

Research Article

Brain Tumor Detection Using PCA And Neural Networks From MRI Images**M S Mallika^{1,*}, Chinthapalli Durga Sumathi², V Sushma Naga Sri³, Geddada D N Prasad⁴ and
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Abstract: Early diagnosis improves treatment outcomes, making brain tumor detection a crucial task in medical image analysis. In this study, we offer a method for detecting brain tumors using MRI scans. In order to improve MRI pictures, the suggested system does preprocessing operations such converting to grayscale, scaling, and histogram equalization. In order to extract useful features, one uses Principal Component Analysis (PCA) to lower the dimensionality and capture the most important ones. A neural network classifier is trained using these variables to categorize MRI scans as normal, benign, or malignant based on the presence or absence of tumors.

Keywords: Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Principal Component Analysis (PCA), Neural Networks, Image Processing.

1. Introduction

When it comes to medical image analysis, detecting brain tumors is among the most crucial responsibilities. Brain tumors can be better treated and patients have a better chance of survival if caught early [1-3]. The capacity of magnetic resonance imaging (MRI) to produce comprehensive pictures of brain tissues has led to its extensive usage in the diagnosis of brain disorders [4-7].

Medical professionals may make mistakes and lose valuable time when they manually analyze MRI pictures. Consequently, there has been a lot of focus on developing automated techniques to detect brain tumors in the past several years. Tumors can be more precisely and swiftly identified with the use of image processing and machine learning [8-12].

In this work, a brain tumor detection system is proposed using Principal Component Analysis (PCA) and Neural Networks. MRI images are first preprocessed using grayscale conversion and resizing. PCA is then applied for feature extraction by reducing the dimensionality of the MRI images while preserving the most significant features. These extracted features are used to train a neural network classifier [13-15].

The trained neural network classifies MRI images into three categories: a normal brain, benign tumor, and malignant tumor [16-17]. The proposed system aims to improve the efficiency and accuracy of brain tumor detection and assist medical professionals in diagnosis.

2. Literature Review

A lot of research has focused on medical imaging as a means of detecting brain tumors recently. Due to its ability to produce detailed pictures of brain tissues, magnetic resonance imaging (MRI) is frequently employed for the detection of brain disorders. Several studies have suggested automated ways for detecting brain cancers through the use of machine learning and image processing.



Several studies have used image preprocessing techniques such as grayscale conversion, noise removal, and image normalization to enhance MRI images before analysis. These preprocessing techniques improve image quality and help in extracting meaningful features from MRI scans.

The extraction of features from medical images has made extensive use of Principal Component Analysis (PCA). PCA extracts the most relevant information from images while reducing their dimensionality. Classification algorithms benefit from principal component analysis (PCA) because it reduces large amounts of raw image data to a manageable number of relevant features.

Neural networks have also been applied for brain tumor classification due to their ability to learn complex patterns from data. Neural network models can classify MRI images into different tumor categories such as normal, benign, and malignant. These automated systems assist medical professionals in diagnosing brain tumors more efficiently and accurately.

3. Proposed Methodology

The proposed brain tumor detection system follows a sequence of image processing and machine learning steps. Initially, the MRI brain image is provided as input to the system. The image is then preprocessed to improve its quality and make it suitable for further analysis. Principal Component Analysis (PCA) is used for extracting significant features from the MRI images. Finally, a neural network classifier analyzes these features and classifies the MRI image into normal, benign tumor, or malignant tumor categories. The overall workflow of the proposed system is illustrated in Fig. 1.

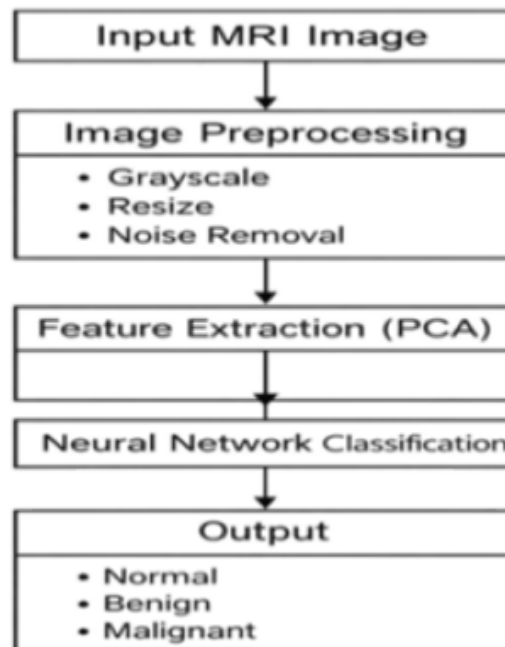


Figure 1: Proposed Block Diagram

A. Image Acquisition

The first step in the proposed system is image acquisition. MRI brain images are taken as input to the system through a graphical user interface (GUI). MRI images are widely used for brain tumor detection because they provide detailed information about brain tissues and

abnormalities. The acquired image is then forwarded to the preprocessing stage for further analysis.

B. Image Preprocessing

In order to get MRI images ready for feature extraction, image preprocessing is done to improve their quality. This step involves applying various preprocessing techniques to the image in order to clean it up and make it clearer. The preprocessing steps include grayscale conversion, image resizing, and noise removal. These techniques help in improving the quality of MRI images and make the data suitable for further processing.

C. Feature Extraction using PCA

Brain tumor identification relies on feature extraction. The suggested method uses Principal Component Analysis (PCA) to glean useful information from magnetic resonance imaging (MRI) scans. PCA extracts the most relevant information from images while reducing the dimensionality of the data. The MRI image is converted into a feature vector, and PCA identifies the principal components that represent the most relevant features of the image. These extracted features are then used for classification.

D. Classification using Neural Networks

In the final stage, the extracted PCA features are provided to a neural network classifier. The neural network is trained using labeled MRI images from the training dataset. Based on the learned patterns, the classifier identifies whether the input MRI image corresponds to a normal brain, benign tumor, or malignant tumor. The classification result is then displayed as the final output of the system.

4. Results and Discussions

The graphical user interface (GUI) developed for the proposed brain tumor detection system is shown in Fig. 4. The interface allows the user to interact with the system through several processing buttons such as Browse, Load Database, Training, and NN Classification. The GUI simplifies the process of selecting MRI images and obtaining classification results.

1. GUI Interface

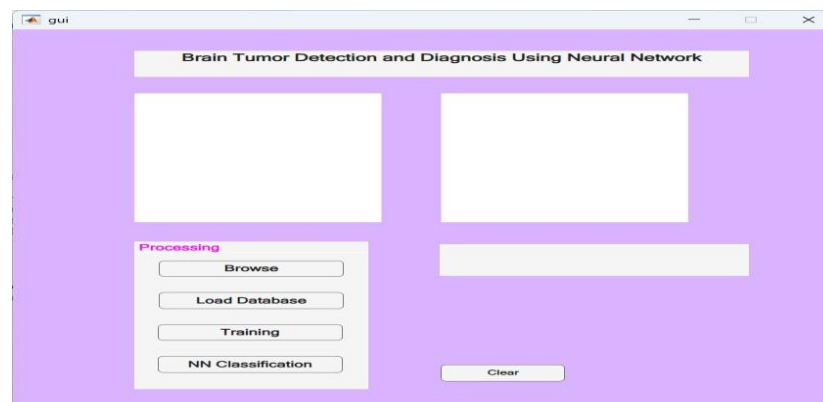


Figure 2: Graphical user interface of the proposed brain tumor detection system.

Fig. 2 shows the graphical user interface developed for the proposed brain tumor detection system. The GUI allows the user to select an MRI image using the browse option. The system then loads the training database, performs preprocessing, and extracts features using PCA. Finally, the neural network classifier identifies the tumor category and displays the result.

2. Input MRI Image Selection

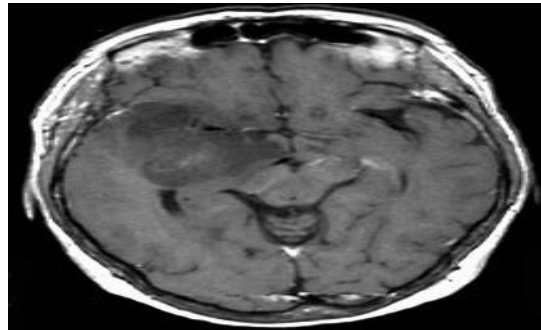


Figure 3: Selected MRI brain image using the browse option

The MRI brain image is provided as input to the system through the graphical user interface. MRI images provide detailed information about brain tissues, which helps in identifying abnormal regions such as tumors.

3. Database Loading and Training

After selecting the MRI image, the Load Database button is used to load the training dataset into the system. A confirmation message is displayed indicating that the database has been loaded successfully. The Training button is then used to train the neural network using the stored MRI image dataset. During this process, the system compares the extracted features with the training data to learn patterns associated with different tumor categories.

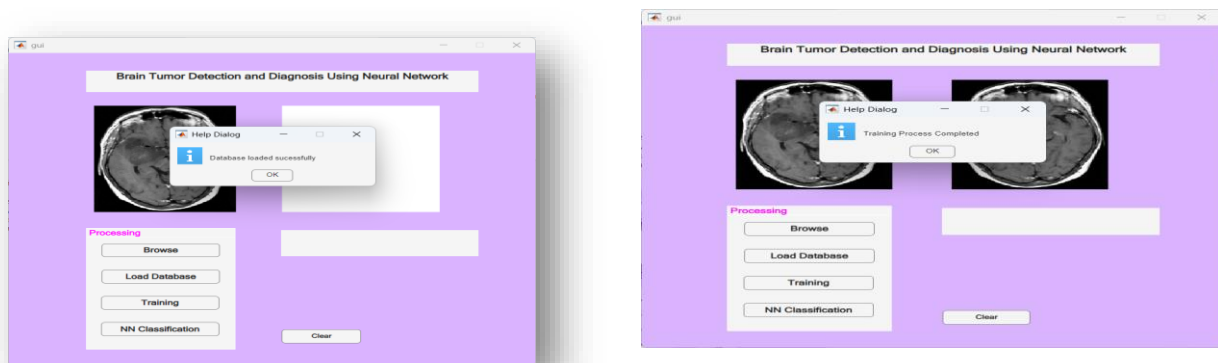


Figure 4: Database loading and neural network training process.

4. Tumor Classification Result

Once the training process is completed, the NN Classification button is used to classify the input MRI image.



Figure 5: Classification results show the detected tumor type.

The system analyzes the extracted features and compares them with the trained neural network model. Finally, the system displays the classification result indicating whether the tumor is Normal, Benign, or Malignant. In the experimental result shown in Fig. 5, the system successfully identifies the tumor as a Benign tumor.

The suggested approach can accurately identify and categorize brain cancers using magnetic resonance imaging (MRI) scans, according to the experimental results. Reduce the dimensionality of the picture data while keeping the relevant attributes by using Principal Component Analysis (PCA). This improves the efficiency of the classification process and reduces computational complexity.

The neural network classifier is trained using the MRI image dataset and is capable of learning the patterns associated with different tumor types. After training, the system can effectively classify the input MRI images into different categories such as normal brain, benign tumor, and malignant tumor.

The graphical user interface developed in MATLAB allows users to easily upload MRI images, load the training database, and obtain classification results through simple button operations. The experimental results demonstrate that the proposed PCA and neural network based system can effectively classify MRI brain images with good accuracy.

5. Conclusion

This paper presents a brain tumor detection and classification system using MRI images based on Principal Component Analysis (PCA) and Neural Networks. The proposed system performs image preprocessing, feature extraction using PCA, and classification using a neural network model. The graphical user interface developed in MATLAB allows users to easily select MRI images, load the training database, perform training, and obtain classification results.

The suggested system successfully normalises, benignises, and malignantizes MRI brain pictures, according to the experimental results. Using principal component analysis (PCA) to reduce the dimensionality of the picture data while keeping critical features increases the neural network classifier's performance. Using the created technology, doctors will be able to detect and diagnose brain cancers earlier.

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