

Deep Learning in Neuro Oncology: An Approach to Brain Tumor Detection

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Abstract— Brain is the central part of human nervous system, brain tumor are the abnormal growth of cells in the brain that leads to death. Brain tumors are the vital neurological disorder, the common and precise classification and segmentation of brain tumor is obtained through medical imagining techniques like MRI and CT scans of brain. However, detecting brain tumor using MRI scans images, usually depends on human interpretation, which adds more time, requires expertise and is prone to human errors. However, detecting brain tumors physically or manually is a very difficult task and time-consuming which might lead to imprecision. We have developed a brain tumor system that uses the CNN (Convolutional Neural Network) model and the U-Net design model to accurately identify and classify pituitary gland tumors, glioma tumors, and meningioma tumors in order to address this issue. To improve the performance of our suggested model, image enhancement techniques such as data augmentation techniques, which apply various filters to the original images, will be used to improve the visual representation of the MRI scans. A diverse range of cases, 3558 glioma photos, 2758 pituitary images, 3592 meningioma images, and 2580 non-tumor images make up the collected data. In this work, we presented a unique method that uses deep learning algorithms to detect tumors from MRI scan images. The suggested model outperformed the CNN and U-Net models in terms of brain tumor classification and segmentation, with testing accuracies of 97.54% and 99%, respectively.

Index Terms—neurological, segmentation, meningioma, augmentation

I. INTRODUCTION

Brain tumors are one of the most vital conditions that affect human nervous system, the abnormal growth of cells within the brain and its surrounding tissues, is a brain tumor. These tumors are very dangerous to the patient leading to potential impairments. Early detection and accurate detection of tumors are essential for improving patient survival outcomes. There are more than 100 types of brain tumors. However, all brain tumors have some factors in common.

The common symptoms include:

- Unusual or new headaches
- The person may have a abnormal movements with full body shaking, dizziness, and the person is unconscious.
- Also some people experience memory, personality, or behavioral changes.
- Other people may develop blurred hazy vision.
- The symptoms also include difficulty controlling movement.

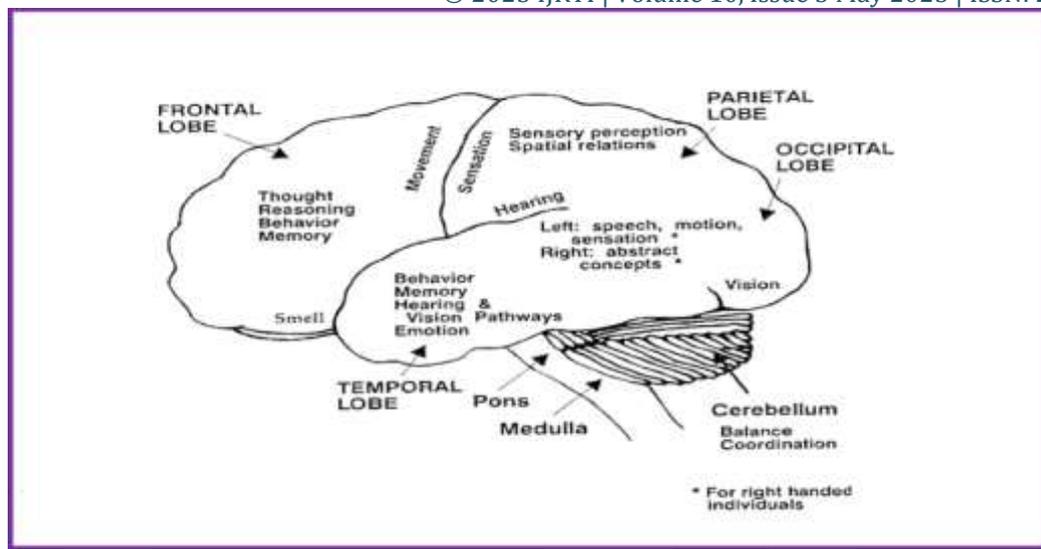


Figure: Brain parts and its functions

Symptoms are often related to the location of the tumor. As in the above diagram, different parts of the brain have distinctive functions. The frontal lobe controls thoughts, logical, analysis, reasoning, and primary movement. The parietal lobe adjusts the sensation, sensory insight and spatial relationships. The temporal lobe acts on memory, emotion, and hearing and visions. The cerebellum controls balance of the activities in body. The brain system has many connections to and from the spinal cord to the brain.

To decide whether a patient with these symptoms has a brain tumor or not, an MRI scan which remains the standard medical imaging technique for brain tumor diagnosis. If a person with these neurological symptoms, a CT scan is commonly the first test done, if a tumor cells present from the results of the CT scan, and then the doctors go through an MRI scanning. Once a tumor has been identified, tissue samples of the brain tumor are diagonalized to determine the nature of the tumors.

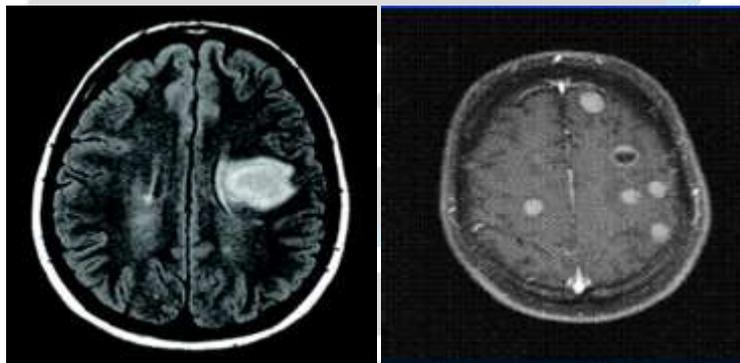


Figure: Sample MRI scans images

The most common tumor types include meningioma and glioma. The meningioma arises from the meninges, the covering of the brain. The picture on the left shows the tumor, the large white spot in section of the brain. Meningiomas are commonly slowly growing and may not recover if the tumor is completely removed.

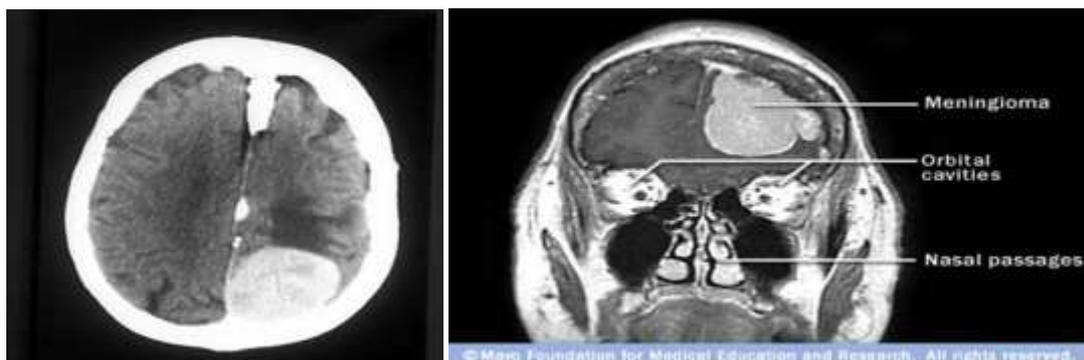


Figure: MRI scans images of meningioma tumor

The glial cells that envelop the brain's nerve cells give birth to gliomas. Glioblastomas and other malignant primary brain tumors usually develop more quickly than other tumors and engulf surrounding tissue.

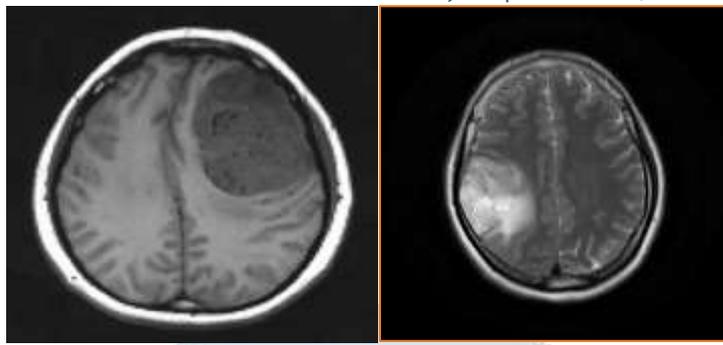


Figure: MRI scans images of gliomas tumor

II. LITERATURE SURVEY

Recent advancements in brain tumor classifications and tumor precise segmentation using advanced deep learning approaches have shown significant analysis results using brain MRI scan images. By processing large number of patterns in MRI scans, ANN shows reliable classification and detection of brain tumor and supports robust segmentation methods.

Early studies devastated the efficiency of CNN model for tumor classifications highlights concerns of overfitting issues due to the small dataset [1]. The hybrid model of CNN architectures, such as ResNet18 has improved segmentation accuracy [2].

Hussain et al. (2022) proposed a hybrid CNN model combining ResNet and DenseNet for tumor classification such as gliomas tumor, meningiomas tumor, and pituitary tumor which achieved 91.7% accuracy. Methods based on CNN with ensemble model and transfer learning and AlexNet model for classification of brain images is proposed by [5], [6],[7].

The scope of the review is on the use of medical imaging technique, MRI scans images as a preliminary tool for brain tumor analysis. It explores traditional manual methods, semi-automated tools and other recent advancements in AI and deep learning techniques such as image processing approaches for tumors classifications, tumor detection and tumor segmentation.

CNN is the most promising method for accurate classification issues in terms of feature and pattern extractions, according to this research review. Data augmentation is used to improve classification accuracy and address the problem of insufficient training data.

III. METHODOLOGY

The proposed system integrates **deep learning techniques** to analyze brain tumors, **tumor classification** (to identify the type of tumor) and **tumor segmentation** (to locate and delineate the tumor in an image). The below architecture diagram illustrates the precise procedure of brain tumor analysis system, which adds classification and segmentation modules to analyze from MRI scan of medical brain imaging technique to detect the brain tumors.

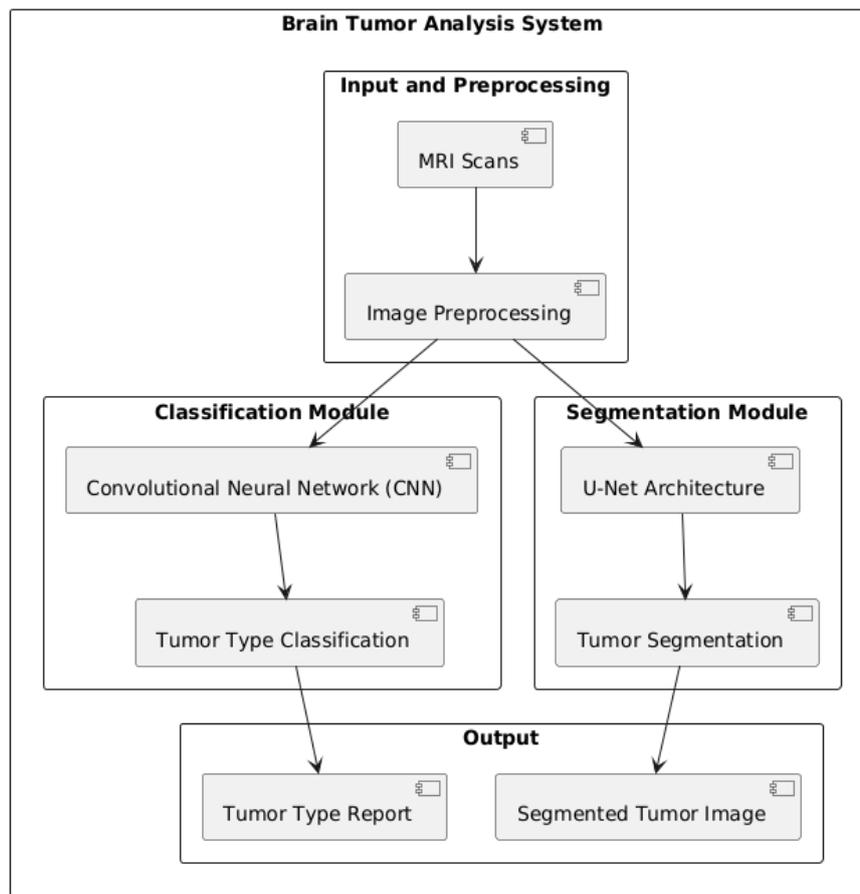


Figure: System Architecture

Input and preprocessing

Input are MRI scan images, the system starts working by sending MRI images of brain as a input to the system. These scanned images of MRI undergo preprocessing steps to enhance the requirements for the analysis.

Normalization techniques are used to adjust the pixel values for consistent input, resizing takes place to standardize the input dimensions, each and every input data goes under noise reduction to remove the unwanted artifacts or noise in the images. To enhance the dataset with additional variations such as rotate, flipping of the images the data augmentation is performed on the data to obtain the good quality and standard range of the input data.

Classification module

This module focuses on differentiating the type of tumor present in the brain, this is achieved by the implementation of CNN.

CNN is a deep learning algorithm, which is well particularly useful for finding patterns like edges, textures, shapes in images to recognize brain tumor type.

Based on the common features, CNN categorizes the tumor into predefined classes: Gliomas tumor, meningiomas tumor, pituitary tumor, no tumor.

Segmentation module

The U-net design is a fully convolutional neural network that will function on pixel-wise prediction, making this module perfect for medical photo segmentation. This module precisely segments the area of the brain tumor using the U-Net model. The decoder creates a thorough segmentation map that displays the borders of the tumor areas after the encoder collects features from the input pictures. Bottleneck processes the smallest spatial resolution which abstracts high level features.

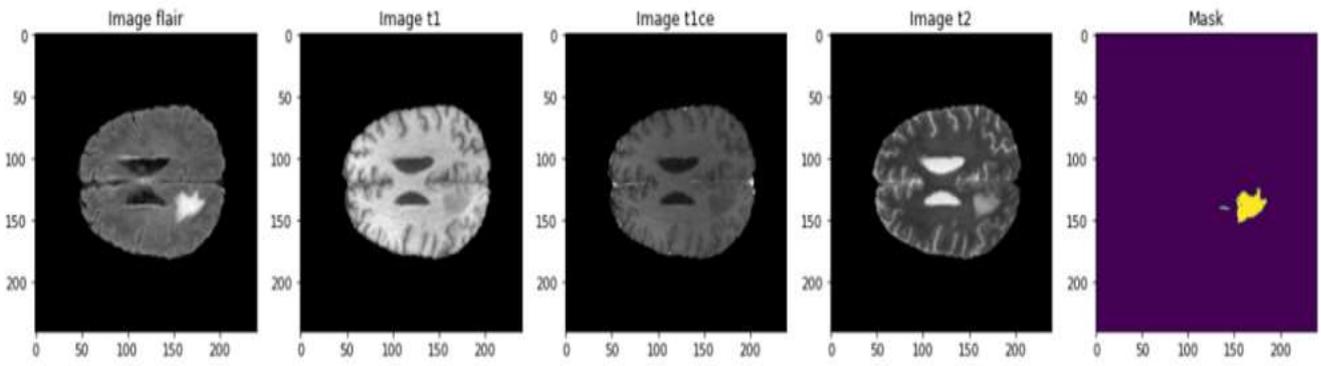


Figure: Brain tumor slices and masks

Output

This module produces the report of the patient with respect to brain tumor analysis. A classification report predicts the tumor type for the given MRI scan with the most high accuracy. Segmentation report gives us the visual output where exactly the tumor is segmented assists the diagnosis and treatment planning of the patient.

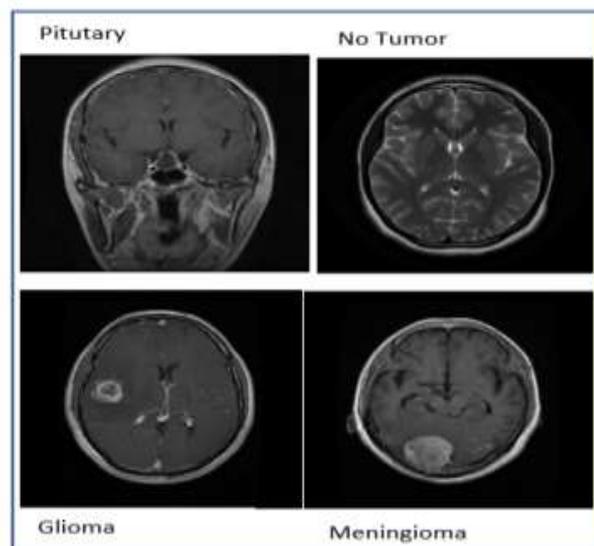


Figure: Sample MRI images of types of tumors

IV. EXPERIMENTS AND RESULTS

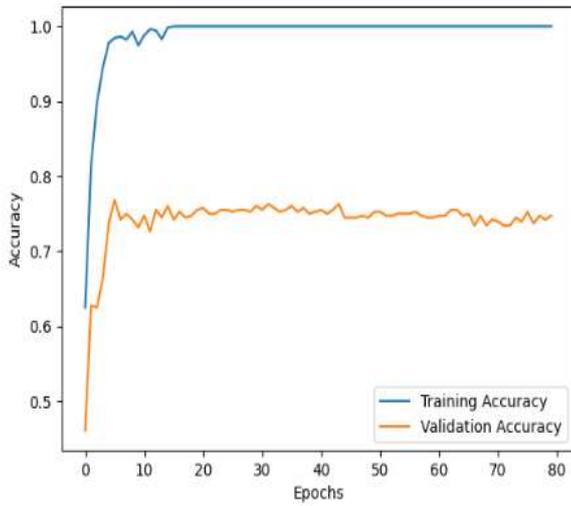
In-depth brain tumor analysis was obtained during the construction and assessment of the system for brain tumor classification and segmentation, thanks to the experiment and findings.

The proposed model outperformed the traditional edge based and region based detection methods by 5% improvement in accuracy and reduced false positives by 10%.

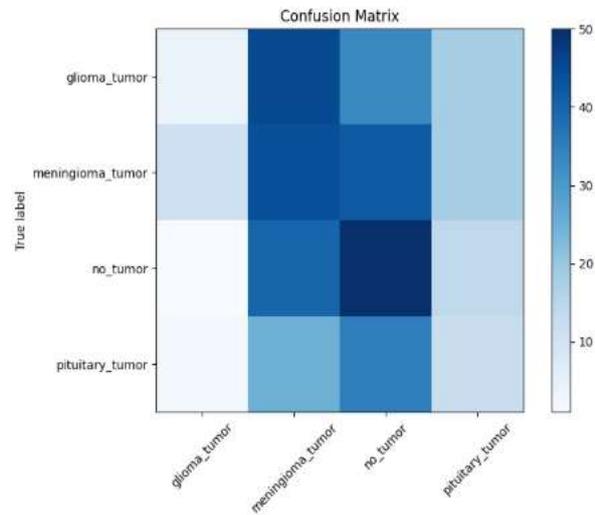
The detection and classification module achieved around accuracy 98.3%, precision 94.2%, recall (sensitivity) 94.8%, specificity 97.9%.

Segmentation module performed well in accuracy by achieving 98% accurately delineating tumor boundaries, even in cases of irregular shapes. This module achieves accurate boundary region detection in high-contrast regions and overall it predicted the segmentation with the ground truth images. The segmentation process achieves accuracy 98%, precision 95.8%, recall (sensitivity) 96.8%, specificity 94.3%, F1 score 97%

The outcomes of training and assessing the deep learning model for brain tumor classification and segmentation tasks are shown in the graphs below.



(a)

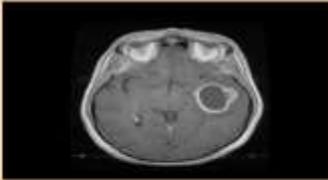


(b)

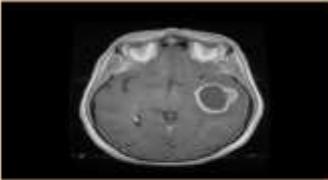
These are the results that show up when classifying and segmenting brain tumors from MRI scan pictures. The difference between training and validation accuracy results is displayed in the graph below. The model accuracy graph (a) indicates the difference over time between the results the model predicts and the actual outcomes. By comparing the true labels displaying true positives, true negatives, false positives, and false negatives, a confusion matrix (b) is a table that is used to assess each classification model's performance.

BRAIN TUMOR PREDICTION

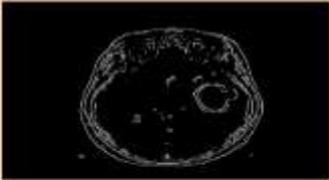
Selected Image



Gray



Edge Detection

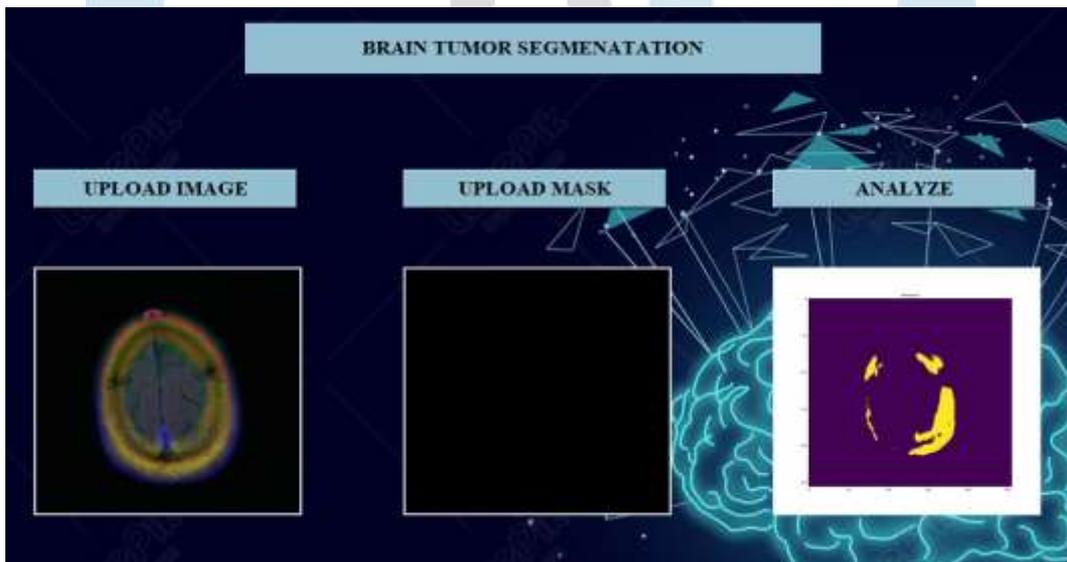
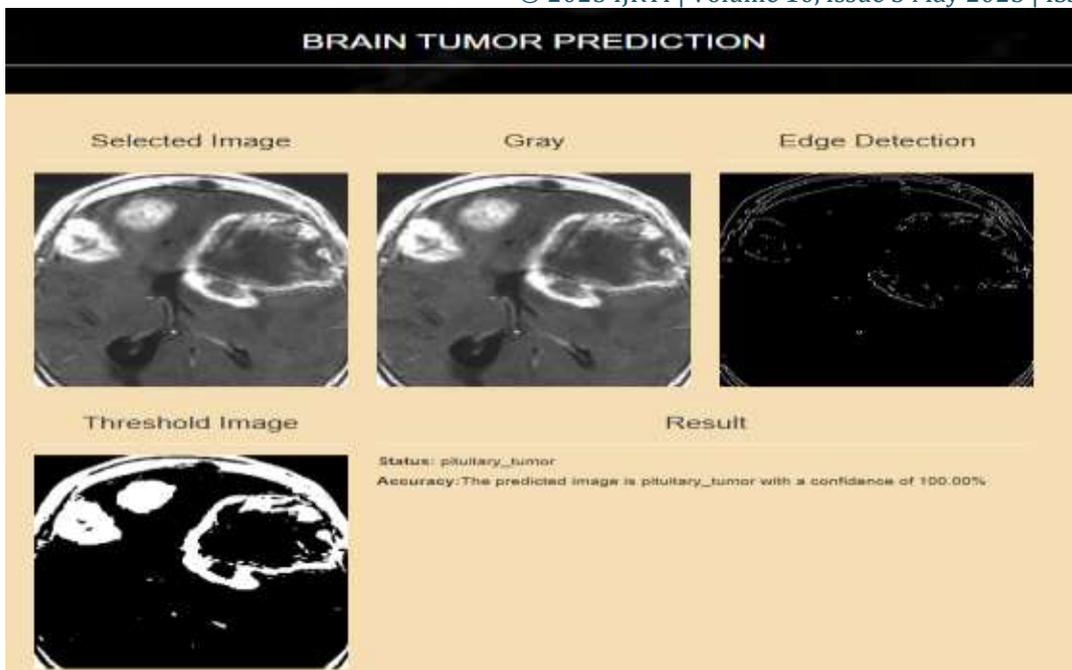


Threshold Image



Result

Status: no_tumor
Accuracy: The predicted image is no_tumor with a confidence of 100.00%



V. CONCLUSION

This project successfully developed a brain tumor analysis system using CNN and U-Net architecture for both brain tumor classification and segmentation. The objectives were:

- To implement the edge detection and thresholding methods to highlight the important and unique features in brain images.
- To evaluate various classifications accurately identifying tumor types.

While this system adds more benefits, including enhanced detection and real-time processing for clinical applications.

This paper offers a thorough assessment of the deep learning classifications and segmentation of brain tumors, namely meningioma, glioma, and pituitary, based on CNN and U-Net. In accurately identifying the particular tumor class and segmenting the tumor location, CNN and U-Net both performed well. The suggested approach generated the best results in brain tumor identification, yielding an overall accuracy of 99.51% on both training and testing samples.

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