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Analysis of Diagnosis for Malignant and Benign Brain Tumor MRI Images using CNN and DWT Technique

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Abstract: The article describes the use of image processing in the search for the brain tumor. Tumors are a worldwide health crisis that may manifest in any part of the body. If a brain tumor is not diagnosed and treated early on, it may significantly reduce a patient's lifespan. Malignant and benign tumors of varied stages were discovered. This illness is now affecting a sizable population. Each year, more and more people are screened every day in an effort to discover diseases early. Manual screening is not only a time-consuming process, but it also raises the possibility of making mistakes. Some people could become even more distracted. Therefore, it is more ideal to use an AI-based system for the screening process than a human one. Specialists employ MRI (Magnetic Resonance Imaging) scan images to identify brain cancers; however, these images include noise that must be minimized in the first phases of processing if accurate findings are to be achieved. In this research, we provide a refined Discrete Wavelet Transform (DWT) filtering technique along the used of artificial Intelligence for this purpose. Image filtering and image segmentation are the system's two main components. Brain tumor MRI images from the Kaggle dataset will be used as test data for the filter.

Keywords: *Artificial Intelligence, Discrete Wavelet Transform (DWT), MRI (Magnetic Resonance Imaging), image filtering, image segmentation*

1. Introduction

The human brain, which is made up of hundreds of billions of neurons, is the most interesting and intricate mechanism in the human body, inspiring much research into it. Campbell et al. (2009) note that the human brain's primary roles include motor control, perception, memory, learning, language, emotion, intellect, and consciousness. The forebrain, midbrain, and hindbrain are the three primary regions of the brain. The left and right cerebral hemispheres, the diencephalon, the brain stem (midbrain, pons, and medulla oblongata), and the cerebellum are the four major brain regions[1]. Structure, function, and primary anatomical compartments of the human brain About 80% of a person's brain mass is located in the cerebrum (cerebral cortex). The functions of the various lobes of the brain, such as those responsible for language, smell, hearing, vision, memory, sophisticated learning, and behavioral reactions, are all located in different parts of the cerebrum[2]. Cerebral spinal fluid (CSF) fills the space between the brain's two hemispheres, which also include granule cells from the brain's White Matter (WM). Myelinated axons and glial cells make up the bulk of WM, which is responsible for relaying impulses from the brainstem to the cortex. Most neurons, dendrites, and capillaries are found in the GM[3, 5]. The cerebral spinal fluid (CSF) is a fluid that circulates throughout the brain and spinal cord. The functioning of the brain will decline if any area of the cerebrum sustains an injury or tissue damage.[6]

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2. Characteristics of Brain Tumors

Brain tumors are characterised by the abnormal and uncontrolled growth of cells. Some are considered "primary" because they manifest first in the brain. Some, known as secondary, have metastasized to this area from elsewhere in the body. There will be no metastasis (the spread of cancer) from the brain at this point, although any given tumor might progress to malignancy or remain benign. Both benign and malignant tumors provide serious health risks. The danger to human life increases when the cancerous areas expand inside the little skull area[7]. When the pressure within the skull rises too high, blood can't reach certain parts of the brain, leading to edoema and, eventually, the cessation of normal tissue function and the death of cells. In fact, brain tumors are the second largest cause of cancer-related mortality in those under the age of 30. By the end of 2011, 64,530 new instances of primary brain and central nervous system tumors will be detected, as reported by the Central Brain Tumor Registry of the United States (CBTRUS). There are presently about 600,000 cases of the illness worldwide. [8].

There are two types of brain tumors: primary and secondary. The aberrant cells in the main brain tumor grow very slowly, making the tumor safe to leave alone.

In this phase, treatment for the tumor consists of taking the right medicine at the right times. Secondary brain tumors develop when original tumors are left untreated. Malignant refers to the second-stage of brain tumors, which has rapidly proliferating aberrant cells. Radiation therapy is recommended for patients with malignant brain tumors since at this time the tumor cannot be managed by medicine or surgery[9]. Surgery is used to remove the aberrant brain cells, and subsequent treatment with medication is intensive. An abnormal development of tissue that may be seen in the brain is called a tumor[10-14]. Brain tumors are very rare, and unlike tumors in other regions of the body, they can only spread from one brain cell to another inside the brain. Brain tumor cells tend to proliferate rapidly for reasons that are not well understood. Gliomas are cancers that begin in the glial tissues, which are responsible for facilitating communication between the brain and the rest of the body. Although gliomas are the most common primary brain tumors, others, such mixed gliomas, ependymomas, and astrocytomas, may develop from gliomas. (Greenberg et al., 1999) [15].

Benign and Malignant Brain Tumors

In its early stages, when it affects fewer cells and does not spread, a tumor is considered benign. They are completely reversible with surgical excision and do not spread to neighbouring tissues[16-18]. Malignant tumors are ones that have progressed to the later stages and have invaded healthy tissue around them. Damage is long lasting, and the suffering is excruciating. Cells with this kind of tumor lose their borders and become very collapsed. The pressure within the skull rises fast when a tumor has progressed to a malignant stage. Brain and spinal cord tumors are examples of primary tumors[19]. These are very uncommon and go from the periphery of the CNS all the way to the brain.

Segmentation of Brain Images

Segmentation is the process of dividing a picture of the brain into smaller parts based on the shared features or locations of its constituent pixels. When an image is segmented, its functional components are used to isolate the area of interest from the remainder of the picture[20]. Similarity or discontinuity of intensity levels of the item are the primary qualities on which segmentation relies. The supplied picture is therefore broken down into its constituent parts. In general, segmentation may be used on any kind of digital picture. When used to medical imaging like CT scans, MRIs, etc., the approach requires both biological and computer science expertise in order to automatically produce the desired result[21]. The thing (organ) under examination, as well as its surrounding objects, are all present in the picture acquired by medical modalities. It is a difficult but crucial duty to determine what item is being discussed. This is made possible with the use of segmentation methods in digital image processing. Region-growing approaches, clustering methods, edge detection methods, and thresholding methods are the four main categories into which image segmentation techniques may be broken down. Among the various knowledge-based approaches that fall under these umbrella categories are clustering techniques, as well as intensity, discontinuity, similarity, graph, pixon, and hybrid approaches[22, 23].

Clustering methods

Images are broken down into clusters of similar pixels. A piece of the picture might be represented here. Clusters of pixels with comparable values are then separated out into their own groups. When dissecting a human body, this technique is useful for isolating certain organs. Clustering, however, may not provide obvious dissimilarity among pixels when segmentation within an organ is necessary.[24]

Threshold based techniques

These methods divide a picture into high-intensity (pixels) and low-intensity (pixels) categories based on their intensity levels relative to a predetermined threshold. In other words, there are bright spots and shadowy corners. The lack of a guarantee for object coherency is the fundamental drawback of this approach. The picture might feature blank spots or additional pixels[25].

Rationale For MRI

Magnetic resonance imaging's (MRI) principal use has been in the study of neurological illnesses, and it has been utilised efficiently in the identification of musculoskeletal problems. Thanks to technological advancements and advancements in MRI equipment, MRI is now widely used for diagnosing diseases that cause harm to or affect the human body's internal organs. Medical imaging techniques such as X-ray, MRI, CT scan, PET scan, etc. have expanded into new realms thanks to many studies and applications. Digital image processing has entered a new phase, which is particularly important in the detection of life-threatening disorders like cancer. There are benefits and drawbacks of MRI. Despite the fact that MRI only produces a black-and-white picture, it plays a crucial part in the diagnosis of medical issues, notably in the detection of cancer. The sharpness of the picture is the main cause behind this.

The contrast between the object's hard surfaces and soft tissues is improved by MRI due to the former's greater image quality. The process of tumor localisation and cancer staging is aided by this. Researchers have shown that magnetic resonance imaging (MRI) is superior to other radiologic modalities for assessing the local staging of cancer, particularly brain cancer. Although the radiology specialist will pay most attention to the picture from the axial plane, the coronal and sagittal planes are not to be discounted. MRI provides excellent imaging in the coronal and sagittal planes. Images of the brain may be taken in cross section using MRI and seen from a variety of perspectives.

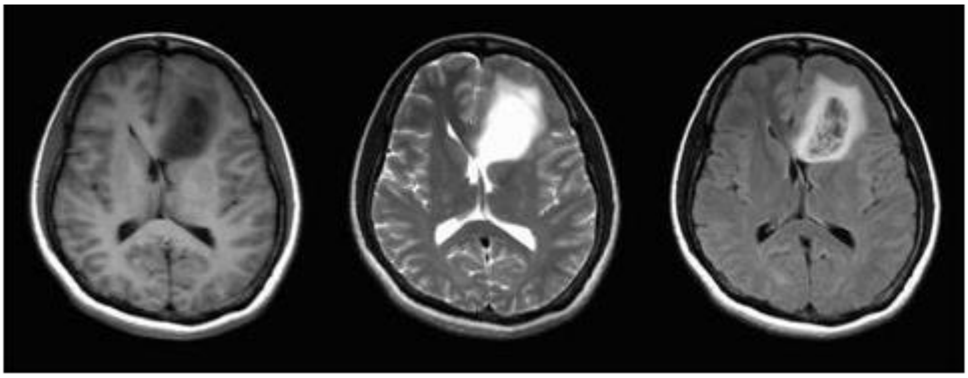

Fig 1. Examples of MRI weighted images(From left to right: T1- weighted, T2 weighted and FLAIR-weighted images)

3. Literature Review

Geethanjali N et.al (2023) The mass of aberrant cells that make up a brain tumor. Brain tumors may be either malignant (cancerous) or benign (not cancerous). Brain tumors are among the most prevalent malignant tumors, and they may be devastating if not caught early. Classification of a brain tumor is a crucial first step in developing a successful treatment strategy after the diagnosis of a tumor. Therefore, early diagnosis not only aids in developing more effective treatments, but also has the potential to save lives. The MRI scans of human brains utilised as data in this experiment. It includes MRI scans of the brain that show both tumors and healthy tissue. Data pre-processing follows, during which several image processing methods, including filtering, blurring, cropping, etc., are used. There are separate "training" and "testing" sets inside the dataset. Information is added to them via a variety of random processes. A Convolutional Neural Network (CNN) model is given the pre-trained dataset. The model then determines whether the tumor is present. If the tumor is present, there are three distinct types that may be identified. Glioma, meningioma, and pituitary tumors are the three main types.

Sumit Hassan Eshan et.al (2023) This study discusses the process of designing an antenna made out of the unique material Kapton polyimide for the detection of brain tumors. A brain tumor is one of the deadliest diseases since it may cause cancer to spread to other parts of the body. The primary focus of this study is on using a new material and monitoring fluctuation in the S1,1 parameter to detect brain tumors. To detect the presence of a brain tumor, researchers used a K-band, on-body microstrip patch antenna and a brain phantom model with tumors of three different sizes. The frequency range of this antenna is 4 to 14 GHz. In open space, the suggested antenna was found to have a resonance frequency of 12.96 GHz. In addition, we found a VSWR of 1.00 and an S1,1 level of 92.06 dB. S1,1 in the normal brain is at 49.93 dB at 8.58 GHz and at 40.51 dB at 11.87 GHz in the brain with a tumor.

Hanming Hu et.al (2021) Magnetic resonance imaging (MRI) is a useful first step in the process of identifying brain tumors for clinicians and researchers. When an MRI scan reveals a tumor, a biopsy or surgical resection is often performed to learn more about the nature of the growth. However, it takes time for brain tumor specialists to determine the tumor kind from a tissue sample. Misdiagnosis is also possible if the neurosurgeon treating the tumor is inexperienced. Therefore, the purpose of our study is to apply deep learning technology to the problem of diagnosing and detecting brain tumors using an MRI scan of the brain. In order to determine which deep learning model is the most effective and efficient, this study tested a number of them. To further boost classification precision, we also used a YOLO model to precisely cut out the tumor from the MRI picture. Using YOLO detection and visual augmentation turns out to reduce classification accuracy. Our studies show that deep learning models may greatly aid in the detection of brain tumors, both in terms of accuracy and speed of diagnosis, opening the door to their potential application in the future for the treatment of this and other complicated disorders.

Deependra Rastogi et.al (2021) Due to the wide range of glioma sizes and intensities, brain tumor segmentation is notoriously challenging. Glioma tumors are the most common kind of malignant brain tumors, and they have a high mortality rate and a morbidity rate of above 3%.

Magnetic resonance imaging (MRI) is the gold standard for diagnosing brain tumors in hospitals. The overlap in intensity distributions between healthy, enhancing, non-enhancing, and edoema areas makes automatic segmentation challenging. Treatment monitoring, post-diagnosis monitoring, and patient impact assessment may all benefit from multi-modal MRI scan image segmentation of brain cancer regions. Clinical brain tumor segmentation still relies heavily on manual segmentation, which is time-consuming and prone to wide performance differences among human operators. This is why research into reliable methods of automated segmentation is essential. The impressive learning capabilities of convolutional neural networks (CNNs) have showed promise in the segmentation of brain tumors. In order to improve segmentation and prediction of brain tumors, the authors of this research propose a 2D-VNet model. Brain tumors were correctly classified by the provided model, which also accurately predicted the outcome of an enhancing tumor and its actual enhancing counterpart. We conducted experiments on the BRATS2020 benchmarks dataset and obtained the following results: Loss (.0025), Dice Coefficient (.9974), and Accuracy (.9971) in training;.0032,.9967, and.9968, respectively, in testing; and Accuracy (.9971) in validation.

Sakshi Ahuja et.al (2021) Disease analysis utilising several types of medical imaging is a significant challenge for medical professionals. The proposed study introduces a CAD tool for the detection and classification of brain tumors based on deep learning. The CA-MRI brain dataset (in axial, sagittal, and coronal views) is used to train the CAD tool for tumor classification and localization purposes. Preprocessing is performed on the input brain MRI dataset, which is then split into three parts: a training set (70%), a testing set (15%), and a validation set (15%). The ineeption-ResNet-v2 deep learning model is trained using an expanded training dataset. Various statistical metrics are used to assess the efficiency of the deep learning model once it has been pre-trained. Accuracy on the training set was 98.72 percent, recall was 99.56 percent, and the Area Under the Curve (AUC) was 1. To pinpoint the tumor in photographs taken from different angles, a CAD programme is built using a deep learning model that has already been trained and a set of feature maps.

Milan Acharya et.al (2020) High grade glioma is a kind of brain cancer with a median survival duration of 1–3 years. For picture categorization and cancer identification, the state-of-the-art method now is Convolutional Neural Network (CNN). Compared to existing frameworks, our technique significantly improves the accuracy and speed with which brain tumors may be segmented from MRI scans. To improve upon the state-of-the-art model, we used a Deep Neural Network (DNN) model, which required us to tweak the segmentation and feature-extraction phases to get better results. Using ten different MRI data sets from patients with brain tumors, we compared our model's accuracy and efficiency to the gold standard. First, compared to the state-of-the-art method, our suggested model's segmentation accuracy (M=90%) is much better. Second, our suggested model performed better than the state-of-the-art in terms of tumor detection processing time (M=34 ms vs. M=73 ms). Therefore, we confirmed prior research by demonstrating that automated segmentation is useful for detecting brain tumors. Our work expands on prior research by suggesting a methodology that can more accurately categorise brain tumors in less time. The model should be validated using a bigger dataset.

V. Sravan et.al (2020) Brain tumor extraction is a crucial part of medical imaging anatomy. This helps doctors identify illnesses, which is the first step in treating them. The purpose of this study is to provide a variety of ways for segmenting MR brain images, from simple threshold methods to more advanced approaches including deformable methods and hybrid approaches. The goal of this research is to identify and locate the brain tumor at an early stage. The most common kind of malignant brain tumors, gliomas, are the primary subject of this research. This paper showcases many deep learning approaches, including Convolutional Neural Networks, for use in brain tumor segmentation research.

Sneha Grampurohit et.al (2020) Growing abnormal cells in the brain may lead to the sickness known as a brain tumor. Brain tumors may be either benign (not cancerous) or malignant (cancerous), with the former being the more common kind. Brain tumors are rare and come in many various forms, making it impossible to estimate how long a patient with one will survive. British studies have shown that 15 out of every 100 persons diagnosed with brain cancer may expect to live for ten years or more when treatment begins. Variables such as tumor type, degree of cellular abnormality, tumor location, and prognosis all influence how a brain tumor is treated.

DWT features

The MR image of the brain is decomposed into its approximate, horizontal, vertical, and diagonal components using a two-dimensional discrete wavelet transform (DWT). The wavelet transform is useful for classification because it allows for the time-frequency localisation of a signal. The decomposed subbands exist in a space with several levels of resolution. Low-frequency components make up the approximate sub band, whereas edges in the horizontal and vertical directions are found in the respective sub bands, and diagonal edges are found in the final sub band. The wavelet is derived from the mother wavelet, which is the original wavelet. The functions G(n) and H(n) indicate the low-pass and high-pass filter coefficients. A 2D DWT is built from these digital filters and down-samplers. The 2D DWT diagram is seen in Figure 2.

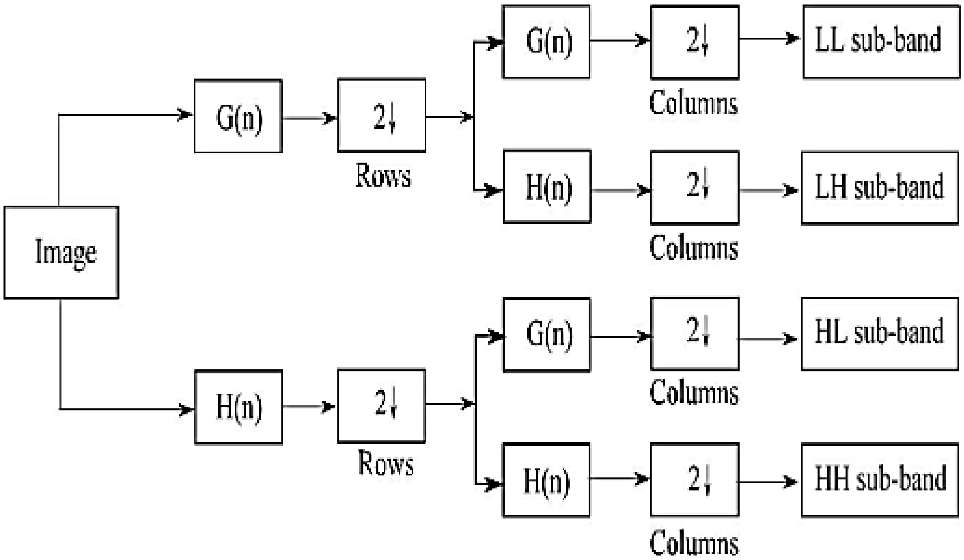

Fig 2. Schematic diagram of 2D DWT decomposition

By passing the picture's rows and columns through the 1D DWT independently, the 2D DWT can be constructed, making the DWT useful in image processing. This results in four sub-band pictures being generated at each level (LL: low-low, LH: low-high, HL: high-low, HH: high-high). These photos are broken down into three sub-bands, each displaying more information in the horizontal, vertical, and diagonal planes. The LL sub-band approximation picture is then employed in the subsequent level of 2D DWT computations. Despite the fact that many other wavelet types have emerged as a result of wavelet analysis's evolution, the Haar wavelet remains a staple of the field. This wavelet is widely used in a number of contexts. Because of its orthogonal and symmetrical properties, Haar wavelet performs well even in a noisy setting. It's lightning quick, too. Therefore, this is helpful for determining an image's fundamental structure. Completed in this work are the approximation coefficients of the Haar wavelet's level-3 decomposition, which serve as features for the normal/abnormal categorization of brain MR images. Figure 3 displays the DWT sub band pictures at the third-level of detail.

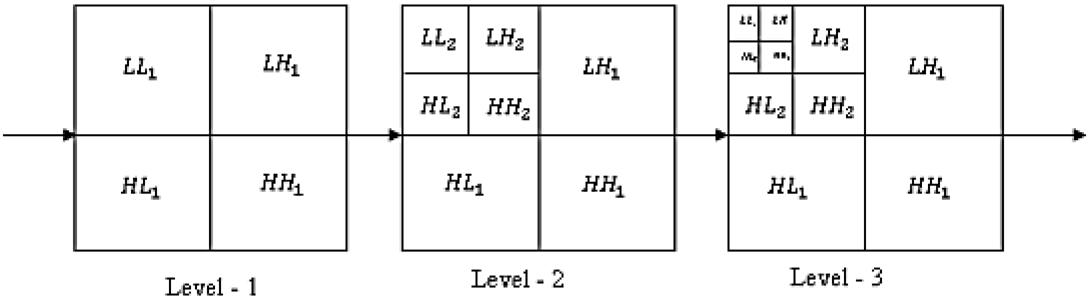

Fig 3. DWT level -3 decomposition

The precise extent of brain tumors may be estimated with the use of MR images that have had their noise reduced and contrast increased. In this work, we provide a high-level overview of the theory and practise of de-noising and enhancement techniques. The specifications of resolution used to describe the improved MR image of the brain tumor are also defined. This chapter suggested and analysed the method to reduce noise by calculating the Peak Signal to Noise Ratio (PSNR), and then went on to discuss how to improve the de-noised MR picture of a brain tumor using the super resolute technique.

Radiologists may rely on the results of automated MR image processing to help them diagnose brain tumors. There is a connection between acquiring an MR picture and the interpretation of that image. The accuracy of computer-aided diagnosis might be enhanced by enhancing the MR image interpretation component. To get good outcomes, make sure your MR pictures are crisp, clear, and devoid of artefacts and noise. For better diagnosis, radiologists are hoping for MR images with greater resolution. The MR picture quality degrades as a result of extraneous noise data. Eliminating noise in MR pictures is a significant obstacle in MR imaging. The smallest details of an MR picture might get distorted between the time it is taken and when it is transmitted. Therefore, MR image interpretation is a difficult process. The film's consistent density is an added bonus. Brightness shifts in MR images are often chaotic, following no discernible pattern. The visual quality will suffer as a result. Imaging brain tumors places a greater premium on image quality. The 'Rician distribution', which governs the significant noise in MR images, is signal dependent. Therefore, it is more important to eliminate noise in MR pictures. It is crucial to protect the margins, since they carry crucial information. The MR image is de-noised using a median filter, which is a cautious technique. Wavelet transformations are used to increase the resolution of MR images to near-photographic levels. To sharpen the MR scans, we used bicubic interpolation to compel the use of discrete, stationary wavelets.

In the realm of nonlinear ordered statistics, the median filter stands out. An image filter will be applied to each pixel of the MR picture. The pixel values in the immediate area are ranked. The area is called a "window" because of its shape. The median filter selects an individual who is typical of their environment. The selected pixel value is swapped out for the median of nearby pixels. The viewing window is a square for 2D pictures. There is a strange amount of pixel values in the window. If there are an even number of pixels in the neighbouring window, the median value is calculated by averaging the middle two values. The median filter estimate is shown in a window in Fig. 4. The median filter examines the surrounding pixels around an origin pixel for each valid pixel in the picture. A three-by-three window is utilised to approximate the output. By arranging the pixel values from lowest to highest, we may get the median value. The median value, shown as 50 in fig. 4, is shown. The origin pixel in the input picture is matched with an output image pixel. The filter order determines the new value that will replace this one. The input image's origin value of 70 was changed to 50 due to the fact that the median value is more conservative than the mean value. A non-representative neighbouring pixel may not be affected by this value. Within the window, one of the pixel values represents the median. The median filter is the one least likely to produce unrealistic pixel values during the transition period. This is why it was chosen as a better method than mean and wiener filters to de-noise the MR picture, protecting the sharp edges in the process.

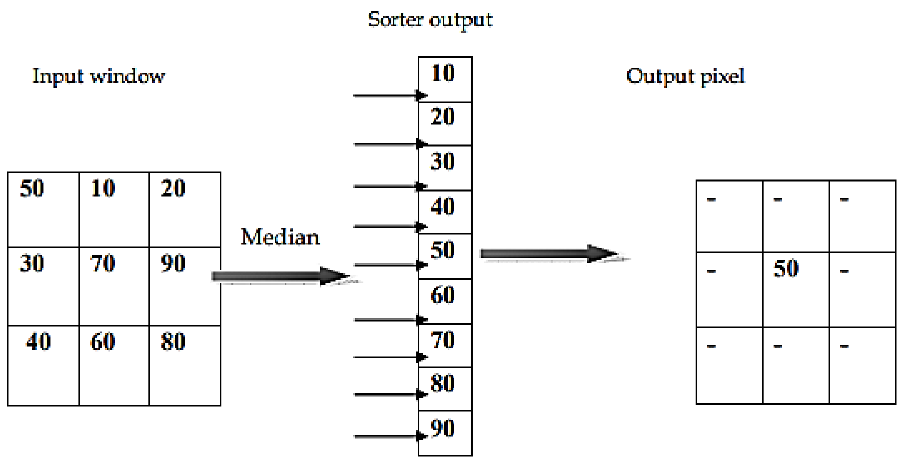

Fig. 4 Illustrate the median filter

MR Image Super Resolute Methodology

The Low resolution MR input picture is resolved using a combination of the Discrete Wavelet Transform and the Stationary Wavelet Transform. The high-resolution block diagram of an MR image is shown in Figure.5.

Applying interpolation for picture intensification may lead to information loss on its edges, i.e., high frequency components. It's crucial to keep the rims safe. The high frequency parts of the picture have been entrusted to DWT. Coefficients of the discrete wavelet transform are effectively interpolated to provide redundancy and shift invariance. Consequently, discrete wavelet transform (DWT) is used to deconstruct the MRI picture into sub band images. High-frequency features of the picture, broken down into LH, HL, and HH subbands. Two-dimensional data points may be interpolated using

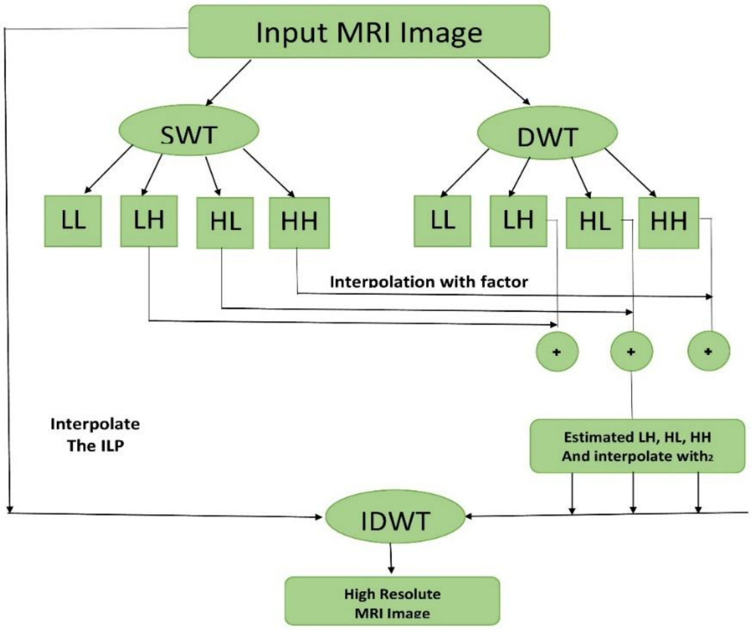

Fig 5: MR Image Super resolute Block diagram

To get a seamless result on a regular grid, bicubic interpolation is used. Bi-cubic interpolation uses the points in the vicinity of a 4x4 matrix to estimate the pixel colour between data points. It estimates pixels between known values using a cubic function. Despite the high cost of computing the cubic polynomials, this approach prevents the occurrence of blurring. This technique is more conservative and produces sharper pictures than bi-linear and closest neighbour approaches because to the faster pixel value changes on the curve.

High frequency sub band pictures are required to use a growth factor of '2' for Bi-cubic interpolation. To make up for data that was lost when DWT down sampled the Sub bands, an adaptation of the Stationary Wavelet Transform (SWT) was developed. Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH) sub band pictures are generated from the MRI Brain tumor image by stationary wavelet transform. The S.W.T. The DWT high frequency sub bands are mixed with the interpolated high frequency sub bands. Interpolating the predicted high-frequency sub bands adds even more intensity. The genuine input picture has superb details compared to the low frequency sub bands. Therefore, the input MRI picture undergoes interpolation once more forcibly. In order to generate a high resolution output picture, inverse discrete wavelet transform is used to merge the interpolated input image with the corrected interpolated high frequency sub bands. The static parameters define the firm picture.

Pre-Processing

For Multimodal fusion to work, it requires information from several sources, not just images. Images often have varying degrees of noise, contrast, and intensity, making pre-processing essential. Therefore, pre-processing methods are done to the photos before feeding them into the suggested framework to make them look more comparable and to make the process smooth and measurable. The goal is to enhance the picture by reducing the amount of distracting noise and bringing out the best qualities of the subject matter. In order to improve the picture quality, we resize it, remove unwanted noise, and perform morphological operations such as erosion as part of our pre-processing.

Multimodal Fusion

Nowadays, multimodal pictures are widely used. It has become increasingly promising to employ many imaging modalities on the same target in biomedical imaging. Our research included fusing images from two different modalities to better understand brain tumors. We employed MRI and CT scans because of the information they gave on the tumor's anatomical components and the clarity of the images they produced. In this study, we concentrate on the multimodal integration of MRI and CT medical images. Multimodal Fusion uses principal component analysis (PCA) to combine MRI and CT, for example. Most of the variation can be explained by the first PC. A smaller selection of principle components may more faithfully describe the data, since each extra component conveys less variation and more noise.

Extraction of textures using GLCMs

Normal and abnormal tissue may be easily distinguished by feeling their textures. Even below the person's degree of expertise, it compares cancerous tissue to normal tissue. Computer-assisted pathology may be used to enhance biopsy techniques by evaluating tissue textures, for example. This method does not account for the relationships between pixels when calculating the frequency of grey levels in a randomly selected area of an image. The frequency is calculated at a fixed grey level in an otherwise randomly selected part of the picture using this method. Pixel associations are no longer considered. The foundation of statistical texture analysis in second-order texture recording is the probability of identifying a pair of grey ranges at extremely great distances and on purpose throughout an entire body. With the Grey Level Co-occurrence Matrix (GLCM), also known as the Grey Level Spatial Dependence Matrix (GLSDM), statistical features of the MR images may be extracted. The correlation between pixels of the same grey level may be statistically explained using Haralick's GLCM. GLCM is a two-dimensional histogram in which the prevalence frequency is (I, j), where (I, j) is the variable. Pixels with intensities I that are about to positively surpass and orientations j relative to adjacent pixels are counted as part of an interval feature with d = 1, a 45°, 90°, or 135° viewpoint and greyscales I and j. This results in the contrast, interdependence, and electricity that make up the statistical field and the grey degree co-occurrence matrix. The top five wavelet decomposition degrees of the LH and HL sub-bands were used to calculate homogeneity and entropy.

Equation Selection of features using PCA

The optimum method for dimension reduction is the element-component analysis. The goal of principal component analysis (PCA) is to reduce the number of dimensions of a dataset while still retaining the variability introduced by the dataset's replications. An efficient monitoring-based classification approach is achieved by restricting the feature vector computed from waves using a combined feature vector component analysis using a feature reduction system to a variable selected by the principal component analysis. The goal of principal component analysis is to simplify the wavelet coefficient. It functions inside a category that is much more specific and detailed.

4. Result

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

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 6. GUI Implementation Segmentation and Classification of Tumor as Benign

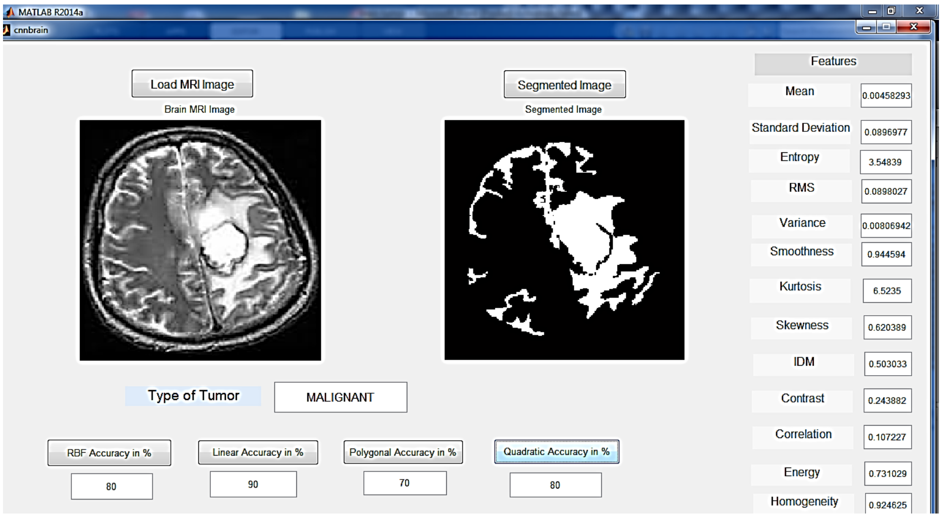

Fig 7. GUI Implementation Segmentation and classification of Tumor as Malignant

Figures 6 and 7 demonstrate the need of using image binarization to precisely estimate the tumor's size. The linearization restricts the partial volume effect and the noise in the MR picture. Median filters are used to clean up the MR scans and get rid of the noise. The threshold technique for image binarization is complicated by the MR image's local grayscale variation, local shading, and insufficient contrast. The MR image's pixel values might be either foreground or background. If the threshold is set incorrectly, the object pixel might be incorrectly identified as background. As a consequence, the binarization's efficiency drops. Identifying the best threshold setting is crucial for reducing the possibility of the pixel values being misread. Optimal threshold discovery is achieved by increasing the inter class variance and decreasing the intra class variance.

5. Conclusion

A growing role in healthcare decision making is being played by the use of computer science to the study of sickness. Many different types of research depend critically on MRI (magnetic resonance imaging). Because of this, the MRI brain image is employed in the actual system. To find the tumor, morphological surgery is performed. You can put this into action quickly and easily. The process of analysing brain scans has been finalised in this research. Reliable brain imaging data may be obtained using this method. When a tumor is identified in a brain image, more processing steps must be taken. The brain image must be preprocessed in order to be segmented accurately. The brain scan has been processed to reduce noise and improve the quality of the image so that it can be studied. This system has been tricked using a threshold-based technique. The method is effective in removing the tissues of the skull from the brain image. Finally, a marker-based strategy was used to divide watersheds. This allows us to classify the intensity of both healthy brain tissue and tumor locations independently. In order to generate the final segmentation map, the image is first divided into sections depicting healthy brain tissue and abnormal tumors. The tumor region is then located using a morphological method in the final segmentation map. In this research, researchers used MRI brain scan images to identify cancerous cells from healthy tissue. The goal of preprocessing is to improve image quality by reducing noise and enhancing smoothness. This means the signal will be easier to hear above the noise. Because of this, we implemented a discrete wavelet transform.

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