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Semantic Segmentation of Brain Tumor from MRI Images and SVM Classification using GLCM Features

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Abstract: Brain tumor is a critical disease caused by the growth of abnormal tissues in the brain, which can severely impact a patient's health. Early and accurate detection of brain tumors is essential to improve treatment outcomes and save lives. This project focuses on the semantic segmentation of brain tumors from MRI images, followed by classification using GLCM features and Support Vector Machine (SVM).
MRI images are first pre-processed using median filtering and skull stripping to enhance quality and remove non-brain regions. Thresholding and watershed segmentation techniques are then applied to accurately segment the tumor region from the brain. Once segmented, texture features such as contrast, correlation, and entropy are extracted using the Gray-Level Co-occurrence Matrix (GLCM) method in MATLAB. These features are then fed into an SVM classifier to determine whether the tumor is benign or malignant.
The proposed system achieves an average classification accuracy of 93.05%, which is higher than many conventional methods. This computer-aided diagnostic (CAD) approach enhances the speed, accuracy, and reliability of brain tumor detection, assisting radiologists in making effective clinical decisions.
Keyword: Brain tumor, MRI images, GLCM features and Support Vector Machine (SVM)., MATLAB Computer-Aided Diagnostic (CAD).

I. INTRODUCTIONS

This project proposes two different methodologies to segment a tumor from an MRI image and determine the type of tumor. For this, one segmentation and one clustering technique have been implemented. Each MRI image is passed through an imaging chain where the image is preprocessed to remove noise and is further enhanced to improve the contrast of the image. This paper proposes two different techniques which are then applied on the image to extract the tumor. These segmentation techniques include SOM Clustering and SVM Classification. Applying each of the segmentation techniques allows us to determine the most appropriate method to segment the tumor from each of the images. The tumor region represents the pixel values for the foreground points extracted using the ginput() command from a texture image. The texture image is generated by applying the rangefilt() method. In order to enhance the texture characteristics of the image, smoothing filter is applied to the texture image. In this project, the major challenge faced was to locate and extract the proper tumor region from the image. Due to several lighting issues, unnecessary white portions were present in the image which could wrongly be segmented as a tumor. Also, the unwanted noise and reduced contrast displays several regions from the image that are falsely claimed as a tumor. Another challenge faced was degraded quality of the MRI image due to several problems that would have occurred during the acquisition stage.

This becomes even more crucial if there is a medical emergency. Though cancer can be detected in human body through MRI images, the intensity of MR images and also the shape complexity of organs pose a threat to accurate detection. Also, during the diagnosis and treatment phase, the doctors are majorly interested in the problem area and not the entire human body. That is the reason that image segmentation comes into play. Segmentation subdivides the area of interest to provide a better and clear view of the organ or part under observation. It should be noted that segmentation is only a pretreatment step. The detection of cells or of structures interior to cells can be considered as an image segmentation problem within digital image analysis. Different algorithms can be employed to segment an image.

The algorithms discussed in this paper include Genetic Algorithm and Watershed Algorithm. Watershed algorithm uses multi-threshold values in CT images, interpreted on the basis of grey levels. Comprehensive methods take advantage of de-noising and gradient construction. The grey level of a pixel is interpreted as its altitude. Local minimum values are set. Intuitively, the watershed of a relief corresponds to the limits of the adjacent catchment basins of the drops of water.

Image processing is a developing and growing field in context to medical applications. Many methods have been developed and replaced with newer methods. So it becomes of prime importance to develop and select newer methods to suit the requirements of the current times and problem specifications. Likewise, 3D image analysis, reconstruction of the MRI slices, and accurate boundary detection are of prime importance. Softening of cells is a major problem in cancer, and various 3D orthogonal planes (sagittal, coronal, transverse) are acquired. Due to the shape of liver, its overlapping regions with lungs and heart and the artifacts of motion and pulsation, automatic liver segmentation is a difficult process. Also, the CT images show grayish values of range between 90-92 out of 0–255 for a normal cancer-free liver, but if there is cancer, then the images become darker and the range is also ambiguous.

It is felt that it’s high time to design and implement a quick, responsive, and exact calculative liver segmentation method for medical image analysis, which supports analyzing the benefits and problems of liver transplantation and the treatment method of liver cancers. Magnetic Resonance Imaging is a far better method than CT scan because it is free of ionizing radiation and provides better imaging of soft tissue structures.

Genetic Algorithm is a computing model that results from biological heredity and mutation processes in nature and manifests thoughts through selection, crossover, and mutation operators. Its main characteristics are the searching strategy and the exchange of information between individuals in a group. It is particularly appropriate for complex and nonlinear problems, especially those difficult to resolve using traditional methods. GA demonstrates its unique strength in combinatorial optimization, adaptive control, artificial life, and other advanced application areas.

In recent literature, several prevailing segmentation techniques such as Region Growing, Thresholding, Level Set, Statistical Modeling, Active Contour, Clustering Algorithms, Histogram-Based Approach, and Gray Level Analysis have been discussed. Each of these techniques has their pros and cons, and the selection depends on the application context. In one paper, segmentation was based on contourlet transform and watershed algorithm. It stated that a medical image usually contains a region of interest which holds the most diagnostic information. Due to irregular shapes of human organs, differences in imaging equipment, and noise, these images often have low resolution and poor contrast. The proposed algorithm in that study included three steps: contourlet transformation of the original image, watershed segmentation of the low-frequency image, and reconstruction using inverse contourlet transformation to enhance clarity. Such multi-step hybrid methods reinforce the importance of combining techniques for better medical image analysis.

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB stands for matrix laboratory, and was written originally to provide easy access to matrix software developed by LINPACK (linear system package) and EISPACK (Eigen system package) projects. MATLAB is therefore built on a foundation of sophisticated matrix software in which the basic element is array that does not require pre dimensioning which to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of time.

MATLAB features a family of applications specific solutions called toolboxes. Very important to most users of MATLAB, toolboxes allow learning and applying specialized technology. These are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control system, neural networks, fuzzy logic, wavelets, simulation and many others.

A. Problem Statement

The primary problem addressed in this project is the accurate detection and classification of brain tumors from MRI images. Manual identification is inefficient, inconsistent, and lacks reproducibility. It is vital to automate this process to reduce human error, save time, and assist radiologists in early and accurate diagnosis. Existing methods often struggle with low accuracy, are computationally expensive, or fail to generalize across different datasets.

This project aims to develop a technique that uses GLCM features for texture extraction and combines Watershed segmentation and SOM clustering for precise tumor boundary identification. The segmented region is then classified using SVM, ensuring improved accuracy and faster processing. The main goal is to replace manual procedures with a reliable, cost-effective, and automated diagnostic tool for real-time applications in medical settings.

B. Research Objectives

The objectives of the project are designed to achieve comprehensive and automated analysis of brain MRI images for tumor detection. These include:

- To acquire brain MRI images and perform preprocessing using filtering and skull stripping to remove non-relevant structures.
- To segment tumor regions using hybrid techniques like Watershed algorithm and SOM clustering for efficient tumor localization.
- To extract GLCM features such as contrast, correlation, entropy, and homogeneity from the segmented region to represent textural information.
- To classify the extracted features using Support Vector Machine (SVM) into benign or malignant tumor types.
- To improve accuracy and reduce false positive rates compared to conventional segmentation and classification techniques.
- To provide a MATLAB-based GUI tool that can be used by radiologists for assisting in real-time diagnostic procedures.
- To analyze performance metrics such as classification accuracy, processing time, and segmentation efficiency to validate the effectiveness of the proposed system.

II. LITERATURE SURVEY

Hala Al-Shamlan et al. (2010) proposed an image processing framework for detecting breast cancer tumors using feature extraction. Their two-step approach involved enhancing the contrast in mammogram images and performing segmentation to identify regions of interest. Although their study focused on breast cancer, the enhancement and segmentation methods laid a strong foundation for texture-based tumor identification.

Martins et al. (2009) introduced a technique for mass detection in mammograms using gray-level co-occurrence matrices (GLCM) and k-means clustering. Their work demonstrated that statistical texture features could successfully differentiate between benign and malignant regions. Classification using Support Vector Machines (SVMs) achieved an accuracy of 85%.

Vishnukumar K. Patel et al. (2012) enhanced mammogram images using Gabor filters and contrast optimization techniques. Their study highlighted the impact of filtering on tumor visibility and used Peak Signal-to-Noise Ratio (PSNR) to evaluate enhancement quality. This work demonstrated the importance of preprocessing and texture feature analysis for accurate segmentation.

I.Emmanouil et al. (2004) applied wavelet-based processing for mammogram enhancement. Using histogram equalization and Discrete Wavelet Transform (DWT), they improved the visibility of tumor regions with a 91% success rate, effectively distinguishing between healthy and tumorous tissues.

Sampaio et al. (2011) combined geostatistical features and convolutional neural networks (CNNs) for mass detection. Their approach used morphological shape descriptors like circularity and eccentricity to identify tumors and achieved high true positive rates with minimal false positives.

Sundaram et al. (2010) developed a histogram-based local contrast enhancement algorithm that preserved important image details while improving visibility. Their performance was validated using standard metrics like PSNR and entropy.

III. IMAGE PROCESSING

A. Digital Image Processing

Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human perception. However, unlike humans, who are limited to the visual band of the electromagnetic (EM) spectrum, imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate on images generated by sources that humans are not accustomed to associating with images. These include ultra-sound, electron microscopy, and computer-generated images. Thus, digital image processing encompasses a wide and varied field of applications. There is no general agreement among authors regarding where image processing stops and other related areas, such as image analysis and computer vision, start. Sometimes a distinction is made by defining image processing as a discipline in which both the input and output of a process are images.

We believe this to be a limiting and somewhat artificial boundary. For example, under this definition, even the trivial task of computing the average intensity of an image (which yields a single number) would not be considered an image processing operation. On the other hand, there are fields such as computer vision whose ultimate goal is to use computers to emulate human vision, including learning and being able to make inferences and take actions based on visual inputs. This area itself is a branch of artificial intelligence (AI) whose objective is to emulate human intelligence.

B. Images and Pictures

As we mentioned in the preface, human beings are predominantly visual creatures: we rely heavily on our vision to make sense of the world around us. We not only look at things to identify and classify them, but we can scan for differences, and obtain an overall rough feeling for a scene with a quick glance. Humans have evolved very precise visual skills: we can identify a face in an instant; we can differentiate colors; we can process a large amount of visual information very quickly.

However, the world is in constant motion: stare at something for long enough and it will change in some way. Even a large solid structure, like a building or a mountain, will change its appearance depending on the time of day (day or night); amount of sunlight (clear or cloudy), or various shadows falling upon it. We are concerned with single images: snapshots, if you like, of a visual scene. Although image processing can deal with changing scenes, we shall not discuss it in any detail in this text. For our purposes, an image is a single picture which represents something.

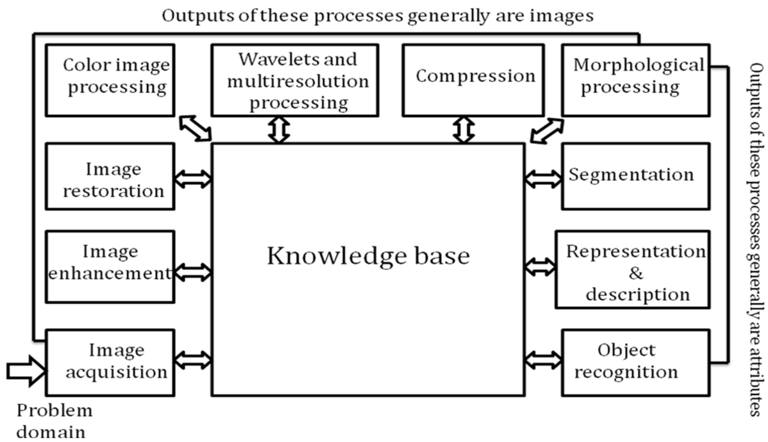

Figure 1: Fundamental steps in Digital Image Processing

Wavelets are the foundation for representing images in various degrees of resolution. Compression, as the name implies, deals with techniques for reducing the storage required to save an image, or the bandwidth required to transmit it. Although storage technology has improved significantly over the past decade, the same cannot be said for transmission capacity. This is true particularly in uses of the Internet, which are characterized by significant pictorial content. Image compression is familiar (perhapsinadvertently) to most users of computers in the form of image file extensions, such as the jpg file extension used in the JPEG (Joint Photographic Experts Group) image compression standard. Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region (i.e., the set of pixels separating one image region from another) or all the points in the region itself. In either case, converting the data to a form suitable for computer processing is necessary. The first decision that must be made is whether the data should be represented as a boundary or as a complete region. Boundary representation is appropriate when the focus is on external shape characteristics, such as corners and inflections. Regional representation is appropriate when the focus is on internal properties, such as texture or skeletal shape. In some applications, these representations complement each other. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing.

IV. PROPOSED METHOD

In this project, we have described our objective in two parts, the first half deals with detection of brain tumor that is the presence of the tumor in the provided MRI. The other part that is the second part contains the classification of the tumor. Here, we will analyze the MRI images which will conclude the stage of the tumor as benign or malignant. In general the diagram for our process MRI of Brain images This is the first step of our proposed project .In this the data is been provided that is the magnetic resonance images(MRI) that are been collected in their original format's

Images Enhancement and Filtering In this project image improvement that is the improvement of digital image quality with none of the data concerning the first supply image degradation. The enhancement of the image starts by first converting the gray scale image to black and white image this is done by the use of function im2bw(gray_image)[7]. Here the threshold value taken in our project is 0.6.As Image improvement strategies improve the visual look of pictures from tomography and also the distinction enhancing brain volumes are linearly associated. For image sharpening the imsharpen()[7] is been used,similiarly imadjust()[7] for image adjustment, freqz() for setting frequency response of image are been used.

1. MRI of Brain Images

↓

2. Pre-Processing

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3. Feature Extraction

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4. Segmentation Technique

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5. Image Analysis

The Gaussian smoothing operator is been for the two dimensional image convolution operators that is used to `blur' images and remove detail and noise. Gaussian is random incidence of white intensity worth and its intensity worth is drawn from Gaussian distribution, thus it is very much use to reduce Gaussian noise and as with linear filter it's computationally economical and enhances image quality with the image boundaries. for implementation of gaussian filter the imgaussfilt()[7] is been used in our project. Color areas,which indicate the colors in an exceedingly benchmark approach by employing a reference frame and a topological space within which every color is delineated by one point of the coordinate system. The colour spaces used in our image processing methods are Gray, Binary form and RGB.
in this project means the method of partitioning a picture to many segments however the most difficulties in segmenting are associated with degree of pictures and pictures is also non-inheritable within the continuous domain like on X-ray film, or in distinct house as in MRI. In 2-D distinct pictures, the placement of every activity is termed an element and in 3-D pictures, it's referred to as a voxel. For simplicity, typically we use the term ‘pixel’ to see each the 2-D and 3-D cases. When the constraint that regions be connected is removed, then determinant the sets referred to as pixel classification and also the sets themselves are called classes. Pixel classification instead of classical segmentation is usually a fascinating goal in medical pictures, significantly once disconnected regions happens to a similar tissue category ought to be known.

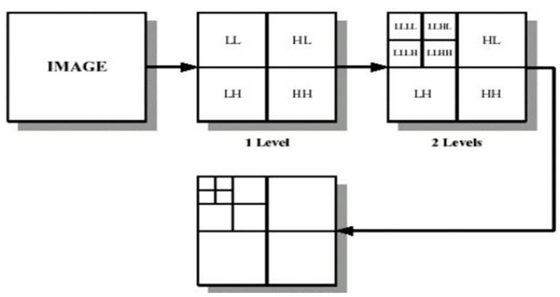

Figure 2: 2D IMAGE dwt operation

The foundations of the DWT go back to 1976 when Croiser, Esteban, and Galand devised a technique to decompose discrete time images. Crochiere, Weber, and Flanagan did a similar work on coding of speech images in the same year. They named their analysis scheme as sub-band coding. In 1983, Burt defined a technique very similar to sub band coding and named it pyramidal coding which is also known as multi resolution analysis. Later in 1989, Vetterli and Le Gall made some improvements to the sub band coding scheme, removing the existing redundancy in the pyramidal coding scheme. Sub band coding is explained below. A detailed coverage of the discrete wavelet transform and theory of multi resolution analysis can be found in a number of articles and books that are available on this topic, and it is beyond the scope of this tutorial.
After passing the image through a half band low pass filter, half of the samples can be eliminated according to the Nyquist’s rule, since the image now has a highest frequency of □/2 radians instead of □ radians. Simply discarding every other sample will subsample the image by two, and the image will then have half the number of points. The scale of the image is now doubled. Note that the low pass filtering removes the high frequency information, but leaves the scale unchanged. Only the sub sampling process changes the scale.

V. RESULTS AND DISCUSSIONS

Consider the brain MR image with tumor and edema shown in Fig 3 as an input image. The image is a gray level image of size 144x144 and of bmp format. Original gray level image is converted to pseudo image as shown in Fig 3 by using jet command. The output image obtained after applying jet command is a color image having size 144x144 and of bmp format.

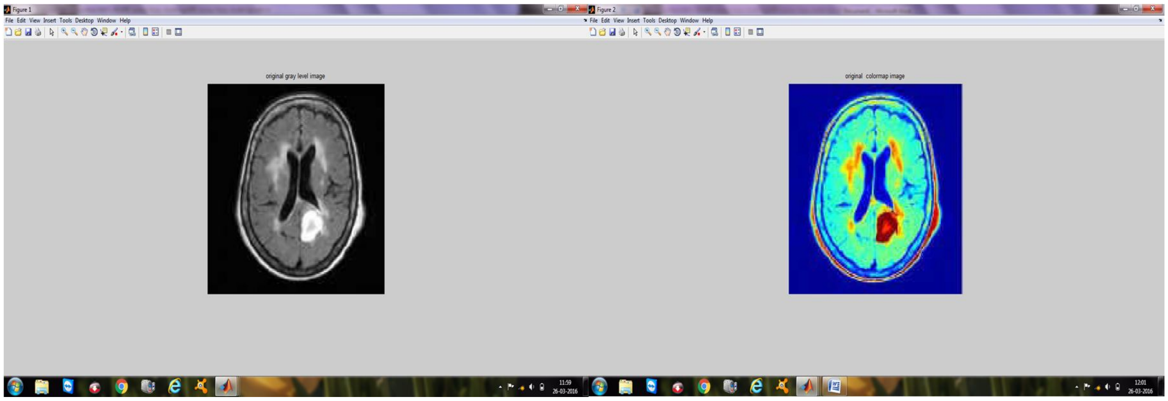

Figure 3:Gray level images and Original colormap image

The pseudo image is converted into color space translated image as shown in Fig 4 by using L,a,b true color tone correction. The output image now obtained is a color image of size 144x144 and of bmp format.

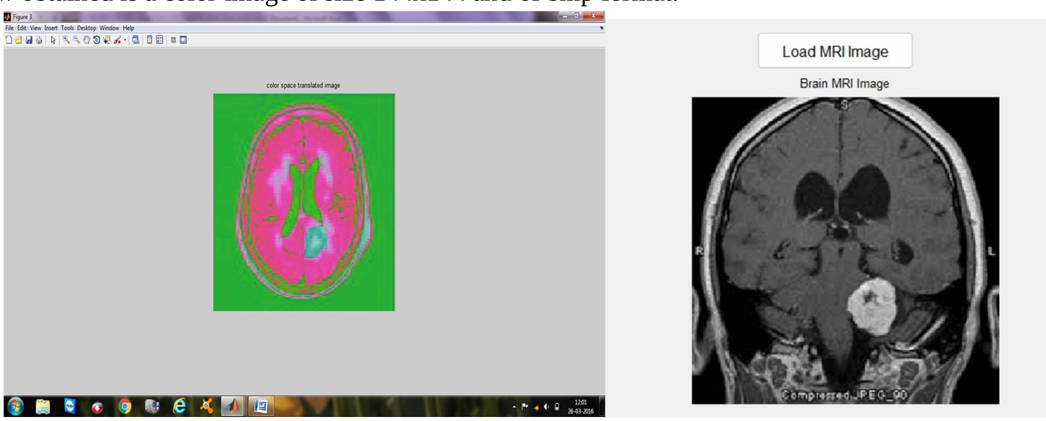

Figure 4: Color space translated image

k-mean clustering algorithm is applied to the color space translated image. In k-means clustering k represents the number of clusters .In this, the pixels in the image are divided into three clusters. The output thus obtained has three clusters (Black,White and grey) as shown in Fig 5 .The output image has a size of 144x144 and of bmp format.

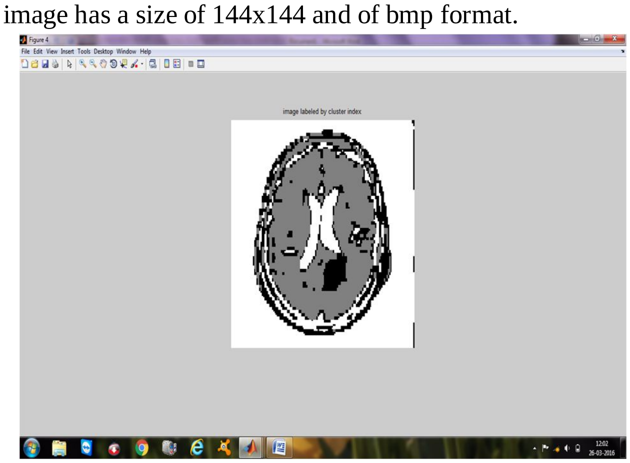

Figure 5: Image labelled by cluster index

Image representation of the first cluster image is represented as shown in Fig 6 and it also represents both tumor and edema areas with blue and red color spaces. Image representation of the second cluster image is represented as shown in Fig 6 and it also represents the non tumor area in brain. Image representation of the third cluster image is represented as shown in Fig 6 and it shows the celebral spinal fluid(CSF) in the brain.

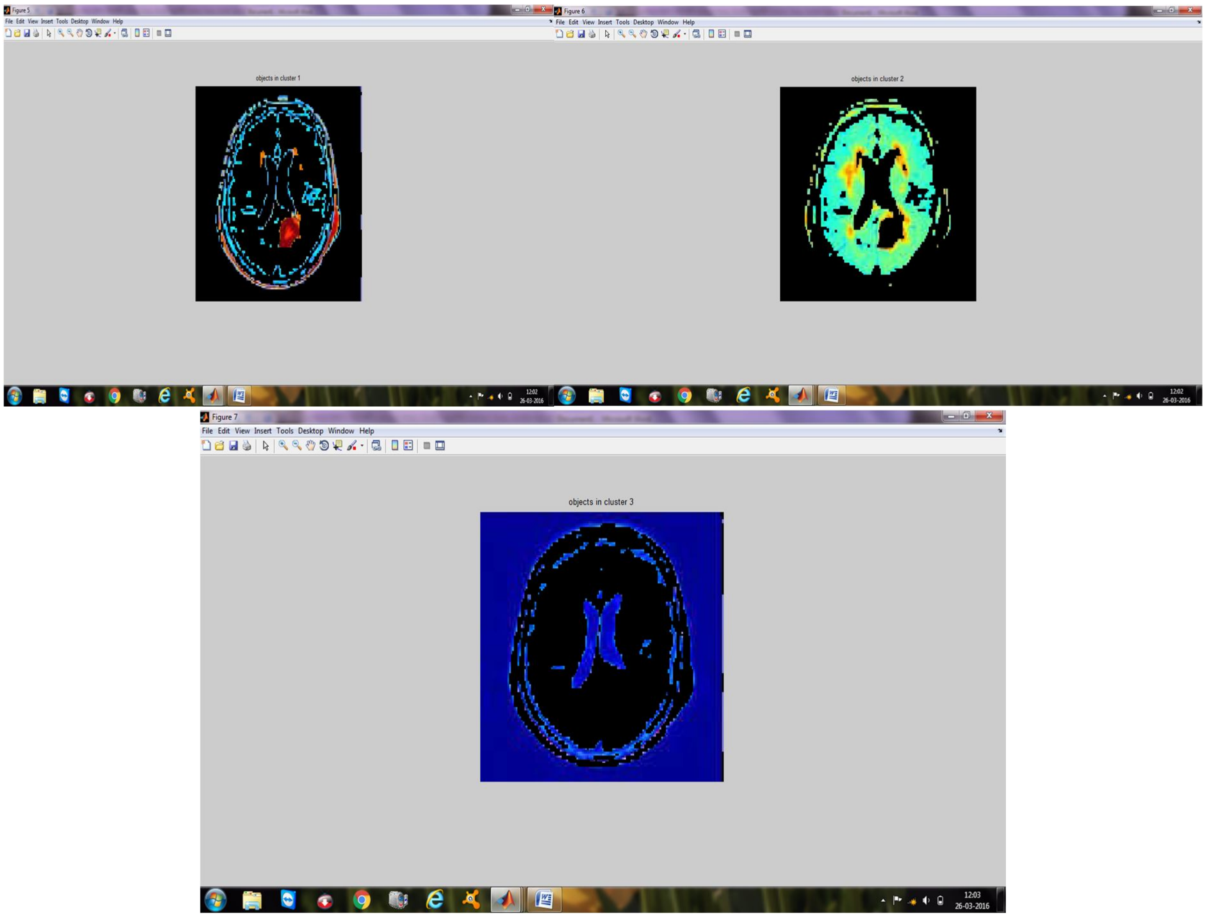

Figure 6: Objects in cluster 1,2,3

Once the clustering is done by using k-mean algorithm the tumor gets extracted from the brain as shown in Fig 7. Once the tumor gets extracted the area of tumor is calculated .The area of tumor is 4.1992

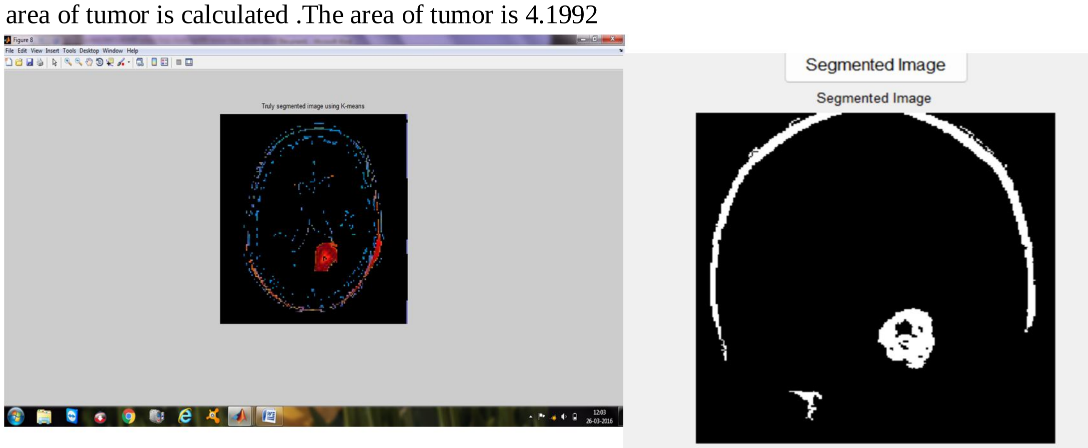

Figure 7: Truly segmented image using k-means

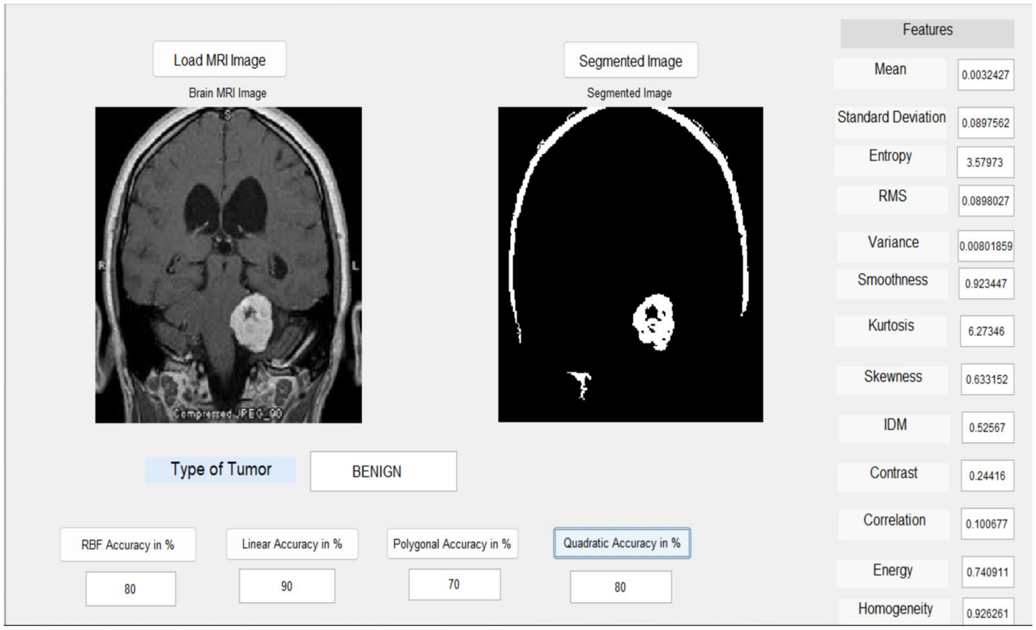

Figure 8: Benign Tumour Type Output

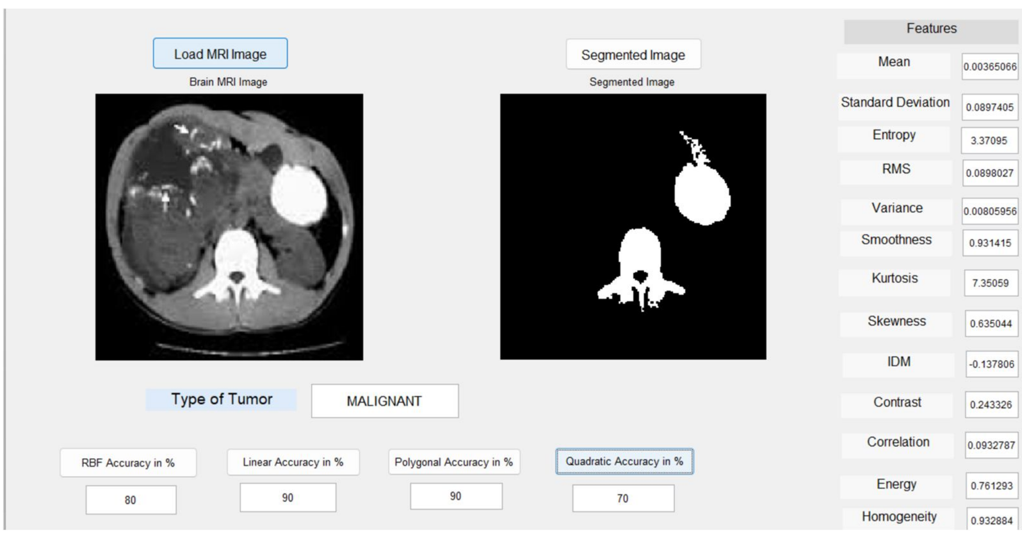

Figure 9: Malignant Tumour Type Output

A. Discussions and Output

This image showcases the Graphical User Interface (GUI) of a medical imaging system designed for brain tumor detection and classification from MRI scans. The interface integrates image visualization, tumor segmentation, feature extraction, and classification outputs.

Key Sections of the GUI:

- Load MRI Image Button:
- Allows the user to upload an MRI scan into the system for processing.
- Brain MRI Display (Left Panel):
- Shows the uploaded MRI image. A visible white mass indicates the potential tumor area. The file name suggests a compressed image format.
- Segmented Image (Middle Panel):
- Displays the result of segmentation—isolating the tumor from the rest of the brain tissue. White areas represent the tumor.
- Tumor Classification and Accuracy (Bottom Panel):

- Tumor Type: Labeled as "BENIGN", meaning non-cancerous.
- Accuracy Metrics: Performance of various classification models:
  - Linear: 90%
  - RBF (Radial Basis Function): 80%
  - Quadratic: 80%
  - Polygonal: 70%

- Feature Extraction Panel (Right Side):
- Lists various statistical and texture features extracted from the segmented tumor region, including:
  - Mean, Standard Deviation, Entropy, RMS, Variance
  - Smoothness, Kurtosis, Skewness, Contrast, Correlation
  - Energy, Homogeneity, IDM (Inverse Difference Moment)

Purpose and Usefulness:

This system:

- Automates tumor segmentation and analysis from brain MRI images
- Classifies tumors using machine learning models
- Displays diagnostic accuracy, aiding radiologists and clinicians in medical decision-making

VI. CONCLUSIONS

There are many different kinds of tumours that might be discovered in today's world. There is a possibility that the tumours are malignant across the whole brain, or they might be a mass inside the brain. Take into consideration the following scenario: If there is a mass, then the K-means approach is enough to extract it from the brain cells. It is necessary to remove any noise that could be present in the MR image before the K-means approach is carried out. While the tumour is being excised from the MRI scan, the noise-free image is being supplied as an input to the k-means algorithm. This occurs simultaneously. In the next stage, the cancer will be segmented using fuzzy C means in order to properly extract the shape of the malignant tumour. After that, the output of the feature extraction process will be thresholded. In the next stage, an approximation of the reasoning that underlies the calculation of the position and shape of the tumour will be performed. The results of the experiment are compared to the results of other algorithms in order to draw further conclusions. In order to get more precise outcomes, the approach that has been proposed is used. Using 3D slicers in conjunction with MATLAB, it will be feasible in the not-too-distant future to produce a three-dimensional study of the brain.

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