BRAIN TUMOR CLASSIFICATION USING MACHINE LEARNING APPROCH

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Abstract- **the project proposes an automatic support system for stage classification using Probabilistic Neural Network (Machine Learning) to detect Brain Tumor. The detection of the Brain Tumor is a Challenging Problem due to the structure of Tumor cells. The Probabilistic Neural Network will be used to classify the stage of Brain Tumor that is benign or malignant. The Probabilistic Neural Network is used to segment the tumor regions from MR Brain image accurately. The Segmentation results will be used as base for a Computer Aided Diagnosis (CAD) system for early detection of Brain Tumor which will improves the chances of survival for the patient. The Probabilistic Neural Network with radial basis function will be employed to implement an automated Brain Tumor Classification. Decision making was performed in two stages: Feature Extraction using GLCM and the Classification using PNN-RBF network. This method provides fast and better recognition rate than previous classifiers.**

Keywords— **Brain tumor image classification, probabilistic Neural Networks, Discrete wavelet transform, Dimensionality reduction, Feature extraction**

I. INTRODUCTION

An image is a two-dimensional picture, which has a similar appearance to some subject usually a physical object or a person. Image is a two-dimensional, such as a photograph, screen display, and as well as a three-dimensional, such as a statue. They may be captured by optical devices such as cameras, mirrors, lenses, telescopes, microscopes, etc. and natural objects and phenomena, such as the human eye or water surfaces. An image is a rectangular grid of pixels. It has a definite height and a definite width counted in pixels. Each pixel is square and has a fixed size on a given display. However different computer monitors may use different sized pixels. The pixels that constitute an image are ordered as a grid (columns and rows); each pixel consists of numbers representing magnitudes of brightness and colour.

Brain tumor is caused by abnormal growth of cell within brain. So detection of brain tumor in early stage is a key of its cure. It is classify using machine learning approach. Machine learning approach is used to detect whether a MRI (Magnetic Resonance Image) of brain contain a tumor or not

Brain tumor is one of the most Common and deadly diseases in the world. There are many different types of brain tumors that make the decision very complicated. So classification of brain tumor is very important, in order to classify which type of brain tumor really suffered by patient. A good classification process leads to the right decision and provide good and right treatment Classification of tumor is to identify what type of tumor it is. The conventional methods, which are present in diagnosis, are Biopsy, Human inspection, Expert opinion and etc. The biopsy method takes around ten to fifteen days of time to give a result about tumor. The human prediction is not always correct, sometimes it becomes wrong but a computer cannot. The expert, himself cannot take the decision rather he refers to another expert to give his opinion, this process continues for long time.

In general, early stage brain tumor diagnose mainly includes Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRl) scan, Nerve test, Biopsy etc. At present with the rapid growth of the Artificial Intelligence (AI) development in Biomedicine, computer-aided diagnosis attracts more and more attention.

II PROPOSED METHOD

Here the proposed method is probabilistic neural network, Computer aided diagnosis system and discrete wavelet transform. Daubechies wavelet filter of order two is used and found to yield good results in classification and segmentation of tumor from the brain CT images. By applying 2D DWT, two level wavelet decomposition of region of interest (ROI) is Performed which results in four sub bands. In 2D wavelet decomposition the Image is represented by one approximation and three detail images, representi sng the low and high frequency contents image respectively. The approximation can be further to produce one approximation and three detail images at the next level of decomposition, wavelet decomposition process LL1, LL2 represent the wavelet approximations at 1^{st} and 2^{nd} level respectively.LH1, HL1, HH1, LH2, HL2, HH2 represent the details of horizontal, vertical and diagonal directions at 1^{st} and 2nd level respectively, and are high frequency part of the images

The Discrete Wavelet Transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).

The wavelet can be constructed from a scaling function which describes its scaling properties. There restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere.

III PROBABILISTIC NEURAL NETWORK

Probabilistic Neural Network is a type of Radial Basis Function (RBF) network, which is suitable for pattern classification. The fundamental architecture having three layers, an input layer, a pattern layer, and an output layer. The pattern layer constitutes a neural implementation of a Bayes classifier, where the class dependent Probability Oensity Functions (POF) are approximated using a Parzen estimator. Parzen estimator determines the POF by minimizing the expected risk in classifying the training set incorrectly. Using the Parzen estimator, the classification gets closer to the true underlying class density functions as the number of training samples increases, the pattern layer consists of a processing element corresponding to each input vector in the training set. Each output class should consist of equal number of processing elements otherwise a few classes may be inclined falsely leading to poor classification results. Each processing element in the pattern layer is trained once. An element is trained to return a high output value when an input vector matches the training vector. The probabilistic neural net (PNN) is based on the theory of Bayesian classification and the estimation of probability density function (PDF). The idea of PNN was first introduced by Donald F. Specht in 1990. Because of ease of training and a sound statistical foundation in Bayesian estimation theory, PNN has become an effective tool for solving many classification problems. In fact, By replacing the sigmoid activation function often used in neural networks with an exponential function, a probabilistic neural network (PNN) that can compute nonlinear decision boundaries which approach the Bayes optimal is formed. Probabilistic neural network (PNN) is closely related to Parzen window pdf estimator. A PNN consists of several sub-networks (PNN) is closely related to Parzen window pdf estimator. A PNN consists of several sub-networks, each of which is a Parzen window pdf estimator for each of the classes.

The first layer shows the input pattern with n features. The number of nodes in the pattern layer is equal to the number of training instances. The number of nodes in the summation layer is equal to the number of classes in the training instances. The input layer is fully connected to the pattern layer. The input layer does not perform any computation and simply distributes the input to the neurons in the pattern layer. The pattern layer is semi- connected to the summation layer. In addition, this could saturate the feature space with overlapping Gaussian functions that would increase the rate of misclassification. PNN is often used in classification problems. When an input is present, the first layer computes the distance from the input vector to the training input vectors. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes.

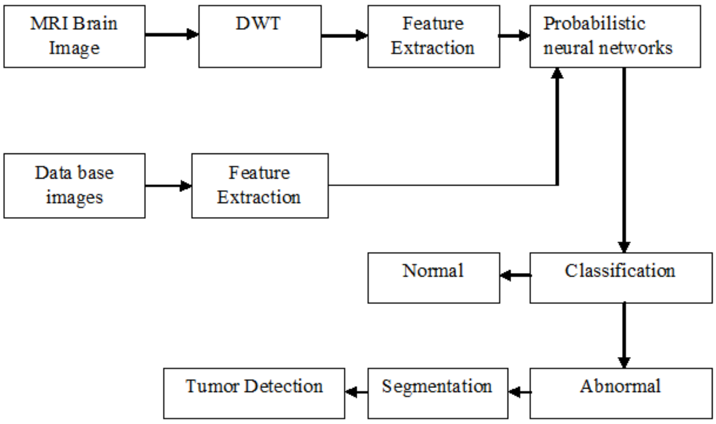

Figure: 1.Block diagram of Brain Tumor Classification

IV COMPUTER AIDED DIAGNOSIS SYSTEM

Computer- aided design (CAD) is the use of computer systems to assist in the creation, modification, analysis, or optimization of a design. CAD software is used to increase the productivity of the designer, improve the quality of design, improve communications through documentation, and to create a data base for manufacturing. CAD output is often in the form of electronic files for print, machining, or other manufacturing operations.

CAD is an important industrial art extensively used in many applications, including automotive, ship building, and aerospace industries, industrial and architectural design, prosthetics, and many more. CAD is also widely used to produce computer animation for special effects in movies, advertising and technical manuals, often called DCC Digital content creation. The modern ubiquity and power of computers means that even perfume bottles and shampoo dispensers are designed using techniques unheard of by engineers of the 1960s. Because of its enormous economic importance, CAD has been a major driving force for research in computational geometry, computer graphics (both hardware and software), and discrete differential geometry.CAD is a relatively young inter disciplinary technology combining elements of artificial intelligence and digital image processing with radiological image processing. A typical application is the detection of vector to the training input vectors. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes.

For instance, some hospitals use CAD to support preventive medical check-ups in mammography (diagnosis of breast cancer) and lung cancer. Computer-aided detection (CADe) systems are usually confined to marking conspicuous structures and sections.

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Computer-aided diagnosis (CADx) systems evaluate the conspicuous structures. For example, in mammography CAD high lights micro calcification clusters and hyper dense structures in the soft tissue. This allows the radiologist to draw conclusions about the condition of the pathology. Another application is CADq, which quantifies, e.g. the size of a tumor or the tumor's behaviour in contrast medium uptake. Computer-aided simple triage (CAST) is another type of CAD, which performs a fully automatic initial interpretation and triage of studies into some meaningful categories (e.g. negative and positive).CAST is particularly applicable in emergency diagnostic imaging, where a prompt diagnosis of critical, life threatening condition is required. At the present stage of the technology, CAD cannot and may not substitute the doctor, but rather plays a supporting role. The doctor (generally a radiologist) is always responsible for the final interpretation of a medical image.

V RESULTS

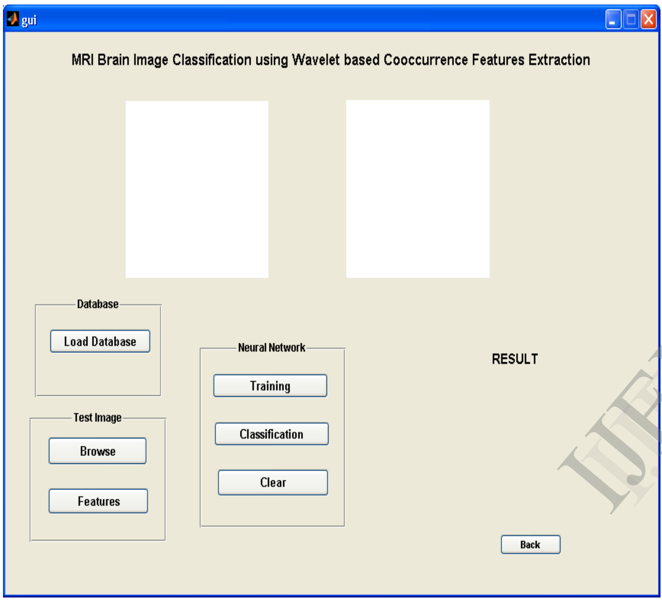

Figure 2.1(a) Steps in Brain tumor classification

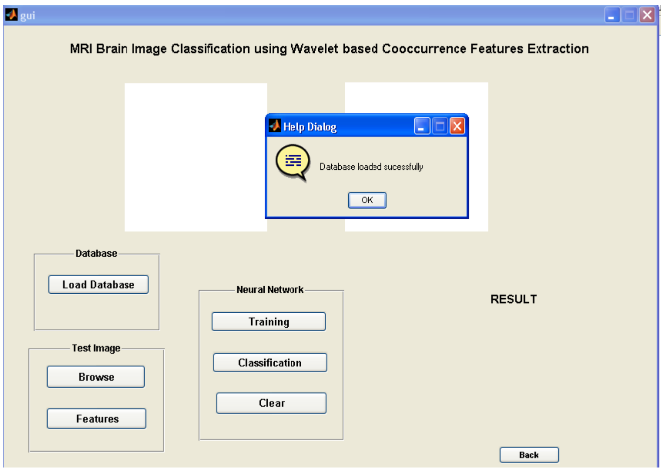

Figure 2.1(b) Load the database

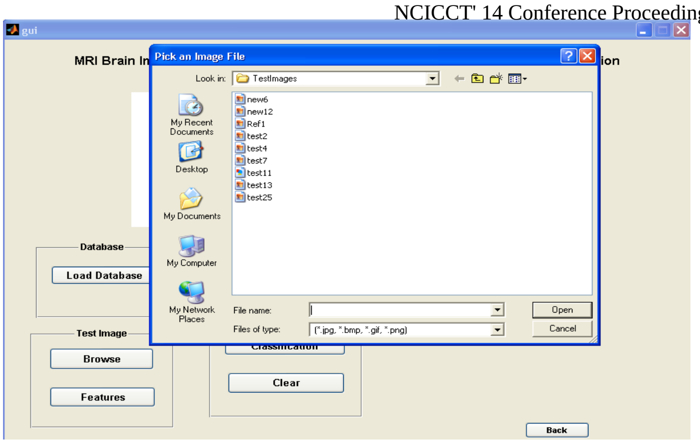

Figure 2.1(c) Test images of brain

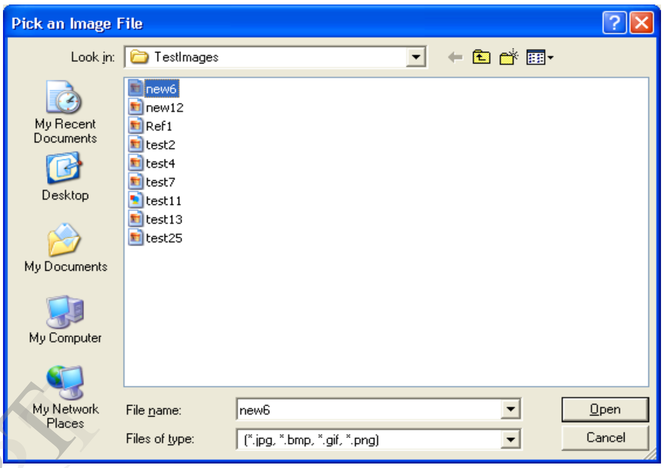

Figure 2.1(d) browse the image

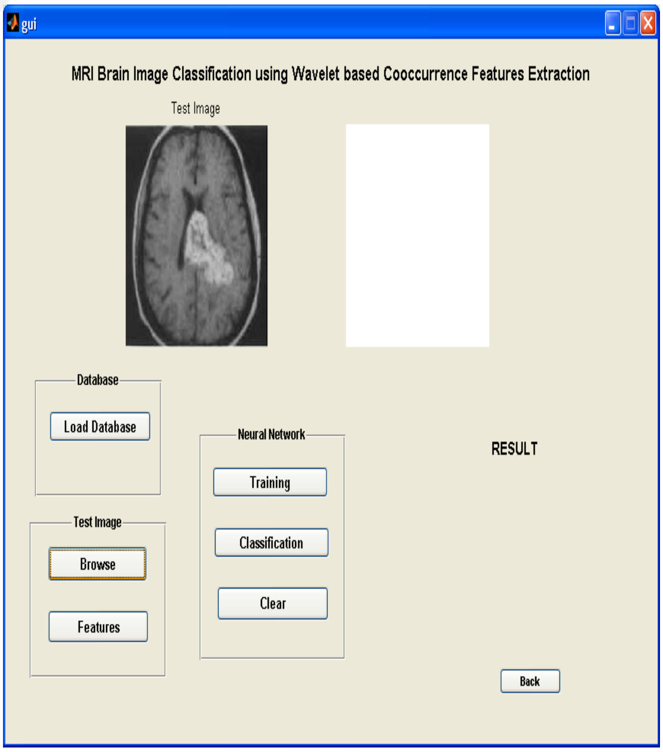

Figure 2.1(e) Image after browsing

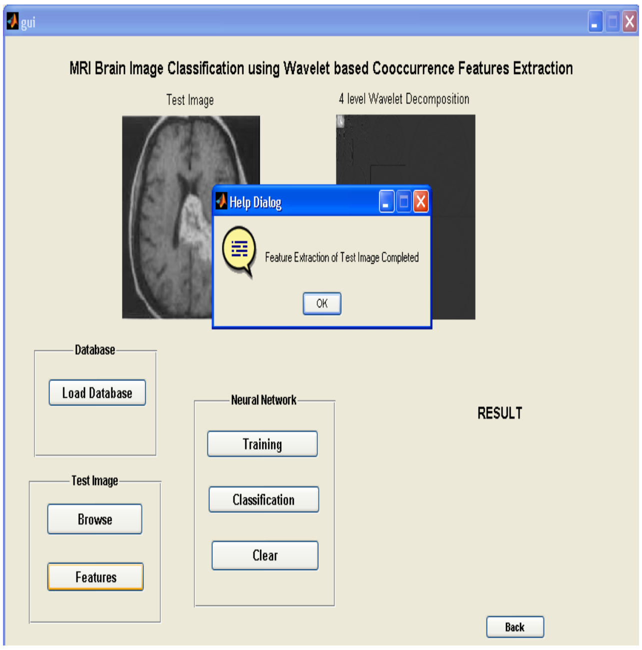

Figure 2.1(f) Feature extraction

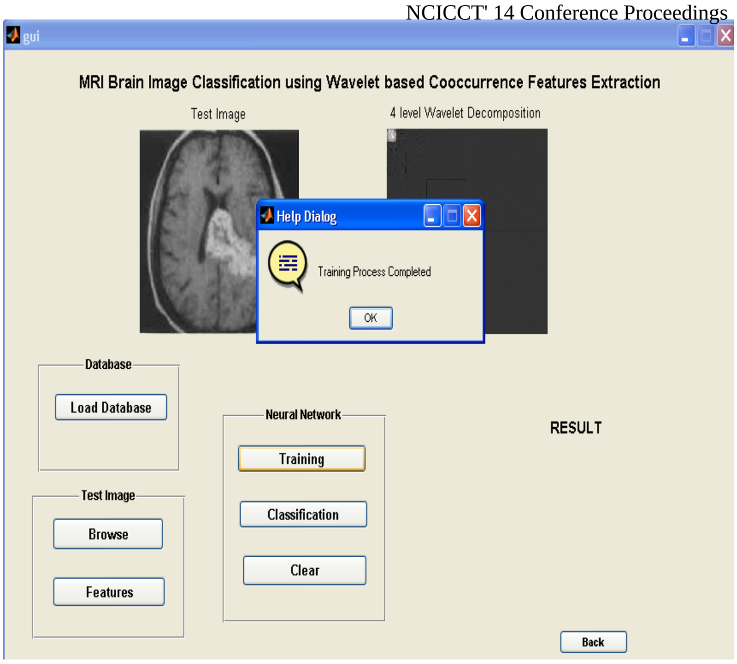

Figure 2.1(h) Training process

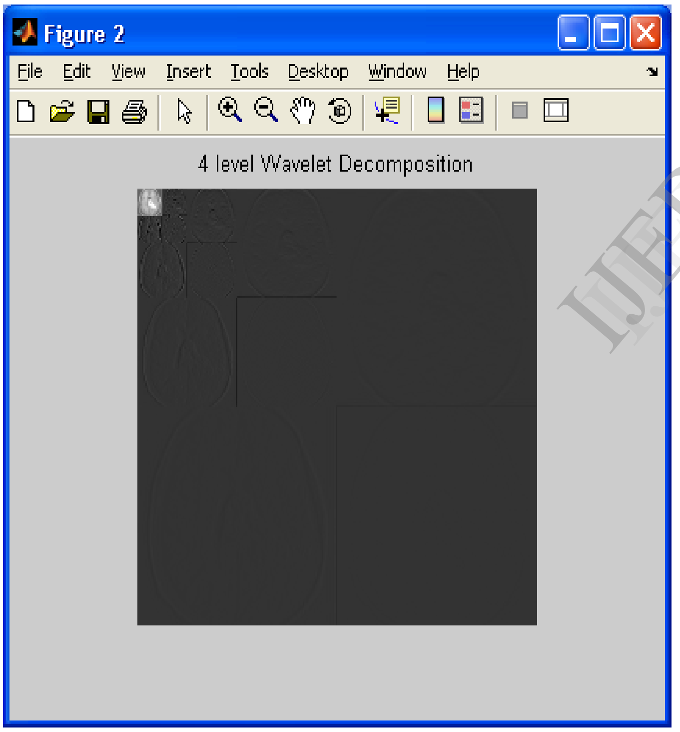

Figure 2.1(g) discrete wavelet decomposition

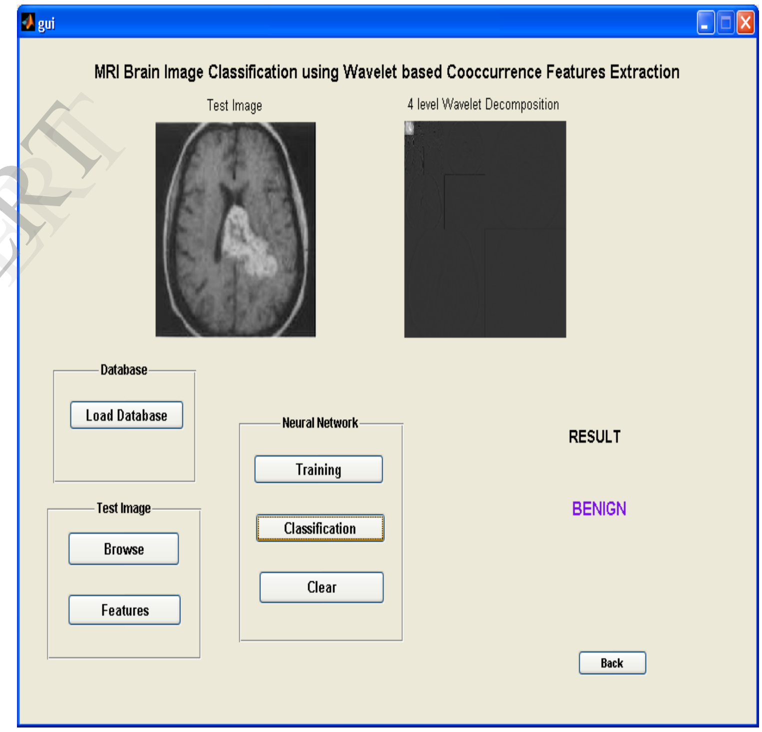

Figure 2.1(j) Classification of brain tumor

CONCLUSION

Thus the machine learning approach detect whether a MRI image of brain contain a tumor or not. The probabilistic neural network classify the stage of brain tumor is benign or malignant. Dimensionality reductions are performed using DWT. Feature extractions are performed by GLCM. This method gives high speed processing capability than other methods.

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