
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
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www.ijmece.com

IJMECE
International Journal of modern electronics and communication engineering
ISSN 2321-2152
www.ijmece.com
Vol 9, Issue 3, 2021

Brain Tumor Identification based on MRI Images

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ABSTRACT

In several medical diagnostic applications, automated flaw identification in medical imaging has emerged as a new discipline. In Magnetic Resonance Imaging (MRI), automated tumor identification is particularly important since it gives information about aberrant tissues that is needed for treatment planning. Human inspection is the standard procedure for finding flaws in magnetic resonance brain imaging. Using this strategy with a lot of data is not practicable. Thus, approaches for automatically detecting tumors are developed in order to save radiologists' time. Because brain cancers vary and are complex, MRI brain tumor identification is a challenging undertaking. In this work, machine learning techniques are used to identify tumors in brain MRIs. The three components of the proposed study are as follows: first, brain MRI images are subjected to preprocessing processes; second, texture characteristics are retrieved using the Gray Level Co-occurrence Matrix (GLCM); and third, a machine learning method is used for classification.
Keywords: machine learning, texture features, feature extraction, segmentation, and magnetic resonance imaging.

1. INTRODUCTION

The human body is made up of several cell kinds. Every cell serves a distinct purpose. The body's cells divide and expand in a predictable way to produce new cells. The human body needs these new cells to be healthy and function correctly. Certain cells proliferate in an unorganized manner when they are unable to regulate their own growth. A tumor is a mass of tissue made up of the excess cells. The tumors may be cancerous or benign. Benign tumors are not cancerous, while malignant tumors cause cancer. The Central Brain Tumor Registry of the United States (CBTRUS) released a study stating that 39,550 individuals had diagnoses for benign and malignant brain tumors in 2002. It shows that there are 14 primary brain tumors per 100,000 people, whether they are benign or malignant [3].

Medical image data from various biomedical equipment that employ various imaging methods, such as X-ray, CT scan, and MRI, is a crucial component in medical diagnosis. The method known as magnetic resonance imaging (MRI) is based on measuring magnetic field vectors that are produced in the nuclei of hydrogen atoms found in a patient's water molecules after the proper excitation of high magnetic fields and radio frequency pulses [5]. Since an MRI scan doesn't include radiation, it is a much more effective diagnostic tool than a CT scan. MRI allows radiologists to assess the brain. The existence of a brain tumor may be detected using the MRI method. By human examination, tumors in MRI images are often found using this standard technique. It takes a lot of time to use this strategy. For a lot of data, it is inappropriate. Additionally, noise from operator interaction in the MRI might result in incorrect categorization. Due to their higher cost-effectiveness, automated methods are required for the analysis of large volumes of MRI data. Since dealing with human life requires great precision, automated tumor diagnosis in MRI images is required.

Using feature extraction techniques in conjunction with supervised methods like artificial neural networks and support vector machines, as well as unsupervised methods like selforganization map (SOM) and fuzzy c-means, the MR human brain pictures are categorized. Pixels are also grouped using other supervised classification methods, including k-nearest neighbors (k-NN), according on how similar each feature is [19].

It is possible to classify MR pictures as abnormal or normal using both supervised and unsupervised algorithms. This research proposes the use of machine learning techniques to develop an effective automated brain MRI categorization system. The brain MR picture is classified using the supervised machine learning technique.

2. RELATED WORK

A approach for detecting brain tumors in MRI brain pictures was suggested by Natarajan et al. [1]. After applying morphological operations and a median filter for preprocessing, the MRI brain images are segmented using threshold segmentation, and the tumor location is eventually found using an image subtraction approach. This method provides the precise tumor form in the MRI brain imaging. A brain tumor detection and classification method was suggested by Joshi et al. [2] based on MR images. The technique involves extracting the tumor section from the brain image, utilizing Gray Level Co-occurrence Matrix (GLCM) to extract the textural properties of the identified tumor, and using a neuro-fuzzy classifier to classify the tumor.

A neural network and segmentation based technique was suggested by Amin and Mageed [3] to automatically identify the tumor in brain MRI images. The MRI brain image's retrieved features are first classified using Multi-Layer Perceptrons (MLP) after Principal Component Analysis (PCA) is used to extract the features. Peak recognition rate is 96.7 percent, while average recognition rate is 88.2%. Brain tumors may be identified from MRI images using an image segmentation approach introduced by Sapra et al. [4]. An artificial neural network (PNN) is then used to classify brain tumors in MRI data. The suggested PNN approach handles the categorization of brain tumors more precisely. An unsupervised neural network learning method for classifying brain MRI images was suggested by Suchita and Lalit [5]. The tumor is removed using segmentation after the MRI brain images have initially undergone preprocessing, which includes noise reduction and edge identification. Gray-Level Co-occurrence Matrix (GLCM) is used to extract textural information, and Self-Organizing Maps (SOM) are then utilized to categorize the brain as normal or abnormal, that is, whether or not it contains a tumor. Prior to using an MRI picture in an application, Rajeshwari and Sharmila [6] suggested pre-processing approaches that are employed to enhance the image quality. The Discrete Wavelet Transform (DWT) approach, which is based on interpolation, is used to improve resolution. The average, median, and wiener filters are employed to remove noise. These methods are assessed using the Peak Signal to Noise Ratio (PSNR).

In order to improve the MRI picture more successfully, George and Karnan [7] devised an MRI image enhancement approach based on Histogram Equalization and the Center Weighted Median (CWM) filter. By first extracting the features using Principal Component Analysis (PCA) and Gray-Level Co-occurrence Matrix (GLCM), Daljit Singh et al. in [8] proposed a hybrid technique for automatic classification of MRI images. The extracted features are then fed as an input to Support Vector Machine (SVM) classifier, which classifies the brain image as normal or abnormal. The technique for brain tumor identification and categorization was suggested by Gadpayleand and Mahajani [9]. The MRI brain picture is classified as normal or abnormal brain utilizing segmentation to identify the tumor, GLCM to extract textural information, and lastly BPNN and KNN classifiers. With the KNN classifier, the accuracy is 70%, and with the BPNN classifier, it is 72.5%. A modified Fuzzy C-Means (FCM) method for MR brain tumor diagnosis was proposed by Shasidhar et al. in [10]. After extracting the texture characteristics from the brain MR image, the modified FCM algorithm is used to identify brain tumors. The updated FCM algorithm yields average speed-ups of up to 80 times compared to the standard FCM method. An expedient substitute for the conventional FCM method is the modified FCM algorithm. Brain MR image categorization based on feed-forward neural network classifier and rough set theory was suggested by Rajesh and Malar [11].

MRI scans are processed using Rough Set Theory to extract features. The chosen characteristics are supplied into a feed forward neural network classifier, which distinguishes between brain abnormalities and normal brain tissue with an accuracy of about 90%.

3. PROPOSED METHOD

A search of the literature revealed that automated brain tumor identification is critical since human life is at stake and high accuracy is required. Machine learning algorithms are used for feature extraction and classification in the automated tumor identification process in magnetic resonance imaging. This work proposes a technique, shown in figure 1, to automatically identify tumors in MR images.

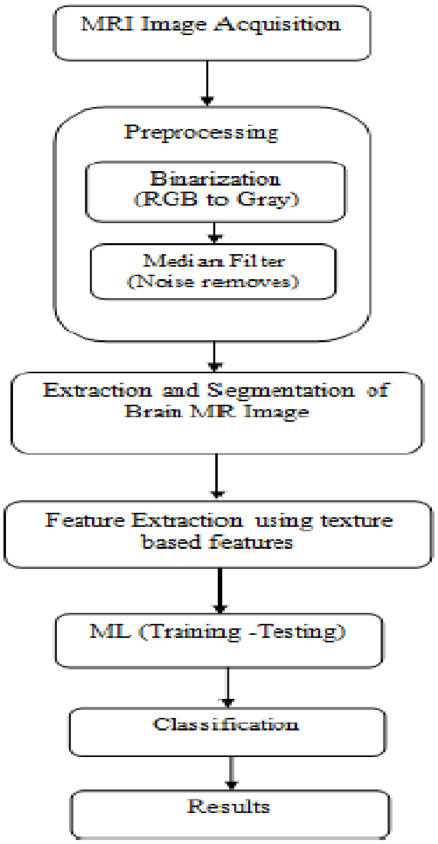

Figure 1: Suggested Approach for Identifying Brain Tumors in MR Images

Image Acquisition: After being obtained, the MRI brain pictures are used as input for the pre-processing phase. In figure 2, the example brain MR pictures are shown.

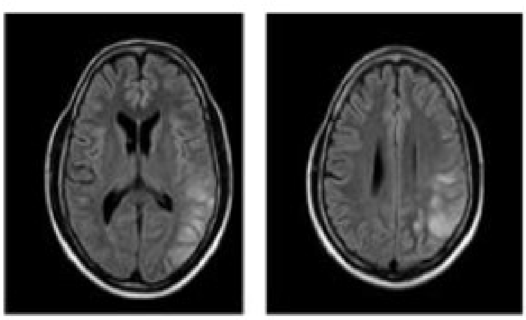

Fig 2. Samples of brain MR image

Preprocessing: Preprocessing is necessary because it improves the picture data, highlighting certain elements that are crucial for further processing.

The MR image undergoes the following pre-processing steps:

As shown in figure 3(b), the RGB MR picture is transformed to a grayscale image, and the median filter is then used to remove noise from the brain MR images. Since great precision is required for future processing, the noise must be eliminated.

Next, as shown in figure 3(c), edges are identified from the filtered picture utilizing clever edge detection. For the purpose of segmenting the picture, the edge detected image is required.

Subsequently, as seen in figure 3(d), watershed segmentation is carried out to locate the tumor in the brain picture.

The process of breaking a picture up into several pieces is called segmentation. The goal of segmentation is to transform an image's representation into one that is easier to examine. Label image is the output of watershed segmentation.

Each distinct item in the label picture will have a different pixel value; for example, the first object's pixels will all have value 1, the second object's pixels will all have value 2, and so on [23]. Figure 3 displays the different preprocessing techniques used on the brain MR image.

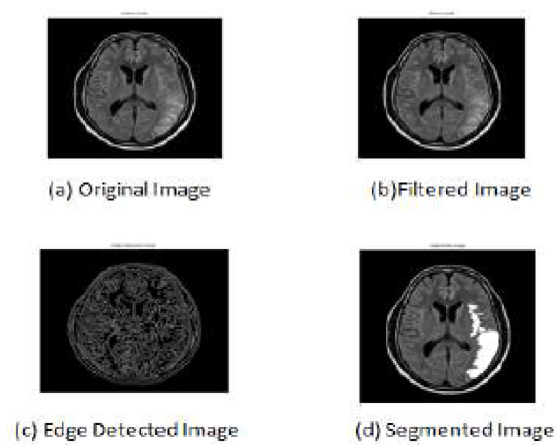

Figure 3(a-d). preprocessing procedures for the input brain picture

Feature Deletion: An algorithm's input is reduced to a feature vector—a reduced, representative collection of features—when it is too big and redundant to handle in one go. Feature extraction is the process of transforming an input data collection into a set of features [5]. The critical characteristics required for picture categorization are extracted in this stage. In order to display the texture property of the picture, texture characteristics are extracted from the

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ISSN 2321-2152
www.ijmece.com
Vol 9, Issue 3, 2021

segmented brain magnetic resonance image. The Gray Level Co-occurrence Matrix (GLCM), a reliable and effective approach, is used to extract these properties. Because using fewer gray levels minimizes the size of GLCM, which lowers the computational cost of the algorithm while maintaining the high classification rates, the GLCM texture feature extraction approach is very competitive. The GLCM characteristics are used in the differentiation of aberrant and normal brain.

The following are the retrieved GLCM texture features:

Energy: It provides a textural homogeneity metric, i.e., a pixel pair repetition measure.

$$E = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j)^2 \;.........(1)$$

Range=[0,1]

(2) Contrast : It gives a measure of intensity contrast between a pixel and its neighbor over the whole image.

$$Con = \sum_{n=0}^{N_g-1} n^2 \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j)^2 \;......$$

Range=[0,1]

(3) Correlation : It gives a measure of how correlated a pixel to its neighbor over the whole image.

$$C = \frac{1}{\sigma^x \sigma^y} \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i,j)p(i,j)^2 - \mu_x \mu_y \;.$$

Range=[-1,1]

(4) Homogeneity : It gives a measure of closeness of distribution of elements in GLCM to GLCM diagonal.

$$H = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{p(i,j)}{(1+\mathrm{mod}(i,j))} \;.....(4)$$

Range=[0,1]

In order to categorize the brain as normal or pathological, MRI brain pictures are gathered, followed by preprocessing and segmentation. GLCM is used to extract texture characteristics from the segmented picture and extract features from it. Matlab 2012a is used for the preprocessing and feature extraction processes.

(5) Grouping: The MR brain picture is classified as normal or abnormal using machine learning methods. Making intelligent judgments automatically is the main goal of machine learning algorithms. The feature set created using the previously mentioned approach was used to classify images using Multi-Layer Perceptrons (MLP) and Naive Bayes. A feed forward artificial neural network model called MLP [3] converts sets of input data into sets of suitable outputs. Because it doesn't have any cycles and the network output is solely dependent on the active input instance, it is known as feed forward. Every node in MLP has a nonlinear activation function and is a neuron. Its foundation is the supervised learning approach. After each piece of data is analyzed, learning occurs via the adjustment of connection weights according to the degree of inaccuracy in the goal output relative to the anticipated result. The learning process aims to reduce error by optimizing the weight values that are currently assigned to each edge. The model is called back-propagation because of this process of the weights shifting backward.
Naive Bayes is a statistical technique for classification and supervised learning. It is a straightforward Bayes theorem-based probabilistic classifier. It makes the assumption that a feature's value is independent of other features' existence or absence. The posterior probability is determined by computing the prior probability and likelihood. For parameter estimation, the greatest posterior probability technique is used. Just a little quantity of training data is needed for this approach to estimate the parameters required for classification. Less time is needed for categorization and training.

4. EXPERIMENTAL RESULTS

212 brain MR scans were used in the investigation. Weka is utilized for classification once texture-based characteristics are retrieved from each picture [28]. GLCM is used to extract texture-based properties including energy, contrast, homogeneity, and correlation. For classification, the Multi-Layer Perceptron (MLP) and Naïve Bayes with 66% percentage split are used. Sixty-six percent of the instances are divided between training and testing, with the remaining instances being utilized for testing.

Table 1: Analysis of experimental results

ML Algorithm	Total samples	Model Build Time	Classification Rate (%)
MLP	210	61.82	98.6
Naive bayes	210	0.02	97.6

From the Table 1, we can find the classification rate of brain MR images using MLP and Naive bayes. The accuracy of about 98.6% and 91.6% is obtained respectively.

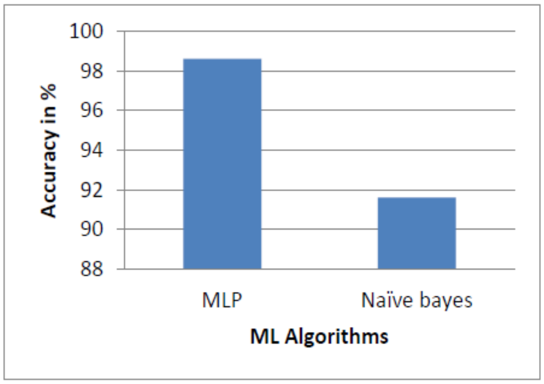

Fig 4. Graphical representation of accuracy

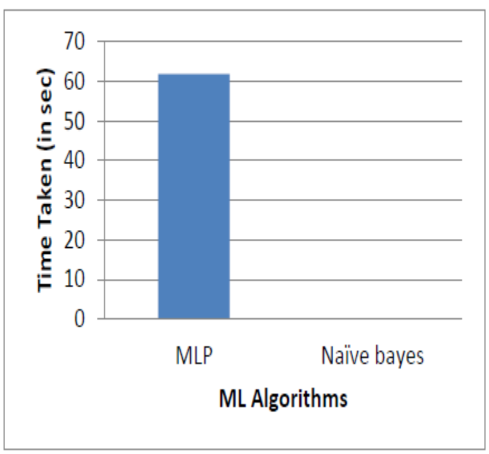

Fig 5. Graphical representation of time taken

While Naïve Bayes takes less time and produces less accurate results, the MLP produces more accurate results and requires more effort to develop the model. Owing to the many forms and intricacies of tumors, the suggested approach provides satisfactory accuracy. Given that human life is at stake, great precision is preferred.

5. CONCLUSION

This research suggests developing a machine learning algorithm-based system for the identification of brain tumors. The Gray Level Co-occurrence Matrix (GLCM) is used to extract the texture-based information (19). The textural properties of the picture that are taken into account in this suggested work include homogeneity, energy, contrast, and correlation. 212 samples of brain MR images are taken into consideration in order to reach the highest accuracy of 98.6% and 91.6% when using the Multi-Layer Perceptron and Naïve Bayes machine learning algorithms for classification. By taking into account a large data set and extracting intensity-based characteristics in addition to texture-based features, this accuracy may likely be improved.

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