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PERFORMANCE EVALUATION OF MRI IMAGE USING DISCRETE WAVELET TRANSFORM FUSION

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Abstract

Brain MR images that are quickly and accurately detected are crucial for medical analysis. Tumor categorization is a topic that has been covered extensively in the literature. In this study, we offer a technique for automatically segmenting MR brain images to identify and characterize any abnormality segments (such as those caused by tumor) present in the picture. The initial phase in the process of extracting features from an input picture is proposed in this study, and it involves using a DWT-discrete wavelet transform. To do this, principal component analysis (PCA) is used on the feature picture to minimize the number of dimensions. Kernel support vector machine (KSVM) is used to process the down sampled image of retrieved features. There are a total of 90 MR pictures of the brain in this data collection, representing seven different prevalent illnesses. For the KSVM procedure, these pictures are necessary. The suggested classification approach employs a Gaussian Radial Basis (GRB) kernel, which, in comparison to a linear kernel, achieves a maximum accuracy of 98%. (LIN). The results of the study demonstrated that the GRB kernel technique was superior to the previously used approaches. When an aberrant MR picture containing a tumors is detected using this classification, the appropriate portion is extracted and segmented using a thresholding method.

Keywords: *Discrete Wavelet Transform (DWT), Principle component Analysis (PCA), Kernel Support vector Machine (KSVM), Thresholding*

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INTRODUCTION

Magnetic resonance imaging (MRI) is a powerful method that yields high-quality pictures of human anatomical components, especially the brain. Moreover, it provides minuscule data useful for both clinical practise and research. It’s crucial for interpreting brain pictures [1-5].Classification approaches, including feature extraction, feature reduction, and the application of a classifier, are used for the analysis of MR brain images. Magnified values of MR images acquired by correct classification are shown in [6-8] and are used for diagnostic purposes. The wavelet transform is a powerful method for extracting features from MR brain images for classification purposes. The wavelet transform's ability to evaluate the MR brain picture at several resolutions requires more storage space and computational resources than would otherwise be necessary to extract the feature. DWT with a Fejer-Korovkin filter is utilized for feature extraction [9]. Principal component analysis (PCA) is used to reduce the need for the massive amounts of space and money that were previously required. Due to the decreased feature vector size, less space is required for its storage [10]. The challenging part of the process is determining how to categorize the MR image in the input data. Recently, academics have proposed a plethora of methods for categorizing things into two groups. Firstly, there is the supervised classification, which uses a support vector machine (SVM) [11], and secondly, there is the unsupervised classification, which uses tools like the self-organization feature map (SOFM) [11] and the fuzzy c-means [13]. Both types of classifiers may provide respectable outcomes, but the supervised classifier is favoured due to its many benefits over their less reliable counterpart, the unsupervised classifier (success classification rate). While Linear Kernel (LIN) and Artificial Neural Network (ANN) have been used to classify data before, their combined accuracy is lower than 95%. When comparing several supervised classification approaches, support vector machine is among the top machine learning algorithms. The benefit is that it introduces kernel SVMs (KSVMs), which are in between the original linear SVMs and the nonlinear SVM classifiers [17], and requires a relatively small amount of data [16].Using KSVM [18] in the new feature space yields the maximum-margin hyper plane. In this research, we use the GRB kernel approach to classify images and the thresholding technique to segment tumors images; we then compare and contrast these two sets of findings and briefly discuss the table's contents. Part II's approach is described in full below; it makes use of the discrete wavelet transform (DWT), principal component analysis (PCA), and thresholding technique.

Among the spectrum of potentially fatal illnesses, brain tumor are among the most worrisome and rapidly on the rise in the human population. The global incidence of mortality from cancer is rising quickly [2], as shown by statistics from worldwide scientific organizations like the American Cancer Society (ASCO) [1]. One of the leading causes of death in both children and adults, brain tumor may take many shapes and sizes and manifest in many areas of the brain. It has been determined that, during the previous few decades, the annual rise in the number of persons suffering and dying from brain tumor has been about 300. A brain lesion is usually given as the main diagnosis. Cancerous tumor is abnormal, but normal tumor are not. Pressure within the skull may rise as tumor both healthy and malignant, develop. This may lead to irreversible brain damage and is potentially fatal. Primary (benign) and secondary (malignant) brain tumor are distinguished [4]. Around 250,000 new cases of primary brain tumor are diagnosed each year, making up a small percentage of the total number of cancer cases (less than 2%) throughout the globe. Brain tumor are the second most prevalent kind of cancer among children under the age of 15 [5], behind acute lymphoblastic leukemia. Hence, MRI-based brain cancers may be automatically detected with the use of computer-assisted diagnosis, which allows for very accurate reconstruction of original pictures of the tumors and improved diagnostic time. One of the most important areas of study in medical image processing is the categorization of MRIs of the brain. Although MR scans of the brain are a great tool for detecting the spread of tumor, accurately segmenting brain pictures is a challenging and time-consuming operation [6]. Classifying brain MRI images manually is time-consuming and not always accurate. As a result, there is a need for advanced methods of automated categorization. Using these methods, a classifier is initially trained with data (pictures) from a set of classes, after which it can reliably categorise unseen images into one of those classes [7].

LITERATURE SURVEY

Kiran et al [1] Tumors are masses of tissue formed by the steady proliferation of malignant cells; the brain, as the organ responsible for controlling and regulating all of the body's most important functions, is therefore particularly vulnerable to this threat. To put it simply, a brain tumor is a tumor that has spread to, or formed within, the brain. No underlying cause of brain tumor growth has been identified. Although not extremely common, brain tumors (1.8% of all documented malignancies worldwide) have a high mortality rate because they develop in the brain, the most vital organ in the body. Thus, accurately identifying brain tumors at an early stage is critical for reducing fatality rates. We have introduced a computer-assisted radiology system that will assess brain tumor from MRI scans for the purpose of managing brain tumors diagnosis. In this paper, we used the Watershed and PSO algorithms, the DWT and PCA methodologies, and feature extraction to create a model that can reliably identify tumorss using SVM.

Muhammad Assam et al [2] The discipline of medical imaging has arisen as a consequence of the exponential growth in computer power and the development of cutting-edge tools for the analysis, interpretation, processing, and display of images, which have substantially expanded the medical sciences. Magnetic Resonance Imaging (MRI) is a cutting-edge imaging method that provides exceptionally clear pictures of the human body, including the brain, for medical professionals to study. In this study, we present a simple but effective method for sorting MRI scans of the brain into two categories: healthy and diseased. In addition to normal photos, it also incorporates those from the public dataset established by Harvard Medical School that show signs of brain tumor, acute strokes, and Alzheimer's disease. The suggested model consists of the following four stages: The four steps are as follows: 1) Pre-processing; 2) Features Extraction; 3) Features Reduction; and 4) Classification. Being one of the most effective algorithms, the median filter is utilized in the pre-processing stage to get rid of distracting elements like the scalp and skull as well as undesired noise like salt and pepper. After this step, the gray scale photos may be further processed into colour images. The second stage involves applying the Discrete Wavelet Transform (DWT) method to the pictures in order to pull out specific details. The third step involves the use of Color Moments (CMs) to narrow down the features to a manageable collection. A variety of classifiers are used to categorize photos based on the attributes they have extracted from the images. Classification accuracy was highest for the Random Subspace with Random Forest (RSwithRF) and lowest for the Random Subspace with Bayesian Network (RSwithBN), both of which used the 10-Fold cross validation technique. The individual classifier, Feed Forward - ANN (FF-ANN), was split 65%-35% for training and testing. The encouraging results demonstrate the robustness and efficiency of the proposed approach in contrast to other classification techniques, especially those that need a larger number of optimum characteristics.

Rajat Mehrotra et al [3] It is well acknowledged that a brain tumors is a terrifying diagnosis. It's a mass of abnormally growing cells that appears in the brain. Magnetic resonance imaging (MRI) of the brain is a time-consuming and laborious process for detecting and classifying tumor-infected areas. Human anatomy in all its variety may be seen using different Image Processing methods. Yet, it might be difficult to spot abnormal brain structures using conventional imaging techniques. Magnetic resonance imaging (MRI) is a useful modality for discerning and shedding light on the complex human brain architecture. There are a number of imaging methods available for analyzing the brain's inner structure. In this study, we provide an investigational approach to BT diagnosis. To improve speed and reduce complexity, this article focuses on noise reduction, features extraction using a gray-level co-occurrence matrix (GLCM), and BT segmentation using a Discrete Wavelet Transform (DWT). When segmentation produces unwanted noise, a morphological procedure may be used to clean it up. The effectiveness of BT detection is evaluated by means of a Support Vector Machine (SVM)-based classifier. The effectiveness of the suggested method is shown experimentally, with a classification accuracy of 98.87%.

Sanjay Kumar C.K et al [4] The tumors tissues vary in appearance from person to person, making it challenging to automate the process of tumors recognition and categorization from brain MRI images. In many circumstances, tumors seem practically identical in appearance to normal brain tissues. If improved feature extraction techniques are used that can characterize the tumors in its entirety, an accurate classification should be anticipated. The study employs a selection and feature extraction approach that draws on the statistical properties of both segmented and unsegmented pictures to produce a hybrid feature set. SVM classifier model is constructed using these combined characteristics. For classification of brain tumorss into benign and malignant categories, the SVM is modeled as a non-linear classifier using various kernel functions such as Linear, quadratic, and RBF.

F. P. Polly et al [5] The glial cells in the brain may become malignant and form tumors called gliomas. Low-grade gliomas develop slowly, but high-grade gliomas spread quickly (fast growing). Glioma grades are used by doctors to determine the best course of therapy for patients with brain tumors. The tumor's current state is crucial for therapy. In this study, we present an automated approach for classifying MRI images of the brain as either high-grade (HGG) or low-grade (LGG) tumors, therefore distinguishing between normal and diseased brain. In the suggested automated system, k-means is used as the segmentation approach for clustering, and Discrete Wavelet Transform (DWT) and Principle Component Analysis (PCA) are used as the primary elements of the feature extraction and feature reduction procedures, respectively. After feature extraction and reduction, our proposed method uses a support vector machine (SVM) to categorize aberrant brain tumors in the LGG and HGG.

A. S. Methil et al. [6] in 2021 hypothesized a novel approach to detecting brain tumors, with the primary foundation being a combination of convolutional neural network design and digital image processing methods. Digital image processing algorithms such histogram equalization and opening and closing were used in the first step of processing. To train the network, the author then built a convolutional neural network model in the second stage. The author employed a number of digital photos that differed in terms of tumors size, kind, and location. The author drew from a dataset including over 4000 photographs, some of which were of tumors and others of which were not. Based on the outcomes, the author achieved about 99.7 percent accuracy during the training phase and nearly 100 percent accuracy during the testing phase.

G. Raut et al. [7] in 2020 a piece of brain tumors were identified in MRI scans using a deep learning approach based on neural networks. The author used a convolutional neural network model to detect tumors of the brain in the provided photos. The author pre-trained a deep learning model to detect normal and tumor-containing pictures using the provided dataset. Auto encoders, which are used to filter out background noise in pictures, were included into the algorithm sometime in the middle. The author utilized the K-means technique to segment the images. The author utilized the 250-image Kaggle dataset that was publicly accessible. The author reports a 95 percent success rate in his trials using the recommended method.

T. M. Devi et al. [8] in 2018 categorized digital input pictures from magnetic resonance imaging of the brain into normal and abnormal categories to aid with the diagnosis of brain tumorss. The adoption of a discrete wavelet transform (DWT) technique aided the authors in extracting useful features from the base picture. With the help of principal component analysis, we were able to reduce the size of the main picture by a significant margin. Following this step, the digital image's features were sent into KSVM. The primary dataset consisted of 90 brain MR digital pictures, 30 of which were deemed normal and 60 deemed abnormal, with 7 of the same disorders represented. The authors' implementations of discrete wavelet transformations and Fejer Korovkin discrete filters yielded results that are both mathematically and practically sound, with high classification accuracy. Thresholding is used to divide tumors into smaller pieces. Classification accuracy of 98% was achieved by the authors using the Gaussian Radial Basis kernel as opposed to the 92% achieved by the linear kernel.

Magnetic resonance imaging

When it comes to diagnosing brain tumors, imaging is both sensitive and penetrative. When it comes to diagnosing, planning for surgery, and following up on the effectiveness of treatment for brain tumors, magnetic resonance imaging (MRI) is without peer. By non-invasively collecting the tumor's delicate and complicated anatomical characteristics, MRI creates high-quality 3D scans of the brain [25]. Axial, sagittal, and coronal views are all possible in an MRI scan, representing the three main anatomical planes. The axial plane, often known as the horizontal or x-y plane, divides humans into superior (top) and inferior (bottom) halves. The sagittal plane is a y-z plane that runs perpendicular to the ground and divides the human body along its long axis, from left to right. The x-z coronal plane runs perpendicular to the ground and divides the human body in half from front to rear (back). By replacing potentially dangerous ionising radiation sources like X-rays and CT scans with MRI, glioma may now be diagnosed more quickly and with less discomfort than ever before. To create pictures of the body's interior structures, MRI makes use of radio waves and a uniformly strong magnetic field from outside the body. The magnetic field intensity of an MRI scanner may vary anywhere from 0.5 tesla to 3 tesla. When the scanner moves from one section of the body to another, the external magnetic field intensity may be adjusted. By injecting gradient magnetic fields and altering the local magnetic field, it is even possible to localize and photograph the location of interest inside the human body.

The majority of clinical diagnoses are made using a 1.5 tesla MRI scanner. On the other hand, 3 tesla scanners are increasingly commonplace in both academic and medical contexts. Increasing the field strength has several benefits, including better signal-to-noise ratio, enhanced resolution, etc.

Nevertheless, it suffers from a serious drawback in that it is affected by a variety of motion abnormalities such the eddy current artifact and the magnetic field instability [16]. The duration of a clinical MRI operation typically ranges from 15 to 45 minutes, while this timeframe is highly variable based on factors such as the region of the human body being scanned, the number of slices of the target area being captured, the kind of MRI being taken, etc. It might take a long time to gather a few photographs. Gadolinium-based contrast agents are administered into certain patients during scanning operations to acquire more enhanced slices of scanned region. Enhancing contrast on MR images allows for better visibility of aberrant and healthy tissue [10]. In spite of the fact that significant strides have been achieved in these areas, there is still a pressing need to make this service (by using a high field strength scanner) more affordable, broadly accessible, and user-friendly. Hence, MR imaging is a crucial and helpful diagnostic tool for characterizing glioma tissues in great detail. Also, MRI may be used correctly if its limits are recognized. The correct use of magnetic resonance imaging (MRI) in the diagnosis of gliomas has recently become standard practice, potentially avoiding the need for invasive surgical procedures.

MR imaging techniques in glioma

Current traditional procedures for comprehensive diagnosis of glioma, such as neurological inspection, surgical biopsy, and manual assessment of imaging scans, present a number of difficulties, as discussed previously. These problems may be effectively addressed by using computer-aided glioma diagnosis through digital MR imaging scans and MRI image processing techniques. MRI scans are now routinely used in the treatment of gliomas. For glioma patients, it is often the first line of treatment in order to pinpoint the tumor's precise location and determine its histological profile. It paves the way for a higher-resolution, multi-contrast imaging of the glioma tumor's soft tissues. Traditional MRI sequences for gliomas include T1-weighted (T1w), T2-weighted (T2w), contrast-enhanced T1-weighted (T1-ce), and fluid-attenuated inversion recovery (FLAIR). These structural modalities provide high-resolution multi-planar structural features and are commonly accessible. Intracranial pressure, tumors size, and tumor localization are the primary functions of structural MRI methods used in the first assessment of tumors [12]. Also, a variety of cutting-edge MRI methods are presented, each with the potential to compare and contrast image-guided molecular characteristics of glioma tumors. Perfusion weighted imaging using dynamic susceptibility contrast (DSC) or dynamic contrast enhanced (DCE), amide proton transfer (APT) imaging, and magnetic resonance spectroscopy are all examples of cutting-edge methods (MRS). There are several biological aspects of gliomas that may be further explored using specialized MRI techniques. Information regarding glioma MRI techniques and their applications in diagnosis and prognosis are provided here, with a focus on the role that MR imaging may play in enhancing clinical care of glioma patients.

1. T1w: It visualizes and evaluates the tissue architecture to provide delicate anatomic de- tails. Gliomas are generally hypo intense on T1w images [13]. The elements like blood, fat are highly intensified with pre-contrast T1-weighted scan.
2. T1-ce: It assesses the tissue organization. The blood vessels or blood-brain barrier is generally seen with bright signal that helps to show enhancing sub region within tumor [34]. Consequently, non-enhancing area and necrotic regions can also be visually delineated. Since there is a strong association of contrast enhancement with high-grade gliomas, T1-ce images helps for assessment of WHO grades [15].
3. T2w or T2-FLAIR: It also evaluates architectural elements of tissue like T1-weighted. Gliomas are generally hyper intense on T2w images. Bright intensity is observed in per temporal edema, injury in white matter, non-enhancing tumor area, tumor boundaries [16]. T2-FLAIR provide robust difference between solid tumor and peri-tumoral edema.
4. DWI: It computes apparent diffusion coefficient (ADC) maps to probe for diffusion of water. The regions with restricted diffusion of water molecules are presented as bright and regions with free-flowing diffusion are dark in DWI. It produces high signal intensity for regions in tumors with increased cellularity [17].
5. DTI: It computes fractional anisotropy, axial diffusivity, and radial diffusivity. The tractog- raphy obtained with DTI reveals the connection between white matter tracts and tumor, which can help for surgical planning for glioma patient. DTI also carries potential to detect invading growth pattern of glioma tumors [18].
6. Perfusion Imaging: It measures cerebral blood flow (CBF) and cerebral blood volume (CBV) and their abnormal variations in gliomas can be well observed with this imagingscan [39].
7. APT: It reflects cellular proliferation in tumor tissues. It supports diagnosis of glioma to characterize edema and to differentiate between pseudo-progressions versus true pro- gression of tumor. This modality is yet to be commonly applied in clinical management[40].

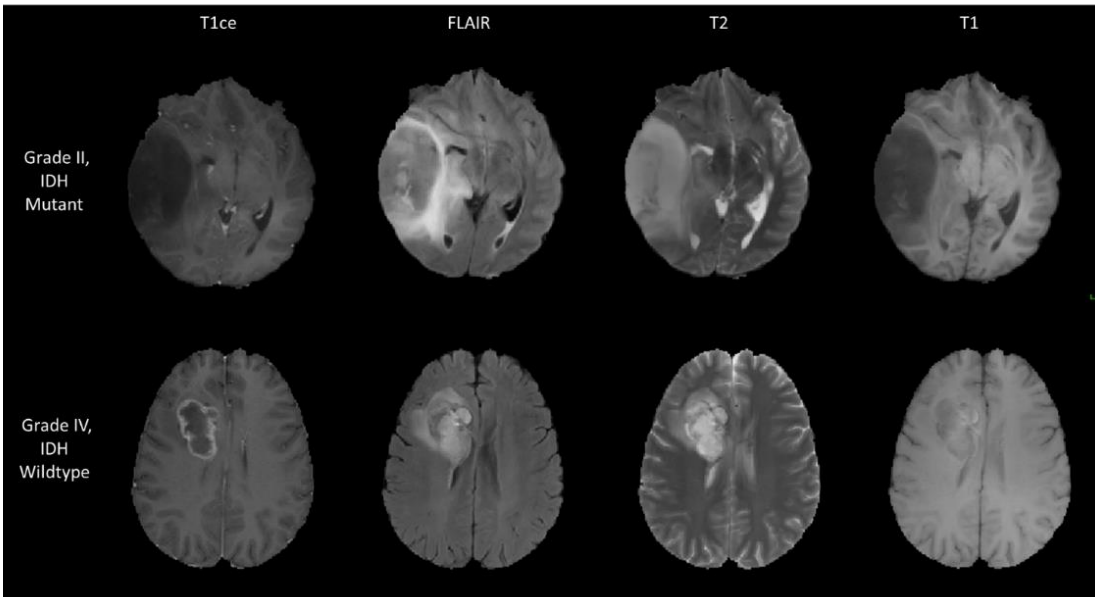

Figure 1: Sample MRI images of glioma

Brain tumor segmentation

While creating a computer-aided diagnostic system for the characterization and therapeutic management of gliomas, neoplasm segmentation is an essential first step. Internally, gliomas have complicated pathological characteristics including necrosis, edoema, an enhancing core, and a non-enhancing tumor area, and their development is infiltrative and sporadic. Tumor segmentation is the process of identifying the precise location of the tumor and separating malignant tissues (such as active tissue, necrotic tissue, and edematous tissue) from healthy surrounding tissue. The outcome is the definition of a 2D or 3D region of interest (ROI) or volume of interest (VOI). Segmented example of a 2D picture of a glioma displaying internal features (including enhancing, non-enhancing, necrosis, and edoema). Expert neuro-radiologists or other specialists often use MR imaging to detect and isolate brain tumors. Manual segmentation, although possible, is laborious and yields unpredictable results. Thus, in recent years, research into the development of reliable algorithms for automated segmentation has emerged as a central topic. Based on how much human input is required, segmentation methods are classified as manual, semi-automated, or fully-automated.

1. Manual segmentation: It involves the assistance of experienced neuro-radiologist to do manual annotation of area of interest (ROI) of tumor. Method comprises the professionals to review multimodal MRI images slice by slice, identifying the tumor features concurrently with his expertise and knowledge, and manually marking sub regions of tumor carefully. This job is exceedingly tiresome, long and also vulnerable to inter-rater or intra- rater variations. Nonetheless, the manual segmentation by experienced radiologist is still being utilized regularly to assess the efficacy of fully-automatic or semi-automatic approaches.

2. Semi-automatic segmentation: Yet, few semi-automatic segmentation methods combine the best features of both manual and fully automated segmentation techniques. They may manually fix a segmented tumors mask with minimal human intervention. Certain configurations, such choosing a starting point for a ROI, picking thresholds, tweaking pre-processing parameters, getting feedback on how well an automated process performed, and making necessary revisions, may need human intervention. Semi-automatic approaches use the conventional picture segmentation techniques, such as image growing or thresholding. It's true that

these techniques save time and effort compared to more manual procedures, but there's still room for error when it comes to defining the ROI because of human error. Thus, the majority of recent segmentation-related studies have focused on fully automated approaches.

3. Automatic segmentation: A.I., ML, and DL (deep learning) algorithms form the basis of these techniques [43]. MRI scans of gliomas reveal a wide range of changes in tumors intensity, shape, size, location, and texture [15]. Moreover, tumors borders are often vague and ill-defined. The 3D representation adds another layer of complexity to multimodal MRI data. Correctly addressing these concerns is necessary for robust, repeatable, completely autonomous segmentation. Automatic procedures may be broken down into two major groups: generative and discriminative. To comprehend the connection between the input and the ground truth picture, discriminative methods use supervised learning methodologies to learn the feature. As opposed to the probabilistic models generated by generative algorithms, which rely on information such as normal brain anatomical maps, geographic coordinates, and the geographical extent of tumorss.

   Pre-processing, feature extraction (or feature reduction), segmentation classification, and post-processing are the usual stages in an automated method's processing pipeline. With the introduction of the BRATS benchmark in 2012, a worldwide competition has been held to evaluate the efficacy of various segmentation techniques, and a publicly available benchmarked database has been made available in conjunction with the BRATS challenge of brain tumors segmentation annually since then. While these conventional automated approaches show promise, the state-of-the-art findings for tumors segmentation [14] have been produced by the deep learning trend that has emerged in recent years. The state-of-the-art approaches in many computer vision and pattern recognition problems are now derived from deep learning methods as Stacked Auto Encoders, Restricted Boltzman Machine (RBM), Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), etc. According to research conducted during the past several years, these methods have seen extensive usage in the field of medical imaging segmentation.

Two Dimensional Discrete Wavelet Transform (2D DWT)

Wavelet Transform's multi-resolution analytic capability makes it a useful tool for extracting features from MRI brain images. When it comes to elaborating on picture data, the multi-resolution representation might be a straightforward answer. Using the 2D discrete wavelet transform, an image can be broken down into four distinct sub bands: those with lower frequency in the horizontal direction (representing details in the vertical), those with high frequencies inside the horizontal direction (representing details in the horizontal), those with shorter wavelengths for both directions (representing an approximation image), and those with higher frequency in both directions (representing details in the vertical) [12, 13]

Principal Component Analysis (PCA)

In order to simplify the tumor classification process, it is necessary to reduce the amount of unnecessary characteristics that must be calculated or stored in memory. As the (PCA) effectively lowers the dimensionality of the data, it may be used to analyze fresh data with less computer resources. PCA is a fantastic method for maintaining much of the variability while decreasing the dimensionality of a data set that contains many linked variables. Data is transformed into a new collection of variables that are prioritized or ranked by their variances or significance. This method accomplishes three goals at once: it renders the input vector components orthogonal and hence uncorrelated; it ranks the generated orthogonal components according to their contribution to the data's variability; and it removes the ones that contribute the least. [14]

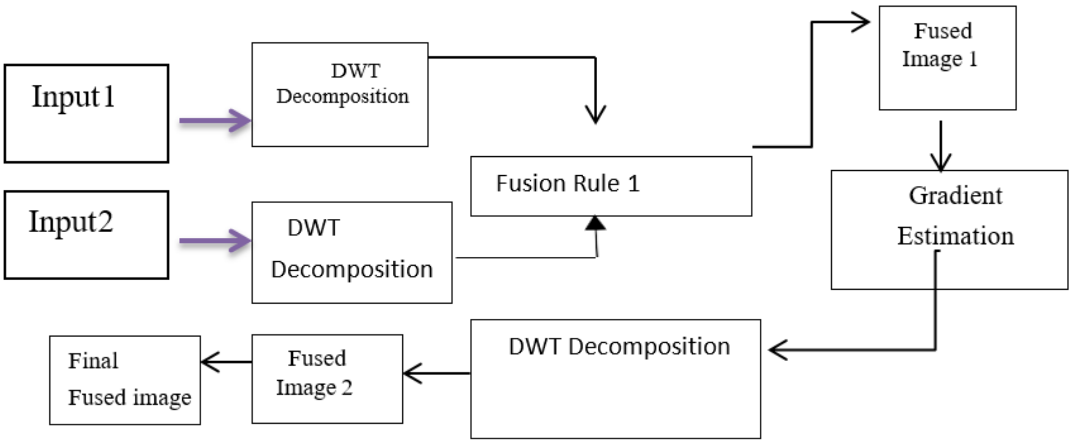

Fig.2 Flow diagram of proposed method

Pre-processing

- The suggested system's action upon receiving an image as input is to: • Resize the picture into suitable dimensions.
- Remove the colour information from the provided picture while keeping the brightness and contrast.
- The grayscale picture must be converted into a binary image by first calculating a global threshold. This cutoff is an intensity value between zero and one after being adjusted.
- Including this threshold allows for the picture to be transformed into a binary format.
- Any pixels whose brightness is over the threshold value in the output picture will have a value of 1 (white), while all other pixels will have a value of 0 (black).

Segmentation

Segmentation is a vital process in picture analysis. There are a total of eight types of segmentation techniques used today, including those that rely on thresholding, region growth, classifiers, clustering, Markov random field models, artificial neural networks, deformable models, and atlas guidance. [11] For tumor segmentation in this system, we used the K-means clustering technique. To implement this method, the Euclidean distance between the centroid of k clusters and each pixel is first determined

Feature Extraction

When you extract features from data, you're essentially reducing the amount of information required to accurately describe it. More computing resources and time may be required to process the whole picture data set for categorization. In order to accurately identify the original picture, a feature extraction procedure is used to extract the many forms of significant information included within it. The classification model is trained using the features. Similarity in feature sets across images in the same category may be used to identify them. Geometrical and topological local and global aspects [20]. Here, the picture is processed so that its most fundamental characteristics may be retrieved. For the most part, brain MRIs are categorized using texture, shape, statistical, and intensity-based criteria.

Texture Analysis

Texture analysis is the process of labeling areas of a picture according to their texture characteristics. Surface textures are multi-layered visual patterns made up of smaller patterns with their own unique luminance, hue, hue value, slope, size, etc. Quantifying the range of intensity values and grey levels is the goal of texture analysis. Finding these boundaries, known as feature segmentation, may be accomplished by texture analysis. Texture analysis is employed for brain tumor classification; with methods including the grey level co-occurrence matrix (GLCM) [21] and the Gabor texture [24]. In order to extract statistical texture characteristics, also known as Harlick features; the GLCM approach is often used. [14]

Wavelet Transform

Brain tumor classification from MR images is a common use of DWT-based feature extraction algorithms. Raising the DWT quality causes the coefficients to become smaller, and it also improves the image's representation at lower resolutions. Because of this, feature extraction may be performed using just the DWT coefficients, rather than the whole picture, as shown in [6, 7], [8, 9]. Because the data in a brain MRI is so precious, DWT is useful for downscaling without losing quality. Similarly, an image's DWT coefficients may serve as a feature vector [3, 12]. For brain MRI classification, we may claim that DWT is the approach that can be utilized for both preprocessing and feature extraction. Classification using DCT coefficients is possible [13]. From a dimension-scaling standpoint, certain studies have shown that HAAR wavelets perform better than db4 wavelets. [25].

Result

This picture is required for preprocessing if the brain image contains the tumour area. For the input brain picture, we use the average filter. This study used a filter with a 5-by-5-inch square aperture. The smoothed picture is the result of the removal of the noise. Table 1 and Table 2 provide contrasting data for benign and malignant tumors, respectively.

Table 1 Sub- bands values different values of trained Images & statistical field for Benign Tumor

Image	Contrast	Correlation	Energy	Homogeneity	Entropy
Image 1	0.208843	0.199005	0.7621	0.935159	3.17346
Image 2	0.271691	0.0930892	0.76857	0.933815	3.26983
Image 3	0.24416	0.100677	0.740911	0.926261	3.57973
Image 4	0.216073	0.138167	0.754802	0.93249	3.31556
Image 5	0.233315	0.128439	0.749118	0.930775	2.66316
Image 6	0.25584	0.0895255	0.755693	0.931415	3.07565

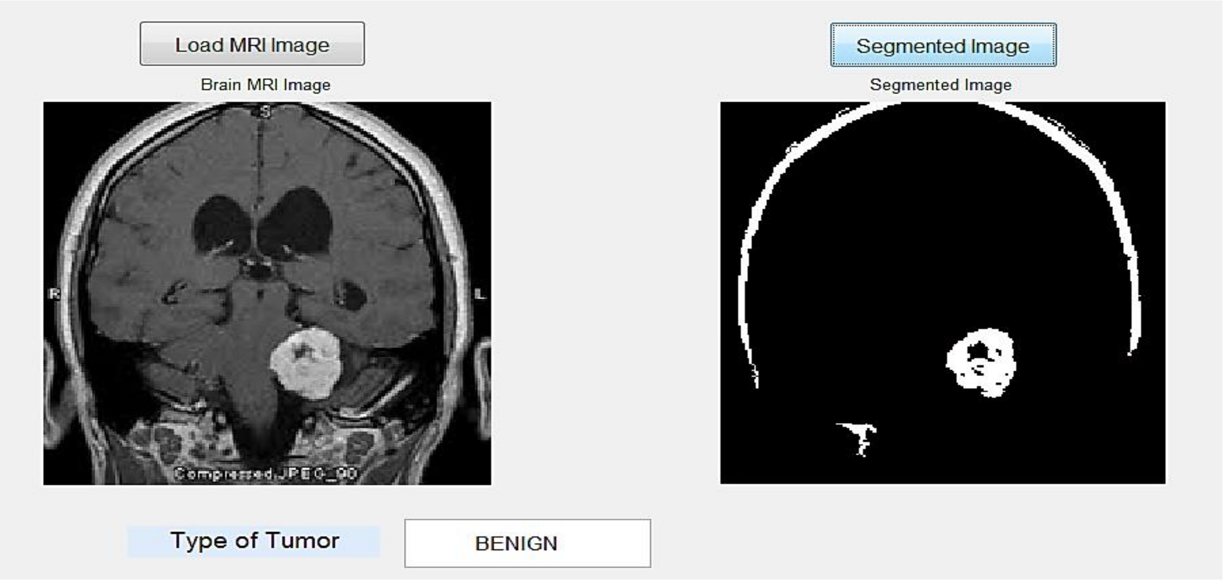

Fig 2 GUI Implementation of the Image with segmentation for Benign tumor

Table 2 Sub- bands values different values of trained Images & statistical field for Malignant Tumor

Image	Contrast	Correlation	Energy	Homogeneity	Entropy
Image 1	0.305895	0.142097	0.786231	0.937931	3.20515
Image 2	0.227197	0.13258	0.743862	0.929018	3.6046
Image 3	0.243326	0.0932787	0.761293	0.932884	3.37095
Image 4	0.275028	0.117994	0.7688	0.934555	3.02899
Image 5	0.231368	0.107236	0.741808	0.92976	3.55162
Image 6	0.215517	0.0950755	0.737835	0.927359	3.62834

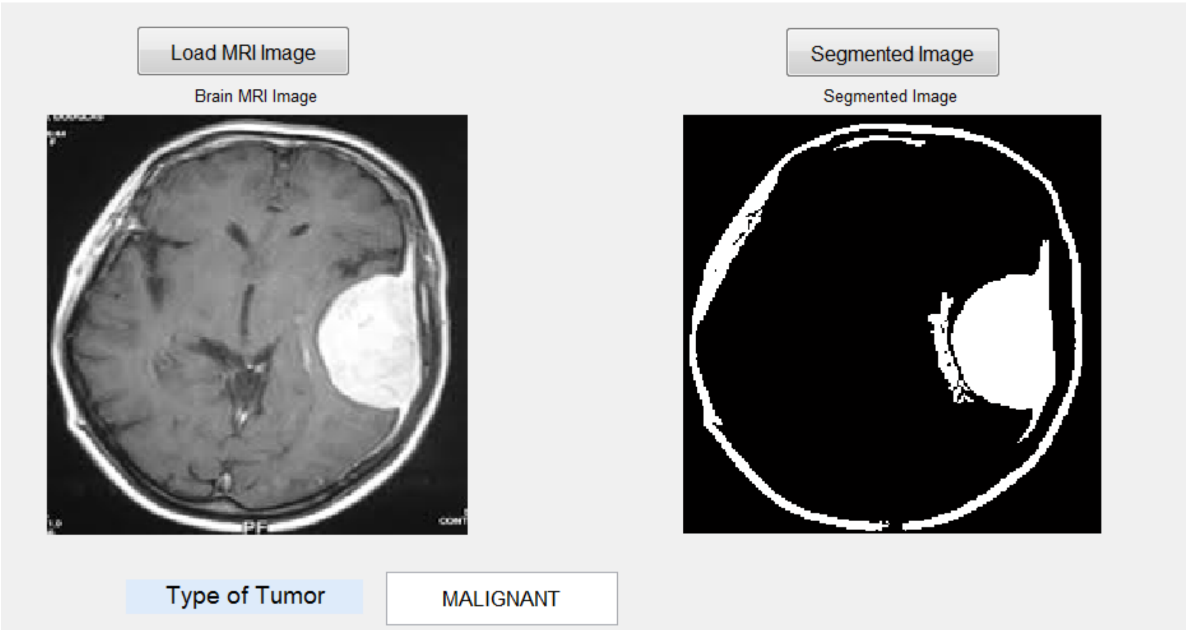

Fig 3 GUI Implementation of the Image with segmentation for Malignant tumor

CONCLUSION

The use of computing science to the study of illness is playing an increasingly significant role in medical decision making. The use of MRI (magnetic resonance imaging) is crucial in a wide variety of studies. Hence, the MRI brain picture is used for system implementation. The tumor area is located using a morphological surgery. It's quick and simple to put into action. The procedure of testing brain images has been completed in this study. This technique yields trustworthy results for brain imaging. Further processing procedures are required if a tumor area is detected in a brain picture. To properly segment the brain picture, preprocessing is a must. With the noise removed and the picture smoothed down, the brain scan is now ready for analysis. A threshold-based skullduggery has been performed on this system. This technique successfully eliminates the skull tissues from the brain picture. In a final step, watersheds were divided using a marker-based method. As a result, we can categorize the intensity of both normal brain tissues and tumor regions separately. The final segmentation map is created by partitioning the picture into normal brain tissue and tumor. Then, a morphological procedure is used to identify the tumor area in the final segmentation map. Images from magnetic resonance imaging (MRI) of the brain were utilized to distinguish between normal brain tissue and malignant tissue in this study. The purpose of preprocessing is to remove noise and smooth out photographs. The strength of the signal above the background noise is therefore improved. Thus, we used a discrete wavelet transform.

transformation, which deconstructs the picture to get the GLCM discovered by structural methods. The PNN classifier has the potential to detect malignancies in MRI scans of the brain. Research shows that self-diagnosis of a brain tumor is quicker and more accurate than medical expert diagnosis. The best parts of it also show that it works better by boosting PSNR and MSE measures.

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