Int. J. of Comp. & Info. Tech., (2017) 5(2): 81-92.

IJOCIT

ISBN: 2345-3877
www.ijocit.org
Volume 5, Issue 2

Review Paper

Detection of Malarial Parasite in Blood Images by two classification Methods: Support Vector Machine (SVM) and Artificial Neural Network (ANN)

Saeid Afkhami [1, *]
Hassan Rashidi Heram-Abadi[2]

Received: 11 Dec 2016
Accepted: 02 Apr 2017

Abstract
Malaria is an infectious disease caused by microorganism and it poses major threat to global health zone. Brisk and accurate diagnosis is required to control the disease. Automation of the evaluation process in the diagnosis of malaria is high important. There are many systems that describe the computerized methods of image analysis that common involves three main phases. First, pre-processing, where the images are corrected for luminance and transformed to a constant color space. Second, a histogram based image segmentation processing where the maximum artifacts and over stained objects are avoided. Third, feature extraction where may be along with a multi-layer, feed forward, back propagation neural network was employed for classifying the objects. We have review on artificial neural networks (ANN) and support vector machine (SVM) for the diagnosis of the disease in the red blood cell. In this methods features and parameters are computed from the data obtained by the digital holographic images of the blood cells and is given as input to ANN or SVM which classify the cell as the infected one or otherwise. The support vector machine (SVM) models are a close cousin to classical multilayer perceptron neural networks and using for develop an image processing algorithm to automate the diagnosis of malaria on thin blood smears.

Keywords: Malaria, blood cells, microscopic images, classification, feature extraction, ANN, SVM.

Citation: Afkhami, S., Rashidi Heram-Abadi, H., (2017). Detection of Malarial Parasite in Blood Images by two classification Methods: Support Vector Machine (SVM) and Artificial Neural Network (ANN), *Int. J. of Comp. & Info. Tech. (IJOCIT)*, 5(2): 81-100.

[1] Faculty of Computer and Information Technology Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran
[2] Department of Mathematics and Computer Science, Allameh Tabataba'i University, Tehran, Iran
[*] Corresponding Author: afkhami@qiau.ac.ir

Introduction

Malaria is an ancient disease present majorly in the tropical countries having a huge social, economic, and health burden. In recent times, as a result of climatic changes due to global warming, it is predicted to have unexpected effects on Malaria. Both increase and fluctuation in temperature affects the vector and parasite life cycle. An efficient diagnostics is essential for the proper medication and cure. Major clinical diagnostics to identify RBCs affected by malaria is based on microscopic inspection of blood smears, treated with reagents, which stains the malarial parasite. A technician visually inspects these smears to identify malaria-infected red blood cells (RBCs). In developing countries, visual identification of malarial RBCs may become inefficient due to lack of sufficiently trained technicians and poor-quality microscopes and regents. During such hematologic disorder the changes occur in the structure and viscoelastic properties of individual RBCs. So studying their physical properties can thus contribute greatly to the understanding and possible discovery of new treatments for such diseases. Thus, new advanced mathematical computing techniques are valuable for determining and distinguishing between the healthy and diseased RBCs [1].

In [2], Anand and at el. have used correlation technique on the images obtained from DHIM to discriminate the malarial cells from the healthy ones. An efficient computational techniques, based on the 3-D images produced by digital holographic interfeometric microscopy (DHIM) [3], to automatically discriminate between malarial and healthy RBCs can be very beneficial. It will be advantageous if such DHIM capturing instruments are portable and easy to use. We propose the technique to distinguish the malaria infected RBCs from the healthy ones using Artificial Neural Network (ANN), based on its physical or statistical features that are extracted from the images obtained from Digital Holographic Interferometric Microscope (DHM). Artificial Neural Network (ANN) for malaria diagnosis is one time trained intelligent program which is easy to use, portable, low cost and make malaria diagnosis more rapid and accurate [4].

A hologram is the photographically or otherwise recorded interference pattern between a wave field scattered from the object and a coherent background, called the reference wave. The digital holographic interferometric microscopy, comparisons of phases at the image plane, obtained from the recorded holograms with the object present and with just the background, provides object phase information. This can be converted into thickness information of cells. Then efficient computational techniques will be applied on the 3-D images produced by DHM for micro objects, to automatically discriminate between malarial and healthy RBCs [5]. Dennis Gabor invented holography in 1948 as a method for recording and reconstructing the amplitude and phase of a wave-field. The word holography is derived from the Greek words ‘holos’ meaning ‘whole’ or ‘entire’ and ‘graphein’ meaning ‘to write’. A hologram is the photographically or otherwise recorded interference pattern between a wave field scattered from the object and a coherent background, called the reference wave.

Literature Review

The literature review summarizes all the relevant literature researched during the course of this paper. It presents certain approaches used by many researchers for classification. It also compares the performance of all classifier with other common classifier with same parameters. Finally the best parameters and classifier combination is discussed.

Various works are going on analyzing microscopic images to point out the presence of infection. According to the World Health Organization (WHO), it causes more than 1 million deaths arising from approximately 300–500 million infections every year. Manual microscopy for the examination of blood smears is widely accepted as a good standard for malaria diagnosis. An automated diagnosis system can be designed by understanding the diagnostic expertise and representing it by specifically tailored image processing, analysis and pattern recognition algorithms [6]. A complete system must be equipped with functions to perform: image acquisition, preprocessing, segmentation (object localization), and classification tasks [7, 8, 9]. In order to perform diagnosis on peripheral blood samples, the system must be capable of differentiating between malarial parasites, artifacts, and healthy blood components.

In [10] illustrate a technique for identifying the malaria for blood cell images. This paper involves the counting of Blood cell using an adaptive OTSU thresholding technique. Which use to segment the image and separate the RBC and WBC for Counting? The paper also considers the area of cells to declare severity. The paper uses SVM as Classifier for declaring the result of whether the patient is affected by Malaria or not. The proposed automated method for segmentation and classification of cell is simple [11, 12]. An approach is proposed to detect

red blood cells with consecutive classification into parasite infected and normal cells for estimation of parasitemia. The extraction of red blood cells achieves a reliable performance and the actual classification of infected cells. Sensitivity of system is 93.12%, and Specificity is 93.17%. Shape based and statistical features are generated for classification. The features are selected for recognition of two classes only. This approach leads to the high specialization of each classifier and results in an overall increase in accuracy.

Raviraja and et al. [13] introduces a blood image processing for detecting and classifying malarial parasites in images of Giemsa stained blood slides, in order to evaluate the parasitamia of the blood. To detect the red blood cells that are infected by malarial parasites, statistical based approach is used. To separate automatically the parasites (trophozoites, schizonts and gametocytes) from the rest of an infected blood image, color, shape and size information are used and later the image is compared with infected images after transformation of image by scaling, shaping to reconstruct the image. The images returned are statistically analysed and compare to generate a mathematical base [14]. Also the evaluation of the size and shape of the nuclei of the parasite is also considered.

The last proposed systems mainly concentrate on development of sensitive malarial detection system for images of (JSB) stained thick blood slides acquired from conventional light microscopes. Malaria is a life-threatening disease caused by parasites that are transmitted to people through the bites of infected mosquitoes. Light microscopy enables the visualization of malarial parasites in a thick or thin smear of the patient's blood [15].

Part I: ANN Classification on RBC

A. Digital Hologram

The general set-up for recording off-axis holograms is shown in figure 1. Light with sufficient coherence length is split into two partial waves by a beam splitter (BS). One wave illuminates the object, is scattered and reflected to the recording medium, e.g. a photographic plate. The second wave, called the reference wave, illuminates the plate directly. Both waves are interfering. The interference pattern is recorded, e.g. by chemical development of the photographic plate. The recorded interference pattern is called a hologram.

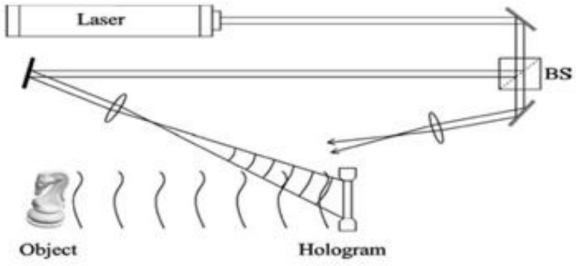

Figure 1. Hologram Recording [2].

The original object wave is reconstructed by illuminating the hologram with the reference wave, figure 2. An observer sees a virtual image, which is indistinguishable from the image of the original object. The reconstructed image exhibits all the effects of perspective and depth of focus.

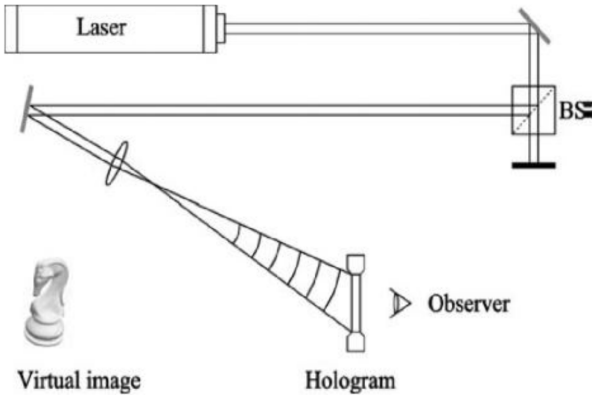

Figure 2. Hologram reconstruction [2].

The holographic process is described mathematically as follows:

$$O(x,y) = o(x,y)\exp\left(i\varphi_o(x,y)\right) \quad (1)$$

Equation (1) the complex amplitude of the object wave with real amplitude o and phase φ_0 and,

$$R(x,y) = r(x,y)exp(i\varphi_R(x,y)) \quad (2)$$

Equation (2) gives the complex amplitude of the reference wave with real amplitude r and phase φ_R both waves interfere at the surface of the recording medium. The intensity is calculated by:

$$I(x,y) = |O(x,y) + R(x,y)|^2 \quad (3)$$

$$= \left(O(x,y) + R(x,y)\right)(O(x,y) + R(x,y))^*$$

$$= R(x,y)R^*(x,y) + O(x,y)O^*(x,y) +$$

$$O(x, y)R^*(x, y) + R(x, y)O^*(x, y)$$

where * denotes the conjugate complex. The amplitude transmission $h(x, y)$ of the developed photographic plate (or any other recording media) is proportional to $I(x, y)$, that is,

$$h(x, y) = h_0 + \beta\tau I(x, y) \quad (4)$$

where β is a constant, is the exposure time and h is the amplitude transmission of the unexposed plate. $h(x, y)$ is also called the hologram function. In digital holography using charge-coupled device detector CCDs as recording medium h can be neglected. For hologram reconstruction the amplitude transmission has to be multiplied with the complex amplitude of the reconstruction (reference) wave:

$$R(x, y)h(x, y) = [h_0 + \beta\tau(r^2 + o^2)]R(x, y) + \beta\tau r^2 O(x, y) + \beta\tau R^2(x, y)O^*(x, y) \quad (5)$$

The first term on the right side of this equation is the reference wave, multiplied by a factor. It represents the diffracted wave passing through the hologram (zero diffraction order). The second term is the reconstructed object wave, forming the virtual image. The factor only influences the brightness of the image. The third term produces a distorted real image of the object. For off-axis holography the virtual image, the real image and the undiffracted wave are spatially separated.

B. Recording in Digital holography

In a set-up for digital recording of off-axis holograms is shown in figure 3. A plane reference wave and the wave reflected from the object are interfering at the surface of a CCD. The resulting hologram is electronically recorded and stored. The object is, in general, a three-dimensional body with diffusely reflecting surface, located at a distance d from the CCD.

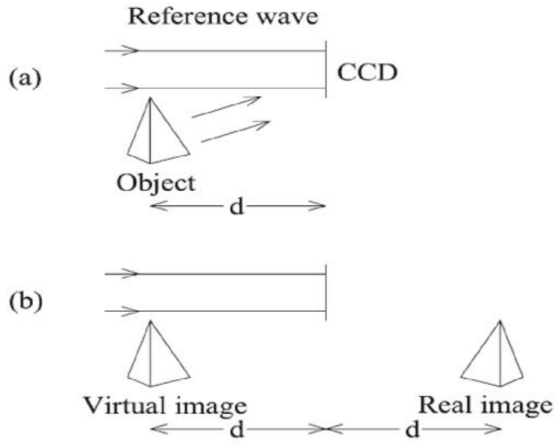

Figure 3. Digital holography: (a) recording, (b) reconstruction [2]

In optical reconstruction the virtual image appears at the position of the original object and the real image is formed also at a distance d, but in the opposite direction from the CCD, see figure 3(b). The diffraction of a light wave at an aperture (in this case a hologram) which is fastened perpendicular to the incoming beam is described by the Fresnel–Kirchhoff integral.

$$\Gamma(\xi,\eta) = \frac{i}{\lambda}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(x,y)R(x,y)\frac{\exp(-i\frac{2\pi}{\lambda}\rho)}{\rho} \times \left(\frac{1}{2}+\frac{1}{2}cos\theta\right)dx\,dy$$

$$\rho = \sqrt{(x-\xi)^2+(y-\eta)^2+d^2} \quad (6)$$

Where, ρ is the distance between a point in the hologram plane and a point in the reconstruction plane, see figure 4. The angle θ is also defined in figure 4. The diffraction pattern is calculated at a distance d behind the CCD plane, which means it reconstructs the complex amplitude in the plane of the real image. Equation (6) is the basis for numerical hologram reconstruction. Because the reconstructed wave field (ξ, η) is a complex function, both the intensity as well as the phase can be calculated. This is in contrast to the case of optical hologram reconstruction, in which only the intensity is made visible.

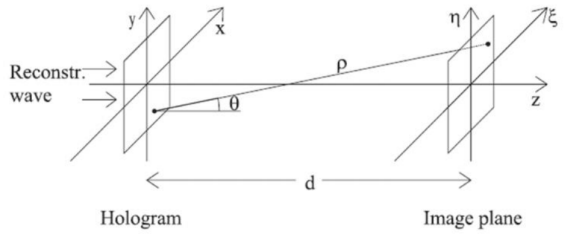

Figure 4. Coordinate system [2]

The set-up of figure 4 is often used in digital holography, because a plane wave propagating perpendicularly to the surface of the CCD can be easily arranged in the laboratory. Another advantage is that for this geometry the reconstructed real image has no geometrical distortions.

C. Reconstruction by the Fresnel transformation

For x and y values as well as for ξ and η values which are small compared to the distance d between the reconstruction plane and the CCD expression (4) can be replaced by the first terms of the Taylor series:

$$\rho = d + \frac{(\xi - x)^2}{2d} + \frac{(\eta - x)^2}{2d} - \frac{1}{8}\frac{[(\xi - x)^2(\eta - x)^2]}{d^3} + \ldots \approx d + \frac{(\xi - x)^2}{2d} + \frac{(\eta - x)^2}{2d} \quad (7)$$

With the additional approximation $\cos(\theta) \approx 1$. By replacing the dominator in (3) by the following expression results:

$$\Gamma(\xi,\eta) = \frac{i}{\lambda d}\exp\left(-i\frac{2\pi}{\lambda}d\right)\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} R(x,y)h(x,y) \times \exp\left[(-i\frac{\pi}{\lambda d})((\xi - x)^2 + (\eta - y)^2)\right] dx\, dy \quad (8)$$

If we carry out the multiplications in the argument of the exponential under the integral we get:

$$\Gamma(\xi,\eta) = \frac{i}{\lambda d}\exp\left(-i\frac{2\pi}{\lambda}d\right)\exp\left[\left(-i\frac{\pi}{\lambda d}\right)(\xi^2+\eta^2)\right] \times \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} R(x,y)h(x,y)\exp\left[\left(-i\frac{\pi}{\lambda d}\right)(x^2+y^2)\right] \times \exp\left[i\frac{2\pi}{\lambda d}(x\xi + y\eta)\right] dx\, dy \quad (9)$$

This equation is called the Fresnel approximation or Fresnel transformation. It enables reconstruction of the wave field in a plane behind the hologram, in this case in the plane of the real image. The intensity is calculated by squaring:

$$I(\xi,\eta) = |\Gamma(\xi,\eta)|^2 \quad (10)$$

The phase is calculated by:

$$\varphi(\xi,\eta) = arctan\frac{Im[\Gamma(\xi,\eta)]}{Re[\Gamma(\xi,\eta)]} \quad (11)$$

Where, *Re* denotes the real part and *Im* the imaginary part. These phase values are used for further processing of the DHMI of the RBCs.

D. Artificial Neural Networks (ANNs)

Artificial Neural Network (ANN) is massively parallel, distributed processing systems representing a computational technology built on the analogy to the human information processing system. They are massively connected networks of simple processing elements called neurons. They have a natural propensity to learn and save the knowledge to make it available for use. ANNs can be used for classification, pattern recognition and function approximation [16]. It is an information processing system consisting of large number of interconnected processing units. It works in a way our nervous system processes the information. It is basically a dense interconnection of simple non-linear computational elements. It has been successfully applied to problems involving pattern classification, function approximation, regression, prediction and others. The biological aspects of neural networks were modeled by McCullough and Pitts in 1943 [17]. This model exhibits all the properties of neural elements like excitation potential thresholds for neuron firing and non-linear amplification which compresses the strong input signal. Various kinds of Neural Networks are used for different purpose. Single-layer Perceptron, Multi-layer Perceptron,

Hopfield recurrent networks, Kohonnen self-organizing networks, Radial Basis Function Networks, Support Vector Machines and Extreme Learning Machines are most common amongst them [18]. The fundamental element of neural network is neuron. It is an operator, which maps $\mathbb{R} \rightarrow \mathbb{R}$ and it is explicitly described by the equation.

$$y_j = f\left(\sum_{i=1}^{n} w_{ji}x_i + w_0\right) \quad (12)$$

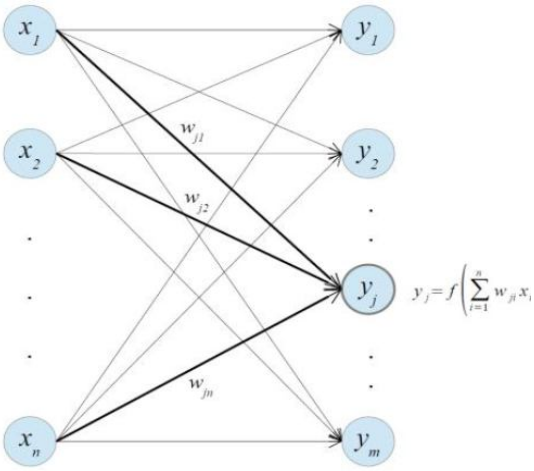

Figure 5. Feed forward Neural Network [19]

The Networks are categorized into mainly two categories: Feed Forward and Recurrent. The learning algorithms are categorized in three types: supervised learning, unsupervised learning and reinforced learning. We have used multi-layer network Radial Basis Function Network, which is a supervised learning algorithm. Learning (or Training) is a process by which a network adapts changes by adjusting its changeable parameters i.e. weights. They change in such a way that there is an association between set of inputs and desired outputs. In Artificial Neural Networks, The general rule for weight updating is: $W_{k+1} = W_k + \Delta W_k$.

ANN plays a primary role in contemporary artificial intelligence and machine learning. The use of ANN in function approximation resulted from the following facts [19]:

- Cybenko and Hornik proved that the multi-layered Neural Network is universal approximate. It can approximate any continuous function defined on compact set.
- The Back-propagation algorithm used for the training of the feed-forward Neural Networks with the hidden layers.

The Multi-layer feed forward network (MFFN) trained with Back Propagation Rule is one of the most important neural network model. In the real practical situations when there is the lack of the mathematical model for the system, the ANN can be trained with the help of input-output pairs without fitting any kind of model to the system. The fundamental element of neural network is neuron. We can refer to neuron as an operator, which maps $\mathbb{R} \rightarrow \mathbb{R}$ and is explicitly, described by the equation (13).

$$x_j = \Gamma\left(\sum_{i=1}^{n} w_{ji}u_i + w_0\right) \quad (13)$$

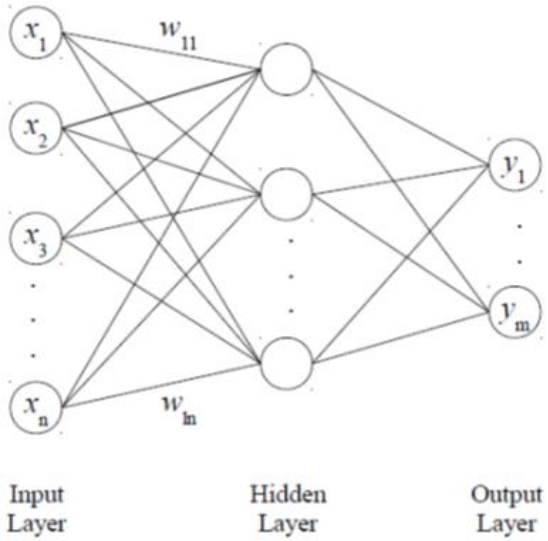

Figure 6. A Multi Layered Feed-Forward Network [19]

E. Experimental Results

We have the holographic image data for 48 RBC, which are processed and then various features are obtained in following manner. The phase data for the cells are obtained in gray scale to which thresholding or masking is done for the selection of portion of the image to work with. The images obtained after converting it into grey scale for image

of edge for different mask values 0.28 and 0.3 is shown in following figures:

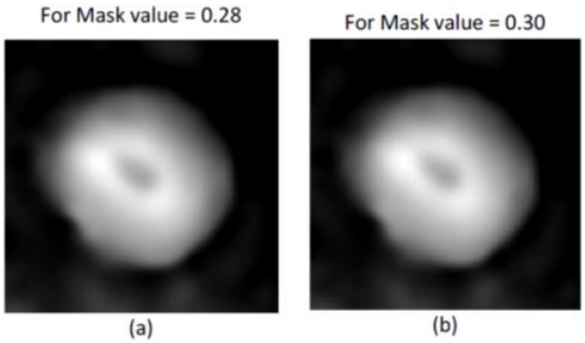

Figure 7. Image obtained after converting to black and white [1]

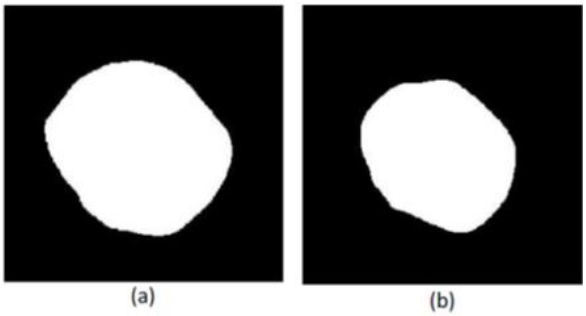

Figure 8. Image obtained after converting into binary, to find area of RBC

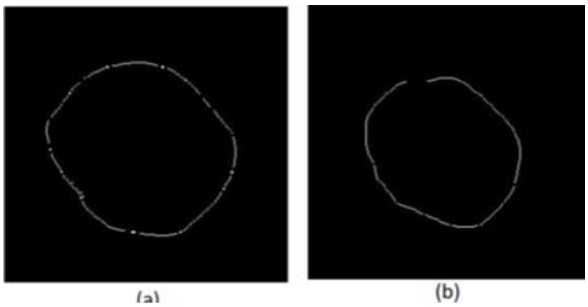

Figure 9. Image obtained after detecting edges, to find perimeter of RBC [18].

Once the portion of RBC image was selected the parameters were calculated for it like taking average of the phase of the image, standard deviation and coefficient of variation. To find the area we count the number of pixels selected for processing and the border pixels to obtain the perimeter. Circularity is calculated using the formula:

$$c = \frac{4\pi A}{p^2} \tag{14}$$

Ideally, healthy RBC is doughnut shaped and infected RBC becomes spherical due to growth of parasites within the RBC. In our work the detection of healthy and infected RBC is done using six parameters. Table 1 and Table 2, shows such calculated values of six parameters: area, perimeter, circularity, mean, standard deviation, and covariance. These parameters were obtained using holographic images of 24 healthy RBC and 24 infected RBC.

Table 1. Parameter values for Healthy cells [19]

	Parameters of 24 Healthy cells					
	Area	Perimeter	Circularity	Mean	Std	Cov
1	32983	589	1.0930	0.6479	0.8203	0.6729
2	29156	560	1.0809	0.5883	0.8281	0.6858
3	22000	515	1.0210	0.5446	0.8771	0.7693
24	19314	475	1.0372	0.4604	0.7787	0.6064

Table 2. Parameter values for Malaria infected cells [19]

	Parameters of 24 Malarial cells					
	Area	Perimeter	Circularity	Mean	Std	Cov
1	23987	558	0.9839	0.5146	0.8028	0.6445
2	26365	534	1.0779	0.5585	0.7518	0.5651
3	22401	480	1.1053	0.4538	0.7012	0.4916
24	22640	498	1.0711	0.3867	0.6574	0.4322

The six parameters obtained after preprocessing on holographic images are used as inputs for the detection of malaria infected and healthy cells to the Artificial Neural Network (ANN). The outputs of ANN are binary bipolar, -1 stands for healthy and 1 stands for infected RBC. MATLAB is used to create Feed-forward neural network. The training was done using Back-propagation. We had 48 patter10s consisting of 24 healthy and 24 malarial cells, out of which 5 healthy and 5 malarial random patterns are kept for testing and remaining 38 patterns are used for training purpose. We considered an ANN with architecture this network got trained in 120 iterations as shown in figure 10. The error convergence and the state performance as shown in figure 11.

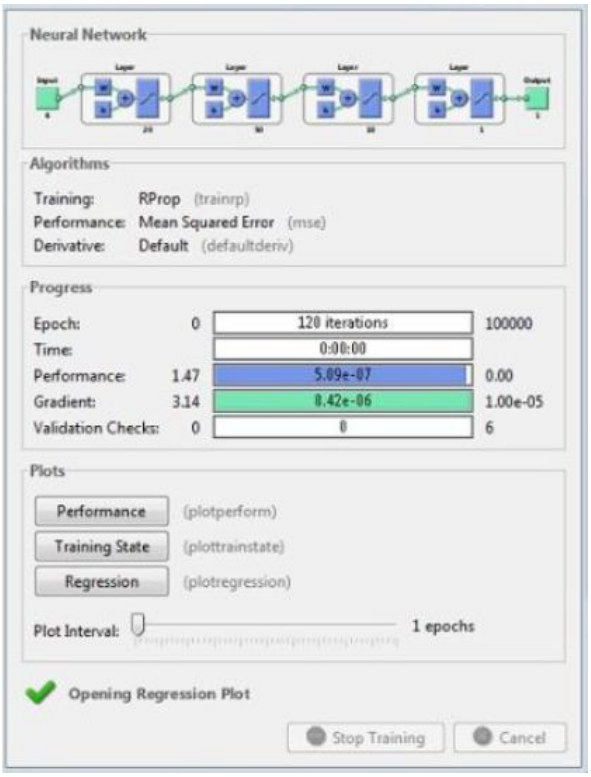

Figure 10. Trained ANN Window

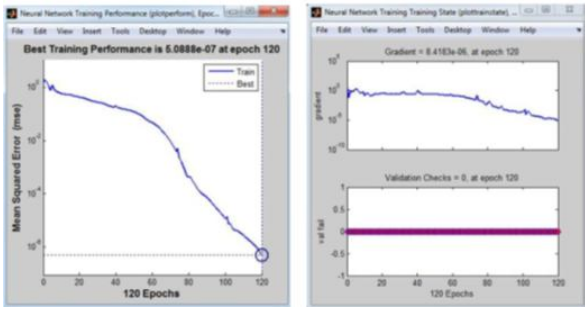

Figure 11. Training Performance and Training state

This trained network is the tested for the remaining testing patterns. The simulation results for the trained as well as testing inputs are as shown in the Figures 12 (a) and (b). The 90% results for the testing inputs are encouraging and justify the use of ANN for detection of the disease.

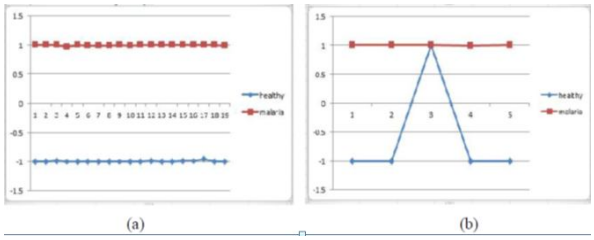

Figure 12. The classification by ANN for the: (a) training and (b) testing patterns

Part II: SVM Classification

A. System Modeling

There is problem with identifying the malaria diseases manually through the microscope and with the process of Giemsa the method is not so accurate. To solve this problem we have come with automatic algorithm that uses blood cell images to identify whether the patient is affected by malaria or not [20]. The objective is to develop an algorithm to identify the given blood image is affected by malaria or not. So, to achieve this problem I will develop an algorithm which serves as the preprocessing tool for the image analysis. A prototype consisting of existing software packages such as *Matlab* is used for feature extraction and classifier implementation.

The biggest detraction of microscopy, namely its dependence on the skill, experience and motivation of a human technician, is to be removed. Used with an automated digital microscope, which would allow entire slides to be examined, it would allow the system to make diagnoses with a high degree of certainty. It would also constitute a diagnostic aid for the increasing number of cases of imported malaria in traditionally malaria-free areas, where practitioners lack experience of the disease [6].

B. Working Methodology

The test algorithms illustrated above give an insight about the algorithm to be used for each stage. The process is given below (figure 13).

- Image Acquisition and database collection
- Image Analysis
- Image Segmentation
- Feature Generation
- Classification of Parasite and result verification

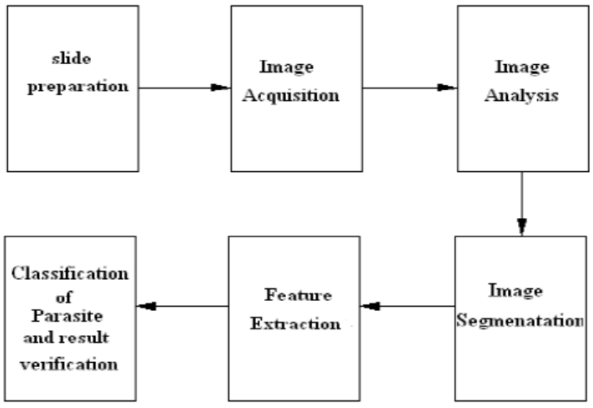

Figure 13. Process flow

Image Data Collection

The JSB stain is a rapid staining method for the detection of malarial parasites. This stain is superior to the Field's stain as the parasites stain clearer and the morphology of the parasites is visible even in thick smear. The JSB stain constitutes of JSB

- solution 1 (methylene blue (Medicinal) 0.5 gm, sulphuric acid (H2SO4) 1%, 3.0 ml, potassium dichromate (K2Cr2O7) 0.5 gm, disodium hydrogen phosphate dihydrate (Na2H PO4 2 H2O) 3.5 gm, distilled water 500 cc) and
- Solution 2 (eosine 1.0 gm, distilled water 500 cc).

The preparation of stain procedure was followed as recommended National Vector Borne Disease Control Programme (NVBDCP). Chromatin (part of the parasite nucleus) is usually round in shape and stains deep red. Cytoplasm occurs in a number of forms, from a ring shape to a totally irregular shape. It always stains blue, although the shade of blue may vary between the malaria species [21]. Images were acquired using microscope system – Leica DM1000 which is interfaced to a Leica DFC 295 camera using IEEE 1394 [7]. The slides are examined under oil immersion with 1000x magnification maintaining a constant image size of 640X480 pixels.

Image Processing

An image from JSB stained sample (thick) is prone to differ widely in the foreground or background color due to several conditions. This may be due to difference in the light source or filters, cameras, slide preparation. In order to have an analysis towards constant color characteristics, the images are normalized. The different Pre-Processing Techniques such As Filtering, Noise Removing and etc., can be applied.

Feature Extraction

A total of 60 samples were used for training. Each samples had number of normal and infected cells along with artefacts. The objects extracted from these samples are Parasites, WBC and artefacts. In order to classify the detected objects, twenty three image features were extracted from the detected objects for training the system. The feature includes intensity based Histogram features and shape measurement features. These features are extracted for different channel of color spaces namely gray, hue, saturation and luminosity (standard deviation). First order statistical features or histogram features: the histogram counts and the bin locations are pixelcounts and bin (256) respectively. The first order features are defined by the following equations (15 -21):

$$Mean = M = \frac{sum\ (bin\ .*\ pixelcounts)}{Total\ Number\ of\ pixels} \quad (15)$$

$$Variance = V = \frac{sum\ \left((bin - M)^2 .*\ pixelcounts\right)}{Total\ Number\ of\ pixels - 1} \quad (16)$$

$$Standard\ Deviation = SD = \sqrt{V} \quad (17)$$

$$Skewness = sk = \frac{sum\ \left((bin - M)^3 .*\ pixelcounts\right)}{Total\ Number\ of\ pixels - 1} \quad (18)$$

$$kurtosis = kr = \frac{sum\ \left((bin - M)^4 .*\ pixelcounts\right)}{Total\ Number\ of\ pixels - 1} \quad (19)$$

$$Fifth\ standard\ moment = M5 = \frac{sum\ \left((bin - M)^5 .*\ pixelcounts\right)}{Total\ Number\ of\ pixels - 1} \quad (20)$$

$$sixth\ standard\ moment = M6 = \frac{sum\left((bin - M)^6 . * pixelcounts\right)}{Total\ Number\ of\ pixels - 1} \quad (21)$$

Shape Measurement Features

Since these features are independent of color spaces, the following equations were directly applied to the binary mask image. Shape measurements can detect the changes in the size. The advantage of shape measurements is straightforward interpretation of the calculated feature values.

C. Neural Networks

To implement neural network Classifier neural network tool box (Mat lab 7.1) is used. The description of process can be easily got from mat-lab help [21]. To implement the Neural Network classifier the data set of table (5.2) is used from which 70% for training 15%Test and 15% for validating the network is used.

D. Support Vector Machine

A Support Vector Machine (SVM) performs classification by constructing an N-dimensional hyper plane that optimally separates the data into two categories. SVM models are closely related to neural networks. In fact, a SVM model using a sigmoid kernel function is equivalent to a two-layer, perceptron neural network shown by Fig. Support Vector Machine (SVM) models are a close cousin to classical multilayer perceptron neural networks. Using a kernel function, SVM's are an alternative training method for polynomial, radial basis function and multi-layer Perceptron classifiers in which the weights of the network are found by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard neural network training [22].

In the parlance of SVM literature, a predictor variable is called an attribute, and a transformed attribute that is used to define the hyper plane is called a feature. The task of choosing the most suitable representation is known as feature selection [23]. A set of features that describes one case (i.e., a row of predictor values) is called a vector. So the goal of SVM modeling is to find the optimal hyper plane that separates clusters of vector in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other size of the plane. The vectors near the hyper plane are the support vectors. The figure 14, presents an overview of the SVM process.

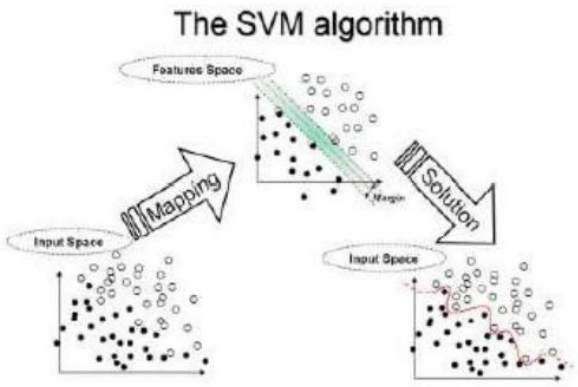

Figure 14. SVM Concept

E. Result Analysis

The performance of classifier is defined by the feature used to train the classifier. The results for the experiment are given in table. For the malaria images database the result obtained are as follows.

Table 1. Shows accuracy of algorithm for different methods

Method	Neural Network	ANFIS	SVM
Accuracy	65.23%	75.64%	97.12%

and for computational time:

Table 2. Computational Time

Method	Time Required
Neural Network	6.12
ANFIS	4.23
Support Vector Machine	2.56

In total, 20 images of blood cells were classified into categories of affected by malaria or unaffected. The performance of system is defined by a classifier used with existing set of a database. The result for the experiment is given in tables which show the accuracy of algorithm for different classifier in terms of percentage. Among 20 images for Test 15, 17 and 19 are correctly classified by Neural Network, ANFIS and SVM. The use of parameter extracted using GLCM and Other method work good with Neural Network better with ANFIS and finally best by using SVM as classifier.

Conclusion

Malaria is one of the most common diseases caused by mosquitoes and is a great public health problem worldwide. Currently, for malaria diagnosis the standard technique is microscopic examination of a stained blood film.

In the part I, we have determined various parameters by processing the holographic images of healthy as well as infected RBCs. We have used Artificial Neural Network (ANN) for the detection of malaria infected RBCs. In the proposed techniques for the detection of malaria infected RBCs done using ANN gives results almost from 90-100%. These results can be refined more by increasing the number of parameters and also the sample size of the data provided.

Also, in the part II, This project addresses how the identification of malaria diseases is possible using image processing by effectively analyzing various parameter of blood cell image by using GLCM as Energy and other like Skewness, Kurtosis, Standard Deviation. The experimental results indicate that the proposed approach is a valuable approach, which can be significantly support an accurate identification of malaria diseases in a little computational effort. There can be mistake in counting manually the number of RBC & WBC (process of Giemsa) as the boundaries are not clearly defined or visible which lead us to the error in wrong decision. So to solve this problem the developed algorithm be more helpful the other techniques. As this system can meet the real time application requirements, so we can easily have the standalone working version of this system.

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