Design of ANN Based System for the Detection of Malaria in Blood Smear Images

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Abstract: In many countries of the world including India, malaria is the foremost source of demise and illness. The efficient medication and managing of the infection are a speedy and precise identification. In the detection of the malaria, traditional microscopic technique considered as the gold standard one. However, it has not only an issue with replicating the results but also susceptible to several limitations, like time consumption. So, employing stained thin blood smear s, a précised, rapid, and appropriate technique is designed for malaria detection in our study. Our technique examines thin blood smear s for the presence of malaria parasites using an ANN.The input s of blood smear cells are processed, segmented, and then categorized into healthy and unhealthy s based on retrieved features.

Index Terms **– Malaria detection, blood smear s, image processing, ANN.**

I. INTRODUCTION

Malaria is considered one of the deadly international illnesses and can spark-off demise quick on the off risk that it's miles untreated. In 2018, five hundred million cases of malaria were identified, which triggered around five lakh deaths [1]. Malaria is not unusual within tropical along with subtropical areas close to equator like Asia, Sub-Saharan Africa, and Latin America. It is impossible to resist malaria infection brought about through nonessential blood parasite of family Plasmodium. Malaria is Iran's main parasitic disease with a long background of episodes. Malaria fever is spread using infected Anopheles female mosquitoes through their salivary glands that carry Plasmodium sporozoites. The kind Plasmodium has 4 organisms which can cause human distress: falciparum, vivax, ovale, and malaria. The famous process of life has arranged different development within the human and mosquito structure. The sporozoites join the process as a tainted mosquito blessing from the blood of an individual and transfer to the liver where they develop abiogenetically. Since 2015, WHO has advocated malaria disease symptomatic trying out by way of both mild microscopy and rapid demonstrative, [2]. RDT is applied wherein microscopy microscope isn't on hand; this technique gives second outcomes however number one disservice of RDT is that parasite thickness cannot be assessed. Microscopy approach is "Best remarkable level" for recognizing malaria parasites and assessing parasite thickness [3]. Varieties of blood films are arranged for minute localization: flimsy and smooth [4]. A small blood stain is used to distinguish parasite types, since the parasite identity is preserved. To distinguish the closeness of parasite and parasite thickness a dense blood stain is introduced. A dense blood smear is more susceptible to multiple times than a thin blood smear, as it requires a greater amount of blood to be assessed.

Malaria is generally diagnosed by manual microscopic examination of blood slide, which is named as “gold standard”. However, the manual method of diagnosis is tedious, requires expert technicians and prone to human errors. In addition, it also incurs a high cost for the training of technicians [6]. Considering these problems, the automatic analysis of the microscopic s for the diagnosis of malaria disease has gained importance. This motivated us to carry out this study with an aim to develop -contrast enhancement and segmentation methods for a rapid and accurate diagnosis of malaria through microscopic blood s [14].

Malaria is a deadly protozoan disease caused by Plasmodium parasites in the peripheral blood, spleen, or liver. Malaria can be diagnosed using a variety of approaches. These approaches can be divided into two groups based on their cost and effectiveness. These are the high-cost and low-cost techniques, respectively. High-cost technologies include polymerase chain reaction (PCR)-based techniques for detecting specific nucleic acid sequences and Third Harmonic Generation (THG) imaging of Hemozoin emission utilising infrared ultrafast pulsed laser excitation. These strategies have been found in studies to have great sensitivity and specificity when it comes to diagnosing malaria. However, because of the expensive cost, specialised infrastructure requirements, and handling challenges, they are rarely employed in developing nations where the disease is endemic. RDTs are a relatively quick way to diagnose malaria and can be delivered by non-medical staff. Their results, however, can be unreliable. Furthermore, commercially accessible RDT kits are available.

From the above review on malaria diagnosis techniques, it is to be concluded that the more modern the technique, more précised. But in places where malaria is a severe concern, modern techniques are costly and unaffordable. Simple approaches, in contrast, are cheaper, but their results are not necessarily précised. By including a processing component in their output, the precision of cheaper malaria diagnosis techniques can be enhanced. As a result, we may create a new classification system for malaria diagnosis approaches based on the degree of difficulty in detection and processing. Hence, based on the complexity of detection and processing, we may be able to design a new categorization system for malaria diagnosis methods.

II. REVIEW OF LITERATURE

Lucy Gitonga, et al. [1] provide a method for identifying parasite life stages and species by examining microscopic images of thin blood smears stained with hematoxylin and eosin. Giemsa has been created. Designing and training Artificial Neural Network (ANN) classifiers to perform the classification of infected erythrocytes into their various phases and species was part of the technique. The method correctly identified 96.79% of the stages and 95.4 percent of the plasmodium species.

Daniel Maitethia Memeu, et al [2] propose a malaria diagnostic system based on stained thin blood smear images that is accurate, quick, and economical. To detect plasmodium parasites in thin blood smear images, the method uses Artificial Neural Networks (ANN). Images of infected and non-infected erythrocytes was acquired, pre-processed, and significant features extracted, after which a diagnosis was performed based on the extracted features. 94.0 percent classification accuracy.

The approach of evaluating the clinical status described by MagudeeswaranVeluchamy, et al [3] is counting of cell kinds based on attributes that it possesses. There is a need for a rapid, repeatable approach for cell classification that is superior to human examination. Quantitative image digital- analysis is used to solve these challenges, and a unique approach for separating damaged blood cells from normal blood cells in a microscopic section image is offered. These images of blood cells were taken from patients with sickle cell anaemia, sickle cell disease, and healthy individuals. Furthermore, we employ a back propagation neural network to classify blood cells more effectively. Based on the features collected from the images, a decision was taken. 96.0 percent classification accuracy.

Automatic methods for detecting and classifying malarial parasites in thin blood smears are presented by Dipti D. Patankar et al [4]. Artificial Neural Networks (ANN) and Bayesian Networks (BN) are two promising methodologies utilized for this. To identify infected erythrocytes and the type of plasmodium, morphological parameters such as form, and size are used.

Chawla, et al. [5] Medical images must be noiseless to be used in the diagnosis process. Most of the images, however, are marred by noise and artefacts. An effective CT image de-noising technique is proposed to achieve this de-noising of CT images. The suggested technique improves image quality by removing additive white Gaussian noise from CT images. Preprocessing, training, and testing are the three steps of the proposed project. The CT image that is impacted by AWGN noise is altered using multi wavelet transformation in the preprocessing step during the training period. In the training phase the obtained multi-wavelet coefficients are fed as input to ANFIS.

Sudhansu Kumar Mishra, et al [6] introduce a functional link ANN (FLANN) as an alternative ANN structure for image de-noising. In contrast to a multilayer perceptron (MLP), the FLANN is a single layer structure in which nonlinearity is introduced by augmenting the input pattern with nonlinear function expansion. Three distinct expansions are used in this work. Image de-noising is a difficult task in digital image processing research and application, according to Yazeed A. Al-Sbou et al [7]. This necessitates the development of a reliable mechanism for completing the task. The performance of employing neural networks as a noise reduction method is evaluated in depth in this research.

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Image restoration is a key aspect of image processing, according to Suchitra Sarangi, et al [8]. This research provides a functional link artificial neural network-based image restoration technique that can reduce the amount of Gaussian noise in an image. After that, a comparison was made between the proposed filter and the current filters. Finally, some conclusions are offered, as well as future study lines.

JunyuanXie, et al. [9] offer a unique solution to low-level vision issues that combines sparse coding and pre-trained deep networks with de-noising auto-encoders (DA). We offer a new training approach for image de-noising and blind painting that successfully adapts DA, which was initially designed for unsupervised feature learning, to these tasks.

The creation of four ANNs for de-noising of digital images contaminated with additive white Gaussian noise or salt and pepper noise is described by Snigdha Mohanty, et al [10]. Multilayer perceptron using the popular back propagation algorithm, DLFANN, FLANN, and MFLANN have all been implemented in this study, and extensive computer simulation has been carried out to compare the performance of these algorithms.

Leipo Yan, et al. [11] offer a new method for image denoising based on a new neural network dubbed the noisy chaotic neural network (NCNN). The original Bayesian framework for image de-noising is restated using continuous relaxation labelling as a restricted optimization problem. To solve the optimization problem, the NCNN is used, which combines the simulated annealing technique with the Hopfield neural network (HNN).

Sheenum Marwaha, et al. [12] give a brief overview of computer-assisted automated diagnosis strategies that employ Digital Image Processing, their advantages, and the diseases that these systems diagnose. However, because the CAD system has numerous flaws, new approaches must be developed that combine the advantages of other categorization systems with CAD.

Ms. Deepali G., et al. [13] discuss computerized diagnostics, which will aid in the early discovery of the disease to a degree, allowing for adequate treatment of the malaria patient. A reliable image processing algorithm is also utilized to detect the presence of malaria. By extracting red blood cells (RBCs) from blood photos and identifying them as normal or parasite infected.

S. S. Savkare, et al., [14] proposes an automatic technique for detecting malaria parasites from blood photographs. Manual parasite counting is arduous and time intensive, necessitating the assistance of experts. The proposed automated approach is implemented. For cell segmentation, Otsu thresholding is used on the grey image and green channel of the blood image, the watershed transform is used to separate touching cells, color and statistical features are extracted from segmented cells, and the SVM binary classifier is used to classify normal and parasite infected cells.

Image analysis experiments aimed at automated diagnosis or screening of malaria infection in microscope images of thin blood film smears are reviewed by Pallavi T. Suradkar, et al, [15]. Malaria is a mosquito-borne infectious disease that affects people and other animals and is caused by Plasmodium parasites (a type of microorganism). The parasites are introduced into the body through a bite from a female mosquito that has been infected.

III. METHODOLOGY

This work focuses on detecting malaria through imaging. Detection of erythrocyte parasites is very important for the detection of malaria. In the thin image, the blood smear was highlighted in the process model. Noise reduction was thought to reduce unwanted image effects that frequently occur during sample preparation and imaging, such as uneven lighting, salt and pepper

noise, and image blur. This operation served to remove any parasitic noise present in the image. Images were pre-processed by median filtering with a 5 x 5 filter kernel to remove noise. Then I scaled the image to the same size. Then, identification of infected erythrocytes was performed with a trained neural network using the RGB functions of erythrocytes as input. General Block Diagram of Malaria Detection process is shown in fig.3.1.

FIGURE

The projected ANN Based System for the Detection of Malaria in Blood Smear Images consists of five steps:

1. Extraction of abnormal images from input images
2. Segmentation of affected parts by means of segmentation algorithm
3. Feature extraction from segmented areas.
4. Diagnosis based on the extracted features.
5. Classification of the infected and uninfected by malaria.

The steps that have been applied with inside the process are: -

A. Image Filtering

In image processing, filtering is a method of improving forms and selectively emphasizing on specific data. To remove noise from the image, standard median and mean filters are applied.

B. Image Pre-processing

The purpose of this stage is to improve the image quality so that it may be used in later procedures. The major goals of image pre-processing are basically two. The first is to resize the image in order to either magnify it through digital zooming or to reduce its size in order to speed up processing. The second goal is to improve image brightness for visual assessment.

C. Image Segmentation

The goal of image segmentation was to accomplish two things. The first was to separate individual RBCs from the blood, and the second was to separate Plasmodium parasites from infected RBCs. There are two image segmentation schemes. The first is histogram thresholding, which is an outdated image segmentation approach, and the second is the use of an ANN for picture segmentation. The entire blood cells are detected via image segmentation.

The algorithm steps for RBC segmentation are:
•Load a s pre-processed sample image that is to be segmented.
•Notice the corresponding image of the HSI sample.
•In RGB images, notice the green component image, and in HSI images, notice the hue and saturation components.
•Segment RBCS in the green, hue, and saturation component images using Otsu's technique.
•Find the coordinates of the bounding rectangles that surround each object.

D. Feature Extraction

Once image segmentation is complete, features can be derived from the image and diagnostic algorithms can be developed to accurately detect infected /uninfected regions. These parameters are grouped together in a vector form and are called feature vectors. Attributes can be generated from images, such as average image intensity, image histogram moments, shape signature, and object area, or they can be extracted directly from images, such as raw image pixel values.

E. Classification

The classification of sample images is done using ANN. The ANN is supplied with feature extracted images. A feedforward network with one input layer consisting of three neurons, one hidden layer and two output neurons, is shown in figure 3.2.

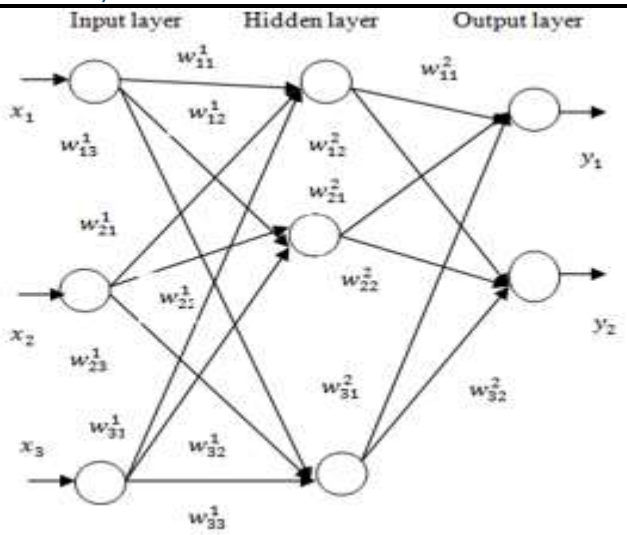

Fig.3.2 Feed forward artificial neural network

In the above figure, x_i is the input to the network, w^1_{ii} is the weight of the input x_i to the hidden layer, and y_i is the output. The network is trained using the Back Propagation technique.

IV. EXPERIMENTAL VALIDATION

A. Image Rescaling: Figure 4.1 displays the pre- and post-scaling normalization of two images from the CDC and KEMRI. Figure 3(a) is a CDC image with a resolution of 1600 x 1600 pixels, while Figure 4.1(b) is a KEMRI blood sample image. The generated images after image rescaling are shown in Figures 4.1 (c) and (d).

After image rescaling, the CDC image size was decreased to 300 x 300 pixels, and it was also necessary to preserve useful elements such as erythrocytes, parasites, and background regions, which were all preserved. After rescaling, the KEMRI image size remains unchanged. As a result, the image rescaling algorithm has generated the desired rescaling results for both KEMRI and CDC images. Image rescaling is a time-consuming process. Image rescaling is essential for making computations at various phases of image processing, such as feature extraction and image segmentation, go as quickly as possible.

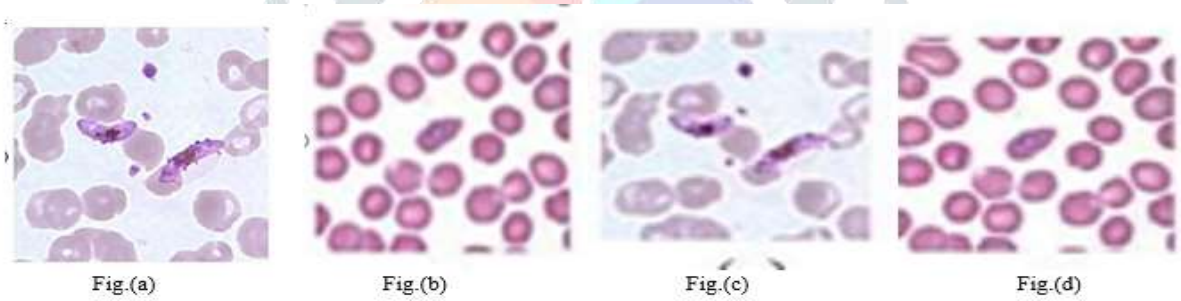

Fig.4.1. CDC and KEMRI images pre- and post-scaling

B. Noise Reduction: The rescaled KEMRI and CDC images are shown in Figures 4.2 (a) and (d), respectively, (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. The median filter is used to filter the pictures, and the erythrocytes are segmented before and after filtering. As can be observed from the data, there is no difference between two binary pictures for the KEMRI image, however image segmentation

after filtering resulted in a significant improvement in binary image quality for the CDC image. This is due to noise, which has deteriorated the CDC images. This effect is mitigated by median filtering. Unbalanced lighting of the sample in the microscope, sample degradation, or inadequate sample preparation are all possible sources of noise. Random noise, often known as salt and pepper noise, was minimized and image quality was maintained as a result of median filtering.

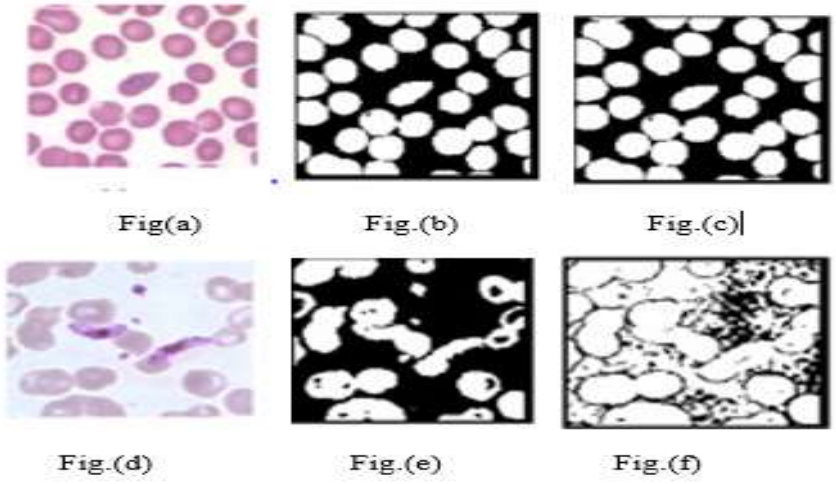

Figure 4.2. Effect of image filtering

C. Erythrocyte Segmentation Using Histogram: Otsu's technique is utilized with their threshold values to obtain the Histograms of sampled images from CDC and KEMRI. Figures 4.3 show the results of erythrocyte segmentation tests using CDC image histograms. Figure (a) shows pre-processed image from CDC, whereas (b), (c), and (d) shows resultant binary images obtained from thresholding the green, hue, and saturation component images. The green component image segmented the erythrocytes well in the CDC image, but it also recorded the plasmodium parasite patches in the foreground. The color component produced a binary image with chaotic borders in the foreground (erythrocyte areas). Instead of producing erythrocytes as the objects, the saturation component segmented the parasites.

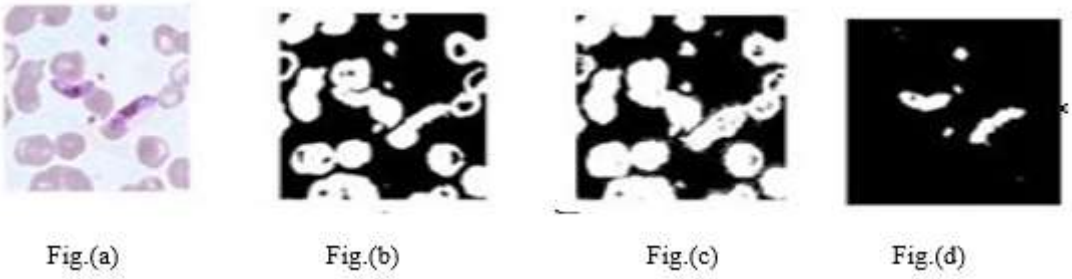

Figure 4.3. CDC image histogram thresholding

The same test was performed on a KEMRI image to see which color component image would provide the best erythrocyte segmentation results. Figure 4.4 displays the KEMRI image in fig.(a) and the binary images that resulted are shown in fig.(b),(c) and (d).

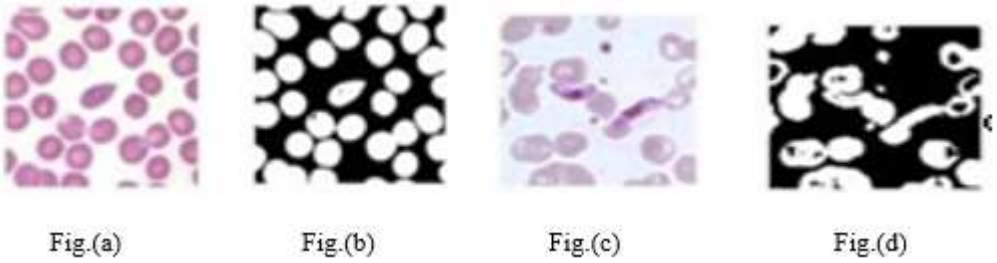

Figure 4.4. KEMRI image histogram thresholding

The image color components green, hue, and saturation are derived from the equivalent green, hue, and saturation image color components. The binary images from the green component of RGB images and the saturation component image created nice erythrocytes regions, while the hue component image produced a noisy binary image, as seen in the CDC image.
The green color component of an RGB image is the most suitable for segmentation utilizing histogram segmentation approaches, based on these findings.

D. ANN Segmentation of Erythrocytes: Two ANN classifiers were employed to segment erythrocytes. The first classifier was taught using only RGB picture pixel values, while the second classifier was trained using both RGB and HSI image pixel values. The classification accuracy in percentage achieved by the two ANN classifiers is shown in Table 4.5. The performance of both ANN classifiers is outstanding, i.e. above 96%, as shown in Table 4.5, however the performance of the network trained solely with RGB features has provided a decent result when compared to the network trained with both RGB and HSI variables.

Table 4.5. Performance of erythrocyte segmentation using ANN classifiers

Sl.No.	Feature vector	Training %	Validation %	Testing %	Over all %
1	RGB Feature vector	100	100	100	100
2	RGB+HSV Feature vector	100	96.3	100	98.4

The same images used in histogram segmentation, one from KEMRI and the other from CDC, were segmented using the Artificial Neural Network trained with RGB characteristics which are shown in figure 4.6. Figure (a) is the pre-Processed image from KEMRI, (c) is the pre-processed, image from CDC.It should be noted that figure (b) and(d) are the resultant binary images obtained as the outputs of ANN trained to segment erythrocytes.
The ANN succeeded to catch the erythrocyte areas well in both the CDC and KEMRI pictures, as can be seen in these images.

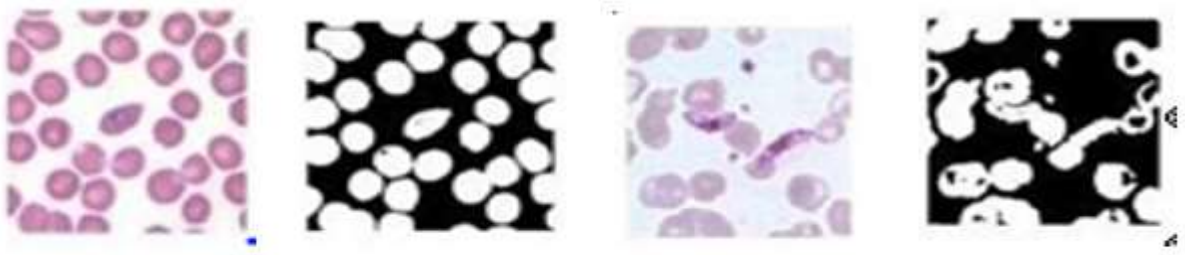

Fig.(a) Fig.(b) Fig.(c) Fig.(d)

Figure 4.6. ANN Segmentation of Erythrocytes

V.CONCLUSION

The results show that when using histogram segmentation approaches, the green color component of an RGB image is the most suitable for segmentation.
The Artificial Neural Network Algorithm produces exceptional results, with a success rate of over 96%. When compared to the network trained with both RGB and HSI features, the network trained exclusively with RGB features performed somewhat better. As a result, we may conclude that the neural network classification accuracy drops as the number of features increases while the sample size remains constant. RGB characteristics are sufficient for utilizing an ANN to differentiate erythrocytes from the rest of the thin blood smear image.

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 Maitethia Memeu, Kenneth Amiga Kaduki, Mjomba Allen Christopher Kale, Njogu Samson Muriuki, "Determination of Plasmodium Parasite Life Stages and Species in Images of Thin Blood Smears Using Artificial Neural Network", Open Journal of Clinical Diagnostics, 4,2014, pp: 78-88.
[3] MagudeeswaranVeluchamy, Karthikeya Perumal and Thirumurugan Panchami "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, Kavita Grewal, "Hybrid Filtering Technique for Image Denoising Using Artificial Neural Network", IJEAT Volume-1, Issue-3, August 2012.
[6] Sudhansu Kumar Mishra, Ganapati 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] Subhadra Sarangi, Shubhendu Kumar Sarangi, Sunita Sarangi, "Performance Analysis of Filter based on Functional Link Artificial Neural Network", IJCA, Volume 93 – No 1, May 2014.
[9] JunyuanXie, Lilius, Enhong Chen, "Image Denoising and in painting with Deep Neural Networks", Advances in Neural Information Processing Systems 25 (NIPS 2012), pp:1-9.
[10] Snigdha Mohanty, 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] Akutagawa Mastake, ChanYongjia, Katayama Masato, YohsukeKinouchi, QinyuZhang, "Additive and multiplicative noise reduction by back propagation neural International, 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] Sheenum Marwaha, Hemant Monga, 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. Deepali Ghate, 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 Estimating Parasitemia", 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.