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SEGMENTATION PROCEDURE AND DISEASE DETECTION OF BRAIN TUMOR MRI IMAGE USING CNN AND 2D- DWT APPROACH

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ABSTRACT
In the recent era of technology the real time medical disease diagnosis is one of the important factor. When it comes to the early and precise identification of brain tumors, medical imaging is essential since it allows for prompt intervention and better patient outcomes. In this work, we introduce a unique method for analysing and diagnosing benign and malignant brain tumors from MRI images by combining the capabilities of 2 dimensional Discrete Wavelet Transform (2D-DWT) with hidden layer of Convolutional Neural Networks (CNNs). There are multiple parameter like mean, Mean, Standard Deviation, Entropy , Skewness , Kurtosis, Energy Qualifies , Contrast, Homogeneity or the Inverse Difference Moment , Correlation , Coarseness corresponding with accuracy of finding the result, the ability to extract features and classify them will be improved, leading to an increase in diagnostic precision.

Keywords: - Benign , Malignant , 2 Dimensional Discrete Wavelet Transform (2D-DWT), Hidden layer of Convolutional Neural Networks (CNNs)

INTRODUCTION
A cutting-edge method in medical image processing is the identification of brain cancer utilizing magnetic resonance imaging (MRI) images and a combination of 2-dimensional discrete wavelet transform (2D-DWT) and the hidden layer parameters of Convolutional Neural Networks (CNN). This method combines two well-known techniques: convolutional neural networks (CNNs) with hidden layer parameters, which are useful for image identification, and 2D-DWT, which is useful for extracting key parameters from given photos at varying sizes. The required magnetic resonance imaging (MRI) pictures are typically pre-processed and segmented using 2D-DWT, which divides the image into parametric observation. By breaking images down in this manner, we may access data in the spatial and frequency domains, which help us see subtle patterns and details.

The output will be generated from the segmented photographs using the 2D-DWT approach. Next, convolutional neural networks (CNNs) will be used to identify the hidden layer parameters' output. A deep learning architecture is used to obtain and classify these traits. A combination of convolutional, pooling, and fully connected layers gives the CNN its tumor-identifying and -classifying prowess. These layers let the CNN to discover complex correlations and patterns in the returned data. Since the technology can differentiate between normal brain tissue and aberrant spots that may suggest cancer, healthcare practitioners may utilize this crucial information for diagnosis and therapy planning. Still, this method is in its infancy, so there's plenty of space for performance and accuracy improvements. We can teach the CNN to concentrate on the most significant and critical features by merging the 2D-DWT with CNN, which might boost the accuracy and efficiency of tumor identification. It is possible to circumvent the diagnostic detection technique using the CNN method's hidden layer, which is a fully supervised learning approach. Because CNN can learn data properties and complete learning-related tasks without human input, it finds wide usage in machine vision, text translation, voice recognition, and other domains. This makes it different from prior segmentation approaches. Using deepening network layers, CNN can learn both the local and global aspects of an image at the same time, making it superior to manually constructed features. As a consequence, compared to more traditional methods, the CNN-based segmentation strategy yields superior results. But the underlying network design is the same as U-Net. Overall, the building has also remained unchanged. Vision (2020) Detection Furthermore, fully convolution neural networks (FCNs) are a popular CNN structure for medical picture segmentation. In particular, it substitutes the fully linked convolutional layer, allowing the network to process images of any size. Thanks to its integrated deconvolution layer, the up-sampling procedure is able to learn the network parameters by back-propagation. [5]

LITERATURE REVIEW

Saikat Islam Khan et al., 2022 In this study, we provide two DL models that can distinguish between benign and malignant binary brain tumors as well as multiclass tumors such as meningioma, glioma, and pituitary. We make use of two open-source datasets, one including 3064 MRI pictures and the other containing 152. Given the abundance of magnetic resonance imaging (MRI) pictures in the initial dataset, we train our models using a 23-layer convolution neural network (CNN). We demonstrate the difficulties of underfitting with the second dataset using our suggested "23-layers CNN" architecture. In the end, they tackle this problem by combining our suggested "23 layers CNN" design with the VGG16 architecture, all via the process of transfer learning. By comparing the suggested models to those that have previously been published, they conclude with an evaluation. Our testing findings show that our models outperform all current state-of-the-art models, with classification accuracy as high as 97.8% and 100% for the datasets we examined, respectively.

Adesh Kumar et al. 2022 compares and contrasts several image segmentation methods for the diagnosis of brain tumors. A few examples of these methods include CNNs, Otsu's, watersheds, level sets, K-means, and HAAR Discrete Wavelet Transform (2D-DWT). The MATLAB Brain Tumor Image Segmentation Benchmark (BRATS) dataset from 2018 is used to evaluate each approach. In addition to measurements like recall, accuracy, precision, and F-measures, we also examine reaction time to see how well these strategies work. Specifically, the following accuracy values were recorded for the following methods: Otsu's, watershed, level set, K-means, 2D-DWT, and CNN: 71.42%, 78.26%, 80.45%, 84.34%, 86.95%, and 91.39. A reaction time of 2.519 s was recorded by CNN in the MATLAB simulation environment for the intended technique. This research adds to the growing body of evidence showing that convolutional neural networks (CNNs) outperform alternative techniques in brain tumor image segmentation. Finding the best convolutional neural network (CNN) and deep learning-based hardware algorithms for brain tumors is a priority for companies, while researchers use the estimated and simulated parameters to build machine learning models and pick the optimal method for embedded devices.

Mohammad Alshayej et al (2021) Automatic tumor categorization is suggested by the authors of this paper using a two-layer convolutional neural network architecture. Hyperparameters are fine-tuned using Bayesian optimization. Improving the accuracy of tumor classification is at the heart of the suggested approach, the primary objective of which is to restore trust in medical technology. When compared to its rivals, this study's 97.37% accuracy in predicting the categorization of MRI inputs outperforms the dataset's accuracy range of 84.19% to 96.13%.

M.O. Khairandish et al 2021 A substantial improvement is made by the suggested hybrid model by merging the finest characteristics of the CNN and SVM models. An integrated method for image recognition and classification has been developed to identify brain cancers in magnetic resonance imaging (MRI) scans. In the end, the hybrid CNN,SVM achieved an accuracy of 98.4959 percent. .

Milica M. Badža et ak 2020 This study's authors demonstrate that three different kinds of brain tumors may be differentiated using a novel convolutional neural network (CNN) architecture. The newly-generated network outperformed its predecessors on T1-weighted contrast-enhanced MRI. We tested the network on two datasets and ran two 10-fold cross-validation processes. One of ten ways to test the network's generalizability was subject-wise cross-validation, which made use of an enhanced image database. Using record-wise cross-validation on the modified data set was the most successful use of the ten-fold cross-validation approach, resulting in a 96.56% accuracy. The newly developed CNN architecture has great generalizability and quick execution, making it useful for radiologists to make judgments when identifying medical concerns.

As of 2018, Sangeetha Saman carried out research intends to automatically classify malignancies by integrating two kinds of convolutional neural networks and adjusting their hyperparameters using Bayesian approaches. The primary goal of the proposed solution is to increase public confidence in medical technology by enhancing the accuracy of tumor categorization. Comparative studies using the same dataset found accuracies between 84.19% and 96.13%, but our study outperforms them with a 97.37% accuracy rate in predicting the sorting of MRI inputs.

Amin Kabir Anaraki et .al (2018) In this paper, a method for non-invasively classifying various glioma grades using MRI is presented, which is based on genetic algorithms (GA) and convolutional neural networks (CNNs). Current approaches for selecting deep neural network architectures depend on trial and error or accept predetermined common structures; the suggested method, on the other hand, uses evolutionary algorithms to build the CNN's anatomy. To further reduce the variation of the prediction error using the GA's best-performing model, bagging is used as an ensemble approach. Just so you know, one case study summed things up by correctly identifying three different Glioma grades with a 90.9% success rate. An extra case study showed a 94.2% accuracy rate for glioma, pituitary, and meningioma tumor types. The findings show that the suggested strategy is effective for classifying brain tumors using MRI images. Thanks to the procedure's flexibility, it may be easily used in clinical practice, enabling early detection of brain tumors.

PROPOSED METHODOLOGY OF BRAIN TUMOR ANALYSIS

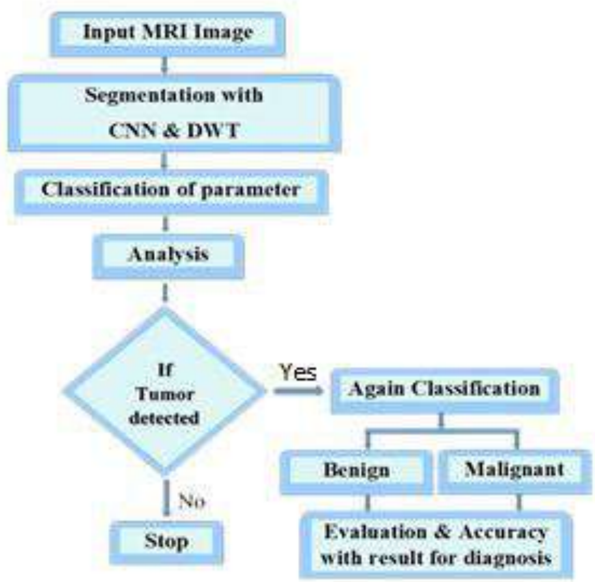

Fig. 2 Proposed methodology of brain tumor

The methodology presented in this section involves obtaining an MRI image dataset, segmentation with CNN & 2D-DWT, the extraction of MR image features using 2D-DWT and finally classification of MR images into benign and malignant using CNN. Figure 2 depicts the suggested methodology's process flow diagram. The proposed study is carried out using MATLAB R2018a.

The proposed work's algorithm

Step 1: Gather input MR images of the brain.

Step 2: Pre-processing and Segmentation of MR images.

Step 3: After segmentation different types of parameter will be classify.

Step 4: An SVM-based classification algorithm is used to detect the existence of BT in the MR image. Step 5: Finally, the identified tumor's area is determined. [9]

Magnetic Resonance Imaging (MRI)

One particularly innovative and flexible radio imaging method is magnetic resonance imaging, or MRI. Radiation from electromagnetic fields may damage internal organs in humans. Thanks to magnetic resonance imaging (MRI), a non-invasive method, anomalies in the body's soft tissues and bones may now be imaged. When compared to X-rays, magnetic resonance imaging (MRI) is safer in terms of radiation exposure. The arrival of radio waves to a person's body causes a rearrangement of hydrogen atoms. Magnetic resonance imaging (MRI) may produce pictures of varying brightness by adjusting two imaging characteristics: transverse relaxation time (T1) and longitudinal relaxation time (T2). Magnetic resonance imaging (MRI) has the potential to improve our understanding of the anatomy of the brain, chest, abdomen, and pelvis. It also aids in the diagnosis of many different diseases by medical professionals.

Brain MRI Imaging

Brain MRI imaging is incredibly helpful for detecting infections in the brain early on, especially in tumors in the brain. When conventional CT scans miss white matter illnesses, magnetic resonance imaging (MRI) is the go-to tool for finding them. Magnetic resonance imaging (MRI) contrast and intensity are mainly determined by the T1 and T2 relaxation durations. The magnetic resonance imaging (MRI) technique offers several advantages, including a high signal-to-noise ratio, high resolution, and excellent imaging of soft tissues. Additionally, compared to CT scanning, the time required to get an MRI picture is much longer.

Need for segmentation

Using characteristics including color, contrast, darkness, texture, and grey level, segmentation divides an image into smaller pieces. Segmentation is most often used in medical imaging for three major purposes: estimating the Region Of Interest (ROI), determining the size of tumors, and helping radiologists with radiation dosage planning before treatment.

A image may be "segmented" into smaller parts by using characteristics like color, texture, contrast, and brightness. Medical image segmentation aims to estimate the ROI, examine the anatomical structure of body components, calculate the tumor size, and assist the radiologist in planning the amount of radiation prior to radiation therapy.

Block structure of proposed methodology of brain tumor

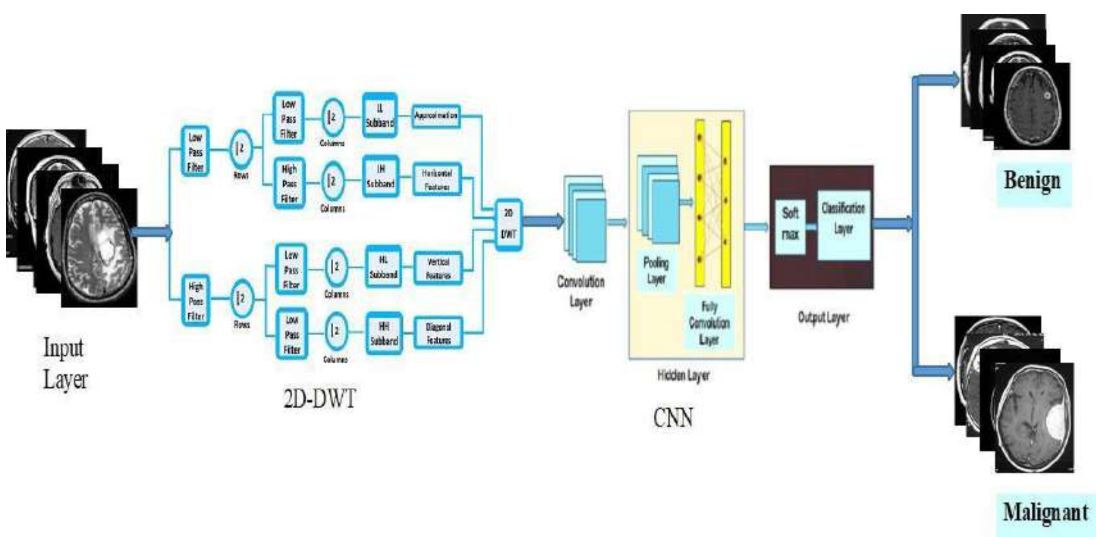

Fig. 3 Block structure of proposed methodology of brain tumor

2D-DWT for image segmentation

Image segmentation makes use of 2D-DWTs, which are a kind of wavelet transform that use discretely sampled wavelets. 2D-DWT was first used in 1976 to decompose discrete-time signals. For the same purposes, sub-band coding—sometimes called speech signal coding—is used. In 1983, a technique similar to sub-band coding called pyramidal coding was used [12]. The 2D-DWT technique is now one of the more exciting ones. The extra important qualities of the wavelet transform, such as progressive reconstruction, make it a powerful tool for data compression. Our main emphasis in this study is the discrete wavelet transform. We use the Discrete Wavelet Transform on both color and grayscale pictures because wavelets may provide frequency information in addition to time-space localization. Their multi-resolution capabilities also make it possible to see colors at different sizes. The 2D-DWT is a signal processing technique utilized in many commonplace processes and applications; it works especially well with non-stationary signals, defined as signals whose spectral properties do not vary with time. Among the many intriguing features that make the wavelet transform (2D-DWT) a valuable tool for picture analysis is its high energy compaction trait, which we shall discover more about as we go along. The approximation information is associated with one expansion and the detail coefficients with the other. The 2D-DWT sequence is comprised of these two expansions [14].

2D Discrete wavelet transform (2D-DWT)

The 2D 2D-DWT When working with two-dimensional pictures, the 2D-DWT is applied independently to each dimension. In Figure 3, we can see a simplified diagram of 2D 2D-DWT. Thus, LL, LH, HH, and HL are the four sub-band images that make up each scale. The sub-band LL is used by the subsequent 2D 2D-DWT. Imagine the LL subband as the approximation component of the picture, and the LH, HL, and HH subbands as the detailed components. The approximation component shrank in size while becoming rougher in texture as the decomposition quantity increased. Consequently, wavelets provide an easy-to-understand hierarchical structure for visual data analysis. Our method included level-3 decomposition using Harr wavelet for feature extraction. The 2D-DWT often makes use of the digital filter, which is connected with the approach problem of border distortion. Masking the picture will cause it to extend outside its bounds, hence padding the pixels outside the image is necessary. In order to determine the boundary value, our strategy used the symmetric padding approach

[28]..

Segmentation

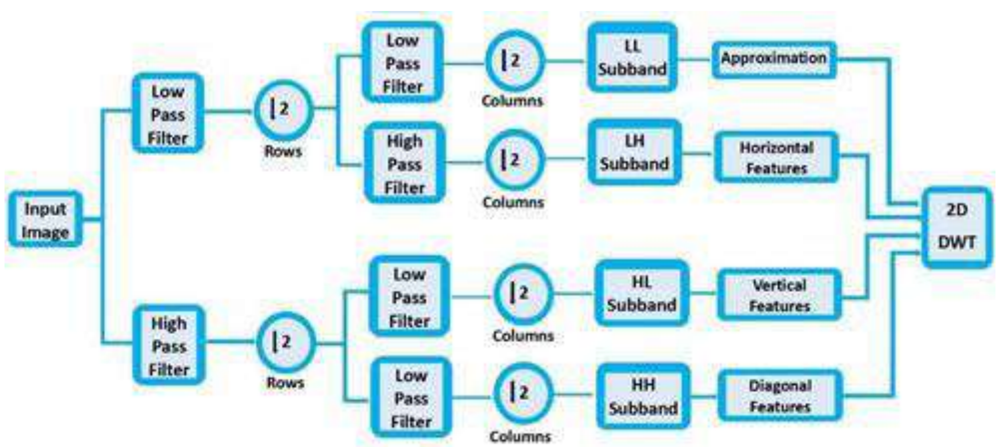

Fig. 3 2D Discrete wavelet transform (2D-DWT)

LL - provides an approximation by passing via two simultaneous LPFs. LH - Horizontal characteristics (HPF along rows) after passing via LPH.

HL - Passing via HPF followed by LPF. Vertical characteristics (HPF along col.)

HH - Going through two HPFs at the same time — Diagonal features (HPF spread proportionally throughout both rows and col)

CNN Segmentation for hidden layer identification:

The 2D-DWT features that are extracted are fed into a CNN that is specifically made for segmentation tasks using hidden layer. The CNN architecture could be made up of encoder-decoder architectures that are segmentation-optimized, such as FCN (Fully Convolutional Network), U-Net, or other similar architectures.

Convolutional Neural Networks (CNN) model for hidden layer identification:

We propose a system that classifies genres using CNN. Convolutional neural networks (CNNs) were developed specifically for the purpose of picture classification based on spatial information [10]. CNN requires reduced preparation time for classification tasks compared to competing techniques. Both the spatial and temporal aspects of a picture may be captured by the algorithm. Figure 4 demonstrates this. Pattern recognition using convolutional neural networks for the identification of tumors: The pre-processed picture is passed into the CNN model's input, convolution, and fully connected layers. Each of these levels activates a certain neuron to generate a specific output or judgment. The input image is the layer that takes in data. The picture is shown using a 256x256 pixel matrix. Each pixel reveals unique characteristics. In the first convolution layer, the input picture is sequentially passed through eight filters, each with a kernel of size three by three, in order to extract features. Eight feature maps are generated as a consequence of this. [7] The main objective is to extract information about the input image's outline, color, gradient, and orientation. It is feasible to use many layers of convolution, with the first filter capturing lower-level characteristics and the following layers capturing higher-level features. In order to decrease the processing power required for the data, the pooling layer employs dimensionality reduction to reduce the spatial size of the convolved feature. On top of that, it makes note of the most important aspects of the input. Most of the time, max pooling is preferred over average pooling because of its superior noise suppression capabilities. For low-cost feature learning with the fully linked activation layer, the convolution layer produces an output that reflects non-linear combinations of high-level features.

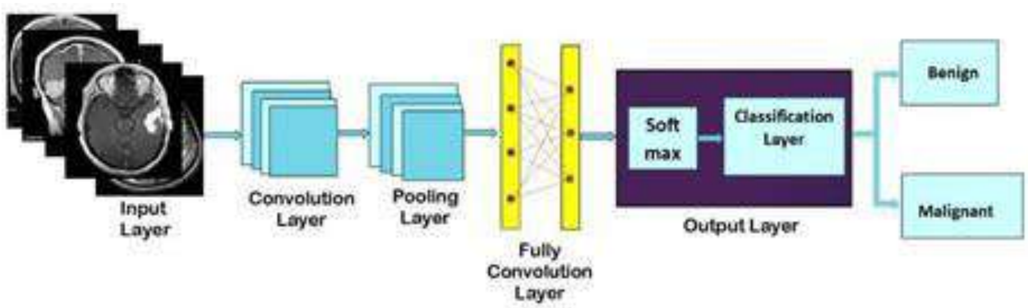

Fig. 4 Architecture OF Convolutional Neural Networks for tumor detection

Segmenting photographs into different groups based on their shared attributes is called image classification. It's a method used to organize picture databases. Image segmentation methods based on clustering, such as k-means clustering, are the most often used.

Objects and regions of interest may be extracted from images using image segmentation. The picture may be divided or clustered using a variety of segmentation approaches to find the target characteristics. These techniques include (i) histogram-based techniques, (ii) cluster techniques, (iii) edge detection techniques, (iv) region growth techniques, etc. Image segmentation is a method for dividing images into distinct, mutually exclusive regions. It means that the regions of interest are all physically close to one other and that the pixels within each region are homogeneous according to some standard. The segmentation process made advantage of the widely-used KMeans clustering algorithm. In this study, we used the segmentation method to examine the finer points of a brain image.

The following quality assessment parameters are also needed to ensure better result analysis on brain MR images. [16]

1) **Mean (Mn):-** The mean of an image is calculated by summing all of the image's pixel values and dividing by the total number of pixels.

$$M_n = \frac{1}{a\ b} \sum_{P=0}^{a-1} \sum_{Q=0}^{b-1} f\ (P,Q)$$

2) **Standard Deviation** ***(S.D.)*:-** The standard deviation represents the variability in pixel values and can indicate the level of contrast in an image. A higher value suggests greater intensity levels and sharper edges.

$$S.D = \sqrt{\frac{1}{P\,X\,Q} \sum_{a=0}^{P-1} \sum_{b=0}^{Q-1} (\ f\,(a,b)\ -M)^2}$$

3) **Entropy (En) :-** Entropy is used to measure the randomness in a texture image and is defined as a formula

$$En = \sum_{a=0}^{P-1} \sum_{b=0}^{Q-1} f\ (a,b)\ \log_2 f\ (a,b)$$

1) **Skewness (Skn):-** Skewness measures the symmetry or lack thereof in a random variable and is denoted by a symbol Skew, and is defined as a formula

$$Skn = \left(\frac{1}{P\,Q}\right) \frac{\sum (f\ (a,b)-M)^3}{S.D^3}$$

2) **Kurtosis (Kur) :-** The parameter Kurtosis describes the shape of a probability distribution for a random variable. It is denoted by a symbol and defined by a formula

$$Kur\ = \left(\frac{1}{P\,Q}\right) \frac{\sum (f\ (x,y)-M)^4}{SD^4}$$

3) **Energy Qualifies (Eq) :-** Energy quantifies the extent of repeated pixel pairs and serves as a measure of image similarity. If energy is calculated using Haralick's GLCM feature, it is also known as angular second moment, and it is denoted as

$$EQ = \sum_{a=0}^{P-1} \sum_{b=0}^{Q-1} f^2\ (a,b)$$

4) **Contrast (Cont):-** Contrast is a measure of the intensity difference between pixels. It can be calculated using a formula.

$$Cont = \sum_{a=0}^{P-1} \sum_{b=0}^{Q-1} (a-b)^2 f\ (a,b)$$

5) **Homogeneity (Hog) or the Inverse Difference Moment (IDM):-** A measurement of an image's local homogeneity is called the inverse difference moment. To identify whether an image is textured or not, IDM can have a single value or a range of values.

$$Hog = \sum_{a,b} \frac{P(a.b)}{1+|a-b|}$$

6) **Directional Moment (D.M) :-** D.M a textural property of an image, that is calculated by using the image's alignment as a measure in terms of angle and is as follows:

$$D.M = \sum_{a=0}^{P-1} \sum_{b=0}^{Q-1} f(a,b)|\ a-b|$$

7) **Correlation (Cor) :-** The correlation feature describes the spatial dependencies between the pixels and is defined as where Ma and del a are the mean and standard deviation in the horizontal spatial domain and Mb and del b are the mean and standard deviation in the vertical spatial domain. Directional moment is a textural property of the image calculated by taking the image alignment as a measure in terms of the angle.

$$Cor = \frac{\sum_{a=0}^{P-1} \sum_{b=0}^{Q-1} (a,b)\ f(a,b)-MaMb}{\sigma_a \sigma_b}$$

8) Coarseness (Coar) :- Coarseness (coar) In the textural analysis of an image, cons is a measure of roughness. A texture is considered more coarse for a fixed window size if it has fewer texture elements than one with more. A higher coarseness value corresponds to a rougher texture. The coarseness values of fine textures are smaller. As defined, it is

$$Coar = \frac{1}{\frac{P+Q}{2}} \sum_{a=0}^{P-1} \sum_{b=0}^{Q-1} f(a,b)$$

SEGMENTATION TECHNIQUES IN MRI BRAIN IMAGE ANALYSIS

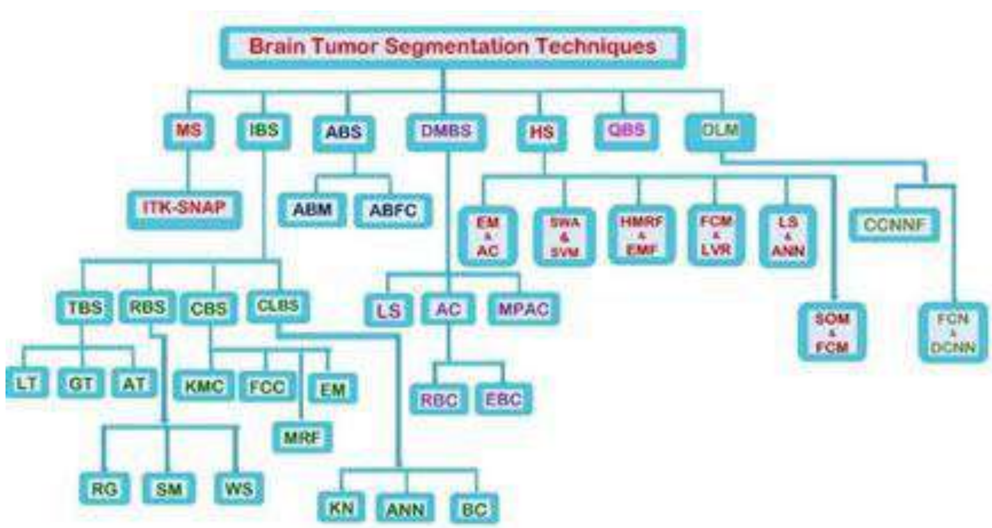

Fig. 5 Various segmentation techniques in MRI brain image analysis

MS-Manual Segmentation

IBS: - Intensity based segmentation ABS:-Atlas based segmentation

DMBS: - Deformable model based segmentation

HS: - Hybrid learning method ABM:-Atlas based method

ABFC: - Atlas based Fuzzy connections

LS: - Level set

AC: - Active counters

RBC: - Region based contours EBC:- Edge based contours

MPAC: - Multi phase active contours TBS:-Threshold based segmentation LT:- Local Thresholding

GT: - Global Thresholding AT:- Adaptive Thresholding RBS:- Region growing

SM: - Spitting & Merging

WS: - Watershed segmentation

CBS:-Clustering Based segmentation KMC:- K- Means clustering

FCC: - Fuzzy C-means clustering MRF:- Markov random field EM:- Expectation Maximisation

CLBS:-Classification Based segmentation

KN: - K –nearest neighbour ANN;- Artificial Neural networks BC:- Bayesian classifier

EM & AC: - Expectation maximisation & active contours

SWA & SVM: - Segmentation by weighted aggregation & support vector machine

HMRF: - Hidden markov Random field

EMF: - EM Framework

FCM * LVQ: - Fuzzy C –mean & learning vector quantization

SOM: - Self organizing map

CCNNF: - Cascaded CNN framework

FCN & DCNN:- Fully convolutional network & Deep convolutional neural network

ITK – SNAP – Insight segmentation & Registration

Toolkit: - software application

Manual Segmentation

Using manual segmentation to find tumor regions on all adjacent slices where the tumor is suspected to be found is an expensive, labor-intensive, and time-consuming procedure. Moreover, it is susceptible to human mistake, which increases the possibility that different observers may find tumors or lack thereof in different ways, or even that the same observer would see tumors or lack thereof at different times. Clearly, brain tumor segmentation using an automated technique is necessary.

Intensity-based (or pixel-based) segmentation

These methods use pixel or voxel intensity to categorize them. Brain MRIs may distinguish between three primary types of tissue, mostly by intensity: white matter, gray matter, and cerebrospinal fluid. In order to separate the three main types of tissues just by intensity, tools for controlling MRI artifacts including noise, partial volume, and intensity inhomogeneity must be included. The intensities of brain and non-brain tissues also overlap; for example, the scalp and brain tissues have similar intensities. The next sections provide a synopsis of methods that rely on clustering, pixel classification, region-based, and threshold-based analysis.

Threshold-based segmentation

One simple and tried-and-true method of image processing, intensity thresholding compares the brightness of individual pixels in an image to a set of predefined standards. One way to convert grayscale photos to binary format is by using image thresholding. This technique divides the original image's pixel values into two or more categories based on a threshold value. A pixel is considered a feature pixel if its value is more than the threshold, and a background pixel if its value is less than the threshold. Global, local, and adaptive thresholding algorithms are the three most used options. Local or global threshold-based segmentation approaches are a good place to start when it comes to segmentation. Use the global thresholding approach when items in the input MR image are highly contrasted with the backdrop or have comparable intensities. All images are subject to a single threshold value in this approach.

Region-based segmentation

An approach to picture segmentation that uses clusters of similarly enhanced pixels or voxels is called region expanding, which is also called region merging. Each pixel in an image is linked to a narrow, precisely connected area or item using this technique. To begin, it requires an object-sized seed point. An operator has the option of using the seed locating tool or manually selecting the seed site.

algorithm that naturally sets the seed state. Then, if the intensities of all neighboring pixels are close enough, area growing will include them in the expanding zone. This continues until the increasing zone can no longer accommodate any further pixels. The most common approach for segmenting MR brain tumors is the region-growing technique, which incorporates watershed segmentation. Divide items with precisely defined borders using the hierarchical approach for region growth, region splitting and merging. The region expanding approach may be used to segment volumetric pictures (voxels), which are made up of big linked homogenous patches. Consequently, it is useful for medical image analysis when segmenting MR images of different organs, tissues, or lesions.

Classification-based segmentation

By using data with specified labels, classification algorithms partition the visual feature space. While intensity or pixel values are often associated with images, they may also be linked to texture and other properties. Supervised and unsupervised classification methods exist. Supervised classification necessitates training photos, which are manually segmented and then used as standards for the automated segmentation of new images. Due to their failure to include neighborhood information, supervised classification algorithms suffer from the drawback of being noise-sensitive. Nonetheless, findings may be skewed when subject-to-subject differences in anatomy and physiology are ignored when applying the same training set over several photos. In order to derive structure from a dataset, unsupervised classification algorithms need a model of data similarity. These methods may be used to any imaging dataset without the need for specialized training data or collection protocols. When it comes to segmenting brain tumors, the three most popular supervised classification approaches are k-nearest neighbour, artificial neural network, and Bayesian classifier. K-Nearest Neighbor (KNN) is an algorithm that does not need any parameters to be filled in. The KNN classifier generates new classes for the voxels according on their agreement with a set of class-specific attributes.

They pioneered KNN MR-intensity-based statistical classification; nevertheless, their approach fails to segregate structures including skin, brain, ventricles, and tumors because MR intensity ranges in the picture overlap. While other methods make assumptions about brain tissue MR intensity distributions, this one doesn't. The presence of substantial quantities of diseased brain tissue (such as tumors or lesions) precludes the use of this approach for accurate tissue class labeling. Noise or inappropriate characteristics may drastically reduce a KNN's accuracy. Artificial neural networks (ANNs) learn from input and can perform classification tasks rule-free. They are quite good in difficult, multidimensional, non-linear, and noisy problems. The main advantage of ANNs is that they do not need assumptions on the underlying probability density functions.

Atlas-based segmentation methods

When large, space-occupying tumors or lesions change the shape and placement of brain structures and sub-structures, it may be challenging to execute accurate visual segmentation. When compared to previous approaches, the atlas-based segmentation methodology has the potential to segment the image without necessitating an explicit connection between regions and pixel intensities. Segmenting items with similar structures (such textures) may be challenging when the information required to distinguish them is derived from their morphometric features or their spatial connections. These techniques consider both the lesion's development and the tumor's likely point of origin.

Clustering-based Image Segmentation

There are two approaches that can be used to segment images by clustering. Divisive clustering and Agglomerative clustering. In Agglomerative clustering, we label a pixel to a nearby cluster and then iteratively enlarge the clusters. The steps involved in agglomerative clustering are Similar clusters with smaller inter-cluster distances (WCSS) are merged, Each pixel is regarded as a separate cluster and The actions are carried out again. The procedure used in Divisive Clustering are a single cluster is designated for each and every pixel, over some epochs, the cluster splits into two with a significant inter cluster distance, until the ideal number of clusters is reached, the steps are repeated.

K-means Clustering

k-means is one of the clustering algorithms that is most frequently used. The k in this case stands for the number of clusters, not the k-nearest-neighbour. k-means' operation is as follows:

1. Initially, choose k initial clusters at random
2. Each data point should be arbitrarily assigned to one of the k clusters
3. Determine the centers of these groups
4. Determine every point's separation from each cluster's center.
5. The closest cluster receives the points based on this distance.
6. Determine which way the newly formed clusters are oriented.
7. Lastly, continue steps (4), (5), and (6) until the set number of iterations is reached or the center of the clusters remains unchanged.

Region-based

Using this first method, pixels from segments that are next to each other directly are compared for similarities. Because the pixels closest to one another are more likely to belong to the same object, this technique compares and contrasts neighbouring pixels to identify the boundaries of the object. This technique's drawback is that the contrast and lighting in the picture could cause the object parameters to be defined incorrectly.

In the above table, several brain tumor segmentation approaches are reviewed, including manual segmentation, intensity-based segmentation, quantitative segmentation, model-based segmentation, and hybrid segmentation methods. Furthermore, the benefits and drawbacks of various strategies are highlighted. [12]

RESULT AND DISCUSSION

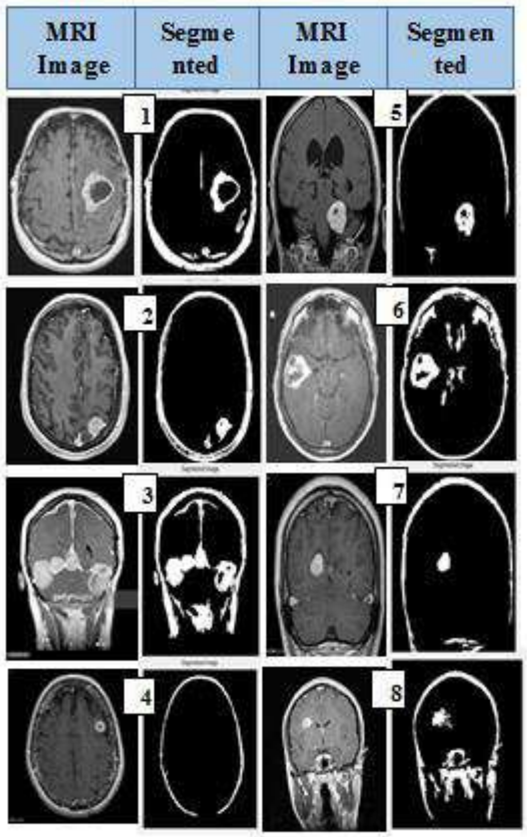

Fig.7 Benign MRI Images to Segmented Image

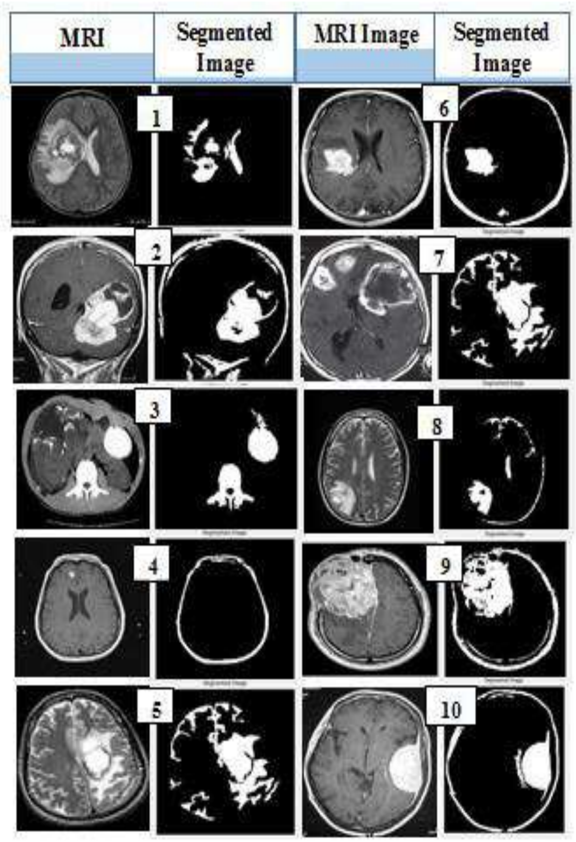

Fig. 8 Malignant MRI Images to Segmented Images

In the above images there are multiple MRI images which are being segmented to identify the proper location of tumor. In further process by using hidden layer convolution layer it also calculated parameters like Mean, Standard Deviation, Entropy (En), Skewness (Skew), Kurtosis (Kur), Energy Qualifies (Eq), Contrast (Cont), Homogeneity (Homo) or the Inverse Difference Moment (IDM), Correlation (Cor), Coarseness (Coar) with the types of tumor which is mention in the table 2 and 3 Benign and Malignant

Textural Features of Benign Images

Images	Mean	Standard Deviation	Entropy	RMS	Variance	Smoothness
Image 1	0.00193931	0.0897938	3.65493	0.0898027	0.00798716	0.87826
Image 2	0.00253273	0.089779	3.07565	0.0898027	0.00805623	0.904047
Image 3	0.00352304	0.0897456	3.05619	0.0898027	0.0080274	0.929107
Image 4	0.00068659	0.0898121	2.74648	0.0898027	0.00806289	0.718636
Image 5	0.00341193	0.0897499	2.9949	0.0898027	0.00805202	0.926967
Image 6	0.003242727	0.897562	3.5797373	0.0898027	0.008018599	0.923447
Image 7	0.002509545 4	0.0897795	3.31556	0.0898027	0.0080626	0.903246
Image 8	0.002068181	0.0897909	3.51816	0.0898027	0.00803049	0.884969
Image 9	0.001931818	0.0897939	2.66316	0.0898027	0.00805185	0.877845

Table 1. Brain Image Textural Features of Benign Images

Images	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity
Image 1	5.81169	0.340779	1.0015	0.203281	0.112589	0.755387	0.933106
Image 2	7.7971	0.577419	-0.2601	0.25584	0.0895255	0.755693	0931415
Image 3	7.48478	0.52124	1.03923921	0.234149	0.132059	0.752994	0.931526
Image 4	10.9703	0.73646	0.119006	0.26891	0.0976505	0.7861145	0.940953
Image 5	7.68008	0.631759	0.3816163	0.243326	0.129391	0.760611	0934441
Image 6	6.27346	70.633152	0.52567	00.24416416	0.1006777	0.740911	0.926261
Image 7	6.23204	0.312064	0.563091	0.216073	0.138167	0.754802	0.93249
Image 8	6.7672	0.441261	0.546199	0.224972	0.0991065	0.769087	0.936531
Image 9	7.27071	0.611709	0.0366395	0.233315	0.0128439	0.749118	0.930775

Table 2. Brain Image Textural Features of Benign Images

Tables 2 and 3 show some of the prominent features of Benign Images. Table 2 and 3 also indicates the measure of Mean, Standard Deviation, Entropy , Skewness , Kurtosis, Energy Qualifies , Contrast , Homogeneity or the Inverse Difference Moment , Correlation , Coarseness and their values present in the segmented image.

Textural Features of Malignant Images

Images	Mean	Standard Deviation	Entropy	RMS	Variance	Smoothness
Image 1	0.00630907	0.0895928	3.20515	0.0898027	0.00801767	0.959133
Image 2	0.00425992	0.0897136	3.6046	0.0898027	0.00804977	0.940642
Image 3	0.00365066	0.0897405	3.37095	0.0898027	0.00805956	0.931415
Image 4	.000435998	0.0897088	3.07728	0.0898027	0.0080587	0.941925
Image 5	0.00458293	0.0896977	3.54839	0.0898027	0.00806942	0.944594
Image 6	0.00528247	0.0896592	3.19429	0.0898027	0.00805359	0.951576
Image 7	0.00423595	0.0897148	3.55162	0.0898027	0.00803605	0.940326
Image 8	0.00458293	0.0896977	3.54839	0.0898027	0.00806942	0.944594
Image 9	0.0058914	0.0896212	2.6807	0.0898027	0.00804689	0.956362
Image 10	0.00348476	0.0897471	3.52392	0.0898027	0.00798925	0.928384
Image 11	0.00282896	0.0897701	3.62834	0.0898027	0.00803589	0.913222

Table 3. Brain Image Textural Features of Malignant Images

Images	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity
Image 1	12.2408	1.10481	1.2156	0.305895	0.142097	0.786231	0.937931
Image 2	5.99721	0.521797	0.36996	0.227197	0.13258	0.743862	0.929018
Image 3	7.35059	0.635044	-0.137806	0.243326	0.0932787	0.761293	0.932884
Image 4	10.3215	0.825022	0.271848	0.265017	0.125116	0.76831	0.934423
Image 5	6.5235	0.620389	0.503033	0.243882	0.107227	0.731029	0.924625
Image 6	9.73182	0.991423	1.85456	0.278643	0.142678	0.76042	0.932114
Image 7	6.06145	0.510428	0.313019	0.231368	0.107236	0.741808	0.92976

Image 8	6.5235	0.620389	0.503033	0.243882	0.107227	0.731029	0.924625
Image 9	11.6802	1.2348	1.28377	0.279477	0.172915	0.757519	0.932796
Image 10	6.52204	0.497891	1.65244	0.251669	0.073405	0.740242	0926743
Image 11	5.32384	0.322997	1.04188	0.215517	0.0950755	0.737835	0927359

Table 5. Brain Image Textural Features of Malignant Images

Some of the most notable characteristics of Malignant Images are shown in Tables 4 and 5. Mean, Standard Deviation, Entropy, Energy Qualifies, Skewness, Kurtosis, Contrast, Homogeneity or the Inverse Difference Moment, Correlation, Coarseness, and their values are also shown in Tables 4 and 5.

CONCLUSIONS AND FUTURE WORK

This research examines several methods for segmenting brain tumors, including manual, intensity-based, quantitative, model-based, and hybrid approaches. The benefits and drawbacks of various approaches are also highlighted. Image processing algorithms have revolutionized medical diagnostics, particularly in the detection of brain cancers. For improved model performance, it is recommended to increase the amount of the dataset, use hybrid and deep learning approaches, and analyze more features.

These days, the number one cause of death globally is brain tumors (BT). These days, a variety of methods are used to swiftly pinpoint the BT. The idea is that if the illness can be detected early on, it will be easier to treat and, maybe, cure. To identify BT using MRI, the proposed method demonstrates a sufficient level of competence. The suggested solution outperforms the status quo when compared to other common methods. This method makes BT identification and classification a snap. More data for testing and training, together with other methods for feature extraction and classification, could be doable down the road. [9]

Research into cancer detection software and medical image analysis is an ever-expanding area of study. Tumor detection via medical image segmentation may be useful in some cases. A number of researchers and scientists worked together to create and improve this technology. Brain cancer detection in MRI images is accomplished in this study using a Matlab GUI interface. Optimal performance is generated by this program's interface using a range of image processing algorithms, filters, and segmentation combinations. It is possible to apply hybrid approaches to further enhance the accuracy of the proposed strategy.

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