International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.7057
***Article Received**: 08 March 2023 **Revised**: 30 April 2023 **Accepted**: 18 May 2023*

Machine Learning Algorithm for Early Detection and Analysis of Brain Tumors Using MRI Images

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Abstract

Among the human body's organs, the brain is the most delicate and specialized. It is proven that after the heart stops then also brain death occurs within 3 to 5 minutes of death or within 3 to 5 minutes of loss of oxygen supply. A brain tumor is a life-threatening disease that can be detected at any age from an infant to an old person. Though a lot of people did research in the detection and analysis of a tumor, but then also detecting tumors at the early phase is still a much more arduous field in the biomedical study. This paper focuses on the comparative study of various existing algorithms in this field. This paper addresses the challenges and some issues in MRI brain tumor detection which are also addressed in this research.

Keywords: Brain Tumor; Biomedical field; MRI images.

I. Introduction

Numerous different cell types make up the human body. The brain is a delicate and incredibly sensitive organ. It controls all the organs in the body or rather we can say all the organs follow the instructions sent by the Brain. It is proven that after the heart stops then also Brain death occurs within 3 to 5 minutes of death or within 3to 5 minutes of loss of oxygen supply. After that other parts of the body can be kept working for days to months with the help of a machine but the brain never recovers. So, if the brain stops working a person will collapse within 3 to 5 minutes[16].

A Brain tumor is a life-threatening disease which can be detected at any age from an infant to an old person. The tumor is nothing but a mass. In the human body when the cells/tissues get divided and grow as a mass excessively then the tumor occurs. The growth and division of cells are controlled by the body. In a body, new cells are created so that the old ones can get replaced or to perform a new function. Damaged cells or cells which are not required need to die to make a room for a new one. If the balance between cell growth and mortality is off, a tumor will develop. When a cell's normal function is disrupted, a tumor develops as a result. Increasing numbers of irregular cells are produced when the aberrant cell continues to divide[9].

Both primary, as well as secondary brain tumors are two different forms of tumor. A tumor which starts to spread in the brain but does not extend to other parts of the body then it is classified as a primary tumor[24]. An abnormal growth called a primary brain tumor originates in the brain and frequently does not extend to other areas of the body. Benign or malignant primary brain tumors are also possible.

Non-cancerous/benign tumors are those that are not malignant. A benign tumor does not invade further body regions. It is regional. Most benign tumors respond favorably to treatment if found early on[26]. Nevertheless, certain benign tumors have the potential to become huge and cause significant disease if left untreated. Malignant tumors can sometimes look like benign tumors. On the other side, malignant tumors are cancerous. They grow faster than benign tumors. They spread to nearby brain areas. There is a chance of coming back from malignant tumors after the treatment[28].

In the medical field a variety of medical imaging methods, including positron emission tomography (PET), magnetic resonance imaging (MRI), functionalMRI (fMRI), computed tomography (CT), and single photon emission figured tomography, are utilized to detect any aberrant changes in tissues (SPECT)[29]. These images are used to visualize the interior structure. The anatomy of the human soft tissues is shown through MRI. It is the method most frequently employed for observing and assessing brain malignancies.

Radiologists or other clinical professionals must spend a lot of time and effort segmenting, detecting, and extracting the infected tumor region using magnetic resonance (MR) images, and their success is entirely completely reliant on their expertise. To get beyond these constraints, computer-aided technology becomes absolutely essential. Over the years many researchers have put forward a variety of brain tumor detection methods. If the Brain tumor got detected and analyzed at the proper time, it would be a great help to the doctor to start with the line of treatment required to cure it. In this paper, existing approaches in brain tumor detection and analysis are discussed.

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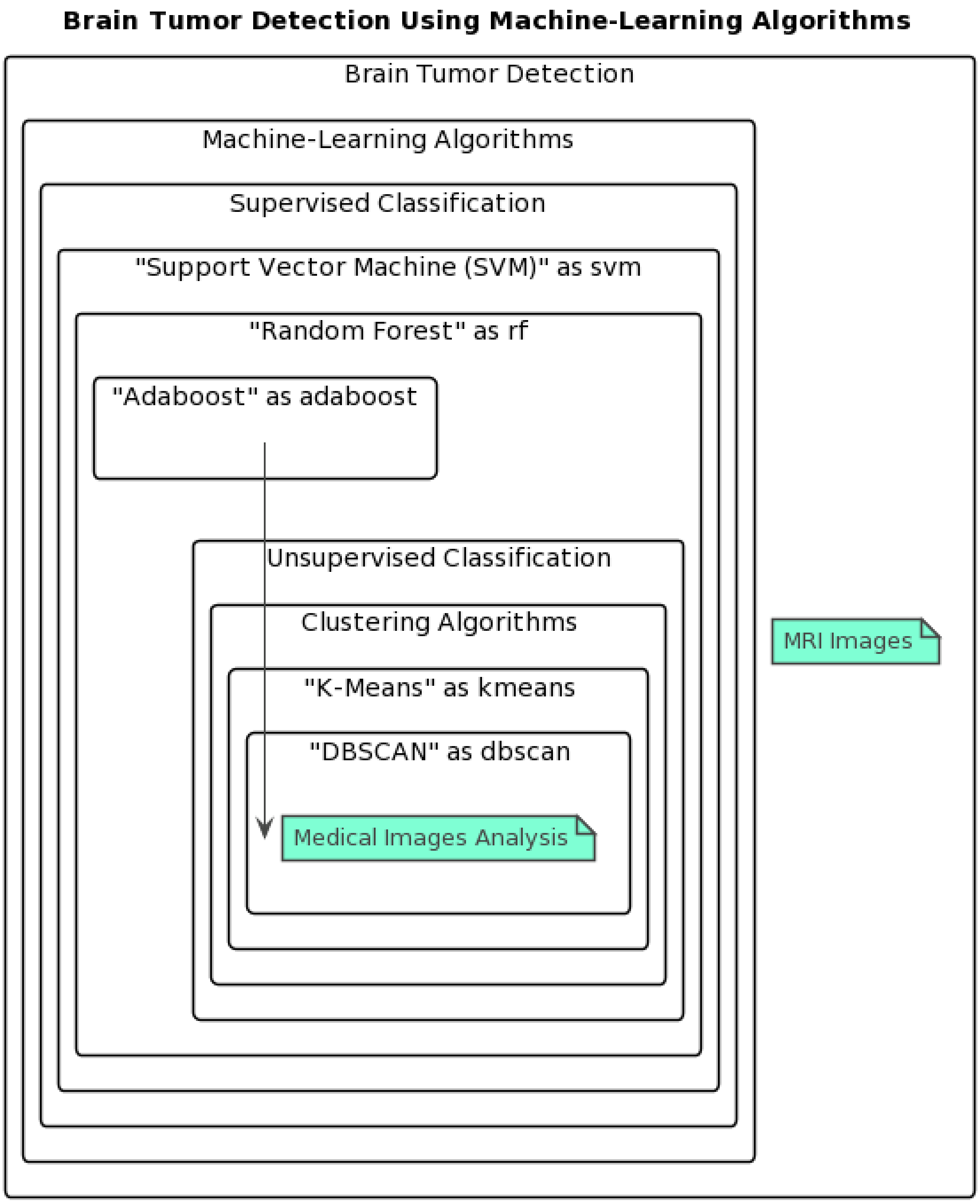

Figure.1 Taxonomy for Brain Tumor Detection Using Machine-Learning Algorithms

II. Literature Review

All ages of people are susceptible to the potentially fatal illness known as a brain tumor. For better patient outcomes and survival rates, early detection is essential. A popular imaging method that offers thorough anatomical data about the brain is magnetic resonance imaging (MRI) [6]. For the early detection and analysis of brain tumors in MRI images, machine learning methods have become increasingly popular. To improve picture quality and reduce noise, MRI images must be preprocessed. Intensity normalization, picture registration, and noise removal are some of the approaches used to increase the accuracy of tumor analysis and identification. In order to extract useful data from MRI scans, feature extraction is essential. To precisely characterize the tumor patches, a number of parameters are retrieved, including shape, texture, intensity, and statistical measurements [7]. Additionally, feature selection approaches are used to decrease dimensionality and boost

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computational effectiveness. Algorithms for supervised learning are frequently employed to identify and categories brain tumors. The methods Support Vector Machines (SVM), Random Forest, and Artificial Neural Networks (ANN) are frequently used to identify tumors as benign or malignant based on labeled MRI scans. These algorithms use features that have been retrieved to produce precise predictions. To find hidden patterns and groups within MRI pictures, unsupervised learning algorithms are used, such as clustering approaches [8]. Algorithms such as fuzzy clustering, hierarchical clustering, and K-means clustering are used to divide tumor sections and aid in tumor analysis. Convolutional and recurrent neural networks, in particular, have demonstrated encouraging results in the study and identification of brain tumors using deep learning approaches. These algorithms can perform a variety of tasks, such as tumor segmentation and classification, at the cutting edge of technology by autonomously learning hierarchical representations from MRI scans. Machine learning algorithms' efficacy is measured using performance evaluation metrics like accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) [10]. However, issues including uneven datasets, a lack of labeled data, and the interpretability of deep learning models continue to be major barriers in this discipline. Future studies should concentrate on overcoming the difficulties involved in detecting and analyzing brain tumors using machine learning [11]. The incorporation of multi-modal imaging data, the creation of hybrid models incorporating various algorithms [12], and the use of cutting-edge methods like explainable AI and transfer learning show promise for enhancing early tumour identification and precise analysis.

III. Preprocessing

We observe many film artifacts like marks, unwanted or critical parts, labels, and details of patients in medical images. These should be removed before processing those images. The pre-processing should be done on acquired images that contain film artifacts for the improvement of results and it can be more suitable than the original image in a better manner. Table 1 shows review regarding same.

a. Filters

Filters enhance the appearance and quality of images. If MRI images are too noisy or blurred, then it would not be easy to process those images. They should be filtered and sharpened to extort the essential information. A filter removes unwanted atmospheric noise, removes non-brain voxels, and converts the data so they accurately represent the reflected or emitted radiation to find out a change between two images precisely.

b. Median filter

This nonlinear filter is proposed to clean up the MRI image's salt-and-pepper noise again without affecting the edges by [3,13,15].

c. High pass filter

This was proposed to improve the image's quality by highlighting fine details in the image. High-frequency elements of an image are enhanced byHPF[1,5].

d. Wiener pass filter

It was the first time proposed by [23] to remove additional noise from MRI images. After this filter operation, the final image would appear the same as the original image.

e. Average filter

In average filtering, every pixel would get replaced by a mean value of that pixel and neighboring pixels[5]. It reduces the sharp transitions in the gray level. As random noise consists of sharp transitions, the average filter is also utilized to eradicate random noise.

f. Thresholding

Thresholding, where edges are determined based on a threshold value[4]. The threshold value got selected depending on the intensity of pixels from the image. It identifies the background and object from the image based on edges. In [27] author converted the grayscale imagesinto binary imagesthrough thresholding.

$g(m,n) = 0$ for $f(m,n) < T$
$g(m,n) = 1$ otherwise
Where, $g(m,n)$ is threshold image.
$f(m,n)$ is original image.

g. Sobel operator

This is the first time proposed by [4] to find gradient values of MRI images of the brain. Gradient values were considered for finding more prominent edges of brain tumors in later calculations.

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Table 1. Preprocessing, Skull Stripping and Feature Extraction methods

Work	Preprocessing								Skull Stripping			Feature Extraction					
	FILTER	MD	HPF	WN	AV	TH	SO	Hs	TH	MO	FILTER	HS	TH	ED	DWT	GLCM	TRA
Swapnil et al. (2016) [1]		√	√						√	√		√					
Boucif et al. (2016) [2]											√			√			
Eman et al. (2015) [3]		√				√				√			√				
Asara et al. (2015) [4]						√	√							√			
Gursangeet et al. (2016) [5]		√	√		√								√				
Shereen et al. (2017) [6]															√		
Vishnumurthy et al. (2016) [7]						√									√		
Jahanavi et al. (2016) [8]	√					√			√	√						√	
Rahul et al. (2016) [10]															√		
Usman et al. (2017) [11]	√							√		√	√				√		
Ravindra et al. (2016) [12]						√			√	√					√		
Astina et al. (2017) [13]	√	√														√	
Pham et al. (2016) [14]	√													√			
Ramya et al. (2016) [15]		√															√
Nandha et al. (2010) [18]		√	√														
Nemir et al. (2015) [19]													√	√	√		
Amiya et al. (2016) [20]	√											√				√	
Yehualashet et al. (2015) [21]									√	√							
Vaishnavee et al. (2015) [22]	√					√										√	
Kimmi et al. (2014) [23]				√		√							√				
Deepthi et al. (2014) [27]		√		√			√	√									
Shree et al. (2018) [37]															√		
Mehrotraet al. (2020) [38]															√		
Naziret al. (2019) [39]															√		
Ramesh et al. (2021) [40]		√													√		

MD - Median Filter, HPF - High Pass filter, WD - Wiener filter, AV - : Averaging filter, TH - Thresholding, SO - Sobel Operator ,MO - Morphological operation, HS - Histogram, ED - Edge Detection , DWT - Discrete Wavelet transform, GLCM - Gray Level Co-occurrence Matrix.

Table 1 shows detailed review with respect to various preprocessing algorithms.

h. Skull Stripping

Many authors had proposed different algorithms for skull stripping. This scheme would be the first step toward the detection of brain tumors. Before detecting tumors in the brain it is essential to remove non-brain tissues [1] from MRI images.

Brain surface extractor was first proposed by [3] to eradicate non-brain tissues like the skull, scalp, and eye from MRI images of the brain. It extracts the brain from the whole MRI image. With thresholding, and morphological operations [11], non-brain tissues were removed and filters for noise removal and edge preservation.

IV. Segmentation

In medical research, segmentation of MRI images is the most vital process after extracting and classifying the features from an image. This is usually considered the first step toward the analysis and evaluation of brain tumors. Due to advanced technologies, MRI images of the brain can give a huge amount of data. It would be the most challenging task for doctors and for diagnosis' to analyze complex and large MRI data. In medical imaging, Segmentation help to extract region of the interest and also differentiate the pixels present in the tumor area and pixels from the non-tumor

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area. Depending on the similar features extracted partitioning of the MRI brain image is done in segmentation. The process continues till the required object in the application has been isolated. In tumor, detection segmentation would stop when it isolates the tumor area from an MRI image of the brain. The segmentation techniques preferred by researcher are discussed here.

a. *Thresholding*

Local thresholding is implemented in [5] depending on the intensity of the MRI image. The threshold value divided the pixels into two groups based on the intensity values of the pixels. It helped to separate the background from the object [23]. Brain tumor detection can identify the tumor from an MRI image of the brain.

Otsu's thresholding based on global thresholding has been proposed in [14]. It finds the optimal thresholding value from the histogram of the image. The image got converted into black and white and the tumor has been identified based on this binary image after segmentation.

Table 2 describes various Segmentation and Classification Techniques for Brain tumor detection from MRI image.

Table 2. Segmentation and Classification Techniques for Brain tumor detection from MRI image

	Segmentation										**Classification**
	TH		**LSM**					**CH BASED**			**SVM**
Work	**TH**	**OTSU**	**LSM**	**VLSM**	**MO**	**ED**	**WTR**	**KM**	**FCM**	**K + FCM**	
Swapnil et al. (2016) [1]								√			√
Boucif et al. (2016) [2]			√						√		
Eman et al. (2015) [3]	√		√			√				√	
Asara et al. (2015) [4]						√					
Gursangeet et al. (2016) [5]	√						√				
Shereen et al. (2017) [6]		√									√
Vishnumurthy et al. (2016) [7]					√						
Jahanavi et al. (2016) [8]										√	√
Rahul et al. (2016) [10]											√
Usman et al. (2017) [11]											
Ravindra et al. (2016) [12]											
Astina et al. (2017) [13]	√										
Pham et al. (2016) [14]		√			√						
Ramya et al. (2016) [15]	√				√		√				
Kalaiselvi et al. (2015) [17]									√		
Nandha et al. (2010) [18]									√		
Nemir et al. (2015) [19]						√					
Amiya et al. (2016) [20]											√
Yehualashet et al. (2015) [21]									√		
Vaishnavee et al. (2016) [22]											√
Kimmi et al. (2014) [23]	√				√		√				
Zhang et al. (2017) [25]				√		√					
Soomro et al. (*2022) [33]*											√
Vadhnaniet al. (2022) [34]											√
Kibriyaet al. (2021) [35]											√
Krishnakumaret al. (2021) [36]										√	√
Vankdothuet al. (2022) [42]											√
Lather et al. (2022) [43]											√

TH-Thresholding, OTSU-Otsu's Thresholding, LSM- Level Set Method, VLSM- Variational Level Set Method, MO-Morphological Operations, ED- Edge Detection, WTR-Watershed Transformation , KM- K Mean, FCM-Fuzzy C Mean, LK- Linear Kernel , RBFK-Radial base function kernel, PSVM-Proximal Support Vector Machines,AD- Adaboost Classifier, RF- Random Forest.

b. *Level set method (LSM)*

It has initially put out by [2]. In this case, the curve is started with a level set function. It directs the zero-level set's mobility toward the direction of the desired visual features, like edges and corners. Level set methodhas been applied to define the shape and boundary of tumors from MRI images.

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c. Variational level set method (VLSM)

In this scheme, boundary/shape extraction has been done with an energy function considering the Heaviside function. According to the author, variational level set method gets rid of some problems that make the level set function nearly equal to a signed distance function. Consequently, the expensive re-initialization operation is wholly eliminated.

d. Morphological segmentation

In this approach, the main aim was to separate a tumor from an image of the brain. Morphological operators have been applied to the binary image for good results. Here structure and shape of the image were taken into account while segmenting the MRI image. The author claims that the tumor region has high intensity than the other region of the image after the binary conversion of the image. The author proposed first erosion and then a dilation process to identify tumors form MRI images[7].

e. Edge detection

This approach has been proposed in [4] wherein the Sobel operator has been applied to get gradientsof the image. Sobel also helps in removing noise from the image. Depending on the intensity of the gradient image, edges were found from thresholding. As thefinal step closed contour algorithm was applied to the threshold image to segment the tumorregion from the MRI image.

f. Watershed transformation

In this approach, region growth was based on the local minima of the gradient image. Watershed segmentation is succeeded by a morphological opening operation to identify the tumor from the brain [15].

g. K-mean

In [1], an MRI image of the brain was divided into k clusters based on image features. To form clusters, Euclidean distance is utilized to find out the minimum distance between the pixel and the corresponding centroid. This helped to group the pixel in one of the clusters. Clustering divides the image based on the features and attributes of the image.

h. Fuzzy C-mean (FCM)

This method has been proposed along with the level set method in [2]. In this unsupervised method, clustering was achieved by the k-mean algorithm. Later LSM is employed to detect the edges of the tumor. Tumor cells get predicted accurately by Fuzzy C-mean than K Mean [3].

i. K+ FCM

If the image contains noise or other artifacts the segmentation with Fuzzy C-mean would fail. Here author proposed a combination of k-mean and Fuzzy C-mean techniques. Accurate detection of tumor cells is achieved by Fuzzy C-mean and for fast execution K-mean.

V. Classification

For brain tumor detection, various machine-learning algorithms have been implemented and are being used by researchers for the classification of MRI images. Classifiers play a vital role in many medical applications. Classifiers such as SVM, Random forest, and Adaboost are widely applied to images to do an analysis of medical images. Both supervised and unsupervised categorization techniques exist. By creating a function based on trained examples, supervised classification maps the input to the necessary output.

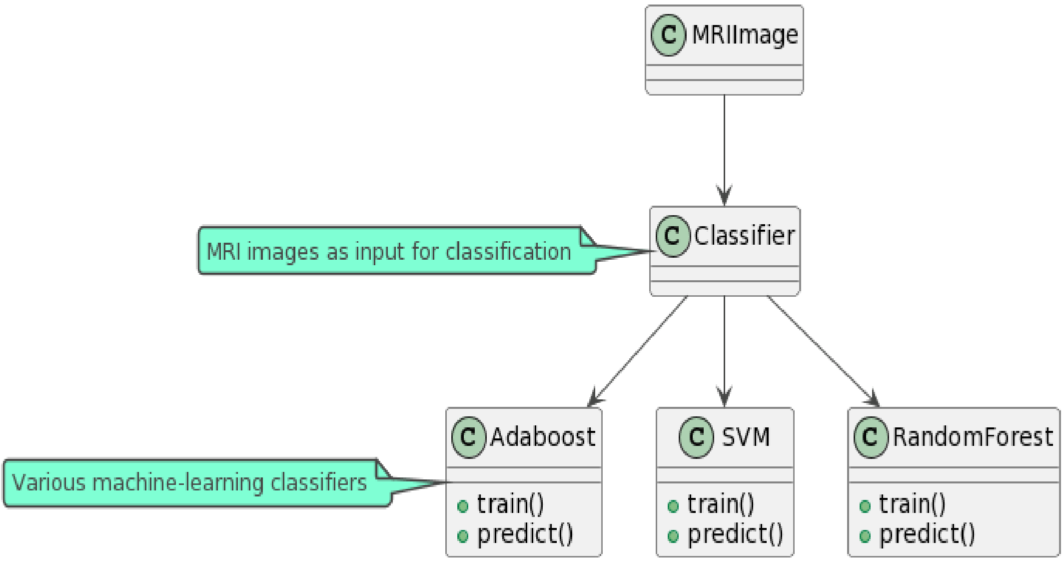

Figure.2 Brain Tumor Detection Using Machine-Learning Algorithms

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a. Supervised Classification: The main goal of this sub-component is to categorise images of brain tumours by using labelled data to train a model. Three particular algorithms are shown there as rectangles:

- Support Vector Machine (SVM) is a supervised learning technique that uses a hyperplane to divide data into various classes.
- A supervised learning technique called Random Forest builds a group of decision trees and generates predictions based on the results of those trees.
- Adaboost: A supervised learning technique that boosts accuracy by combining weak classifiers into a powerful classifier.

b. Unsupervised Classification: This sub-component deals with techniques for clustering unlabeled images of brain tumours to find patterns or groups. It contains two particular algorithms shown as rectangles:

- K- Means : An approach for grouping data into k clusters based on similarity
- DBSCAN: A clustering algorithm that clusters data points according to their densities.

VI. Parameters for Evaluation and Analysis

In this section, different criterion have been represented which would assist to analyze and examine the effectiveness of various approaches for finding brain tumors. In [35,36], key parameters for evaluating and analyzing the performance of brain tumor detection techniques have been discussed. Here, we have discussed those parameters along with other which needs to be considered.

a. *Type (TY)*

There are various types of brain tumors that are present in different areas of the brain. Identification of tumor type, whether it is Begin or Malignant is essential for the line of treatment doctors would give to the patient.

b. Shape and Size (SH and SZ)

The shape and size of the tumor may vary in different MRI images.

c. True Positive (TP)

If a tumor is detected or present in an MRI image of the brain and also in a ground truth test, in that case, the result is considered as true positive.

d. True Negative (TN)

If a tumor is not detected or present in an MRI image of the brain and also absent in a ground truth test (manually segmented image by a radiologist) as well, in that case, the result is considered as true negative [31].

e. False Positive (FP)

If the final results show that a patient has a brain tumor when they actually don't, the screening test is regarded as being a false positive.

f. False Negative (FN)

Tumor is not detected in the final result but it is actually present in the truth test, then the result is a false negative.

g. Jaccard Coefficient (JC)

The Jaccard coefficient is used to determine how similar the obtained features of the brain are to the actual image. Jaccard coefficient gives results in one and zero. Zero means lower similarities and one means best similarities. It is also known as Jaccard Index [31].

$$Jaccard(P,T) = \frac{(P \cap T)}{(P \cup T)} = \frac{TP}{(TP + FP + FN)} \quad (1)$$

Where, P is Result obtained after segmentation or the true positive value.

T is a manually obtained ground truth image.

h. Dice Coefficient (DC)

It is applied to find out the association, similarity, or overlap between segmented and ground truth images [30].

$$Dice = \frac{2 * (P \cap T)}{(P + T)} \quad (2)$$

i. Sensitivity

It is the proportion of true positives which a medical assessment correctly detects. The value of sensitivity should be high.

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (3)$$

j. Specificity

It is the percentage of the true negatives appropriately acknowledged by a diagnostic test. The value of specificity should be high [31].

$$Specificity = \frac{TN}{(TN + FP)} \quad (4)$$

k. Accuracy

It defines the proportion of true positive or true negative results.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (5)$$

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l. Execution Time

This is the total time required for detecting tumors in the brain. Ideally, this time should be as less as possible.

Efficiency

It defines how effectively the system can find out the tumor in the brain.

m.Precision

It is the proportion of true positives which a medical assessment correctly detects [41].

$$Precision = \frac{TP}{(TP + FP)} \qquad (6)$$

n. Recall

It is a ratio of tumors detected or present in an MRI image of the brain and also in a ground truth test to a truly positive and false positive. Ideally, recall should be a minimum that is zero.

$$Recall = \frac{TP}{(TP + FN)} \qquad (7)$$

Table 3. Parameters for evaluation and analysis of brain tumor detection

	Parameters for Evaluation and analysis																
Work	**SH**	**TY**	**SZ**	**TP**	**TN**	**FP**	**FN**	**JC**	**DC**	SEN	**SPE**	**ACC**	**ET**	**EFFI CI**	**PRE**	**REC**	**E R**
Swapnil et al. (2016) [1]	√	√	√														
Boucif et al. (2016) [2]	√	√										√	√				
Eman et al. (2015) [3]	√		√	√	√	√	√					√	√		√	√	
Asara et al. (2015) [4]	√		√	√		√						√					
Gursangeet et al. (2016) [5]	√		√	√	√	√	√					√	√	√			
Shereen et al. (2017) [6]	√		√	√								√	√				
Vishnumurthy et al. (2016) [7]	√			√	√	√	√	√	√			√	√				
Jahanavi et al. (2016) [8]	√			√	√	√	√			√	√	√					
Singh et al. (2016) [10]	√	√		√	√	√	√										
Usman et al. (2017) [11]	√			√	√	√	√	√	√	√	√	√	√				
Sonavane et al. (2016) [12]	√			√	√	√	√			√	√	√	√				
Minz et al. (2017) [13]	√									√	√	√		√			
Tra et al. (2016) [14]	√	√										√		√			
Ramya et al. (2016) [15]	√		√									√		√			
Kalaiselvi et al. (2015) [17]	√		√	√	√	√	√			√		√	√	√			
Nandha et al. (2010) [18]												√		√			√
Al-Azzawi et al. (2015) [19]	√		√	√	√	√	√			√	√	√			√	√	√
Halder et al. (2016) [20]	√		√	√	√	√	√			√	√	√		√			√
Megersa et al. (2015) [21]	√		√	√	√	√	√	√	√	√	√	√					
Vaishnavee et al. (2015) [22]	√		√	√	√	√	√			√	√	√	√	√	√	√	√
Zhang et al. (2017) [25]								√							√	√	
Ahmed et al. (2022) [32]										√		√					
Polat et al. (2021) [41]												√					√

SH- Shape, Ty-Type, SZ-Size, TP-True Positive, TN-True Negative, FP-False Positive, FN-False Negative. JC-Jaccard Coefficient , DC- Dice Coefficient , SEN-Sensitivity, SPE-Specificity, ACC- Accuracy, ET- Execution Time, EFFICI-Efficiency ,PRE-Precision, REC-Recall, ER-Error Rate.

In table 3, all necessary parameters are listed which would help in evaluation and further analysis.

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***Article Received**: 08 March 2023 **Revised**: 30 April 2023 **Accepted**: 18 May 2023*

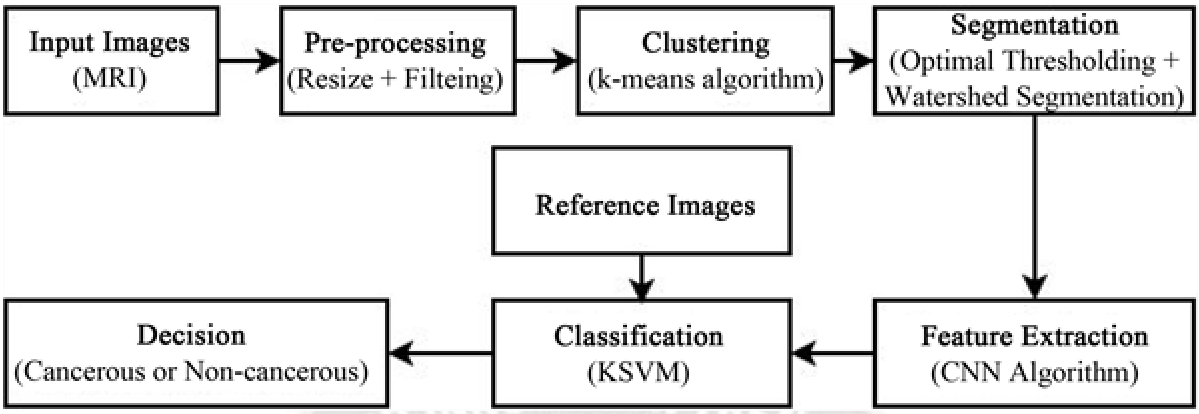

Fig.ure 3. This is the caption for the figure. If the caption is less than one line then it needs to be manually centered

Figure 1 shows the block diagram of MRI brain tumor detection using segmentation. Under this research, an average of 128 image were selected for the training and testing datasets, with 30% (38 images) of the data set aside for testing and the remaining 70% (90 images) set aside for the training dataset. To prepare the input image for classification, noise was reduced, the image was smoothed, and was sharpened using Gaussian, high pass, and median filtering algorithms, which demonstrate the efficiency of the clustered and segmentation process. Then, using the MLS method the tumour separated from the input image. Finally, utilising the features vector, the CNN technique was used to extract features and identify the brain image as having a malignant or non-cancerous tumour.

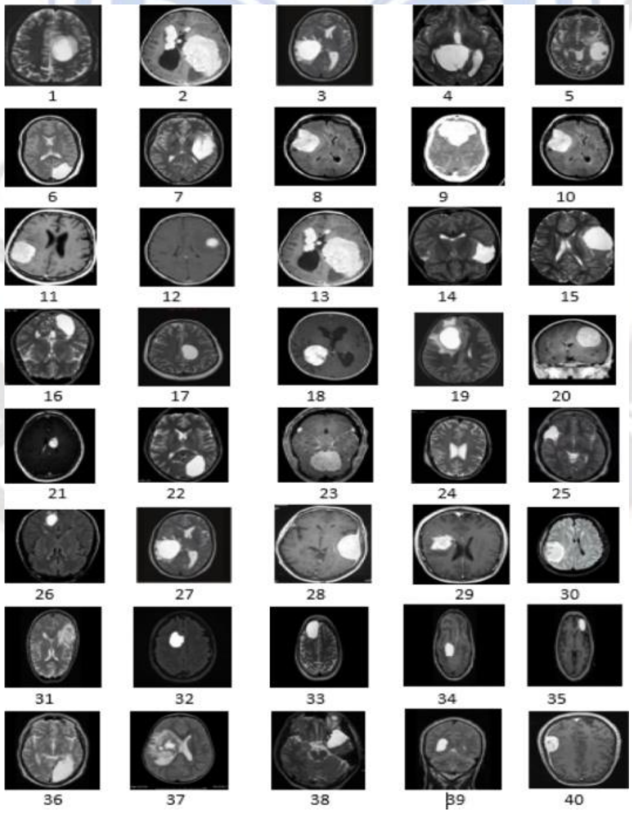

Fig.ure 4. MRI images as a database for brain tumor detection[45]

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.7057
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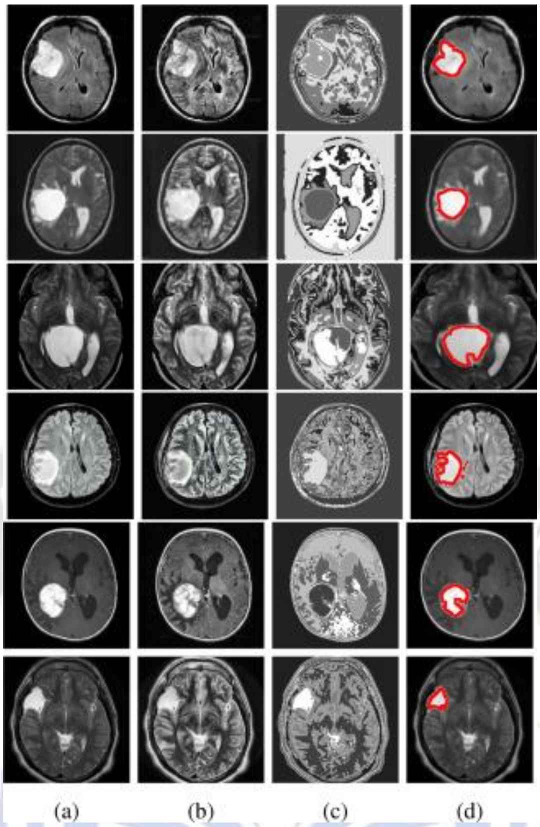

Fig. 3. (a) Input MR images (b) Image enhanced using filters (c) Segmented image (d) Detected tumor in red color.[45]

Figure 5. shows the database used for tumor detection and figure 3 shows result after simulation. Image preprocessing, image enhancement, segmentation algorithms are applied to get desired result from simulation. [45]

VII. Challenges and Issues in MRI Brain Tumor Detection

Despite the fact that this topic has seen a lot of academic research, there are still many issues and challenges that need to be investigated. Some of them are covered here.

Extracting the features plays a crucial role in the computation of each pixel so that they can be categorized into normal and abnormal parts. Extracting the right features of the brain plays a key part in successful diagnostics procedures. Because brain tumors can vary in growth, shape, position, and appearance, diagnosing one can be challenging. A 3D MRI of a tumor brain can measure the tumor's size and assess the nature and phase of the tumor.

More work can be done on classification using a machine-learning algorithm. It would help to classify the detected tumor according to its Malignancy level. There are many types of brain tumors which can be detected; it would be a challenging task to identify a particular type.

VIII. Conclusion

This paper gives a close insight into the different algorithms implemented by researchers to detect tumors more accurately in MRI images of the brain. Still, there are many challenges and problems to look into. One is to find out suitable variations in existing segmentation algorithms which would help to analyze and evaluate the brain tumor detection procedure more efficiently. The information or data extracted from MRI images is huge, so reducing the data before the analysis would save processing time. As per the research done till now, there are different types of tumors, therefore classifying tumors based on their type can be get done in the future.

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