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Efficient Classification of Lung Tumor using Neural Classifier

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ABSTRACT: In this paper a new classification algorithm is proposed for the Efficient Classification of Lung Tumor. In order to develop algorithm 80 CT scan images of patients have been considered consisting of Benign Tumor, Malignant Tumor and Normal Lung Computed tomography (CT) Scan image. With a view to extract features from the CT scan images after image processing, an algorithm proposes (DCT) discrete cosine Transform domain coefficients. The Efficient classifiers based on Multilayer Perceptron (MLP) Neural Network. A separate Cross-Validation dataset is used for proper evaluation of the proposed classification algorithm with respect to important performance measures, such as MSE and classification accuracy. The Average Classification Accuracy of MLP Neural Network comprising of one hidden layers with 7 PE's organized in a typical topology is found to be superior (100 %) for Training . Finally, optimal algorithm has been developed on the basis of the best classifier performance. The algorithm will provide an effective alternative to traditional method of Lung Computed tomography (CT) scan image analysis for deciding the tumor in lung is Benign or Malignant.

KEYWORDS: Neural solution, MatLab, Excel, CT scan images.

I. INTRODUCTION

The early detection of lung cancer is a most challenging problem to identify in human body, due to the different different cells structure of cancer, where most of the cells are overlapped with each other. Cancer diagnosis is one of the most danger problems in the medical domain. Most of researchers have focused try to improve performance and possible to obtain Best and satisfactory results. The correct classification of cancer is an important real-world medical problem. Cancer has become one of the most harmful Death disease around the world and research into Lung cancer diagnosis and treatment has become an one of the most important issue all over the world.

In the modern age of computerized fully automated trend of living, the field of automated diagnostic systems plays an important and vital role. Automated diagnostic system designs in Medical Image processing are one such field where numerous systems are proposed and still many more under conceptual design due explosive growth of the technology today [1]. Lung cancer is considered to be the main cause of cancer death worldwide, and it is difficult to detect in its early stages because symptoms appear only in the advanced stages causing the mortality rate to be the highest among all other types of cancer. More people die because of lung cancer than any other types of cancer such as breast, colon, and prostate cancers. There is significant evidence indicating that the early detection of lung cancer will decrease death rate [2].

The proposed algorithm provides Efficient Classification of Lung Tumor based on (MLP) Multi-layer Perceptron neural network ap- proach and tested on the Lung 80 CT scan images comprising of features extracted using (DCT) discrete cosine Transform domain co-efficient.

II. RELATED WORK

One of the most popular nearest neighbor search algorithm for learning and classification techniques introduced by Fix and Hodges [6] which has been proved to be a simple and power full recognition algorithm. Cover and Hart [7] showed that the decision rule performs well considering that no explicit knowledge of the data is available. *k*-NN rule is a



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simple generalization of this method where a new pattern is classified into the class with the most members present among the k-nearest neighbors, can be used to obtain good estimates of the Bayes error and its probability of error asymptotically approaches the Bayes error.

Classification technique has become most popular due to increase number of cancer is detected throughout the world and now a day it's most challenging task in medical diagnosis. In the medicine area, many expert systems (ESs) [4] were designed. Knowledge discovery and data mining have found numerous applications in business and scientific domain. Valuable knowledge can be discovered from application of data mining techniques in healthcare system [3].

There are many application domains where artificial neural network model has been used for diagnosis breast cancer data [9]. In the author's proposed system focuses on the solution of two problems. One is how to detect tumors as suspicious regions with a very weak contrast to their background and another is how to extract features which categorize tumors where SVM classifier uses for classification. Supervised Learning technique used Diagnosis of Lung Cancer Disease [5].

Supervisory delta learning approach is used to train the model. The model is developed using multi layer perceptron network and trained by established Lung cancer data. This model is then used for the test data. Tested data is again compared with the clinical diagnosed report and the model is reconfigured by including the current information and new training weights are computed [8]. In the authors use k-NN algorithm for Wisconsin breast cancer database problem. In breast cancer diagnosis based on a SVM-based method combined with feature selection has been proposed.[9]

III. PROPOSED ALGORITHM

A. Research methodology :



Figure1 Methodology of work

It is proposed to study Efficient Classification of Lung Tumor using Neural Classifier. Data acquisition for the proposed classifier designed for the diagnosis of Lung Cancer shall be in the form of CT Scanned images. Image data will be Collected from the different- different hospitals of the country .The most important un correlated features as well as coefficient from the images will be extracted .In order to extract features, statistical techniques, image processing techniques, transformed domain will be used.



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1) Images Collected

We have collected the 80 CT-Scan images of lung cancer from the private hospital. By using this CT scan images an algorithm is developed which proposes two-dimensional discrete cosine Transform domain coefficients in addition to Average, Standard Deviation, Entropy, Contrast, Correlation, Energy, Homogeneity total coefficients Iget in excel sheet by using MatLab Code.

2) Feature Extraction

Collected Lung tumor CT Scan images are in .jpg format. By using CT scan images processing & cropping the region of Tumor the 128 features are extracted .



Fig. 2 Few Samples of input processed CT scan images of lungtumor. (Above lung images are of Benign, Malignant and Normal types)

Each Lung CT image is represented by a feature vector, F; which is comprised of 128 different parameters. The dataset contains 80 instances (exemplars) for three different classification The classifier based on neural network is trained from the training dataset, where a feature vector is mapped on to a particular class or name of the Lung disease. The neural network learns from data (training exemplars) and the connection weights and biases are estimated as a result of this learning.

3) Neural Networks

Following Neural Networks are tested:

a) Multilayer perceptron (MLP)

The most common neural network model is the multi layer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A graphical representation of an MLP is shown below:





Fig 3. The structure of neural network model multi layer perceptron (MLP)

The MLP and many other neural networks learn using an algorithm called backpropagation. With backpropagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (backpropagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training". [10]

Learning Rules used:

> Momentum

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

> Conjugate Gradient

CG is the most popular iterative method for solving large systems of linear equations. CG is effective for systems of the form A=xb-A (1) where x_is an unknown vector, b is a known vector, and A _is a known, square, symmetric, positive-definite (or positive-indefinite) matrix. (Don't worry if you've forgotten what "positive-definite" means; we shall review it.) These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: $dwij = r^* ai^* ej$, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The



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vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

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> Quick propagation

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

> Delta by Delta

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IV. SIMULATION RESULTS

1) Computer Simulation

The MLP neural network has been simulated for 80 tumor CT Scan images out of which 72 (90% of total images) were used for training purpose and 8 (10% of total images) were used for cross validation.

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



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Fig.4 MLP neural network trained with CG learning rule

2) Results

Output / Desired	Name(B)	Name(M)	
Name(B)	2	0	
Name(M)	1	5	

Table I. Confusion matrix on CV data set

Output / Desired	Name(B)	Name(M)	
Name(B)	16	0	
Name(M)	5	51	

TABLE II. Confusion matrix on Training data set

Here Table I and Table II Contend the C.V as well as Training data set. B stand for Benign And M stand For Malignant tumor identification.

Performance	Name(B)	Name(M)	
MSE	0.123708494	0.106485585	
NMSE	0.52782291	0.454338497	
MAE	0.222684843	0.174526192	
Min Abs Error	0.035862221	0.014454896	
Max Abs Error	0.888622265	0.896501761	
r	0.725388702	0.755035898	
Percent Correct	66.66666667	100	

TABLE III. Accuracy of the network on CV data set



Performance	Name(B)	Name(M)	
MSE	0.061921873	0.061786789	
NMSE	0.299722679	0.299068828	
MAE	0.136682908	0.137811342	
Min Abs Error	0.004978186	0.000653647	
Max Abs Error	0.891820022	0.900494857	
r	0.836982108	0.839146248	
Percent Correct	76.19047619	100	

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TABLE IV. Accuracy of the network on training data set

Here Table III and Table IV Contain the Training and C.V result. Table III show the result or identify the Benign 66.66% and Malignant 100% or Table IV show the result or identify the Benign 76.19% and Malignant 100%.

Learing Rule	Processing Elements	Training		Cross Validation	
		Benign	Malignant.	Benign	Malignant.
МОМ	1	76.19%	100%	66.66%	100%

TABLE V. Multilayer Perceptron Neural Network Transform Domain : (DCT) Discrete cosine Transform

Here Table V Show the Finale result of this paper .It show the 1 Processing element with Momentum algorithm of Neuro Solution. it show the Benign 76.19% - 66.66% in C.V and Trainign and Malignant 100% in both of them.

V. CONCLUSION AND FUTURE WORK

The MLP classifier with CG learning rule gives best performance of 100% in Training for malignant and benign tumor is 76.19% and in Cross validation 66.66% benign and 100% Malignant.

Using our Algorithm, Doctor can Classified lung cancer with enough confidence. Moreover, our Algorithm can also be used by the experts in order to confirm their decision.

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