Modified Multi-Category Digital Learning Networks for Red Blood Cell Inspection

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Abstract

This paper reports research conducted into classification of red blood cells using multi-category digital learning networks. It is an effective solution for providing healthcare with reduced cost, especially for the rural and far away patients. Digital learning network offer an alternative approach to neural network design. It often referred as(RAM-Based Architectures) , or (Weightless Neural Networks), since their neurons can be implemented by RAM node that usually input and output binary values with no weight between nodes. The system presented in this paper fulfills the requirements of simplicity and efficiency making it attractive to practical use in present day for industrial and medical environments. Many parameters have been investigated in detail which affects the recognition rate. These parameters are presented to allow the system to be optimized, giving an increase in the performance of the system. Modification method of Feedback Digital Learning Network, which is an improving process of Digital Learning Network, has been implemented. The obtained results showed that high performance can be achieved (96.6% as correct, 2.2% as reject, and 1.1% as error), providing evidence of the validity of the proposed technique.

Keyword: (Pattern Recognition, Digital Learning Network, Red Blood Cells, Morphological Operation, Discriminator)

الشبكات المتعلمة الرقمية متعددة الاصناف المحورة لاغراض فحص كريات الدم الحمراء

الخلاصة

في هذا البحث تم اجراء التصنيف على خلايا الدم الحمراء باستعمال شبكات التعلم متعددة الصنف الرقمية . ويعتبر هذا التصميم حل فعال لتزويد الرعاية الصحية بكلفة مخفضة , خصوصا للمرضى البعيدين في المناطق الريفية .أن شبكات التعلم الرقمية توفر بديل عن الشبكات العصبية ,وغالبا ما يشار اليها بالدوائر المستندة على ذاكرة الوصول العشوائي أو الشبكات العصبية الخالية من الاوزان , حيث يمكن بناء خلاياها العصبية باستخدام عقد ذات دواخل ومخارج ثنائية بدون اعتمادها على الاوزان .تؤمن المنظومة المقترحة متطلبات البساطة والكفاءة التي تجعلها جذابة في التطبيقات العملية في الوقت الحاضر وخصوصا للبيئات الصناعية والطبية. لقد تم التحري باسهاب عن العديد من العوامل المؤثرة في سرعة التمييز .وقد تم عرض هذه العوامل من اجل الحصول على منظومة مثالية من حيث التحسن في الأداء . وتم تطوير المنظومة من خلال أستخدام طريقة التغذية الاسترجاعية للشبكات المتعلمة الرقمية .لقد بينت النتائج المستحصلة الى أن أداء أفضل يمكن الحصول

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عليه حيث تم استحصال النتائج التالية (96% للنتائج الصحيحة و2,2% للنتائج المرفوضة و1,1% للنتائج الخاطئة), وهذا يبين دلالة على نجاح التقنية المقترحة .

Introduction to RBC and its shape:-

Blood cells are composed of erythrocytes (red blood cells (RBCs)), leukocytes (white blood cells (WBCs)), and thrombocytes (platelets). The shape of RBC change when the body suffers from different diseases such as anemia, there is several kind of anemia that causes abnormal shape in the RBCs [1]. In this work six types of RBCs will be used, in order to classify them using the DLN approach .Description of the six types of RBCs is shown in Figure (1) which illustrates these types and the associated condition to each one:-

The shape	RBC Abnormality	Description of Cells	Associated Condition
	Normal Erythrocytes	Normal individual, Approximatly 7mm diameter.	
	Sickle Cells	Irregular, Curved cells with pointed ends.	Sickle Anemia, Hemogloben S-beta, Thalasemia.
	Tear Drops	Cell in shape of tear drop	Anemia of renal failure,Hemolytic Anemia, Thalasemia.
	Elliptocytes	RBCs with elliptical or oval shape	Thalassemia , Sickle cell trait, Iron deficiency Anemia ,Megaloblastic Anemia
	Target cells	Round area of central pigmentation	Thalassemia ,Iron deficiency Anemia Liver diseases
	(Burr cells) Sea urchin cells	RBC with many tiny spicules (10-30) evenly distributed overcell	Uremia , Hepatitis of the newborn

Figure (1): six classes of RBCs that will be classified in this paper [2][3]

The erythrocyte (RBC) shape deformability is serious to the filterability of blood, which has drawn large attentions into the pathology research in medical related blood diseases. Diagnosing is usually performed by human experts and it shows some drawbacks, such as time-cost consuming, inaccuracy and put a lot of amount of stress to medical laboratory technicians. In order to avoid large weakness, better and more pattern recognition and classification should be used in diagnosing blood cells [4] [5] [6].The data used in this paper was obtained from many Iraqi hospitals laboratory, in order to get real medical image. To collect the data a high-resolution digital camera type (CANON with Resolution5 Mega Pixels) mounted on a microscope type (OLYMPUS.CX41/ ZELSS) is used in this work.

Image Processing for Medical RBCs Data used:-

Image processing is a popular technique in many domains, like medical diagnosis, and security. Image processing, helps in improving the medical image quality, enhance and analysis it. It can be noticed that the complexity and diversity of medical image need suitable processing techniques that can achieve a considerable improvement in the recognition [7].Figure (2) shows the steps of preprocessing and segmentation of the medical image in this work.

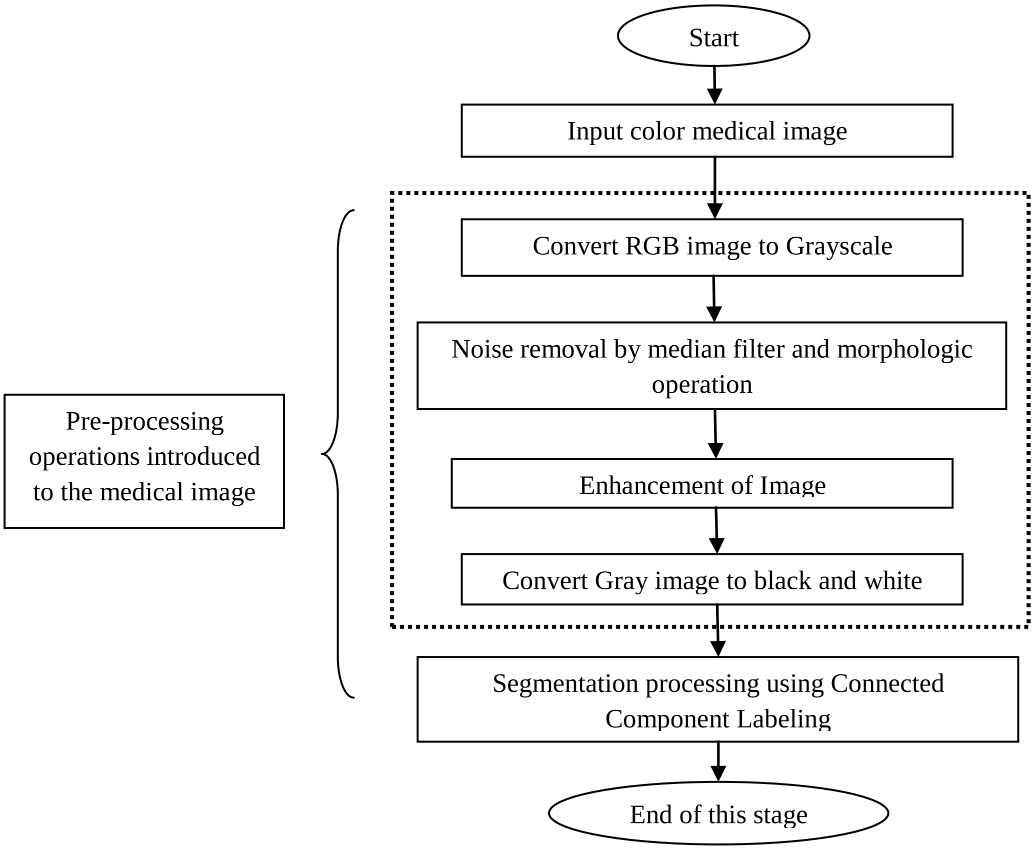

Figure (2):-Steps of preprocessing and segmentation of the medical image

All the pre-processing operation is achieved using Matlab (Matrix Laboratory) software version 2011, a programming language for matrix-based computation and image processing tool. First step is converting medical image from RGB to Gray scale. Next step is to remove noise from the image by using median filter. It is a smoothing technique that causes minimal edge blurring. It involves in replacing the pixel value at each point in an image by the median of the pixel values in a neighborhood about the point. Mathematical morphology operations (Erosion and Dilation) are used in this part. Erosion is use in order to remove image components and to disconnect features in an image by separate them. Dilation is use for expands the components of an image. These operations will eliminate background noise. Since all noise components are smaller than the other cells in the medical image, this operation will smooth the image. Enhancement of the image is done by adjust the intensity of the image, adjusting a low- contrast of grayscale image. This process increases the contrast of the output image by using Gamma threshold parameter [8]. Last step in preprocessing is converting grayscale image to Black and White image. The output image is black and white replaces all pixels in the input image with luminance greater than level with the value '1' for white color, and replaces all other pixels with the value' 0' for black color. Segmentation for B/W medical image is produce finally by connected component labeling operation which is used to detect connected regions in binary images. Boundaries between regions are determined, removed unwanted regions and finally a label corresponding to anatomical structure is assigned to each group pixels in the medical image [9].Finally after the preprocessing and segmentation operations the RBC image is ready for classification in DLN, which will be explained in the following section.

Digital Learning Networks for Classification of RBCs:-

In this paper pattern classifier based on n-tuple has been used which utilizes a digital learning networks (DLN) technique. The n-tuple technique proposed by Bledsoe and Browning in1959 is one of the oldest memory based techniques of pattern recognition. Then the hardware implementation in 1968 by Aleksander and Albrow by using models of memory elements (RAM) is introduced. Later on several systems of digital learning network have been developed [10]. DLN uses the n-tuple states which defined as particular combinations of 0's and 1's for the n-tuple as features from the binary image. This will be the input of the RAM's in the DLN.A single layer digital learning network is shown in figure (3).The input image ($\overline{X}$) to be recognized consists of (R) pixels:

$$\overline{X} = (x_1, x_2 \ldots\ldots x_{R-1}, x_R) \quad \ldots(1)$$

These pixels can have only the logical value of '1' or '0'. Each RAM is connected at random to the input image to an n-tuple of the binary pattern. The value of 'n' is determined by the number of inputs to the RAM and the n-tuple is interpreted as an address. Such n-tuple can have 2^n state and each state is characterized by the total bit pattern of the group of 'n' pixels. The state of the ith n-tuple is defined by:

$$C[a] = \sum_{j=1}^{n} a(i, j).2^{j-1} \quad \ldots(2)$$

where

'i' is the number of tuple , and 'j' is the number of the element in tuple . The bit 'C[a] ', stored at the activated memory represents the output of the RAM [11]. A discriminator is a group of 'K' RAMs where:

$$K=R/N \quad \ldots.\ (3)$$

A discriminator is made to cover the image just once, in one –to-one manner. One-to-one means that once having selected 'n' pixels randomly, these cannot become part of any other n-tuple. DLN classifier employs one discriminator for each category of pattern in the data set. Thus, if the number of classes in a particular problem is 'C', this implies the existence of 'C' discriminators. In this paper there are six classes of RBCs, each discriminator representing one class [12] [13]. Figure (3) shows one discriminator for multi-category digital learning network that contain six classes each discriminator related to one class.

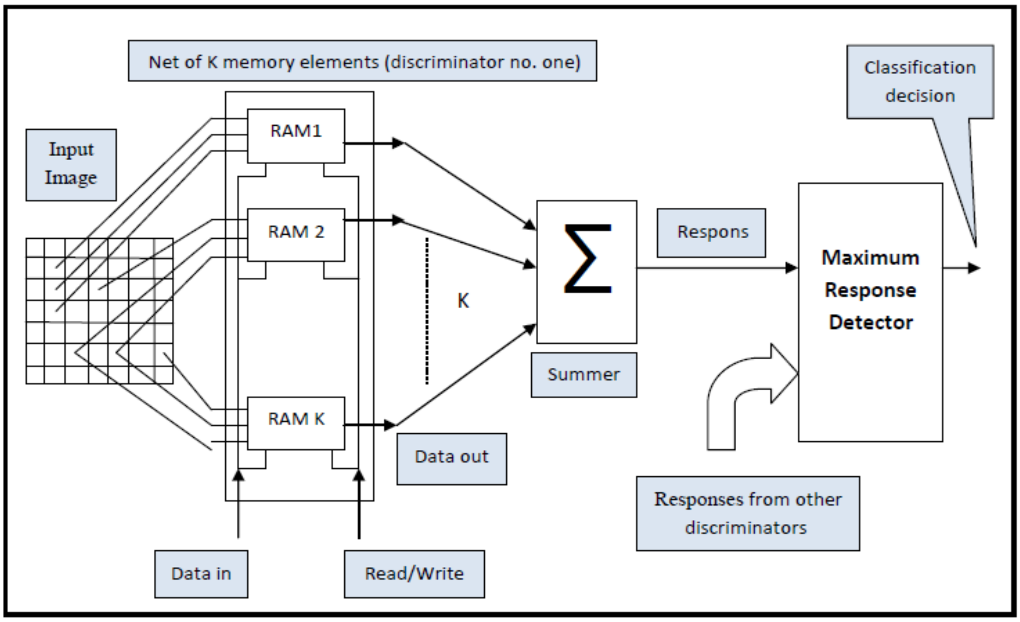

Figure (3): Multi-Category Digital Learning Network

During the training process of the system, discriminator 'i' is shown examples of patterns in the ith class. The discriminator is trained by the application of a pattern sample to the inputs of each RAM and the transmission of logical '1' to the 'data in' terminal. A signal at the (read/write) terminal enable the 'data in' information to be stored in the RAM (the RAMs have been initially set to logical '0'). The training of each pattern and each discriminator is sequential [14].

When testing with an unknown pattern $'\overline{X1}'$, the output of the RAM is examined, and an input address accesses the appropriate store location giving a data output .The input image is mapped to n-tuple. For each discriminator, the RAM cells addressed by the tuple values are read, thus if the n-tuple value had occurred in the training phase then that RAM would output a '1', otherwise a '0'. The response 'r_i' of the ith discriminator is the sum of the outputs for each RAM. Because of the output of a RAM is either '0' or '1', 'r_i' must be an integer in the range:

$$0 \leq ri \leq K \qquad \text{for all 'i' from 1 to C} \qquad \text{.....} \ (4)$$

and the response vector of the classifier to $\overline{X}$, is:

$$Z(\overline{Xt}) = (r_1, r_2, \ldots, r_c) \quad \ldots\ldots (5)$$

A decision of the classifier C_d is made on the basis of $Z(\overline{Xt})$.
The unknown pattern is classified as belonging to the class whose discriminator G gives maximum response, as shown below:

$$C_d = G\ MAX\ [Z(\overline{Xt})] \quad \ldots. (6)$$

While the actual response of the discriminator in written as:

$$F = MAX\ [Z(\overline{Xt})] \quad \ldots. (7)$$

In case that two or more discriminators give an equal maximum response, the pattern under test is classed as ' rejection '. It is generally accepted that the provision of a rejection category is preferable to misclassification [15] [16].

The difference between the discriminator with the highest response and the next highest response is a measure of relative confidence .This is shown in equation below

$$R_c = [(r_{max} - r_{n\ max}) / r_{max}] * 100\ \% \quad \ldots. (8)$$

Where
r_{max} is the maximum response and the $r_{n\ max}$ is the next highest response and the R_c is the relative confidence [17].

The DLN has the property of generalization which enables patterns other than those occurring in the training set to be classified. The capacity of this generalization is determined by the number and nature of the patterns which are encountered during training. In general the size of the generalization set is given by:

$$[G_A] = \prod_{J=1}^{K} H_j \quad \ldots (9)$$

Where
' H ' is number of different n-tuple state that is seen by the 'jth' RAM during training phase [18]. The n-tuple size is a key parameter of the classifier structure and its relationship with the recognition performance is quite complex. Using large n-tuple is in general consistent with better recognition performance but requires large training sets to achieve it [13]. Experiments were initially carried out with all patterns in order to provide a reference point and determined the optimum characteristics of DLN.

Six classes of RBCs are used, so there will be six discriminator one for each class. Input matrix for DLN is [32 ×32] bits. In each experiment thirty patterns per class [180 patterns in total] are used, half of them for training and the rest for testing, so fifteen pattern for each class are using for training and testing phases.

Many experiments were intended to permit determination of the optimum performance of the system with respect to n-tuple size that provides optimum recognition. It is an important condition that the training set is sufficient both in size and quality, undesirable over-generalization can occur with large amount of training size. It was found that n-tuple size "8" gives optimum recognition performance for the used pattern classes, using equation (3), it was found that there will be (128) RAM for each discriminator. Table (1) and Figure (4) shows classification of RBCs with DLN.

Table (1): Classification with DLN Using Different n-tuple Size

Classification in DLN						
Classification of Multi Category of DLN	n-tuple	4	6	**8**	10	12
	Correct	72.3%	84.5%	**90%**	88.8%	63.3%
	Reject	20%	10%	**5.5%**	6.6%	25.5%
	Error	7.7%	5.5%	**4.5%**	4.6%	11.2%

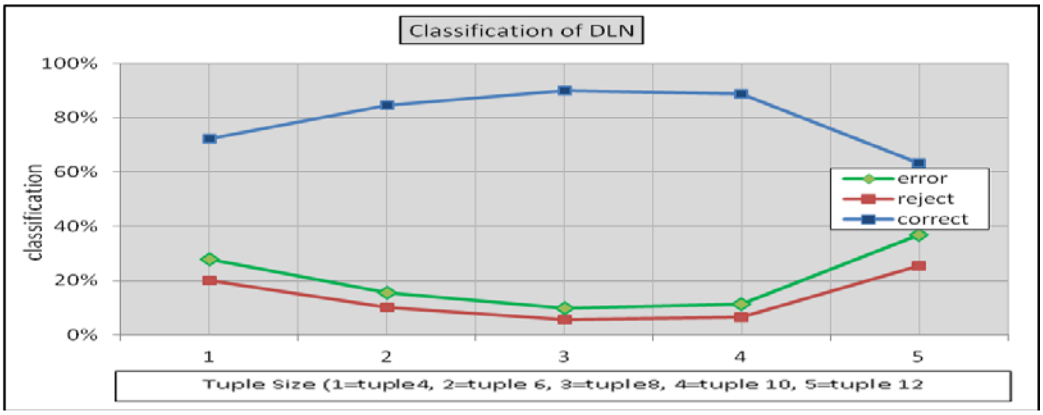

Figure (4): Shows the Result for Classification of DLN that Indicate the Percentage of Correct, Reject, and Error Rate for Each Category

The performance of correctly classified test patterns rise to 90% beside that the reject level decreased from 20% to 5.5%, and the error level decreased from 7.7% to 4.5%. The result shows that the system is sensitive to the n-tuple size and the training set size. As shown from the result in Table (1) and Figure (4).

The input mapping determines the way in which the input pattern is transformed into the discriminator inputs .This mapping may be ordered or random. A random mapping is generally chosen. an ordered map may be useful for a certain class of patterns which exhibit local properties while the random map is more likely to detect global properties. All the experiments carried out in this work used the same mapping namely one-to-one random mapping [19]. The measurements of the system performance, illustrate that care must be adopted in the selection of these basic system parameters for practical application [20] [21].

Modified Structure of Digital Learning Network FDLN:-

The difference between patterns of different classes cannot be completely defined in advance, as it is hoped that the system will settle into an optimum state if a representative set of patterns is available for training each class discriminator separately. However, the common features between patterns of different classes can result in common n-tuple samples (n-tuple state) throughout the training process.

The probability of common n-tuple occurring throughout a complete training set is high. Therefore a major improvement for all classes in multi-category classification can be obtained if the information on the distribution of states for each individual n-tuple for different classes is available in the recognizer itself. These common features can be computed by introducing the response histogram for each input pattern.

Response histogram can be defined as the probability distribution of tuples values in an image. Using response histogram gives more advantages to consider the common features between the n-tuple for all classes, and then the recognition performance will increase [22]. A modification scheme of DLN is proposed in this paper, whereby final decision depends on adding the distribution of each state of individual n-tuple in all classes. The feedback technique FDLN is used to make the common feature occur in each individual n-tuple state for all classes available to the system. This is done by using the response histogram for all classes that obtained from histogram generator. Histogram generator can produce numerical responses in the form of a histogram [23]. Using feedback technique, the output pattern will become dependent not only on the current input pattern, but also on all previous patterns input to the network. This will increase the recognition of patterns.

The training phase of FDLN technique is carried out in two parts. The first part start, when each discriminator is trained on all the patterns of its class, simply by setting the bits access by the n-tuple in the 'ith' discriminator, of the 'i' class. As more patterns are seen by the discriminator the teaching procedure gradually builds up a composite logic function for the' ith' discriminator which defines the 'ith' pattern class. This procedure is repeated for all classes to be distinguished. Figure (5) shows the training phase of FDLN.

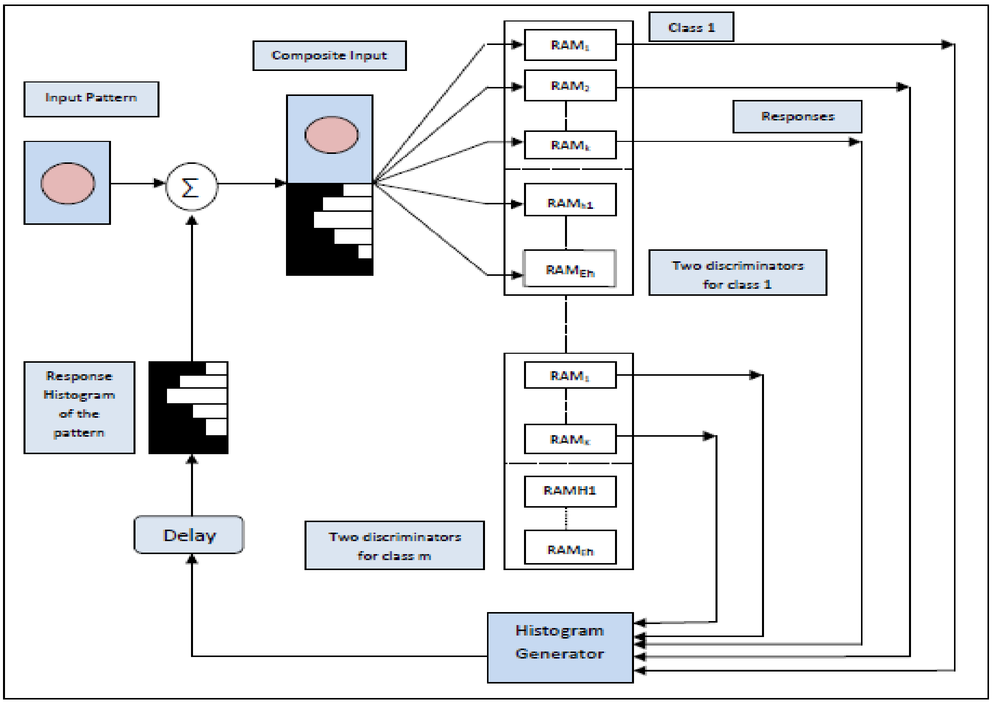

Figure (5): Structure of the Training phase of FDLN

The second part of training phase, response histogram for input patterns is generated. Training pattern is presented to the system and a histogram is generated at the output. This histogram can now be feedback and mixed with the input training pattern. Training process is employed with introducing both patterns (pattern from the training of the second part) with the response histogram for all classes. The structure of the system will contain two discriminators represent each class, one for the input pattern and the other for responses histogram. The delay part is using in order to give a period for generating responses histogram and organized the sequence of the operation. Finally the responses histograms of all classes are feedback via delay to form part of the input to the discriminators. The final response of each discriminator is taken by adding the corresponding responses of that discriminator. The procedure is employed for all classes independently [24] .Figure (6) shows the classification phase of FDLN.

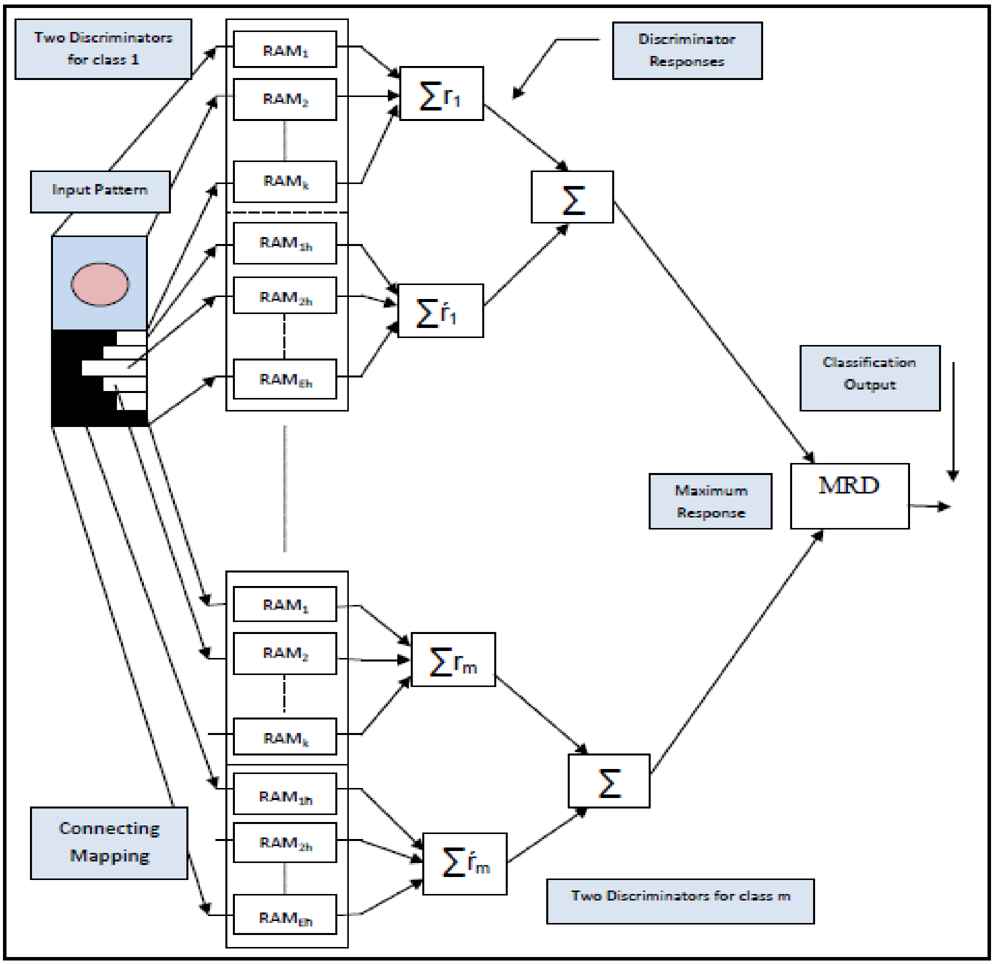

Figure (6): Structure of the Classification Phase of FDLN

During the testing phase the patterns which were allocated for testing is using as input images to determine the performance recognition of the FDLN on them. Initially the testing pattern is presented to the system, and the input matrix will contained the responses histogram pattern mixed with the testing pattern. This responses histogram patterns are obtained via delay to enhance the original decision. The scores of all other discriminators are computed, and the discriminator that has the highest score is assigned to the input pattern. So the pattern under test will belong to class where the total of both of its discriminators have the highest response. This operation will be done by the MRD (maximum response detector) as shown in Figure (6) and equation below:

$Z(Xt) = (r_1+ŕ_1 , r_2+ŕ_2 ,.......r_m +ŕ_m)$ ….. (10)

where $(r_1, r_2, .. r_m)$ are the responses of the origin n-tuple for 'm' classes ,and $(ŕ_1 , ŕ_2 ,ŕ_3, ..ŕ_m)$ is the responses vector of the histogram for 'm' classes .

MRD= G MAX [Z (Xt)] … (11)

Algorithm for FDLN Training and classification Phases:-

Algorithm in table (2) shows the training and classification phases of FDLN used in this paper. Let consider that:

- C = number of classes, include [c_1, c_2, …..c_m]
- X = the complete set of training pattern , the subset of patterns of class 'c ' is denoted as 'X_c ' , and' x_{ci}' is the 'i_{th}' pattern in the' cth' class.
- $b_j(x)$ = an address which are used to access memory elements.
- The size of the address space of each memory (n_{cj}) is (σ^n) where (σ=2) for binary input space .
- N_c = All memory values for all the n-tuple mappings for a given class
- M_c = All memory values for all the n-tuple for response histogram
- m_{cl} [b] = Content of the memory (RAM_h) for response histogram for class 'c'
- r_c = Response of the class 'c'
- $\acute{r}_c$ = Response of the histogram for class 'c'

The training phase is performed initially by adjusting the values that stored at each address for each pattern in each class to be zero. When an address [$b_j(x)$] is accessed by a pattern 'x' of class 'c' under mapping 'n_j' then the address of that tuple is set to one .For the second part of training, the response histogram of that tuple Set mcl [b_l (h)] is set to one also [23]. For testing phase the total output for each class is the sum of the outputs for each n-tuple in that class, which will be the mixed between the two responses. Finally the 'MRD' will take the highest score of both responses as shown in equation (12).

Table (2): Algorithm for Training and Classification FDLN [23]

<u>Step 1: Initialize all n-tuples:-</u>

t = number of n-tuple

h = response histogram for pattern

For each class $c \in C$

For each n-tuple $n_{cj} \in N_c$

For each memory $mcl \in M_c$

For each address $b=0$ to $\sigma^n -1$

Set ncj [b] = 0 Set mcl [b] = 0

<u>Step 2: Train all n-tuple on all training patterns:-</u>

For each class $c \in C$

For each pattern $x_{ci} \in X$ For each tuple j=1 to t

Set current address $bj\ (x) = \sum_{k=1}^{n} x_{ci}\ (a_{jk}) * \sigma^{k-1}$

For each l = 1 to d

Set current address $b_l\,(h) = \sum_{k=1}^{n} h_{ci}\,(a_{jk}) * \sigma^{k-1}$

Set ncj [b_j (x)] =1 Set mcl [b_l (h)] =1

<u>Step 3: RAM contents of each n-tuple in each class in testing phase:-</u>

For each j= 1 to t

$$\text{Set} \quad bj\,(x) = \sum_{k=1}^{n} x\,(a_{jk}) * \sigma^{k-1}$$

For each class c ∈ C

Set $(n_{cj}) = n_{cj}\,[b_j(x)]$

Set $r_c = r_c + n_{cj}\,[b_j\,(x)]$

Step 3: RAM$_h$ contents of each n-tuple in each class in testing phase:-

For each L =1 to d

$$\text{Set} \quad b_l\,(h) = \sum_{k=1}^{n} h\,(a_{lk})* \sigma^{k-1}$$

For each class c ∈ C

Set $(m_{cl}) = m_{cl}\,[b_l\,(h)]$

Set $\acute{r}_c = \acute{r}_c + m_{cl}\,[\,b_l\,(h)]$

Step4: Classification:-

Index of r_{max} is the class

$$r_{max} = \text{GMax}\,[\,r_c + \acute{r}_c\,] \qquad \dots (12)$$

A series of experiments were carried out in order to test the feasibility of employing the proposed feedback technique. The result shows that a considerable improvement in the performance takes place by using FDLN with histogram responses. The results indicate that the classification of the networks increases, according to the size of the training set. Form Table (3) ,and Figure (7) it can be noticed that the performance of the FDLN improves the classification to 96.6% , beside that the reject classification decrease to2.2% , and the error decrease to 1.1%. The FDLN has always obtained best recognition level, comparing with ordinary DLN with variable system parameters. Finally FDLN technique gives better optimum classification performance for the six types of abnormal RBC cell**.** Table (4) and Figure (8) indicate a comparison between DLN and FDLN the result indicate that there is considerable improve in FDLN from 90% to 96.6%.

Table (3): Classification with FDLN by Using Different n-tuple Size

Classification of FDLN						
The Classification of Feedback Digital Learning Network	n-tuple	4	6	**8**	10	12
	correct	93.3%	95.5%	**96.6%**	94.4%	91.1%
	reject	4.4%	3%	**2.2 %**	3.4%	6.6%
	error	2.3%	1.5%	**1.1%**	2.2%	2.3%

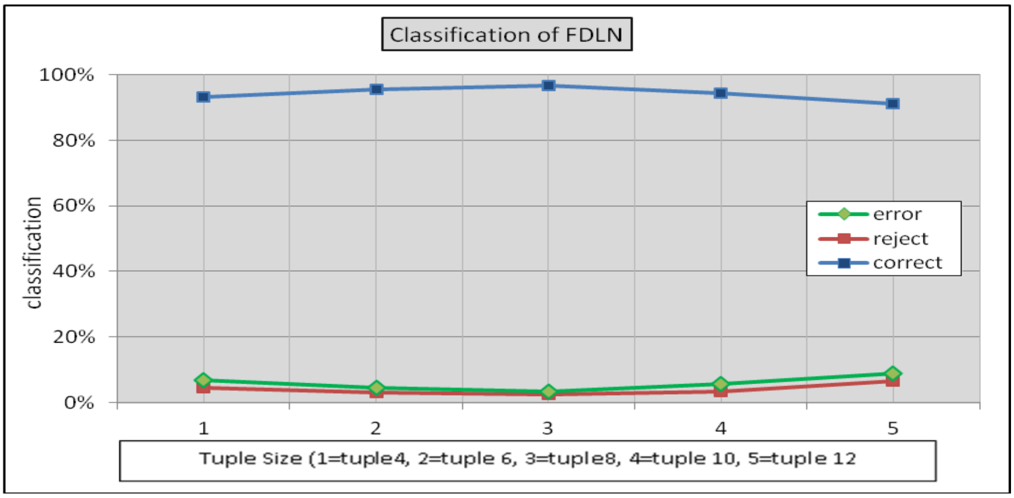

Figure (7): The Result for Classification of FDLN that Indicate the Percentage of Correct, Reject, and Error Rate for Each Category

Table (4): Classification of Patterns for All Classes, by Using DLN and Then by Using FDLN Technique

Classification with DLN and FDLN					
Type of Network	4- tuple	6-tuple	**8-tuple**	10-tuple	12-tuple
Classification with DLN	72.3%	84.4%	**90%**	88.8%	63.3%
Classification with FDLN	93.3%	95.5%	**96.6%**	94.4%	91.1%

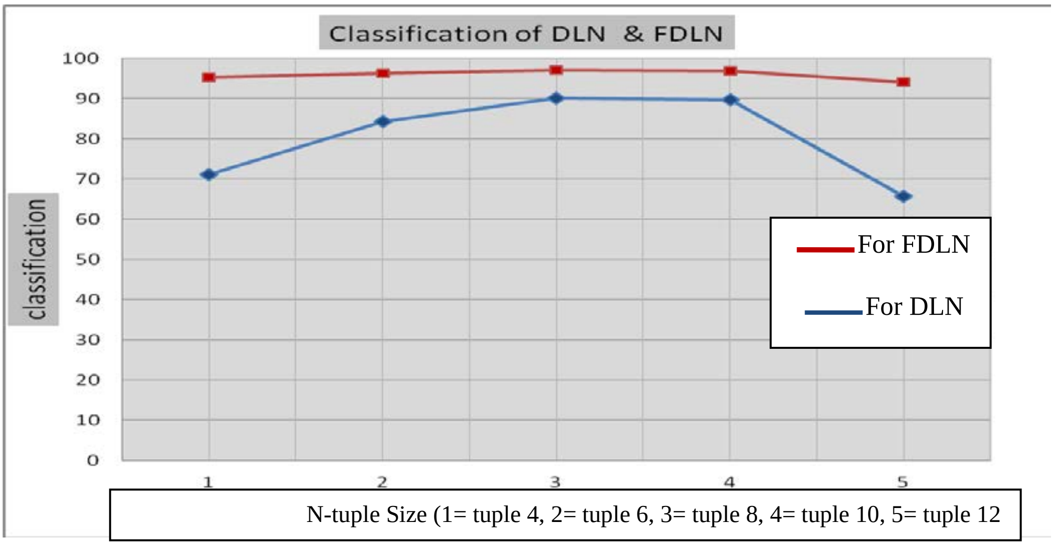

Figure (8): The Classification of DLN and FDLN Both with Maximum Rate of Training (90 Patterns for All Classes, 15 Patterns per Class).The Red Line is for FDLN, the Blue Line is for DLN

Figure (9) and (10) shows GUI that indicates the result of some abnormal RBCs which is tear drop type and sickle cell type. The recognition is 90.8% for tear drop type and 99.4% for sickle cell type.

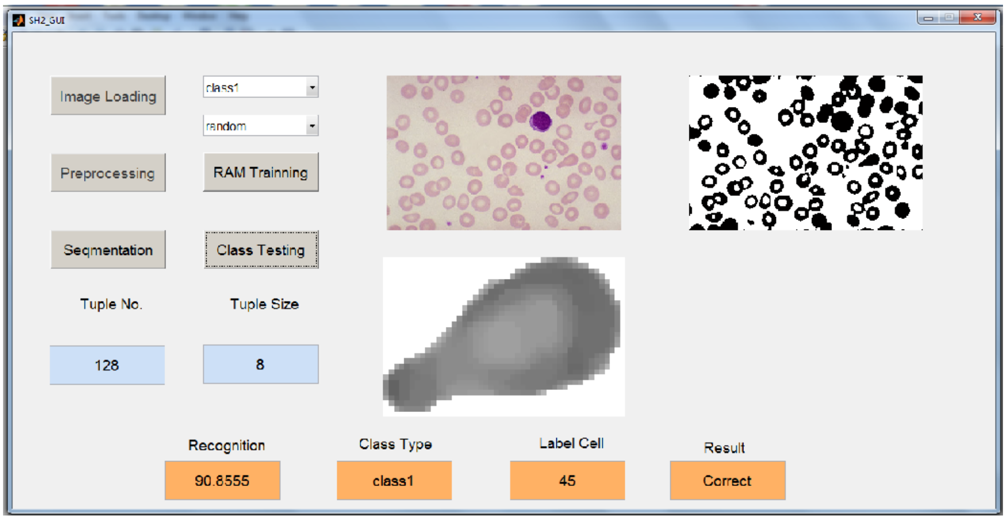

Figure (9): GUI of tear drop type which is the first class in this classification

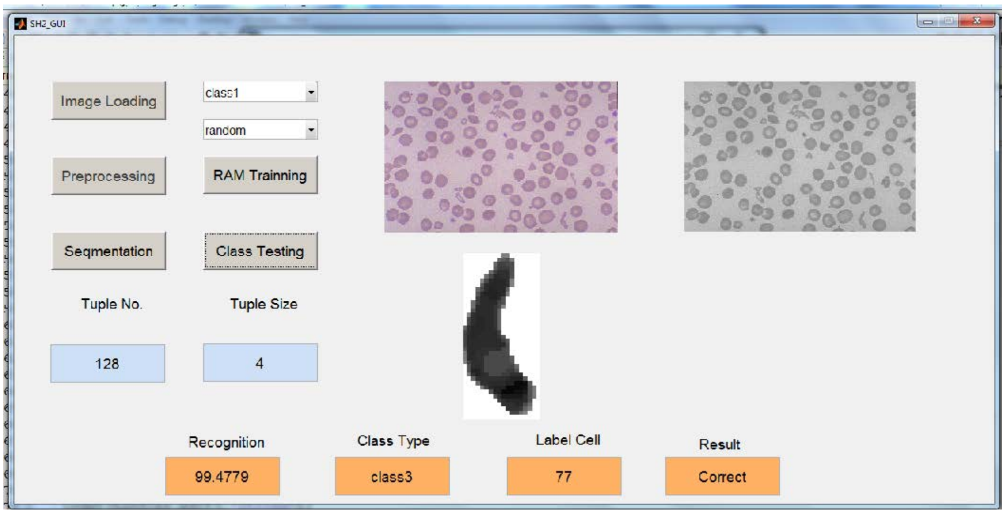

Figure (10): GUI of sickle cell type which is the third class in this classification

Conclusion

The main objective of the work reported in this paper was to investigate the design of multi category digital learning network for medical diagnosis of RBCs. Six classes were used that recognize six kinds of RBC cells. Thirty images were collected for each class. A special image processing including several preprocessing and segmentation operations were done in order to improve the image to be in a suitable form for DLN. DLN firstly introduced to test the classification of the abnormal cell FDLN a modification for DLN is proposed to optimize the classification of RBC. Whereby, performance improvement in multi-category DLN can be obtained by considering the common features for each individual n-tuple of different classes. These common features computed by introducing the response histogram for each input pattern .Many experiments were done to investigate the relation between the training pattern size and n-tuple size in order to get optimum performance for the DLN. The results have revealed that a variation in the system performance as a function of n-tuple size, training set size and connection mapping is possible. The performance analysis showed that the FDLN improved the recognition performance in classification of RBC. FDLN technique enhanced the correct recognition to 96.6%. Beside that the rejection was decreased to 2.2%, and the error to 1.1%.

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