Volume 5, Issue 10, October-2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Detection of Malaria Disease through Soft Computing

[1]Upendra Kumar Chandra, [2]Yogesh Bahendwar
[1]M.E. (Communication) Scholar, Department of Electronics & Telecommunication, SSCET, Bhilai, Chhattisgarh, India
[2]HOD, Department of Electronics & Telecommunication SSCET, Bhilai, Chhattisgarh, India

Abstract- Malaria is the leading cause of mortality and morbidity in tropical and subtropical countries.Rapid and exact diagnosis of the disease is key to its effective treatment and management Conventional microscopy is the Gold standard in the diagnosis of the disease. However, difficultness in reproducing results and it is prone to some shortcomings which include time consumption.Therefore in this work, an accurate, speedy and reasonable system of malaria detection using stained thin blood smear images was developed. The method uses Artificial Neural Network (ANN) to investigation for the existence of plasmodium parasites in thin blood smear images. Images of infected and non-infected erythrocytes were extracted,image segmentation, pre-processed, relevant features extracted from them.

Keywords-Ultrasound Imaging, ANN, RDT, THG, PCR

I. INTRODUCTION

Malaria is a common but serious protozoan disease caused by peripheral blood, spleen or liver parasites of the genus Plasmodium. Several methods exist for malaria diagnosis. These methods can be classified into two, based on their cost and performance. These are the high cost methods and low cost methods. Polymerase Chain Reaction (PCR) based techniques that detect specific nucleic acid sequences and Third Harmonic Generation (THG) imaging of emission from the Hemozoinusing infrared ultrafast pulsed laser excitation, belong to the class of high cost methods. Studies have shown that these techniques can yield high sensitivity and specificity to malaria diagnosis. However, they are rarely used in developing countries where the disease is endemic because of the high cost, specialized infrastructure needs and handling difficulties. RDTs are relatively fast in malaria diagnosis and can be administered by unskilled personnel. However, their results can be unreliable. Besides, commercially available RDT kits are specific to single species of plasmodium parasites and in cases where mixed infection is suspected, all the four kits should be used. This makes the technique relatively expensive. Conventional microscopy is the gold standard method of malaria diagnosis. The most serious limitation of this technique is time consuming. Besides, the results obtained are difficult to reproduce.From the above discussion of malaria diagnosis methods, it can be deduced that the more sophisticated the technique is, the more reliable the result of the diagnosis. However sophisticated techniques are expensive and unaffordable in places where malaria is a serious problem. On the other hand, less sophisticated techniques are affordable but their results are not always reliable. Low cost malaria diagnosis techniques can be improved by incorporating some processing component in their out- puts. As a result we can devise a new framework of classifying malaria diagnosis techniques based on the complexity involved in detection and processing.

II. LITERATURE SURVEY

Some of the important contribution in this field is presented in this section as follows-

Lucy Gitonga, et al [1] introduces a technique for identifying the parasites lifestages and species using microscopic images of thin blood smears stained with Giemsa was developed.The technique entailed designing and training Artificial Neural Network (ANN) classifiers toperform the classification of infected erythrocytes into their respective stages and species. The system recorded99.9% in recognizing stages and 96.2% in recognizing plasmodium species.

Daniel MaitethiaMemeu, et al[2]proposesan accurate, speedy and affordable system of malaria detection using stained thin blood smear images was developed. The method uses Artificial Neural Net- work (ANN) to test for the presence of plasmodium parasites in thin blood smear images. Images of infected and non-infected erythrocytes were acquired, pre-processed, relevant features extracted from them and eventually diagnosis was made based on the features extracted from the images. Classification ac- curacy of 95.0% in detection of infected erythrocyte was achieved with respect to results obtained by expert microscopists.

MagudeeswaranVeluchamy, et al [3] describes the method of evaluating the clinical status is counting of cell typesbased on features that it contains. There is a need for a rapid, reproducible method, superior to humaninspection and for the classification of cells. For solving these problems, quantitative digital-image analysis is applied and a novel method for classifications of affected blood cells from normal in an image of a microscopic section is presented. These blood cell images are acquired from differentpatient with sickle cell anemia, sickle cell disease and normal volunteers. Approach: Thesegmentation of blood cells is made by morphological operations such as thresholding, erosion anddilation to preserve shape and size characteristics. In addition, we use back propagation neural network to classify the blood cells more efficiently.

Dipti D. Patankar, et al [4]presentsautomatic methods for detection and classification of malarial parasites in thin blood smear. For thisArtificial Neural Network (ANN) and Bayesian Network (BN) are used as promising techniques. Morphological features suchas shape, size are considered to identify infected erythrocytes and possible type of plasmodium.

ParasChawla, et al[5] In order to use medical images for the diagnosing process, it must be noiseless. However, most of the images are affected by noises and artifacts. In order to achieve this de-noising of CT images, an effective CT image de-noising technique is proposed. The proposed technique removes the Additive white Gaussian Noise from the CT images and improves the quality of images. The proposed work is comprised of three phases; they are preprocessing, training and testing. In the preprocessing phase, the CT image which is affected by the AWGN noise is transformed using multi wavelet transformation. In the training phase the obtained multi-wavelet coefficients are given as input to the Adaptive Neuro-Fuzzy Inference System (ANFIS).

Sudhansu Kumar Mishra, et al[6]presents an alternate ANNstructure called functional link ANN (FLANN) for imagede-noising. In contrast to a feed forward ANN structure i.e.a multilayer perceptron (MLP), the FLANN is basically asingle layer structure in which non-linearity is introducedby enhancing the input pattern with nonlinear functionexpansion. In this work three different expansions isapplied. Yazeed A. Al-Sbou, et al [7] describes the image de-noising is a challenging task in the digital image processing research and application.This makes it imperative to find a robust method to comply that task. In this paper, a detailed performanceevaluation of using the neural networks as a noise reduction tool is presented.

SuchitraSarangi, et al [8]discusses image restoration is an important part of image processing. This paper presents a functional link artificial neural network based technique for image restoration which has the capacity of reducing the Gaussian noise present in an image. Then a comparison has been carried out between the proposed filter & the other existing filters. Finally, some conclusion & future work lines are presented.

JunyuanXie,et al,[9] propose anovel approach to low-level vision problems that combines sparsecoding and deep networks pre-trained with de-noising auto-encoder (DA).We proposean alternative training scheme that successfully adapts DA, originally designedfor unsupervised feature learning, to the tasks of image de-noising and blindin painting.

SnigdhaMohanty,et al[10]describes design the four artificial neural networks(ANNs) for de-noising of digital image corrupted withadditive white Gaussian noise or salt and peppernoise is presented. Here, Multilayer perceptron(MLP) using the popular back propagationalgorithm, Direct Linear Artificial Feed-throughNeural Network (DLFANN) , Functional Link sArtificial Neural Network (FLANN) and Modified-Functional Link Artificial Neural Network (MFLANN)have been implemented in this regard andextensive computer simulation have been carried outfor performance comparison among thesealgorithms.

Leipo Yan, et al[11]proposesa new approach to address image de noisingbased on a new neural network, called noisy chaoticneural network (NCNN). The original Bayesian frameworkof image de-noising is reformulated into a constrained optimizationproblem using continuous relaxation labelling. TheNCNN, which combines the simulated annealing techniquewith the Hopfield neural network (HNN), is employed tosolve the optimization problem.

SheenumMarwaha, et al, [12]provides a brief review of computerizedaided automated diagnosis techniques which use Digital ImageProcessing, their benefits and the types of diseases diagnosed bythese systems. However CAD system is having many problems,so new methods need to be introduced by combining the benefitsof other classification techniques with CAD.

Ms. DeepaliGhate, et al, [13] discusses computerized diagnosis, which will help in immediate detection of the disease to some extent, So that the proper treatment can be provided to the malaria patient. Also the image processing algorithm is used which will reliably detect the presence of malaria parasite from Plasmodium falciparum species in thin smears of Giemsa stained peripheral blood sample.

S. S. Savkare, et al,[14]presentsan automatic technique is proposed forMalaria parasites detection from blood images by extracting red blood cells (RBCs) from bloodimage and classifying as normal or parasite infected. Manual counting of parasite is tediousand time consuming and need experts. Proposed automatic approach is used Otsu thresholdingon gray image and green channel of the blood image for cell segmentation, watershed transformis used for separation of touching cells, color and statistical features are extracted fromsegmented cells and SVM binary classifier is used for classification of normal and parasiteinfected cells.

Pallavi T. Suradkar,et al,[15]reviews image analysis studies aiming at automated diagnosis or screening of malaria infection in microscope images of thin blood film smears. Malaria is a mosquito-borne infectious disease of humans and other animals caused by parasites (a type of microorganism) of the genus Plasmodium. Infection is initiated by a bite from an infected female mosquito, which introduces the parasites via its saliva into the circulatory system, and ultimately to the liver where they mature and reproduce.

Deepa.A.Kurer, et al, [16] presentsthe image processing algorithm to automate the diagnosis of malaria in blood images is developed in this project. The image classification system is designed to positively identify malaria parasites present in thin blood smears, and differentiate the species of malaria.

III. METHODOLOGY

In this work the main emphasis is on the detection of malaria using image processing. For detecting malaria detection of Erythrocyte parasites is very important. in thin blood smear images has been highlighted in the process model. Noise reduction was considered to reduce some undesirable effects in the images which often are acquired during the process of sample preparation and image acquisition such a non-uniform illumination, salt and pepper

noise and image blurring. This operation served to remove spurious noise present in the images The images were pre-processed by performing median filtering operation with a filter kernel of 5 by 5 to remove noise. The images were then spatially rescaled to a uniform size. Identification of infected erythrocytes was then done by a trained ANN using erythrocytes RGB feature as its input.

There are five phases included in the proposed computer aided diagnosis system for disease detection whichis as follows:

1. Extraction of abnormal region from computer tomography images, ultrasonic Images, magnetic Resonance Images etc.
2. Segmentation of diseased region using segmentation algorithms
3. Feature extraction from the segmented region
4. Formation of diagnosis rules from the extracted features.
5. Classification of occurrence and non occurrence of disease in the body.

Following stages were implemented in the process-

A. Image Filtering

Filtering in image processing is a process that cleans up appearances and allows for selective highlighting of specific information. Standard median filter and mean filter are used here to make the image noise free.

B. Image Pre-Processing

The goal of this step is to make the acquired images more suitable for subsequent processes-mainly image segmentation and feature extraction. Basically, there are two main objectives for image pre-processing.

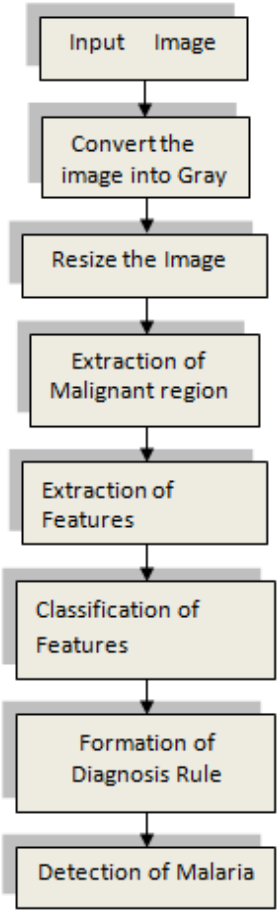

Figure 1 General Block Diagram of Malaria Detection

One is to resize the image for the purposes of either magnifying the image through digital zooming, or reducing the image size in order to speed up processing. Second objective is to enhance the image contrast for visual evaluation.

C. Image Segmentation

There were two objectives of image segmentation. First was to isolate individual erythrocytes from the rest of blood constituents and the second was to partition Plasmodium parasites from the infected erythrocytes. Two image segmentation schemes were found.One was the traditional image segmentation technique of histogram thresholding and the other was the use of artificial neural network for image segmentation. Image segmentation is usedto detect the entire blood cells.

D. Feature Extraction

After the segmentation is performed on the Image, the features can be obtained from it and the diagnosis rules can be designed to exactly detect the candidate region. These parameters are grouped together in vector form and are referred to as feature vectors. Features can be obtained directly from images e.g., raw image pixel values or they could be derived quantities such as average image intensity, image histogram moments, shape signature and object area.

Pre-processing steps for KEMRI and CDC images

1) Load a sample image, I_s and specify its source, either KEMRI or CDC.
2) Perform median filtering using a 5 by 5 square filter to Is
3) Determine the spatial resolution I_s
4) If the image size is greater than 300 square pixels, resize the image by a scale factor of "sf"

Where

Sf=300/minimum(image width, image length)

5) Determine the Centre coordinates, (x_o, y_o) of the resulting image and use it to crop a subset of the image using the following parameters;

Top left coordinates = $(x_o - 150, y_o - 150)$

Width of the image to be cropped = 300

Height of the image to be cropped = 300

NB: MATLAB code for executing step 5 is given below

I_s = imcrop (I_s, $[x_o - 150, y_o - 150, 300, 300]$)

6) Create a copy of the resized image and convert it into HSI colour space.

Algorithmic steps for Erythrocyte segmentation are as follows-

1. A pre-processed sample image to be segmented is loaded.
2. Observe the corresponding HSI image of the sample.
3. Observe the green component image from RGB images and hue and saturation components from HSI images.
4. Use Otsu's algorithm to segment erythrocytes in the green, hue and saturation component images.
5. Determine the coordinates of bounding rectangles enclosing every object.

E. Artificial Neural Network

Feature extracted images are fed to the network. Feed forward network with one input layer consisting of three neurons, one hidden layer and two output neuron as shown in given figure

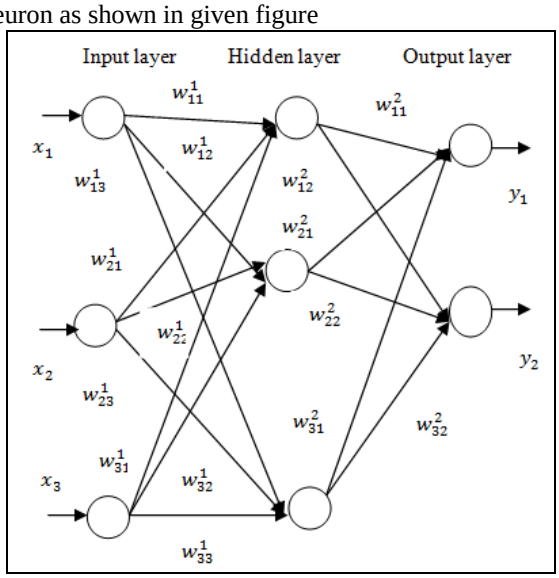

Figure 2 Multilayer Perceptron network

Here x_i is the input to the network, w^1_{11} is the weight of input x_1 to hidden layer and y_1 is the output. Back Propagation algorithm is used for training the network.

IV. EXPERIMENTAL RESULTS

A. Test Results for Image Size Rescaling

Figure 5.1 shows normalization of two images from CDC and KEMRI before and after scaling.Figure 3(a) is an image from CDC whose size is 1600 by 1600 pixels while Figure 3 (b) is an image captured from KEMRI blood samples. Figures 3(c) and (d) give the resultant images after image rescaling operation.

CDC image size reduced to 300 by 300 pixels after image rescaling and it is also needed to maintain its useful features such as erythrocytes, parasites and background regions which has been conserved. There is no change in the KEMRI image size after rescaling. Thus it is can be said that the image rescaling algorithm has produced the desired results of rescaling images

from both KEMRI and CDC. Image rescaling isvery necessary for making the computation very fast at various stages of image processing i.e., feature extraction, image segmentation.

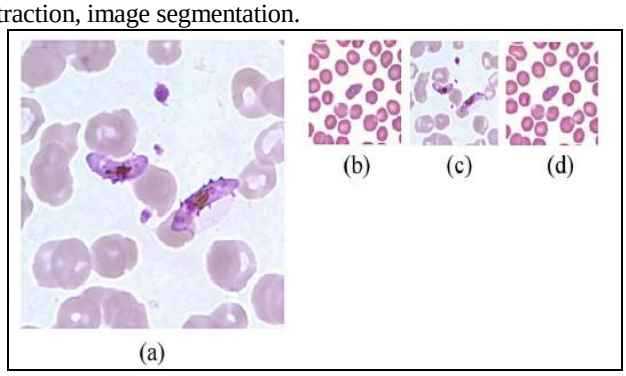

Figure 3 Results of image rescaling, (a) CDC image, (b) KEMRI image, (c) and (d) rescaled CDC and KEMRI images respectively.

B. Test Results for Noise Reduction

Figures 4(a) and (d) shows the rescaled KEMRI and CDC images respectively. The filtering is done using the median filterand before and after filtering erythrocytes of these images is segmented. It can be seen from the results that for KEMRI image, the difference between two binary images is nothing,but for CDC image segmenting after the filteringthe imageis resulted to a notable improvement of the binary image quality. This is due to noise which means CDC images have been degraded by noise this effect is corrected by median filtering. Some of the possible sources of such noise include unbalanced illumination of the sample in the microscope, sample degradation or a poor sample preparation.

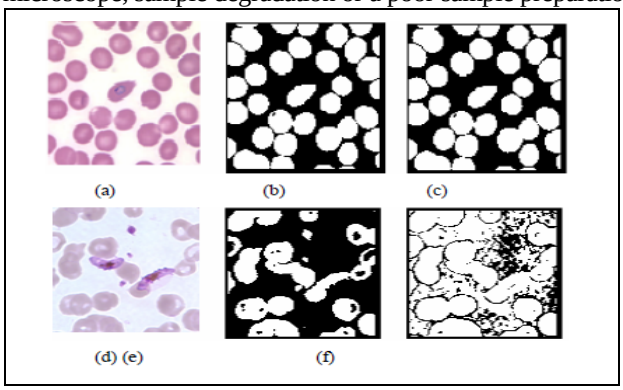

Figure 4 .Effect of image filtering, (a) and
(d) pre-processed KEMRI and CDC images, (b) and (e) binary images obtained from the pre-processed images, (c) and (f) binary images obtained from raw images from KEMRI and CDC respectively

By performing median filtering random noise also referred to as salt and pepper noise was reduced and due to which quality of image is maintained.

C. Test Results for Erythrocyte Segmentation Using Histogram Segmentation

In order to obtain the Histograms of sampled images from CDC and KEMRIOtsu's algorithm is used with their threshold values.Test results of erythrocyte segmentation using image histogram are presented in figure 4 and figure 5.The green component image produced good segmentation results for erythrocytes for CDC image, but it also captured the plasmodium parasite regions as part of the foreground. The hue component resulted to a binary image whose foreground (erythrocyte regions) had noisy boundaries. The saturation component failed to produce erythrocytes as the objects but instead segmented the parasites.

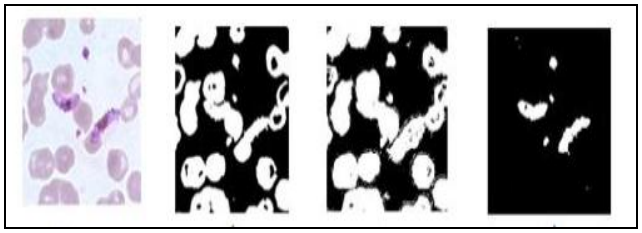

Figure 5: CDC image histogram thresholding, a) pre-processed image from CDC, b), c), and d) resultant binary images obtained from thresholding the green, hue, and saturation component images.

KEMRI image has also undergone through the same test to determine which colour component image would produce the best erythrocyte segmentation results. Figure 6 shows the KEMRI Image, and the resulting binary images

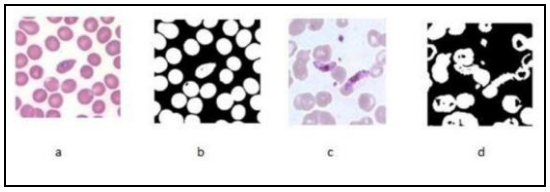

Figure 6: KEMRI histogram thresholding, a) pre-processed image from KEMRI, b, c, and d) resultant binary images obtained from thresholding the green, hue, and saturation component images

Table 1.1: Performance of erythrocyte segmentation using ANN classifiers

Feature vector	Training %	Validation %	Test session %	Overall %
RGB feature Vector only	100	100	100	100
RGB and HSI Features	100	92.9	100	93.9

From its corresponding green, hue, and saturation image colour components. It can be observed from the figure above that the binary images from green component of RGB images and saturation component image produced good erythrocytes regions but as in the case of CDC image, hue component image produced a noisy binary image.
From these results, it is concluded that the green colour component of RGB image is the most suitable for segmentation using histogram segmentation techniques.

D. Test Results for Artificial Neural Network Segmentation of Erythrocytes

Erythrocyte segmentation using two ANN classifiers were used. The training of first classifier was donewith only pixel values of RGB images while the other classifier was trained with both RGB and HSI image pixel values. Table 1.1 gives the classification of accuracy in percentage achieved by the two ANN classifiers.From the results given in Table 5.1, the performance of both t ANN classifiers is excellent i.e above 90%but the performance of the network trained only with RGB features has produced a good result as compare to other which is trained with both RGB and HSI . The Artificial Neural Network trained with RGB features was used to segment the same images used in histogram segmentation, one from KEMRI and the other from CDC. The binary images of Figure 7 (b and d) were obtained. From these images it can be observed that the ANN managed to capture the erythrocyte regions well in both CDC and KEMRI images.

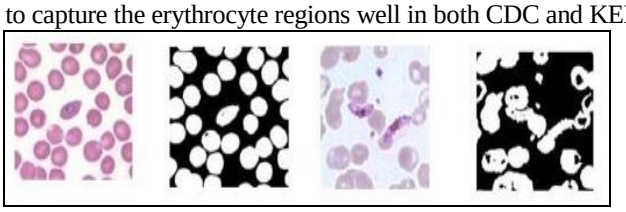

Figure 7: Erythrocyte segmentation results of artificial neural network; (a) is the pre-Processed image from KEMRI, (c) is the pre-processed,image from CDC,(b) and(d) are the resultant binary images obtained as the outputs of ANN trained to segment erythrocytes.

V. CONCLUSION

From the results, it is concluded that the green colour component of RGB image is the most suitable for segmentation when histogram segmentation techniques is used.
The Artificial Neural Network Algorithm provides the excellent results i.e above 90%. However, on comparing the network trained only with RGB features performed marginally better than the one trained with both RGB and HSI features. By this we come to a conclusion that the neural network classification accuracy decreases with the increasing number of features and sample size is held constant. It can be concluded that RGB features are adequate to distinguish erythrocytes from the rest of the thin blood smear image using an ANN.

REFERENCES

[1] Daniel Maitethia Memeu, Kenneth Amiga Kaduki, A. C. K. Mjomba, Njogu Samson Muriuki, Lucy Gitonga, "Detection of plasmodium parasites from images of thin blood smears" , Open Journal of Clinical Diagnostics, 3 (2013) 183-194.

[2] Lucy Gitonga, Daniel MaitethiaMemeu, Kenneth Amiga Kaduki,Mjomba Allen Christopher Kale, Njogu Samson Muriuki, "Determination of Plasmodium Parasite LifeStages and Species in Images of Thin BloodSmears Using Artificial Neural Network", Open Journal of Clinical Diagnostics, 4,2014,pp: 78-88.

[3] MagudeeswaranVeluchamy, KarthikeyanPerumal and ThirumuruganPonuchamy"Feature Extraction and Classification of Blood Cells Using Artificial Neural Network" American Journal of Applied Sciences 9 (5):, 2012,ISSN 1546-9239,pp: 615-619

[4] Dipti D. Patankar, "Exploring the use of Artificial Neural Network and Bayesian Network for Malaria Detection", Sixth IRAJ International Conference, 6th October 2013, Pune, India. ISBN: 978-93-82702-32-0,pp:24-27

[5] ParasChawla, Ruchi Mittal, KavitaGrewal, "Hybrid Filtering Technique for Image Denoising Using Artificial Neural Network", IJEAT Volume-1, Issue-3, August 2012.

[6] Sudhansu Kumar Mishra, Ganpati Panda, SukadevMeher, "Chebyshev Functional Link Artificial Neural Networks for Denoising of Image Corrupted by Salt and Pepper Noise", International Journal of Recent Trends in Engineering, Vol. 1,No.1, May 2009.

[7] Yazeed A. Al-Sbou, "Artificial Neural Networks Evaluation as an Image Denoising Tool", IDOSI Publications, 2012.

[8] SuchitraSarangi, Shubhendu Kumar Sarangi, SunitaSarangi, "Performance Analysis of Filter based on Functional Link Artificial Neural Network", IJCA, Volume 93 – No 1, May 2014.

[9] JunyuanXie, LinliXu, Enhong Chen, "Image Denoising and Inpainting with Deep NeuralNetworks", Advances in Neural Information Processing Systems 25 (NIPS 2012), pp:1-9.

[10] SnigdhaMohanty, PrajnaParamitaBehera, "Image Denoising Using Adaptive Filter Based on Computational Efficient Modified Functional Link Artificial Neural Network", SPC ERA IJSTE Vol-1, No-1 Oct-Dec. – 2014.

[11] AkutagawaMastake, ChanYongjia, Katayama Masato, YohsukeKinouchi, QinyuZhang,"Additive and multiplicative noise reductionby back propagation neural Internationale,Lyon", France August 23-26, 2007 IEEE(2007).

[12] Leipo Yan, Lipo Wang, Kim-HuiYap,"A noisy chaotic neural network approach to image denoising" International Conference on Image Processing (ICIP) 2004,pp:1229-1232.

[13] SheenumMarwaha, HimanshuMonga, Shelza, "Automatic Diagnosis Systems Using Image Processing-A systematic Study", International Journal of Computer Science and Information Technology & Security (IJCSITS), ISSN: 2249-9555Vol. 2, No.2, April 2012,pp:388-391.

[14] Ms.DeepaliGhate,Mrs.Chaya,C. Dr. N Usha Rani, "automatic detection of malaria parasite from blood images", International journal of advanced computer technology | Volume 4, Number 1, ISSN:2319-7900,pp:129-132.

[15] S. S. Savkare, S. P. Narote, "Automatic Detection of Malaria Parasites for EstimatingParasitemia", International Journal of Computer Science and Security (IJCSS), Volume (5) : Issue (3) : 2011, pp: 310-315.

[16] Pallavi T. Suradkar, "Detection of Malarial Parasite in Blood Using Image Processing", International Journal of Engineering and Innovative Technology (IJEIT)Volume 2, Issue 10, April 2013, pp:124-126.

[17] Deepa.A.Kurer, Vineeta.P.Gejji"Detection of Malarial Parasites in Blood Images", International Journal of Engineering Science and Innovative Technology (IJESIT), Volume 3, Issue 3, May 2014,pp:651-656.

