Brain Tumor Detection Using Machine Learning Algorithm

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Abstract - *Detecting brain tumors via Magnetic Resonance Imaging (MRI) is crucial but challenging due to the intricate nature of these abnormalities. A proposed method involves several steps, including sigma filtering, adaptive thresholding, and region detection, to analyze MR images. Shape features such as Major Axis Length, Euler Number, Minor Axis Length, Solidity, Area, and Circularity are extracted to characterize the tumors. This method employs two supervised classifiers: a C4.5 decision tree algorithm and a Multi-Layer Perceptron (MLP) algorithm. These classifiers distinguish between normal and abnormal brain cases, with abnormalities further classified into benign or malignant tumors. With a dataset of 250 brain MR images, the MLP algorithm achieves a notable precision of approximately 80%.*

Key Words*: *Magnetic Resonance Imaging (MRI), Image Acquisition, Detection Region, Image preprocessing, Image Segmentation, Feature Extraction

1.INTRODUCTION

Brain tumors are solid neoplasms found within the skull, arising from uncontrolled and abnormal cell division. They typically develop in the brain itself, but can also manifest in other locations such as lymphatic tissue, blood vessels, cranial nerves, and brain envelopes. Additionally, brain tumors can result from the metastasis of cancers originating elsewhere in the body. The classification of brain tumors hinges on factors like their location, the tissue type from which they originate, their malignant or benign nature, and other considerations.

Primary brain tumors originate within the brain and are named based on the cell types from which they originate. They may be benign, such as Meningioma, which cannot metastasize. Conversely, they can be malignant and invasive, exemplified by Lymphoma (characterized by a ring-like appearance), cystic oligodendroglioma (displaying rounded cells with distinct borders and a central nucleus resembling a "fried egg"), Ependymoma (arising from ependymal cells and exhibiting malignant behavior despite benign histology), and Anaplastic astrocytoma (a common high-grade astrocytoma).

Secondary brain tumors, also known as metastatic brain tumors, develop from cancer cells that have migrated to the brain from other parts of the body. Typically, these cancers originate from primary tumors in organs such as the kidneys, lungs, breasts, or from melanomas on the skin. A brain scan offers a detailed visualization of the brain's internal structure. Among the most frequently utilized methods for brain imaging is MRI (Magnetic Resonance Imaging), renowned for its ability to provide exceptional insights into the human body. To categorize MR Images, two primary methodologies are employed: supervised techniques like support vector machines, k-nearest neighbors, and artificial neural networks, and unsupervised techniques such as fuzzy c-means and self-organizing maps (SOM). Many studies have utilized a combination of both supervised and unsupervised techniques to distinguish MR Images as either normal or abnormal. This study employs supervised machine learning techniques to categorize five distinct types of abnormal brain MR Images, including Ependymoma, Lymphoma, Cystic Oligodendroglioma, Meningioma, and Anaplastic Astrocytoma, alongside normal images

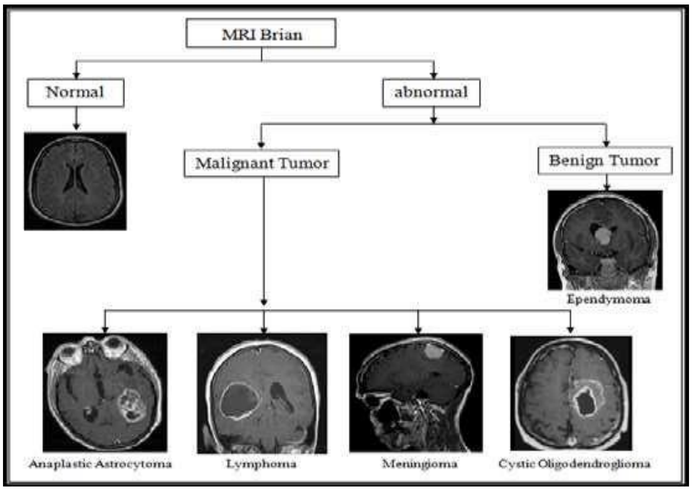

Fig 1. Types of MR images

2. LITERATURE WORK

1. Suraj Grover and fellow writers unveiled an unfamiliar method for segmenting brain tumors in 3D MR pictures. Initially, segmentation of brain MR pictures was carried out utilizing an inventive technique for tumor detection. Afterward, tumor detection leaned on selecting uneven regions. This technique considers the brain's asymmetrical plane and utilizes blurry classification. The results act as the

foundation for setting in motion a segmentation process that integrates spatial relations and deformable models, leading to precise segmentation of brain tumors.

2. Mahesh S. and friends put forth a methodology focused on texture characteristics, particularly the Gray Level Co-occurrence Array (GLCM) derived from MR pictures. They employed a Sequential Forward Selection algorithm to pinpoint discriminative characteristics. Afterward, the method categorized MR images into usual and unusual categories by applying an advanced kernel-centered technique, just like the Assistance Vector Machine (SVM).

3. M. Jayan and friends put into practice a hybrid algorithm devised for brain tumor detection, leveraging statistical characteristics and a Vague Assistance Vector Machine (SVM) classifier. Their technique includes a four-step process. Initially, they implemented an anisotropic filter to diminish noise in the first step. Next, texture characteristics were taken out from MR pictures in the second step. Afterward, Principle Constituent Analysis (PCA) was utilized to reduce the characteristics of MR pictures to the most necessary ones in the third step. Eventually, tumor classification into usual and unusual categories was executed employing a Managerial classifier based on Vague Assistance Vector Machine in the final step. The classification precision accomplished was 95.80%.

4. Tanmay Kapur and friends took advantage of data from both magnetized reverberation (MR) imaging and magnetized resonation spectroscopy (MRS) to help in clinical diagnosis. Their proposed technique encompasses numerous stages, encompassing segmentation, characteristic extraction, and characteristic selection. A classification model was then built to segregate between usual and unusual brain cases. They employed a segmentation technique founded on blurry connectedness to outline tumor mass fences in MR pictures. Besides, they utilized the concentric circle technique to extract characteristics from regions of interest. Characteristic selection was implemented to remove repetitious characteristics. Experimental discoveries highlight the efficiency of their approach in faithfully categorizing brain tumors in MR pictures.

5. Prachi Gadpayle and friends contrived a system specialized in detecting and categorizing brain tumors. They exploited a spectrum of picture processing techniques, encompassing preprocessing, picture enrichment, segmentation, morphological actions, and characteristic extraction, custom-made for pinpointing brain tumors in MRI pictures. Noticeably, they included texture characteristics like the Gray Level Co-occurrence Array (GLCM) in tumor detection. Using classifiers just like the Backing Neural Network (BPNN) and the K-Nearest Companions (K-NN) algorithm, they efficiently classified MRI brain pictures into unusual and wholesome ones.

6. Ramteke and Monali recommended an automatic classification of brain MR pictures into two sections Usual and Unusual based on picture characteristics and automatic mistake detection. The Statistical texture characteristic set is picked up from usual and unusual pictures and then KNN classifier is utilized for classifying picture. The KNN attains 80% classification rate. Xuan and Liao recommended statistical structure examination founded tumor segmentation technique. The intensity-based, symmetry-based, and texture-based characteristics are extracted from MR picture. Then, classification technique employing AdaBoost is utilized to classify the MR picture into usual tissues and unusual pictures. The normal accuracy of about 96.82% is attained. Othman et al. in recommended Probabilistic cerebral network technique for brain tumor classification. Primarily, the characteristics are extracted utilizing the predominant component analysis (PCA) and the classification is executed utilizing Probabilistic Neural Network (PNN). Ibrahim et al is recommended Neural Network technique for the classification of the magnetized reverberation human brain pictures. The characteristics are extracted utilizing principal Constituent Analysis (PCA) and then Back-WebDriver Neural Network is utilized as a classifier to classify MRI brain pictures as usual or unusual.

3. PROPOSED METHOD

Developing an Machine Learning Based Brain Tumor Detection Model: Methodology

3.1. Image Acquisition

In our system, we leverage real-time data comprising MRI images sourced from various hospitals and online repositories.

To ensure consistency, we standardize the dimensions of the images to 224x224 pixels. Upon acquisition, each image undergoes a thorough preprocessing stage to prepare it for analysis.

In image processing, image accession is done by reacquiring an image from dataset for processing. It's the first step in the workflow sequence because, without an image no processing is possible the image that's acquired is fully undressed. Then we reuse the image using the train path from the original device.

3.2. Image Preprocessing

The MRI dataset utilized in our study encompasses approximately 2100 images, representing both normal and abnormal brain scans. To enhance the quality of these images, we employ a technique known as sigma filtering to reduce noise interference.

This process involves analyzing the pixels within a designated area and smoothing out variations that exceed a certain threshold. By applying sigma filtering, we aim to improve the clarity and accuracy of the images, thus facilitating more precise tumor detection.

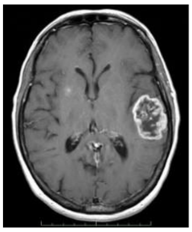

Fig 2(a)

MRI before filter

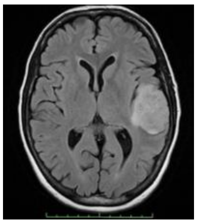

Fig2(b)

MRI after filter

3.3. Segmentation

After processing the images, the subsequent step is segmented. Hither, segmentation is being done employing thresholding. The underlying concept of thresholding is to simplify the visual data analysis. Thresholding bethinks a vastly popular segmentation technique utilized to differentiate the object pondered as a forefront from its surrounding. In this scenario, we are utlilizing binary thresholding for segmentation. In binary thresholding, each pixel endures the same threshold value. Suppose the pixel intensity value is lesser than the threshold, it gets set to 0 (black); if not, it gets set to 255 (white).

Segmentation stands as the process of carving an image into myriad segments and isolating the tumor from regular tissues. Segmentation method owns the capacity to recognize or determine the aberrant portion from the image, catering to the analysis of size, volume, location, texture, and shape of extracted image.

3.4. Feature Extraction

Feature extraction is a pivotal step in harnessing the potential of big data sets, particularly in the realm of medical imaging analysis such as brain MRI scans. By selecting and combining variables into meaningful features, we can significantly reduce the redundancy inherent in these datasets. This reduction not only streamlines the data processing pipeline but also enhances the learning speed of machine learning algorithms.

In our approach, we utilize morphological operations to extract features from the acquired brain MRI scans. These operations allow us to highlight distinct patterns and structures within the images, providing valuable insights into the underlying characteristics of the brain tissue.The transformed data, now represented by a reduced set of informative features, is referred to as a feature vector. This vector encapsulates the essential information necessary for subsequent analysis and model building. In our case, we focus on extracting features that capture the textural properties of the segmented brain MRI images.

To achieve this, we employ the Gray Level Co-occurrence Matrix (GLCM) method, renowned for its robustness and high performance in texture analysis. GLCM quantifies the spatial relationships between pixel intensity values, thereby encoding textural information that is instrumental in differentiating between various tissue types and pathological conditions in brain scans. By leveraging GLCM-based feature extraction, we aim to enhance the discriminative power of our model and facilitate accurate tumor detection and classification.

3.5. Classification

Classification can be defined as the process of predicting a class or category from observation values or given data points. The bracket of a biomedical image is a veritably important step for an automated Computer backed Design(CAD) system. At the end of these segmentation and discovery process, decision has been taken rainfall that MRI image consists of any excrescence or not and the normal or the abnormal state has been checked.

4. RESULT

4.1. Performance Measures

The algorithm's efficacy has been rigorously evaluated across diverse performance metrics, encompassing True Positives (TP) and True Negatives (TN). TP quantifies the algorithm's capacity to accurately discern damaged regions, while TN reflects its precision in identifying non-damaged areas. Conversely, False Positives (FP) denote instances where the algorithm incorrectly identifies non-damaged regions as damaged, while False Negatives (FN) indicate its failure to recognize damaged regions. Leveraging TP, TN, FP, and FN values, key metrics such as Accuracy, Specificity, and Sensitivity are derived to comprehensively assess the algorithm's performance. This multifaceted evaluation underscores the algorithm's distinguishing between damaged and non-damaged regions, thus contributing to its efficacy in clinical applications.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1.1)$$

$$Sensitivity = \frac{TN}{TP+FN} \quad (1.2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (1.3)$$

4.2. Experimental Results

The experiment was carried out on 250 brain MR images. From each image, the texture based features are extracted and weka tool is used for classification . The texture based features such as energy, contrast, correlation, homogeneity areextracted using GLCM. The Multi-Layer Perceptron (MLP) and Naïve bayes with 66% percentage split is used for classification. In 66% percentage split, 66% of the instances are used for training and remaining instances are used for testing.

Table -1: Result of NLP algorithm

Brain tumor type	TP Rate	FP Rate	Precision
Ependymoma	0.821	0.011	0.543
Meningioma	0.708	0.04	0.718
Lymphoma	0.71	0	1
cystic oligodendroglioma	1	0.048	0.834
anaplastic astrocytoma	0.716	0.011	0.817
Normal	1	0	1
Average	0.825	0.018	0.818

Table -2: Experimental result analysis

ML Algorithm	Total samples	Model Build Time	Classification Rate (%)
MLP	250	60.1	88.2
Naive bayes	250	0.01	80.7

From the Table 1, we can find the classification rate of brain MR images using MLP and Naive bayes. The accuracy of about 88.2% and 80.7% is obtained respectively

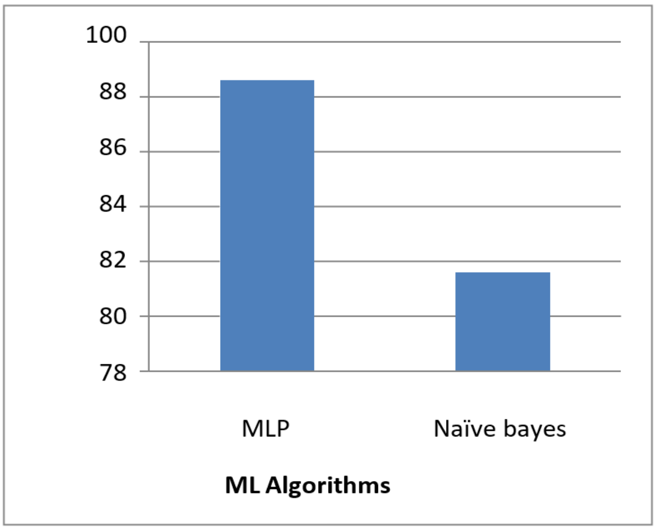

Chart -1: Accuracy representation

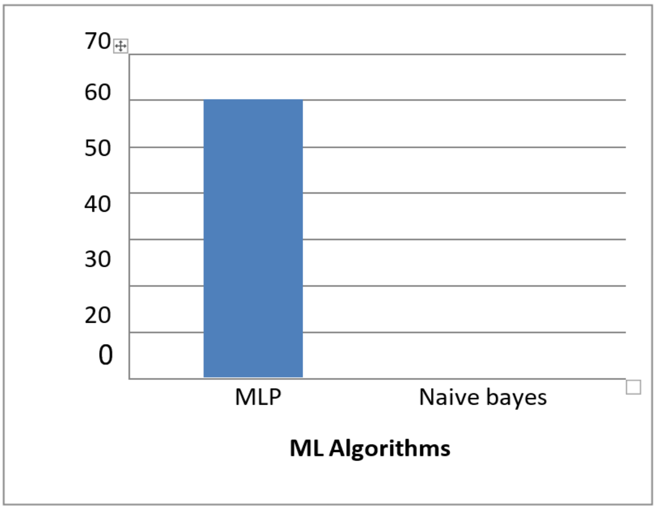

Chart -2: Time taken representation

In the realm of brain MR image classification, the path to achieving accuracy is often a balancing act between time investment and precision. Here, the Multi-Layer Perceptron (MLP) emerges as the frontrunner, boasting commendable accuracy at approximately 88.2%. However, its triumph comes with a caveat - the construction of its model demands a considerable amount of time

5. CONCLUSION

The accurate brain excrescence discovery is still veritably demanding because of tumor appearance, variable size, shape, and structure. Although excrescence segmentation styles have shown high eventuality in assaying and detecting the tumor in MR images, still numerous advancements are needed to directly member and classify the excrescence region. Being work has limitations and challenges for relating substructures of excrescence region and bracket of healthy and unhealthy images. In short, this check covers all important aspects and rearmost work done so far with their limitations and challenges. It'll be helpful for the experimenters to develop an understanding of doing new exploration in a short time and correct direction. The deep literacy styles have contributed significantly but still bear a general fashion. These styles provided better results when training and testing are performed on analogous accession characteristics(intensity range and resolution); still, a slight variation in the training and testing images directly affects the robustness of the styles. In unborn work, exploration can be conducted to descry brain excrescences more directly, using real case data from any medium(different image accession(scanners). Handcrafted and deep features can be fused to ameliorate the classification results. also, light weight styles similar as amount machine literacy play significant part to ameliorate the delicacy and efficacity that save the time of radiologists and increase the survival rate of cases.

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