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An Intelligent Diagnosis and Tumor Segmentation Method based on MRI Images Using Pre-trained Deep Convolutional Neural Networks (CNNs)

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Abstract

The correct segmentation detection and classification of brain tumors in MRI images plays an essential role in discovering neurological problems at early stages and their subsequent treatment management. Deep learning has made Convolutional Neural Networks (CNNs) highly effective for complex medical imaging processing because they perform self-learning to find subtle features present within the data. Testing four CNN models for brain tumor segmentation was conducted using 1,251 MRI images from BraTS2021 dataset through CaPTk, 2DVNet, EnsembleNets and ResNet50 evaluation. The research relied on the combination of DSC and HD to perform quantitative analysis. The EnsembleUNets achieved the best performance since they produced the lowest HD of 18 and the highest DSC of 0.92. The suggested EnsembleUNets delivered exceptional capability through a CCC measurement of 0.75 and achieved the lowest RMSE value of 0.52 together with the highest TDI value of 1.9 for tumor segmentation and classification tasks in clinical scenarios. The obtained results indicate EnsembleUNets effectively segment brain tumors and identify their type as well as classify them in medical settings.

Keywords: Brain tumor, Segmentation, ResNet, Deep neural network, CNN, Healthcare, Prediction models.

INTRODUCTION

Human life ends fatally from almost every kind of prime brain tumor. Tumors that travel from other body areas to reach the brain have primary development elsewhere but brain tumors originate from inside the brain tissues. Correct visualization of tumors stands as a vital diagnostic necessity to identify such tumors. The appropriate evaluation of such tumors depends on necessary diagnostic imaging practices [1, 2]. Medical practice relies on standard high-resolution examinations which include MRI scans as well as CT and PET techniques. MRI enables brain structure investigations because its assessments lead to the diagnosis and evaluation of brain tumors [3, 4]. The origin of brain cancers starts from within brain tissue (primary) or through outside origins (secondary) until their development in the brain tissue. The non-invasive MRI technique allows patients to benefit from diagnosis assessments by using its broad applications in brain medical evaluations. The machine creates different body segment images through its processing of waves in conjunction with electronic signals. One vital element in MRI devices operates within a cylindrical unit that houses the MRI instrument with magnets which enwrap its total enclosure. The entry point access by magnet guides patients toward moving to the scanning table in the designated MRI exam area [5, 6]. During the patient-enclosed space, a strong magnetic field redirects the hydrogen atom protons. The examination device produces body pictures through the conversion of radio wave signals after they pass through body-based protons [7].

Temporal Analysis

Now that customers possess many options for purchase the modern consumer market requires customized products. At present doctors employ beneficial magnetic fields combined with radio signals to construct diagnostic imaging pictures that monitor changes in body growth by using MRI as their technology. Picture segmentation represents the operational method for splitting digital images into their lowest structural components which include pixels alongside other picture elements [8, 9]. The technique requires medical professionals to turn pixels from specific regions into distinct clusters which emerge through analyzing color intensity coupled with texture measurements. The technique delivers improved viewing performance as structures inside the body transition slightly [10]. Medical experts can observe small human body elements with clarity because MRI technology provides detailed imaging in biomedicine. The detection of tissue shows enhanced capabilities through this technology when compared to regular imaging methods thus revealing tissue distinctions. The evaluation of brain tumor presence by radiologists through MRI scans historically required long periods of their time dedication [11, 12]. The field of image segmentation research has accumulated many completed studies since the previous decades through extensive studies. Figure 1 shows both Brain scan results combined with MRI scan images of the brain while including and omitting tumor identification. A superior diagnostic solution materializes from performing an MRI Scan examination.

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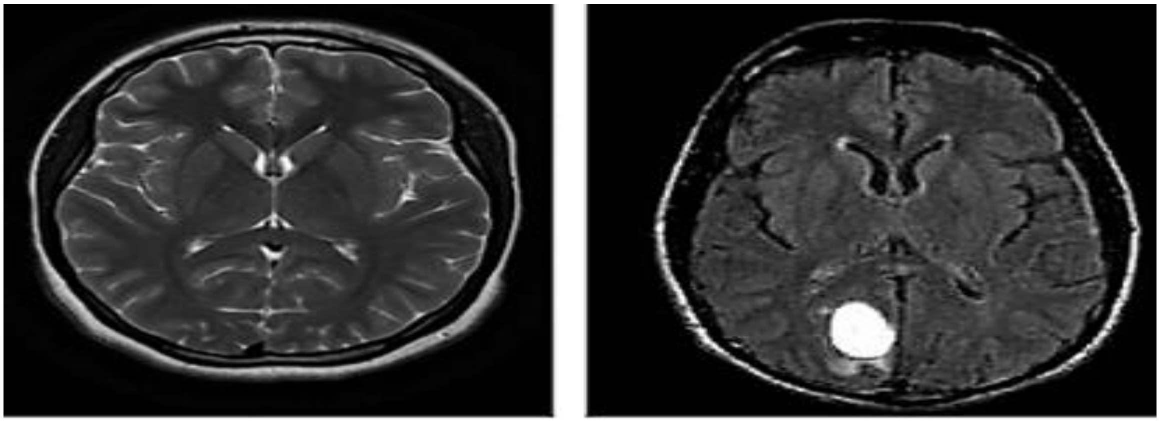

Figure 1.
MRI Images (a) with Tumor and without Tumor [13]

LITERATURE REVIEW

This section reviews recent studies about deep learning methods in brain illness detection through the investigation of CNN techniques for brain tumor MRI scan segmentation. Several research works utilize CNNs to develop methods that segment brain tumors. The 3D CNN model proposed by Urban demonstrated successful tissue class prediction through 3D patches used as inputs when working on multimodal MRI glioma segmentation [14, 15]. The researcher generated a technique to convert 4D medical data into 2D image patches to allow 2D-CNN networking for brain tumor segmentation. The previous research projects implemented various CNN architectures to perform brain tumor segmentation [16]. They designed a CNN to predict component classifications of multi-level data structures through a two-stage training system that addresses class imbalance. Rao obtained features from MRI modality images using four unique CNN architectures while fixing multiple plane settings per pixel. Researchers in recent times presented new CNN architectural frameworks for conducting brain tumor segmentation [17].

Brain MRI Classification

A CNN-based Classification created by researchers integrates the comprehension of broad brain tissue context information and specific brain MRI accuracy. The segmentation of brain tumors benefits from using three different CNN-based glioma approaches with 3x3 estimated channels during their convolutional phases [18]. Different scientists investigated the combination of multi-view knowledge-based collaborative deep learning with hybrid CNN-DWT-LSTM approaches to segment and classify brain tumors. CNNs have experienced tremendous growth in the past decade as a preferred deep-learning technique for medical imaging activities. The ability of CNNs to detect medical anomalies like cancers in different human organs has been confirmed through numerous research studies [19]. The research field of segmentation stays active because evaluation systems need full completion for different methods. The main purpose of 2D MRI data analysis involves the accurate division of brain tissues together with tumor differentiation. The definition of tumor boundaries reaches its best success through MATLAB software methods working together with additional hardware solutions [20, 21]. Segmentation approaches consist of manual and half-automatic and completely automatic methods among their three main categories.

Manual segmentation techniques have decreased as radiologists now analyze MRI images with expert opinions for their work but this process requires long durations and produces possible errors. Users are required to supply input information during semi-automatic method execution for labeling activities yet the methodology delivers inconsistent results [22, 23]. Multiple brain disease detection and segmentation processes are shown through research studies that adopt deep learning methods. The research investigates deep examination of CNN methodology designs that detect brain diseases [24, 25]. The inception of artificial neural network investigations leads to deep learning research by developing perceptron models in the first place [26].. Neural networks perform automatic data feature extraction because it is a machine learning technique that uses different layered models to recognize patterns starting from basic to advanced. CNNs along with RNNs represent the most ubiquitous choices from existing neural network frameworks. Image and video recognition change because CNNs duplicate the visual cortex's organizational design [27, 28]. The majority of contemporary research emphasizes automatic methods that aim at improving the handling of image variability. Traditional computers function differently than neural networks because they imitate brain processing methods. Many interconnected units (neurons) in neural networks employ examples for problem-solving rather than following strict programming algorithms. High accuracy in automatic segmentation through deep learning methods depends on well-prepared training datasets [29, 30]. Developing trustworthy and efficient tumor detection methods using CNN technology remains the main research focus. The task of segmenting brain tumors from preoperative MRI scans performed by neuroradiologists becomes challenging because tumors exhibit irregular shapes with indistinct boundaries in addition to scan distortions.

The processing duration extends and increases in complexity because of this condition [31, 32]. The medical sector has achieved exceptional results by applying deep learning techniques for automatic tumor segmentation procedures. A CNN architectural structure uses multiple hidden layers for convolution and activation which successfully identifies various diseases such as skin cancer brain tumors and breast cancer [33, 34]. Many deep learning approaches have proven effective for brain tumor segmentation yet researchers have not conducted a comprehensive evaluation of their accessibility and dependability characteristics. This research responds to a gap by performing an extensive evaluation of the accuracy standards used in widely adopted brain tumor segmentation algorithms. This research evaluates how usable and dependable four popular automated deep learning methods namely CaPTk software, 2DVNet, Ensemble UNets, and ResNet50 for brain tumor segmentation [35, 36].

Convolutional Neural Network

Research about mammalian visual cortex mechanisms formed the basis of Convolutional Neural Networks (CNNs). CNNs reproduce brain functionality which enables neurons to analyze various spatial patterns in visual information [37, 38]. CNN architecture refers to an essential mathematical approach that enables weight sharing along with local processing and spatial pattern retention. The LeNet-5 model created by Kate and Shukla marked the first successful implementation of CNNs for handwritten number detection during the 1980s [39, 40]. Document recognition progressed a great deal after the model introduced gradient-based learning mechanisms. CNNs demonstrate exceptional performance in data arrangements with grid-like structures such as images that equal two-dimensional pixel grids. The study reviewed the foundation of neural networks and their advanced structures alongside their primary medical diagnostic applications [41, 42]. The research explored the historical development of these networks starting with biological prototypes up until their modern applications where CNNs took center stage because of their transformative effects on medical image diagnostics. The review addressed major barriers that involved working with extensive labeled data collections and enhancing model comprehensibility simultaneously with showing how neural networks have substantially boosted diagnostic precision [43, 44].

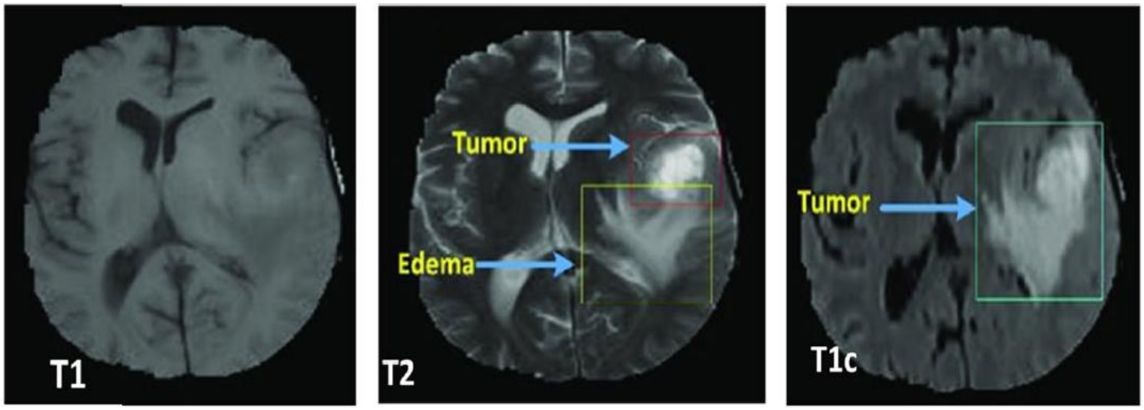

Figure 2.
Analysis of (a) Image Stage 1, (b) Image Stage 2 (c) Image Stage 3 positive Brain Tumor [45]

The CaPTk brain tumor segmentation module utilizes Deep Medic as its CNN method while basing its training on the BraTS2021 dataset. The brain lesion detection process of Deep Medic depends on an 11-layer deep CNN (Convolutional Neural Network) structure. The network platform operates on three-dimensional images while assessing different size levels. It functions by applying the 3D conditional random field (CRF) to enhance segmentation accuracy according to Deep Medic. The effective identification of brain lesions in medical images becomes achievable through this processing method used by Deep Medic. Each section within the network operates as two parts and utilizes 33 kernels to perform a detailed analysis of 3D image data [46, 47]. The deep 3D multi-scale CNN incorporates a system of two fundamental processing paths. The original setup included 53 kernels but Deep Medic implemented 33 kernels within its pathways. The second pathway compresses the same data after processing by condensing it into a third of its original size which it pursues to the central point together with the first pathway. The compression process allows the system to monitor a wide field that spans 51^3 voxels. The attributes detection process takes place in a 17 space during the final stage of both pathways. This investigation adopted default command line settings from CaPTk developers when executing the experiment [48, 49].

The Volumetric Convolutional Network (V-Net) focuses on helping medical classification systems by detecting brain tumors from diverse MRI scan data through its image analysis features. The V-Net system has two operational units with the encoder segment placed on the left side and the decoder unit located on the right side. The encoder compresses the signals, while the decoder decompresses them to their original size. Through its processing, V-Net maintains multiple spatial map resolutions and spatial relationship awareness [50, 51]. The developed system reaches high performance and establishes accurate geographical location because lateral connections transfer information between the encoder and decoder. The Parametric Rectified Linear Unit (PReLU) helps V-net recognize patterns in the input data through which it can detect outlines according to known designs. An existing pre-built 2D V-Net model received HGG BraTS2020 dataset training to evaluate study results against alternative models [52, 53]. The CNN-based U-Net model functions as one of the primary choices for executing segmentation tasks in medical picture analysis. U-Net shows outstanding performance when it comes to identifying brain tumors through combining multiple MRI imaging methods. The U-Net design incorporates a sequential operation of decreasing path units to create contextual areas while simultaneously decreasing the scale of detail and increasing the path that utilizes this contextual information to produce high-detailed segmentation results. Developed a sequential system of models that contained 3D U-Net along with 3D MI U-Net and 3D+ 2D MI U-Net ensemble model. In the third model, all 2D slices together with the second model outputs operate while the first model works with 3D MRI image patches. An integrated integration of these three models enhances the accuracy of segmentation results as a result of their combined application. This study applied the specified pre-trained model as its foundation [54, 55]. The brain MRI scan segmentation particularly depends on ResNet50 as one of its several models used for image separation functions. TensorFlow/Kera's frameworks utilize the original ResNet50 model which contains skip connections in residual blocks allowing the model to train while operating independently from large prediction to ground truth mismatches. The architecture contains 50 layers which makes it larger than the models with 18 and 34 layers such as ResNet18 and ResNet34. The picture classification system together with extractive features deploys ResNet50 because it demonstrates excellent performance. We used ResNet50 which has undergone prior training for tumor segmentation of BraTS2020 brain MRI scan data. CSV logger was used as part of process checking during training while ReduceLROnPlateau was used for learning rate optimization [56].

METHOD & MATERIALS

Convolution Neural Network-based Brain Tumor Segmentation (CNNBTS)

The local objective function of the i-th client is denoted by fi(t) while x represents the current model parameter and ξ indicates the data point sampled for local training In these assumptions LOF represents local and SOF demonstrates second-order function smoothness and LH stands for Lipschitz convexity. Lastly, SCOF and COF express objective function convexity while $f(x1) \geq f(x2)+(x1-x2)T\nabla f(x2)$ indicates the coercive property and CF denotes the existence of a global minimum. BG, BV along BGD determine conditions required to prove convergence. The function characteristics of convexity in MOG are described by two properties: first SCOF and COF while second $f(x1) \geq f(x2)+(x1-x2)T\nabla f(x2)$ establishes the rules of convexity and the coerciveness of f (x) follows a pattern of $\lim x \rightarrow \infty\ f(x) \rightarrow \infty$. When CF applies it guarantees the existence of a worldwide minimum for the objective function. The properties of gradients are captured through BG, BV, and BGD. This situation emphasizes the need to combine technological expertise with legal and ethical considerations when approaching such problems. The Proposed Technique relies on the following algorithm.

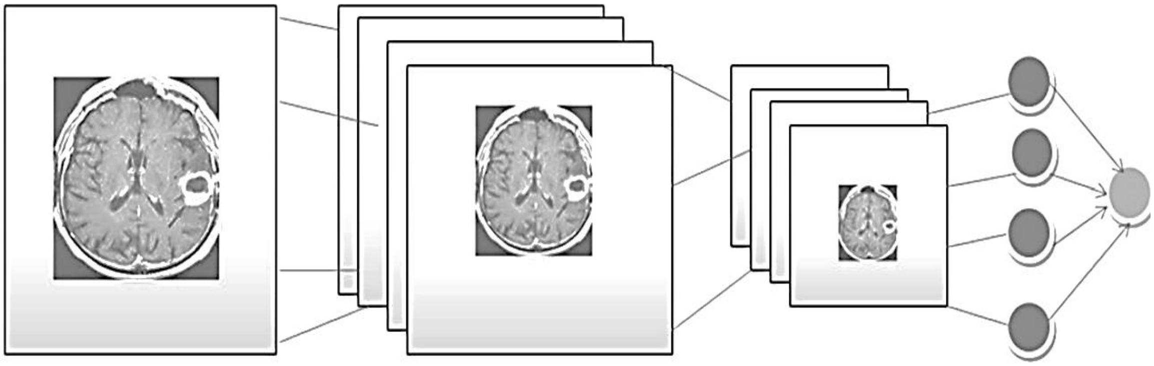

Figure 3.

Proposed Framework for Skull Segmentation using Convolution Neural Network (CNN)

Data Description

The research works with data obtained from the RSNA-ASNR-MICCAI Brain Tumor Segmentation Challenge 2021. BraTS2021 provides medical scans from 2000 participants obtained through TCGA-GBM and TCGA-LGG in addition to Ivy-GAP and CPTAC-GBM and other institutions [57]. The research selected 1251 cases comprising low-grade glioma (LGG) and glioblastoma (GBM) patients from the provided private institutional dataset. Each MRI scan from the 2000 subjects contained four modalities of T1, T2, T1-contrast enhanced (T1ce) and FLAIR in NIfTI format at dimensions of 240x240x155. The benchmark used for the comparative assessment comprised pre-segmented BraTS2021 scans that received radiology specialist verification for their segmentation. Reference segmentations functioned to improve treatment planning while also providing enhanced tumor evolution understanding through specific identification of three tumor regions: peritumoral edema (ED) enhancing tumor (ET) and necrotic/non-enhancing tumor (NCR).

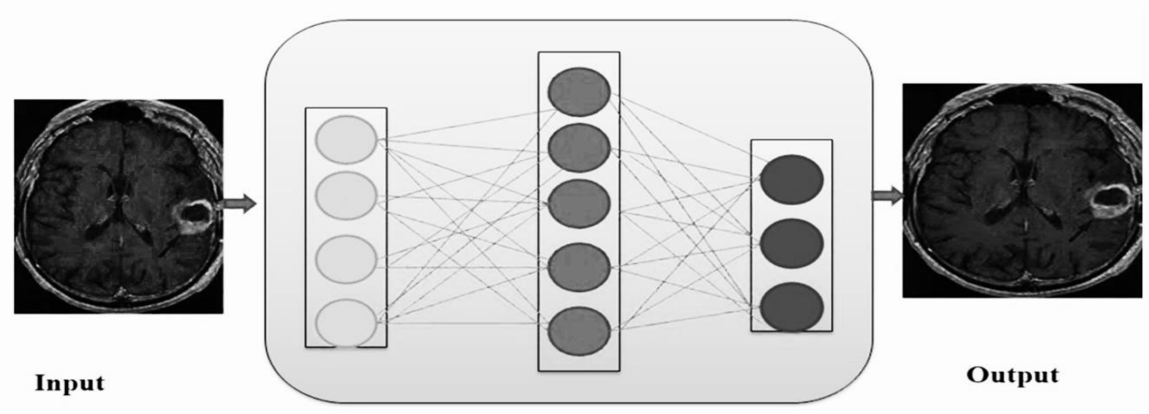

Figure 4.

Framework for Tumor Identification Using Convolution Neural Network (CNN)

Results and Classification of Performance

The local objective function of the i-th client is denoted by fi(t) while x represents the current model parameter and ξ indicates the data point sampled for local training In these assumptions LOF represents local and SOF demonstrates second-order function smoothness and LH stands for Lipschitz convexity. Lastly, SCOF and

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$$\boldsymbol{d_{AHD}(X,Y) = (\frac{1}{X}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(x,y) + \frac{1}{Y}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(x,y))/2} \qquad \textbf{Eq (1)}$$

$$\boldsymbol{d_{AHD}(2,31) = (\frac{1}{2}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(2,31) + \frac{1}{31}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(2,31))/2} \qquad \textbf{Eq (2)}$$

$$\boldsymbol{d_{AHD}(4,41) = (\frac{1}{4}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(4,41) + \frac{1}{41}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(4,41))/2} \qquad \textbf{Eq (3)}$$

$$\boldsymbol{d_{AHD}(2,n) = (\frac{1}{2}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(2,n) + \frac{1}{n}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(2,n))/2} \qquad \textbf{Eq (4)}$$

The Average Hausdorff Distance (AHD) is another statistic that defines the shift of two sets of points and is often used to assess a segmentation method, for example, CNN-based Brain Tumor Segmentation.

$$\rho_c = \frac{2a_{12}}{(\mu_1 - \mu_2)^2 + \sigma_1^2 + \sigma_2^2} \qquad \text{Eq (5)}$$

The formula for Cohen's d calculates the impact magnitude in a two-sample t-test, useful for comparing two CNN models' segmentation performance for brain tumors.

μ_1 and μ_2: Mean performance metrics of two models (e.g., Dice score, accuracy).

σ_1 and σ_2: Standard deviations of the performance metrics.

σ_{12}: Covariance between the models' performances.

A higher effect size indicates a more significant performance difference, while zero means no difference. In brain tumor segmentation, Cohen's d helps quantify the magnitude of performance differences between CNN models. Gaussian statistics are used to demonstrate the correlation between these two-reference strategies (variable 1) and alternative techniques (variable 2). The means (μ_1 and μ_2), typical deviations (σ_1 and σ_2), and covariance (σ_{12}) of these variables define them.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_1 - \bar{Y})^2} \qquad \text{Eq (6)}$$

The measure of prediction success by a CNN model for brain tumor segmentation is determined through the R-squared value calculation.

Y_i: Shows the actual segmentation outcome for the i-th MRI scan. The CNN model generates its predicted segmentation output Y_hat_i from an earlier provided scan. Y_bar: The average of all actual segmentation results. A higher value of R-squared indicates that the model provides accurate predictions of actual segmentation results. A value of R-squared at 1 indicates complete accuracy in predicting segmented areas. The model completely misses every pattern that contributes to the segmentation outcomes when R-squared equals 0. The model shows the relationship to the segmentation results between 0 and 1. During CNN model evaluation for brain tumor segmentation R-squared proves useful for identifying the right model and represents how well the data is reflected through its value strength. The predictive formula uses Y_i as the reference value Yˆ_i . as the projected value and Y¯as the average actual value.

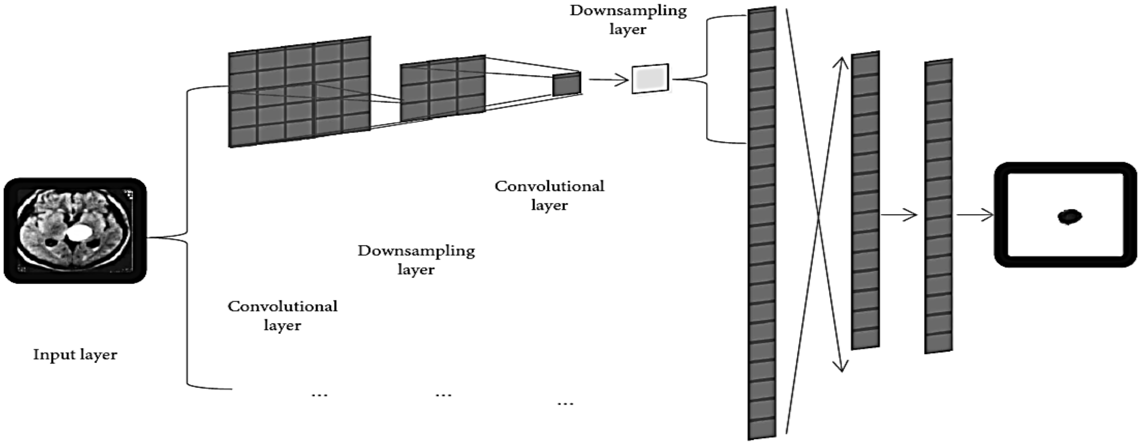

Figure 5.
Framework for Skull Segmentation

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \qquad \text{Eq (7)}$$

The formula represents one important parameter for evaluating the precision of brain tumor segmentation models is the Root Mean Squared Error (RMSE).

Y_I: The actual label for a voxel in the MRI scan (tumor = 1, non-tumor = 0).

Ŷ_i: The predicted label for the voxel from the segmentation model.

n: The total count of voxels within the MRI scan.

The Mean squared error calculates the average value of squared differences between a true object label and a predicted label through an operation that divides the squared label difference by the total number of image Voxel and divides this outcome by the number of scanned images. The division of clustering components reduces the RMSE value below actual values thus allowing the model to generate an enhanced tumor subdivision. CNN-based brain-tumor segmentation networks achieve optimal segmentation using the model that exhibits the lowest RMSE value for performance assessment among models. Y_i represents reference values while Y<_(i) shows projected values in this formula which uses the value of n for data points.

$$\mathrm{TDI} = \sqrt{(\Delta C)^2 + (\Delta\sigma)^2} \qquad \mathrm{Eq}\ (8)$$

The Total Distance Index (TDI) formula evaluates the accuracy of brain tumor segmentation:

TDI: Measures the distinction between the CNN-segmented tumor and the ground truth.

ΔC: Difference in centroid locations of the segmented tumor versus the ground truth.

Δσ: Difference in standard deviations, reflecting tumor spread.

A lower TDI indicates better segmentation accuracy and helps compare and improve CNN models. The combined results of the two sets of studies provide insightful information about which strategy most closely resembles the reference technique, enabling a reliable and accurate segmentation decision.

$$JSC = \frac{|X \cap Y|}{|X \cup Y|} \qquad \mathrm{Eq}\ (9)$$

Jacquard Measures of the Similarity Coefficient measure the similarity among the predicted tumor boundaries and the reference outlines. Where Y is the reference outline and X is the expected tumor boundary.

$$\mathrm{BDE} = \frac{1}{|\mathrm{Y}|} * \sum (\mathrm{D}(\mathrm{x}, \mathrm{Y})) \qquad \mathrm{Eq}\ (10)$$

Boundary Displacement Error measures the average distance between the predicted tumor boundary and the reference outline. Where: x is a point on the predicted tumor boundary, Y is the reference outline, where the distance between x and the closest point on Y is expressed as d(x, Y). The accuracy measures the proportion of the correctly classified instances both true positives and true negatives out of all instances. *TP:* True positives which malicious queries are correctly classified as malicious. *TN:* True Negative which benign queries correctly classified as benign. *FP:* False positive which benign queries incorrectly classified as malicious. *FN:* False Negatives which malicious queries are incorrectly classified. The accuracy, precision, and Recall is defined below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{Eq (19)}$$

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP+FP}} \quad \textbf{Eq (20)}$$

.

$$\textbf{Recall} = \frac{\textbf{TP}}{\textbf{TP + FN}} \quad \textbf{Eq (21)}$$

The F1 Score is the harmonic mean of the Precision and Recall, Which provides a single metric to balance both.

$$F1 - Score = 2 \,.\frac{Precision\,.Recall}{Precision+Recall} \quad \textbf{Eq (19)}$$

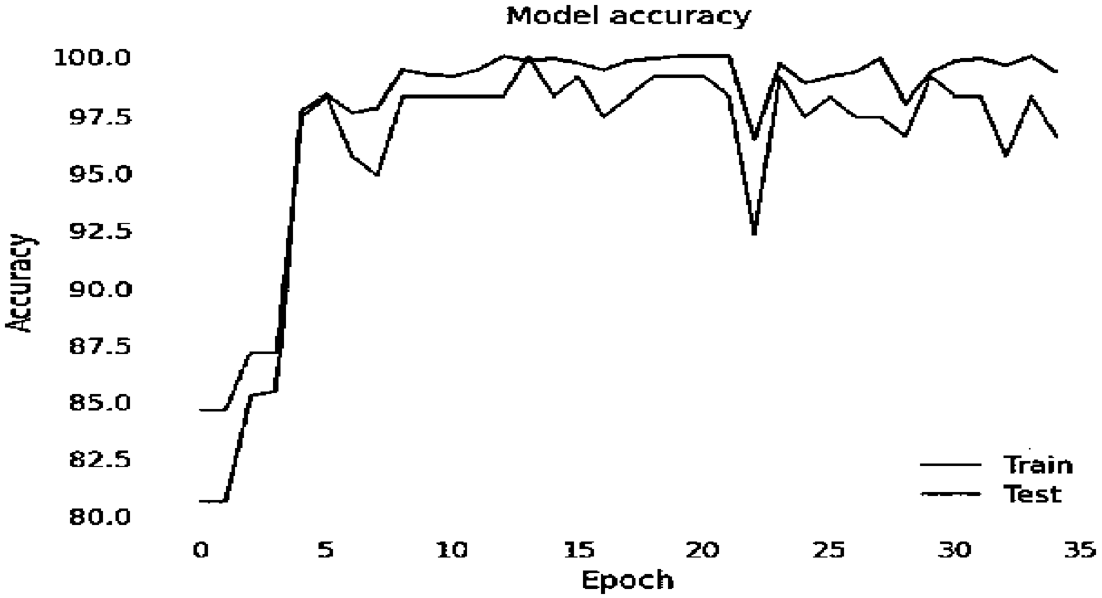

Figure 6.
Brain MRI Segmentation accuracy curve for train and Test

Brain tumor segmentation comparison utilizes four distinct techniques to segment brain tumors in 1251 people, each with four different sorts of photos. Each scan consists of 155 slices, with three distinct sections identified Edema (ED), necrosis/non-enhancing tumor (NET), and enhancing tumor (ET) are observed on each slice. The dark regions in T1ce images show necrosis, while edema is found in the bright areas in FLAIR and T2 images. To present how well these approaches work, several slices were chosen to show the results. As seen in the figure Every sub-region on a T1ce and T2 MRI scan has a label visible in a single slice. Necrosis is highlighted in red, the improving blue and yellow for the tumor, and green for the edema. These labels are compared with the ground truth and tumor segments generated by 2D-Vnet, EnsembleUNets, CaPTk, and ResNet50.

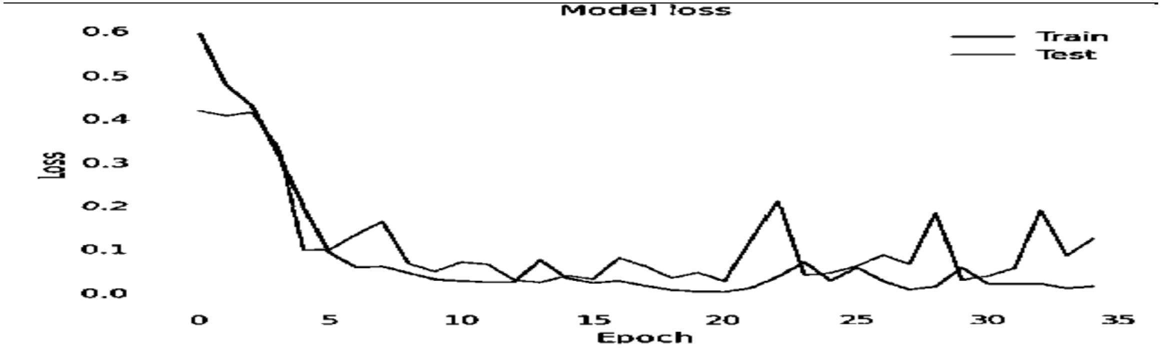

Figure 7.
Brain MRI Segmentation Loss curve for train and Test

Figure 8.
Confusion Matrix of Brain MRI Segmentation with and without Tumor

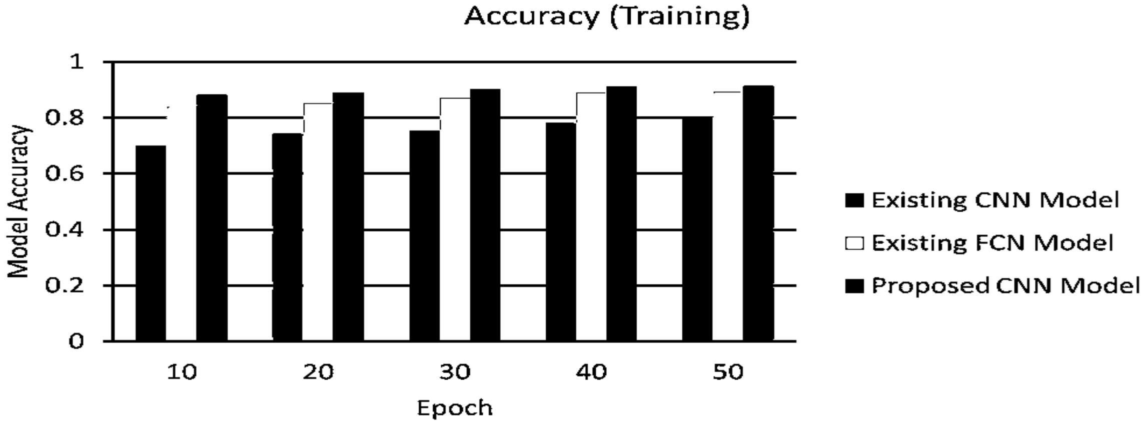

Figure 9.
Training accuracy of proposed and Current CNN and FCN

Sunway Medical Centre uses multimodal MR imaging as its main diagnostic tool for detecting brain tumors. The technique stands as both simple and strong and contributed to the development of radiomics which extracts quantifiable features from MR images. The accuracy of these attributes depends largely on how well tumors get distinguished from their surrounding image area. Research has developed plenty of deep learning approaches for brain tumor segmentation yet a complete evaluation of their performance remains unsettled. The research evaluated several common brain tumor segmentation methods to determine which one delivered optimal results. Our findings are clear. We applied CaPTk, 2DVNet EnsembleUNets and ResNet50 to the BraTS2021 dataset's 1251 samples of T1, T2, T1ce and FLAIR mpMRI images that used an expert-radiologist generated pre-segmented reference image as baseline.

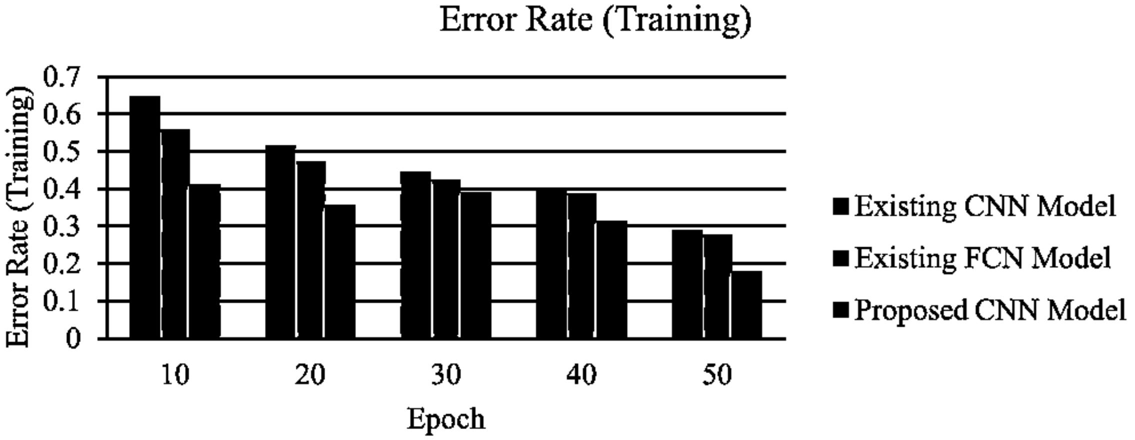

Figure 10.

Training Error rate of proposed and Current CNN and FCN

The use of Pyradiomics for post-segmentation produced 4852 features from each examined subject. EnsembleUNets maintained the prime position as the best performer among different statistical metrics through outstanding results across direct tumor segmentation and radiomic feature extraction tasks. The method achieved success because it brings together three unique models (U-Net (3D), MI-U-Net (3D), and MI-U-Net (3D+2D)) using both 3D and 2D image types for precise segmentation. EnsembleUNets shows excellent performance in tumor segmentation which enables better clinical diagnosis and specific tumor classifications and optimized treatment planning, especially for radiation therapy requiring precise tumor outline definition. By being effective the approach could facilitate the connection between radiometric characteristics and genetic information and establish groundwork for developing individualized treatment strategies in disease management research.

Table 1.

Comparative Analysis of Proposed and Current Techniques

				1st Round for Core Tumor Region (CT)				
Classifier	**Computation Time**	**JC**	**Dice Score**	**Sensitivity**	**Accuracy**	**Specificity**	**Precision**	**F-Score**
NBB	*K* = 22	0.6185	0.6421	0.6486	0.6415	0.6437	0.6435	0.6483
E-CNN	*K* = 22	0.6415	0.6481	0.6486	0.6285	0.6465	0.5245	0.6485
SVM	*K* = 22	0.6285	0.6483	0.6485	0.6415	0.6447	0.7627	0.6486
RNN	*K* = 22	0.612	0.6445	0.6484	0.6285	0.6486	0.7442	0.6487
SVM	*K* = 22	0.6222	0.6485	0.6432	0.6485	0.7484	0.6433	0.6487
Proposed CNN	*K* = 22	0.8485	0.8425	0.9325	0.8485	0.8432	0.8444	0.8485

Table 2.

Comparative Analysis of Proposed and Current Techniques

19th Round for Core Tumor Region (CT)

Classifier	Computation Time	JC	Dice Score	Sensitivity	Accuracy	Specificity	Precision	F-Score
NBB	*K* = 28	0.8185	0.7421	0.8415	0.7481	0.8415	0.6435	0.6483
E-CNN	*K* = 28	0.8415	0.7481	0.6486	0.8415	0.7481	0.5245	0.6485
SVM	*K* =28	0.8285	0.7783	0.6485	0.8285	0.8221	0.8875	0.6486
RNN	*K* = 28	08612	0.7375	0.6484	08612	0.9482	0.9775	0.7481
SVM	*K* = 28	0.8222	0.8875	0.8222	0.8875	0.8222	0.8285	0.7783
Proposed CNN	*K* =28	0.9485	0.9275	0.9485	0.9775	0.9485	08612	0.7775

Table 3: Comparative Analysis of Proposed and Current Techniques

36th Round for Core Tumor Region (CT)

Classifier	Computation Time	JC	Dice Score	Sensitivity	Accuracy	Specificity	Precision	F-Score
DT	*K* = 15	0.6185	0.6421	0.6486	0.6415	08612	0.9482	1.6483
RNN	*K* = 15	1.6415	1.8415	0.7481	1.8185	0.8875	0.8222	0.6485
NBB	*K* = 15	1.6285	1.6486	0.6185	0.6421	0.6185	0.9485	1.6486
E-CNN	*K* = 15	1.612	1.6485	1.6415	1.8415	1.6415	0.7442	1.6487
SVM	*K* = 15	0.6222	0.8875	1.6285	1.6486	1.6285	0.6433	0.6487
Proposed CNN	*K* = 15	1.485	1.9775	1.612	1.6485	1.612	1.4444	1.3485

CONCLUSION AND RECOMMENDATIONS

This paper evaluates four widespread CNN-based algorithms that perform identification work in addition to segmentation and clustering tasks for glioma medical treatment preparation from MRI pictures. The authors state they found novel results about how segmentation performance measures link to radiomic descriptors of tumor areas since no studies tackled this relationship to date. All performance assessment metrics unanimously indicate that EnsembleUNets represents the best solution compared to alternative methods. EnsembleUNets provides an appropriate solution for researchers and clinical institutions who want precise and fast tumor identification. The development of methods should improve EnsembleUNets' tumor detection precision because accurate segmentation forms the base for medical decisions in patient care. EnsembleUNets demonstrates superiority among all proposed solutions for multivariate brain tumor detection and segmentation tasks using MRI images.

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