Evolution of Information, Communication and Computing Systems (EICCS)
https://publisher.uthm.edu.my/bookseries/index.php/eiccs

Classification Technique for Brain Tissues Diagnoses: Segmenting Healthy, Cancer Affected and Edema Brain Tissues

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Abstract:
Brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is crucial to improve patients' quality of life. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate, etc. Primarily, in this work, MRI images are used to diagnose a tumor in the brain. However, MRI scans' huge amount of data thwarts manual classification of tumor versus non-tumor at a particular time. However, with some limitations, accurate quantitative measurements are provided for a limited number of images. Hence, trusted and automatic classification schemes are essential to prevent the human death rate. The automatic brain tumor classification is a very challenging task in large spatial and structural variability of the surrounding brain tumor region. This work proposes automatic brain tumor detection to segment the Region Proposal Network (RPN) by the Faster R-CNN algorithm. Here, the concept of transfer learning is used during training. The proposed system helps predict the correct type of tumor with better accuracy, about 99%, and classifies using Convolutional Neural Networks (CNN). The deeper architecture design is performed by using small kernels. Experimental results show that the CNN archives rate of 98% accuracy with low complexity compared with all other states of arts.

Keywords:
Brain tumor · MRI · FFBNN · CNN

1. Introduction

Image segmentation is the route of dividing a digital image into various segments. The objective of segmentation is to simplify and/or modify the illustration of an image into something more meaningful and ease to evaluate. Edge is one of the prime features of an image. It helps us analyze, infer, and decide on various image processing applications. This system proposes a supervised variation level set segmentation model in this project. Anomalous progression of tissue in an intensified manner within a living organism account for tumor. The cells within the tissue of a malignant tumor are responsible for

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self-multiplying themselves and replicating all over feasible regions of a human physique. Tumor existing at varied stage causes a diversified effect on the human body.

Tumor cells usually demolish the well-being nature of normal tissue by creating diverse symptoms like inflammation in the affected portion or generating an added pressure in other organs of the physique, consequently causing a surge of pressure within the infected part of the tumor [1]. In particular, a brain tumor prevailing in the stage of a metastatic level is designated as cancer that is traversed from other organs to the brain. During its preliminary stages, the transferring nature of a tumor that resembles a simple communicable disease is terminal if it is not recognized. Hence, a better brain tumor processing methodology is a prerequisite for the present scenario. In general, images acquired through Magnetic Resonance (MR) are utilized for the identification of brain tumor. To construct a perfect and robust brain tumor segmenting procedure, the faults surviving in the pre-existing techniques are assessed in this paper to suggest further improvisations in the methodology that is to be proposed in this research.

In the existing system, the system used a region based segmentation method. This method has two processes. There are region growing processes and region split and merge processes. In the region growing process, the technique compares the candidate pixel and neighbor pixel. The process has been used in the region split & merge process to identify the segment part. In this work proposes the statistical inference and global spatial properties to address the mentioned problem. It would improve region-of-interest (ROI) segmentation with heterogeneity and blurred boundaries in medical images. The system considers an image in a continuous domain to be partitioned into two segments: the foreground and the background.

2. Literature Review

Image processing is essential to get the image clear; zoom in to enlarge the picture and eliminate the noise contents in the image. This section presents the theory of image segmentation and then reviews some image processing methods using a neural network. The neural network is becoming more and more popular nowadays, even in image processing.

Brain Magnetic Resonance Imaging (MRI) images' data extraction techniques can diagnose brain tumors and other diseases by the classification method. Some segmentation and classification algorithms to extract the data for the diagnosis of brain tumor, such as Decision Tree (DT), Support Vector Machine (SVM), Fuzzy C-Means (FCM), Artificial Neural Network (ANN) and K means cluster. It is tough to tag a single data extraction algorithm as the best fit for the brain tumor detection or classification in the analysis. Consider segmentation of brain tumor is one of the complicated operations in the medical field because the scene of the edema district is considerably to pinpoint. The force of the tumors diverges in every patient, making the strict margin scene of the wounds seem blurred in the MRI images. Besides that, a serious cost of the texts studied tells new aspects of brain tumor segmentation [2]. The diagnosis by computer can improve and increase the diagnostic skills of physicians in as little time as possible with greater accuracy of diagnosis. The proposed mixture attitude of Faster R Convolution neural network for image segmentation and artificial neural network (CNN-ANN) method, have been proven as perfect, fast and forceful techniques [3].

There are more techniques of scans like MRI scan, CT scan, and PET scan for diagnosis, but MRI scan is considered the best one because it does not upset the human body and does not habit any radioactivity. There are more types of the method developed for brain tumor detection. Thus, two procedures are used for segmentation and classification to deliver the perfect result for tumor and its grade. The tumor may be two-level primary (low grade) or secondary (high grade). If it's a foundation, then it's known as primary. If the part of the tumor is supper to another apartment and grown-up as its own, then it's known as secondary.

In general, the tumor in the brain causes strokes. The doctors treat the strokes but not treats the tumors. Therefore, the diagnosis of tumors is very significant for treatment. So, the lifespan of the patients with a brain tumor can arise if it's diagnosed detected at primary stage and may save the patient's life or increase the lifespan by about 1 to 2 years [4].

2.1 Feature Extraction and Classification Techniques

Feature extraction is important procedure in brain tumor disclosure and classification. The best feature set should have effective features and reduce the repetitive feature space to avoid the ''curse of dimensionality'' problem. Feature extraction considered by CAD schemes is feature analysis, and extraction [4, 5] is an important classification stage.

The conversion of a photo into its set of features is known as feature extraction. The valuable features extraction of the image is for classification purposes. There are many techniques for feature extraction, such as texture features, Gabor features, feature based on wavelet transform, principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, non-parametric weighted feature extraction and spectral mixture analysis [6]. Classification is the technique for addressing the input into analogous classes. Select of appropriate classifier, and it has to require consideration of many factors, such as classification accuracy, algorithm performance, and computational resources.

Table 1 shows a survey on the classification techniques for brain MRI. There are many classification algorithms for classifying the brain MRI, and these algorithms have advantages and disadvantages. The main ways of classification of the human brain in MRI are possible via:

i. Supervised techniques like artificial neural networks and support vector machine

ii. Unsupervised classification techniques like SOM and fuzzy C-means, but there are other supervised classification techniques, like k-NN, to classify the normal/pathological T2-weighted MRI images [6].

iii. Hybrid intelligent systems classification includes fuzzy logic, neural networks, and bio-inspired optimization algorithms (genetic and genetic programming).

From Table 1, it can see:

i. Discrete wavelet transforms, and texture analysis is widely used methods for feature extraction

ii. Hybrid systems are widely used method for classification and pre-feature extraction and give the best accuracy combined with different machine learning techniques

iii. In Hybrid intelligent systems, the integrated methods or more from intelligent like convolution neural network and artificial neural network gives more efficiency and accuracy to classification and segmentation systems (in the range 97–100%) [6].

Table 1: Feature extraction and classification techniques for brain MRI

Writer	Feature extraction	Technique of Classification	Accuracy (%)	Data
Louis.D.N et al (2007) [7]	(TA)	(HAC)	NA	hospital's database

Maitra (2008) [8]	(IODWT)	(FCM) clustering	100	Harvard
Maitra ,(2006) [9]	DWT	(ANN+SVM)	100	Harvard
Zacharaki et al. (2009) [10]	(CLDA)	Based on SVM	97%	From 100 case patients.
Georgiadis et al. (2008) [11]	(TFE)+(WRS)	(LSFT–PNN)	NA	Air force Hospital, of Athens
El-Dahshan et al. (2010) [12]	(DWT) + PCA	(FPANN)+ k-NN	NA	Harvard
Kharrat et al. (2010) [13]	(SGLDM) +WT	GA + SVM	95	Harvard
Zhang et al.(2010) [14]	DWT + PCA	(ACPSO–FNN)	98	Harvard
Selvaraj et al. (2007) [15], Chaplot, Patnaik, and Jagannathan (2006) [16]	(TFEX)	SVM (MLP) (RBF) k-NN	97.9 97.6 93 93.41	Indian Devaki Cancer Institute, Devaki Cancer Hospital Madurai
Chaplot et al. Wu, and Wang (2011) [16]	(DWT)	SOM SVM SVM	94 96 98	Harvard
Zhang et al. (2011) [14], Zollner et al. (2012) [17]	WT + PCA	(BPNN)	100	Harvard
Zollner et al. (2012) [17]	(PCC), PCA and (ICA)	SVM + PCA SVM + PCC SVM + ICA	85 82 79	DSC–MRI data (patient data included 101 preoperative patients
Yamamoto et al. (2010) [18]	(MGLE)	(LSM+SVM)	84.3	Brain MR FLAIR images;
Grana et al. (2011) [19]	(FA) + (MD)	SVM	100	from Hospital (Vitoria-Gasteiz)

2.2 MRI Brain Tumors

Tumors are of various kinds and have different attributes and multiple medications [20], while cerebrum tumors are delegated essential mind tumors and metastatic cerebrum tumors. The previous starts in mind and generally remains in the cerebrum; the last starts as a malignancy somewhere else in the body and spreads to the cerebrum. Mind tumors are partitioned into two kinds: considerate and dangerous. The World Health Organization (WHO) has issued the most broadly utilized reviewing plan. It arranges mind tumors into evaluation I to IV under the magnifying lens. By and large, grade I and grade II are amiable mind tumors (low grade); grade III and IV are harmful cerebrum tumors (high-grade). For the most part, if a second rate cerebrum tumor isn't dealt with, it is probably going to break down to a high-review mind tumor.

Imaging modalities assume a significant job in assessing patients with mind tumors and significantly affect persistent consideration. In the last years, appeared a new imaging modality, such as X-ray, CT, MEG, EEG, PET, SPECT, and MRI. These modalities provide two important things,

i. Show the detailed and complete aspects of brain tumors, and
ii. Improve clinical diagnosis to study of brain tumors for better treatment.

Clinical specialists assume a significant job in mind tumor evaluation and treatment. When a cerebrum tumor is clinically suspected, a radiologic assessment is required to decide the area, the degree of the tumor, and its relationship to the encompassing structures. This data is significant and basic in choosing the various types of treatment, for example, medical procedure, radiation, and chemotherapy.

Thusly, the assessment of mind tumors with imaging modalities is presently one of the key issues of radiology offices. MRI is a non-invasive great delicate tissue differentiate imaging methodology that gives important data about the shape, size, and restriction of cerebrum tumors without presenting the patient to high ionization radiation [21]. MRI is drawing in an ever-increasing number of considerations for the mind tumor determination in the clinical [22]. In the current clinical routine, the images of different MRI sequences are employed to diagnose and delineate tumor compartments.

These sequence images include T1-weighted MRI (T1w), T1-weighted MRI with contrast enhancement (T1wc), T2-weighted MRI (T2w), Proton Density-weighted MRI (PDW), Fluid-Attenuated Inversion Recovery (FLAIR). Fig. 1 shows an axial slice of four standard sequences for a glioblastoma, which is a type of brain tumor patient [23]. Since T1w allows for easy annotation of the healthy tissues, it has become the most commonly used sequence image for brain tumor structure analysis.

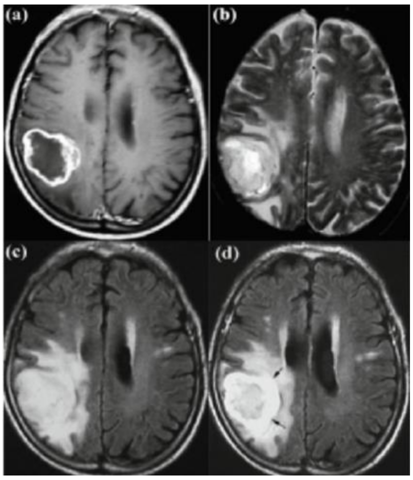
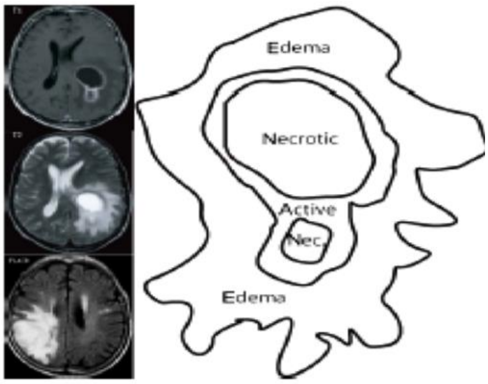


Figure 1: Four imaging modalities: (a) T1-weighted MRI, (b) T2-weighted MRI, (c) Flair, and (d) Flair with contrast enhancement [11]

Moreover, T1-weighted contrast-enhanced sequence images can make the brain tumor borders brighter because the contrast agent accumulates there due to the disruption of the blood-brain barrier in the proliferative brain tumor region. The necrotic core and the active cell region can be distinguished easily in these sequence images.

In T2w, the edema region can appear brighter than in other sequence images of MRI. Since the signal of water molecules is suppressed in the imaging process of FLAIR, a highly effective sequence image helps separate the edema region from the CSF. Because of the enormous measure of cerebrum tumor pictures that are at present being produced in the clinics, it is not workable for clinicians to physically clarify and section these pictures in a sensible time. Subsequently, the programmed segmentation has turned out to be unavoidable. Cerebrum tumor segmentation is to fragment strange tissues, for example, dynamic cells, necrotic center, and edema. Fig. 2 shows ordinary mind tissues, including GM, WM, and CSF [24]. As of late, medicinal imaging and delicate processing have made critical progressions in the field of mind tumor segmentation.

When all is said in done, a large portion of anomalous mind tumor tissues might be effectively recognized by cerebrum tumor segmentation strategies. Be that as it may, precise and reproducible division results and portrayal of variations from the norm have not been explained the whole distance.



(a) (b)

Figure 2: (a) Three types of brain MRI tumor images: T1 with contrast, T2 and Flair image; (b) three main components after segmenting brain tumor

3. Methodology

Since mind tumor division has incredible effects on finding, observing, arranging treatment for patients and clinical preliminaries. This segment centers around MRI-based cerebrum tumor segmentation and presents a moderately nitty-gritty review of the current existing MRI-based brain tumor division techniques. In our system, the data sets (MRI images) are taken from the internet and handled as shown in the chart in Fig. 3.

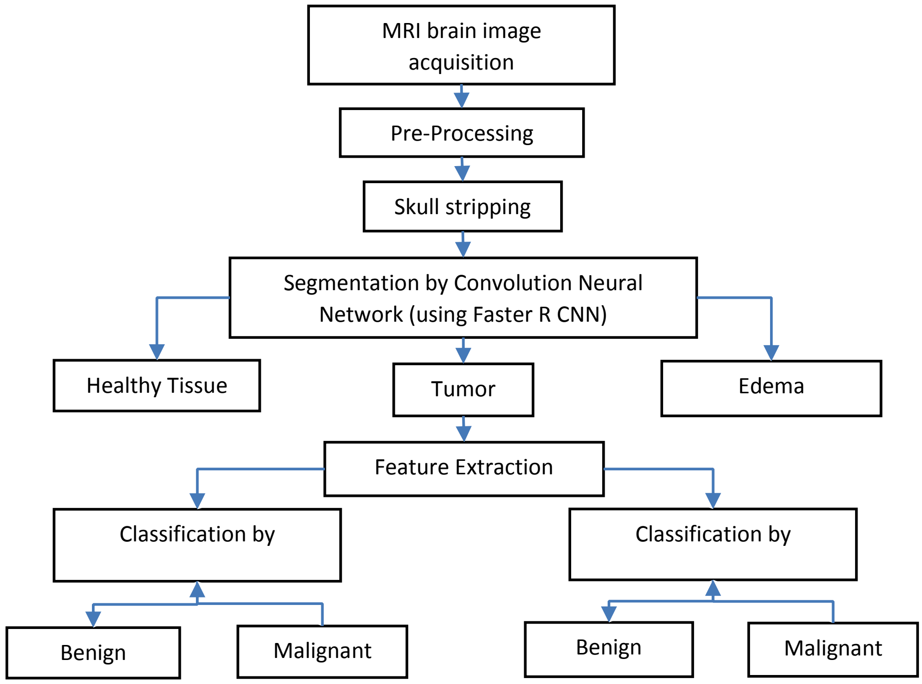


Figure 3: Flowchart of the proposed system

3.1 Image Acquisition

Pictures are acquired utilizing a MRI check, and these filtered pictures are displayed in two-dimensional grids with pixels as their components. These grids are reliant on framework size and its field of view. Images are put away in Python language and shown as a dark scale picture size 256×256. The sections of a dark scale picture extend from 0 to 255, where 0 demonstrates all-out dark shading, and 255 shows unadulterated white shading. Passages between this range change in power from dark to white [25]. Pictures of various brain tumors are collected and stored in the database to recognize their condition. The MRI picture is put away alongside our entire record from different sources.

3.2 Pre-Processing

Image pre-processing aims for noise removal and improves the clarity of the image or alters the quality of an image to suit a purpose [26, 27]. Image pre-processing aims for noise removal and improves the clarity of the image or alters the quality of an image to suit a purpose [26, 27]. Pre-processing of data is to prepare it for the primary prepossessing or for further analysis. This process can be applied to any first or preparatory processing stage when there are several steps required to prepare data fr the user.

3.3 RGB to Grayscale Conversion

As the name indicates, the image may consist of shades of gray. A 'gray' color is one in which the red, green and blue elements have similar intensity in RGB space. A grayscale image contains the grayscale values, but some MRI images contain primary (RGB) content [28]. These images need to be converted into grayscale images ranging from 0 to 255 pixel values.

3.4 Noise Removal using Median Filtering

Filtering is a technique used for eliminating the noise present within an image. During the conversion of an image from RGB to gray some sort of noise creeps into the image. Thus, this noise needs to get removed using filtering [28]. It is applied to eradicate the noises such as salt and pepper from the converted grayscale image. It exchanges the value of the pixel in the center with the median of the intensity values in the neighboring pixels [29].

3.5 Image Enhancement

Images acquired may have disadvantages, such as insufficient contrast. These defects have a significant impact on image contrast. When the contrast is insufficient, the contrast enhancement technique comes into play. In this case, the gray level of each pixel is measured to improve contrast. The image of MRI has been improved through enhanced contrast techniques [30].

3.6 Skull Stripping

Skull stripping is a significant method in medical image examination, and it is necessary for the effective analysis of MRI brain tumor images [31, 32]. The stripping of skull is the route of disregarding the non-brain tissues in the brain images. It is probable to eliminate every cerebral tissue like fat, skin, and skull in the brain images. A number of techniques exist for skull stripping; some of the common skills are automatic stripping of skull by image contour, depending on subdivision and morphological processes, and depend on histogram analysis or a threshold value offers the level of the skull stripping process. This system utilizes the skull stripping [33] method that is constructed on a threshold operation to remove skull tissues. The cerebral cortex can be seen as a black ring that backgrounds the brain in the axial images, and the proposed method of stripping the skull are:

i. Binarization via Thresholding,
ii. Morphological Operators, and
iii. Region-Based Binary Mask Extraction.

3.7 Segmentation

These grayscale images require through analysis to diagnose a disease [34]. The digital images are in the form of matrices and require mathematical analysis to extract the information [35]. At the end of the segmentation, the image is divided into a set of segments, which collectively form the actual image.

Segmentation Definition and Challenges Segmentation refers to the conversion of a digital image into a set of partitions that represent the volume in region-of-interest (ROI) or organs. The digital image is in the form of a set of pixels, which represent the ROIs that required multiple images stacked together [36]. Segmentation is carried out to partition the common characteristics of pixels into several non-overlapping.

3.8 Convolutional Neural Network

In this system proposed, all brain tissue is divided and defined on the basis of the type and represented in the brain tissue in the image taken from MRI, and the division of tissue depending on the Region Proposal Network (RPN) by Faster R-CNN algorithm. Generally, there are hundreds of types of brain tumors depending on the location and size of the tumor. Doctors rated levels of brain tumors in stages as Grade I, II, III, IV based on the growth, size and symptoms of brain tumor. In prior works segmentation mechanism are used to segment brain tissues by segmenting the tissue area.

In this system object segmentation algorithm Faster R-CNN are applied to segment the tissue in brain and produce bounding box on tissues with tissue name. Faster R-CNN algorithm for object segmentation via deep CNN [37], used pre-trained CNN model and RPN. Region proposals are used for tissues segmentation, but Faster R-CNN uses RPN.

RPN produce applicant ROIs for given brain images. It was FCNN which contains of three convolutional layer and one proposal layer. The incidences of tissues are tested by regression and segmented using bounding boxes provided by RPN.

3.9 Feature Extraction and Reduction

The tissue analysis distinguishes normal, abnormal tissues simply for human graphical view and machine learning. It also affords a difference between malignant and benign tissues, which may not be observable to the human eye. It increases accuracy by selecting quantifiable features for primary diagnosis in effect. At first, the primary-order statistical analysis of the image intensity graph and grayscale frequency measurements were extracted in random image positions. It does not consider correlation or co-occurrences. The link or shared presence is not between pixels. The second-order textural analysis-features were extracted based on the likelihood of gray altitudes at arbitrary distances and over entire image coordination.

3.10 Classification

Classification is a process of categorizing a given set of data into classes, It can be performed on both structured or unstructured data. The process starts with predicting the class of given data points. The classes are often referred to as target, label or categories. In this work, two methods of classification have been used which are FFBNN and CNN, that have been compared based on the accuracy between these two methods.

4. Experimental Setup

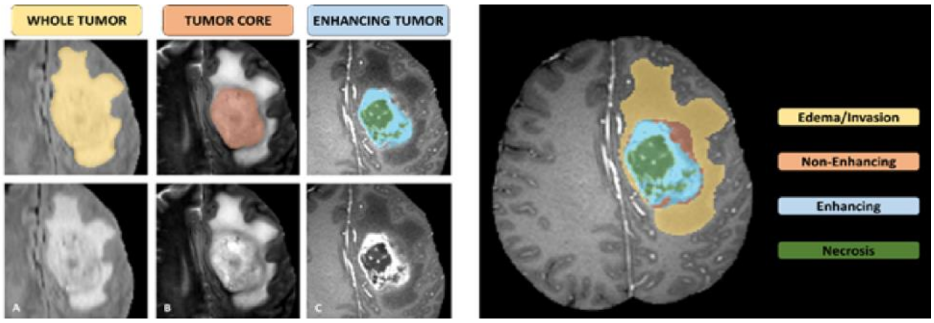
An experimental system implemented on Intel® core™ i7-7700HQ@ 2.80GHz with 16 GB RAM running on windows 10-pro-64-operation system, x64-based processor, the GPU NVidia GTX1080Ti with 8GB of memory. The server has 768GB of memory and 64GB of GPU. The implementation was done in Anaconda3, Python language with Keras, Tensor Flow; the dataset contains 285 cases of brain MRI images obtained from Perlman School of Medicine, University of Pennsylvania https://www.med.upenn.edu/sbia/brats2018/data.html. Ample multi-institutional routine clinically-acquired pre-operative multimodal MRI scans of glioblastoma (GBM) it is divided into:

i. high-grade glioma (HGG)
ii. low-grade glioma (LGG)

All BraTS multimodal scans are available as NIfTI files (. nii.gz) and describe as:

i. negative (T1)
ii. post-contrast T1-weighted (T1ce)
iii. T2-weighted (T2)
iv. (FLAIR) volumes

The data sets were attained with unalike clinical procedures. Different scanners from multiple (*n* = 20) institutions were segmented manually by one to four technicians, following the same explanation procedure, and experienced neuro-radiologists approved their clarifications. Comments comprise the enhanced tumor (ET label 4), the pretumoral edema (ED label 2), and the necrotic and non-enhancing tumor core (NCR:NET label 1), as described in the BraTS [38], as in Fig. 4. After their pre-processing, the delivered data are dispersed, co-registered to a similar functional template, included to the same resolution (1 mm3) and skull-stripped.



(a) (b) (c) (d)

Figure 4: Glioma ‘regions; (a) the image areas show from left to right: the whole tumor (yellow) seen in FLAIR, (b) the tumor core (light red) seen in T2, (c) the active tumor structures (light blue) seen in T1ce, neighbouring the cystic/necrotic components of the core (green), (d) the segmentations are shared to generate the final labels of the tumor regions: ED (yellow),‘NET (red), ‘NCR cores (green), AT (blue)[38]

4.1 Download and Converted the Dataset

The first step was to download the dataset from BraTS link above and convert the extension from 240 × 240 (. nii.gz) formula to 240 × 240 (.png) formula.

4.2 Shuffle and Mix

The second step is puts the new files of HGG and LGG in an array and shuffles randomly. Shuffle and mix the data helps the training converge fast. It also prevents any bias during training process and prevents the model from learning the order of the training.

4.3 Divide Data and Repair to Segment

The third step was to divide the data into a segment of each HGG and LGG to training data and test data so that it takes 80% from each grade to train and 20% from each grade to test; for 285 (all cases), it divided to,

i. HGG is 210 cases (168 for training and 42 for testing)
ii. LGG is 75 cases (60 for training and 15 for testing)

4.4 Segmentation using Faster R CNN

The fourth step is segmentation using Faster R CNN. Three types of brain tissues are taken as three classes: healthy tissues, edema tissues, and tumor tissues. The convolution layers output of Faster R CNN are “convolutional feature map”, which is an input to RPN and ROI layer. While, RPN involve of three convolution layer and proposal layer to produced nominee ROI. The RPN convolution layer predicts object score and regression coefficients for actual location of ROI.

The input of the proposal layer is regression coefficient and object score and generated boxes by using regression coefficients. The overturn of images on every epoch causes increasing in data. The function of NMS is to reduce the border boxes as small as possible for the candidate area. Faster R-CNN needs of anchor target layer and proposal target layer to produce target values and target segment labels for the segment of tissues in the training phase used in loss functions. Identifying brain tissues in MRI images is based on End to End training method. Fig. 5 and 6 represent the results of the segmentation of LGG and HGG.

4.5 Feature Reduction and Classification

The fifth step is feature reduction and classification; the main goal of classification is classifying the tumors into two categories;

i. Benign = low grade glioma = LGG, or
ii. Malignant = high grade glioma = HGG.

The proposed system used two techniques to classify CNN and FFBNN, and the performance of these techniques are compared.

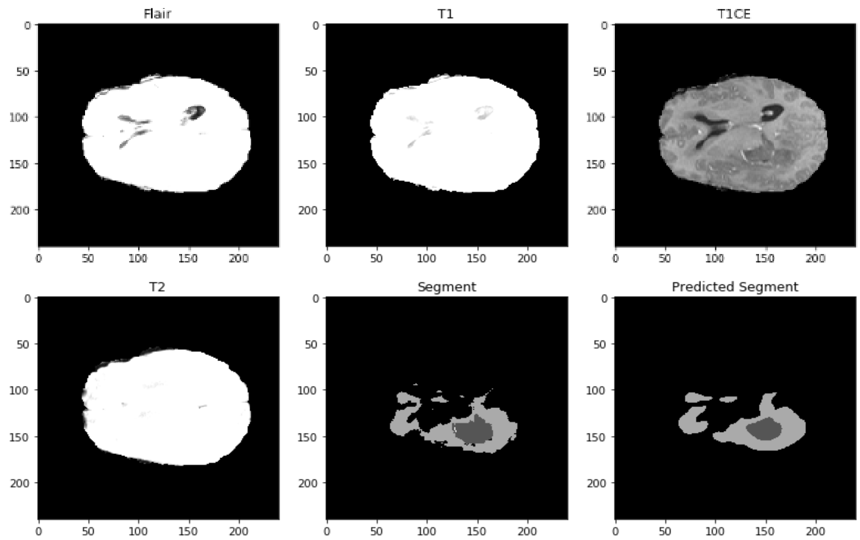


Figure 5: Images of (Flair, T1, T1CE, T2, Segment) and the predicted segment as a result of segmentation of LGG

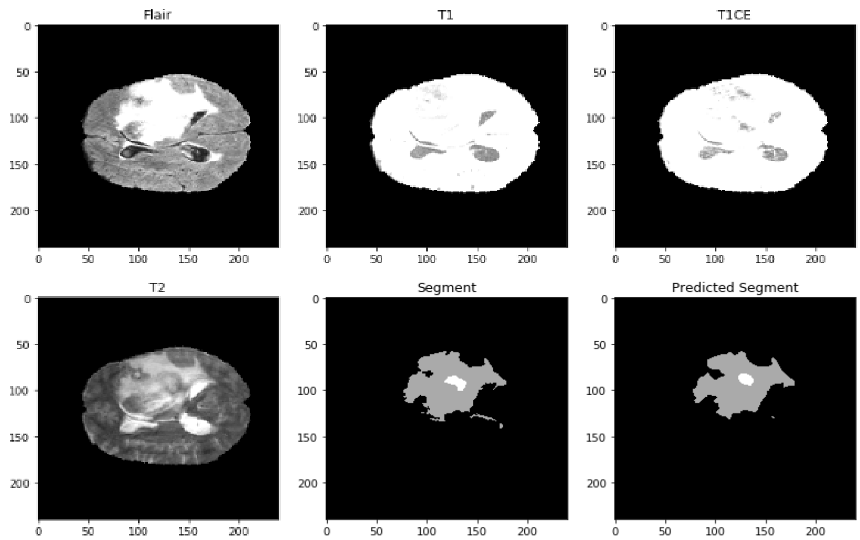


Figure 6: Images of (Flair, T1, T1CE, T2, Segment) and the predicted segment as a result of segmentation of HGG

4.6 Convolution Neural Network (CNN)

The CNN lies in the income, convolution, ReLU, pooling, and fully connected layers. In the ending layer, a fully connected layer is utilised to produce the classifying mark or labelling mark value constructed on the likelihood in 0 or 1 using sigmoid function because it has a binary output (0,1).

4.7 Feed Forward Back Propagation Neural Network (FFBNN)

The FFBNN is called as feedforward because it information flows through the function being evaluated from input through the intermediate computations used to define with the activation function, and finally to the output. There are no feedback connections in which outputs of the model are fed back into itself. FFBNN has linear inputs, so it has to divide the image pixels by 155×240×240×3 = 26784000 to convert from convolution to linear.

5. Result

5.1 Segmentation

After the segmentation operation using the Faster R CNN system has been obtained, the results are tabulated in Table 2. From Table 2, it can be seen that the accuracy of 99.58% after testing with 508,896,000 pixels for 57 cases, thus it achieved the task of segmentation with a mean square error (MSE) of 0.0135 and peak signal-to-noise ratio (PSNR) of 28.22. In brief , sensitivity in this context is also referred to as the true positive rate or recall, and precision is also referred to as positive predictive value. Other related measures used in classification include true negative rate and accuracy. True negative rate is also called specificity.

Table 2: Performance of Faster R CNN

Technique	No of pixel of 57 testing cases	Specificity (%)	Sensitivity (%)	F1-score (%)	Accuracy (%)
Faster R CNN	503132989	99.90	99.94	99.92	99.58
	1523542	82.30	86.18	84.20	
	3232207	86.63	82.40	84.46	
	1007262	77.69	69.74	73.50	
Total/Avg	508896000	99.72	99.73	99.72	

5.2 Classification

The classification operation used the outcome of segmentation as input data of classification for the same data sets using FFBNN and 2D CNN techniques. After executing this technique, the system obtains the evaluation value in terms of accuracy and other parameters of FFBNN and 2D CNN, as shown in Table 3.

Table 3: Performance of FFBNN and 2D CNN

Technique	Type of tumor	No. of testing cases	Specificity (%)	Sensitivity (%)	F1 score (%)	Accuracy (%)
FFBNN	Benign	15	92.86	86.67	89.66	86.67
	Malignant	42	95.35	97.62	96.47	97.61
	Total/Avg	57	94.69	94.74	94.68	94.74
2D CNN	Benign	15	93.75	100	96.77	100
	Malignant	42	100	97.62	98.80	97.62
	Total/Avg	57	98.36	98.25	98.26	98.25

5.3 Evaluation

After all, the "segmentation and classification" results have emerged, the proposed system must be evaluated in terms of accuracy, sensitivity, specificity, and reliability based on the input data. The system determines which is better by assessing the values of the "f1-score". It not only assesses performance in terms of sensitivity and quality but others. On the other hand, it divides the analysis into two parts according to the technology used and the classification. It then chooses the best technique based on the data and the results. In this analysis, performance of the technique in general, regardless of the type of tumor if it is benign or malignant can be accessed, as well as calculate the total values of each parameter depending on the weighted average and this gives an indication of the final decision in the selection of the best technology that can be seen in Fig. 7. The performance between the two technologies for all evaluation parameters is observed with an average difference of up to 3.5675. This confirmed the superiority of 2D CNN technology in terms of performance.

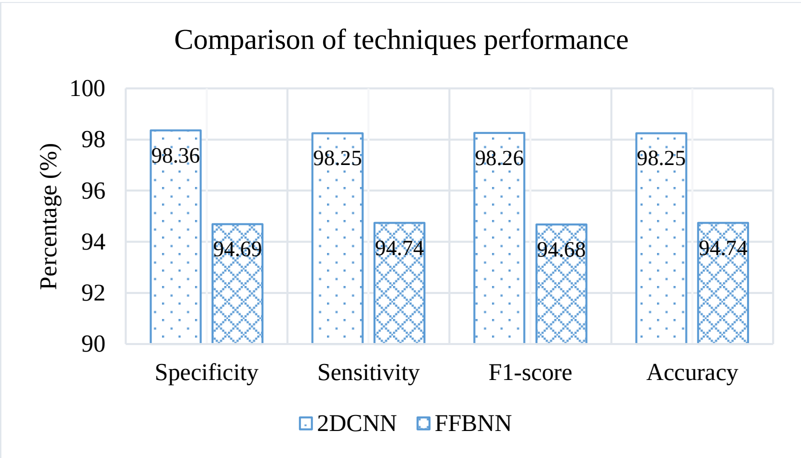


Figure 7: Performance of 2DCNN and FFBNN

This analysis can determine the strengths and weaknesses of each technique used in terms of accuracy, sensitivity and specificity and knowledge. The values of parameters by type of tumor can be seen in Fig. 8 and 9, respectively. Based on Fig. 8, the performance of accuracy and sensitivity of FFBNN are weak compared to the accuracy and sensitivity of 2D CNN. While in the malignancy, it was noted the accuracy, sensitivity, specificity and f1-score values show great convergence of both technologies.

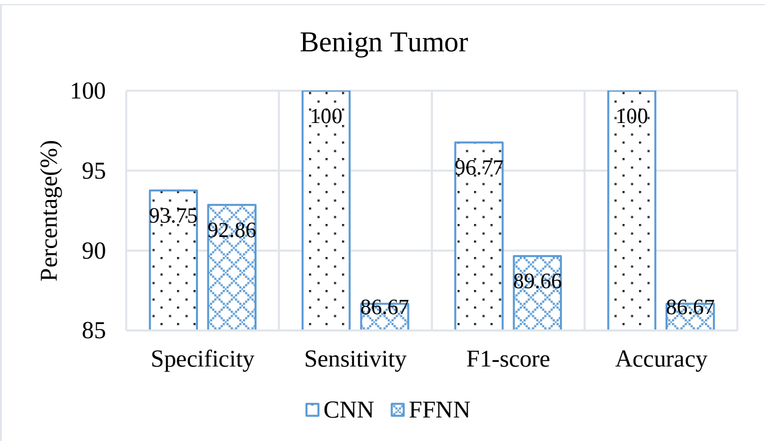


Figure 8: Performance of 2DCNN and FFBNN in Benign Tumor

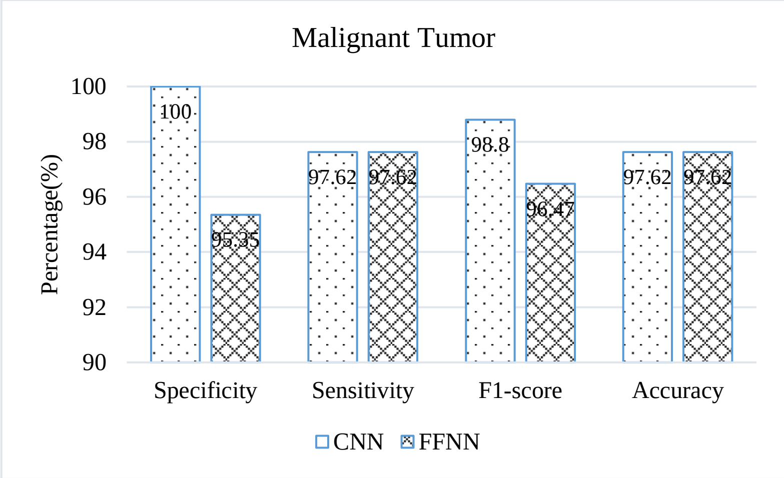


Figure 9: Performance of 2DCNN and FFBNN in Malignant Tumor

6. Conclusion

Faster R CNN technology is useful for segmentation because it performs three regions of interest simultaneously, takes one layer at a time, and the data processing is very fast and accurate. In terms of classification, FFBNN technology is ineffective with few data, and its results are unsatisfactory compared to 2D CNN technology, even with the same set of data. It results in a good performance; however, it requests large buffers and a high-speed GPU that are quick to do data in parallel processing. Thus, the higher the training data, the higher the sensitivity and specificity values with better and closer to 100%. Finally, the Faster R CNN may be suitable for the segmentation process, whereas 2D CNN is more suitable for the classification process.

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