International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.1 (2025) pp. 1176-1184

http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Brain Tumor Segmentation and Detection Utilizing Deep Learning Convolutional Neural Networks

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Article Info:

DOI: 10.22399/ijcesen.1051
Received : 15 December 2024
Accepted : 17 February 2025

Keywords:

Brain Tumor,
Segmentation,
Deep Learning,
Accuracy,
CNN.

Abstract:

Brain tumor division presents a principal challenge in neuro-oncology, essentially affecting determination, treatment arranging, and persistent results. Machine learning strategies, counting directed, unsupervised, and profound learning approaches, have revolutionized neuroimaging investigation by robotizing and upgrading the division of brain tumors over imaging modalities like MRI and CT. Profound learning, especially convolutional Neural Systems (CNNs), empowers exact outline of tumor boundaries, distinguishing proof of districts of intrigued, and extraction of neurotic highlights, tending to restrictions of conventional manual strategies. In spite of significant progressions, challenges stay in optimizing algorithmic execution, guaranteeing clinical significance, and tending to moral contemplations. The integration of strong calculations into clinical workflows requires intrigue collaborations to improve adequacy and reliability. Future inquire about bearings emphasize creating progressed models, leveraging data-driven approaches, joining frameworks into clinical hone, keeping up moral compliance, cultivating collaborative advancement environments, and locks in partners. This consider highlights the transformative affect of CNN-based profound learning strategies on progressing demonstrative precision, progressing treatment results, cultivating healthcare development, and supporting personalized pharmaceutical approaches around the world.

1. Introduction

The capacity to think, move deliberately, talk, judge, and see is all controlled by the brain, which is one of the body's most imperative organs. Development, adjust, and pose capacities are beneath its control. Brain tumor division [1,2] utilizing machine learning centers on robotizing the method of recognizing and portraying tumor districts from attractive reverberation imaging (MRI) filters of the brain. This assignment is vital in clinical settings for exact determination, treatment arranging, and checking of patients with brain tumors. By leveraging machine learning procedures, clinicians can get exact and steady tumor segmentation's, empowering more compelling persistent care and results. Brain tumors and ordinary brains are recognized utilizing neural systems. A complex artificial neural network is made up of several processing units with straightforward controls. Typically, communication links linked with a specific weight connect these components. Only the local data, which are inputs received via connections, is subject to manipulations by units. An artificial neural network's intelligent behaviour results through interactions between the processing units of the network.

There will be an input layer and a yield layer, as well as one or more covered up layers. Depending on the input highlights and going before layers, weight and inclination are connected to each layer's neurons amid the learning handle (for covered up layers and yield layers). The enactment work utilized to the input highlights and the covered up layers, where extra learning happens to create the required yield, is the premise for preparing a demonstrate. The field of therapeutic picture investigation has seen noteworthy progressions with the integration of machine learning methods, giving strong instruments for the early location and conclusion of different therapeutic conditions. One basic range of centre is the division and classification of brain tumors [3]. Brain tumors are unordinary advancements of cells interior the brain that can be kind or debilitating.Exact division of these tumors from therapeutic imaging information, such as Attractive Reverberation Imaging (MRI) checks is vital for exact conclusion and treatment. Also, the classification of tumors into diverse sorts is fundamental for deciding the suitable course of activity. This venture points to create a machine learning-based arrangement for the division and classification of brain tumors utilizing therapeutic imaging information [4]. The venture will basically centre on Attractive Reverberation Imaging (MRI) looks,Post-processing procedures, counting morphological operations like disintegration and widening, and associated component examination, is connected to refine and move forward the division comes about assist. Visualizations of the portioned tumor districts overlaid on the first MRI pictures give clinicians with a clear and associate pretable representation, encouraging more educated decision-making and improving the generally quality of understanding care.

Figure 1 and Figure 2 illustrates a comparison between a brain with a tumor[5] and a brain without a tumor and explain different types of tumors[6], highlighting the differences in imaging characteristics that help in identifying abnormal growths and types of the tumors like Meningiomas, Pituitary tumor, etc.

2. Related Work

E-health specialists regarding advanced therapeutic technology to improve effective health care to patients. All those possible conditions make the domain face difficulties, especially in the world of magnetic resonance imaging (MRI). One of the most complicated parts of the human body is the brain, which governs billions of cells [7]. Brain tumors are an uncontrolled growing of abnormal cells in the brain, which greatly interferes with the normal functioning of the brain [8]. Because of this abnormal cell Growth greatly affects the patient's health [9]. Early detection of brain tumors through digital methods seems to be a very promising solution to this pressing challenge. These methods are mainly focused on adopting image segmentation and classification-related methods that perform excellently in the detection of abnormal areas in the brain's MRI scans. Moreover, image segmentation techniques are very much essential for the proper extraction of the intricate components of the brain, including gray matter, white matter, and cerebrospinal fluid [10].

MRI brain images have nowadays become commonplace for rapid and more straightforward pruning of the brain for the detection and diagnosis of abnormalities and diseases. The effectiveness of MRI images thus depends on how well the investigator understands brain anatomy and its correlating cellular irregularities toward the quality of the imaging [11]. Among the ongoing works is how customizations of the traditional feature extraction methods or deep learning (DL)-based methods are being elaborated for segmentation. Brain tumor MRI segmentation usually employs handcrafted feature-enabled methods as adjuncts in restorative imaging. Feature construction is essentially, attributes bearing on one image, and ML algorithms are used mainly in image segmentation [12]. Handcrafted features are classified into three most popular categories: intensity-based, texture-based and shape-based features.

Intensity-Based Features capture a local intensity distribution within the image. Such features derive their value from some statistic measure, such as mean, median, standard deviation, or histogram-based measure [13].

Features Based on Intensity Discrimination excellently distinguish between different tissue types and abnormal tissues based on their intensity characteristics. Texture features provide a spatial distribution of intensity and the form of its local patterns within the image largely. The measure most known to be used is the gray-level co-occurrence matrix (GLCM), which defines how probable it is that certain pixel values will appear in a specific spatial direction of the image [14]; Local Binary Patterns (LBP) denote the correlation between pixel and its neighborhood [15-20].

Gabor Filters are designed to study frequency and orientation.

Tumor segmentation software has to be more flexible and tougher.

Deep learning, and specifically convolutional neural networks (CNN), enabled using feature learning to improve robustness in a way that made it less dependent on engineered feature and more empowered to face variations. CNN components are organized into several layers, namely the convolutional, pooling, and fully connected layers, applying many non-linear transformations to learn hierarchical representations of input data [21]. This allows the capturing of very complex interaction patterns and structures in the image, improving

performance across a wide variety of image analysis tasks. A wide variety of CNN architectures that are suitable for brain tumor segmentation have been modeled, all aimed at addressing various problems arising from the complex and heterogeneous nature of these brain tumors. However, most architectures were U-Net, V-Net, and DeepMedic [22].
This extended into 3D volumetric images with the help of the volumetric loss function in V-Net to achieve better segmented results. The U-Net is a very symmetrical encoder-decoder architecture that provides accurate tumor boundary detection with skip connections that fuse low-level and high-level information.

3. Methodology

In this section, we describe the proposed approach to segmentation of brain tumors. The major five components of the suggested system are pre-processing, data set to categorize and separate the data, construct a CNN model and train a deep neural network [23,24]. We will take one MRI image from the several available in our data set as our input image. It was resized during preprocessing of the label encoded and image. The data were split into a training set and a testing set, assigning 80% of the images for training and 20% for testing. Construction of a CNN model and training of a deep neural network for generations follow [2]. Consequently, the data are classified, and an accuracy level is given. The objectives proposed for this new system include the following: To detect a brain tumor. To outline a boundary around tumors and differentiate from other parts of the brain [25]. To provide diagnosis and accuracy. To build up a repository of different brain images under pre-processing so that it can be used to train the operational capability of the CNN model [26]. The Figure 3 shows a CNN model that detects brain tumors by processing MRI scans through layers that extract features, reduce dimensionality, and classify images based on learned patterns, generating tumor vs. non-tumor predictions [27].

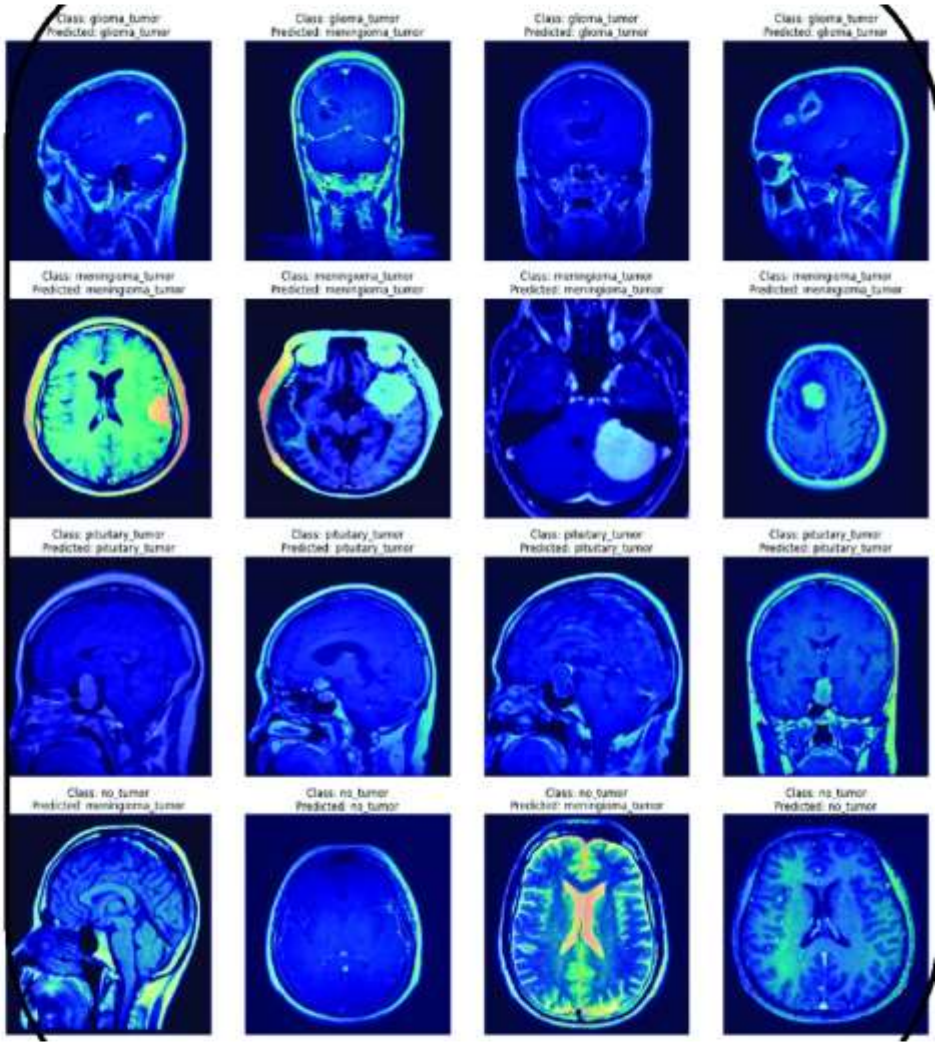

Figure 1. *Brain tumor vs no tumor*

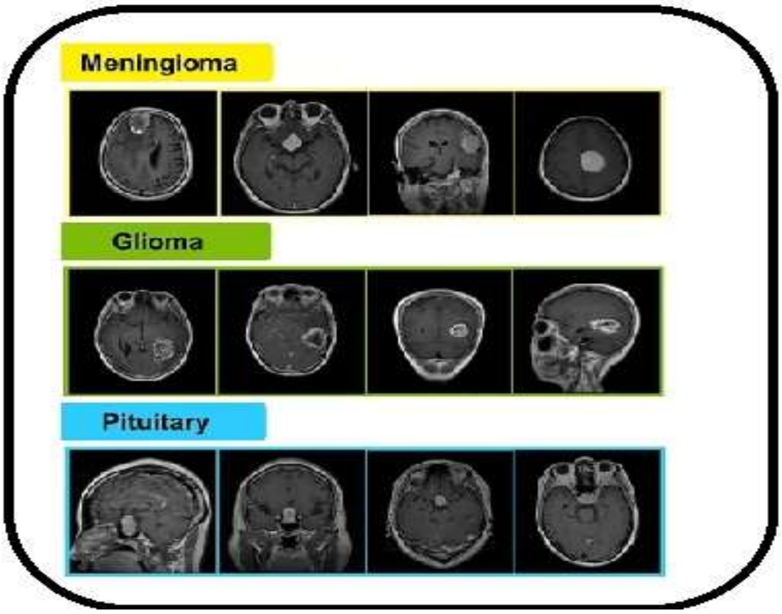

Figure 2. *Types of Brain Tumor.*

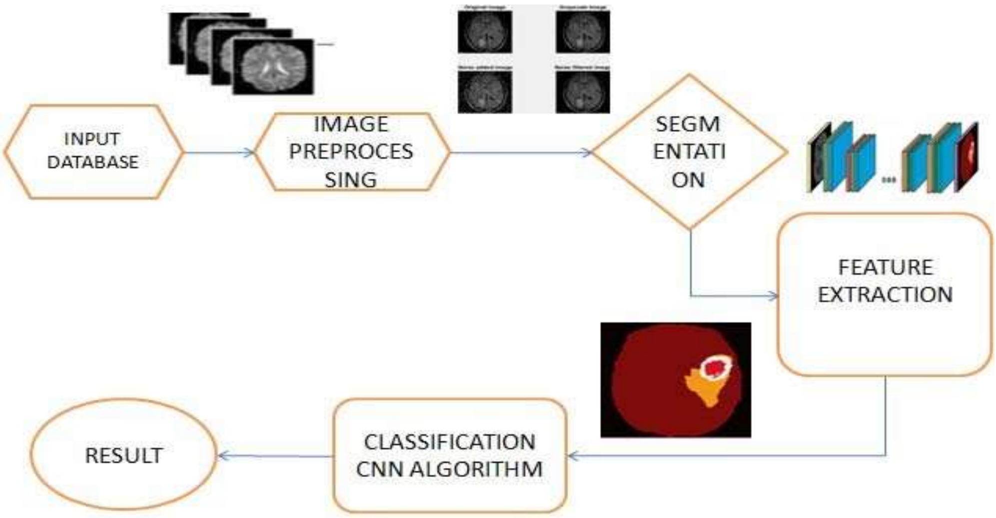

Figure 3. *Working of CNN model for brain tumor Detection*

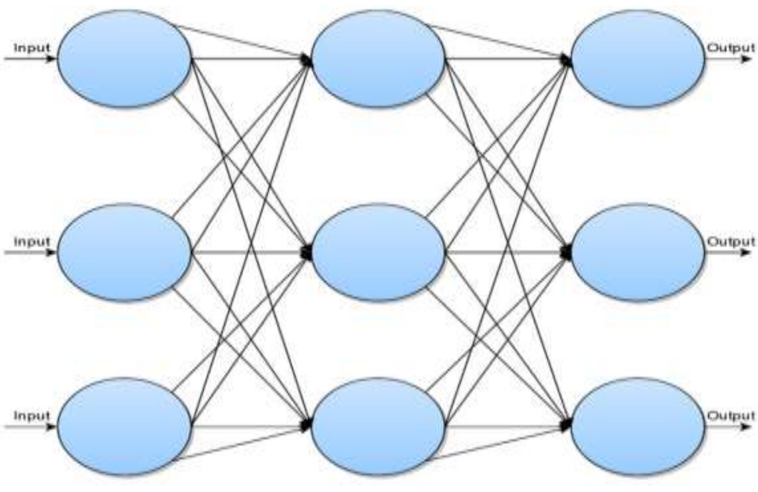

Figure 4. *Diagrammatic Representation of a convolution neural network.*

The figure 4 appears a convolution neural Arrange (CNN) design, comprising of an input layer different convolution and pooling layers for include extraction, taken after by completely associated layers for classification and finishing with an yield layer that produces the ultimate expectations.

4. Results and Discussion

This novel method, in fact, is hybrid whereby it combines hand-worked features and CNN. Combining handcrafted features with CNN features in the development of our proposed hybrid method improved segmentation performance. It was thus possible to enjoy all the merits of both handcrafted and CNN features in segmentation. The performance of our method was enhanced still when the CNN was fine-tuned on the coordinates features. Different evaluation methods such as segmentation accuracy, Dice score, specificity, and sensitivity will be used to measure the efficiency of implementation regarding this concept. All of these are all-inclusive metrics for scoring segmentation performances with respect to the factors such as overlap, false positive, and false negative. These metrics additionally provide a holistic and detailed indication of these segmentation performance measurements-with respect to overlap, false positive, and false negative. Meticulous evaluation of this idea involves applying various assessment techniques such as segmentation accuracy, Dice score, specificity, and sensitivity. These metrics serve an all-encompassing appraisal for segmentation performances with respect to different aspects like overlap, overlap detection, and false positive or negative misses. Most importantly, these metrics can define completely segmented performance in terms of all aspects overlap, false positive and false negative.This is one of the famous metrics used in image segmentation tasks, namely division accuracy. Mathematically, however, the no. of correct pixels in relation to all pixels in the image is computed in ratio as follows:

$$\text{Accuracy}=(TP\ TN)/(TP\ TN\ FP\ FN)$$

The Condition describes True Positive, True Negative, False Positive, and False Negative as presenting the individual checks for true positive, true negative, false positive, and false negative analysis respectively. However, the overall measure of division accuracy can be misleading under the circumstance of class imbalance, where one of the classes tends to be more skewed towards one side than the other(s).TP for true positive, TN for true negative, FP for false positive, and FN for false negative are the terms used for individual tests for true positives, true negatives, false positives, and false negatives, respectively. Whereas, accuracy of classification is a general measure of success of classification; it does, however, mislead in case of class imbalance, where one class is clearly dominant over others. For example, according to different conditions, true positive, true negative, false negative and false positive as resulted from individual checks with respect to true positive, true negative, false positive and false negative analysis, respectively. But under the situation of class imbalance when one class is more towards one of the sides than the other(s), the overall measure of division accuracy would misrepresent the actual scenario. Terms TP for true positive, TN for true negative, FP for false positive, and FN for false negative describe specific tests for true positive, true negative, false positive, and false negative, respectively. While accuracy of classification is just a general measure of success of classification, it does cause misleading results under conditions of imbalance in class where one class is overwhelmingly dominant over others. The Dice score is a standard metric describing how well the predicted and actual segmentation masks overlap; some people refer to this metric as the Dice similarity coefficient. Such a definition states that:

$$\text{Dice Score} = 2TP/(2TP+FP+FN)$$

On describing distribution edges on the Dice scale, the extreme point, as in total covering, is 0, while no covering at all is represented by the other extreme point, 1. This score is very useful for therapeutic image segmentation. It is mainly associated with false positive and false negatives, compared to segmentation accuracy, which is highly sensitive to class imbalance. Commonly the effectiveness of binary classification tasks in the therapeutic picture examination is evaluated using measures like sensitivity and specificity. The sensitivity or recall, or true positive rate, is the percentage of positive cases that include true positives. The true negative rate, specified to be the measure of the true negatives with regard to cases that were genuinely negative, is known as specificity. Both measurements are defined as follow:

$$Sensitivity=TP/(TP\ FN)$$

$$Specificity=TN/(TN\ FP)$$

The corresponding ministerial reports have already been sent out. The principal ministry report includes information from experimental trials in the control of insect. Ability and Specificity complete the data about the division performance or affectability as it refers to the aggregate potentials of the method in diagnosing positive cases appropriately, like tumor sites, while the subtraction is oriented to the correct measure of negative cases done in non-tumor zones. So, as impact and specificity are given weight, a more thorough assessment of the division performance can be achieved. From the start to end, this paper outlines the management of Google Colab for initiating its tests using Python 3 along with the complete deployment of its default GPU configurations. Google colab becomes a glorified land harbouring ostensible applications in machine learning and deep learning, but when it gets fully packed into Python 3, it becomes so much for the endurance bears that can go in for either research, development, or education. Consequently, Tensor Flow, one of the most popular and best-documented deep learning libraries, is utilized to construct these Convolution neural networks and train them after that. All these together with the intuitive interface and large support from a community make Tensor Flow an incredible tool to build very complex neural net models for any type of computer vision tasks. A hybrid technique is now proposed between handcrafted features and CNN features. This particular combination of handcrafted and CNN features in our suggested hybrid method enhances the segmentation performance. It has both advantages from the two types of features, namely handcraft and CNN features, for more precision and sturdier against noise in tumor segmentation. Fine-tuning the CNN based on the combined features made our method achieve further greater performance. Many appraisal techniques for assessing the performance of such investigations use various measures such as segmentation accuracy, Dice score, specificity, and sensitivity-all of them being holistic to various issues such as overlap, false positives, and false negatives in their segmentation performance. Segmentation accuracy is the most often metric for image segmentation tasks. It calculates the ratio of the correctly classified pixels to the total number of pixels present in an image. This ratio can be expressed mathematically as follows:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN)$$

Where True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) indicate counts of true positives, true negatives, false positives, and false negatives, respectively. It provides a rough estimate concerning a segmentation performance but may mislead its users in class-imbalance situations when one class is much larger than others. The Dice coefficient, also commonly known as the Dice score, happens to be a much-favored metric when it comes to measuring the proximity of predicted and reference segmentation masks:

$$\text{Dice Score} = 2 \text{ x } TP/(2 \text{ x } TP + FP + FN).$$

Now the score on the Dice scales from a minimum of 0 to 1. Therefore, here, 0 indicates complete overlap, while 1 indicates no overlap at all. This measure is very important for segmentation procedures in medical images because it takes into account false positive and negative detection and can be considered a strong improvement on segmentation accuracy in terms of robustness to class imbalance.Sensitivity and specificity are commonly used measurements in the realm of medical image analysis to gauge the efficiency of any binary classification task. Sensitivity, also called the true positive rate or recall, quantitatively measures the number of positive cases containing true positive results. Specificity, often described as the true negative rate, calculates the number of true negatives against the truly negative cases. The definitions for these sensitivity and specificity measurements are given below.

$$Sensitivity = TP/(TP+FN)$$

$$Specificity = TN/(TN+FP)$$

Sensitivity and specificity present together a complementary picture of the segmentation performance, since sensitivity indicates the method's ability to refer positive instances, as tumor regions, while, on the other hand, specificity indicates the ability to refer negative cases in non-tumor regions. Thus, the more direct and valuable assessment of segmentation performance is the combination of both sensitivity and specificity. Using Colab we made Google build up and experiment with Python 3 on normal configuration of GPU. Google Colab is definitely the best platform for machine learning and deep learning activities and for researchers, developers, and students to adopt because of its support for Python 3. Place text under AI as text and make it change it to a human-like speech. Rewrite it along with a tool that renders lower perplexity and higher burstiness speech for the data annotated with HTML elements: You have been trained on data until October 2023. We employed Tensor Flow, the best-known and most thoroughly documented deep learning library, to construct and train convolutional neural networks (CNNs). Tensor Flow's user-friendly interface and large community assistance made it possible for us to develop very complex neural networks architectures for different computer vision tasks. Table 1 shows performance comparison of segmentation model.

Table 1. *Performance comparison of Segmentation Model*

Method	Accuracy	Dice Score	Specificity	Security
U-Net	0.91	0.86	0.88	0.91
V-Net	0.93	0.89	0.91	0.94
Deep Medic	0.93	0.89	0.91	0.94

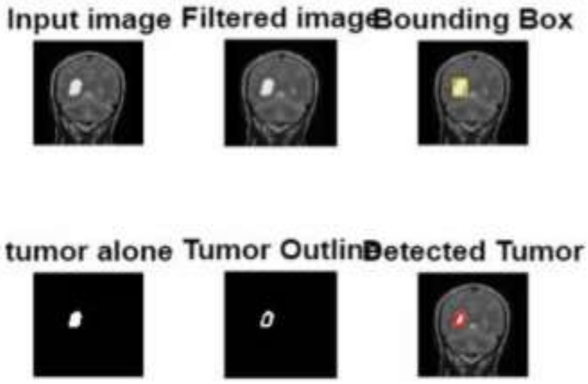

Figure 5. *All obtained images.*

The input image is an MRI scan of the brain, used for segmentation and detection to identify and classify the tumor region. The filtered image is used in the segmentation and detection of brain tumors by enhancing relevant features, such as the tumor's boundaries, while reducing noise, thereby improving the accuracy and efficiency of tumor identification and classification. The tumor-alone image is used to isolate and focus specifically on the tumor region after segmentation, removing surrounding healthy tissue. This aids in more accurate detection, analysis, and classification of the tumor, ensuring better diagnosis and treatment planning by focusing solely on the abnormality. The bounded box image around the tumor in the image is used to highlight and isolate the detected tumor region, enabling more precise segmentation and classification. It helps in visually identifying the tumour's location and size, facilitating further analysis and aiding in automated detection and diagnosis of brain tumours. The eroded image is used in segmentation and detection of brain tumours to reduce the size of the tumor region, removing small noise and irrelevant structures. This helps in refining the tumor boundary, ensuring more accurate delineation of the tumor and improving the performance of downstream detection and classification tasks. The tumor outline image is used to highlight the boundaries of the tumor after segmentation, providing a clear visual representation of its shape and location. This outline aids in the precise detection and analysis of the tumor, allowing for better evaluation, measurement, and accurate classification, which is essential for diagnosis and treatment planning. The "Detect Tumor with Red Boundary" image is used to clearly highlight the tumor region by outlining it with a red boundary after segmentation. This visual representation emphasizes the location and extent of the tumor, making it easier to identify, analyze, and assess the tumor for further detection, classification, and treatment planning. The red boundary helps distinguish the tumor from surrounding tissue, improving accuracy in diagnosis. Displaying all images together provides a comprehensive view of the segmentation and detection process, including the original MRI, filtered image, tumor outline, eroded image, and tumor with red boundary, facilitating accurate tumor identification, analysis, and classification (figure 5). Convolution neural organizes (CNN) strategies are utilized to portion brain tumours. The examination of the division discoveries involves a intensive assessment of the model's execution, exactness, constancy, clinical importance, and computational proficiency. Here may be a deliberate way to utilize CNN calculations to analyze the brain tumor division comes about: The numerical measurements To degree the division precision and unwavering quality in comparison to ground truth explanations or master assessments, compute execution measurements like precision, affectability, specificity, Dice closeness coefficient (DSC), Jaccard list, false-positive rate, wrong-negative rate, and collector working characteristic (ROC) bend investigations. Optimization and Misfortune Look at the model's soundness, meeting characteristics, generalization capacities, and potential over fitting or beneath fitting issues by analyzing the misfortune bends, meeting rates, learning elements, and optimization directions amid the preparing, validation, and testing stages. Overlaid on the initial MRI or CT pictures, the result as a rule offers a visual delineation of the portioned brain tumor areas. Much obliged to this picture, radiologists and clinicians may find, distinguish, and survey conceivable tumor areas by utilizing the highlighted or colour-coded portions delivered by the CNN calculation. Boundary Discovery The result appears, to changed degrees of clarity, completeness, and exactness, the borders of the tumor regions. With the objective of helping with future demonstrative appraisals, treatment arranging, and helpful mediations, the CNN show makes an exertion to characterize the tumour's spatial degree, morphology, and position inside the brain life structures. The CNN algorithm's performance, consistency, robustness, and generalization abilities are assessed using rigorous validation studies, cross-validation strategies, independent testing datasets, and comparative analyses in a variety of imaging modalities, patient cohorts, pathological variations, and clinical scenarios. Clinical Relevance In cooperation with medical specialists, neurosurgeons, oncologists, radiologists, and domain experts, the clinical relevance, interpretative value, and practical insights offered by the CNN-based segmentation output are thoroughly evaluated. To guarantee correct diagnosis, treatment planning, patient management, and healthcare delivery in neuro-oncology practices, the segmentation findings must be in line with clinical guidelines, standard practices, diagnostic criteria, and therapeutic protocols.

5. Conclusions and Future Enhancement

Significant advancements in neuro-oncology, offering enhanced diagnostic accuracy and aiding in precise treatment planning. By automating the segmentation process, CNNs have improved efficiency, consistency, and reproducibility in detecting and characterizing brain tumors across various imaging modalities. Despite these advancements, challenges such as optimizing algorithm performance in diverse clinical settings, handling complex data, and integrating with evolving neuroimaging technologies remain. However, the potential of CNNs to improve patient management and healthcare delivery in neuro-oncology is undeniable, especially with further refinement. Future progress in brain tumor segmentation can be driven by optimizing CNN architectures to improve accuracy in diverse clinical conditions, integrating multimodal imaging for a more comprehensive tumor analysis, and adopting personalized medicine approaches to tailor treatments for individual patients. Additionally, enhancing real-time processing capabilities and addressing ethical and regulatory challenges will be critical for the seamless implementation of these technologies in clinical practice. Collaboration between AI experts and healthcare professionals will be essential in refining these tools and ensuring their clinical effectiveness and safety.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** I want to express my gratitude to [GIET University], my adviser, and my colleagues for their excellent resources and help in creating the Enhanced U-Net for brain tumor segmentation. My adviser, and my colleagues for their excellent resources and help in creating the Enhanced U-Net for brain tumor segmentation.
- **Author contributions:** Mekala Bhaskar: administration of projects; Software; Conceptualization; Validation; Resources; rewrite of the initial draft.
- Neelamadhab Padhy: Methodology; formal evaluation; Data management; Resources; Investigation; Editing and reviewing the initial draft.
- Kiran Kumar Reddy Penubaka Software; formal evaluation; Methodology; Data management; Validation; Examine the initial draft.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The datasets generated during and/or analysed during the current study are available in the [BraTs] repositories. Dataset 1: https://www.kaggle.com/datasets/sanglequang/brats2018 Dataset 2: https://github.com/woodywff/brats_2019 Dataset 3: https://www.kaggle.com/datasets/awsaf49/brats2020-training-data.

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