Convolutional Neural Network System for Brain Tumor Detection

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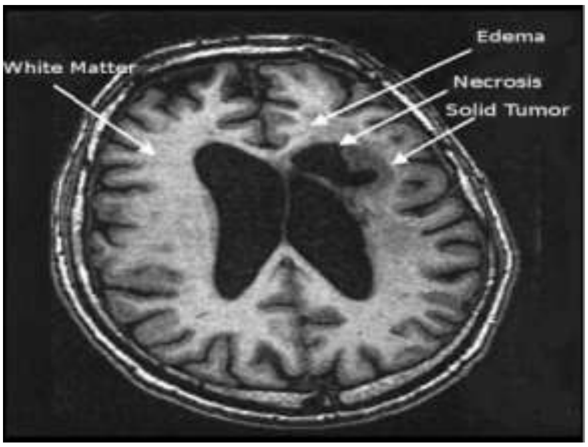
Abstract
Inspects and makes sense of the processes and methods utilized in brain or cerebrum cancer recognition relying upon attractive magnetic resonance imaging (MRI) analysis segmentation Convolution Neural Network (CNN) Framework techniques, which were directed in the various processes of the Computer Aided Detection Framework (computer aided design) after the image information (MRI)were collected. After the MRI image analysis have been upgraded all through the pre-processing and post-processing stages and have been made more manageable to analysis, an edge is applied to the images to segment them using the applied mean gray level strategy. The statistical features analysis was used in the second stage to extort properties from images. These properties were created from conditions of Haralick's elements in view of the spatial gray level dependence matrix (SGLD) of images. Then, at that point, the elements that were picked on the grounds that they were suitable and the best ones to use to identify where the tumor was found. In the third step of the process, the Artificial intelligence methodology that was planned with supervised learning was applied as an automated way for arranging the images that were under investigation as either having tumor or not having tumor. Performance of the network were tested and reviewed with success, and they reached the best possible outcomes.
Keyword: Brain tumor, MRI image, Texture Analysis, Haralick features extraction, Convolution Neural Network System

1. Introduction

One of the most well-known and widespread types of brain illnesses is cancer, namely tumors. According to statistics provided by the World Health Organization (WHO), more than four lakhs people around the world are diagnosed with tumors every year. Therefore, diagnosis and treatment are extremely crucial. Recent advances in therapeutic imaging techniques have made it possible to apply them in a limited number of medical specialties. These specialties include computer-assisted diagnosis of diseases, surgical planning and guidance, and longitudinal study. The unusual and unconstrained development of cells in the brain is named a cerebrum cancer or brain tumor, and there are two sorts of mind growths: benign and malignant. Among all of the helpful imaging modalities, mind cancers or brain tumor are the most well-known. Brain disease is a broader term for dangerous cancers in the cerebrum or brain. As a rule, the development pace of harmless growths is significantly lower than that of dangerous cancers [1]. The National Brain Tumor Establishment (NBTF), which funds research in the US, appraises that every year in the US, 29,000 individuals in the nation are determined to have essential cerebrum cancers or brain tumor, and north of 13,000 individuals die because of these cancers. Each year, more than 4,200 people in the UK are given the diagnosis of having a brain tumor (2007 estimates). There are around 200 different kinds of tumors that are detected every year in the UK. [2] There are a total of 80,271 people in India who are afflicted with various forms of cancer (2007 estimates). [3] The diagnosis and therapy are both determined by a number of different aspects, such as the kind of tumor, its size, its location, and how far along it is in its development. According to research, a significant number of persons whose lives are affected by brain tumors do not survive due to erroneous diagnosis [4]. Due to the heterogeneous nature of the tumor and the difficulty in determining its boundaries, it is imperative that a precise diagnosis be made in order to facilitate prompt and effective treatment. In the event that the tumor is recognized at a beginning phase, the irregularities can be shared with, and unexpected issues can be



stayed away from. Since it can create more detailed images, magnetic resonance imaging (MRI) analysis segmentation is presently perhaps the best innovation that can analyze brain tumor growths. Automatic detection in magnetic resonance imaging (MRI)can be exceptionally useful in an assortment of diagnosis and medicinal applications [5, 6], [23]. T1-weighted, T2-weighted, and PD-weighted images are the three essential kinds of MR images that are usually utilized. The utilization of automated strategies like computer aided design frameworks and Artificial neural network system, the two of which are subject to digital image processing learning and involved separating images, segmentation, and component extraction, was carried out to make radiologist analyze more precise. [7].The most common way of addressing a crude image in its diminished structure to work with independent direction and exercises like example arrangement is known as feature extraction. Feature extraction can be considered a procedure or technique that is utilized to quantify the various qualities of image segments. A group of characteristics like these can be utilized to describe each divided portion of a scene. The Spatial Gray Level dependence matrix(SGLD) generator is a texture analysis approach that was utilized in this work. This approach dissolves the input image into texture characteristics (Haralick's features). [11]. An Artificial neural network is major areas of strength for a data model that is efficient for catching and representing complicated input/output connections [8]. Acknowledged major surgery or clinical treatment requires detailed data about the edge of the tumor. Furthermore, it offers a powerful tool that can help clinical experts in inspecting, designing, and in any case sorting out clinical information across a wide range of clinical image applications. The vast majority of applications for ANNs and CNNs in medical application are categorizing issues, like pattern recognition. This implies that the current goal is to assign the patient to one of a limited number of classes centered on the measured features of the patient. [9][10]. The back propagation network, which is one of the kinds of artificial neural network learning system, was used in this study. After the network has been created, the training processing will begin. This will be done via transfer functions, which will utilize a training algorithm to produce a layer's result on its net input. Back propagation network training utilizes supervised learning, which is the ideal strategy for simples that incorporate non-level changes like sigmoid transfer function approach [12]. Back propagation network model is of the supervised learning system. Imaging procedures like computed tomography (CT) and magnetic resonance imaging are the ones that are applied in the field of neurosurgery and neuroscience the most frequently. A significant work that should be finished is the segmentation of items, basically physical or anatomical designs and diseases, from MR images. This is because the results of this task frequently contribute the basis for a variety of applications. Depending on the particular application and image modality being used, there is a wide scope of various procedures that can be used to do segmentation. In addition, the segmentation of medical images is a challenging work because these images typically contain a considerable quantity of data, as well as occasionally a few artefacts due to the limited acquisition time of the patient and the delicate tissue boundaries, which are typically not clearly defined. When dealing with brain tumors, a number of various difficulties can occur, which makes it challenging to segment them? There is a huge class of tumor forms, each of which can take on a variety of configurations with regard to size and shape. It is possible for it to appear in any location and in a variety of image intensities. Some of them cause the surrounding structures to become deformed, and others may be related to edoema, which causes alterations in the image intensity around the tumor. In addition, the fact that there are multiple MR acquisition procedures provides a variety of information regarding the human brain. In most cases, the focus of each image is directed at a particular area of the tumor. It is challenging to implement automatic segmentation that uses previous models or that makes use of previous knowledge. With regards to the exploration of tumor growths and the treatment of them, the exact segmentation of the inside designs of the cerebrum or brain is a source of considerable excitement. It works on lowering the mortality rate as well as improving the effectiveness of surgical or radio therapeutic procedures used to treat malignancies. In the field of mind oncology, it is also preferable to have a suggestive human cerebrum or brain model that can arrange the data about tumors that is recovered from MRI and CT filters. This information includes localization, type, shape, functional positioning, and influence on other brain structures. In spite of the many efforts that have been made and the encouraging outcomes that have been produced in the field of medical imaging, accurate and reproducible segmentation as well as the characterization of anomalies are still challenging jobs. The currently available methods have a great amount of room for improvement in terms of automation, applicability, and correctness.

2. Literature Review

The following is a brief review of the various pieces of literature that were researched and reviewed in relation to the progressive collapse of the building structures. The segmentation of the region of interest from an object, as well as the tumor from an MRI, is one of the tasks that is both one of the most difficult and one of the most demanding. The brain image project is quite ambitious. The use of a model that is based on neural networks has been increasingly common in recent years due to the increasingly accurate results that can be obtained through this technique. Havier et al., (2017) [13] provided a delineation of cerebrum or brain tumor segmentation by applying artificial neural network to MRI images of glioblastomas with both low and high grades. This specific variety of cerebrum growth or brain tumor can have created in any part of the brain, and it can likewise be of any structure, size, or difference. A utilization of the AI learning algorithm known as the convolutional neural network is displayed in this article. With the end goal of tumor segmentation, it utilizes both local and global features. For research purposes, the author utilizes the BRATS dataset. According to Ism et al (2016).'s [14] discussion, one of the most difficult challenges in the area of medicine is the segmentation of brain tumors. A quicker diagnosis of a brain tumor increases the likelihood that the patient will live longer. The manual segmentation of vast amounts of data for brain tumors is a process that takes a lot of time. As a result, there is a requirement for the use of automatic segmentation. Nowadays; techniques for deep learning are utilized in automated segmentation instead of traditional strategies. It can convey powerful segmentation for a critical volume of MRI-based image information. The paper offered a basic investigation of the most cutting-edge ways to deal with deep learning. The standard automated segmentation approaches either expect earlier information into probabilistic maps or the choice of exceptionally representative features for classifiers, the two of which are hard task. Although, the convolutional neural network technique naturally learns the relevant complex properties for both solid brain tissues and malignant tissues utilizing multimodal MRI cerebrum or brain images as the information source. A segmentation technique was proposed by Hussain et al., (2017) [15] in order to identify gliomas as a type of brain tumor. To find the tumor, which has an unpredictable shape, this strategy utilizes a convolutional neural network method for brain tumor. In this way, appropriate segmentation of the cerebrum growth or brain tumor results in an expanded possibility of the patient enduring the diseases. Through the execution of max-out and drop-out layers in the patch processing, the issue of overfitting can be settled. The proposed procedure also utilizes a pretreatment technique to get rid of the undesirable noise, and it utilizes post processing to get rid of the finite number of false misleading by utilizing morphological operators. Convolutional neural networks were suggested by Wang et al., (2017) [16] as having the best cutting edge presentation for automated clinical image segmentation [22]. Yet, it doesn't create powerful outcomes for clinical usage. It is not feasible to derive object classes that have not been encountered before, which is one of its constraints. By integrating CNN into bounding boxes and scribble- based supervised pipelines, an interesting deep learning-based intelligent segmentation system has been developed, which considers the issue to be fixed. The recommended strategy makes the CNN model versatile to a specific test image, which could conceivably be directed. Khawaldeh et al., (2018) [17] presented a widely used machine learning method for the categorization and segmentation of medical images. This method classifies brain medical images using a convolutional neural network to distinguish between healthy and diseased brain images. The brain tumor is sorted into low grades and high grades as per the method that was carried out. To order the MRI of the brain tumor, it utilizes the Alex krizhevsky network deep learning design. Rather than focusing on individual pixels, the whole image is breaking down to analyses the tumor growth. Segmentation of brain lesions, which is a difficult process, was accomplished with the help of a three-dimensional convolutional neural network, as described in Konstantinos et al (2017).'s [18] research. For the purpose of extracting local as well as broader contextual information, the dual route architecture was utilized. This architecture operates on an input image at several scales. The use of a three-dimensional totally associated conditional arbitrary field allowed for false consideration. The method of segmentation was used to separate between lesion on multichannel MRIs that were brought by traumatic brain tumor injuries, mind cancers, and ischemic strokes. The three-layered convolutional neural network (three dimensional (CNN) is an efficient technique that offers great segmentation without expanding how much handling effort required or the quantity of preparing boundaries. In recent decades, numerous strategies for automatically dividing up MRI scans of brain tumors have been developed and applied. These strategies can be basically separated into two classifications: the first is hand-created features, and the second is classifier techniques in view of traditional learning, for example, support vector machine (SVM) and random forest learning techniques. Both of these categories are subdivided further into individual subcategories. The subsequent methodology is an absolutely automatic technique that utilizes the Convolutional Neural Network and depends on the idea of deep learning (CNN).The first category technique employs the usage of manually separated characteristics, which are then sent to classifiers as input. after the identification of hand created characteristics. During the training process, the classifiers do not alter the features in any way. Nonetheless, in the subsequent classification, the elements and models can be altered to do a specific task including preparing information. Deep convolutional neural network CNNs are currently used within the computer vision community.

3. **Methodology**

The unusual growth of cells inside the brain is known as a cerebrum growth or brain tumor. The most common kinds of tumors are those that are benign and those that are malignant. Primary tumors are distinguished from secondary tumors by their location on the body. Primary tumors originate in the brain, while secondary tumors travel to other parts of the body after the primary tumor has already spread. Imaging methods utilized in medical science involve X-radiation, magnetic resonance imaging (MRI) analysis segmentation, and numerous others (Magnetic Resonance Imaging).MRI brain scans, as a result of the instrument's high resolution and generally high image quality. It is critical to remove the tumor growths from the MRI brain image once the image has been caught utilizing a MRI on the brain. When planning radiation, it is helpful for the radiologist to have medical images that have been accurately segmented. It is essential to segment tumors from brain imaging in order to provide additional diagnostic. This is because of the intricate structure of the brain tissues, which makes it difficult to see. In addition, it can be challenging to execute a precise demarcation when performing radiation. Because of this, it is imperative that throughout therapy no damage is done to the areas that are responsible for linguistic, motor, or sensory function. The manual segmentation of brain tumors requires a significant amount of effort, and the results of this segmentation are dependent on the experience of the operator as well as their own subjective decision making. As a result, there is a requirement for methods of segmentation that is entirely automatic, objective, and reproducible. Because of the extensive variety of brain tumor regarding size, shape, consistency, area, and their heterogeneous appearance, there are numerous obstacles and completely automated calculations for the segmentation of cerebrum growths. Brain tumors can take on many different forms. The approaches that were proposed to be employed for this study (figure 1) and ended up being used are summarized here in three stages: The first stage in the process is the preparation of the MRI images. In the subsequent stage, images are subjected to post-processing methods like segmentation, morphological activities, feature extraction, etc. The last stage includes the execution of the elements of images for design identification in order to distinguish tumor.

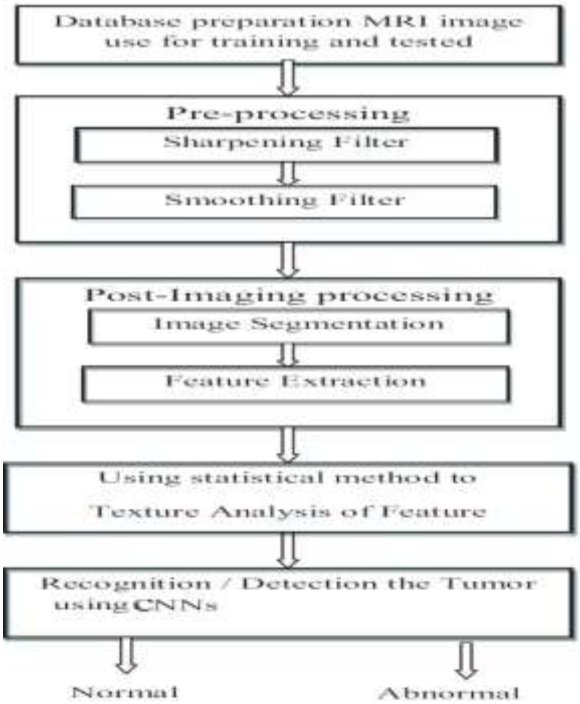


Figure 1: Flow chart of proposed method

A. Data Base

In the system that was presented, a digital magnetic resonance image database was used. The images in this database came from a medical college as well as other places. Because there are no major changes seen in the image pattern after the age of 18, the MRI brain scans were acquired from people whose ages ranged from 18 to 20 years old. Images of both male and female subjects are remembered for the information base. Each image contained in this information base has a goal of 256 pixels on each side and uses an 8-digit grayscale.

B. Preprocessing Steps

During the preprocessing phases, filters that sharpen and smooth the image are applied. A sharpening filter can be applied to an image in order to enhance its already-existing sharpness, bring out its finer details, or bring out details that had previously been obscured by blurring. The Smoothing Filter is an instrument that can be utilized to get rid of or lessen the noise.

C. Image Segmentation

In most cases, the segmentation of intensity images is accomplished by the utilization of the following five primary methods: a) threshold, b) border detection, c) region-based processing, d) pixel intensity, and e) morphological methods.
When doing segmentation based on morphological watersheds, it is common to run into the problem of excess segmentation. This is especially true if the image is degraded by a variety of different types of sounds throughout the transmission and storage times.
During the post-processing step, which utilized the limit way to deal with split the gray level of the MRI image into a binary image, the tumor was represented by grey level 1, while the backdrop was represented by 0 as equation 1.

$$f_s(x,y) = \begin{cases} 255 \rightarrow f_{(x,y)} \geq Z \\ 0 \rightarrow f_{(x,y)} < Z \end{cases} \qquad (1)$$

Where $f_{(x,y)}$ = gray level of MRI image, Z= threshold value and $f_s(x,y)$= thresholding image or binary image.

D. Feature Extraction

The process of extracting features requires streamlining the number of resources used to correctly define a large data set. When conducting research on intricate data, one of the most significant challenges comes from the large number of variables that are involved. Exploration with a greater number of variables typically requires a greater amount of memory and computing capacity, or else a stratification approach that is tailored to the training sample but simplifies to new samples poorly.

E. Convolution Neural Network

In challenges involving pattern and image recognition, a convolution neural network, also known as a CNN, is utilized because, in comparison to other methods, it possesses a number of benefits. In this white paper, the fundamentals of CNNs are broken down, providing an explanation of the several layers that can be applied. A convolutional neural network, often known as a CNN, is comprised of a ranking of units that incorporates a pooling layer, a non-linear layer, and a convolution layer. Deep convolutional neural network (CNNs), which recently have consisted of the request for ten or so such units and have been prepared on huge labeled datasets, for example, ImageNet, have yielded common features that are relevant in various identification task varying from image grouping to matter detection to semantic segmentation to texture identification. These generic features have been useful in recent times. Deep learning, in its most essential structure, is made out of three layers: the convolutional layer, the activation layer, and the pooling layer. Different layers incorporate the information layer as well as the totally linked layer. Layering is the standard method for convolutional neural networks. Layers are built out of various 'nodes' that are interconnected with each other and have a 'activation function' design are conveyed to the network through the 'input layer,' which then, at that point, convey with at least one 'hidden layers (the 3 levels),' which are the places at which the real processing is carried out using a network of weighted 'associations.' Later, the hidden layers' attach with what is known as a "output layer" or "completely connected layer," which is where the solution is display.The idea of "simple" and "complex" cells, which, in a progressive layer-wise association scheme, can be utilized to develop complex, non-level features extractors, is one of the properties of CNNs. Receptive fields are another properties of CNNs, and they are responsible for the extraction of local features. In addition, the idea of weight sharing has the effect of dramatically reducing the number of free parameters in the CNN. As a result, this improves conversions, decreases the amount of time needed for computing, and raises the capacity for generalization. There has been a significant development in terms of the CNN method that has been accomplished. The CNN architecture developed by LeCun et al. was presented, and they trained it using the Back Propagation algorithm. Utilizing this system, the features to be removed are not chosen "physically," but instead consequently by the calculation, which learns them by minimizing the provided global error function. The way that the CNN needn't bother with to be prepared layer-by-layer is one more benefit of this model. Instead, all of the boundaries are revised at each training iteration, which makes it possible to use the modelonline. This is particularly useful in situations in which not all of the training data is available right away.

3.Results and Analysis

3.1 Effects of Haralick's Features:

After you have determined Haralick's features in general, plot the qualities curve to each. This will permit you to pick the best boundaries, which have great execution and give the actual outcome for identifying tumor, as shown in figures 1 through 15.

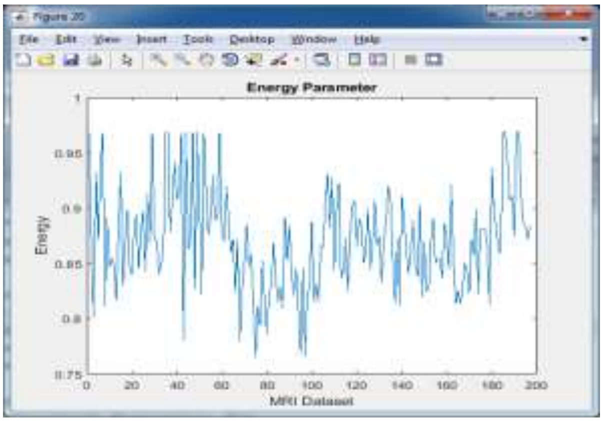


Figure 2: Energy's feature

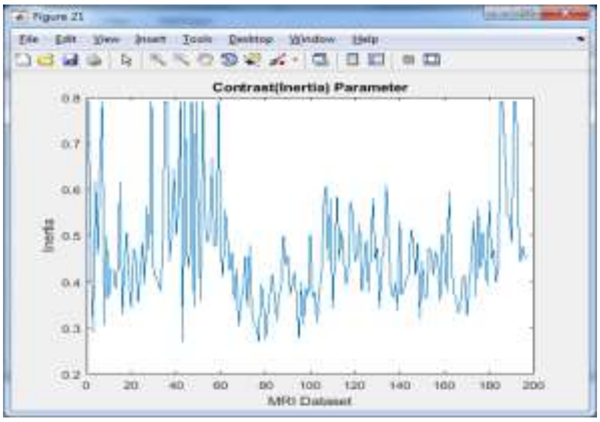


Figure 3: Contrast Parameter

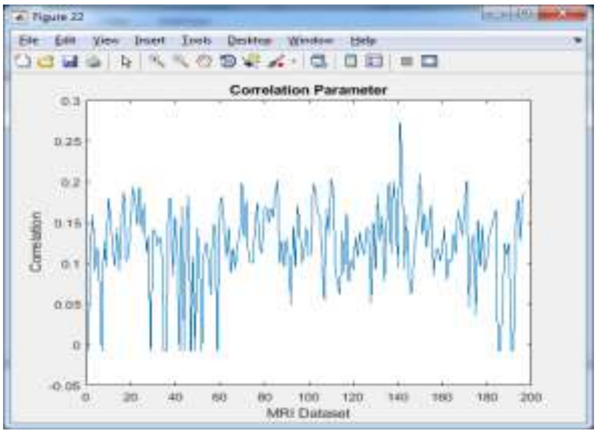


Figure 4: Correlation Parameter

The results of the experiments that were conducted using the suggested technique are presented in this part of the discussion. For the purpose of evaluating the anticipated improved neural network and watershed algorithm based tumor segmentation, the MRI image dataset that was made available on dataset was utilized.

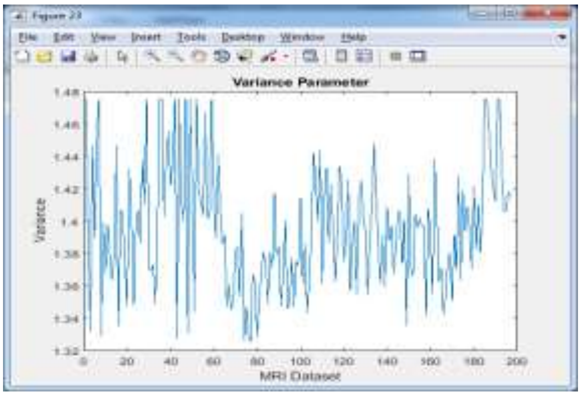


Figure 5: Variance Parameter

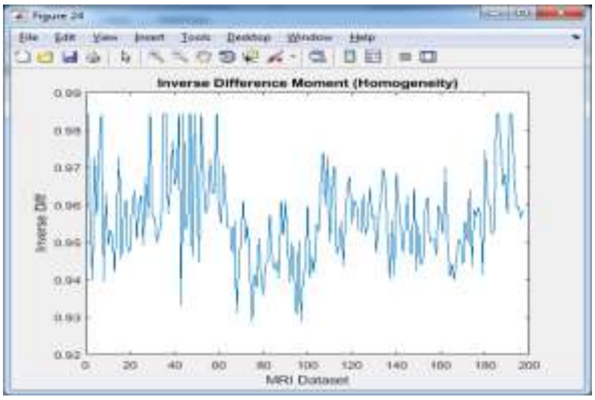


Figure 6: Inverse Difference Moments

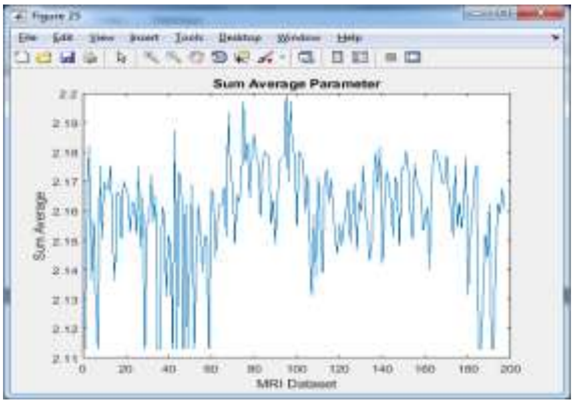


Figure 7: Sum Average Parameter

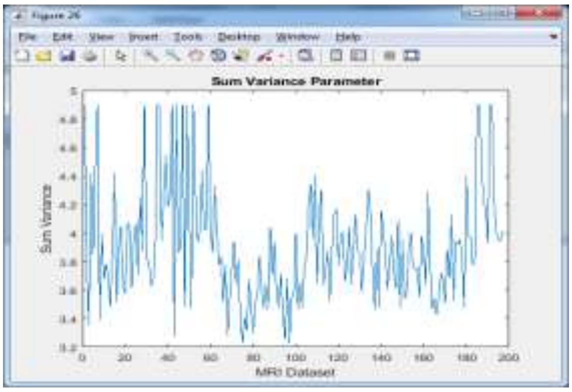


Figure 8: Sum Variance Parameter

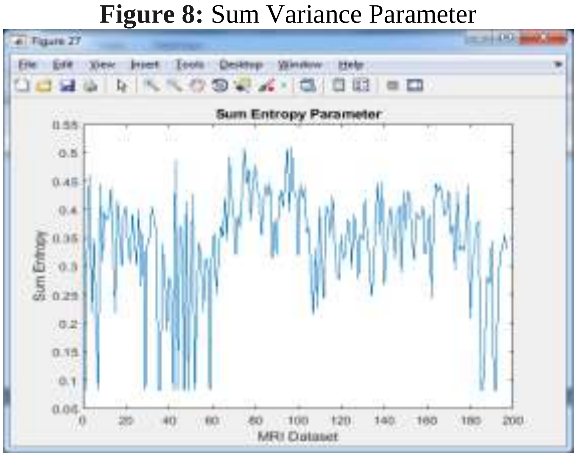


Figure 9: Sum Entropy Parameter

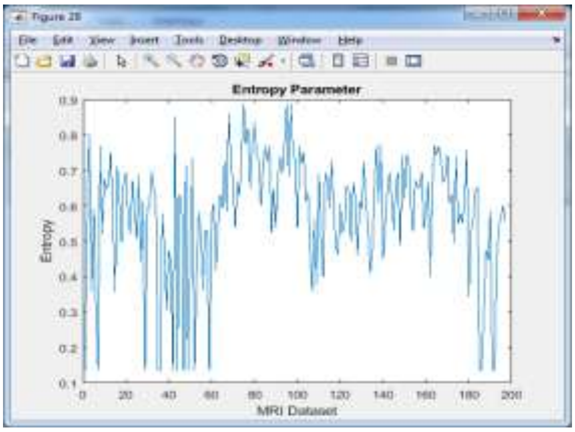


Figure 10: Entropy Parameter

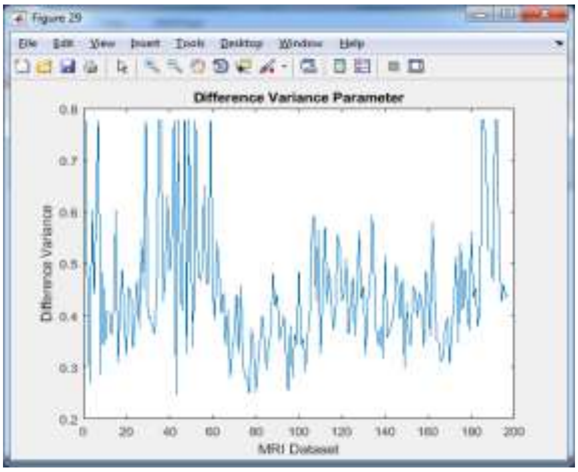


Figure 5.10: Difference Variance Parameter

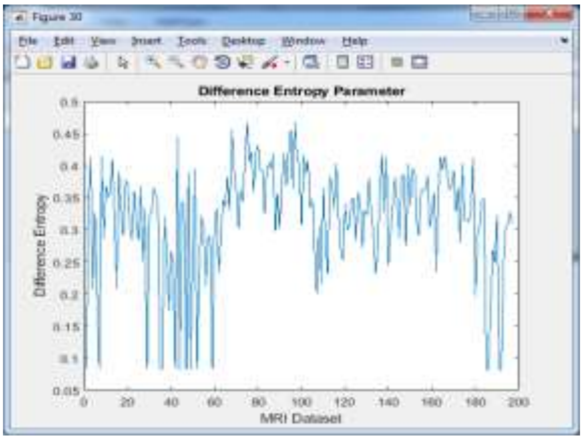


Figure 5.11: Difference Entropy Parameter

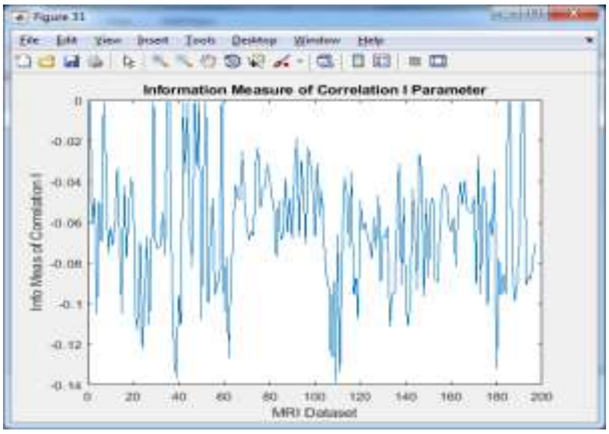


Figure 13: Information Measure of Correlation-I Parameter

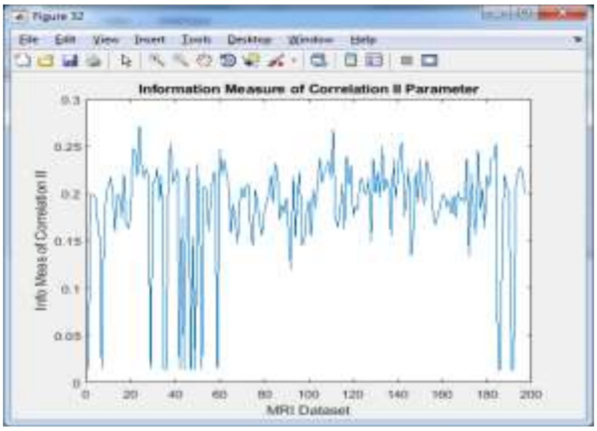


Figure 14: Information Measure of Correlation-II Parameter

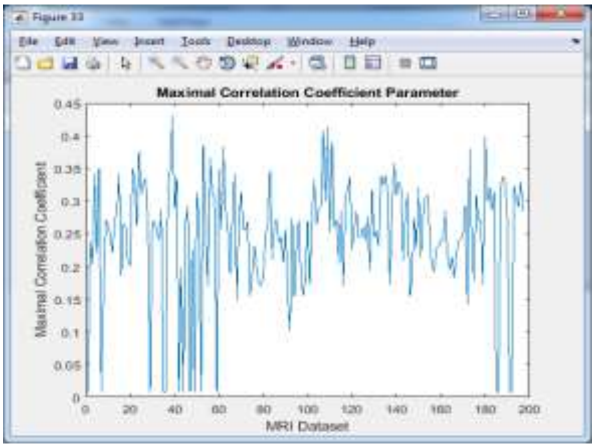


Figure 5.14: Maximal Correlation Coefficient Parameter

The eight most important features were chosen from the figures presented above and utilized as input to a convolutional neural network.

3.2 Effects of Convolutional Neural Networks Training: Random parameter:

In the first place, select a boundary at irregular from the arrangement of thirteen features that Haralick has created; the boundaries are EG, CO, IN, EN, SA, DA, and IC-1 and IC-2, and their exhibition is assessed based on how well they can identify tumor in error matrices of networks. Consequently, pick another eight elements, including SA, SV, SE, DA, DV, DE, Data IC-1 and IC-2, and their presentation to identify the brain tumor in the error matrices of networks. In conclusion, select the eight boundaries: EG, CO, IN, EN, SV, SE, IC-1, and IC-2. The presentation of these boundaries to identify tumors is shown in figure 16 of the error matrix for networks.

Figure 16: Confusion Matrix

3.3 Effects of Graphic User Interface (GUI):

This segment introduced outcomes of Realistic UI (GUI) widow to specify the complete proposed calculation from load image to identify the tumor bit by bit.

Figure 17: Load the input image

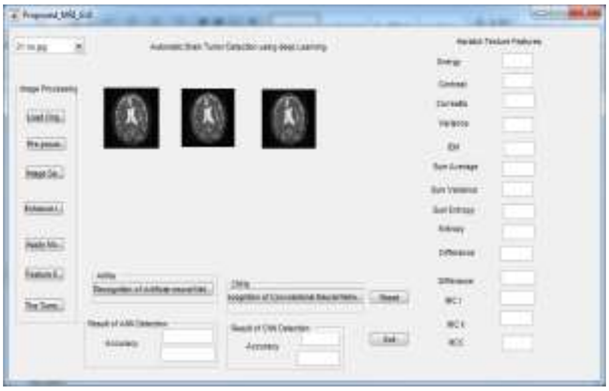


Figure 18: Pre-processing the image

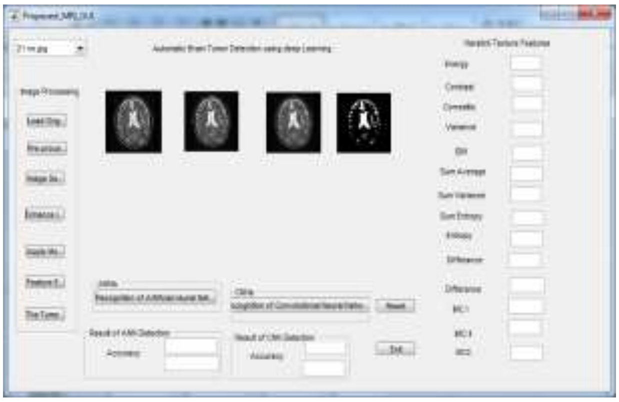


Figure 19: Image segmentation

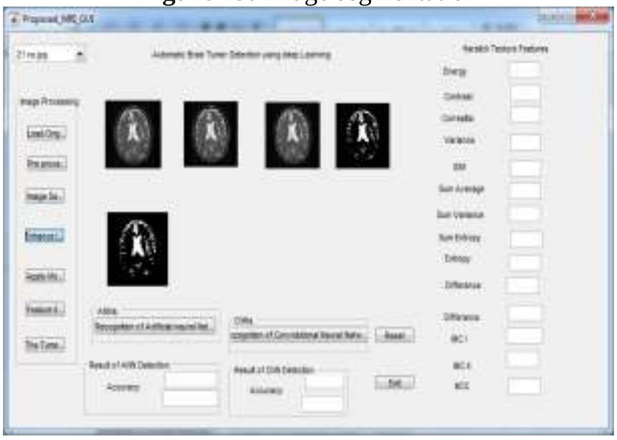


Figure 20: Image Enhancement

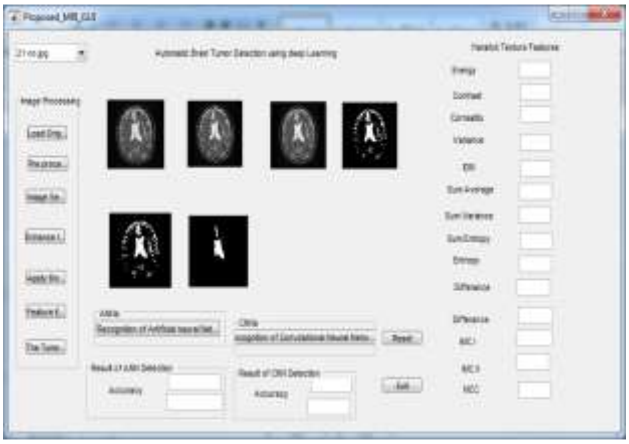


Figure 21: Apply Morphological Operation

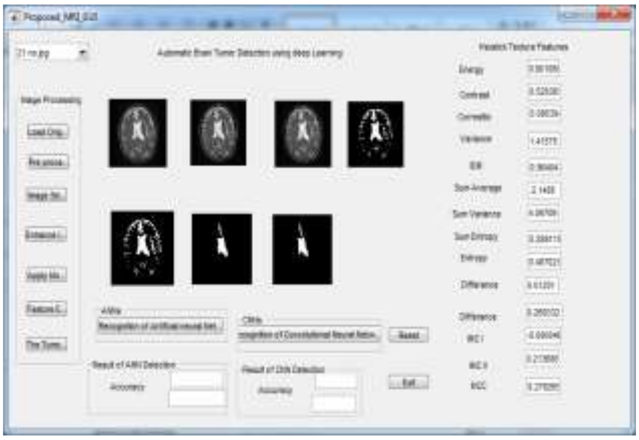


Figure 22: Feature Extraction

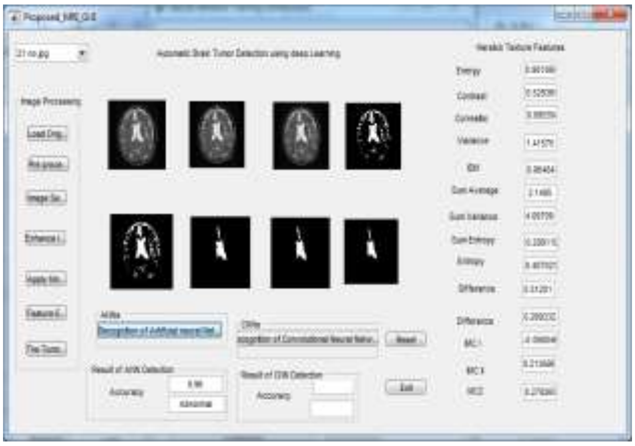


Figure 23: Recognition by ANN

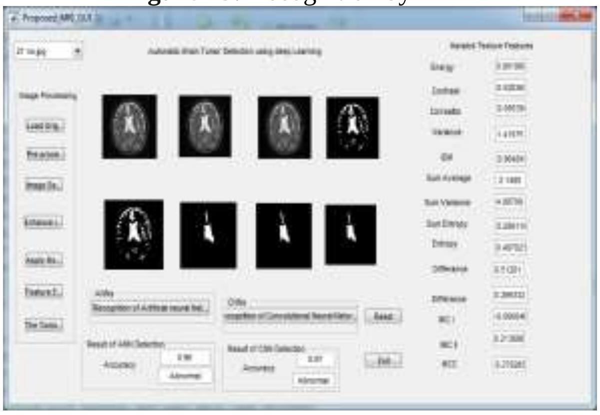


Figure 24: Recognition by CNN

Percentage Correct Classification by CNN: 93.000000%
Percentage Incorrect Classification by CNN: 7.000000%
As Figure 24 compares, the ANN and CNN as per accuracy parameter.

4.Conclusions

The purpose of this research was to develop an automatic method that could detect brain tumors using MRI images and convolutional neural networks. It has been determined that the design, implementation, and testing of an algorithm with available brain tumor MRI was successful. The purpose of this effort was to provide a collection of image segmentation algorithms and feature extraction methods that produce desirable results. The information that has been gathered and processed in order to make it acceptable for detection. In order to extract features from images, statistical feature analysis was utilized. These highlights were created using conditions of Haralick's elements that depended on the SGLD matrix network of images. To order the classifying image as either having or not having malignancy, a convolutional neural network with supervised learning was used. The findings demonstrate that the method that was used contributes to the detection of tumors that are enhancing, as well as the specification of tumors to the real tumor region exclusively.

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