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BRAIN TUMOUR EXTRACTION FROM MRI IMAGES USING MEYER'S FLOODING WATERSHED ALGORITHM

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Abstract— **The brain is the most complex and powerful organ in the human body. The brain performs a wide range of difficult tasks. Brain imaging can detect a wide range of brain diseases, including brain tumours, strokes, and paralysis. One way to see the brain is using MRI (magnetic resonance imaging) (MRI). It's utilised to get to the bottom of things. In a brain tumour, cells grow and multiply in an unregulated way, appearing unrestrained by the usual cell regulatory mechanisms that govern normal cell proliferation. A watershed approach based on various feature combinations, such as colour, edge, orientation, and texture, is being used to extract the tumour area from an MRI brain picture in this research. A comparison is made between the findings and the real photos. Results were compared using Dice and Tanimoto coefficients for the extraction of the tumored area employing markers. The method described here seems to provide good results.**

Keywords— **Brain Imaging, Brain Tumor, MRI, Segmentation, Watershed, Dice Coefficient, Tanimoto coefficient**

I. Introduction

The brain is a soft mass of tissue surrounded by the bones of the skull and tiny layers of tissue called meninges and cerebrospinal fluid. Sometimes aberrant tissue development develops in the brain, resulting in a brain tumour. Epilepsy is a brain illness in which clusters of nerve cells form and brain messages become aberrant. Neurons generate electrical impulses that work on other neurons, glands, and muscles to form human thoughts, emotions, and actions. The regular pattern of neural activity was disrupted, resulting in abnormal feelings, emotions, behaviour, and loss of consciousness. Tumours are divided into two types:

A. *Benign Brain Tumour:*

The benign tumour has homogenous cell structure and does not include malignancy cells. They do not spread to other sections of the body. Benign tumours may engulf critical parts of the brain and create major health problems. Benign tumours may be removed and seldom come back.

B. *Malignant Brain Tumour*:

The cell structure of malignant brain tumours is heterogeneous. They are prone to proliferate quickly and plunder neighbouring healthy brain tissue. MRI is a sophisticated medical imaging method used to check many parts of the human body. When treating brain tumours, ankles, and feet, MRI imaging is employed. We can get precise anatomical information from these high-resolution pictures in order to evaluate the normal human brain and find anomalies. Fuzzy approaches, neural networks, atlas methods, knowledge-based techniques, and variation segmentation are some of the techniques used today to categorise MR images. T1 weighted, T2 weighted, and PD (proton density) weighted images are used in MRI.

There are additional varieties, but all tumours have the same symptoms, which vary based on the area of the brain afflicted. Headaches, convulsions, eye difficulties, vomiting, and mental disturbances are common symptoms.

A. *Magnetic Resonance Imaging (MRI):*

Anatomical and physiological processes in the body may be seen with MRI, a medical imaging method often employed in radiology. This kind of imaging is done using a combination of powerful magnetic fields, gradients of magnetic fields, and radio waves. MRIs do not employ X-rays or ionising radiation, unlike CT and PET scans, which do. There are several uses of nuclear magnetic resonance that may be employed in MRI, including NMR spectroscopy, which can also be used for imaging.

In hospitals and clinics, MRIs are often utilised for medical diagnosis, staging, and follow-up of diseases. MRI scans of soft-tissues, such as the brain or belly, are better contrasted than CT images. It is, however, more difficult for patients to feel at ease because of the lengthier and noisier measurements in a long, constrained tube. As a result, certain individuals may not be eligible for MRI testing because they have metal in their bodies that cannot be removed.

A flexible imaging method, MRI was first developed in the 1970s and 1980s. Mummies, for example, may be studied using MRI technology, which is most often used in medical diagnostics and scientific research. For example, functional MRI may be used to measure brain blood flow, whereas diffusion MRI can be used to track the movement of neurons. Growing demand for MRIs has led to questions regarding their cost effectiveness and over diagnosis within healthcare systems.

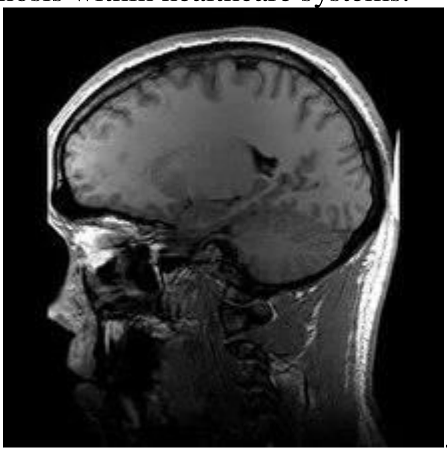.

Fig 1 MRI Image

B. *Histogram Equalization:*

The technique is effective in photographs with both bright and dark backgrounds. Improved x-ray views of bone structure and improved picture detail may both be achieved using this technique, according to the researchers. A fundamental feature of the approach is that it is a very simple methodology that is adaptable to the input picture and an inverted operator. A histogram equalisation algorithm may theoretically be used to recover a previously unknown histogram. In terms of processing power, this calculation isn't taxing. The method's indiscriminate nature is a drawback. Contrast between background noise and acceptable signal may be enhanced.

In scientific imaging, where spatial correlation is more significant than strength of signal (such as distinguishing DNA segments of quantized length), the modest signal to noise ratio often hinders visual identification.

However, it is highly effective for scientific pictures like thermal or satellite images or x-rays, typically the same class of images to which fake colour is applied. Histogram equalisation sometimes gives artificial effects in photos. On the other hand, applying histogram equalisation on photos with limited colour depth might result in undesired effects (such as an apparent visual gradient). Color depth (the amount of distinct shades of grey) is reduced even more if this technique is used on an 8-bit picture presented with an 8-bit gray-scale palette. Continuous data or 16-bit gray-scale pictures are most suited for histogram equalisation, since they have a colour depth much greater than the palette size. A histogram is a graphical representation of the intensity distribution of an image and Histogram equalization is a computer image processing technique and it spreading out most frequent intensity values to improved contrast of an image, better contrast is acquire from histogram of the image, after that using histogram equalization that permit low contrast area to gain higher contrast by stretching out the intensity range of the image. For create a histogram from an image, the (hist) function is used.

Any grayscale image can be viewed as a topographic surface where high intensity denotes peaks and hills while low intensity denotes valleys.

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You start filling every isolated valleys with different colored water. As the water rises, depending on the peaks nearby, water from different valleys, obviously with different colors will start to merge. To avoid that, you build barriers in the locations where water merges. You continue the work of filling water and building barriers until all the peaks are under water. Then the barriers you created gives you the segmentation result. This is the philosophy behind the watershed.

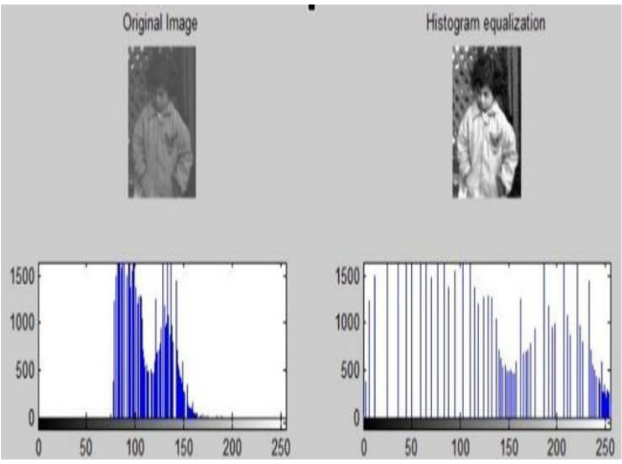

Fig 2 Histogram Equalization of an Image

C. *Water Shed Segmentation:*

A watershed segmentation is a transformation defined on a grayscale picture in image processing research. Symbolically, the term relates to a geological watershed that divides nearby drainage basins. Images are treated as a topographic map, with each point's brightness signifying its height, and lines are found along the crests of ridges.

It is possible to define a watershed in a number of ways. There are many ways to establish watershed lines in graphs: on nodes, on edges, or a mix of the two. The continuous domain may also be used to define watersheds. Watersheds may be calculated using a plethora of various methods. If you're looking to segment a picture, you'll most likely employ watershed techniques in your image processing. This makes it possible to count the items or do further analysis on the items that have been separated.

D. *Meyer's Flooding Algorithm:*

Several enhancements, generally known as Priority-Flood, have been made to F. Meyer's early 1990s watershed method. These upgrades include variations appropriate for datasets consisting of billions of pixels. The algorithm use a grayscale picture as its input. It is necessary to establish watersheds with contiguous catchment basins in order to flood the grey value relief repeatedly. The basins should appear at the boundaries of the gradient picture after this flooding operation. Typically, this results in an over-segmentation of the picture, particularly for noisy image data, such as medical CT data. Pre-processing the picture or merging the sections based on similarity criteria is required.

II. LITERATURE REVIEW

There is an article by Bagwig et al. that compares Fuzzy C-means, K-means and Hierarchical clustering formulas/algorithms for detecting cancerous cells in a brain tumour. They are evaluated on both DICOM and non-DICOM MRI brain images using these three clustering techniques. After extensive testing, it was determined that DICOM pictures outperformed computer images in terms of productivity (.jpg,.png,.bmp etc.). Hierarchical clustering takes less time to identify brain tumours than fuzzy c-means. K-means, on the other hand, is more accurate than fuzzy c-means and hierarchical clustering. Pre-processing pictures, extracting characteristics, and segmentation and classification are all necessary to fulfil the goal of detecting tumours in the brain. An image segmentation literature review is the goal of this section. The major objective is to demonstrate the benefits and drawbacks of different approaches. K-means, SVM, FCM, k-nearest neighbour, neural network, adaboost, genetic, and other image processing algorithms are used for brain MRI picture segmentation. For brain tumour detection, Amritpal singh and Parveen's approach is a blend of SVM and fuzzy c-means. Contrast enhancement

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and mid-range stretching are used to enhance this picture. Skull striping is accomplished by the use of morphological techniques and double thresholding. The picture segmentation is performed using Fuzzy c-means (FCM) clustering. The grey level run length matrix (GLRLM) is utilised to extract the feature. To categorise the MRI pictures of the brain, researchers used the Linear, Quadratic, and Polynomial SVM techniques. To distinguish between "tumour" and "non-tumor" MRI brain pictures, real data from 120 patients was analysed. The SVM classifier was trained on 96 MRI pictures of the brain, and then tested on the remaining 24 MRI images. 91.66 percent accuracy and 100 percent specificity are provided by SVM classifiers using linear, quadratic, and polynomial kernel functions, respectively. An excellent automated categorization approach for brain MRI using Adaboost machine learning has been suggested by Astina minz and Professor Chandrakant Mahobiya [8]. Features extraction, classification and preprocessing make up the proposed system's three main components.

Raw data noise is eliminated, RGB images are converted to grayscale, and median filtering and thresholding are used. GLCM retrieved 22 characteristics from an MRI. For classification increase (Adaboost). It's 89.90% accurate and results in normal brain or malignant or benign tumour. We can deal with quadratic and polynomial kernel functions later. By adding training database photos, the system's accuracy will improve. The technique works for Glioma and Meningioma.

Dr. M.A. Ansari and Garima Singh suggested Normalization of Histogram and K-means Segmentation. The supplied picture is pre-processed to eliminate undesirable signals or noise. To de-noise MRI pictures, Median, Adaptive, Averaging, Un-sharp masking, and Gaussian filters are utilised. Histogram of pre-processed picture is normalised and MRI is classified. The MRI picture is then segmented using K-means to remove the tumour. NB Classifier and SVM are used to predict and classify MRIs accurately. Naive Bayes and SVM Classifier are 87.23 and 91.49 percent accurate. Better classification accuracy using SVM. Implementation uses MATLAB. The suggested approach can't determine the tumor's exact border.

Future improvements to the method may be made by addressing its constraints and employing better morphological procedures to increase output picture quality.

G Rajesh Chandra and Dr. Kolasani Ramchandra Rao presented de-noising MRI brain images using DWT by thresholding wavelet coeff. A genetic algorithm detects cancer pixels. A genetic algorithm is then utilised to discover the optimal combination of retrieved data. The proposed methodology leverages k-Means clustering methods in Genetic Algorithms to guide the Evolutionary Algorithm in determining the best or sub-optimal data division. Based on ground truth, our technique segmented 82% to 97% of tumour pixels.

This work's wavelet transform requires enormous storage and considerable processing expense.

P.S. Mukambika, K.U. Rani Proposed Image Processing Methodology: Preprocessing, Segmentation, Feature Extraction, Classification. Morphology with double thresholding is used to eliminate the skull from MRI brain pictures. The current paper compares two approaches for MRI tumour detection. The Level set technique employs non-parametric deformable models with active contour to segment brain tumours from MRI images. The other is K-means. After segmentation, decisions are made in two stages: feature extraction using DWT and GLCM, and classification using SVM. Dataset of MRI brain tumour pictures comprises 17 benign and 24 malignant tumour images. SVM with Level Set and K-Means segmentation identify images as normal brain, benign, or malignant with 94.12% and 82.35 % accuracy. K-means segmentation is inferior to Level Set.

Sudharani, Sarma, Rasad Histogram, Re-sampling, K-NN Algorithm, Distance Matrix are proposed approaches. Histogram shows the total number of given pixels in a picture. Resize picture

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to 629x839 for accurate geometry. Brain tumour classification and detection using k-NN. Manhattan metric was used to determine classifier distance. The algorithm is Lab View-based. 48 pictures test algorithm. All photos are identified at 95%.

RaselAhmmed, Anirban Sen Swakshar, Md. Foisal Hossain, Md. AbdurRafiq suggested an approach including picture pre-processing, segmentation, feature extraction, SVM classification, and cancer stage classification using Artificial Neural Network (ANN). In preprocessing, three contrast enhancement approaches including adjusted, adaptive threshold, and histogram imaging employing weiner2 and median2 filter are used. Segmentation is done via TKFCM, which modifies K-means and Fuzzy c-means. Feature extraction is done twice. First order statistics and second order region-based statistics are obtained. The SVM classifies MRI brain images as normal or tumorous. Brain tumour stage is defined by ANN. The number of utilised data for each normal brain, malignant tumour, and benign tumour MRI picture is 39, including 3 normal, 9 benign, 17 malignant I, 6 malignant II, 3 malignant II, and 1 malignant IV stage brain MRI images. 97.44% accuracy of suggested approach.

Lu et al. (2019) use morphological filtering before watershed segmentation. This approach gives erroneous edge positions owing to inadequate pre-processing noise filtering. Hasan and Ahmad (2018) create a method using trilateral filter and median filter preprocessing. This graphic is used to partition watersheds. The authors propose pre-processing approaches may be employed to avoid excessive segmentation by watershed algorithm by decreasing picture texture detail. In addition, similar approaches may be used for noise removal with a median filter, picture sharpening with a gaussian high pass filter, and contrast enhancement. Sivakumar and Janakiraman (2020) suggest adopting ECED to improve segmentation accuracy. A high pass filter is required for the Enhanced Canny Edge Detector. A redesigned watershed segmentation improves accuracy and sensitivity. Dhage et al. (2015) suggest using a median filter for preprocessing. After that, watershed segmentation and CCL are used to find tumour areas. They also calculate algorithm parameters including Mean Square Error (MSE), PSNR, correlation, and contrast. These publications solely use watershed segmentation and a few pre-processing methods. The watershed method and threshold segmentation make tumour separation simpler and the system quicker. It pinpoints the tumour and its limits. However, this combination has downsides such excessive segmentation and high sensitivity to detailed textures in the picture, which may be handled by combining one or more pre-processing methods with other post-processing approaches to improve performance. Preprocessing and watershed segmentation are used in the literature. Tumor identification using the watershed method does not need post-processing, however some approaches may assist improve images and better portray the discovered tumour location. Morphological filtering segments MRI noise and magnetic field. These studies discuss the benefits of post-processing.

Tarhini and Shbib (2020) believe that MRI scans are favoured over CT scans for cancer identification because MRI can provide a more detailed picture of the body component and is better at catching tiny or hard to detect malignancies. There has been substantial study on combining diverse technologies to create automated systems that can recognise brain tumours early. Their suggested technique uses threshold and watershed segmentation to highlight tumours. Morphological operators improve picture quality in post-processing. Deep learning, machine learning, CNN, and image processing are used in these systems (Cui et al., 2009; Hore and Ziou, 2010; Mason et al., 2019). Khan et al. (2019) use a Gaussian filter to extend gamma. Tumour extraction uses watershed segmentation followed by MSER and HOG to extract features and remove unnecessary ones. Using Chi-square distance, features are chosen. Seere and Karibasappa (2020) combine contrast enhancement, median filter, and stationary wavelet to pre-process images. First, they do threshold segmentation, then watershed segmentation to group pixels of comparable brightness. They also employ Support Vector Machine (SVM) to categorise tumours post-segmentation. Shahin (2018) provides a rapid approach to find tumours. The sobel detector is used to get the input image's gradient. Next, the skull is stripped from the picture. Next, watershed segmentation is done. The research divides segmented area characteristics into geometry, texture, and gradient as post-processing procedures to examine and analyse the segmented area. The Top-hat filter reduces picture brightness. Jemimma and Vetharaj (2018) use DAPP as a post-segmentation approach. This approach employs a 55 mask with the central pixel value rotated 45°. This masked picture is twisted with a watershed image and pixel intensity is binarized. Decimal values may now be interpreted as texture intensity. Finally, tumour categorization is done using Convolutional Neural Network (CNN) with two layers, pooling and convolution. Mustaqeem et al. (2012) sharpen the picture using a median filter and a Gaussian high pass filter to find the tumour. Then, they use threshold and watershed segmentation to highlight the cancer. Morphological post-processing methods like erosion and dilation emphasise the cancer location. Oo and Khaing (2014) utilise a mix of pre- and post-processing. They start by filtering the picture to reduce noise then skull stripping to identify the tumour location. This is followed by watershed segmentation and morphological erosion. This procedure eliminates tumor-surrounding tissue to target the targeted area of the brain. It also shows the tumor's size. Sabarinathan, Dr. M. Poonguzhali, M. Pradeepkumar, S. Indhumalini, R. S. Kamalakannan (Bahadure et al., 2017) offer a method that transforms a picture to greyscale. A median filter then reduces picture noise. This pre-processing procedure is followed by watershed segmentation to pinpoint and emphasise the tumour region. The study uses morphological techniques to get a clear picture (Pambrun and Noumeir, 2015; Zhang et al., 2011; Zhao et al., 2006). A combination of pre- and post-processing approaches, watershed algorithm, and threshold segmentation may create a high-speed, low-complexity system to identify brain tumour from MRI image. The system may be reviewed and compared to comparable algorithms based on NAE, SSIM, and PSNR to produce standardised findings.

Brain tumour cells have high proteinaceous fluid density and intensity, hence watershed segmentation is excellent for classifying brain tumours and high intensity tissues. Watershed segmentation can recognise extremely minor intensity differences, whereas snake and level set cannot. Rahul Malhotra proposes a similar approach for tumour identification, although multi-parameter extraction isn't employed. Hossam and P Vasuda's approach for brain tumour identification and segmentation uses histogram thresholding, but it harvests too much brain. Rajeev Ratan, Sanjay Sharma, and S. K. Sharma created a brain tumour identification system that uses multi-parameter MRI analysis. The tumour cannot be segmented in 3D without a 3D MRI image data set. So, a simple technique for brain tumour identification is provided using marker-based watershed segmentation with improvements to minimise over & under segmentation. A picture is segmented by dividing it into similar-looking areas. The goal of many image processing applications is to extract essential characteristics from visual data so the computer can describe, analyse, or comprehend the scene. MRI brain tumour segmentation is vital yet time-consuming.

III.PROPOSED METHOD

The Meyer's flooding watershed method is proposed which comprises two stages: pre-processing, segmentation, and morphological operations. Steps of algorithm are as following:-

1) Give MRI image of brain as input.
2) Convert it to gray scale image.
3) Apply median filter to enhance the quality of image.
4) Compute threshold segmentation.
5) Compute watershed segmentation.

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6) Compute morphological operation.
7) Finally output will be a tumour region.

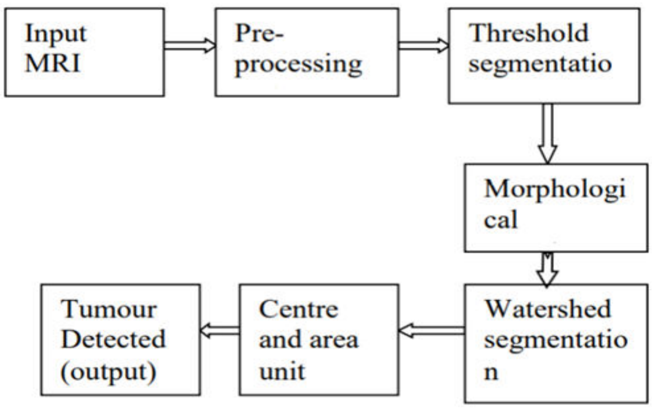

Fig 3 Block Diagram for Brain Tumour Extraction

It works on grayscale images. During the grey value relief floods, watersheds and catchment basins are built. The gradient picture is flooded, and basins should appear around the edges. This leads to over-segmentation of the picture, particularly with noisy CT data. Either the picture must be pre-processed or the areas must be combined by similarity.

Sets of markers and pixels are labelled to indicate where flooding should begin. Neighbouring pixels of each indicated region are injected into a right of way with a grey level matching to the pixel. The pixel with the greatest level is taken from the priority queue; extracted pixel and neighbouring pixel have the same label, thus all non-marked neighbours are placed into priority queue. Process continues till priority queue is empty. The unlabelled pixels represent watersheds.

It works on grayscale images. During the grey value relief floods, watersheds and catchment basins are built. This flooding operation is done on the gradient picture to create basins. This leads to over-segmentation of the picture, particularly for noisy data like medical CT. either the picture must be pre-processed or the areas must be combined by similarity.

IV. EXPERIMENTAL RESULTS

Histogram Equalization Results:

Histograms show frequency distribution. This is the foundation for many spatial domain processing algorithms. Enhancing images using histograms. Image contrast is the intensity difference between two things. When the contrast is too low, two things appear as one. Histogram equalisation is a frequently used contrast-enhancement method in image processing. It is a technique for manipulating an image's dynamic range and contrast by changing its intensity histogram.

Histogram equalisation generates fake effects in pictures, yet it's beneficial for scientific images like thermal, satellite, or x-ray images, the same class to which one would apply false colour. Histogram equalisation may cause unwanted effects (such apparent picture gradients) on low-color-depth photographs. Applied to an 8-bit picture using an 8-bit grayscale palette, it reduces the image's colour depth (number of distinct shades of grey). Histogram equalisation works well on continuous data or 16-bit grayscale photos with good colour depth.

A. *Histogram of Original MRI*

Fig 4 Depicts the initial MRI used to discover the patient's brain tumour. The strategy works on photographs with bright backgrounds and dark foregrounds. The approach may improve MRI pictures of brain tissue and over- or under-exposed images. The approach is a simple, adaptable methodology that uses an invertible operator. The original histogram may be restored if the equalisation function is known.

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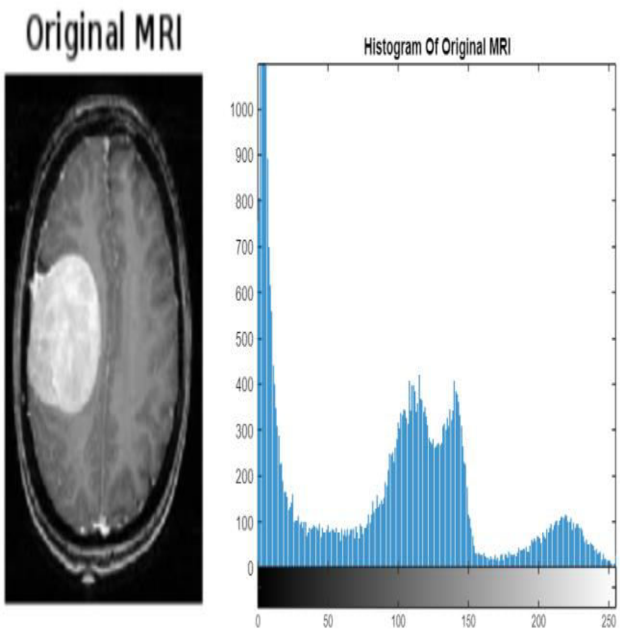

Fig 4 Histogram of Original MRI

B. *Histogram Equalization of Original MRI*

This strategy boosts the global contrast of multiple photos, particularly when the intensity range is limited. With this change, the histogram may use the complete range of intensities equitably. This helps low-contrast regions develop contrast. Histogram equalisation spreads out highly crowded intensity values to reduce picture contrast.

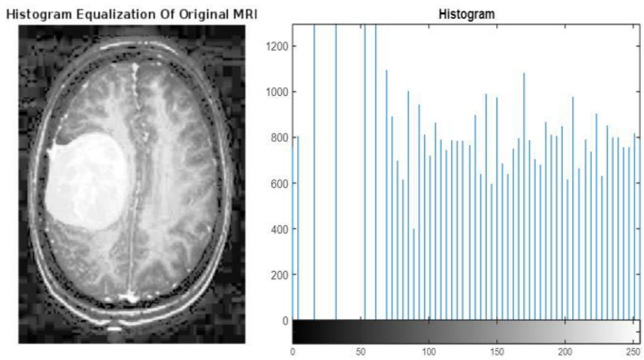

Fig 5 Histogram Equalization of Original MRI

Fig 5 illustrates the histogram equalisation of the original MRI utilised to identify the Brain Tumor. Histogram equalisation of the MRI raises the contrast levels of the image/MRI, which helps identify the tumour by removing noise in the original MRI. It displays brain tissue. Histogram equalisation is employed when there is distortion in the tumor-detection MRI signal. Comparing figures 4 and 5, the histograms are quite different. In figure 4, the original MRI histogram includes noise and distortions, which might induce erroneous brain tumour detection in rare circumstances. In Fig 5, the original MRI histogram is equalised. This approach works well with bright and dark backgrounds and foregrounds. This approach eliminates uncommon false instances while identifying a patient's tumour. This histogram equalisation is only used when MRI scan backgrounds and foregrounds are both bright and dark.

In figure 5, the histogram is improved when compared to the histogram in figure 4 because the contrast levels of the original MRI are improved, so the histogram is easily separated from the noises in figure 4. The sharpness of the original MRI is also increased when compared to figure 4.

C. *Thresholded Image*

Fig 6 Thresholded Image

Fig 6 displays the threshold MRI picture. This threshold picture separates object and background pixels for image processing. So brain tissues and the skull may be differentiated, making it apparent what they are. The simplest thresholding techniques replace each pixel in a picture with a black pixel if the image intensity is less than a predefined value called the threshold T. In the picture above, the dark

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buried tissues become black and the light brain tissues and skull become white.

This approach segments a picture into fine regions. As long as the background and object have grouped grey levels, we may utilise a method-defined threshold to threshold a grayscale picture.

Most segmentation uses thresholding. After determining a set of thresholds, the picture may be segmented by comparing levels of improved contrast.

D. *Objects in Cluster*

Cluster items are shown in Fig 7. It's used to find groupings of comparable things in multivariate data sets from marketing and medicine. In Fig. 7, all items of one sort, i.e. cancer cells, are made as one portion to readily locate the tumour's position in the skull. The corresponding object boundaries are produced for tumour identification in the bio-medical area using the input MRI.

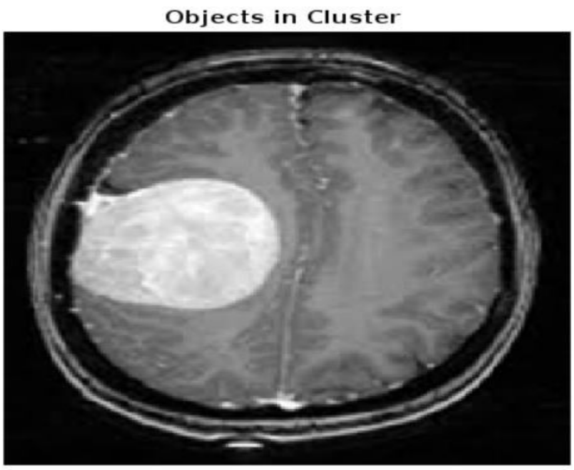

Fig 7 Objects in Cluster

E. *Segmented Tumour*

The segmented tumour shows the specific position of the items and their borders, allowing for easy analysis of the patient's condition and rapid removal of the tumour from the patient's skull. Assigning a label to each pixel in a picture such that pixels with the same label share attributes. In the graphic above, the borders show how the brain tumour cells are spread out. The segmentation of tumours helps locate neighbouring tumours in the body, measure tissue volumes, and plan surgery, virtual surgery, and intra surgery.

Fig 8 Segmented Tumour

F. Detection of Tumour through Watershed Algorithm

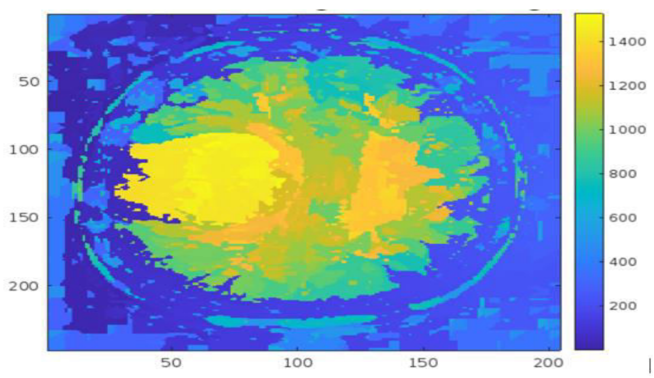

Fig 9 Detection of Tumour through Watershed Algorithm

Fig. 9 depicts the tumor's position. The tumour is light yellow. Other yellow areas indicate portions

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affected by pale yellow tumour cells. Blue indicates non-tumor tissues or cells. This method effectively diagnosed the brain tumor's location. This technique helps doctors distinguish cysts from brain tumours. In certain situations, MRI scans may reveal a brain tumour. This detector determines if a patient has a tumour to avert such occurrences.

1. Based on the findings, this method may be used to detect a tumour in an MRI. The code for MRI tumour detection is quite fast. This real-time programme will benefit radiologists and doctors.
2. Using watershed segmentation to identify and segment red blood cells provides a robust and efficient solution to under- and over-segmentation concerns.
3. The IoT-based weed detection system alerts farmers so they may take immediate action. It employs a CNN and watershed segmentation to identify weeds. Even if weeds and crops overlapped, it still had 91% accuracy.

V. CONCLUSIONS & FUTURE SCOPE

The goal of this work is to identify brain tumours using MRI scans. Image preprocessing, histogram equalisation, and watershed method extract tumour. Segmenting complex structures with varied attributes is difficult in picture segmentation. In this case, apply unsupervised edge detection algorithms. A strong segmentation algorithm is needed to analyse MRI images for better diagnosis and treatment of tumour patients. The brain tumour detection helps physicians, medical imaging, and companies. To better diagnosis and treatment of cancer patients, MRI images must be segmented correctly. Brain tumour identification is a boon for medical imaging and MRI imaging companies.

In the future, a database may be established to find patients with brain tumours. Sequential tumour photos may be used to create a graph of tumour growth. The provided work might need additional features if expanded. It would be helpful to link the system to hospital patient cloud storage. This app may be used on smartphones. If this software analyses all MRI scans of a patient and integrates the results, it may propose therapy and medicine

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