TEXTURE CLASSIFICATION USING WEIGHTED PROBABILISTIC NEURAL NETWORKS

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Abstract – Texture classification is basically the problem of classifying pixels in an image according to their textural cues. This is different from conventional image segmentation as the texture is characterized using both the gray value for a given pixel and gray-level pattern in the neighborhood surrounding the pixel. In this project, the novel temporal updating approach is developed for weighted probabilistic neural network (WPNN) classifiers that can be used to classify the textures. This is done by utilizing the temporal contextual information and adjusting the WPNN to adapt to such changes. Whenever a new set of images arrives, an initial classification is first performed using the WPNN updated to the last frame while at the same time, a prediction using PNN is also based on the classification results of previous frame. The result of both the PNN and WPNN are then compared. Compared to the PNN, WPNN includes weighting factors between pattern layers and summation layer of the PNN. Performance of this approach is compared with model based and feature based methods in terms of signal to noise ratio and classification rate.

I. INTRODUCTION

Automated classification and detection of tumors in different medical images is motivated by the necessity of high accuracy when dealing with a human life. Also, the computer assistance is demanded in medical institutions due to the fact that it could improve the results of humans in such a domain where the false negative cases must be at a very low rate. It has been proven that double reading of medical images could lead to better tumor detection. But the cost implied in double reading is very high, that's why good software to assist humans in medical institutions is of great interest nowadays.

Conventional methods of monitoring and diagnosing the diseases rely on detecting the presence of particular features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated diagnostic systems have been developed in recent years to attempt to solve this problem. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative feature classification problem.

In this project the automated classification of brain magnetic resonance images by using some prior knowledge like pixel intensity and some anatomical features is proposed. Currently there are no methods widely accepted therefore automatic and reliable methods for tumor detection are of great need and interest. The application of PNN in the classification of data for MR images problems are not fully utilized yet. These included the clustering and classification techniques especially for MR images problems with huge scale of data and consuming times and energy if done manually. Thus, fully understanding the recognition, classification or clustering techniques is essential to the developments of Neural Network systems particularly in medicine problems.

II. LITERAUTRE SURVEY

Automated classification and detection of tumors in different medical images is motivated by the necessity of high accuracy when dealing with a human life. Also, the computer assistance is demanded in medical institutions due to the fact that it could improve the results of humans in such a domain where the false negative cases must be at a very low rate. It has been proven that double reading of medical images could lead to better tumor detection. But the cost implied in double reading is very high, that's why good software to assist humans in medical institutions is of great interest nowadays.

III. PROBABILISTIC NEURAL NETWORK

The probabilistic neural network was developed by Donald Specht. This network provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian Classifiers. PNN is adopted for it has many advantages. Its training speed is many times faster than a BP network. PNN can

Approach a Bayes optimal result under certain easily met conditions. Additionally, it is robust to noise examples. Advance hybrid PNN such as done by Georgiadas et all aimed to improve brain tumor characterization on MRI by using PNN and non-linear transformation of textured features. This method employs a two level hierarchical decision tree discriminate the metastatic brain tumor cases from the gliomas and meningiomas (primary brain tumor) cases. At each level, classification was performed using two different LSFTPNN classifier. LSST-PNN then was compared with the support Vector Machines with Radial Basis Kernel (SVM-RBF) and the Artificial Neural Network (ANN) classifiers.

However, we choose a basic Mat lab PNN for its simple structure and training manner.

IV. PROPOSED ALGORITHM

Probabilistic Neural Networks (PNN) is a class of neural networks that combine some of the best attributes of statistical pattern recognition and feed-forward artificial neural networks. It is the neural network implementation of kernel discriminate analysis, and was introduced by Donald Specht in the late 1980's. Conventional PNN is a three layers feed forward network including input layer, pattern layer and summation layer. The input layer contains M nodes to accept input feature vector. The pattern layer consists of K pools of pattern nodes. The kth pool in the pattern layer contains Nk number of pattern nodes. Each node in the pattern layer is connected with every node in the input layer. The summation layer consists of K nodes, one node for each pool in the pattern layer. Pattern nodes of each kth summation node are connected to the corresponding kth summation node in the summation layer.

Gaussian function is often chosen as the activation function, combined with a radial basis function in the pattern layer. For the summation layer, a linear basis function and a linear activation function is used. If there are *N* nodes in the pattern layer representing class A, the conventional PDF estimation for A is where G is the kernel function, d is dimension of input, and σ is the radius factor which is usually chosen by cross validation or by more esoteric methods. However, a single σ may not be always fit for all the patterns, particularly when the number of patterns is large. Hence, covariance matrix Σ corresponding to each pattern might be more suitable. On the other hand, standard PNN assumes that one pattern belongs to only one class. This property limits its usage for MR image classification, in which partial volume effect makes pattern contribute across classes.

A weighted PNN is developed to resolve these problems. The structure of WPNN is close to conventional PNN, except that weighting factors from soft labeling matrix, which can indicate the reference vectors' probabilities of belonging to final target classes, are introduced between pattern-to-summation layer. Unlike PNN, whose weights are either 1 for connection going to the output that the node belongs to, or 0 for all other connections, the WPNN enable every unit in pattern layer contribute to output is the structure of the novel WPNN.

V. METHODOLOGY

A description of the derivation of the PNN classifier was given in Chettri and Cromp. PNNs had been used for classification problems. The PNN classifier presented good accuracy, very small training time, robustness to weight changes, and negligible retraining time. There are 6 stages involved in the proposed model which are starting from the data input to output. The first stage is should be the image processing system. Basically in image processing system, image acquisition and image enhancement are the steps that have to do. In this paper, these two steps are skipped and all the images are collected from available resource. The proposed model requires converting the image into a format capable of being manipulated by the computer. The MR images are converted into matrices form by using MATLAB. Then, the PNN is used to classify the MR images. Lastly, performance based on the result will be analyzed at the end of the development phase.

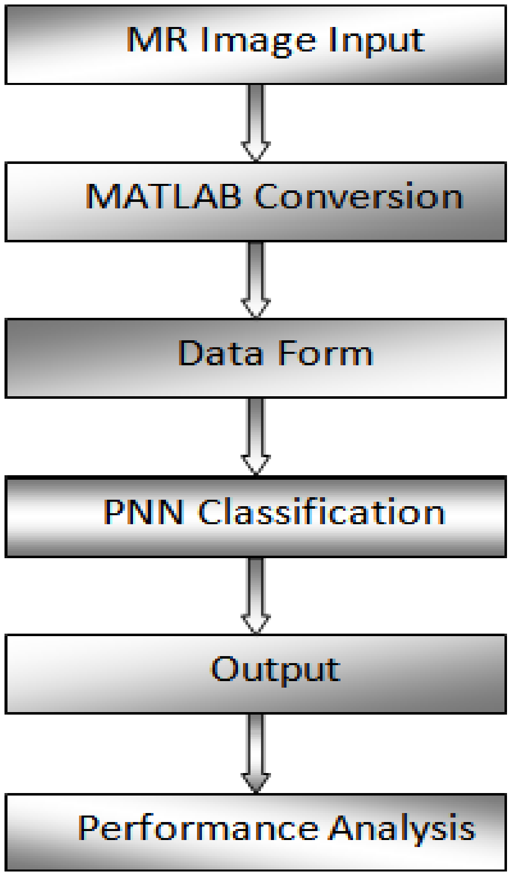

Figure: The proposed system

VI. CONCLUSION

In this project, PNN has been implemented for classification of MR brain image. PNN is adopted for it has fast speed on training and simple structure. Twenty images of MR brain were used to train the PNN classifier and tests were run on different set of images to examine classifier accuracy. The developed classifier was examined under different spread values as a smoothing factor. Experimental result indicates that PNN classifier is workable with an accuracy ranged from 100% to 73%according to the spread value.

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