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Texture Classification using Artificial Neural Network for Diagnosis of Skin Cancer

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Abstract – **This paper attempts to improve the efficiency of the system that proposed in [1] to determine whether a given skin lesion microscopic image is malignant or benign; in case of malignancy, the system can specify its type; whether it is squamous cell carcinoma or basal cell carcinoma (the two leading skin cancer types). The testing of this system was conducted using 80 microscopic images of skin tissues of the types normal, benign and the two types of skin cancer (squamous and basal); the images have been collected from different hospital pathology departments as part of the research work. Some of the collected samples have been used as training and others as testing materials. The proposed system consists of 3 main steps. First, extraction of a set of textural descriptors to localize the abnormal visual attributes which may appear in the tested skin tissue images. Second, selection of the best discriminating texture features. Third, identify the type of skin tissue images using artificial neural network (ANN). In the training phase, the system was trained using 50 skin tissue images, the textural features extracted from training samples were analyzed and their discrimination powers were evaluated in order to get a list of the most suitable features for auto recognition task. When ANN is trained on co-occurrence features the attained allocation accuracy rates was (%97.71) and the diagnosis accuracy rate was (%98.75). While when using ANN with combinations of different types of textural features; the allocation accuracy rate reached to (%97.90) while the diagnosis accuracy rate became (%98.75).**

Keywords – **Medical Image Classification, Skin Cancer Detection, Medical Image Analysis, Textural Analysis, Artificial Neural Network.**

I. Introduction

Today, cancer constitutes a major health problem. Approximately one out of every two men and one out of every three women get cancer at some point during their lifetime. Skin cancer is the most common form of human cancer. The annual rates of all forms of skin cancer are increasing each year [2]. In skin cancer the cancer begins in cells that make up the skin. Skin cancers are named for the type of cells where the cancer starts. Skin cancer is a change in some of the cells of skin such that they grow abnormally to form a malignant tumor. These abnormal cells can invade through the skin into adjacent structures or travel throughout body and become implanted in other organs and continue to grow [3]. The main reason of skin cancer is overexposure to ultraviolet radiation (UVR). Most exposure to UVR comes from sunlight, but exposure can also come from artificial sources such as sun beds. Whereas the short term results from unprotected UVR exposure are sunburn and tanning, long term exposure can cause prematurely aged skin, wrinkles and skin cancer [4]. Skin cancer is the most dangerous type of the diseases that involve this organ. There are three common types of skin cancer, basal cell carcinoma, squamous cell carcinoma (Together, these two are also referred to as non-melanoma skin cancer) and melanoma [5]. A delay in its diagnosis makes definitive surgical treatment difficult and this may threaten patient's life. Until now, the diagnosis of various skin cancers is based on the dermatologist experience that offers him with a high index of suspicion regarding the clinical appearance of a given lesion [6]. However, the definitive diagnosis depends eventually on the results of microscopic (histopathological) evaluation of the sections obtained from the surgically excised suspicious lesion; this is considered the golden standard to achieve the definitive diagnosis [7].

In some instances the definite histopathological diagnosis of malignancy is difficult; this is particularly so when there is overlap in morphological features between some malignant and benign lesions. Computer-based automatic diagnosis system seems to be an important tool for such difficult cases. In other words, it is considered to be a "double reading" system, in addition to pathological interpretation, where pathologists can take into consideration the information provided by the computer before making their final decision. Computer is not more intelligent than human brain, but it may be capable of extracting some information, such as texture features, that may not be readily perceived by human eyes [1].

Recently, computer-aided diagnosis using artificial neural networks (ANNs) has been reported to be an accurate tool for the diagnosis the skin cancer tissues. ANN is considered as important way for classification, it is computational paradigms based on mathematical models that unlike traditional computing have a structure and operation that resembles that of the mammal brain [8].

II. Methodology

We will explain the structure of the introduced system for skin cancer tissue diagnosis from optical microscope images using the artificial neural network method. Figure 1 shows the main component of the proposed system. The developed system flow passes through the following two phases:

a) Enrollment Phase: The input to this phase is a set of known skin tissue images. The first stage is the preprocessing stage; it includes: (i) reading color image data, (ii) color decomposition, (iii) contrast enhancement, (iv) determining the small artificial white gaps, and (v) scalar quantization. The second stage is partitioning the region of interest in the skin tissue images to overlapping blocks (i.e., sub images). The third stage is the feature extraction stage; it includes determination of co-occurrence matrix, run length matrix, local roughness, and global roughness based features to describe the texture

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features. The fourth stage is features analysis and evaluation. In this system all the previous stages have been presented in [1], and they applied in same way in this work. The final stage is the recognition stage which is based on artificial neural network (ANN). In ANN the database contains the values of the nodes' weights of the trained neural network. For determination of proper set of ANN weights the back-propagation training algorithm was used.

b) Detection Phase: in this phase the input is an unknown color skin tissue image. Same preprocessing operations that applied in the enrollment phase are applied in this phase. The next stage is partitioning the whole skin tissue image to overlapping blocks (sub images). Then, the same sets of features that are determined in the enrollment phase are extracted. The final stage in this phase is the identification stage; it is performed to assign to class index of the tested sub-images by using the trained neural network.

A. Image Acquisition

The unavailability of reference database of skin cancer images had obliged us to look for stained sections (glass slides) of skin cancer biopsy cases from the central medical laboratory/ ministry of health and different Iraqi hospital pathology departments. Taking images from these sections, was conducted through using microscope-attached digital camera, it was performed with the help of an experienced pathologist. The pathologist was required to pin-point the areas of interest in histological sections. In this work, 80 samples of skin tissue are collected. The taken samples include both the normal and abnormal skin tissue. The samples images have bitmap (BMP) format with color depth 24 bit/pixel; and the size of each image is (1280x1024) pixels [1].

B. Recognition Based on Artificial Neural Network

In this proposed system the three layers feed forward neural network architecture had been adopted. The adopted neural network consists of one input layer, one output layer, and one hidden layer. As first step, the network architecture is defined by assigning its parameters:

1) *Number of Input Nodes:* The number of input nodes is equal to number features belong to the best combination of discriminating features that leads to highest classification.
2) *Number of Output Nodes:* The output layer consists of a number of nodes; the output of each node represents one digit in the binary output number. The binary rounded values of these nodes are combined to produce one output integer number which represents the nominated class index.
3) *Number of Hidden Nodes:* Initially, it is consist of a specific number of nodes. The trial-and error mechanism had been followed to determine the number of hidden nodes. It is difficult to give a formula that can precisely determine the number of hidden nodes; however a little possible number of nodes was presumed. There are two main reasons for this. The first is concerned with the computation time; because more hidden nodes in the network needs longer time in network training phase. The second reason is concerned with the possibility of over fitting, where using too many hidden nodes results in high accuracy on the training set but a high error rate on the test set.
4) *Learning Rate:* it is an important training parameter since it controls two conflicted requirements: the fast convergence and stable weights estimations.

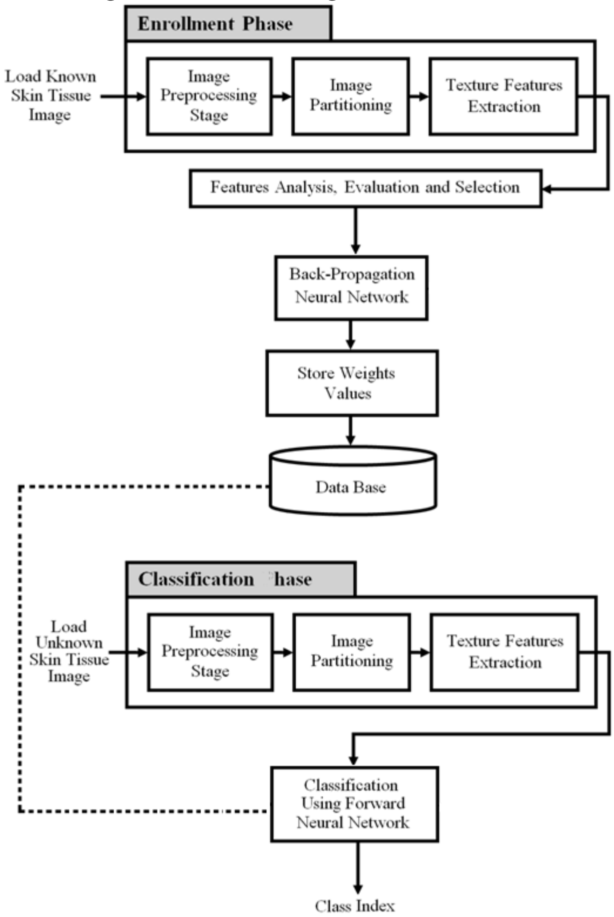

Fig.1. General Diagram of the Proposed System

Before feeding (input) the feature vector to the network the value of the involved features must normalized because it is important to unify the dynamic ranges of all involved features. The applied normalization process maps the extracted feature's values to the range [0, 1]. This was performed by finding the actual dynamic range; i.e., determining the highest (fmax) and lowest (fmin) values for each feature and over all classes, taken into consideration that there are many samples representing each class. The normalization of feature (f) was performed using the following equation:

$$f_{norm} = \begin{cases} 0 & \text{if } f \le f_{min} \\ \frac{f - f_{min}}{f_{max} - f_{min}} & \text{if } f_{min} < f < f_{max} \\ 1 & \text{if } f \ge f_{max} \end{cases} \qquad (1)$$

Where, form is the normalized feature value, f is the real feature value; f_{max} and f_{min} are the highest and lowest features values found over all classes and for all samples listed in the database.

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C. Training a Feed Forward Neural Network

The set of training feature vectors are used to train the established ANN; these vectors are extracted from known skin tissues images and saved in a feature vector database. The training vectors are used to train a feed forward neural network by adjusting its nodes weights and bias values using back-propagation algorithm. The computed weights and bias values of trained network are, also, registered in the dedicated database. In the training stage the network starts with a random set of weights and the training sample is presented at the input layer. Then, the outputs of the network are evaluated and compared with the expected "binary" output vector, the error is calculated and the results were fed back from output layer to adjust weights. These steps are repeated for all training set, and at each time the weights are adjusted. The training continues until one of the stopping conditions is satisfied (i.e., the number of iterations is passed over or the overall error becomes lower than a predefined target error), once one of the stopping conditions is satisfied then then training loop is terminated and the network is considered ready for decision making tasks.

In the established system, the number of iterations is set (10000) as stopping condition, the number of input nodes is set equal to the number of the best combination of discriminating features. One hidden layer was used, the number of hidden nodes was varied to find out the best smallest number of hidden nodes required to get best recognition; taking into consideration that each additional hidden node causes extra computation during both training and classification phases. Also, the best value of learning rate was investigated during the learning phase.

The number of output nodes was taken 3, to represent the tissue class's index in binary form. In general, to train the ANN a sufficient number of samples are needed to be included in the training data set. The remaining samples can be used to test the network; which they have never been encountered during training.

III. Test Results

Table (1) presents the number of samples used for training and for testing the proposed system. The samples images have bitmap (BMP) format with color depth 24 bit/pixel; and the size of each image is (1280x1024) pixels. Two accuracy rates had been used for evaluating the system performance; they are (i) the allocation accuracy rate and (ii) the diagnosis accuracy rate. Allocation accuracy rate signifies the number of correctly recognized image blocks relative to the total number of tested blocks. On the other hand, the parameter "diagnosis accuracy rate" reflects the number of correctly diagnosed image samples relative to the total number of samples.

Since, there are four classes of images samples to be recognized, three output layer nodes were taken. To define the behavior of neural network during the training the effects of the following two training phase parameters have been tested:

1. The attained minimum training error.
2. Number of iterations is conducted in training stage.

Table 1: The List of Number of Samples Used in the Feature Analysis & Testing Phases (when block size = 150x150)

Class Name	Training		Testing	
	No. of Cases	No. of Samples	No. of Cases	No. of Samples
Normal	15	308	20	418
Benign	18	863	28	1368
Basal Cell Carcinoma	7	328	14	636
Squamous Cell Carcinoma	10	502	18	906
Total	50	2001	80	3328

A. The Results of Using Co-occurrence Features

Table (2) presents the adopted default parameters values of the used neural network when the co-occurrence features sets are used for skin tissue recognition task.

Table 2: The Default Values of the Neural Network Parameters Used in Training Stage.

Parameter	Value
Number of input nodes	20
Number of hidden nodes	21
Number of output nodes	3
Range of initial weights	[-1,+1]
Initial learning rate (η)	0.9
Minimum error (ε)	0.001
Size of blocks	200X200
Maximum number of iteration (I)	20000

To evaluate the system performance various values of the involved system parameters have been tested. The considered parameters are:

a) Block size.

b) Number of hidden layer nodes.

b) Learning rate.

A.1. The Effects of Number of Hidden Nodes and Block Size

Deciding the proper number of nodes in the hidden layer is very important part of deciding the overall neural network architecture. The number of nodes in the hidden layer must be precisely selected. Using too few hidden nodes may result in what is called “under fitting”. On the other hand, using large number of hidden nodes can result in several problems; (i) it may result in what is called “over fitting” and (ii) it causes significant increase of the required time to train the network. The trial-and-error mechanism was adopted in this research work to find out the proper number of hidden nodes. Various values of hidden nodes numbers were tested to examine their effect on ANN performance. Table (3) shows the effect of the number of hidden nodes in the hidden layer of the ANN.

The best attained recognition rates are (99.79%) for allocation accuracy rate and (100%) for diagnosis accuracy rate); they occurred when the size of blocks is set to (200x200) and the number of hidden nodes is taken 21.

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Table 3: The Effect of "Number of Hidden Nodes" on the System Performance

Block size=75X75								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	68.36	76.70%	80.60	86.03	87.75	79.09	86.08	88.32
Diagnosis Accuracy Rate (%)	86	88	92	98	98	92	94	98
Min Training Err	0.231	0.225	0.194	0.118	0.120	0.167	0.155	0.100
Block size=100X100								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	78.61	87.89	91.09	90.19	84.52	91.57	89.98	93.03
Diagnosis Accuracy Rate (%)	80	98	98	98	96	100	98	98
Min Training Err	0.176	0.095	0.099	0.079	0.113	0.063	0.086	0.067
Block size=150X150								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	97.32	98.48	99.05	98.10	99.51	99.46	99.24	99.25
Diagnosis Accuracy Rate (%)	100	100	100	100	100	100	100	100
Min Training Err	0.012	0.008	0.005	0.009	0.003	0.003	0.004	0.004
Block size=200X200								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	94.89	97.83	99.77	99.42	99.59	99.10	99.71	99.79
Diagnosis Accuracy Rate (%)	98	100	100	100	100	100	100	100
Min Training Err	0.024	0.011	0.001	0.002	0.004	0.003	0.001	0.001
Block size=225X225								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	98.38	98.36	98.49	99.13	98.92	98.58	98.74	99.29
Diagnosis Accuracy Rate (%)	100	100	100	100	100	100	100	100
Min Training Err	0.009	0.009	0.007	0.006	0.007	0.005	0.007	0.004

A.2. The Effects of Learning Rate Parameter

One of the parameters that affect the accuracy of feed forward neural network is the learning rate; it is used to control the rate of weight adjustments. If the value of learning rate is too small then the learning process takes longer time; and if it is too large then the learning process would be imprecise in determining and adjusting the weight. There is no analytical method for finding the optimal learning rate; it is usually optimized empirically, just by trying different values. Table (4) shows the effect of different learning rate when using values such as 0.1, 0.3, 0.5, 0.7, 0.9 and 1.0, when the size of the block is (200x200) and the number of hidden nodes is set 21 to find out which value leads to the best performance. The results listed in table (4) show that the learning rate value (0.9) leads to the best detection performance.

Table 4: The effect of learning rate on system performance

Learning Rate	Min Err	Allocation Accuracy Rate (%)	Diagnosis Accuracy Rate (%)
0.1	0.005389	99.31915	100
0.3	0.002758	99.65117	100
0.5	0.000961	99.72274	100
0.7	0.002132	99.71986	100
0.9	0.001756	99.79	100
1	0.00188	99.65042	100

The cognition results of testing all 80 samples, when using block size (200x200), 21 hidden layer nodes and learning rate value 0.9 were (%88) for allocation accuracy rate, and (%93.75) for diagnosis accuracy rate. However, when training is accomplished on the whole 80 cases, the cognition results were (%97.71) for allocation accuracy rate, and (%98.75) for diagnosis accuracy rate.

B. The Results of Using All Extracted Features

Table (5) presents the adopted default parameters values of the used neural network on all texture features for skin tissue recognition task.

Table 5: The Default Values of the Neural Network Parameters Used in Training Stage.

Parameter	Value
Number of input nodes	20
Number of hidden nodes	20
Number of output nodes	3
Range of initial weights	[-1,+1]
Initial learning rate (η)	0.9
Minimum error (ε)	0.001
Size of blocks	200x200
Maximum number of iteration (I)	20000

B.1. The Effects of Number of Hidden Nodes and Block Size

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Table 6: The Effect of "Number of Hidden Nodes" of the Hidden Layer"

Block size=75X75								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	85.34	79.27	85.02	85.90	87.82	84.42	87.39	88.54
Diagnosis Accuracy Rate (%)	92	88	92	92	94	92	94	94
Min Training Err	0.162	0.203	0.157	0.168	0.115	0.180	0.129	0.113
Block size=100X100								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	90.40	90.80	93.39	95.04	97.58	95.90	91.48	96.63
Diagnosis Accuracy Rate (%)	96	96	98	98	100	98	96	98
Min Training Err	0.087	0.0760	0.0352	0.0246	0.0121	0.0286	0.0340	0.0241
Block size=150X150								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	97.48	99.11	99.42	99.57	98.39	99.43	99.05	99.68
Diagnosis Accuracy Rate (%)	100	100	100	100	100	100	100	100
Min Training Err	0.113	0.0050	0.0032	0.0023	0.0075	0.0032	0.0049	0.0022
Block size=200X200								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	99.33	99.51	99.48	98.50	99.58	99.65	99.83	99.49
Diagnosis Accuracy Rate (%)	100	100	100	100	100	100	100	100
Min Training Err	0.0048	0.0021	0.0034	0.0091	0.0025	0.0020	0.0016	0.0041
Block size=225X225								
No of Hidden nodes	10	13	16	17	18	19	20	21
Allocation Accuracy Rate (%)	94.01	98.14	99.59	98.10	97.49	99.24	99.16	98.16
Diagnosis Accuracy Rate (%)	96	100	100	100	100	100	100	100
Min Training Err	0.0258	0.0095	0.0030	0.0078	0.0110	0.0038	0.0052	0.0068

Table (6) shows the effect of the number of hidden nodes on the system cognition performance.

The best attained recognition rates (i.e., 99.82% for allocation accuracy rate and 100% for diagnosis accuracy rate) have been achieved when the size of blocks is set to (200x200) and the number of hidden nodes is set 20.

B.2 The Effects of Learning Rate Parameter

Table (7) shows the effect of different learning rate when using values such as 0.1, 0.3, 0.5, 0.7, 0.9 and 1.0, when the size of the block is taken (200x200) and the number of hidden nodes is set 20 to find out which value leads to the best performance. The results listed in the table show that the learning rate (0.9) leads to the best detection performance.

Table 7: The effect of learning rate on system performance

Learning Rate	Min Err	Allocation Accuracy Rate (%)	Diagnosis Accuracy Rate (%)
0.1	0.00309	99.63	100
0.3	0.00610	98.95	100
0.5	0.00264	99.67	100
0.7	0.00228	99.76	100
0.9	0.00160	99.83	100
1	0.00274	99.66	100

The results of testing all 80 samples, when using block size (200x200), 20 hidden layer nodes and learning rate value 0.9 was led to (%88.77) for allocation accuracy rate and (%93.75) for diagnosis accuracy rate. However, when training is accomplished on the whole 80 cases, the result was (%97.85) for allocation accuracy rate, and (%98.75) for diagnosis accuracy rate.

IV. Conclusion

In this paper, an improved automatic system for skin cancer diagnosis is introduced, the system is an improved variant to that proposed in [1], the main difference is using ANN for recognition decision instead of using the traditional statistical approach.

The recognition rates of the proposed system was (%97.71) for allocation accuracy rate, and (%98.75) for diagnosis accuracy rate when using co-occurrence features, While when using combinations of different types of textural features; the recognition rate reached (%97.90) for allocation accuracy rate, and (%98.75) for diagnosis accuracy rate. The attained rates are better than those reached in the previous proposed system [1]; this indicates that the used ANN has good capability to adapt his architecture for recognition task.

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