

A Survey of Techniques for Brain Anomaly Detection and Segmentation Using Machine Learning

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Abstract

In this research report, various Machine Learning (ML) models are discussed for the purpose of detecting brain anomalies like tumors. In the first step, we review previous work that uses Deep Learning (DL) to classify and detect brain tumors. Next, we present a detailed analysis of the ML methods in tabular form to address the brain tumor morphology, accessible datasets, segmentation, extraction, and classification using DL, and ML models. Finally, we summarize all relevant material for tumor detection, including the merits, limitations and future directions. In this study, it is found that employing DL-based and hybrid-based metaheuristic approaches proves to be more effective in accurately segmenting brain tumors, compared to the conventional methods. However, the brain tumor segmentation using ML models suffers from drawbacks due to limited labelled data, variability in tumor appearance, computational memory requirements, transparency in models, and difficulty in integration into clinical workflows. By pursuing techniques such as Data Augmentation, Pre-training, Active-learning, Multimodal fusion, Hardware acceleration, and Clinical integration, researchers and developers can overcome the bottlenecks and enhance the accuracy, efficiency, and clinical utility of ML-based brain tumor segmentation models.

Keywords

BraTS, GLIOMAS, MRI, CNN, U-NET, SVM, K-Means Clustering

1. Introduction

A brain anomaly refers to any abnormality or deviation from the normal struc-

ture or function of the brain. These anomalies can be present at birth or develop later in life due to injury, disease, or other factors. Examples of brain anomalies include changes in the size or shape of the brain, disruptions in neural activity, and alterations in the structure of brain cells. It can include various conditions such as brain tumors, hemorrhages, strokes, aneurysms, and other neurological disorders. Tumors are caused by the aggressively growing cells in the brain, which may end in death if untreated. Detecting, segmenting, and classifying brain anomalies using ML techniques involve leveraging algorithms to analyze medical images and identify regions of abnormality. Differences in tumor location, structure, and proportions make brain tumor detection significantly more difficult.

Gliomas are tumors affecting the central nervous system, and the prognosis for individuals with this condition is typically poor, with a survival rate of less than 15 months.

Gliomas are categorized as low grade and high grade:

Low grade: Grades 1 & 2: Slow-growing cells (seen in young children);

High grade: Grades 3 & 4: Aggressive.

Glioblastoma is grade 4, seen in adults.

The various constituents of Gliomas are:

- 1) Edema-A Collection of fluid or water (FLAIR, T2);
- 2) Necrosis: An Accumulation of dead cells (T1c);
- 3) Enhancing: It is associated with the breakdown of blood-brain barrier (T1c);
- 4) Non-enhancing: The regions in region which is not Edema, Necrosis or Enhancing tumor.

2. Methodology

MR technique is preferred to capture input images because of its non-ionizing, non-invasive method, high spatial and temporal resolution. The principle behind MRI involves the use of a powerful magnetic field to align water molecules in the body, followed by stimulation with radiofrequency energy pulses to produce energy that is captured by the scanner and transformed into images. By adjusting the scanner parameters, multiple complementary images can be obtained, which provide important information about edema, necrosis, enhancing tumor, and NE regions.

The various processes involved in Segmentation and classification are given in **Figure 1**.

- **Data Acquisition:** Input images are captured using magnetic resonance imaging (MRI), computed tomography (CT), or positron emission tomography (PET) scans.
- **Preprocessing:** Acquired pixels are preprocessed to enhance image quality, remove noise, and normalize intensity levels, ensuring optimal input for the ML algorithms.

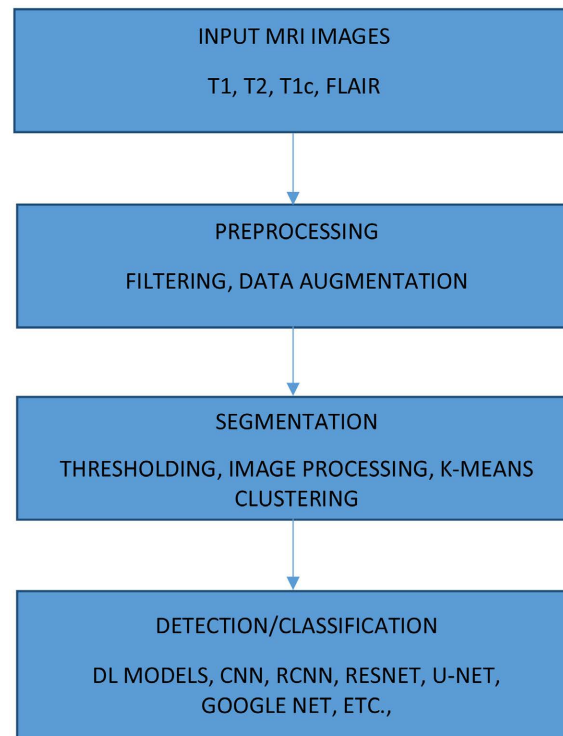


Figure 1. Process of segmentation.

- **Detection:** ML algorithms are trained to detect the presence of brain anomalies. This can be accomplished through supervised learning, where labeled training data with annotated anomalies is used to train the algorithm to recognize patterns and features associated with abnormalities.
- **Segmentation:** Once a brain anomaly is detected, the ML algorithms can perform segmentation to identify and delineate the exact boundaries or regions affected by the anomaly. This step helps in precise localization and measurement of the abnormality. There are six forms of segmentation namely, Intensity based segmentation, Region growing, Water-shed transform, Active contour models, ML based segmentation and hybrid segmentation.
- **Classification:** ML models have the capability to classify brain anomalies by analyzing their unique characteristics. This process entails training the algorithm to differentiate between various categories of anomalies, such as tumors, hemorrhages, or strokes. Through learning to identify pertinent features, the algorithm is able to provide predictions regarding the specific type of anomaly detected. This study presents a detailed analysis of recent research and the observations on the segmentation of tumors where MRI is employed.

The ML techniques offer several advantages in brain anomaly detection, segmentation, and classification. They can automate the analysis process, reducing the time and effort required by medical professionals. ML models can also handle large amounts of data and extract complex patterns that may be difficult for humans to detect. Additionally, these models can be continuously

improved by incorporating new data, allowing for ongoing refinement and enhancement.

However, it is important to note that ML approaches for brain anomaly analysis have limitations. They heavily rely on the availability of high-quality labeled data for training, which can be challenging to obtain due to the scarcity of annotated medical images. The interpretability of ML models is another concern, as their decision-making processes may lack transparency, making it difficult to understand how and why certain classifications are made.

On the other hand, manual segmentation of these different constituents can be time-consuming and introduce inter-rater variability, making automated segmentation methods using ML techniques highly desirable. The BraTS dataset [1] is a collection of medical data from multiple centres that are open to the public, and it includes information about both low and high-grade gliomas. Each patient volume includes FLAIR, T1, T2, T1c, as well as pixel level segmentation masks. Additionally, each MR sequence undergoes a process of skull stripping, registration, and resampling to ensure an isometric resolution. The dimension of the dataset is $240 \times 240 \times 155$, which provides excellent spatial and temporal resolution.

Therefore, MRI, along with automated segmentation methods, can provide vital information about the constituents of gliomas and the treatment techniques and monitoring the disease progression. The MRI of brain shown in **Figure 2** provides the detail about the composition of brain and the planes of imaging. The availability of public datasets such as BraTS has provided researchers with the necessary resources to develop and test developed algorithms for the automated segmentation of tumors, which improves the accuracy and reduces the complexity.

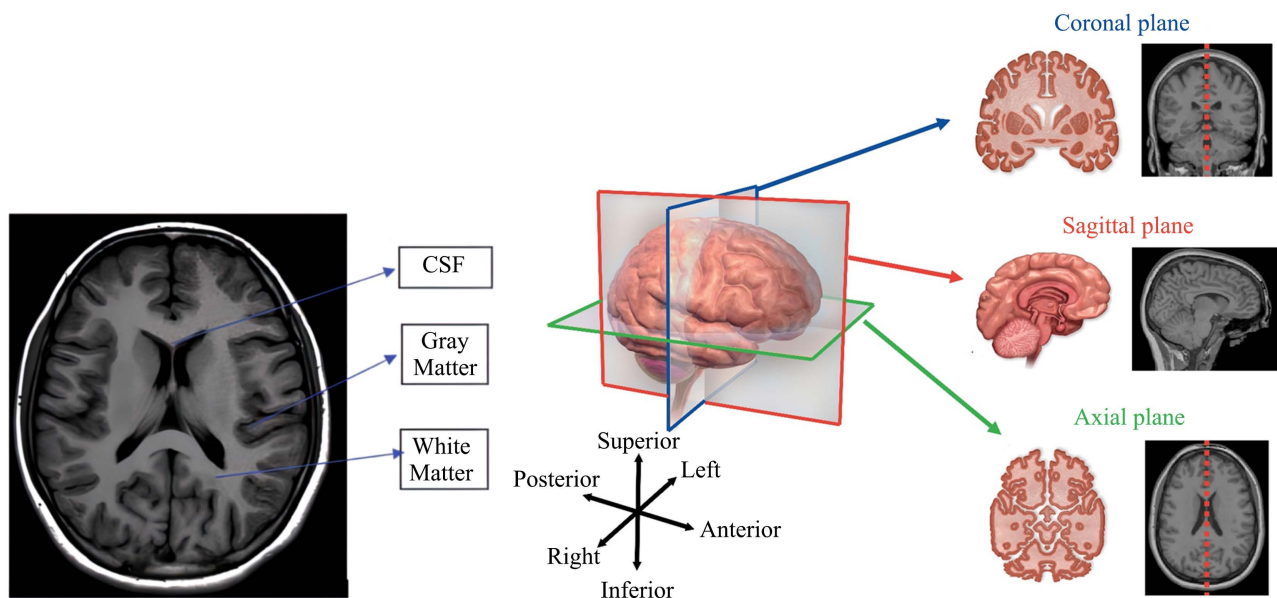


Figure 2. MRI images of brain [https://www.wikiwand.com/en/Sagittal_plane].

3. Segmentation Methods

There are different methods for brain segmentation, and one of them depends on image pixels.

Thresholding and region-based: Thresholding involves using one or more thresholds to classify regions of the image based on their intensities. However, this method has drawbacks such as low convergence rates and low segmentation accuracy due to being trapped in local minimums.

On the other hand, region-based segmentation relies on pre-defined conditions and connected regions of the image. This method involves selecting an initial seed point, locating points in the image, and selecting points with similar intensity values. ML techniques like clustering and classification can also be used in brain segmentation. Classification techniques use known data to train the model and compare it with the test model, while clustering techniques are unsupervised.

The application of Convolutional Neural Networks (CNNs) for brain tumor segmentation has demonstrated encouraging outcomes. CNNs are particularly well-suited for image-based tasks like brain tumor segmentation due to their ability to learn hierarchical representations from raw pixel data.

The most commonly used architectures of CNN are given below:

4. Patch Based CNN for Brain Tumor Segmentation

- CNN trained on 2-D MR to predict the class of centre pixel as shown in **Figure 3**.
- A Separate network used for HGG and LGG.

5. U-Net

The patch-based approach is relatively slow as it only predicts the central pixel of a patch during a single forward pass. To improve inference time, there are two possible strategies:

- 1) Instead of only predicting the class of the central pixel, predicting the class of a subset of pixels within the patch.

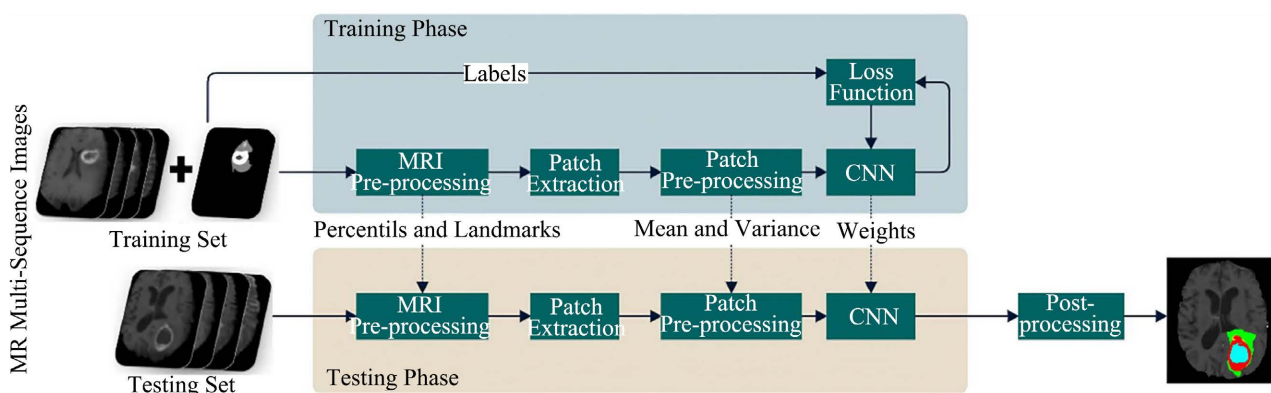


Figure 3. Patch based CNN for brain tumor segmentation [2].

2) In a single forward pass, predicting the class of the pixels within the patch. These goals can be achieved by using fully convolutional neural networks, with an example being the encoder-decoder network architecture.

The network illustrated in **Figure 4** is specifically created to process inputs with dimensions of 240×240 and classify all the pixels within the dimension in a single forward pass. It comprises of an encoder and decoder, where the encoder is comprised of convolutional layers and a max pooling layer, while the decoder consists of transposed convolution and convolutional layers. The network employs skip connections to merge low-level, high-resolution features with high-level, low-resolution features.

6. Classification

The classification approach depends on utilizing existing data to train the model, which is subsequently compared to the test model. Conversely, clustering techniques are unsupervised and do not necessitate prior knowledge of the data. In tumor identification and segmentation, Random Forest (RF) is frequently employed for classification utilizing MRI data. This algorithm functions by constructing numerous decision trees and aggregating their predictions to yield a more precise outcome.

7. Dataset

BraTS dataset is publicly available and contains data from multiple centres. It includes information about both low-grade (75 cases) and high-grade gliomas (210 cases). One of the main advantages of this dataset is that each patient volume includes FLAIR, T1, T2, T1c, and a pixel-level mask. Additionally, each MR sequence undergoes skull stripping, registration, and resampling to ensure an isotropic resolution of 1 mm^3 . The dataset has a dimension of $240 \times 240 \times 155$, representing sagittal, coronal, and axial views.

8. Literature Survey

In this section, we present a description of notable research papers that have

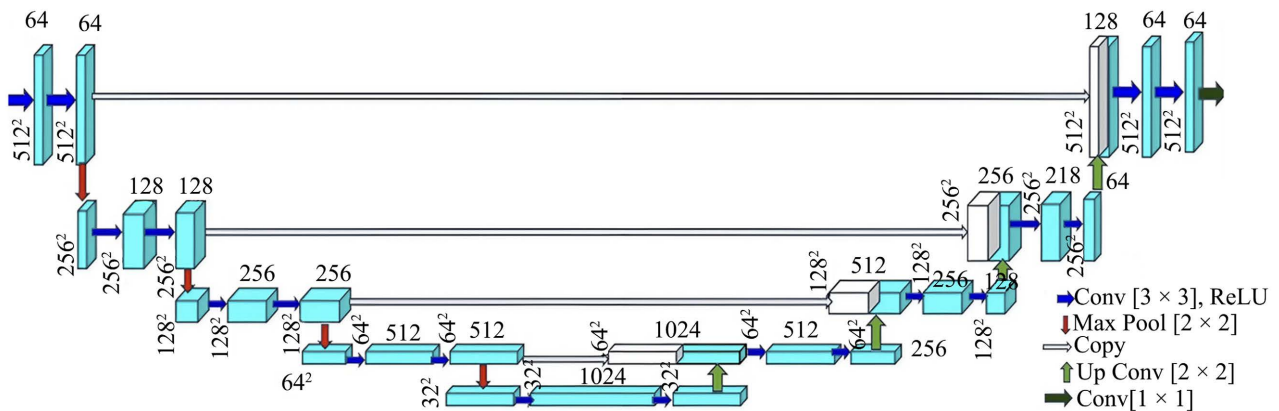


Figure 4. U-NET architecture of CNN [3].

been published recently on brain tumor detection, segmentation and classification based on the MR Imagery. The salient features of each work, its performance, pros and cons have been reported in Appendix.

Accurate diagnosis of brain tumors is essential in saving patients' lives. Artificial Intelligence (AI) can support healthcare professionals, including doctors and radiologists, in this crucial process through Computer Assisted Diagnosis (CAD) systems. In a recent study, a method utilizing ResNet for classifying brain tumors was introduced [4]. The model was trained using a dataset consisting of 3064 MRI, encompassing Meningiomas, Gliomas, and Pituitary tumors. The proposed approach involved pre-processing techniques such as resizing and cropping, along with data augmentation techniques. Remarkably, the model achieved an impressive accuracy of 99%, surpassing previous achievements on the same dataset.

A method is proposed [5] that includes several steps for tumor analysis. The process involves sharpening the images, reducing noise through the application of a median filter, and segmenting the tumor area using a region growing algorithm. The segmented slices are then utilized in an autoencoder model called SSAE for feature extraction. The developed machine learning model is trained and tested on various Brain Tumor Segmentation (BraTS) datasets, resulting in improved accuracy and sensitivity when compared to existing approaches. The developed technique achieves an average accuracy of 100%, 90%, 95%, 100%, 97%, and 95% during the years 2012-2015, accompanied by high AUC scores.

An innovative approach for identification is proposed, which involves a fusion technique that combines information from four distinct MRI sequences into a single image. This fusion process is accomplished using the discrete wavelet transform (DWT), while a noise removal filter called PDDF is applied [6]. The boundaries are obtained using a global Thresholding method. Notably, this methodology achieves a higher level of accuracy when compared to utilizing individual sequences in isolation, as demonstrated on benchmark datasets such as BraTS 2012, 2013, 2015, 2013 Leaderboard, and 2018. Additionally, future extensions of this work may involve the fusion of PET and CT scans to enable even more comprehensive analysis.

The segmentation and classification of tumors are critical tasks in the medical field. Deep convolutional networks have shown impressive performance in medical image classification, but they often require large datasets for effective training. However, acquiring such datasets can be challenging. To tackle this issue, a transfer learning approach with VGGnet is presented in [7], specifically designed for small medical datasets. The authors fine-tuned blocks of the VGGnet architecture and created six different models to assess their impact on two publicly available datasets (BraTS and MRI). In this study, the BT-VGGnet model outperformed state-of-the-art classification methods, achieving accuracies of 97.28% and 98.69% on the respective datasets.

A study was conducted on tumor segmentation with statistical features [8]. The researchers developed an algorithm consisting of multiple stages, including

pre-processing, image manipulation, noise reduction, feature extraction, and classification using a Recurrent Neural Network (RNN) to classify the patterns. The classified patterns were then processed in a subsequent phase to segment the region of interest (ROI). The proposed algorithm achieved an impressive accuracy of 96.26%. The primary objective of this research is to improve the diagnosis of brain tumors, with future studies focusing on determining additional details such as the type, size, and thickness of the tumor region.

For automated identification and classification of tumors in MRI, an efficient algorithm employing the Faster R-CNN and VGG-16 architecture is utilized [9]. Through the utilization of a region proposal network, the algorithm successfully identifies and delineates tumor regions, followed by tumor classification. The results demonstrate that the developed algorithm achieves a precision of 77.60%. Additionally, this approach shows promise for further research applications, particularly in the extension to skin lesion segmentations.

In their study, researchers aimed to explore the utilization of deep learning (DL) networks for the classification of input images [10]. They selected Resnet50 as the foundational architecture and introduced modifications by removing the last five layers and adding eight new layers. The resulting hybrid model achieved an impressive accuracy of 97.2% when evaluated on an MRI dataset obtained from Kaggle. Remarkably, this performance surpassed well-known models such as AlexNet, DenseNet201, InceptionV3, and GoogLeNet. These findings suggest that the modified Resnet50 architecture shows great potential for computer-aided systems designed to detect brain tumors, presenting significant advancements compared to classical RESNET and other existing architectures.

The occurrence of brain tumors involves the abnormal and uncontrolled growth of cells, emphasizing the importance of early diagnosis for the survival of patients. In a recent development [11], a technique has been devised that utilizes the Fully Convolutional Neural Network (FCNN) for pre-processing and the Gaussian Mixture Model (GMM) for feature extraction. This approach effectively captures relevant characteristics from each feature vector. The proposed method, known as DLCR, undergoes three stages of training and is evaluated using the BraTS 2018 dataset. The results demonstrate that the DLCR method outperforms existing techniques in terms of sensitivity, specificity, recall ratio, precision ratio, PSNR ratio, and RMSE. This innovative approach shows promising potential in enhancing the accuracy and efficiency of tumor detection and diagnosis.

An effective approach for the classification of brain tumors in MR images is presented in a study [12]. The method utilizes a generative adversarial network (GAN) to extract features and capture the structure of the input images. Initially, a deep neural network is trained as a discriminator on diverse MR image datasets, with the convolutional layers playing a crucial role. To prevent overtraining, data augmentation and dropout techniques are applied. The proposed method achieves an accuracy of 93.01% on the introduced split and 95.6% on a random split of the data. The authors suggest further investigation into the per-

formance of the method using renowned deep CNN architectures such as VGG-16 or ResNet-152.

The segmentation of tumors using deep learning (DL) can be challenging, but [13] introduces a fully automated and effective solution by utilizing a unified framework based on convolutional neural networks (CNN). The findings of the study demonstrate remarkable accuracy rates of 98.67% for tumor segmentation and 98.26% for classification when applied to input images from the BraTS 2018 dataset. Interestingly, Dense-Net exhibits superior performance in accuracy compared to the Dark-Net classifier. This technique showcases competitiveness and holds great potential for various clinical medical applications. Future research will focus on expanding the method's capabilities by incorporating larger and more diverse datasets.

In the field of medical imaging, the challenge of limited datasets necessitates the use of data augmentation techniques. To tackle this issue, researchers have employed Progressively Growing Generative Adversarial Networks (PGGANs) to augment the BraTS-2016 dataset and enhance tumor detection in conjunction with RESNET-50. The combined approach [14], which compares traditional data augmentation methods with PGGAN-based data augmentation, achieves an accuracy of 91%. However, there is further room for improvement by exploring the integration of noise-to-image and image-to-image GANs. In this study, a two-step GAN-based data augmentation methodology is implemented, involving the generation and refinement of input images with or without tumors. This approach leads to improved tumor detection sensitivity and effectively handles data imbalance. Moreover, the method can also be extended to object detection and segmentation tasks, and it shows potential applications in data anonymization and physician training. Future research will involve defining a GAN loss function that explicitly optimizes results and leveraging unlabelled data during the generative process.

Accurate diagnosis of tumors in input images is crucial for cancer analysis and treatment; however, manual segmentation processes can be time-consuming. To overcome this challenge, two deep convolutional neural network (DCNN) architectures are proposed for efficient identification and classification of different types of tumors. The models are trained and validated using the Figshare and BraTS 2018 datasets. To enhance performance, pre-processing steps such as bias field correction, intensity normalization, and data augmentation techniques are applied [15]. The models achieve a classification accuracy of 97.3% and a Dice similarity coefficient (DSC) of 95.8% when classifying gliomas, meningiomas, or pituitary tumors. Furthermore, in the classification of high-grade gliomas (HGG) and low-grade gliomas (LGG), the second architecture achieves an accuracy of 96.5% with a DSC of 94.3%. The proposed models demonstrate superior performance compared to existing state-of-the-art methods. However, it is important to consider limitations, including smaller datasets and potential inaccuracies in the available information.

For precise separation of tumors from MRI images, a multilevel segmentation technique is developed, which integrates optimal Thresholding, the watershed algorithm, and morphological operations [16]. Tumor classification is performed using features extracted through a CNN and the K-SVM algorithm. The MLS-CNN algorithm achieves an impressive accuracy of 97.4%. The study emphasizes the significance of efficient segmentation techniques and showcases the effectiveness of the MLS-CNN method in accurately detecting and classifying tumors in input images.

Cancer is the second leading cause of mortality worldwide, with brain tumors accounting for a significant portion of cancer-related deaths. Recent advancements in image classification have facilitated computer-aided diagnosis, particularly through the utilization of convolutional neural networks (CNNs). However, CNNs may not accurately identify the focal point of lesions, thereby limiting their effectiveness. To address this issue, a CNN architecture is proposed that incorporates an attention mechanism and a multipath network [17]. This architecture enables the selection of crucial information from the region of interest while filtering out irrelevant details. The multipath network allocates data to multiple channels, applies transformations to each channel, and consolidates the results from all branches. The proposed architecture achieves an impressive accuracy of 98.61% using a dataset of 3064 MRI images of brain tumors. The study acknowledges certain limitations, including overfitting and misclassification of meningioma samples, which could be mitigated through techniques such as data augmentation and improvements in the network structure.

In order to identify tumor slices in MRI images, a study aimed to develop and evaluate multiple CNN models. Six models were designed and trained on the BraTS 2013 dataset, and their performance was evaluated using the WBA dataset [18]. The researchers identified the most effective model for tumor classification and recorded the accuracy achieved by each model. Notably, all six models demonstrated an accuracy range of 96% to 99%. However, a limitation of these models is that they require longer computational time.

In recent years, there has been a growing focus on the development of brain tumor detection techniques using MRI. However, traditional approaches mainly rely on bottom-layer feature extraction methods that may not be optimal for medical imaging. To overcome this limitation, a novel model has been proposed that utilizes the Inception-v3 convolutional neural network (CNN), which is a deep learning mechanism capable of extracting multi-level features for accurate classification and early detection of brain tumors [19]. The model incorporates hyperparameters and utilizes the Adam optimizer, while employing a softmax classifier to classify images into multiple classes. Remarkably, the proposed model achieves an impressive training accuracy of 99.34% and a validation accuracy of 89%.

Detecting and treating brain tumors early are crucial as they pose a significant health risk and can be life-threatening. To support the detection process, DL methodologies were employed on the MRI brain tumor dataset from Kaggle.

Using a convolutional neural network (CNN) architecture, the images were processed and segmented, essential features were extracted, and the output was classified [20]. The proposed approach demonstrated an accuracy range of 90% to 99% on the Kaggle dataset. The system was developed using Keras and Tensor Flow, enhancing its applicability in the medical sector. CNN proves to be an accurate and efficient classification neural network, requiring fewer parameters and less data for training. This model exhibits tremendous potential for future medical applications.

A deep learning model called BrainMRNet was introduced for the classification of MR images [21]. This model incorporates attention modules, the hypercolumn technique, and a residual network, which have gained attention in the field of diagnosis. Utilizing these techniques, the model achieves an impressive 96.05% success rate in classifying brain tumors in magnetic resonance images. BrainMRNet surpasses pre-trained models and effectively distinguishes between abnormal and normal brain MR images using a dataset comprising both types of image data. Notable features of BrainMRNet include attention to relevant regions and the transfer of essential features through the hypercolumn technique. Future research will focus on exploring different datasets and optimization methods for deep learning models.

A new approach called SR-FCM-CNN was proposed for brain tumor detection and type prediction [22]. The proposed method consists of two main steps. Firstly, low-resolution MRI images are enhanced using a super-resolution CNN network to increase their resolution. Then, the enhanced images are segmented using the FCM approach. In the next stage, the augmented images are classified using the SqueezeNet architecture, with the ELM algorithm employed for accurate classification. The accuracy rate achieved is 98.33%, surpassing the performance of FCM. While the approach's performance may vary depending on the training dataset, it represents a novel and promising method for brain tumor classification. Future studies will explore the utilization of this approach as a classifier in different domains and investigate methods to enhance its speed and performance.

An algorithm named BrainNET was developed for the analysis of MRI images. This algorithm demonstrates efficient tumor detection and subsequent classification through segmentation [23]. The integration of technology in healthcare has brought about a transformative shift towards virtual monitoring with remarkable precision, and AI has played a crucial role in enabling innovative imaging solutions. BrainNET provides automated classification capabilities with commendable accuracy. The study introduces five new networks, consisting of a detection network and four classification networks, all exhibiting high accuracy when compared to existing methods. The system includes a user-friendly graphical interface, making it easily accessible and beneficial for radiologists in enhancing their findings. Future research can focus on expanding the number of brain tumor classes to further improve its effectiveness in the medical field.

The article presents a methodology for distinguishing between tumor and non-tumor images using MR scans, with a specific focus on detection and classification [24]. The proposed technique combines deep learning (DL) and statistical models in a hybrid approach. The process involves multiple stages, starting with pre-processing, where a non-local mean filter is applied to suppress noise. Segmentation is then performed using the Bayesian Fuzzy C-means algorithm. Feature extraction incorporates wavelet packet Tsallis entropy (WPTE) and scattering transforms (ST). Lastly, classification is achieved through a Deep Autoencoder (DAE) combined with the Jaya optimization algorithm (JOA) and SoftMax regression. The proposed method demonstrates an impressive accuracy rate of 98.5%, surpassing other selected existing methods. The authors suggest that future research could explore more advanced techniques to further enhance accuracy.

This research introduces a novel system that utilizes deep learning (DL) methods for precise tumor identification in brain images [25]. The system involves multiple activities, including pre-processing, segmentation, feature extraction, optimization, and detection. These activities incorporate various techniques such as a compound filter, Thresholding, histogram analysis, and the gray-level co-occurrence matrix. The system achieves an impressive accuracy of 98.9% in detecting brain tumors and demonstrates superior performance compared to other modern optimization methods. However, further improvements are necessary to enhance the system's capability to detect specific brain tumor types, locations, and sizes.

Segmenting and localizing brain tumors in MRI scans present significant challenges, yet they are crucial tasks in medical analysis. Recent approaches have aimed to utilize multiple MRI modalities to extract distinct and significant features from different parts of the tumor. However, these approaches often prove complex and time-consuming. In addressing these issues, a novel pre-processing method is proposed by the authors [26]. This method specifically focuses on a small region surrounding the tumor patch, reducing computation time and mitigating overfitting concerns. Additionally, a cascade convolutional neural network model is introduced, which effectively extracts both local and global features through two distinct approaches. To enhance segmentation accuracy, a Distance-Wise Attention mechanism is incorporated. Experimental results demonstrate the effectiveness of the proposed technique, showcasing its superiority over other existing approaches.

A technique for the classification of brain tumors in MR images is introduced [27]. Unlike traditional methods that require prior segmentation of the image, this system utilizes the Discrete Wavelet Transform (DWT) to extract relevant features directly from the brain MRI images. These extracted features are then inputted into a deep neural network, specifically a CNN, for classification. Remarkably, this approach achieves an impressive overall accuracy of 99.3%, surpassing the performance of commonly employed methods. The system categorizes the input image into one of three classes: meningioma, glioma, or pituitary

tumor. A notable advantage of this proposed approach is its increased efficiency in terms of time complexity, as it eliminates the need for a separate segmentation step.

An approach for tumor segmentation is presented, consisting of two main phases: segmentation using the SbDL (Super pixel-based Deep Learning) approach and classification achieved by combining DL and DRLBP (Dynamic Region-based Local Binary Patterns) features [28]. The efficacy of the SbDL approach is evaluated using the dice score, demonstrating high performance in segmenting various brain tumor modalities. To enhance texture analysis, deep features from the pre-trained Inception V3 model are combined with DRLBP features. The concatenated features are further optimized using the PSO (Particle Swarm Optimization) method. Subsequently, the optimized features are classified using a softmax classifier, yielding an impressive average accuracy of over 92%. The proposed technique outperforms other methods and holds potential for further improvement, particularly by implementing it on Capsule Net.

MRI images acquired at different stages provide valuable insights for tumor detection through feature extraction and classification methods. Convolutional Neural Network (CNN) algorithms have demonstrated promise in accurately predicting brain tumors at early stages. A survey was conducted to evaluate the effectiveness of 3D CNNs in brain tumor detection, an area still in its early developmental phase due to its complexity, yet holding potential for automated identification of crucial features. A 3D CNN architecture was developed to identify anomalies, utilizing pre-trained CNN models for feature extraction [29]. Subsequently, a correlation-based selection method was employed to identify the most relevant features for classification. The pipelining of RBF kernel and polynomial kernel classification achieved the highest accuracy. However, it is important to note that these networks come with limitations, including high computational costs and an exponential increase in the number of parameters.

Conventional methods such as rotation and patch extraction are employed to enhance the dataset and simplify it by resizing the images to $28 * 28$ pixels [30]. The authors utilize the CapsuleNet architecture to classify Glioma, Meningioma, and Pituitary tumor. The objective of the study is to examine the influence of pre-processing techniques on brain tumor classification using CapsuleNet.

A DL technique for tumor classification is introduced, which investigates different weight initialization and freezing configurations across eight CNN architectures [31]. The study evaluates a total of 40 DL models. The findings indicate that transfer learning-based models with appropriate architectural choices outperform their randomly initialized counterparts. The proposed framework achieves promising results by freezing the initial layers in the transfer learning paradigm, specifically with configurations such as 3LF (freezing the first three layers) and 5LF (freezing the first five layers). The DenseNet family of deep architectures demonstrates promising outcomes, while the relatively shallow VGG19-based models achieve comparable results when only the last three and five convolutional layers are trainable. Additionally, the lightweight MobileNet architecture

shows promising results, offering the potential for more scalable medical image analysis using DL.

A method is developed for segmenting gliomas, an essential task for analysis and treatment [32]. The approach employs a 3D U-Net ensemble that combines picture pre-processing, patch extraction, and multiple model training to accurately segment gliomas using multimodal MRI. The results are promising, demonstrating high mean Dice scores and low Hausdorff distances for various sub-regions. In future investigations, the technique will be further enhanced by employing N-fold cross-validation and a grid search approach, aiming to improve its performance.

The comparison of the performance of different approaches for Tumor detection, segmentation and classification is presented in the Appendix.

9. Conclusions

In conclusion, ML models have demonstrated great potential in brain anomaly detection and segmentation tasks, offering valuable insights for medical professionals and aiding in diagnosis and treatment planning. Different methodologies and strategies have been utilized, with an emphasis on DL models, in particular Convolutional Neural Networks (CNNs). These models have shown remarkable capabilities in learning intricate patterns and features from brain imaging data. Datasets used in these studies such as BraTS play a crucial role, providing labeled examples for training and evaluation. However, the availability of large, diverse, and accurately annotated datasets remains a significant challenge. Merits of ML-based brain anomaly detection and segmentation include improved accuracy and efficiency compared to manual approaches, enabling rapid analysis of large volumes of data.

Despite these merits, there are drawbacks to consider. Interpretability of DL models remains a concern, as they are often regarded as black boxes. Additionally, the reliance on high computational resources and memory for training and inference poses challenges for real-time and large-scale deployment in clinical settings. Future directions in brain anomaly detection and segmentation using ML models include the development of techniques to address limited labeled data through data augmentation, transfer learning, and active learning strategies. Multimodal fusion, incorporating diverse imaging modalities, can enhance the accuracy and comprehensiveness of segmentations. The bottlenecks and challenges in this field include limited annotated datasets, variability in anomaly appearances, computational requirements, generalization to new data, and the need for rigorous validation and clinical integration. Overcoming these bottlenecks requires collaborations between researchers, medical professionals, and technology experts, emphasizing data sharing, benchmarking, and robust evaluation protocols.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

https://docs.google.com/spreadsheets/d/e/2PACX-1vSbkPca2ANXTPETNDw98RUsHQ4QND_aOq9ZVtr_S40lwt3tlK0sLgKjZzz-MZ2F0Pw3w9_rP0ZJgmpA/pubhtml