Classification of White Blood Cells Using Modular Neural Network

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Abstract: **BLOOD tests are frequently employed to evaluate human health. One of the most straightforward blood tests is to quantify and identify the blood cell types. A complete blood count (CBC) is primarily a measure of these cellular components and is one of the most routinely ordered blood tests by clinicians. CBCs, especially white blood cell (WBC) count, provide physicians with key information valuable for diagnosing many different disease states including: anemia, leukemia, autoimmune disorders, fungal, and bacterial infections as well as Recognition and inspection of white blood cells in peripheral blood can assist hematologists in diagnosing many diseases such as AIDS, Leukemia, and blood cancer. Thus, this process is assumed as one of the most prominent steps in the hematological procedure. There are five main phases involved in the system. They are image pre-processing, extraction classifying and segmenting the Five Types of White Blood Cells. For classification neural classifiers in HISTOGRAM are used and also be using a more Efficient supervised learning approaches for more accurate and computationally efficient segmentation. The features are extracted from the Five Types of White Blood Cells using matlab program approach and these accurate features are used to train the neural classifier. Classification of Five Types of White Blood Cells is an essential research topic as it may be advantageous in monitoring many diseases. Therefore the need for fast, automatic, less expensive and accurate method to classify Five Types of White Blood Cells is of great realistic significance. The main aim of our project work to develop a Computer Aided diagnosed system for classification of Five Types of White Blood Cells.**

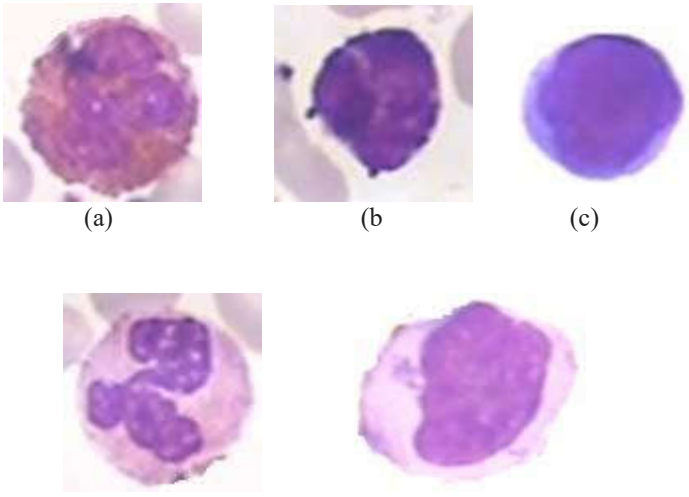
Index Terms: **MatLab, Nuero Solution Software, Microsoft excel, Various Transform Techniques.**

I. INTRODUCTION

For the identification of different kind of hematological diseases the accurate segmentation of different white blood cells are necessary for classification purpose, if the segmentation of cells are not accurate then the further analysis does not give the efficient and required result which may results in incorrect treatment of patients and it may be possible that the patient does not have any hematological disease but the incorrect system show the presence of it. So, the automatic system should be design in such a way that there will be very minimal error rate as compared to the manual. Many researchers tries to focus on the automatic system as they are fast, less error rate as compared to human and not even tiresome, as in manual segmentation and classification

Blood tests are frequently employed to evaluate human health. One of the most straightforward blood tests is to quantify and identify the blood cell types. A complete blood count (CBC) is primarily a measure of these cellular components and is one of the most routinely ordered blood tests by clinicians. CBCs, especially white blood cell (WBC) count, provide physicians with key information valuable for diagnosing many different disease states including: anemia, leukemia, autoimmune disorders, fungal, and bacterial infections as well as a host of other ailments [11], [12]. Currently there are two methods primarily used to obtain a CBC, specifically a WBC count. The first requires a clinician or trained lab specialist to prepare blood smear slides, stain them, and then manually count different WBC types using a hemocytometer under a microscope [13]. To do this they must dilute specimens in a red blood cell (RBC) lysing solution to remove RBCs and count WBCs. Manually counting WBCs is laborious and requires specialized medical equipment and trained personnel. The second method employs a flow cytometer, an extremely bulky and expensive piece of equipment, to perform the cell count [14]. This method requires treatment of the whole blood sample using several reagents; typically, RBC lysing solutions and costly antibodies. However, this technique has an extremely high efficiency in accurately identifying and quantifying different WBC sub-types.

Blood cells are consisted of red blood cell which blood cell, and platelets. white blood cells(WBCs)are the cell of the immune system for protecting the body against both infection disease and foreign invaders. WBCs are also called leukocytes. leukocytes are also called immune cell because of its function. WBCs are divided into granular cells and non granular cells. The granular cells are netrophil, eosinophil, and basophil. The non-granular cell are monocyte and lymphocyte.These five type of WBC cells are diffrent in proportion into thr diseased and non-diseased blood.doctors use these fundamental ideas as the criteria to determine the type or severity of this disease.as a result,the study of WBC classification has a remarkable value for medical diagnosis system.



(a) (b (c)

(d) (e)

Figure. 1. Five major groups of white blood cells in peripheral blood.
(a) eosinophil, (b) basophil, (c) lymphocyte, (d) neutrophil, and (e) monocyte.

Each type of WBC helps in diagnosing many ailments.high number of netrophil in blood indicates cancer disease,high lymphocyte inform about AIDS and high monocyte and eosinophil refer to bacterial infection. For this reason, an automated system is essential for recognizing this five types WBC image[2].

.II. RESEARCH METHODOLOGY

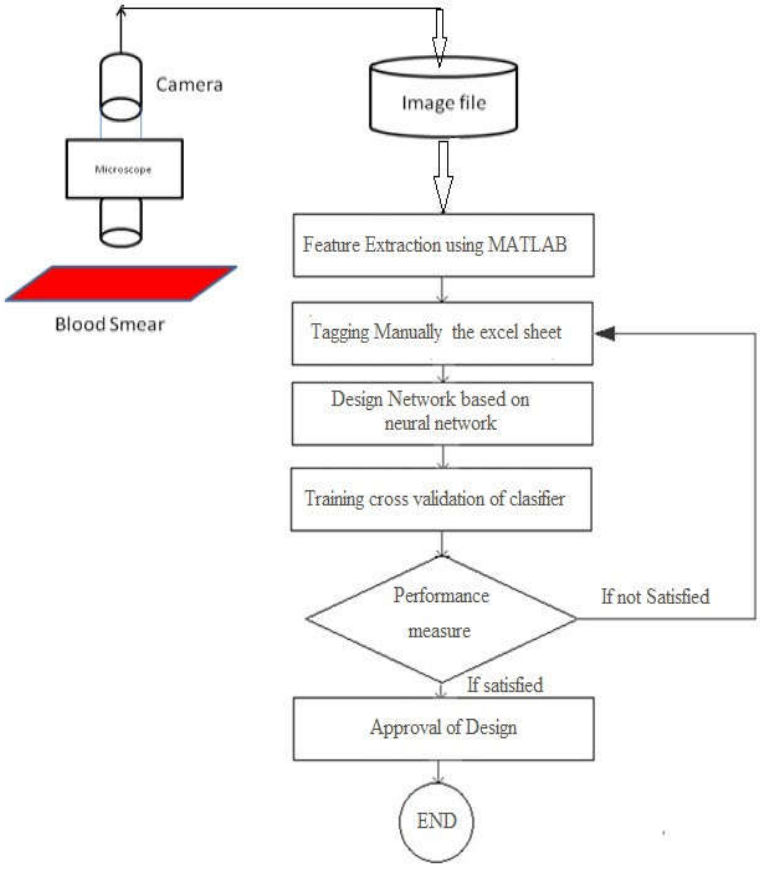


Figure2. Methodology of work.

NEURAL NETWORK

Following Neural Networks is tested:

Modular Neural Network (MNN)

Modular NN (MNN) Modular Neural Network is in fact a modular feed forward neural network which is a special category of MLP NN. It does not have full interconnectivity between their layers. Therefore, a smaller number of connection weights may be required for the same size MLP network with regard to the same number of processing elements. In view of these facts, the

training time is accelerated. There have been many ways in order to segment a MNN into different modules. MNN processes its inputs with the help of numerous parallel connected MLPs and the outputs of these MLP are recombined to produce the results. This neural network is comprised of different sub modules and according to a specific topology; some structure is created within the topology in order to boost specialization of function in each sub-module.
The following topology depicted in Figure 2 of the MNN has produced the best classification results.

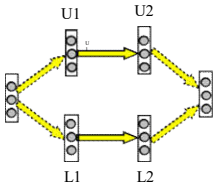


Figure 3: Topology of a Modular Neural Network

This topology is recommended on the basis of experimental evidences, testing and performance measures.

Learning Rules used:

2.1 Momentum (MOM):

Momentum learning rule is an improvement over the straight gradient-descent search in the sense that a memory term, i.e., the past increment in the weight, is set to speed up and stabilize convergence. In momentum learning, the equation to update the weight becomes

$$w_{ij}(n+1) = w_{ij}(n) + n\delta_i(n)x_j(n) + \eta[w_{ij}(n) - w_{ij}(n-1)] \quad \text{.....(1)}$$

Where, η denotes the momentum constant. Normally, η should be set between 0.5 and 0.9. This is called momentum learning due to the form of the last term, which resembles the momentum in machines. It is a robust method to speed up learning. Being a robust method to speed up learning, it is recommended as a default search rule for network with nonlinearities.

2.2 Conjugate Gradient (CG):

The basic idea of the line search is to begin with gradient-descent direction and search for minimum along the line, that is,

$w(n+1) = w(n) + \lambda(n)s(n)$ where $\lambda(n) = J[w(n) + \lambda s(n)]$ (2)

There has been a problem with the gradient direction that it is sensitive to the eccentricity of the performance surface (caused by the Eigen value spread), so following the gradient is not the quickest path to the minimum. Alternatively, one can compute the optimal step size at each point, which corresponds to a line search.

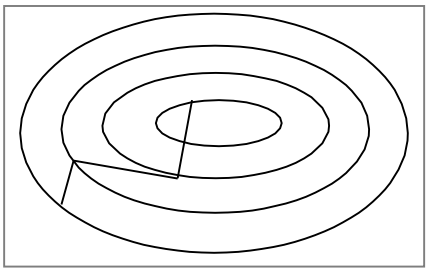


Figure 4**:** Path to the minimum with line search methods

It can be proved that successive direction have to be perpendicular to each other as displayed in Figure 6 and path to the minimum is intrinsically a zigzag path. This procedure can be improved if weight is cut across the zigzag. The formulation becomes

$$s^{new} = -\nabla J^{new} + \alpha s^{old} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (3)$$

Where, α denotes a dynamically computed parameter that compromises between the two directions. This is called a conjugate method. For quadratic performance surfaces, the conjugate algorithm preserves quadratic termination and can reach the minimum in D step, where D denotes the dimension of the weight space.

2.3 Quick propagation (QP):

Quick propagation (QP) is a heuristic modification of the standard back propagation algorithm. Fahlman introduced QP in 1998. QP is not essentially faster than back propagation even though for some application it may prove faster. QP is more susceptible to instability and may stick to local minimum than back propagation. QP changes the network weights after each case. It is a batch update algorithm. It computes the average gradient of the error surface across all the cases before updating the weights at the end of an epoch.

QP works with the assumption that the error surface is locally quadratic, with the axes of hyper-ellipsoid error surface associated with the weights. If this is true, then the minimum of the error surface can be found after only a couple of epochs. Certainly, the assumption is not generally valid, but if it is close to true, the algorithm can converge to the minimum very quickly. On the first epoch, the weights are changed using same rule as the back propagation, based upon the local gradient and the learning rate. On successive epochs, the quadratic assumption is used to obtain the minimum.

The basic QP formula has a number of limitations. If the error surface is not concave, the algorithm can deviate from the desired value. If gradient changes a little or not at all, Then the changes can be extremely large. If the zero error is encountered, a

weight will stop changing permanently. On the first epoch, QP updates weights similar to back propagation. Subsequently, weight changes are calculated using the quick propagation equation.

$$\Delta w(t) = \frac{s(t)}{s(t-1)-s(t)} \Delta w(t-1) \quad \ldots\ldots (4)$$

The system is numerically unstable if s(t) is very close, equal or greater than s(t-1). Since (t) is expressed along the direction of weight gradient, such conditions can only occur if the slope becomes constant, or becomes steeper. In such cases, the weight update formula is

$$\Delta w(t) = \varepsilon \alpha \Delta w(t-1) \quad \ldots\ldots (5)$$

Where α denotes on acceleration constant

2.4 Delta bar Delta (DBD):

Delta-Bar-Delta algorithm is an adaptive step-size procedure for searching a performance surface. The step size and momentum are adapted according to the previous values of the error at the PE. If the current and past weight updates are both of the same sign, the learning rate is increased linearly. The reasoning is that if the weight is being moved in the same direction to decrease the error, then it will get there faster with a larger step size. If the updates have different signs, this is an indication that the weight has been moved too far. When this happens, the learning rate decreases geometrically.

$$\Delta \eta_i(n) = \begin{cases} K & s_i(n-1)\Delta w_i(n) > 0 \\ -\beta \eta_i(n) & s_i(n-1)\Delta w_i(n) < 0 \\ 0 & \text{Otherwise} \end{cases} \quad \ldots\ldots (6)$$

Where: $S_i(n) = (1-\lambda)\nabla w_i(n-1) + \lambda S_i(n-1)$

K= Additive constant

B= Multiplication constant

λ= Smoothing factor

Weight update Equation:

$$\nabla w_i(n-1) = \eta_i \nabla w_i + \rho \Delta w_i(n) \quad \ldots\ldots (7)$$

III. SIMULATION RESULTS

i. COMPUTER SIMULATION

In this Project,90 images have been used which consist of Five type of white blood cell therefore the dimension of the matrix is obtained as 90X(128+7).Out of 90 images 90% used for training & 10% used for cross-validation.

The simulation of best classifier along with the confusion matrix is shown below:

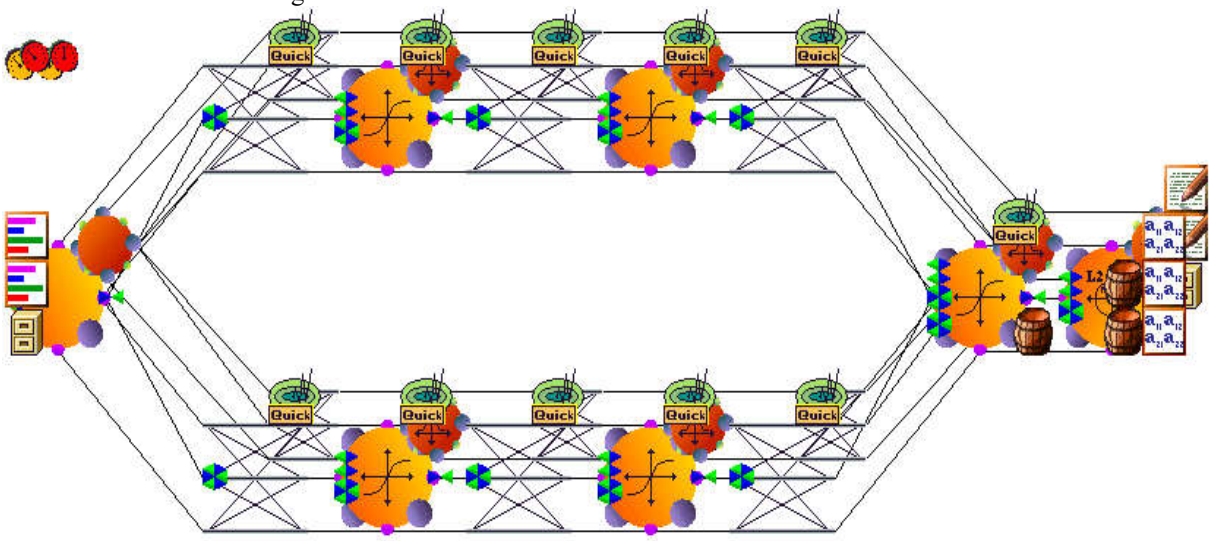


Figure.3 MNN top-1 neural network trained with QP learning rule

2) RESULTS

Best Networks	*Training*	*Cross Validation*
Hidden 1 PEs	47	50
Run #	1	1
Epoch #	1000	1000
Minimum MSE	0.007473953	0.069415781
Final MSE	0.007473953	0.069415781

TABLE I. Training and cross validation Report of the Best Classifier MNN Top 1-QP

Performance	*NEUTROPHIL*	*MONOCYTE*	*LYMPHOCYTE*	*EOSINOPHIL*	*BASOPHIL*
MSE	0.019095819	0.105892422	0.090098508	0.050838549	0.025493265
NMSE	0.119348866	0.661827639	0.563115678	0.317740932	0.159332908
MAE	0.095485509	0.198416823	0.25508749	0.123474512	0.101818998
Min Abs Error	0.0034174	0.002221209	0.032834667	0.001353469	0.004675897
Max Abs Error	0.33293041	0.793237824	0.500919249	0.640349295	0.398619152
r	0.944810156	0.59350065	0.783629866	0.902681039	0.980902604
Percent Correct	100	50	100	100	100

TABLE II. Accuracy of the network on CV data set

Performance	*NEUTROPHIL*	*MONOCYTE*	*LYMPHOCYTE*	*EOSINOPHIL*	*BASOPHIL*
MSE	0.003525806	0.00514849	0.00381059	0.00599169	0.002673456
NMSE	0.022036286	0.035660536	0.022771034	0.041500884	0.014762831
MAE	0.047164047	0.056567077	0.049118294	0.062574976	0.038876151
Min Abs Error	0.000228036	0.000916184	0.001757462	0.001787076	3.16445E-05
Max Abs Error	0.130984424	0.239505393	0.178823966	0.219770586	0.133606815
r	0.994159097	0.988067974	0.995270028	0.984789309	0.995879115
Percent Correct	100	100	100	100	100

TABLE III. Accuracy of the network on training data set

IV. Conclusion and Future Work

From the results obtained in Histogram domain it is conclude that the MNN Top-1 neural network with Quick Propagation(QP) learning rule and hidden layer 2 (H2) gives best result for cross validation (CV) it gives 90% and in training it gives 100% . So overall accuracy is 95%.

The accuracy of the system are often further improved with the utilization Five sort of WBCs images through rigorous training and cross validation. These systems can also be realized in hardware system on chip after thro validation and therefore the systems are often deployed in several Labs.

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