NeuroScan AI

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***Abstract*—In this study, the use of Convolutional Neural Networks (CNN) and U-Net models for brain tumor detection and segmentation from MRI scans is investigated. To increase the diversity and resilience of the training samples, data augmentation techniques were applied, and the MRI dataset was preprocessed to improve image clarity and resolution. By learning key visual patterns associated with the presence of tumors, a CNN-based model was trained to recognize and categorize tumor features. A U-Net model was used to accomplish detailed segmentation after classification, yielding accurate pixel-level mapping of tumor regions. Key performance metrics like accuracy, precision, recall, and F1-score were used to assess the models.Strong performance was shown by the experimental results, with the CNN model achieving high classification accuracy and the U-Net model producing precise and finely detailed segmentations. The results provide important new information for medical image processing by confirming how well this method works to locate and identify brain tumors from MRI images. Larger datasets and more sophisticated deep learning frameworks will be used in future research to increase diagnostic precision and support early tumor detection and treatment planning.**

***Index Terms*—Brain Tumor Detection, Deep Learning, Convolutional Neural Networks (CNN), U-Net, MRI Imaging, Image Segmentation.**

I. Introduction

A crucial field of study in contemporary healthcare is tumor detection and segmentation (BTDS), especially in the fields of medical imaging and diagnostics. Accurate and timely brain tumor identification and detection are essential for patient care, treatment planning, and enhancing survival rates. Because the brain is essential for regulating body functions, brain tumors, whether benign or malignant, can have a profound impact on a person's life. The need for accurate and effective diagnostic systems has increased as more cases of brain tumors are reported worldwide each year. Radiologists frequently manually examine MRI (Magnetic Resonance Imaging) scans as part of traditional diagnostic procedures, which can be laborious and subjective. Furthermore, these techniques might not be able to handle the variation in tumor location, appearance, and intensity among patients. and MRI machines. MRI is regarded as the gold standard among the many imaging modalities available for observing soft tissues, such as the brain. Unlike CT scans, it provides high-resolution images without exposing patients to dangerous radiation. Despite its benefits, MRI data interpretation can be difficult because healthy and abnormal tissues can have similar visual characteristics, which could result in a misdiagnosis.

Medical image analysis has advanced significantly in recent years thanks to the application of artificial intelligence, particularly deep learning. Convolutional neural network (CNN)-based techniques have shown great promise in identifying intricate patterns in MRI scans. Faster and more reliable classifications are made possible by these models' automatic ability to recognize tumor characteristics. Concurrently, U-Net and similar architectures have become more popular for medical image segmentation because they provide accurate tumor boundary delineation at the pixel level. To help clinicians visualize the size, shape, and location of the tumor, brain MRI images are segmented into regions that highlight pathological areas. For treatment decisions like radiation targeting or surgical planning, this step is crucial.

In addition to requiring a great deal of time and experience, manual segmentation techniques are also vulnerable to discrepancies between experts. Automated systems are therefore becoming more and more useful in clinical workflows. These systems seek to increase the speed and accuracy of diagnosis while lessening the workload for medical professionals.

Using MRI data, this study proposes a deep learning-based method for identifying and classifying brain tumors. A U-Net model is utilized for segmentation and a CNN model is trained for classification, resulting in a reliable automated.brain tumor analysis. The suggested system might help with early diagnosis and help doctors make well-informed clinical decisions.

According to the type and presence of tumors, brain MRI images are divided into four different classes in this study. These categories aid in the development of classification models that reliably differentiate between different kinds of tumors and normal brain scans.

1. Meningioma Tumor (Typically Non-Cancerous): Meningiomas arise from the tissues that envelop and shield the brain and spinal cord, known as meningiomas. Though some may exhibit more aggressive behavior, these tumors usually grow slowly and are frequently non-cancerous. They can press against areas of the brain and result in neurological symptoms like headaches, vision issues, or seizures, depending on their size and location.

2. Glioma Tumor (Can Be Cancerous or Non-Cancerous): Gliomas start in the glial cells that surround and support neurons in the brain and spinal cord. Astrocytomas, oligodendrogliomas, and the more aggressive glioblastomas are among the various subtypes that fall under this group. The growth rate and behavior of gliomas can vary greatly. Some invade surrounding brain tissue, making treatment more difficult, while others grow slowly and are controllable.

3. Pituitary Tumor: Usually benign but potentially harmful

The pituitary gland, a tiny but vital gland at the base of the brain that controls hormone levels, is where pituitary tumors start. The majority of pituitary tumors are benign, but they can cause problems like hormonal imbalance or metabolic disturbances by interfering with the production of hormones.

4. No Tumor (Healthy Brain Scan): MRI scans in this category don't reveal any indications of brain tumors. In order to effectively distinguish between abnormal and normal cases, these images are used as a baseline or control group for training and testing classification models.

II. Literature Review

The detection and classification of brain tumors using deep learning and machine learning techniques has seen a great deal of research in recent years. This section examines noteworthy studies that employ MRI data segmentation, classification, object detection, and clustering.

Convolutional Neural Networks (CNNs) are a deep learning technique that Munagalapalli Thanuj et al. (ICIRCA 2023, IEEE Xplore) proposed for the detection and segmentation of brain tumors. Their model achieved a 94.58 precent accuracy rate by incorporating preprocessing and feature extraction stages. DSC and IoU metrics were used for evaluation. The authors proposed real-time implementation and transfer learning as ways to improve.

Nadim Mahmud Dipu, Sifatul Alam Shohan, and K.M.A. Salam (IEEE Xplore, 2021) developed a hybrid method using YOLOv5 for tumor localization and CNNs (FastAI, VGG16, ResNet) for classification. Their approach achieved 90.78percent accuracy in classification and 85.95

Y. Mohana Roopa et al. (IEEE Xplore, 2020) compared a custom CNN with VGG-16 on a dataset of 3,264 MRI scans. Their model achieved 90.22percent accuracy, surpassing VGG-16's 87.21percent, and was computationally more efficient. This highlighted CNNs' strength in rapid and accurate tumor classification.

Ankitha G. et al. (IEEE Xplore, INCET 2023) classified tumor types like glioma, meningioma, and pituitary adenoma using the ResNet50 and Xception architectures. Xception achieved 98.32percent accuracy on 7,023 MRI images, surpassing ResNet50's 98.02percent accuracy while cutting down on training time and computational expenses.

A CNN-based classification model for brain tumor detection was put into practice by Monisha Barakala et al. (ICAISS 2022, IEEE Xplore). Their method maintained low computation requirements while achieving 84percent accuracy. In settings with limited resources, this approach works well for MRI analysis and tumor identification.

Maram Fahaad Almufareh et al. (ICAISS 2023, IEEE Xplore) presented a system that combines Xception and ResNet for classification with Yolo-based segmentation. The system's accuracy reached up to 98.32percent after training on thousands of photos. Their model proved successful in correctly detecting and classifying MRI scan tumors.

Hussna Elnoor Mohammed Abdalla and M.Y. Esmail (International Conference on Computer, Control, Electrical, and Electronics Engineering, 2018) applied a feedforward Artificial Neural Network (ANN) for MRI-based tumor classification. Their model demonstrated ANN's ability to reliably detect tumors in medical imaging, achieving 99percent accuracy and 97.9percet sensitivity.

B. Ramu and Sandeep Bansal (ICOSEC 2024, IEEE Xplore) presented a hybrid system that employs Extreme Learning Machines (ELM) for classification and U-Net for segmentation. Their system demonstrated high reliability for clinical use with 99.87 percentage accuracy, 99.58percentage sensitivity, and 98.96 percentage specificity using the BRATS 2020 dataset.

III. Methodology

Our suggested method for analyzing brain tumors from MRI images uses a two-stage deep learning pipeline. This pipeline combines a Convolutional Neural Network (CNN) for tumor classification with U-Net for tumor segmentation. The main objective is to accurately identify and categorize the tumor type into four groups: pituitary, glioma, meningioma, and no tumor.

1) Tumor Segmentation Using U-Net A popular convolutional neural network architecture for biomedical image segmentation is U-Net. It works especially well in situations where there is a dearth of annotated data. U-Net is used in our study to separate the tumor area from the MRI images. Accurate tumor boundary delineation is made possible by the architecture's symmetric encoder-decoder structure with skip connections that help preserve spatial information.By ensuring that the subsequent classification is solely focused on the pertinent tumor region, this segmentation step enhances performance.

2) CNN for Classifying Tumors Following U-Net segmentation of the tumor region, we classify using a CNN-based model. CNNs can directly learn hierarchical features from pixel data, which makes them useful for image-based recognition tasks. The CNN receives the segmented tumor region as input and assigns it to one of four groups: No Tumor: An MRI of the brain shows no signs of a tumor. Meningioma: Usually a benign tumor that starts in the meninges. Pituitary: Cancers that originate in the pituitary gland, which frequently impact the production of hormones. A glioma is a tumor that develops from glial cells. It can be low-grade or extremely malignant (glioblastoma, for example). A reliable and understandable end-to-end system that accurately segments and categorizes brain tumors is made possible by the combination of U-Net and CNN.

Summary of Workflow:

Preprocessing: MRI scans are resized and normalized.

Segmentation: U-Net segments the tumor region from the full brain MRI image.

Post-Segmentation Processing: The segmented region is cropped or highlighted.

Classification: The segmented tumor is classified using a CNN into the appropriate tumor type.

Users should be able to upload an image and view results with just three clicks thanks to an intuitive interface.The

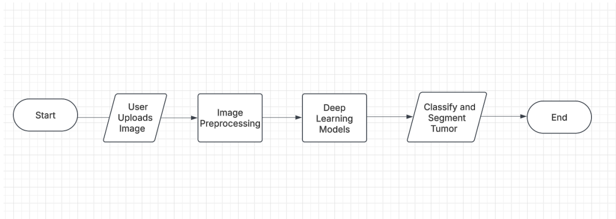


Fig. 1. Processflow for tumor detection.

brain tumor detection and segmen- tation system's sequential workflow is depicted in this process flow diagram. It describes how the system processes an MRI scan in order to identify, cate- gorize, and segment a tumor. Detailed Begin When a user wishes to examine an MRI scan in order to detect brain tumors, the procedure starts. The user uploads an image An MRI scan in JPEG or PNG format is uploaded by the user to the system. For processing, the uploaded image is momentarily stored. Preprocessing Images Preprocessing methods like Resizing Normalization are applied to the uploaded image in order to match the deep learning model's input size. Enhancement of Contrast and Noise Reduction (for better feature extraction). Skull Stripping (removing non-brain regions). Removing parts of the skull that are not part of the brain. Models for Deep Learning Trained CNN and U-Net models are applied to the preprocessed image for: Tumor classification is the process of determining the type and presence of a tumor. Highlighting specific tumor areas in the MRI scan is known as tumor segmen- tation. Categorise and Divide Tumors Tumor Classification Output (such as Glioma, Meningioma, Pituitary Tumor, or No Tumor) is produced by the system. Segmentation Mask (the afflicted area is highlighted if a tumor is found)

IV. RESULTS

TABLE I
PERFORMANCE COMPARISON OF CNN AND U-NET MODELS ON MALICIOUS ACTIVITY DETECTION

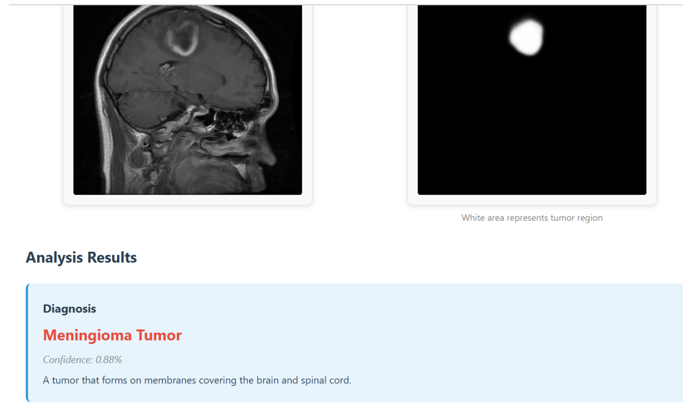
Model	Accuracy (%)	Precision	Recall	F1-score
CNN	85.3	0.84	0.82	0.83
U-Net	89.7	0.88	0.87	0.87

A. Qualitative Evaluation

Visual inspection of the CNN model's predictions showed reliable detection of activity regions. However, the U-Net model produced more accurate segmentations, particularly in scenarios involving overlapping or complex movements. This highlights U-Net's strength in precise spatial localization.

B. user Results

Figure IV-B presents the results that user can see after uploding an MRI image .



V. CONCLUSION

In this study, we used deep learning techniques to create an effective system for brain tumor detection and segmentation. Specifically, we used the U-Net architecture for accurate tumor segmentation and Convolutional Neural Networks (CNNs) for tumor type classification. Combining classification and segmentation allows for the visual localization of tumor regions in MRI scans in addition to the precise identification of tumor types like pituitary, meningioma, and glioma. To enhance model performance and generalization, the suggested system integrates a preprocessing pipeline that includes normalization, augmentation, and contrast enhancement. Our implementation also uses a Flask API to retrieve and manage tumor-related predictions, as well as MySQL for database integration and tumor size calculation. To enable physicians to upload MRIs, an intuitive web-based interface has been created.

Experimental results on public MRI datasets demonstrate high accuracy and reliability of the system, making it a practical tool for aiding radiologists in clinical diagnosis and treatment planning.

The system's high accuracy and dependability, as shown by experimental results on public MRI datasets, make it a useful tool for supporting radiologists in clinical diagnosis and treatment planning.

Even though the current system performs well, there are a few improvements that could be made:

- Using transformer-based architectures or attention mechanisms to enhance focus on important areas of the image. To improve robustness, the dataset will be expanded to include more varied and real-world MRI scans. For a more thorough tumor analysis, multimodal data (such as genetic or clinical records) can be integrated.
- To enable quicker and offline predictions in remote locations, the model can be deployed on edge devices or mobile applications.
- Using longitudinal tumor tracking to track the effectiveness of treatment over time.

Overall, the proposed framework provides a promising foundation for automated brain tumor analysis and supports the ongoing efforts to improve early diagnosis and precision in neuro-oncology.

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