Brain Tumor Detection using Deep Learning

ABSTRACT:

The motivation behind this study is to detect brain tumors and provide better treatment for the sufferings. The abnormal growths of cells in the brain are called tumors and cancer is a term used to represent malignant tumors. Usually CT or MRI scans are used for the detection of cancer regions in the brain. Positron Emission Tomography, Cerebral Arteriogram, Lumbar Puncture, Molecular testing are also used for brain tumor detection. In this study, MRI scan images are taken to analyze the disease condition. Objective this research works are i) identify the abnormal image ii) segment tumor region. Density of the tumor can be estimated from the segmented mask and it will help in therapy. Deep learning technique is employed to detect abnormality from MRI images. Multi level thresholding is applied to segment the tumor region. Number of malignant pixels gives the density of the affected region.

Introduction:

The prevalence of brain tumors remains a significant global health concern, necessitating advancements in diagnostic technologies to enhance early detection and treatment. In recent years, the intersection of medical imaging and deep learning has shown promising results in addressing this challenge. The advent of deep neural networks, particularly convolutional neural networks (CNNs), has revolutionized the analysis of medical images, providing a powerful tool for automatic and accurate detection of abnormalities. This project seeks to contribute to this evolving landscape by leveraging deep learning techniques to develop an efficient and reliable system for the detection of brain tumors from magnetic resonance imaging (MRI) scans.

The motivation behind this project stems from the critical importance of timely diagnosis and intervention in cases of brain tumors. Early detection significantly improves the prognosis and treatment outcomes for affected individuals. Traditional methods of tumor detection in medical images often rely on manual examination by radiologists, which can be time-consuming and subjective. Deep learning algorithms have the potential to automate this process, providing a faster and more consistent analysis of medical images, ultimately aiding healthcare professionals in making informed decisions.

As the field of deep learning continues to mature, its application to medical imaging tasks has shown remarkable success, with numerous studies demonstrating the effectiveness of CNNs in detecting various medical conditions. This project aims to build upon these advancements, tailoring a deep learning model specifically for the nuanced task of brain tumor detection. Through the utilization of advanced neural networks and a carefully curated dataset, the developed system endeavors to contribute to the ongoing efforts in improving the efficiency and accuracy of brain tumor diagnosis, thereby enhancing patient outcomes and healthcare workflows.

Objective

The primary objective of our project is to develop an accurate and efficient system for the detection of brain tumors using deep learning techniques applied to medical imaging data, particularly magnetic resonance imaging (MRI). The overarching goal is to contribute to the advancement of medical diagnostics, enabling early detection of brain tumors and improving patient outcomes. The specific objectives can be outlined as follows:

1. Precision in Detection:
2. Sensitivity and Specificity:
3. Real-time Processing and Efficiency:
4. Generalization and Robustness
5. User-Friendly Integration:

Literature Review

literature review on brain tumor detection using deep learning, highlighting key findings and methodologies from various studies:

1."A Survey on Deep Learning Techniques for Brain Tumor Detection and Classification"

This survey provides an overview of various deep learning techniques employed for brain tumor detection. It discusses the evolution of methods, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention mechanisms.

2."Deep Convolutional Neural Networks for Automated Brain Tumor Detection and Segmentation: A Review"

Focused on the application of deep convolutional neural networks, this review explores advancements in automated brain tumor detection and segmentation. It highlights the effectiveness of 3D CNNs in capturing spatial information from MRI scans.

3. "Multi-Modal Brain Tumor Classification Using Deep Neural Networks"

This study proposes a multi-modal approach for brain tumor classification, combining information from various imaging modalities such as MRI and CT scans. The deep neural network architecture integrates both spatial and spectral features for improved accuracy.

4. "Transfer Learning in Brain Tumor MRI Image Classification: A Systematic Review"

Investigating the impact of transfer learning on brain tumor classification, this systematic review analyzes studies that leverage pre-trained models for MRI image classification. It discusses the benefits and challenges associated with transfer learning in this context.

5. "Ensemble Deep Learning: A Review"

Focusing on ensemble methods, this review explores how combining multiple deep learning models enhances brain tumor detection. It discusses ensemble techniques such as bagging and boosting, emphasizing their potential in improving classification accuracy.

6. "Brain Tumor Detection Using 3D Convolutional Neural Networks: A Comparative Study"

Conducting a comparative analysis, this study evaluates the performance of different 3D CNN architectures for brain tumor detection. It explores how variations in network structures impact accuracy and computational efficiency.

7. "Attention-Based Deep Learning Models for Brain Tumor Detection in MRI Scans"

Investigating attention mechanisms, this study explores the application of attention-based models for brain tumor detection in MRI scans. It discusses how attention mechanisms improve the model's ability to focus on relevant regions.

8. "A Comprehensive Review on MRI Brain Tumor Image Segmentation Techniques"

Focused on segmentation techniques, this comprehensive review evaluates various methods for delineating tumor regions in MRI images. It covers traditional methods as well as deep learning-based approaches, providing insights into their strengths and limitations.

9. "Adversarial Training for Robust Brain Tumor Detection in MRI Scans"

Addressing the robustness of deep learning models, this study introduces adversarial training techniques for brain tumor detection. It explores how adversarial training can enhance the model's resistance to perturbations and variations in input data.

10. "Automated Brain Tumor Detection Using Deep Learning: A Meta-Analysis”

Conducting a meta-analysis, this study synthesizes findings from multiple research articles to assess the overall performance of deep learning models in automated brain tumor detection. It discusses trends, common challenges, and future directions identified across studies.

11. "Exploring Explainable AI in Brain Tumor Detection: A Review"

This review focuses on the interpretability of deep learning models in brain tumor detection. It discusses methods and techniques that enhance the explainability of model predictions, facilitating the understanding of decision-making processes in clinical settings.

12. "Integration of Clinical Data in Deep Learning Models for Brain Tumor Diagnosis"

Addressing the integration of clinical data, this study explores how incorporating patient demographics, medical history, and other clinical information can enhance the accuracy and reliability of deep learning models for brain tumor diagnosis.

13. "Scalability and Deployment Challenges in Deep Learning-Based Brain Tumor Detection: A Review”

This review delves into scalability and deployment challenges associated with implementing deep learning models for brain tumor detection in real-world clinical environments. It discusses considerations related to computational resources, model size, and deployment frameworks.

14. "Semi-Supervised Learning for Brain Tumor Detection: A Literature Review"

Focusing on semi-supervised learning approaches, this literature review explores methods that leverage both labeled and unlabeled data for brain tumor detection. It discusses the advantages and challenges associated with semi-supervised learning in medical image analysis.

15."Deep Reinforcement Learning for Optimal Brain Tumor Biopsy Planning: A Review"

Investigating the application of deep reinforcement learning, this review explores how reinforcement learning techniques can be utilized for optimal biopsy planning in brain tumor cases. It discusses studies that optimize decision-making processes in biopsy procedures.

Each of these studies contributes to the evolving landscape of brain tumor detection using deep learning, offering unique perspectives on methodologies, challenges, and potential advancements in the field. Researchers continue to explore innovative approaches to enhance the accuracy, efficiency, and clinical applicability of deep learning models in the context of brain tumor detection.

EXISTING SYSTEM

The early detection and treatment of brain tumour helps in early diagnosis which aids in reducing mortality rate. Image processing has been widespread in recent years and it has been an inevitable part in the medical field also. The abnormal growth of cells in the brain causes brain tumour. Brain tumour is also referred to as intracranial neoplasm. The two types of tumours are malignant and benign tumours. Standard MRI sequences are generally used to differentiate between different types of brain tumours based on visual qualities and contrast texture analysis of the soft tissue. More than 120 classes of brain tumours are known to be classified in four levels according to the level malignancy by the World Health Organization (WHO) [1]. All types of brain tumours evoke some symptoms based on the affected region of the brain. The major symptoms may include headaches, seizures, vision problems, vomiting, mental changes, memory lapses, balance losing etc [2]. Incidence of brain tumours are due to genetics, ionizing radiation mobile phones, extremely low frequency magnetic fields, chemicals, head trauma and injury, immune factors like viruses, allergies, infections, etc[3]. The malignant tumours, also known as cancerous tumours, are of two types - primary tumours, which start from the brain, and secondary tumours, which originate somewhere and spread to the brain. The risk factors for brain tumour are exposure to vinyl chloride, neurofibromatosis, ionising radiations and so on. Thevarious diagnostic methods are computed tomography, magnetic resonance imaging, tissue biopsy etc. Better treatments are now available for brain tumours. There is a chance of focal neurological deficits, such as motor deficit, aphasia or visual field defects in the treatment. Side effects can be avoided by measuring tumour size and time to tumour progression (TTP)[4] . Estimation of density of affected areas can give a better measurement in therapy. Deep learning is a machine learning technique that instructs computers what to do as a human think and do in a scenario. In deep learning, a computer model is able to do classification tasks from images, sound or text. Sometimes human level performance is being exceeded by deep learning techniques. One of the most popular neural networks is an artificial neural network that has a collection of simulated neurons. Each neuron acts as a node and by links each node is connected to other nodes[5]. The aim of this paper is to build a system that would help in cancer detection from MRI images through the convolution neural network. The proposed method was tested and compared with the existing classification techniques to determine the accuracy of the proposed method.

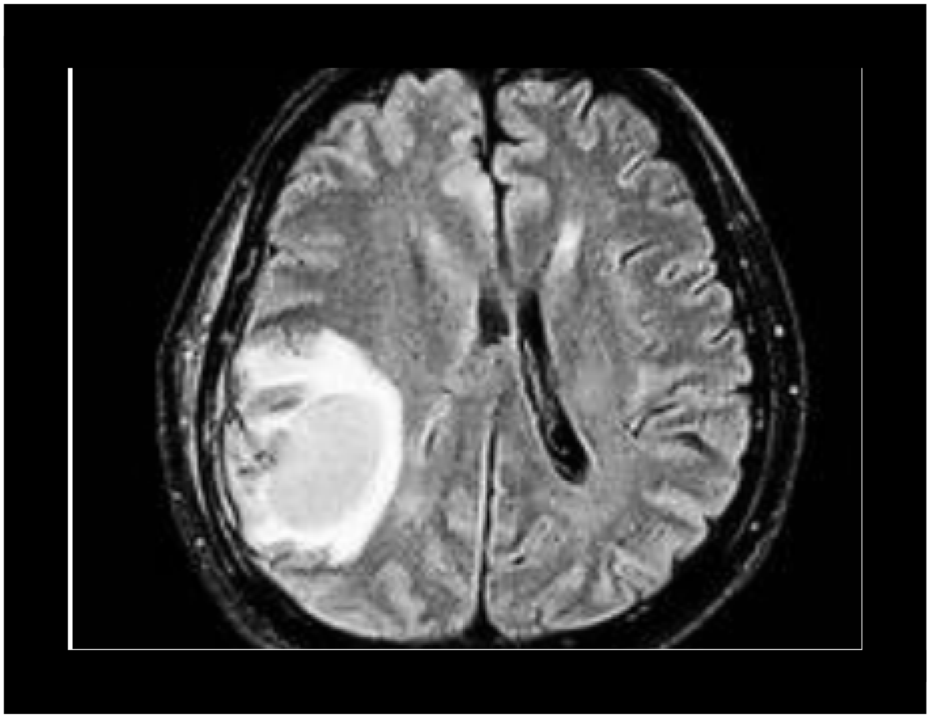

Fig.1 MRI Image

PROPOSED METHOD

System architecture of the proposed system is shown in figure 1. The components are image acquisition, preprocessing, segmentation, feature extraction and classification.

A. Image Acquisition Different bio-medical image records are available for the study of brain tumour detection. Conventional methods are Computer Tomography (CT) and Magnetic Resonance Imaging (MRI). Positron Emission Tomography, Cerebral Arteriogram, Lumbar Puncture, Molecular testing are also used for brain tumour detection. But these are expensive. MRI is working with the principle that both the magnetic field and radio waves can create an image of the interior of the human body by detecting the water molecule present. Portable and miniaturised MRI machines are developed now to avoid the complexity of conventional scanning methods. MRI has a better resolution and contains rich information. The MRI dataset from the kaggle uploaded by Navoneel Chakrabarty has been used here[12].It contains 98 normal brain images and 155 abnormal images. In this dataset, ‘yes’ means tumour images and ‘no’ means healthy images. The augmentation process is also applied here to increase the number of samples. Augmentation step contains a rotation range of 10 degrees, width shift range of 0.1, height shift range of 0.1, brightness range of (0.3,1.0), horizontal and vertical flip. A total of 2530 images were selected from the augmented data. The final dataset contains 980 normal and 1550 abnormal images.

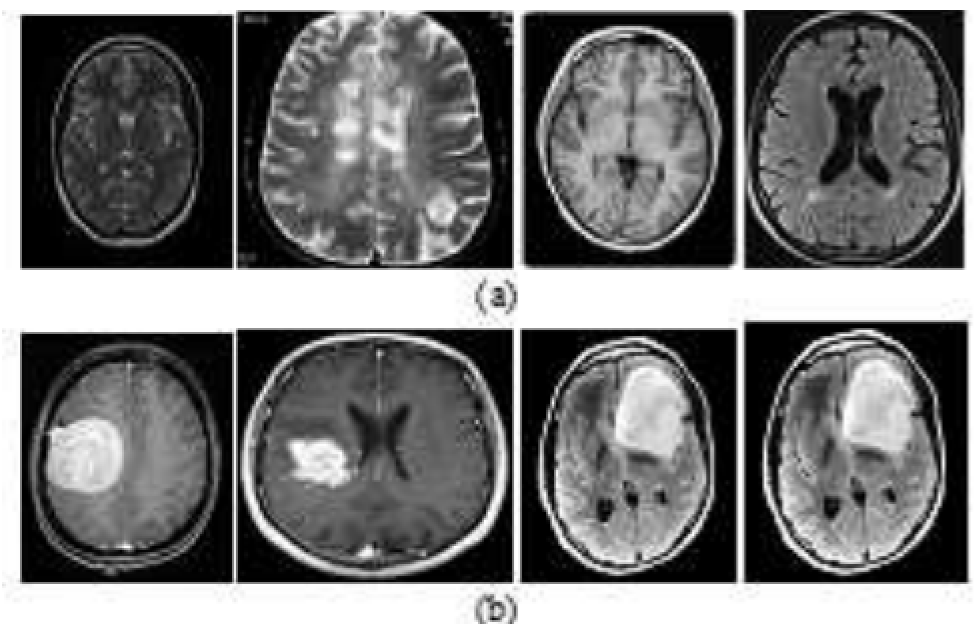

Figure 3 : Brain MRI dataset (a) Normal (b) Tumor

B. Pre processing

The aim of the pre-processing step is preparing the brain images for further processing [13].This process mainly depends on the data acquisition device which has its own intrinsic parameters. Gray scale or 2D conversion is needed, if the raw data is in 3D. Median filtering is best suited for biomedical images to avoid noise. The dataset contains images in different resolutions. As part of the augmentation process , each image is rotated and scaled to a standard format. Histogram equalisation helps to enhance the image quality. Contrast limited adaptive histogram equalisation algorithm is applied to enhance the images.

C. Image Segmentation

In this step a digital image is partitioned into multiple segments. A particular region of the image is being separated from the background This step is very forfeature extraction. Thresholding and morphological operations (erosion, dilation, opening) are the simple steps to segment disease. But in the brain tumour images , the segmentation process at this level will not give the details of tumour regions. The healthy images also have a similar intensity that resembles the tumour region. So the segmentation process can be used to separate the skull of the brain. This Region of Interest (ROI) contains the tumour. OTSU based thresholding algorithm gives a segmented mask of the skull[14]. Active contour method draws the boundary of the enclosed region. Second stage of segmentation can also be applied to the ROI to prepare the mask of tumour region. This method may not give good results in healthy images. This segmented image can be used to study the features of tumour region , which will help in the density estimation.

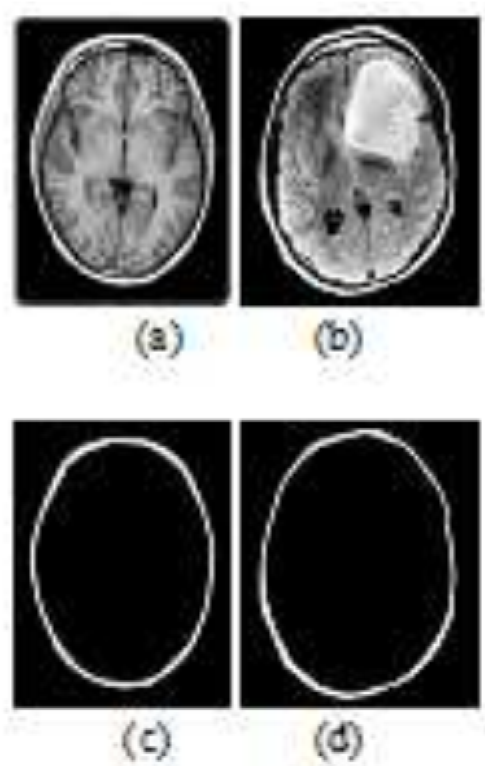

Figure 4 : Skull Segmentation (a) Normal Input image(b) Abnormal Input image (c) Normal Segmented image (d) Abnormal segmented image

D. Feature Extraction

Computing the actual features can be analysed to illustrate the behaviour or symptom of the disease. The classification is mainly influenced with the feature selection. Common features are asymmetry, diameter, and border irregularity[15].

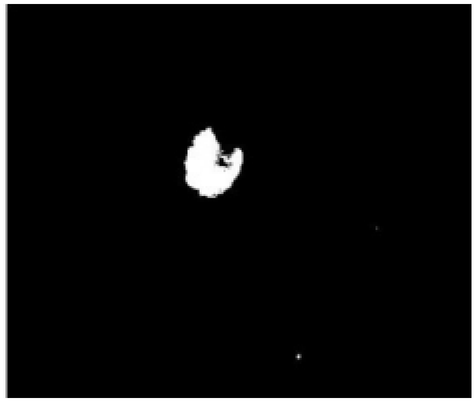

Figure 5 : Segmented tumour region using multiple thresholding

E. Classification

Many machine learning approaches are being implemented in disease detection from brain images. Artificial neural networks can be used here to classify, if the features are extracted in an order[16].An ANN classifier assumes one feature that is not related to any other feature.

Deep learning techniques will be effective here to classify tumour image without segmentation. A deep neural network can be created with Convolutional nueral network algorithm[17]. General architecture ofconvolutional neural networks is shown in figure 6. In deep learning , the feature is extracted from the entire image automatically. Convolution in the CNN architecture performs this operation. Number of feature maps increases with the increase in CONV layer. Reduction of dimension is required to initiate training. Pooling layer down samples the feature dimension. Fully connected layers manipulate the score of each label. Softmax layers prepare the model with feature and class score.

The CNN architecture is slightly modified in its dimension for training the brain tumour images. The modified model architecture is listed in table 1.

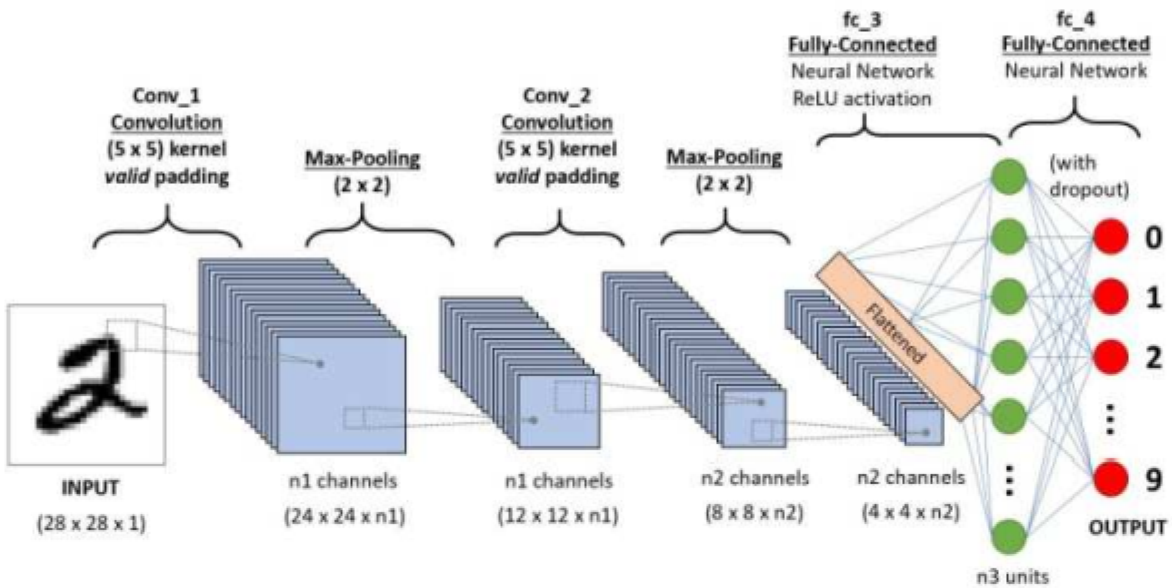

Figure 6 : General architecture of CNN

Model: "BrainTumorDetectionModel"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 240, 240, 3)]	0
zero_padding2d (ZeroPadding2	(None, 244, 244, 3)	0
conv0 (Conv2D)	(None, 238, 238, 32)	4736
bn0 (BatchNormalization)	(None, 238, 238, 32)	128
relu0 (Activation)	(None, 238, 238, 32)	0
max_pool0 (MaxPooling2D)	(None, 59, 59, 32)	0
max_pool1 (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6272)	0
fc (Dense)	(None, 1)	6273

Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64

Table 1: Modified Model architecture

The model is compiled in Keras with ‘Adam’ optimizer and ‘Binary cross entropy’ loss. Default learning rate of 0.001 is used. The model is trained with batch size of 32 for 24 epochs.

For the test images our trained model gives an accuracy of 95.6%. For those images classified as having brain tumour, the tumour location is detected using a combination of multilevel thresholding, morphological operations and contour extraction.

$$g(x,y) = \begin{cases} 1, & f(x,y) > T \\ 0, & f(x,y) \leq T \end{cases} \qquad \text{...........(1)}$$

Where T is the mean of Maximum to Minimum intensities of the image. Morphological Open function is used to segment the regions.

Contours of all regions are plotted and the region with maximum area contains tumour region. The Density of the tumour area can be estimated using Gaussian kernel distribution.

$$f(x) = \frac{1}{n\sigma\sqrt{2\pi}} \sum_{i=0}^{n} e^{-\frac{1}{2}\left(\frac{x_i - x}{\sigma}\right)^2} \qquad \text{..................(2)}$$

images were collected from Kaggle dataset. The count of the data is insufficient for modelling a deep neural network. So 2530 images have been created with augmentation technique.

The extracted cropped images are then resized to (240, 240) resolution. Keras (with Tensorflow backend) framework is chosen creating the model. Two types of segmentation at different level are implemented to analyse the performance of the system. Segmentation was done before and after classification. From the performance analysis, segmentation after the classification gives better result. This algorithm is faster in execution for normal MRI images. If it identifies the abnormal images, it goes to the next step ,ie : segmentation. ROC curve shows the relation between sensitivity and specificity .

MODULAR DESCRIPTION :

1. Data Preprocessing Module:

The Data Preprocessing Module is the foundational component of our brain tumor detection system. In this phase, raw MRI images undergo a series of essential preprocessing steps to ensure optimal input for subsequent deep learning analysis. Intensity normalization is applied to standardize pixel values across images, addressing variations caused by different acquisition settings. Furthermore, image resampling is performed to achieve a consistent voxel size, enhancing the uniformity of the dataset. To mitigate the impact of noise and artifacts, a combination of filtering techniques is employed. Data augmentation strategies, including rotation, flipping, and scaling, are integrated to artificially diversify the dataset, enhancing the model's ability to generalize. By meticulously preparing the input data in this module, we lay the groundwork for a robust and reliable brain tumor detection system that can effectively handle real-world variations in MRI scans.

2. Feature Extraction Module:

The Feature Extraction Module is tasked with extracting discriminative features from preprocessed MRI images using a deep convolutional neural network (CNN). Convolutional layers with varying filter sizes are strategically employed to capture hierarchical patterns and spatial relationships within the images. Pooling layers downsample the spatial dimensions, preserving essential information while reducing computational complexity. Transfer learning is leveraged, utilizing pre-trained CNN models to expedite training and enhance the network's ability to recognize intricate features relevant to brain tumor identification. The modular design allows for experimentation with diverse CNN architectures, ensuring adaptability to evolving deep learning techniques. As the Feature Extraction Module concludes, the learned features are ready to be fed into the subsequent classification module for precise and efficient brain tumor detection. This modular approach not only facilitates current model development but also provides flexibility for future enhancements and model upgrades.

3.Deep Learning Model Module:

The Deep Learning Model Module constitutes the heart of our brain tumor detection system, employing a sophisticated convolutional neural network (CNN) architecture for accurate and efficient analysis of medical images. This module is designed to automatically learn intricate patterns and hierarchical features from 3D MRI scans. Utilizing a 3D CNN allows the model to capture spatial dependencies in the volumetric data, enhancing its ability to discern subtle abnormalities indicative of brain tumors. The architecture may include multiple convolutional layers for feature extraction, pooling layers for spatial down-sampling, and fully connected layers for classification. The model is trained on a diverse and well-annotated dataset, fine-tuning its parameters to optimize its ability to generalize to unseen cases. Regularization techniques, such as dropout, may be employed to enhance model robustness. The successful implementation of this module ensures the accurate identification and segmentation of brain tumors within medical images, contributing to the early diagnosis and treatment of patients.

4.Data Collection Module:

The Data Collection Module focuses on the acquisition and preparation of the dataset crucial for training and evaluating the deep learning model. This module begins by collating a comprehensive dataset of 3D MRI scans with corresponding tumor annotations. The selection of diverse cases, encompassing various tumor types, sizes, and locations, is paramount to ensure the model's robustness. The dataset is preprocessed to standardize image resolution, intensity, and orientation, mitigating potential variations across different acquisition protocols and machines. Data augmentation techniques, such as rotation, flipping, and scaling, are applied to artificially expand the dataset, promoting model generalization. Ethical considerations and patient privacy are prioritized throughout the data collection process, and any identifiable information is anonymized. The curated dataset is then split into training, validation, and testing sets to facilitate robust model training and evaluation. The effectiveness of the Deep Learning Model Module is contingent on the quality and representativeness of the dataset prepared within this module, ensuring the system's reliability in real-world scenarios.

5.Post-processing and Visualization Module:

Following the predictions generated by the deep learning model, the Post-processing and Visualization Module plays a crucial role in refining the results and presenting them in a clinically interpretable manner. Post-processing steps may involve thresholding the predicted probabilities to obtain binary tumor masks and applying morphological operations for smoother and more anatomically plausible segmentation results. False positive and false negative regions may be further addressed through advanced post-processing techniques, such as region-growing or contour refinement. Visualization is a key aspect of this module, providing clinicians with intuitive and insightful representations of the model's findings. Heatmaps overlaid on the original images, 3D renderings of segmented tumors, and quantitative metrics such as Dice coefficient and sensitivity are essential components for result interpretation. This module contributes to the overall clinical acceptance of the system by providing a clear and transparent depiction of the deep learning model's predictions, fostering trust among healthcare professionals and enhancing the system's potential for integration into diagnostic workflows.

System Design

1. Overview and Input Processing:

The system design for brain tumor detection using deep learning begins with the acquisition of input data, typically high-resolution MRI scans. These scans serve as the primary source for detecting abnormal structures within the brain. The first module in the system is dedicated to data preprocessing, encompassing tasks such as image normalization, resizing, and intensity adjustment. This ensures that the input images are standardized and conducive to the subsequent deep learning processes. The flow chart for this stage illustrates the sequential steps, starting from input acquisition and progressing through preprocessing. Once the data is preprocessed, it is ready for the feature extraction phase.

2. Feature Extraction and Model Architecture:

The heart of the brain tumor detection system lies in the feature extraction module, where a deep convolutional neural network (CNN) is employed. The architecture of the CNN is designed to automatically learn hierarchical features from the preprocessed MRI images. Convolutional layers, often stacked in multiple stages, capture local patterns and features at various scales. Pooling layers downsample the spatial dimensions, enhancing the network's ability to recognize relevant patterns. The flow chart for this phase illustrates the sequential progression of the CNN architecture, showcasing the convolutional layers, activation functions, and pooling operations. Transfer learning may be incorporated at this stage, utilizing pre-trained models to boost performance. The output of this module is a set of learned features that encapsulate the discriminative information crucial for brain tumor detection.

3. Classification and Output:

The learned features from the feature extraction module are then fed into the classification module, where a fully connected neural network is often employed. This module is responsible for making the final decision on whether a given input MRI scan contains a brain tumor or not. The flow chart for this stage outlines the steps involved in the classification process, including the activation function, loss computation, and decision-making based on the output probability. The model is trained using labeled datasets, and the classification threshold is set to convert the model's probability score into a binary decision. The output is a visual representation or report indicating the presence or absence of a brain tumor in the input MRI scan.

This modular system design, outlined with corresponding flow charts, ensures a clear and organized structure for brain tumor detection. Each phase contributes to the overall goal, from preprocessing raw input data to extracting meaningful features and making informed classifications. The flow charts serve as visual aids, elucidating the sequential and interconnected nature of the processes involved in the deep learning-based brain tumor detection system.

RESULTS AND DISCUSSIONS

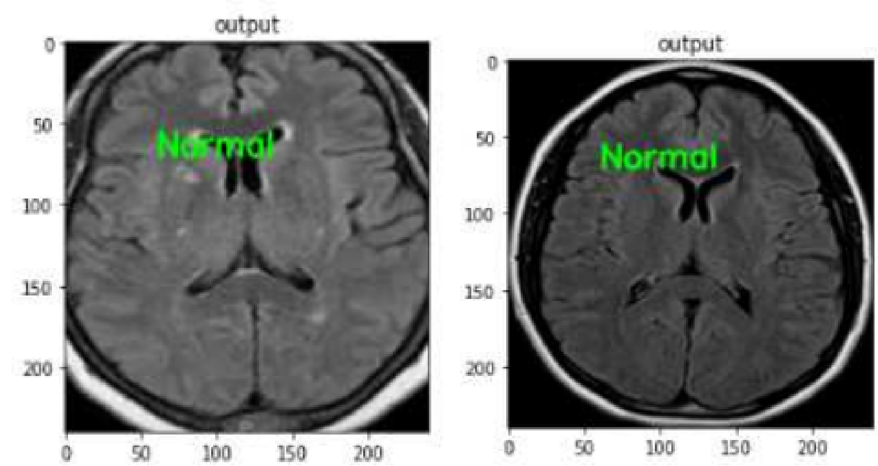

FIG : Normal Images Results

Objective of the proposed system is to classify malignant brain tumour from the MRI images. 253 MRI images were collected from Kaggle dataset. The count of the data is insufficient for modelling a deep neural network. So 2530 images have been created with augmentation technique.

The extracted cropped images are then resized to (240, 240) resolution. Keras (with Tensorflow backend) framework is chosen creating the model. Two types of segmentation at different level are implemented to analyse the performance of the system.

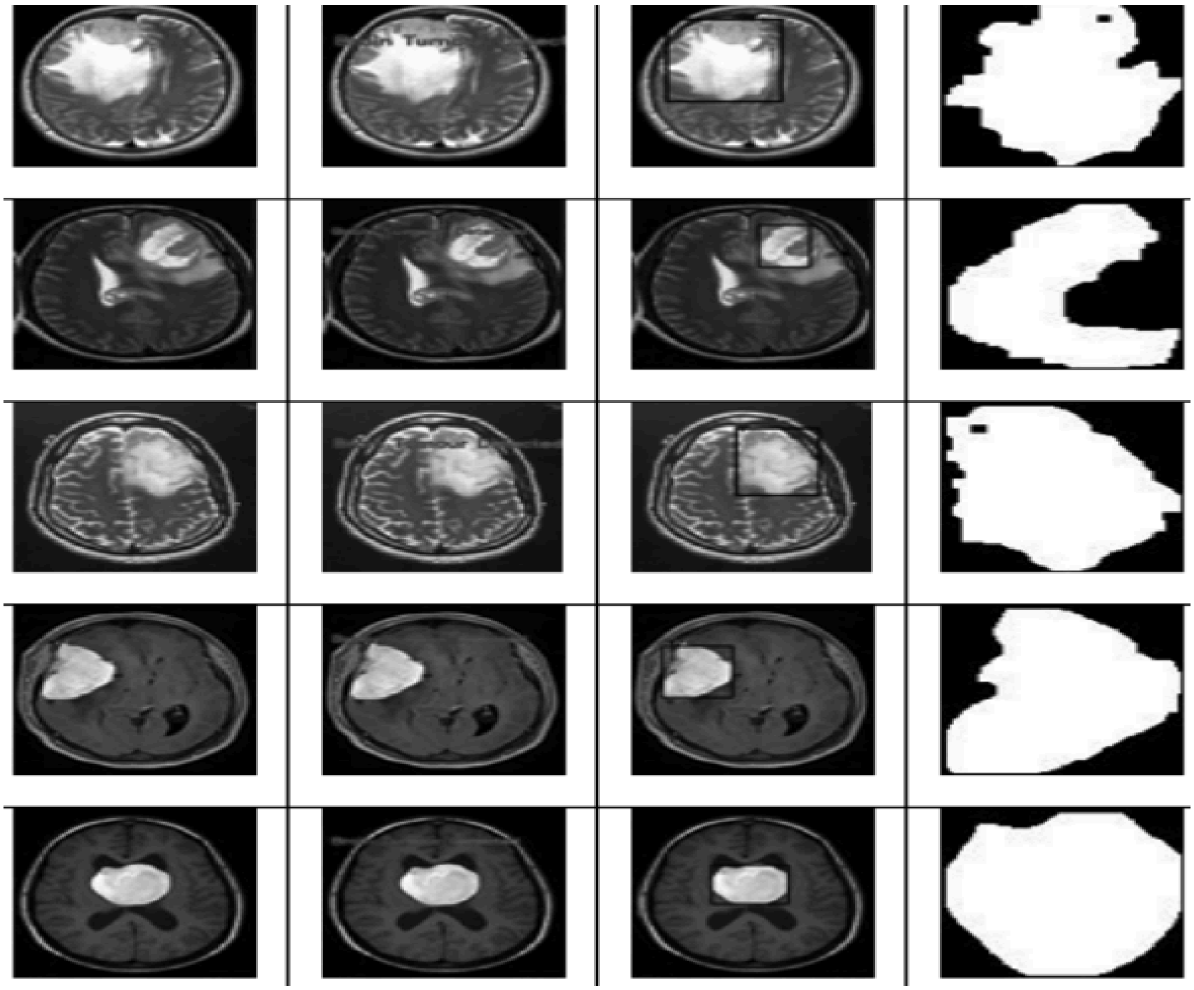

FIG .Tumor detection results : (a) Input Image (b) Abnormality Detection (c) Tumor region detection (d) tumor mask for density estimation

Segmentation was done before and after classification. From the performance analysis, segmentation after the classification gives better result. This algorithm is faster in execution for normal MRI images. If it identifies the abnormal images, it goes to the next step ,ie : segmentation.

ROC curve shows the relation between sensitivity and specificity .

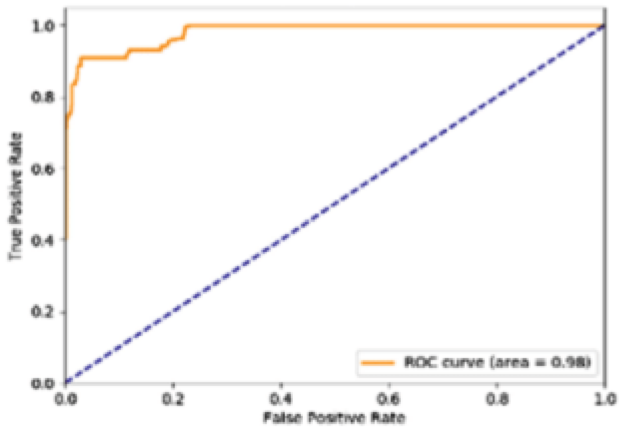

FIG : ROC plot of Normal

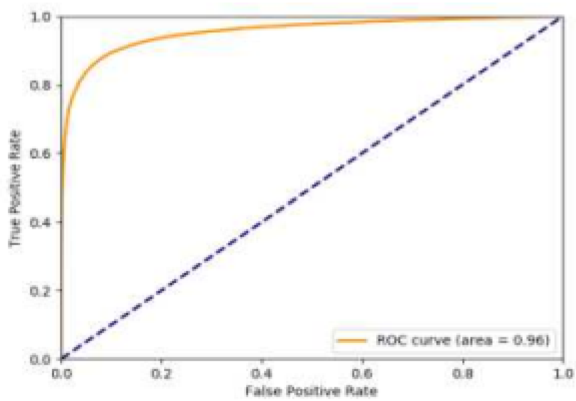

Fig : ROC plot of Abnormal cases

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} = 0.98$$

$$Sensitivity = \frac{TP}{TP+FN} = 0.97$$

$$Specificity = \frac{TN}{TN+FP} = 0.99$$

Table 2: Performance Analysis

Algorithm	Over all Accuracy
Nandpuru[18]	96.77%
El-Dahshan[19]	97%
Ibrahim[20]	96.33%
Rajini[21]	90%
Proposed Method	98%

This paper provides a new method for detecting brain tumour by deep learning method. The early detection of cancer helps timely and effective treatment. Kaggle dataset contains good quality of MRI images for research purposes. Different segmentation algorithms were experimented. From this , multilevel thresholding and OTSU thresholding are the best methods for the dataset. Convolutional Neural Network with modified approach helped to get a result with accuracy 98%. Density estimation method is also proposed using Gaussian kernel distribution. This system can be improved to support with a web interface. Detection of different diseases can be also identified from the MRI images. Apart from the density some other parameters can also estimated for therapeutic purposes.

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