy and F-score. To measure the classification rate, a total of 870 erythrocytes are used in 4-fold cross validation. The database used for the experimental analysis is collected from the registered pathological clinic of the Cachar district, Assam, India. In 4-fold cross validation, one subset is used as the test set and the remaining as training subset. In the classification process, '0' returns the non-infected and '1' returns infected erythrocyte. The average classification rate is estimated after repeating the experiment process for four times.

$$Sn = \frac{TP}{TP + FN} \times 100 \tag{9}$$

$$Sp = \frac{FP}{FP + TN} \times 100 \tag{10}$$

$$Acc = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \tag{11}$$

$$F - score = \frac{2 \times TP}{2 \times TP + FP + FN} \times 100 \tag{12}$$

Where Sn, Sp and Acc represents sensitivity, specificity, accuracy respectively. Further, Tp, TN, FP and FN represents true positive, true negative, false positive and false negative respectively. In Table 3, the overall performance of the classifiers with different feature set is listed. The feature set is formed by IFS technique. From this Table 3, it has been observed that, the performance of all the classifiers vary for all the feature combination. For k-NN classifier, the feature combination of f3+f4 i.e. chrominance histogram and R-G color channel difference histogram gives the better performance with sensitivity 86%, specificity 96.49%, accuracy 95.29% and F-score 80.75%. For SVM classifier, the feature combination of f2+f3 provides the better performance with sensitivity of 90%, specificity of 96.89%, and accuracy of 96.09% and F-score of 84.13% respectively. For ANN classifier, the proposed feature set i.e. f1+f2+f3+f4 gives the highest performance with sensitivity of 93%, specificity of 96.75%, accuracy of 96.32% and F-score of 85.32% respectively, as compared to other feature subsets. For Naive Bayes, the better result is observed with the feature combination of f2+f3+f4 with sensitivity of 90%, specificity of 96.62%, and accuracy of 95.86% and F-score of 83.33% respectively. The 4-fold cross validation results of the classifiers with the optimal feature set is listed in Table 4, Table 5, Table 6 and Table 7 respectively. For the performance analysis, the priority of the classifier will be decided depending on F-score parameter. As F-score considered both the positive prediction value and sensitivity, the accurate classification rate can be observed. The priority of classifiers is arranged as ANN> SVM> Naive Bayes> k-NN according to F-score parameter. In Figure 4, the accuracy of the classifiers with different feature subsets has been shown. The comparative analysis has been performed between the proposed feature set and the existing feature subsets available in the literature [15, 20, 21, 22]. The comparison of the different feature sets have been performed using the different classifiers such as k-NN, Naive Bayes, SVM and ANN as shown in Figure 5. From the experimental analysis, it may be observed that ANN with f1+f2+f3+f4 feature combination provides the higher classification rate in comparison to other classifiers as well as other feature sets. ANN provides an improvement in accuracy of (k-NN: 1.03%, SVM: 0.23%, Naive Bayes: 0.46%) and F-score of (k-NN: 4.57%, SVM: 1.19%, Naive Bayes: 1.99%) has been observed with the proposed feature set i.e. f1+f2+f3+f4.

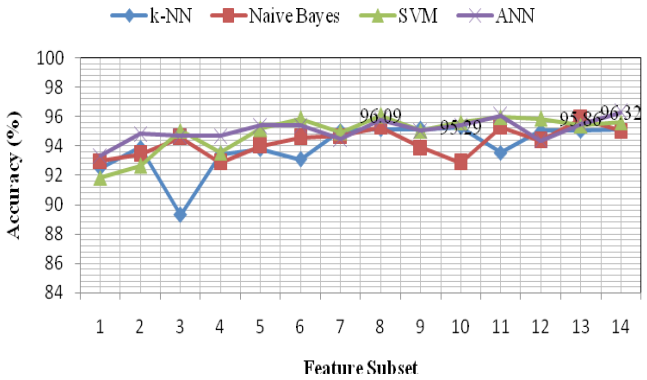


Figure 4. Accuracy of classifiers with different feature combination subsets.

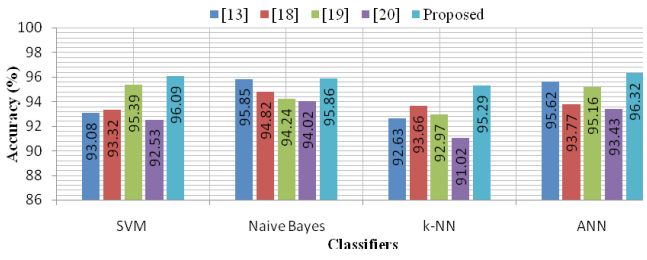


Figure 5. Comparative analysis of classifiers with the optimal feature set and existing feature set in literature. [15, 20, 21, 22]

Table 3. Performance comparison of classifiers with different feature subset

S.No.		k-NN				SVM				ANN				Naive Bayes			
		Sn (%)	*Sp (%)*	*Acc (%)*	*F-score (%)*	*Sn (%)*	*Sp (%)*	*Acc (%)*	*F-score (%)*	*Sn (%)*	*Sp (%)*	*Acc (%)*	*F-score (%)*	*Sn (%)*	*Sp (%)*	*Acc (%)*	*F-score (%)*
1	f1	72	95.19	92.53	68.90	44	98.06	91.85	55.37	78	95.32	93.33	72.90	80	94.68	92.99	72.40
2	f2	83	95.32	93.91	75.80	57	97.28	92.65	64.05	85	96.10	94.83	79.07	82	94.94	93.45	74.21
3	f3	48	94.68	89.31	50.79	87	96.10	95.06	80.18	87	95.71	94.71	79.09	82	96.23	94.60	77.73
4	f4	75	95.84	93.45	72.46	74	96.11	93.57	72.56	81	96.49	94.71	77.88	77	94.94	92.87	71.30
5	f1+f2	80	95.58	93.79	74.77	83	96.76	95.18	79.82	89	96.23	95.40	81.65	90	94.55	94.02	77.59
6	f1+f3	72	95.84	93.09	70.59	86	97.15	95.87	82.71	87	96.49	95.40	81.31	87	95.58	94.60	78.73
7	f1+f4	85	96.36	95.06	79.81	76	97.41	94.95	77.56	86	95.58	94.48	78.18	86	95.84	94.71	78.90
8	f2+f3	83	96.75	95.17	79.81	**90**	**96.89**	**96.09**	**84.13**	90	96.49	95.75	82.95	85	96.62	95.29	80.57
9	f2+f4	85	96.49	95.17	80.19	83	96.62	95.06	79.42	89	95.84	95.06	80.54	88	94.68	93.91	76.86
10	f3+f4	**86**	**96.49**	**95.29**	**80.75**	87	96.76	95.64	82.09	87	96.49	95.40	81.31	77	94.94	92.87	71.30
11	f1+f2+f3	79	95.45	93.56	73.83	87	97.14	95.98	83.25	91	96.75	96.09	84.26	88	96.23	95.29	81.11
12	f1+f2+f4	87	96.09	95.06	80.18	86	97.15	95.87	82.71	82	95.97	94.37	77.00	89	95.06	94.37	78.41
13	f2+f3+f4	83	96.62	95.06	79.43	85	96.76	95.41	80.96	87	96.62	95.52	81.69	**90**	**96.62**	**95.86**	**83.33**
14	f1+f2+f3+f4	85	96.49	95.17	80.19	86	96.89	95.64	81.92	**93**	**96.75**	**96.32**	**85.32**	87	96.10	95.06	80.18

Table 4. 4-fold cross validation results for k-NN classifier

Exp	*Sn (%)*	*Sp (%)*	*Acc (%)*	*F-score (%)*
Subset 1	80	96.87	94.93	78.43
Subset 2	96	95.31	95.39	82.76
Subset 3	80	95.85	94.04	75.47
Subset 4	88	97.92	96.79	86.37
Average	**86**	**96.49**	**95.29**	**80.75**

Table 5. 4-fold cross validation results for SVM classifier

Exp	*Sn (%)*	*Sp (%)*	*Acc (%)*	*F-score (%)*
Subset 1	92	96.88	96.31	85.19
Subset 2	88	95.36	94.47	78.52
Subset 3	96	96.38	96.33	85.51
Subset 4	84	98.96	97.25	87.34
Average	**90**	**96.89**	**96.09**	**84.14**

Table 6. 4-fold cross validation results for ANN classifier

Exp	*Sn (%)*	*Sp (%)*	*Acc (%)*	*F-score (%)*
Subset 1	92	96.88	96.31	85.16
Subset 2	96	96.88	96.77	87.12
Subset 3	88	95.34	94.50	78.52
Subset 4	96	97.93	97.71	90.52
Average	**93**	**96.75**	**96.32**	**85.32**

Table 7. 4-fold cross validation results for naive bayes classifier

Exp	*Sn (%)*	*Sp (%)*	*Acc (%)*	*F-score (%)*
Subset 1	92	96.88	96.31	85.16
Subset 2	84	96.88	95.39	80.56
Subset 3	88	94.82	94.04	77.29
Subset 4	96	97.93	97.71	90.29
Average	**90**	**96.62**	**95.86**	**83.33**

4. Conclusion

The malaria infected erythrocyte classification using the histogram feature set has been proposed. The proposed histogram feature set consists of green channel histogram, saturation histogram, chrominance channel histogram and the histogram of the absolute difference between red and green channels of RGB image. For the proposed system, a total of 36 features have been generated and the optimal feature set is selected for each classifier by evaluating the different combination of features. The classifiers such as ANN, k-NN, Naive Bayes and SVM have been used for the classification of erythrocyte with the histogram feature set. The experimental analysis has been carried out using the microscopic images of thin blood smears collected from the registered pathological clinic of the Cachar district, Assam, India. From the comparative analysis of different classifiers based on F-score parameter, ANN provides the better performance with proposed feature set. However, the best feature selection for the characterization and classification of different life cycle stages of malaria parasite species can be studied in the future.

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6. References

1. World Malaria Report 2013 [Internet]. 2015 [cited 2015 Apr 15]. Available from: http://www.who.int/malaria/publications/world_malaria_report_2013/report/en/.
2. Dhiman S, Baruah I, Singh L. Military malaria in north-east region of India. Defence Science Journal. 2010 Mar; 60(2):213–18.
3. Edison M, Jeeva JB, Singh M. Digital analysis of changes by plasmodium vivax malaria in erythrocytes. Indian Journal of Experimental Biology. 2011 Jan; 49:11–5.
4. Cuomo MJ, Noel LB, White DB. Diagnosing medical parasites: a public health officer's guide to assisting laboratory and medical officers [Internet]. 2015 [cited 2015 May 21]. Available from: http://www.phsource.us/PH/PARA/Diagnosing Medical Parasites.
5. Devi SS, Kumar R, Laskar RH. Recent advances on erythrocyte image segmentation for biomedical applications. Proceedings of Fourth International Conference on Soft Computing for Problem Solving, India; 2015. p. 353–9.
6. Kumar R, Devi SS, Talukdar FA. State of the art survey on image segmentation technique. Proceedings of 3rd International Conference on Computing, Communication and Sensor Network, India; 2014. p. 87–91.
7. Prakash O, Verma M, Sharma P, Kumar M, Kumari K, Singh A, Kumari H, Jit S, Gupta SK, Khanna M, Lal R. Polyphasic approach of bacterial classification — an overview of recent advances. Indian Journal of Microbiology. 2007 Jun; 47(2):98–108.

8. Devi SS, Sheikh SA, Laskar RH. Erythrocyte features for malaria parasite detection in microscopic images of thin blood smear: a review. International Journal of Interactive Multimedia and Artificial Intelligence. 2016 Dec; 4(2): 35–9.
9. Ruberto CD, Dempster A, Khan S, Jarra B. Analysis of infected blood cell images using morphological operators. Image and Vision Computing. 2002 Feb; 20(2):133–46.
10. Tek FB, Dempster AG, Kale I. Malaria parasite detection in peripheral blood images. Proceedings of the British Machine Vision Conference, UK; 2006. p. 347–56.
11. Nicholas RE, Charles JP, David MR, Adriano GD. Automated image processing method for the diagnosis and classification of malaria on thin blood smears. Medical and Biological Engineering and Computing. May 2006; 44 (5):427–36.
12. Diaz G, Gonzalez FA, Romero E. A semi-automatic method for quantification and classification of erythrocytes infected with malaria parasites in microscopic images. Journal of Biomedical Informatics. April 2009; 42(2):296–307.
13. Springl V. Automatic malaria diagnosis through microscopic imaging. [Faculty of Electrical Engineering thesis]. Prague; 2009.
14. Ghosh M, Das D, Chakraborty C, Ray AK. Quantitative characterization of Plasmodium vivax in infected erythrocytes: a textural approach. International Journal of Artificial Intelligence and Soft Computing. 2013; 3(3): 203–21.
15. Savkare S, Narote S. Automatic detection of malaria parasites for estimating parasitemia. International Journal of Computer Science and Security. 2011; 5(3):310–5.
16. Memeu DM. A rapid malaria diagnostic method based on automatic detection and classification of plasmodium parasites in stained thin blood smear images. Doctoral dissertation, University of Nairobi; 2014.
17. Annaldas S, Shirgan SS, Marathe VR. Automatic identification of malaria parasites using image processing. International Journal of Emerging Engineering Research and Technology. 2014 Jul; 2(4):107–12.
18. Das DK, Maiti AK, Chakraborty C. Automated system for characterization and classification of malaria-infected stages using light microscopic images of thin blood smears. Journal of Microscopy. 2015; 257(3):238–52.
19. Das DK, Ghosh M, Pal M, Maiti AK, Chakraborty C. Machine learning approach for automated screening of malaria parasite using light microscopic images. Micron. 2013 Feb; 45:97–106.
20. Das DK, Ghosh M, Chakraborty C, Maiti AK, Pal M. Probabilistic prediction of malaria using morphological and textural information. Proceedings of International Conference on Image Information Processing, India; 2011.
21. Das DK, Maiti AK, Chakraborty C. Textural pattern classification of microscopic images for malaria screening. Advances in Therapeutic Engineering. CRC Press; 2012. p. 419–46.
22. Bairagi VK, Charpe KC. Comparison of texture features used for classification of life stages of malaria parasite. International Journal of Biomedical Imaging. 2016 May 9; 2016. DOI : 10.1155/2016/7214156.
23. Tek FB, Dempster AG, Kale I. A colour normalization method for giemsa-stained blood cell images. Proceedings of the Signal Processing and Communications Applications, Turkey; 2006.
24. Otsu N. A threshold selection method from gray-level histograms. IEEE Transactions on System, Man and Cybernetics. 1979; 9(1):62–6.
25. Cheng J, Rajapakse JC. Segmentation of clustered nuclei with shape markers and marking function. IEEE Transactions on Biomedical Engineering. 2009; 56(3):741–8.
26. Jung C, Kim C. Segmenting clustered nuclei using h-minima transform- based marker extraction and contour parameterization. IEEE Transactions on Biomedical Engineering. 2010; 57(10):2600–4.
27. Hahnel M, Klunder D, Kraiss, Color KF. Texture features for person recognition. Proceedings of IEEE International Joint Conference on Neural Networks; 2004. p. 647–52.
28. Siggelkow S. Feature histograms for content-based image retrieval. Dissertation, Universitat Freiburg; 2002.
29. Altman NS. An introduction to kernel and nearest-neighbor nonparametric regression. The American Statistician. 1992; 46(3):175–85.
30. Weinberger KQ, Saul LK. Distance metric learning for large margin nearest neighbor classification. Journal of Machine Learning Research. 2009; 10:207–44.
31. Devi SS, Roy A, Sharma M, Laskar RH. kNN classification based erythrocyte separation in microscopic images of thin blood smear. Proceedings of 2nd International Conference on Computational Intelligence and Networks, India; 2016. p. 69–72.
32. Cortes C, Vapnik V. Support-vector networks. Machine Learning. 1995; 20(3):273–97.
33. Duda RO, Hart PE, Stork DG. Pattern classification. New Delhi: John Wiley and Sons; 2001.
34. Burges CJC. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery. 1998; 2(2):121–67.
35. Kumar RD, Ganesh AB, Sasikala S. Speaker identification system using mixture model and support vector machines (gmm-svm) under noisy conditions. Indian Journal of Science and Technology. 2016 May; 9(19):1–6. DOI: 10.17485/ijst/2016/v9i19/93870.
36. Roy A, Singha J, Devi SS, Laskar RH. Impulse noise removal using SVM classification based fuzzy filter from gray scale images. Signal Processing. 2016 Nov; 128:262–73.

37. Hagan MT, Demuth HB, Beale MH, Jesus OD. Neural network design. Boston: PWS publishing company; 1996.
38. Rizwan JM, Krishnan PN, Karthikeyan R, Kumar SR. Multi layer perception type artificial neural network based traffic control. Indian Journal of Science and Technology. 2016 Feb; 9(5):1–6. DOI:10.17485/ijst/2016/v9i5/87267.
39. Mamatha P, Venkatram N. Watermarking using Lifting Wavelet Transform (LWT) and Artificial Neural Networks (ANN). Indian Journal of Science and Technology. 2016 May; 9(17):1–7. DOI: 10.17485/ijst/2016/v9i17/93088.
40. Kavita K, Navin R, Shaifali Madan A. Piecewise feature extraction and artificial neural networks: an approach towards curve reconstruction. Indian Journal of Science and Technology. 2016 Jul; 9(28):1–9. DOI:10.17485/ijst/2016/v9i28/84138.
41. Jasjit SS, Dutta M, Aggarwal N. Efficacy of Artificial neural network based decision support system for career counseling. Indian Journal of Science and Technology. 2016 Aug; 9(32):1–9. DOI: 10.17485/ijst/2016/v9i32/100738.
42. Singha J, Laskar RH. ANN-based hand gesture recognition using self co articulated set of features. IETE Journal of Research. 2015 Jul; 61(6):597–608.
43. Roy A, Devi SS, Laskar RH. Impulse noise removal from gray scale images based on ANN classification based Fuzzy filter. Proceedings of 2nd International Conference on Computational Intelligence and Networks, India; 2016. p. 97–101.
44. Russell S, Norvig P. Artificial intelligence: a modern approach. 2nd edn. Upper Saddle River: Prentice hall; 2003.