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Deep Learning-Based Segmentation Of Brain Tumor

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ABSTRACT

The classification and segmentation of images have received a lot of attention. For this, a variety of techniques have been used. Image segmentation is extremely useful, particularly in the biomedical industry for disease diagnosis. The study of brain pictures using magnetic resonance imaging (MRI) is crucial to the field of neuroscience. This research on brain MR images aids in the process of diagnosing brain tumours. From the segmented images, features will be retrieved (based on the tumour region, texture, colour, location, and edge) and selected. Then, using classification techniques, the features will be classified to determine if the patient is normal (having no tumour) or abnormal (having tumour). The first step is to gather and prepare data for analysis. Since current technology has advanced, it is extremely beneficial to research brain tumour segmentation using deep learning (DL) and multimodal MRI images. This work suggests deep learning to conduct research on multimodal MRI image segmentation, aiming to produce accurate diagnoses and treatments for doctors, in order to address the issues of poor efficiency and low accuracy of brain tumour segmentation. In this study, we pre-processed MR images using the bilateral filter (BF) to remove any noise that was present. Binary thresholding, Convolution Neural Network (CNN), ResNet 50 (residual network), VGG 16 (visual geometry group) transfer learning for detecting the brain cancer, and U-Net for image segmentation came after this. Datasets for training, testing, and validation are used. The BRATS 2021 dataset is used for extensive tests, which demonstrate that the suggested model produces results that are competitive. The obtained data demonstrate how well the suggested approach performs in terms of recall, accuracy, precision, and Dice similarity coefficient. Our model demonstrated a Dice similarity coefficient of 82.35% for tumour segmentation and an accuracy of 91% for tumour classification. In order to increase the precision of the diagnosis process, this thesis will make an effort to list and discuss the earlier work of other researchers.

Keywords: Deep Learning, Brain Tumor, classification and segmentation

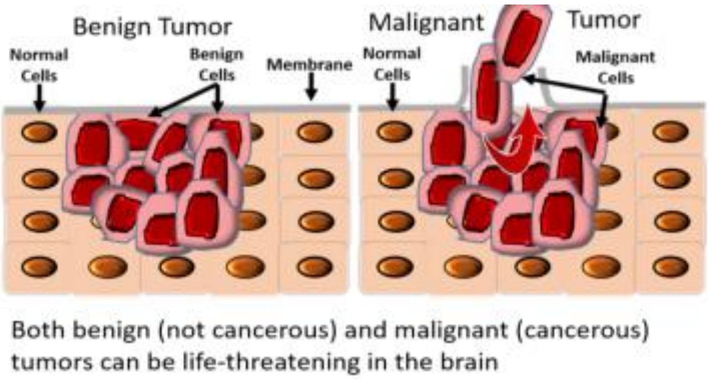
1. INTRODUCTION

The brain is the central organ of the human nervous system which controls almost all functions of the body. It is one of the largest and most complex organs in the human body and is made up of 100 billion neurons and many specialized areas that communicate trillions of connections and work together. It is the main organ of the central nervous system which is located in the head and protected by the skull. A brain tumor is a mass or growth of abnormal cells in your brain. Lots of people in rural and urban areas suffered from brain tumor such as Germ cell tumors, Medulloblastomas, Gliomas etc.[1] The procedure used to identify the ailment is referred to as "medical diagnostic." As a result, making a medical diagnosis is a difficult procedure since it requires a thorough interpretation of the clinician's high-level impressions of the illness process. Traditional diagnostic techniques heavily rely on the expertise and experience of the physician, which results in significant medical data loss and a high percentage of incorrect diagnoses. The world of today demands automated, precise diagnosing methods. With the development of computer science engineering techniques, such as artificial intelligence techniques (machine learning and deep learning) and image processing techniques, which can automatically segment the brain tumour, has garnered interest from clinicians and researchers by providing early detection and easy access for patients[2].

1.1 Brain Tumor

A brain tumour is a growth of brain cells or cells close to the brain. The tissue of the brain can develop brain tumours. Near the brain tissue, brain tumours are also possible. The pituitary gland, pineal gland, and membranes that surround the surface of the brain are nearby structures. Brain tumours can start there. Primary brain tumours are what they are. Cancer can occasionally move from another section of the body to the brain. These tumours are what are known as metastatic or secondary brain tumours. Primary brain tumours come in many distinct varieties. There are some benign brain tumours. These are referred to as benign or noncancerous brain tumours. Noncancerous brain tumours can enlarge and put pressure on the brain tissue over time. Malignant brain tumours, commonly known as brain cancers, are several types of brain tumours. Brain tumours may advance swiftly. Cancerous cells have the ability to infiltrate and kill brain tissue.

Brain tumours can be very little or quite enormous in size. Because they produce symptoms that you can immediately identify, some brain tumours are discovered while they are very little. Before they are discovered, other brain tumours enlarge considerably. The brain has several regions that are more and less active. If a brain tumour develops in a less active area of the brain, symptoms may not appear right away. Before the tumour is found, its size may increase significantly. The sort of brain tumour you have, as well as its size and location, all affect your treatment options. Radiation therapy and surgery are frequent forms of treatment.[3]



(a) (b)

FIGURE-1. Example of brain image a and b with tumor

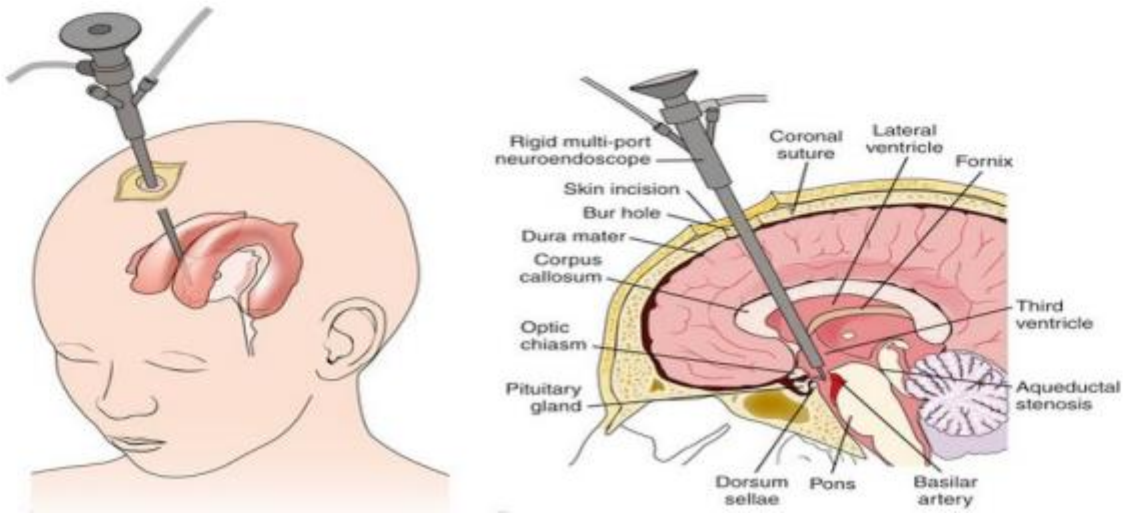


FIGURE-2. Biopsy of brain

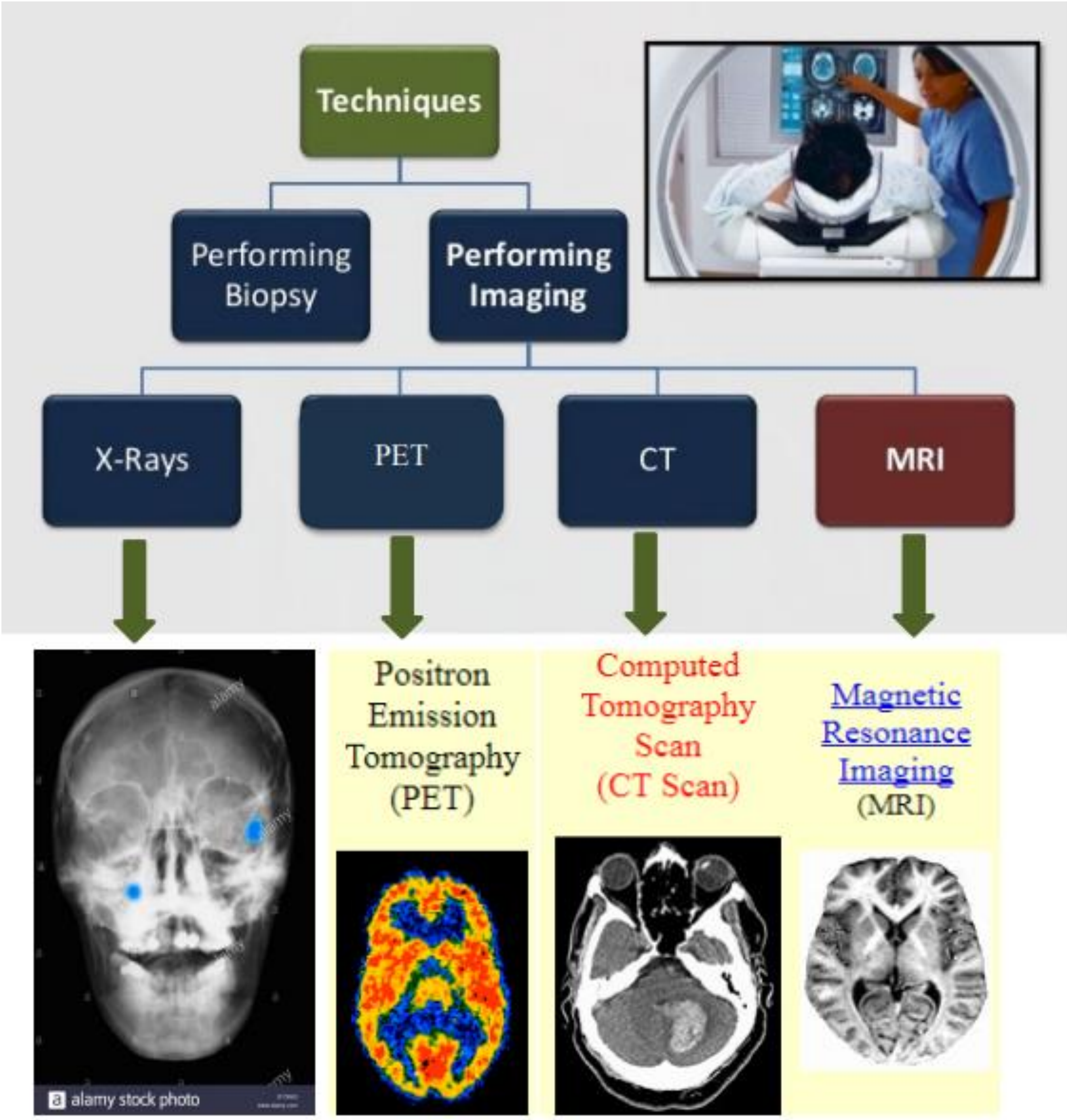


FIGURE-3. Different technique of Brain tumor imaging.

1.1 Image processing and analysis methods

In order to improve the clarity and quality of the image so that an accurate diagnosis can be made, several image processing procedures and techniques are applied. Different approaches are used for this, however the major procedures like filtration, image segmentation, features extraction selection, and classification are the only ones the study specifically targets. These key methods will enable accurate tumour diagnosis from MR images of the brain.

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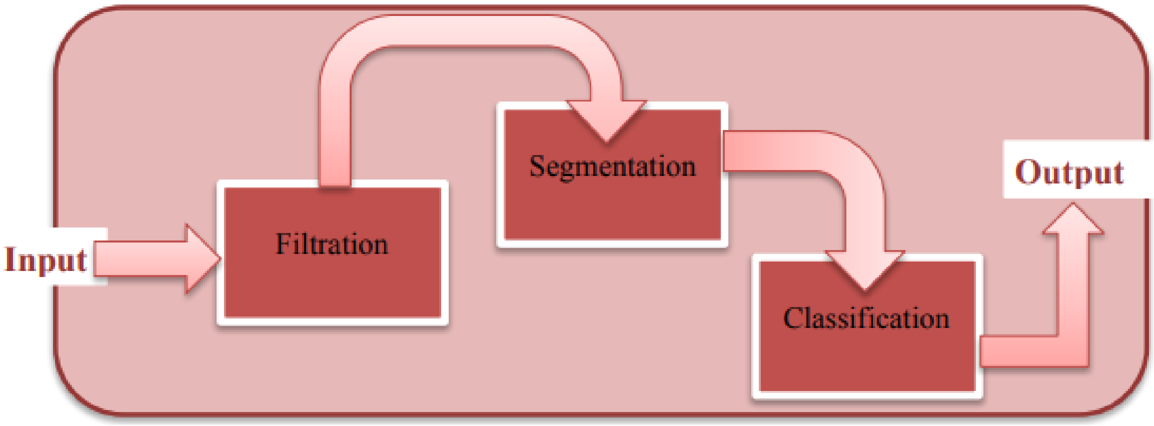

FIGURE-4. Image processing and analysis methods

1.3.1 Image filtration and de-noisy

The first pre-processing stage involving image processing is image filtration and de-noising. De-noising is the process of processing an image to remove induced noise that may have crept into the image during acquisition, transmission, or compression. To produce better and more accurate results, this technique improves and raises the image quality.[6]

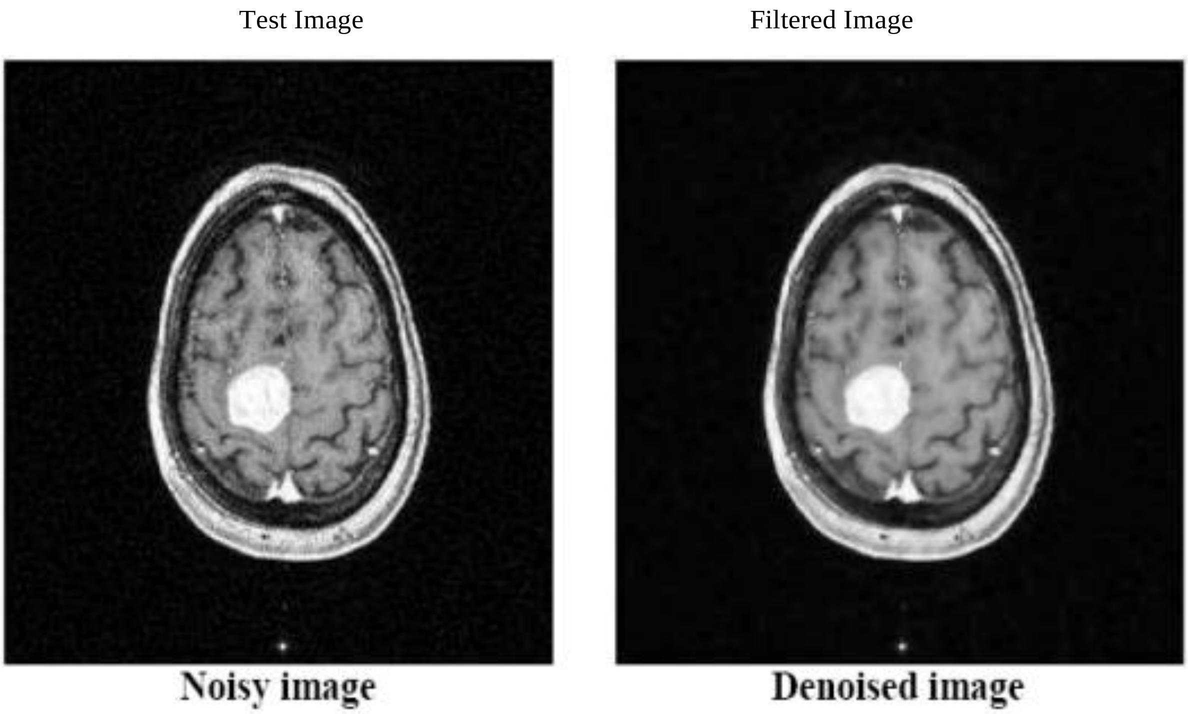

FIGURE-5. Example of noisy and de-noisy image

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1.3.2 Image segmentation

Image segmentation is a technique which divides the images into parts on the basis of dissimilarities and every part (pixel) contain similar features. Segmentation of the image has different types as mentioned in FIGURE 6.

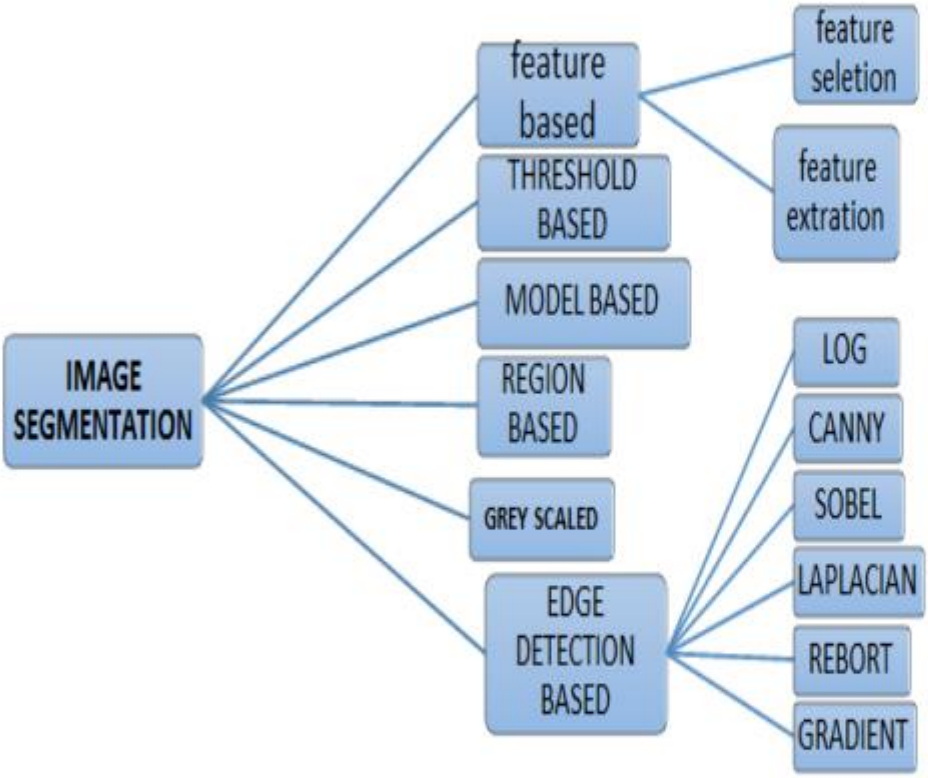


FIGURE-6. Types of image segmentation

1.4 Image classification

The process of obtaining different kinds of information from multiband raster images is known as image classification. Basically, there are three different classification methods: object-based, pixel-wised, and sub-pixel-wised. The primary topic of this work is pixel-wised image classification, which may be further divided into three groups: supervised classification (using user guidelines), unsupervised classification (using software calculations), and unsupervised classification. Both are the most typical ways, however object-based image analysis is much less popular and more recent than the other two approaches. High quality photos are utilised as input in this methodology. FIGURE 7 depicts many types of images classified according to various points of view.

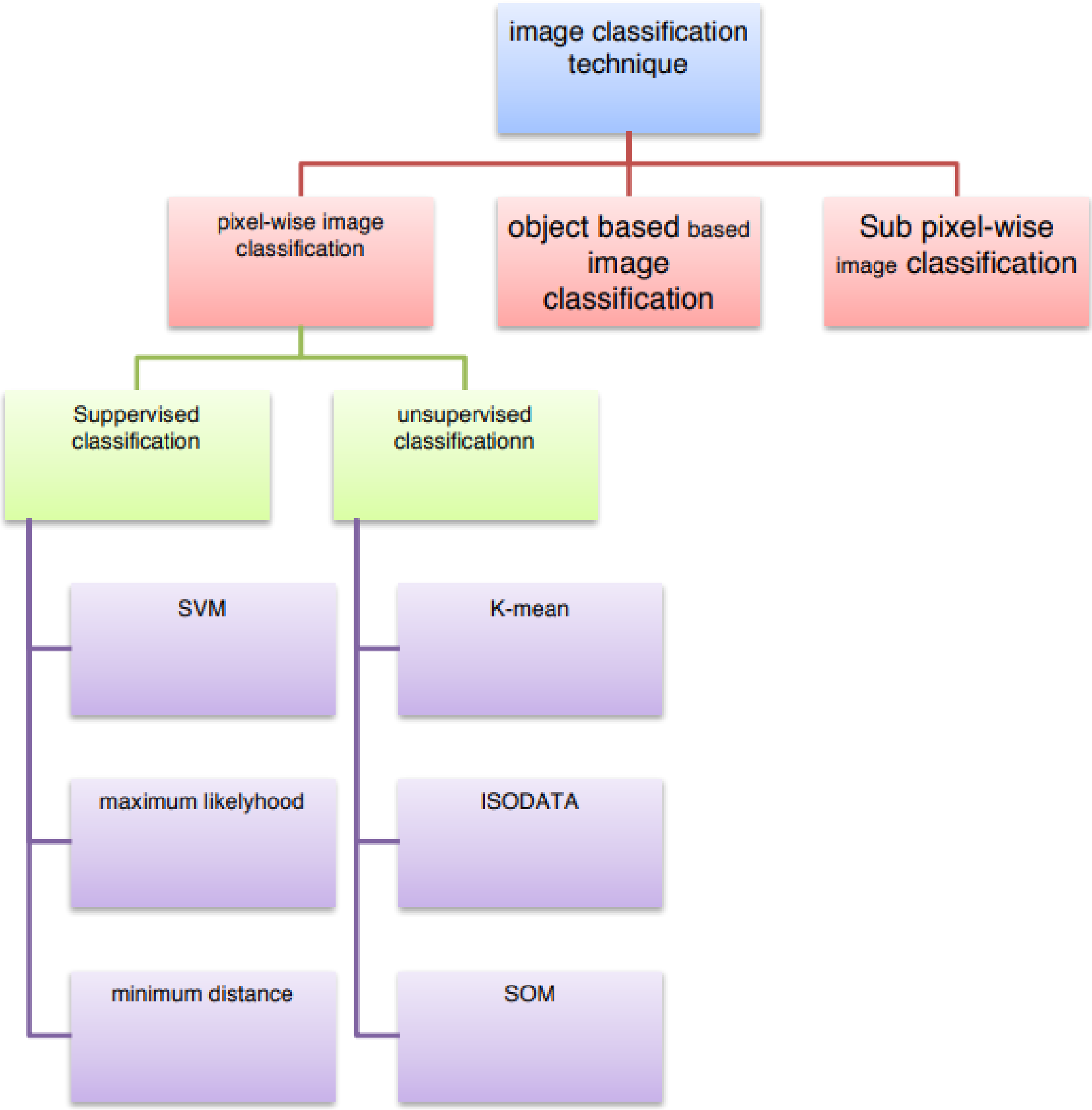


FIGURE-7. Different types of image classification technique

Unsupervised classification is a fairly straightforward technique because samples are not required. To analyse the image, straightforward segmentation and classification processes are taken. The unsupervised techniques K-mean, ISODATA, and SOM are examples of plus a lot more. The supervised classification method also requires training sets of samples. It completes three steps: choosing the training region, creating the file (which contains the details of each class that most closely resembles the training set), and classifying the image. The most popular supervised techniques are minimum-distance classification and maximum likelihood. SVM is another well-known and renowned method for classifying images. SVM is found to work well for supervised classification. But in some circumstances, SVM can act as an unsupervised approach.[7]

2 Research Methodology

This chapter outlines the study's research methods, as the title clearly states. The outline of the study plan, technique, approach, dataset source, and research procedure are provided in more detail in this part.

2.1 Research strategy

The given flow diagram will demonstrate the plan and actions to achieve the objective of study and to reach at its conclusion point.

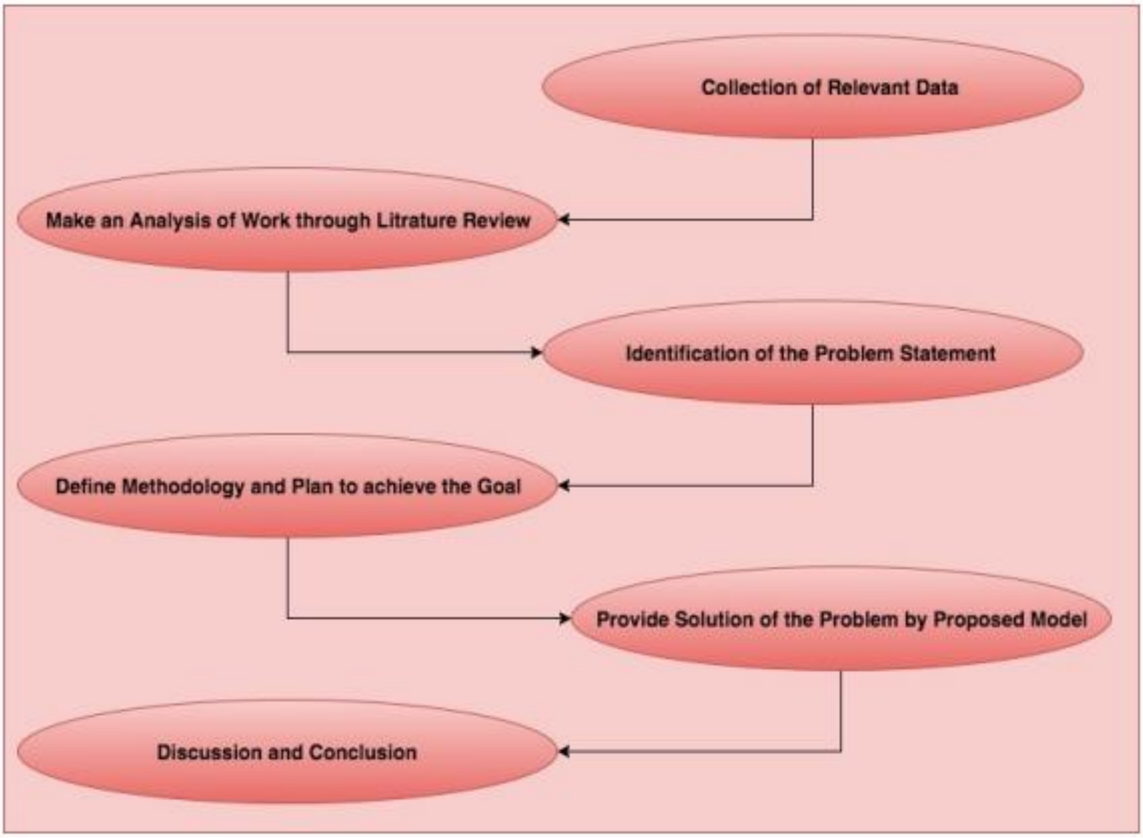


FIGURE-8. Representation of research plan and actions

2.2 Collection of relevant data and analysis

Both descriptive and experimental analysis will be used in this study, and relevant data will be gathered from books, magazines, research papers, articles, thesis, and the internet. All of the study material will then be organised for analysis, and the topic and material will be discussed with the teacher to serve as a guide and to arrive at a conclusion.

2.3 Data analysis and technique

The data will be analysed and compared based on several characteristics. a particular method or algorithm that is used to analyse brain MR images. Deep Neural Network is the method that will be employed in the proposed model to classify MR images. One to two hidden layers are typically present in "normal" neural networks, and these layers are heavily utilised for supervised prediction or classification. Because deep learning neural network architectures have more hidden layers than "normal" neural networks, as shown in FIGURE9, they differ from "normal" neural networks. A computational model with the characteristics of the human brain is called a deep neural network. The DNN is said to connect processing units (neurons) in the human brain. These components specify what a network task is. And groups of processing are separated into layers. The input layer, output layer, and hidden layer are the three layers that make up DNN. When DNN processes photos, the input comes in the form of image leads, and the output is a vector of scores with one score for each object class. The most likely class of object in the image is indicated by the class with the greatest score. The purpose of the hidden layer is to reduce the average loss across the substantial training set. [8]

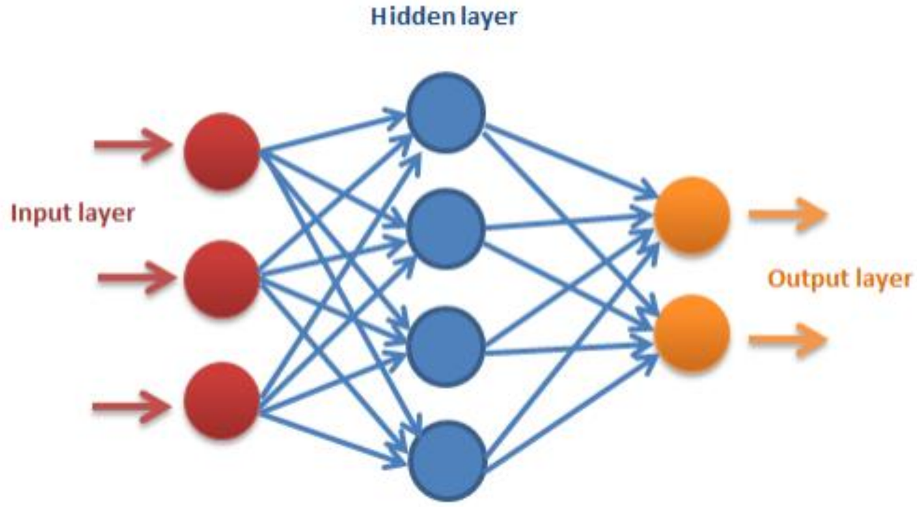


FIGURE-9. Structure of DNN in layers

Because support vector machines, the most popular and widely used classification method, cannot be trained in an unsupervised or supervised manner for both unsupervised and supervised learning tasks, deep learning differs from both "normal" NN and SVM. To improve the quality of the MR image, images will be filtered before to categorization. The filtration will help to de-noise and enhance the MR pictures' quality. For further processing of filtered pictures to prepare them for classification and to obtain better results, grey scaled segmentation will be used. To compute the Area of detected tumour in the brain tumour MR images, classified results will be helpful. The area calculation of the picture method will be employed for this. To calculate the rows and columns and partition the classed image into pixels, use an algorithm.

2.4 Software (analysis tool)

Matlab is a tool for the analysis. Matlab tool from maths work will be used to check and analyze the efficiency of the algorithm and proposed model.

3 Literature review

Haveri et al., illustrated a brain tumour segmentation using deep neural networks to glioblastomas (both low and high grades) MRI image. This kind of brain tumour appears anywhere in the brain and also it has any shape, size and contrast. The article utilizes the convolutional neural network as a machine learning algorithm. It exploits both local and global features for tumour segmentation. The author uses BRATS dataset for research work. [1]

Dong et al., proposed non-invasive magnetic resonance techniques as a diagnostic tool for brain tumour to identify brain tumour without ionizing radiation. Manual segmentation of the 3D MRI volumes needs larger time, and the performance is mainly based on the operators' experience. Hence, the author recommended a u-net based deep convolution network. This segmentation is implemented on BRATS 2015 datasets, which contain 220 high grade glioma brain tumour and 54 low grade tumour cases. The performance of our proposed method was compared to the manual delineated ground truth U-net based deep neural network provides the superior results for the core tumour regions. [2]

Khawaldeh et al., offered a widespread machine learning technique for medical image classification and segmentation. The approach uses conv net for classifying brain medical images into healthy and unhealthy brain images. The implemented method classifies the brain tumour into low grades and high grades. It uses alex krizhousky network deep learning architecture to classify the MRI brain tumour. The tumour classification is performed on the whole image rather than pixels. [3]

Cui et al., developed a novel automatic segmentation based on cascaded deep learning convolutional neural network. It has two sub networks; tumour localization network (TLN) and a intra tumour classification network (ITCN). The tumour region from the MRI brain slice is separated using tumour localization network and ITCN helps to label the defined tumour region into multiple sub-regions. The work was performed on multimodal brain tumour segmentation (BRATS, 2015) dataset, which had 220 high grade glioma (HGG) and 54 low grade glioma (LGG) cases. The evaluation can be performed by dice coefficient, positive predictive value (PPV) and sensitivity. [4]

Chinmayi et al., (2017) conferred a method for MRI brain tumour segmentation and classification using Bhaltacharya co-efficient. The unwanted skull portions were removed using anisotropic diffusion filter. Further, it uses a fast bounding box algorithm to extract the tumour area. It uses deep learning CNN to train the MRI brain tumour image. Finally, the results of the proposed method compared in terms of accuracy, similarity index, PSNR and MSE. The results will help the radiologist to identify the size and position of a tumour. [5]

3.1 Research Limitation

The following limitations will apply to this study: The entire body of past research will cover the last ten years, from 2014 to 2023. The experiment will use a small number of datasets.

3.2 Research gaps:

- The automatic segmentation of the brain tumour is exceptionally challenging as the shape might be irregular. So, there is a need to increase the accuracy.
- As the size of brain tumor different from patient to patient, so there will may be a scope of getting less accuracy for any brain tumor with already developed techniques.

3.3 Justification

- Artificial intelligence techniques (deep learning) build intelligent system that can understand the disease immediately with accuracy as well as to help clinicians in detail diagnosing of a brain tumor.
- Brain tumor segmentation is important in the field of medical. The diagnosis is a key step in the clinical investigation of any disease. In the field of medical picture analysis, an architecture that can be utilised to extract the pertinent facts from the gathered data using artificial intelligence techniques (deep learning) can be built.
- The significance of any automation is to reduce human effort. The automated brain tumor segmentation process is going to make the medical industry smoother. The entire world is getting closer to use machines in their daily life routine as daily drivers for washing cars and cleaning up home. It would be a great advantage if we can automatically segment the brain tumor through deep learning.

4 Proposed work and implementation

This experiment offers the best pairing for image analysis systems, providing an effective method for analysing medical images and identifying their abnormalities. The graphical representation of the proposed work is provided below.

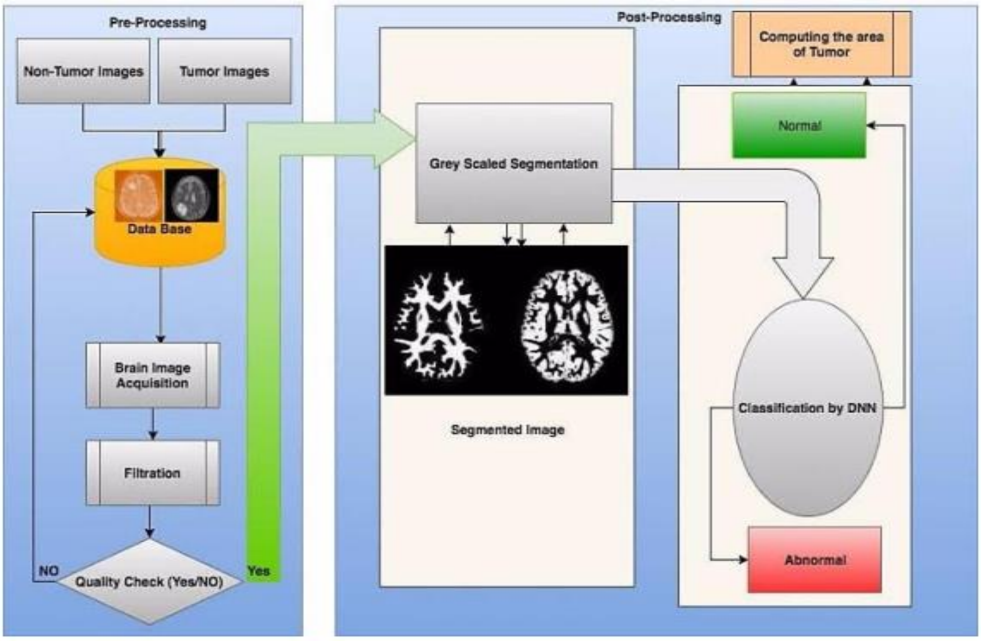


FIGURE-10. Graphical representation of proposed work

4.1 Description of proposed work

The proposed work is divided into two parts. First is pre-processing and second is post pro-processing. Dataset of brain MR Images are using as an input. For the implementation 10 brain MRI images are used in which also contain non-tumor and tumor affected images.

4.1.1 Results

For the purpose of resolving the brain tumour segmentation problem, we proposed and created U-Net based fully convolutional networks in this study. In essence, semantic segmentation is the task that deals with tumour detection and segmentation. In contrast to earlier studies on this subject that used deep learning, we used a thorough data augmentation scheme that not only included rigid or affine-based deformation but also brightness and elastic distortion-based transformation, which was then coupled with the U-Net that uses the skip-architecture.

4.1.2 Classification of Tumor or Non-Tumor

In order to better the classification task, we mixed two different types of gliomas, HGG and LGG, into the BraTS 2021 training set. There were 550 photos with labels on each of the 1100 in the series. For training and validation, this collection was split into two smaller groups (70:30 ratios). Figure 11 displays the effectiveness of the suggested strategy, with accuracy values for the training and validation subsets of 98% and 99%, respectively.

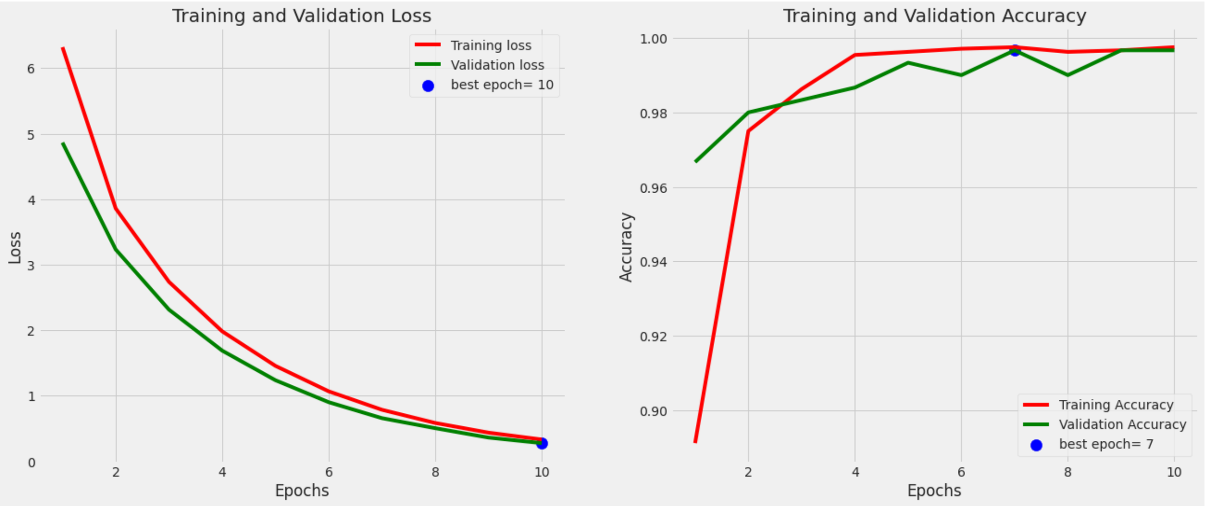


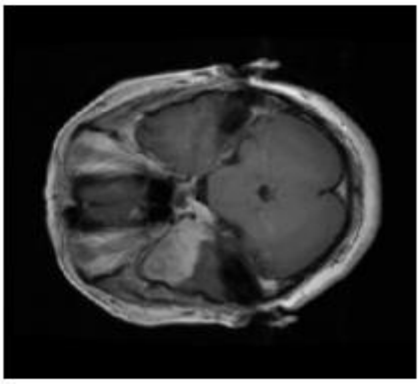
Figure-11: Accuracy and loss of the training and validation subsets as a function of number of epochs.

Table 2: Tumor binary classification: precision, recall and accuracy of the training BraTS 2021 dataset

	Training Subset	Validation Subset
Precision(%)	99	91
Recall (%)	99	91
Accuracy(%)	98	92

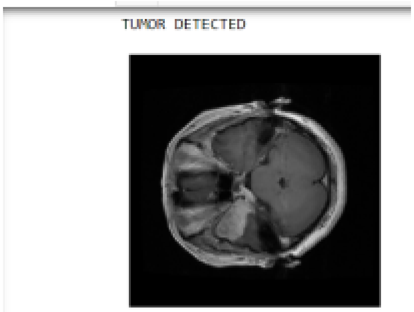
4.2 Tumor Detection

Sample Input:

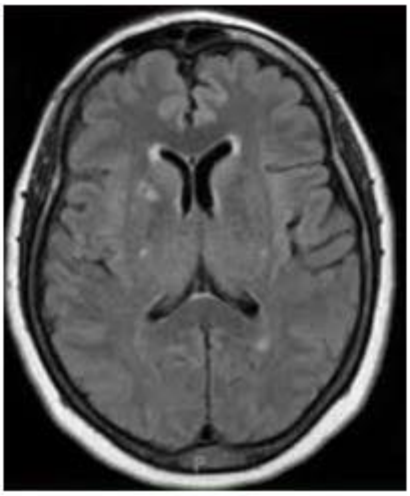


Predicted Output: Yes

Observed Output:



Sample Input:



Predicted Output: No

Observed Output:

NO TUMOR DETECTED

4.3 Tumor Segmentation

On the basis of the dice similarity coefficient between the true label and the prediction, the segmentation method's effectiveness was assessed using the BraTS 2021 training dataset.

	Training Dataset(HGG)	Training Dataset(LGG)	HGG+LGG
Before processing	76.65%	73.45%	75.88%
Post-processing	83.66%	78.67%	81.77%

Table 3: The Dice scores of our segmentation method before and after post-processing on the BraTS 2021 training dataset.

The BraTS 2021 dataset's qualitative segmentation results are shown in Figures 12 and 13. The figures also show that our network has the ability to precisely separate entire tumour regions. Our strategy was successfully evaluated on FLAIR modalities for MRI images outside of the BraTS 2021 dataset, which ensures the effectiveness and power of the suggested methodology.

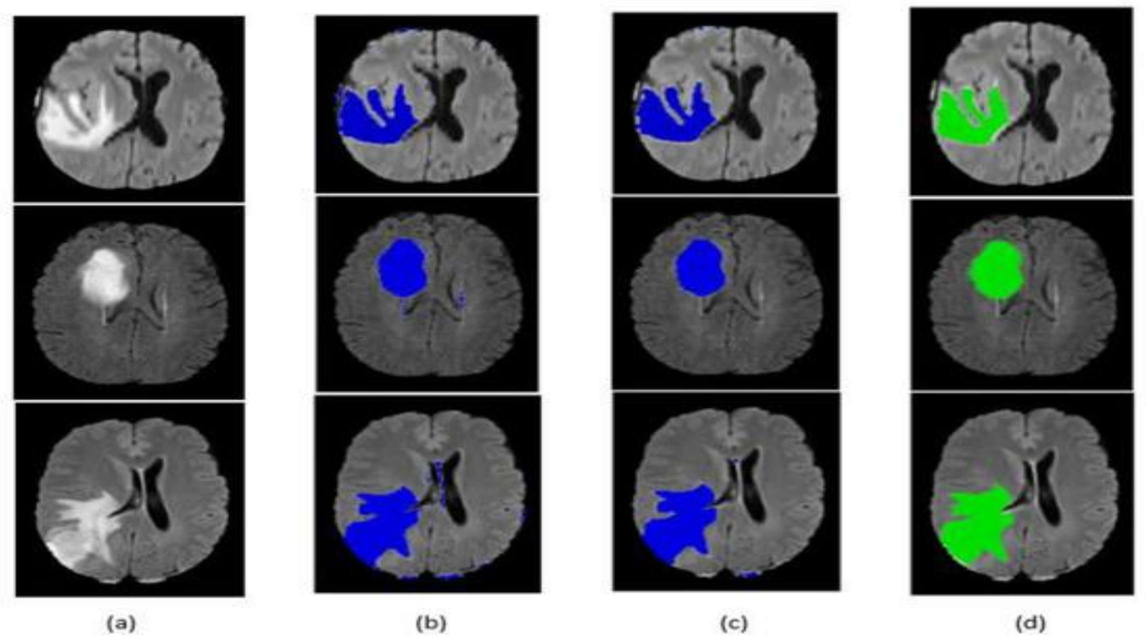


Figure-12: Segmentation result of our method on some BraTS 2021 HGG images: (**a**) original image, (**b**) segmentation before post-processing, (**c**) segmentation after post-processing, (**d**) ground truth

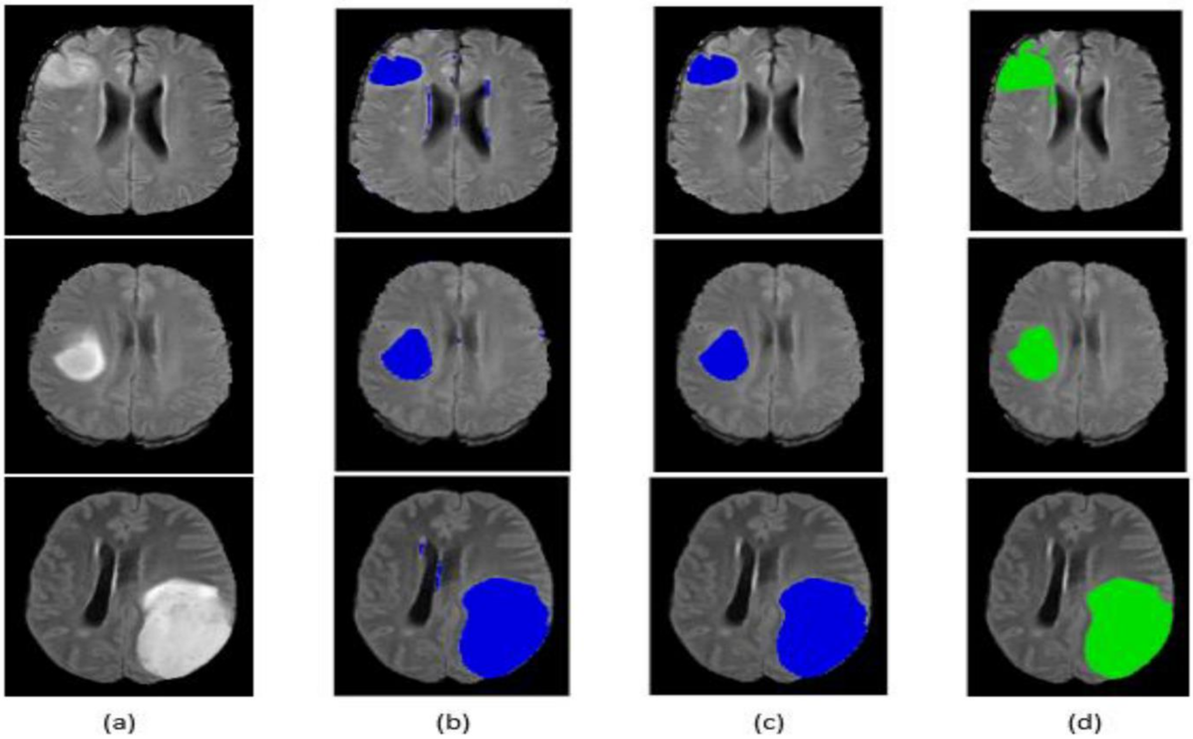


Figure-13: Segmentation result of our method on some BraTS 2021 LGG images: (**a**) original image, (**b**) segmentation before post-processing, (**c**) segmentation after post-processing, (**d**) ground truth

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