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# Recent Development of Brain Tumor Detection and Classification Techniques: A Review

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***Abstract*—A tumor is an enlargement or abnormal growth that happens as a result of unpredictable and uncontrolled cell division. Brain tumors are a particularly hazardous form of tumor. Brain tumors come in a variety of forms and are categorized into four groups. Depending on the kind, intensity, and location of the tumor, medical therapy for brain tumors may vary. If a brain tumor is not found in its early stages, it might be fatal. Magnetic resonance imaging (MRI) images are used by specialists and neurosurgeons to find brain tumors. This study reviews the field of brain tumor detection and compares several methods for identifying and categorizing brain tumors in MRI data.**

***Index Terms*— Brain tumor, MRI, Classification.**

## I. Introduction

The central nervous system of humans is found in the brain. Given that it is a vast network of between 50 and 100 billion neurons, the brain is a difficult organ. An aggregation of unwanted and aberrant cells that are growing in the brain is what causes a brain tumor. Because it takes up space within the skull and it is also known as an intracranial lesion since it tends to raise intracranial pressure. One important illness in particular is brain tumor, while it can affect people of any age; it most frequently affects children, young adults, and individuals in their middle years. In India, there are about 1 million instances of brain tumor recorded annually. Ages impacted by brain tumors were recorded by sources like Apollo Hospitals (India), Columbia Asia Hospital (India), Harvard Medical School (USA), Albert Einstein Hospital (Brazil), World Health Organization (WHO), and other medical advice associations. Image processing is a technology that may transform a physical image into a digital one. It then applies certain operations on the image to produce an improved version or to extract important data. Researchers have developed a number of algorithms for segmenting, detecting, and classifying brain MRI images of neonates and adults, but there are significant differences between them all in terms of the datasets used, segmentation objectives, characteristics, levels of algorithmic complexity, and validation. Due to its potential for examining early development patterns and structural change in Central Nervous System (CNS) problems, both new-born and adult brain MRI scanning and research are of significant interest.

### *A. Magnetic Resonance Imaging*

The term "resonant magnetic field imaging" refers to the use of radio waves and strong magnetic fields in medical imaging produced by a computer to provide comprehensive information and pictures of various bodily

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parts and structures. MRI is safer for the human brain than CT scans since it uses no harmful radiation like X-rays. To detect the existence of a brain tumor, digital image processing techniques including pre-
processing, segmentation, and feature extraction can be applied. It helps by giving a cross-sectional image of the brain that may be examined to pinpoint the position and size of the tumor. If there is one. There is not a lot of physical contact. Magnets surround tube-shaped equipment known as an MRI scanner. The patient must do the examination on a table that fits into the tube-shaped equipment. Water molecules in the body are regularly scattered at random. Protons in hydrogen atoms are brought into alignment with the magnetic field of MRI machines. These atoms' protons emit tiny signals that the MRI equipment can detect when they are subjected to a radio wave beam. These data are then processed to provide MRI pictures for future investigation. Cross-sectional pictures of the brain may be obtained using this approach. With the aid of these scans, the tumor may be located, its size and structural details can be studied, and the best course of action for treating the brain tumor can be determined.

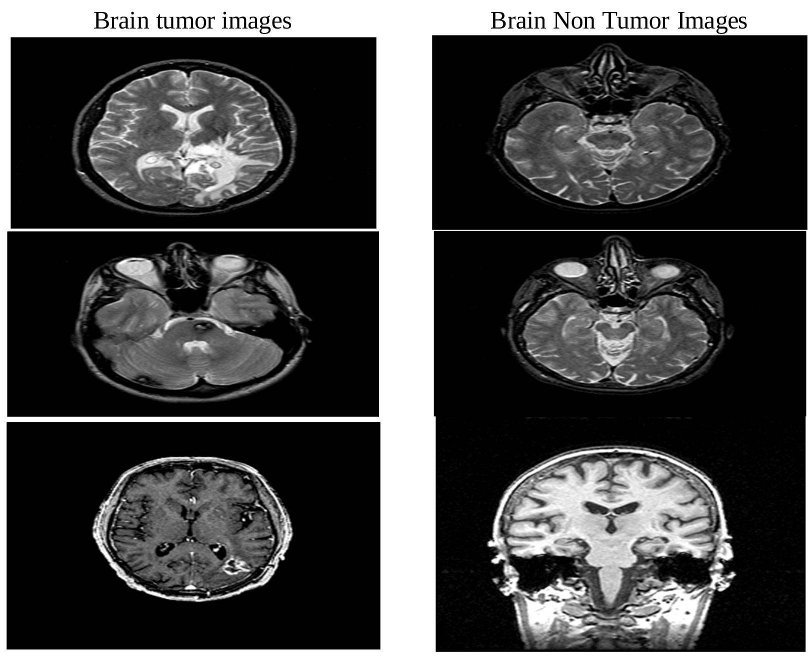



Fig 1: Positive Images versus Negative Images

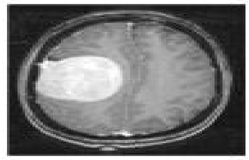
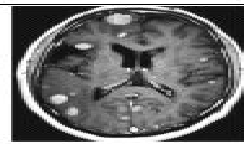
*B. Brain Tumor*

An accumulation or cluster of aberrant brain cells is known as a “Brain tumor”. Malignant (cancerous) or benign brain tumors are also possible. Whether benign or malignant, tumors can make your skull feel more compressed [24]. This might lead to brain damage and perhaps death. The National Brain Tumor Foundation (NBTF) reports a 300% rise in the number of persons who will die from brain tumors in developed nations [25]. There are 150 distinct types of brain tumors that have been identified. Based on their microscopic characteristics, Primary and secondary brain tumors are two categories of tumors recognized by the World Health Organization (WHO). While secondary brain tumors are brought on by tumors that have already developed in other parts of the body, primary brain tumors are frequently born in the brain. Brain tumors are categorized and defined in the Table 1. The improper division of brain cells leads to a benign tumor; benign tumors often develop slowly and don't have the ability to invade nearby organs or other brain tissues. These tumors are not malignant. It is less dangerous to your life and is simple to eradicate. There are no such precise reasons, although stress, family history, food, and exposure to chemicals might all provide a risk.

The most typical benign tumors for meningioma, pituitary adenomas, and hemangioblastomas are detected.

Cancerous cells with the ability to invade other tissues and organs form malignant tumors. The sole channel via which diseased cells can travel to other locations is through blood. Rapid growth means that it can certainly regrow after being removed. It poses a hazard to life. An example of this would be lung cancer, which could spread to the brain, bones, liver, breast, or liver.

TABLE I: DIFFERENT TYPES OF BRAIN TUMOR

| Brain tumor Types | Description | Medical image | Example |
|---|---|---|---|
| 1. Primary brain tumor | Gliomas, which are gial cells, are the primary source of their emergence in the brain. Additionally, they are separated into benign and malignant types. |  | Meningiomas, pituitary adenoma, glioblastoma multiforme, astrocytoma, and gliomas |
| 2. Secondary brain tumor | These are caused by tumors that can be found throughout the body. Including breast cancer, lung cancer, and more. Tumor cells that travel via the bloodstream from other locations and reach the brain are what produce brain tumors. |  | Metastatic cancer |

Brain biopsies are the manual method performed to look for tumors. A biopsy is a procedure used to look under a microscope at an aberrant brain cell that has been removed. The examination's findings will indicate whether the brain cell is a tumor or a normal cell. It entails a significant risk of brain haemorrhage, brain swelling, infections, clotting, and many other things. Thus, medical imaging is employed to address the aforementioned shortcomings. Understanding how the body's organs and disorders operate is useful. Additionally, it aids in early issue detection, which in turn aids in problem diagnosis. It gets around the limitation of the manual approach. Radio waves, magnets, and computers are all used in the magnetic resonance imaging (MRI) method to provide comprehensive data about the human body. Both injuries and tumors can be detected with it [25]. It makes it possible for medical professionals to obtain detailed knowledge about the human body. One of the greatest imaging examinations for obtaining fine details of the brain and other body regions is the MRI scan. As demonstrated in Fig. 2[25], Axial, sagittal, and coronal views of the organ are all possible.

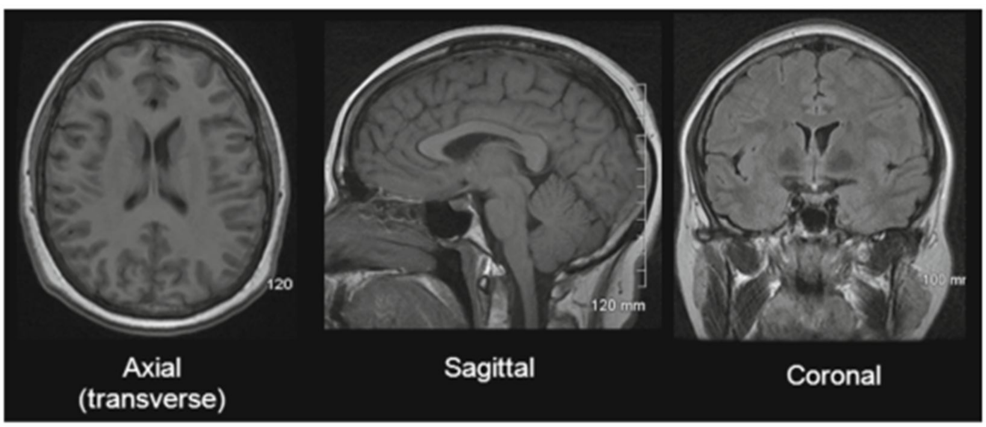



Figure 2: MRI Images

II. RELATED WORK

(Amritpal Singh et al.) [1] The proposed method combines SVM with fuzzy c-means to provide a hybrid solution for brain tumor prediction. To improve the image, contrast enhancement and mid-range stretch are applied. Skull striping employs morphological approaches and double thresholding. The image is segmented using fuzzy c-means (FCM) clustering. The Grey Level Run Length Matrix (GLRLM) is utilized for feature extraction. The Linear, Quadratic, and Polynomial SVM algorithms are then used to classify the brain MRI pictures. To distinguish, the MRI brain scans of 120 people were employed as a valid data set.
(Astin et al.) [2] Using the Adaboost machine learning algorithm, a practical automatic classification approach for brain MRI is projected. The suggested system consists of three steps: feature extraction, pre-processing, and classification. Pre-processing, which also turns the RGB image into grayscale using a median filter and thresholding segmentation, was used to minimize noise in the raw data. 22 properties from an MRI were

extracted using the GLCM feature extraction method. Adaboost is a classification-boosting technique. It can distinguish between benign and malignant tumors as well as healthy brain tissue with an accuracy of 89.90%. Quadratic and polynomial kernel functions may be used in future work. The more images in the training database, the more accurate the algorithm will become. The approach may also be used to a wide variety of classes.

(Ansari et al.) [3] A novel technique has been presented that combines K-means segmentation with histogram normalization. To get rid of any unwanted signals or noise, the provided picture must first undergo pre-processing. To de-noise the MRI images, filters such as the Median filter, Adaptive filter; Averaging filter, Un-sharp masking filter, and Gaussian filter are utilized. The pre-processed image's histogram is normalized, and an MRI classification is done. Finally, the image is segmented using the K-means algorithm to remove the tumor from the MRI. The NB Classifier and SVM effectively classify the MRIs in order to provide exact prediction and classification. Naive Bayes and SVM Classifier had accuracy rates of 87.23 and 91.49 percent respectively. SVM offers classification that is more precise. The difficulty to precisely define the limits of the tumor zone is one of the many shortcomings of the presented method.

(Chandra et al.) [5] The suggested approach thresholds the wavelet coefficient to perform DWT de-noising on a brain MRI picture. A genetic method is employed to find tumor pixels. Based on the chosen criterion, a genetic algorithm is utilized to discover the optimal information extraction strategy. The current technique guides the final evolutionary algorithm's search for the best or worse feasible data split utilizing k-Means clustering approaches with genetic algorithms. based on actuality, Achieved accuracy separate between 82 and 97 percent of tumor pixels. Wavelet transformations involve a high processing and storage overhead, which is a drawback of this study.

(Uma et al.) [5] Image processing through preprocessing, segmentation, and feature extraction is the proposed methodology. Phases of classification. During pre-processing, the morphological approach with double thresholding is used to remove the skull from MRI brain pictures. It compares and contrasts two approaches for MRI image tumor detection. One is based on the Level set approach, which separates the brain tumor from the MRI brain images using non parametric deformable models with active contour. The K-means segmentation algorithm is an alternative. Feature extraction using the Discrete Wavelet Transform and the Grey Level Co-occurrence Matrix and classification using the Support Vector Machine follow segmentation in the decision-making process. T2 weighted 17 benign MRI brain tumor pictures are part of the data set. 24 illustrations of malignant tumors from various people. With 94.12% and 82.35% accuracy, respectively, SVM with Level Set and K-Means segmentation classified images as normal brain, benign, or malignant tumor. The Level Set technique outperforms K means segmentation in terms of performance. Significant computational expense and massive storage.

(Sudharani et al.) [7] Techniques like the histogram, resampling, K-NN algorithm, and distance matrix are included in the recommended methodology. The first thing a histogram offers is the general distribution of pixels in a given image with the stated value. After resampling, the image was enlarged to 629 x 839 to provide a good geometric depiction. k-NN, which is based on k's training, is used for brain tumor classification and detection. The classifier's distance in this study has been determined using the Manhattan metric. The method has been implemented using Lab View. 48 photos have been used to test the algorithm. All photos have an average identification score of roughly 95%.

(Vivek kapur et al.) [6] Proposes an intelligence classification technique to discriminate between abnormal and normal MRI brain images. Effective image preprocessing, picture feature extraction, and subsequent brain cancer classification are made possible by these techniques. During pre-processing, RGB MRI brain images are converted to greyscale images. Median filter is used to reduce the noise in the MRI image. Then, utilizing skull masking, The MRT brain imaging removes non-brain tissue.. Dilation and erosion are two basic morphological methods used to cover the skull. During symmetrical feature extraction, properties of texture and grayscale are extracted. The results show that when 50 images are identified using three different machine learning algorithms, Hybrid Classifier (SVM-KNN) displayed the greatest accuracy, followed by Support Vector Machine (SVM) and K-Nearest Neighbor (KNN).

(Swaskhar et al.) [8] Images are processed using a technique that employs Artificial Neural Networks (ANN) to categorize tumor stage and incorporates, among other things, phase segmentation, feature extraction, and SVM classification. The pre-processing stage employs three contrast-enhancing techniques: adjusted, adaptive threshold, and histogram imaging using the weiner2 and median2 filters. The TKFCM technique,

which slightly alters K-means and Fuzzy c-means, is used for segmentation. For features, two different extraction orders are utilized.. For both first and second order areas, statistical features based on properties are generated. The brain MRI will subsequently be classified by SVM as either normal or tumorous. Brain tumor stages are categorized using an ANN classifier. The proposed approach has a 97.44% accuracy rate.

(Tappan et al.) [9] Employed the super pixel method and transfer learning, respectively, to identify brain tumors and segment the brain. The BRATS 2019 brain was the source of the dataset. This model was developed to address the tumor segmentation utilizing the VGG 19 transfer learning approach with difficulty. Using super pixels, the tumor was separated into LGG and HGG pictures. The average dice index as a consequence was 0.934, which did not reflect the truth.

(Hamid et al.) [10] U-Net for medical image segmentation using semantics. A successful complex 2D segmentation network was built using the U-Net design. The suggested model was assessed and tested using the BRATS 2017 dataset. The proposed U-Net design has a Dice coef of 0.81, 27 convolutional layers, and 4 DE convolutional layers.

*(Ravindra et al.*) [11] To obtain precise findings from MRI scans, deep learning methods employing deep neural networks and the usage of convolutional neural network models. Applying a 3-layer CNN architecture that was also connected to a fully connected neural network was advised. An F-score of 97.33 and an accuracy of 96.05% are both achievable.

(Tati Erawati Rajab et al.*)* [12] Active contour modelling was used to analyse MRI T1-weighted images to determine whether a brain cancer could be present. The efficiency of edges and no-edges morphological active contours, morphological active contours with geodesics, and snake active contours was all investigated. The statistics showed that MGAC performed the best of the three.

(Imran et al.) [13] The use of hybrid classifiers was made. Tumors were divided into benign and malignant categories. The Grey level Co-occurrence Matrix (GLCM) feature extraction method was used to create the feature dataset in this case. To boost effectiveness, a hybrid approach to classifiers using KNN and SVM classifiers was suggested.

(Ingole et al.) [14] Support vector machine (SVM) is suggested as a method to create a fully automatic heterogeneous segmentation. The accuracy of tumor identification in MRI images had been taught and evaluated using a classification method known as the probabilistic neural network classification system. a model that automatically segments meningioma's from multispectral brain data.

(Chen et al.) [15] Used capsule networks with a Bayesian method for the categorization of brain tumors. Instead of using CNN, which might lose vital spatial information, a capsule network was employed to enhance tumor identification outcomes. The team recommended the Bayes Cap framework. They used a reference dataset of brain tumors to evaluate the suggested model.

(Sharma et al.) [16] Edges may be seen in CT and MRI images by combining the Gabor transform with soft and hard clustering. The combined use of 4500 MRI images and 3000 CT images was done. To break up linked traits into smaller groups, K-means clustering was used. The photographs were represented by the author using histogram features using fuzzy c techniques.

*(SJ, Prashantha, and H.N. Prakash*) [26] A technique for analysing images of new born and paediatric brain tumors has been proposed, and it just requires T2-weighted MR scans. The following are the pipeline phases for the suggested work: Using conventional and deep learning (DL) feature extraction approaches, a collection of specialized feature vector descriptions for high-level classification tasks was created in the first step. In the second step, deep features are chosen using a convolutional neural network (CNN) approach that has been developed and a traditional subset of features from a Genetic Algorithm (GA). The final stage involves applying the fusion technique to combine the chosen characteristics. Lastly, determine whether the brain image is normal or abnormal. The outcomes showed that the suggested technique successfully classified objects accurately and exposed its resilience to varying ages and collection procedures. According to the results, the classification accuracy of the support vector machines (SVM) classifier has been greatly improved based on combined deep learning features (DLF) and conventional features, up to 97.00%.

(Soheila Saeedi et al.) [18] The most accurate classification of brain tumors is achieved using the proposed 2D CNN. When comparing the performance of various CNNs and machine learning algorithms for identifying three different types of brain tumors, the 2D CNN performed remarkably well and had the best
execution time without latency. Radiologists and other medical practitioners can utilize this suggested network, which is less complex than the auto-encoder network and employed in clinical systems for the diagnosis of brain tumors. The 2D CNN and auto-encoder networks were found to have average recall values of 95% and 94%, respectively. For both networks, the ROC curve's areas under the curve were 0.99 or 1. K-Nearest Neighbors (KNN) (86%) and Multilayer Perceptron (MLP) (28%), respectively, were the least accurate models. one of the machine learning methods examined.

TABLE II: TECHNIQUES FOR DETECTING AND CLASSIFYING BRAIN TUMORS ARE COMPARED

| References | Techniques | Data set | Accuracy | Benefits | Limitations |
|---|---|---|---|---|---|
| [1] | FCM Segmentation + SVM classification | 120 MRI images | 91.66% | It combines algorithms for classification and clustering. Effective approach | The kind of brain tumor cannot be determined choosing an SVM kernel function is challenging |
| [2] | Adaboost & Neural Algorithms | 50 MRI images | 89.90% & 74.00% | Minimizing errors and saving time ,With regard to already chosen characteristics | It might expand the margin for input data with varying densities and sizes. |
| [3] | Nave Bayes classification using K-Means segmentation, SVM | 110 MRI images | 91.49 & 87.23 | Accurate outcomes. | Despite being rapid and cheap to calculate, it has problems with clusters (in the original input data) of different densities and sizes. |
| [5] | DWT Filtering + Genetic Algorithm | 100 MRI images | 90.00% | Used GA's capacity to address optimization issues with a huge data collection | The wavelet transform has a high processing cost and substantial storage requirements. |
| [4] | SVM classifier with Level set approach and k Means segmentation | 42 MRI images | 94.12 and 82.35 | Improved Reliability and Strong Modelling | Possibility of misclassifying something that should be classified |
| [7] | K Nearest Neighbor | 48 MRI images | 95.00 %, | Implementation is easy and adaptable, and multiclass scenarios are handled | Significant difficulty in finding the closest neighbor preserving data |
| [6] | SVM & SVMKNN classification | 50 MRI images | 98.00% | Multiclass scenarios to be handled Higher Accuracy | A new training dataset is necessary when the dataset changes |
| [8] | SVM classification, TKFCM segmentation, and ANN classification | 39 MRI image | 97.44% | Accuracy classify brain tumors according to their phases of development Higher | Finding the best traits to distinguish across classes may be challenging. It takes time. |
| [19] | Deep CNN and SVM | BraTS2014 and BraTS2016 | SVM 87.05% and CNN 86.69% | Less time and segmentation | Algorithm is not optimized |
| [20] | Google Net and CNN | Fig share | 0.97% SVM classifier and 92.3% DCNN | Improved performance and robustness | Ineffectiveness of transfer modality |
| [21] | Deep CNN and SVM | OASIS | 93.18% | Advancement in multi-class categorization | Since the gradient is negligibly tiny, it prevents |

## III. COMPARISON OF BRAIN TUMOR DETECTION AND CLASSIFICATION TECHNIQUES

A comparison table (Table 2) compiles the findings of a comparison analysis of several approaches for the detection and classification of brain tumors. The majority of the salient characteristics of approaches are included in Table 2 together with the corresponding drawbacks and advantages.

## IV. CONCLUSION

The occurrence of brain tumors has grown globally, which has led to an increase in fatalities. An essential step in tumor identification is tumor detection. There are numerous methods available to identify the tumor from MRI scans. Compared to Manual identification, these technologies produce findings that are more accurate and abstract. In this study, we examined several approaches for identifying and categorizing brain tumors and gave an overview of the techniques used to do so.

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