CLASSIFICATION OF CANCEROUS TISSUES BASED ON PATTERN RECOGNITION AND FEED FORWARD NEURAL NETWORK

S.K.Hemapreethy¹ C.Selvi²
¹P.G.Scholar
¹Centre for Advance Research
¹Muthayammal Engineering College, Rasipuram, Tamil Nadu, India.

Abstract— The classification of cancerous tissues are crucial in the case of cancer diagnosis. This project describes the detection and classification of cancerous tissues based on structural and statistical pattern recognition and neural networks. Image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm. The feed forward neural network is trained using back propagation algorithm which is being employed to classify the cancerous tissues based on its features. Thus our experiment demonstrates that the proposed model leads to higher accuracies and also provides quick results, compared against the pattern recognition technique that uses SVM classifier for quantification.

Key words: Feed forward neural network, classification, pattern recognition, back propagation algorithm, feature extraction.

I. INTRODUCTION

Cancer known medically as a malignant neoplasm is a broad group of diseases involving unregulated cell growth. In cancer, cells divide and grow uncontrollably, forming malignant tumors, and invading nearby parts of the body. The cancer may also spread to more distant parts of the body through the lymphatic blood stream. Not all tumors are cancerous; benign tumors do not invade neighboring tissues and do not spread throughout the body. There are over 200 different known cancers that affect humans.

Cancer can be detected in a number of ways, including the presence of certain signs and symptoms, screening tests, or medical imaging. Once a possible cancer is detected it is diagnosed by microscopic examination of a tissue sample. Cancer is usually treated by chemotherapy, radiation therapy and surgery. The chances of surviving the disease vary greatly by the type and location of the cancer and the extent of disease at the stage of treatment.

Fig.1: Cancerous tissue

The cancerous tissue is depicted in Fig.1. The classification and diagnosis of these cancerous tissues were very difficult in olden days and also lead to numerous death rates. At present it became easier with the help of pattern recognition techniques such as structural and statistical pattern recognition. The implementation of these systems typically requires a deep analysis of biological deformations from a normal to a cancerous tissues as well as the development of accurate models that quantify the deformations.

A. RELATED WORK

For diagnosing the cancerous tissues, many efforts have been contributed in recent years. Erdem Ozdemir and Cigdem Gunduz Demir [1] provided an hybrid classification model for digital pathology using structural and statistical pattern recognition. This work involved the classification of the cancerous tissues based on SVM classifier. A. B. Tosun and C. Gunduz-Demir [2] introduced an effective and robust algorithm for the segmentation of histopathological tissue images. This algorithm constructs “a graph run-length matrix” by counting the number of “graph edge runs” instead of constructing a gray-level run-length matrix by counting the number of gray runs. D. Altunbay, C. Cigir, C. Sokmensuer, and C. Gunduz-Demir [3] , used a new structural method to mathematically represent and quantify a tissue for the purpose of automated and objective cancer diagnosis and grading. In this representation, a Delaunay triangulation is constructed on nuclear tissue components. P.W. Huang and C.-H. Lee [4], proposed two feature extraction methods based on fractal dimension to analyze variations of intensity and texture complexity in regions of interest. Each image can be classified into an appropriate grade by using Bayesinan, -NN, and SVM classifiers, respectively. Leave-one-out and -fold cross-validation procedures were used to estimate the CCR. A. Tabesh, M. Teverovskiy, H. Y. Pang, V. P. Kumar, D. Verbel, A. Kotsianti, and O. Saidi [5] , made use of the most common method for histological grading of prostate tissue, the Gleason grading system. In this system, the tissue is classified into five grades, numbered 1 through 5. The grade increases with increasing malignancy level and, therefore, cancer aggressiveness. Gleason grade characterizes tumor differentiation, i.e., the degree of tumor resemblance to normal tissue. C. Wittke, J. Mayer, and F. Schweiggert [6] , proposed a common method of gleason grading used by pathologists to determine the aggressivity of prostate cancer on the basis of histological slide preparations. C. Demir, S. H. Gultekin, and B.Yener [7] , proposed a work that presents a graph-based representation of histopathological images for automated cancer diagnosis by probabilistically assigning a link between a pair of cells. The contributions of this work are twofold. First, it is shown that without establishing a pairwise spatial relation between the cells , neither the spatial distribution of the cells nor the texture analysis of the images yields accurate results for tissue level diagnosis of brain cancer called malignant glioma. Second, this work defines a set of global metrics by processing the
entire cell-graph to capture tissue level information coded into the histopathological images.

II. METHODOLOGY
This paper proposes a method to differentiate between the abnormalities and the non-abnormalities in the cancerous tissues. This approach generally includes five steps: Tissue graph generation, Query graph generation, Localization of key regions, Feature extraction, Classification using neural network.

A. Tissue graph generation
Tissue imaging is an expanding area that aims to understand the mechanisms of live processes based on recording the locations and dynamics of biomolecules within biological samples. The tissue images are being generated by means of Delaunay triangulation. The graph ‘G’ is being generated using ‘V’ set of nodes, ‘E’ set of edges and ‘µ’ mapping function. It is being represented as $G = \{V,E,\mu\}$. The tissue images are being threshold by means of the Otsu’s method. The image pixels are being quantified as nucleus pixels and non-nucleus pixels.

B. Query graph generation
Query graph are the sub graphs that corresponds to normal gland structures in an image. The generation of the query image is obtained by means of the Breadth first search algorithm. In graph theory, BFS is a strategy for searching in a graph when search is essentially two operations: (a) visit and inspect a node of a graph; (b) gain access to visit the nodes that neighbour the currently visited node. The BFS begins at a root node and inspects all the neighbouring nodes. Then for each of those neighbour nodes in turn, it inspects their neighbour nodes which were unvisited, and so on. The process of k-means clustering operation is being performed in order to split the image into number of clusters and the finally obtains the k-means clustered output.

C. Localization of key regions
The localization of key regions in an image includes a search process. It is being carried out using shortest path algorithm. The search process may be breadth first search or depth first search process.

D. Feature extraction
In pattern recognition and in image processing, feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant then the input data will be transformed into a reduced representation set of features. Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. The features are being extracted as structural features and textural features. The structural features are being generated using Delaunay triangulation and colour graph representation. Similarly the textural features are generated using co-occurrence matrix grid and Gabor filter grid algorithms. The impulse responses of these Gabor filters are created by multiplying a Gaussian envelope function with a complex oscillation. Gabor showed that these elementary functions minimize the space time - uncertainty product. By extending these functions to two dimensions it is possible to create filters which are selective for orientation.

E. Classification using neural network
Artificial Neural Network is a parallel distributed processor that has a natural tendency for storing experiential knowledge. They can provide suitable solutions for problems, which are generally characterized by non-linearities, high dimensionality noisy, complex, imprecise, and imperfect or error prone sensor data, and lack of a clearly stated mathematical solution or algorithm. A key benefit of neural networks is that a model of the system can be built from the available data. Image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm. The topology of the artificial neural network is being depicted in Fig.2.

1) Feed forward Neural Network
In feed forward neural network, back propagation algorithm is computationally effective and works well with optimization and adaptive techniques, which makes it very attractive in dynamic nonlinear systems. This network is popular general nonlinear modeling tool because it is very suitable for tuning by optimization and one to one mapping between input and output data. The input-output relationship of the network is as shown in Fig.3. In Fig.3 ‘$X_m$’ represents the total number of input image pixels as data, ‘$nk_l$’ represents the number of neurons in the hidden unit, k represents the number hidden layer and l represents the number of neurons in each hidden layer.

A feed forward back propagation architecture consists of three layers. The first layer is referred as input layer and the second layer is represents the hidden layer, has...
a tan sigmoid (tan-sig) activation function is represented in Eq.(1)

\[
Y_i(t) = \tanh(v_i)
\]  

(1)

This function is a hyperbolic tangent which ranges from -1 to 1, \(y_i\) is the output of the \(i\)th node (neuron) and \(v_i\) is the weighted sum of the input and the second layer or output layer, has a linear activation function. Thus, the first layer limits the output to a narrow range, from which the linear layer can produce all values. The output of each layer can be represented in Eq.(2).

\[
Y_{N Xi} = [W_{N Xi}X + b_{N Xi}]  
\]  

(2)

where \(Y\) is a vector containing the output from each of the \(N\) neurons in each given layer, \(W\) is a matrix containing the weights for each of the \(M\) inputs for all \(N\) neurons, \(X\) is a vector containing the inputs, \(b\) is a vector containing the biases and \(f(\cdot)\) is the activation function for both hidden layer and output layer.

The trained network was created using the neural network toolbox from Matlab9b.0 release. In a back propagation network, there are two steps during training. The back propagation step calculates the error in the gradient descent and propagates it backwards to each neuron in the hidden layer. In the second step, depending upon the values of activation function from hidden layer, the weights and biases are then recomputed, and the output from the activated neurons is then propagated forward from the hidden layer to the output layer. The network is initialized with random weights and biases, and was then trained using the Levenberg-Marquardt algorithm (LM). The weights and biases are updated according to Eq.(3)

\[
D_{n+1} = D_n - [J^T J + \mu I]^{-1} J^T e
\]  

(3)

where \(D_n\) is a matrix containing the current weights and biases, \(D_{n+1}\) is a matrix containing the new weights and biases, \(e\) is the network error, \(J\) is a Jacobian matrix containing the first derivative of \(e\) with respect to the current weights and biases. In the neural network case, it is a \(K\)-by-\(L\) matrix, where \(K\) is the number of entries in our training set and \(L\) is the total number of parameters (weights+biases) of our network. It can be created by taking the partial derivatives of each in respect to each weight, and has the form as in Eq.(4)

\[
J = \begin{bmatrix}
\frac{\partial F(x_1, w)}{\partial w_1} & \ldots & \frac{\partial F(x_1, w)}{\partial w_L} \\
\frac{\partial F(x_2, w)}{\partial w_1} & \ldots & \frac{\partial F(x_2, w)}{\partial w_L} \\
\frac{\partial F(x_N, w)}{\partial w_1} & \ldots & \frac{\partial F(x_N, w)}{\partial w_L}
\end{bmatrix}
\]  

(4)

where \(F(x_i, L)\) is the network function evaluated for the \(i\)-th input vector of the training set using the weight vector \(L\) and \(w_j\) is the \(j\)-th element of the weight vector \(L\) of the network. In traditional Levenberg-Marquardt implementations, the jacobian is approximated by using finite differences. However, for neural networks, it can be computed very efficiently by using the chain rule of calculus and the first derivatives of the activation functions. For the least-squares problem, the Hessian generally doesn’t need to be calculated. As stated earlier, it can be approximated by using the Jacobian matrix with the formula in Eq.(5).

\[
H = J^T J
\]  

(5)

\(I\) is the identity matrix and \(\mu\) is a variable that increases or decreases based on the performance function. The gradient of the error surface, \(g\), is equal to \(J e\)

III. EXPERIMENTS

A. Training of the Feed Forward Neural Network

Feed forward neural network is trained using back propagation algorithm. There are two types of training or learning modes in back propagation algorithm namely sequential mode and batch mode respectively. In Batch mode learning; weights are updated only after the entire set of training network has been presented to the network. Thus the weight update is only performed after every epoch. It is advantageous to accumulate the weight correction terms for several patterns. Here batch mode learning is used for training.

In order to improve the learning and understanding properties of neural network, noisy image data and filtered output image data are introduced for training. Noisy image data and filtered output data are considered as inputs for neural network training and noise free image is considered as a target image for training of the neural network. Back propagation is pertained as network training principle and the parameters of this network are then iteratively tuned. Once the training of the neural network is completed.

Fig.4: Training of the neural network

Fig.5: Best training performance is NaN at epoch 1339

Thus after 1339 iterations the parameters of the system such as contrast, resolution, energy, homogeneity and correlation are being calculated for each and cancerous tissues. Thus
finally the tissues are being classified as normal tissues, low grade cancerous tissues and high grade cancerous tissues by means of pattern recognition and feed forward neural network.

IV. CONCLUSION

In this paper, we propose a novel method: Neural network based classification of cancerous tissues on structural and statistical pattern recognition. Here feed forward neural network is being adopted for the purpose of quantification. Thus this method based on the feed forward neural network achieves significant improvement on accuracy and probably it provides quicker results when compared with the other conventional methods.

REFERENCES

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