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Brain Tumor Classification using Probabilistic Neural Network

A. Dhineshram

Assistant Professor, Electronics and Communication Engineering, Unnamalai Institute of Technology Kovilpatti, Tamil Nadu, India

Abstract
Brain tumour classification is proposed in this work using probabilistic neural networks to handle images and data processing techniques for autonomous detection. Conventionally, the classification and detection of brain tumours are done by human inspection with a medical resonance image (MRI) of the brain. The manually operated methods could be more practical for massive datasets and non-reproducible. During MRI screening, noise is generated, and it leads to serious accuracy issues in classifying the disease. The real-time difficulties should be overcome with the help of artificial intelligence, which is a better solution for this field. Hence, this paper applied the probabilistic neural network. The proposed work was split into two stages: decision-making, performed in two phases; feature extraction using the principal component analysis; and classification using probabilistic neural network (PNN). The performance evaluation of the PNN classifier was based on the network's training performance and classification results. Probabilistic Neural Network provides better classification and is a promising tool for classifying tumours.

Keywords: Brain Tumour, probabilistic neural network, MR Images, principal component analysis

1. Introduction

Automated classification and detection of tumours are motivated with high accuracy to deal with various medical images to save human life. Also, computer assistance is demanded in medical institutions since it improves results, avoids false negatives, and protects human life at a meagre rate. The process of double-reading medical images could lead to better tumour detection. However, the cost implied in double reading is very high, and human-computer interaction in medical institutions is of great interest nowadays. Conventional methods of monitoring and diagnosing diseases are working on detecting the presence of particular features by a human operator. Due to the vast number of hospital patients suffering and the need for continuous monitoring, several techniques have been developed to solve this problem. This paper proposes an automated classification of brain magnetic resonance images using prior knowledge such as intensity and some anatomical features. Currently, no methods are widely accepted; therefore, automatic and reliable methods for tumour detection are of great need and interest. The application of PNN in data classification for MR image images has yet to be fully utilized. These included the clustering and classification methods, especially for MR image problems with vast data scales that consume the time and energy of the human operator. Thus, to overcome these challenges, a full understanding, recognition, and classification are essential to developing network systems, especially in medicine.

According to studies, brain tumour is the top reason for cancer deaths in children and adults worldwide [1]. The most typical kind of brain disease is a brain tumour. It is an unregulated development of brain cells. Brain tumours are always classified into brain tumours, both primary and secondary. The first starts in the brain and usually stays there, whereas the latter starts as cancer somewhere else in the body and spreads to the brain. There are two different forms of tumours: malignant and benign. A benign tumour is a slow-growing tumour that does not infiltrate nearby tissues; conversely, a malignant one is a very aggressive tumour that spreads from one location to another. Brain tumour diagnosis is highly time-intensive and largely depends on the radiologist's skills and knowledge. Because there are more patients, the amount of data that must be processed has grown significantly, making traditional techniques costly and incorrect. The difficulties are associated with significant brain tumour size, shape, and intensity variations for the same tumour type and similar manifestations of other disease types. A misclassification of a brain tumour can have significant consequences and reduce the patient's survivability. There is a rise in interest in building automated technologies for processing images to overcome the limitations of manual diagnosis [1 and 2] and other related applications [3–5]. Several computer-aided diagnoses (CAD) systems have been created recently to diagnose brain tumours automatically.

The layout of this study is organized as follows: The related works are given in Section 2. The problem statement is given in Section 3, and the proposed method is presented in Section 4. The experimental settings and results are shown in Section 5. The conclusion and future work section is described in Section 6.

2. Related Works

Numerous techniques have been proposed for automatic brain MRI classification using neural networks. The traditional methods comprise several steps: pre-processing, feature extraction, feature reduction, and classification. Most existing medical MR imaging works refer to automatic tumour region segmentation. Recently, numerous researchers have proposed various approaches to detect and segment the tumour region in MR images [6 and 7]. Once the tumour in MRI is segmented, these tumours need to be classified into different grades. In previous research studies, binary classifiers have been used to identify the benign and malignant classes [8 and 9]. For instance, Ullah et al. [8] proposed a hybrid scheme for classifying brain MR images into normal and abnormal with histogram equalization, Discrete wavelet transform, and feed-forward artificial neural network, respectively.

Shree and Kumar [10] divided the brain MRI into normal and abnormal classes. They used a GLCM feature extractor, while a probabilistic neural network (PNN) classifier was employed to classify the brain MR image into normal and abnormal and obtained 95% accuracy. Arunachalam and Savarimuthu [11] proposed a model to categorize normal and abnormal brain tumours in brain MR images. Their proposed model comprised enhancement, transformation, feature extraction, and classification. First, they improved the brain MR image using shift-invariant shearlet transform (SIST). Then, the GLCM feature is extracted, and discrete wavelet transform (DWT) is used. Finally, these extracted features were fed into a feed-forward back-propagation neural network, and a high accuracy rate was obtained. Rajan and Sundar [12] proposed a hybrid energy-efficient automatic tumour detection and segmentation method. Their proposed method comprises seven long phases and reported 98% accuracy. The major drawback of their proposed model is the high computation time due to numerous techniques.

3. Problem Statement

MRI images contain a noise caused by operator performance, which can lead to severe inaccuracies in classification. Hence, developing brain tumour detection using an artificial intelligence method provides an effective solution in this field.

4. Proposed Method

The principal component analysis (PCA) is used in this work as a feature extraction algorithm to reduce the large dimensionality of the data. In this work, the training database consists of a set of MR images. In the training phase, feature vectors are extracted for each image in the training set. The PCA algorithm is a dimensionality reduction technique that transforms the vector $\Phi 1$ to a vector $\omega 1$, with a dimensionality d where $d << M \times N$. For each training image Ωi, these feature vectors ωi are calculated and stored. In the testing phase, the feature vector ωj of the test image Ωj is calculated using PCA. To identify the test image Ωj, the similarities between ωj and other feature vectors, such as ωi's in the training set, are computed. The similarity between feature vectors is calculated using Euclidean distance. The identity of the most similar ωi is the output of the image recognizer. If $i = j$, it means that the MR image j has been correctly identified; otherwise, if $I \neq j$, it means that the MR image j has been misclassified.

4.1 Probabilistic Neural Network

The probabilistic neural network gives a general solution for pattern classification problems by following an approach developed in statistics called Bayesian classifiers. However, a basic Matlab PNN is used in this work for its simple structure and training manner. By using matrix manipulation, the training and running procedure can be implemented, and the speed of PNN can be increased. The PNN classifier classifies the input vector into a particular class since its class has the maximum probability of being correct. The PNN has three layers in this work: Input, Radial Basis, and Competitive Layer. The radial Basis Layer evaluates vector distances between the input vector and row weight vectors in the weight matrix. These distances are scaled nonlinearly by the Radial Basis Function. Then, the Competitive Layer finds the shortest distance among them and finds the training pattern closest to the input pattern based on their distance.

There are six stages involved in the proposed model, which start from the data input to the output. The first stage should be the image processing system. In an image processing system, image acquisition and enhancement are the steps that must be done. These two steps are skipped in this work, and all the images are collected from available resources. The proposed method requires converting the image into a format the computer can manipulate. The MR images are converted into matrices using MATLAB. Then, the PNN classifier is used to classify the MR images. Finally, the performance result will be analyzed at the end of the development phase. The proposed brain MR image classification method is shown in Figure 1.

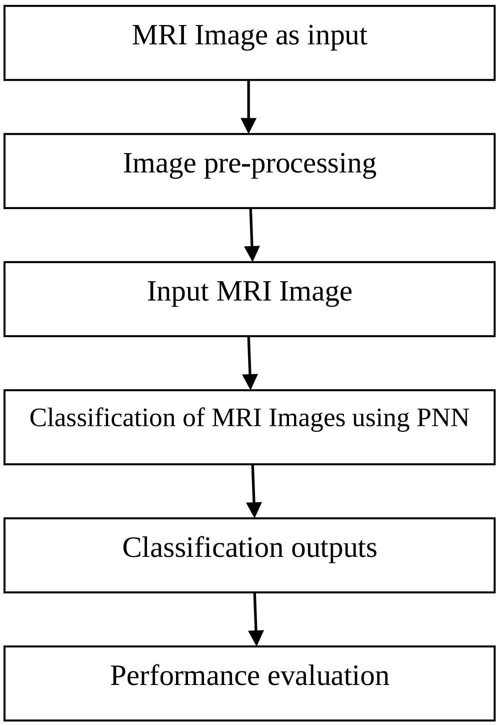

Figure. 1 Proposed workflow for the classification of brain tumours using PNN

5. Results and Discussion

Various experiments were performed, and the sizes of the training and testing sets were determined by considering the classification accuracies. The data set was split into two separate data sets – the training data set (75%) and the testing data set (25%). The training data set was used to train the network. In contrast, the testing data set was used to verify the accuracy and effectiveness of the trained network for the classification of brain tumours.

The PNN was implemented by using the MATLAB software package. The radial basis function's spread value (SV) was used as a smoothing factor, and classifier accuracy was examined when different SV values were used. If SV is near zero, the network will act as the nearest neighbour classifier, and the network will consider several nearby design vectors if its value becomes more extensive. The developed PNNs were examined using 15 testing data. The performance results are shown in Table 1. The classification accuracy of the testing data set for three spread values 1, 2, and 3 of brain images ranged from 100% to 77%. The simulation output for brain tumour classification is presented in Figure 2 to Figure 6.

Table 1 Performance evaluation of PNN for Brain tumor classification

Spread Value	Accuracy (%)
1	77
2	84
3	100

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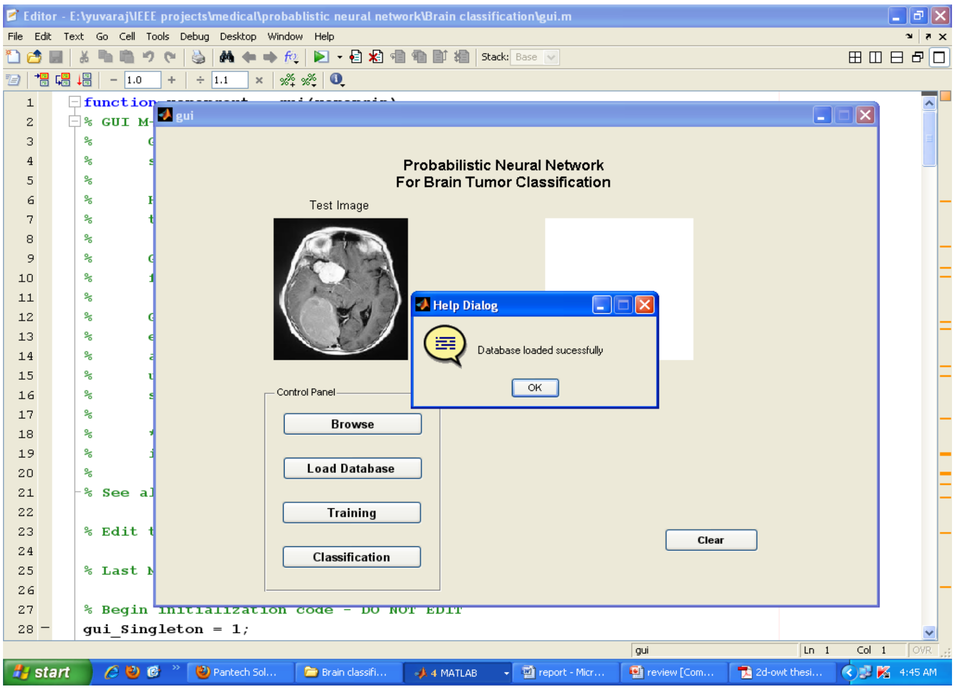

Figure 2 Database Loading

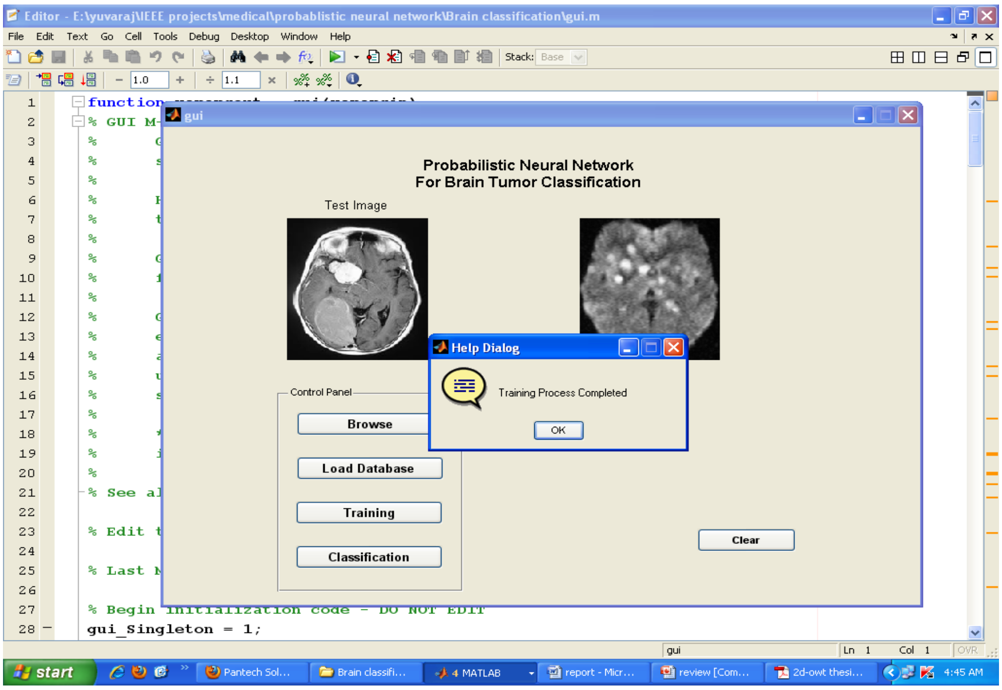

Figure 3 Training Process

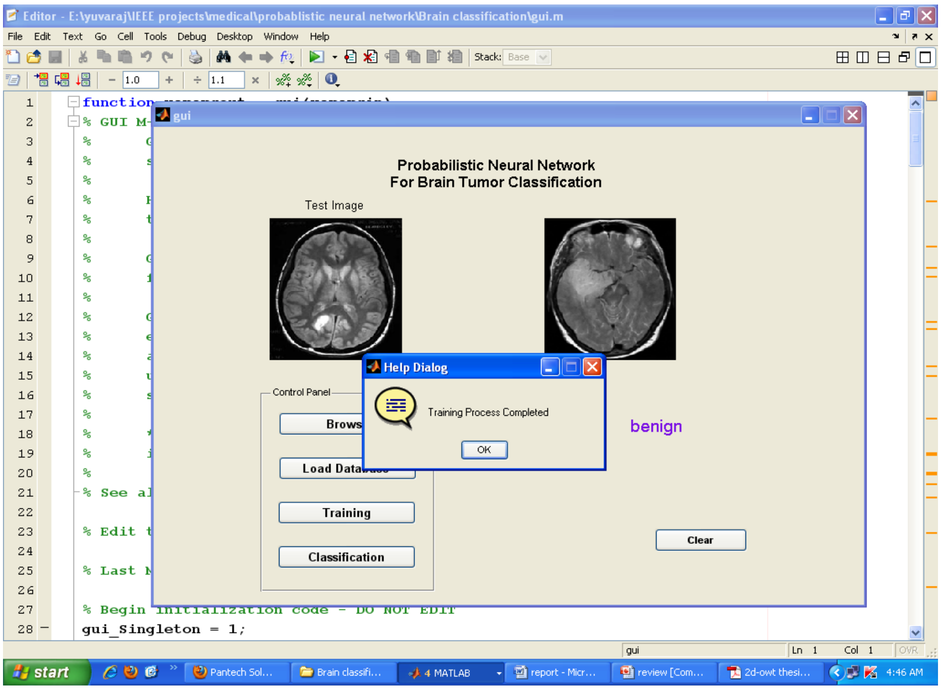

Figure 4 Training Process for Non-Cancerous Tumor (Benign)

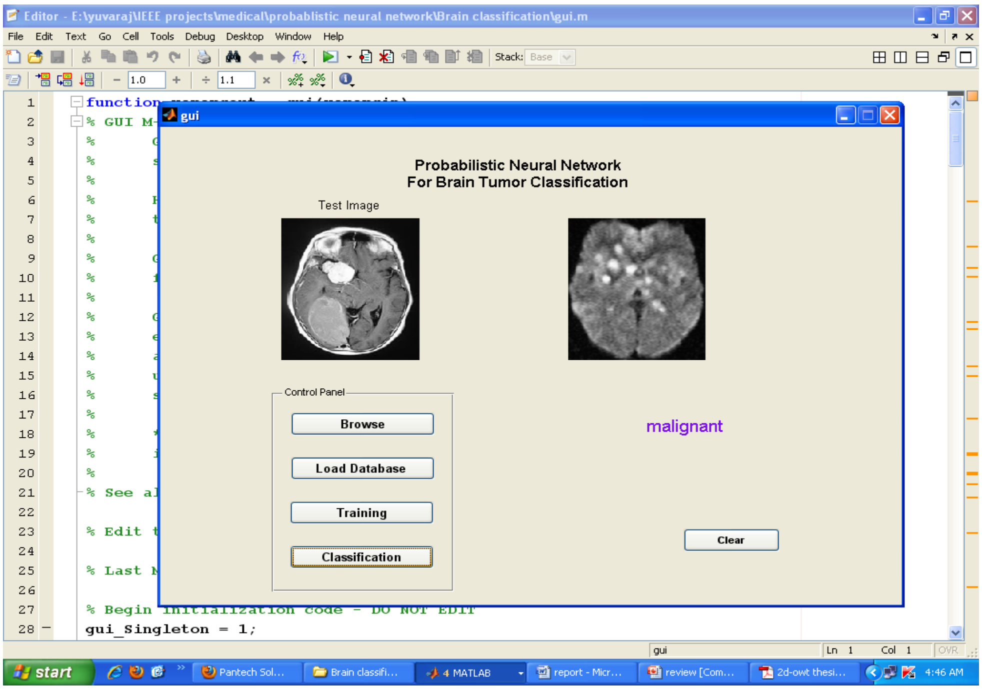

Figure 5 Training Process for Cancerous Tumor (Malignant)

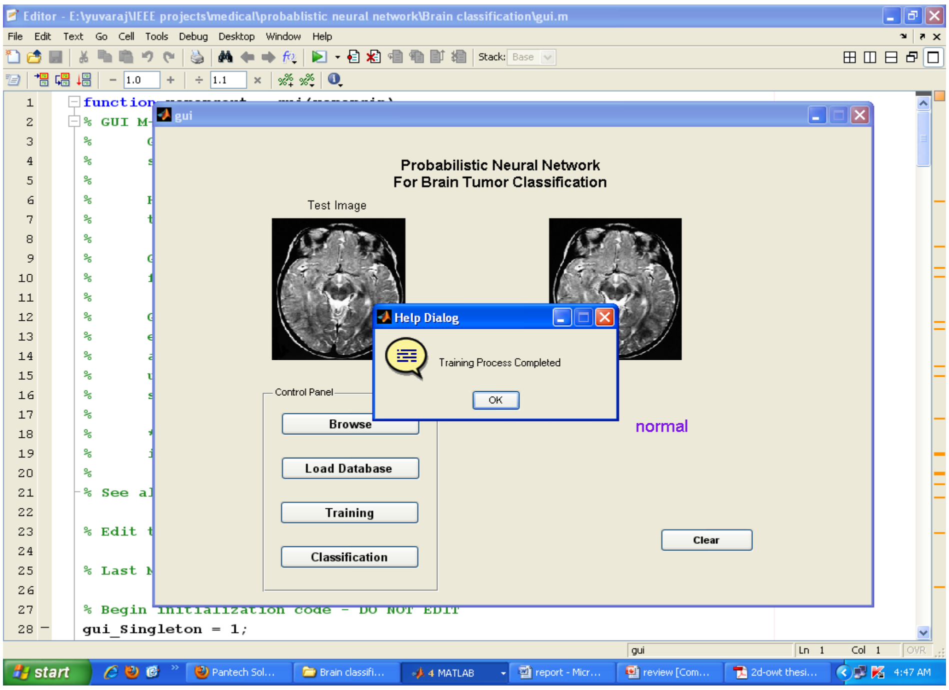

Figure 6 Training Process for Normal Image

6. Conclusion and Future Work

In this work**, a** PNN classifier has been implemented to classify MR brain images. PNN is adopted for fast speed and simple structure in training. The developed classifier was examined under different spread values. The results from the proposed work indicate that the PNN classifier is workable with an accuracy ranging from 100% to 77% according to the spread value. Based on the literature study, it is visible that most research focused only on binary class classification. Hence, as a future work, the classification of multi-class object detection will be carried out.

7. Conflict of interest

None.

8. References

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