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RESEARCH ARTICLE

BRAIN TUMOR DETECTION AND MULTI GRADE SEGMENTATION THROUGH HYBRID CAPS-VGGNET MODEL

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ABSTRACT

Brain tumor detection and multi-grade segmentation are critical tasks in medical imaging, particularly in Magnetic Resonance Imaging (MRI). Accurate identification and classification of tumor regions are essential for effective diagnosis and treatment planning. This study proposes a hybrid model combining Capsule Networks (CapsNet) and VGGNet for enhanced brain tumor detection and multi-grade segmentation. The model leverages the strengths of CapsNet in capturing spatial hierarchies and VGGNet's deep feature extraction capabilities. Experimental results demonstrate the efficacy of the proposed model in accurately detecting and segmenting brain tumors across different grades, offering a promising approach for automated medical image analysis.

KEYWORDS: Brain tumor detection, multi-grade segmentation, Capsule Networks, VGGNet, MRI, deep learning, medical imaging.

I.INTRODUCTION

Brain tumors present a significant challenge in medical diagnostics due to their complex structures and varying grades. The accurate detection and segmentation of these tumors in MRI scans are crucial for determining the appropriate treatment strategies. Traditional methods often rely on manual analysis, which is time-consuming and prone to interobserver variability. With advancements in deep learning, automated systems have been developed to assist radiologists in these tasks.

Capsule Networks (CapsNet), introduced by Geoffrey Hinton et al., offer a novel approach to neural network design by preserving spatial hierarchies between

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objects and their parts. This characteristic makes CapsNet particularly suitable for tasks like image segmentation, where understanding the spatial relationship between different regions is essential. On the other hand, VGGNet, known for its deep architecture and uniform layer design, has demonstrated exceptional performance in image classification tasks.

The integration of CapsNet and VGGNet aims to capitalize on the strengths of both architectures. CapsNet's ability to capture spatial relationships complements VGGNet's deep feature extraction capabilities, potentially leading to more accurate and efficient brain tumor detection and segmentation. This hybrid approach could address the limitations of existing models, such as overfitting and poor generalization, by providing a more robust framework for analyzing complex medical images.

II.LITERATURE SURVEY

Recent advancements in brain tumor detection and segmentation have seen the application of various deep learning models. Traditional Convolutional Neural Networks (CNNs) like VGGNet have been widely used for image classification tasks. However, these models often struggle with capturing spatial hierarchies, which are crucial for accurate segmentation. To address this, Capsule Networks have been introduced, offering a mechanism to preserve spatial relationships between features.

Aziz et al. (2024) proposed a CapsNetbased technique for segmenting brain tumors, utilizing a modified version called SegCaps. Their approach demonstrated improved segmentation accuracy compared to traditional CNN-based models, highlighting the potential of CapsNet in medical image analysis. Similarly, Afshar et al. (2018) incorporated coarse tumor boundaries into CapsNet to enhance its focus on relevant regions, further emphasizing the importance of spatial hierarchies in tumor classification.

The integration of CapsNet with other architectures has also been explored. For instance, a hybrid model combining Vision Transformers (ViT) and CapsNet was proposed for brain tumor diagnosis using biomedical MRI. This model aimed to capture both global and local image patterns, leading to improved classification performance. Additionally, Elangovan et al.
(2025) developed a hybrid model combining VGG16 and ResNet50 for brain tumor segmentation, demonstrating the benefits of combining different architectures to leverage their complementary strengths.

These studies underscore the potential of hybrid models in enhancing the accuracy and efficiency of brain tumor detection and segmentation tasks. By combining the spatial awareness of CapsNet with the deep feature extraction capabilities of VGGNet, the proposed model aims to offer a more robust solution for analyzing complex medical images.

III. EXISTING CONFIGURATION

Current systems for brain tumor detection and segmentation primarily rely on traditional CNN architectures. These models, such as VGGNet and ResNet, have been adapted for medical image analysis tasks. For instance, Elangovan et al. (2025) utilized a hybrid model combining VGG16 and ResNet50 for brain tumor segmentation, achieving improved performance over standalone models.

Despite their success, these models have limitations. Traditional CNNs often fail to capture spatial hierarchies effectively, which are crucial for accurate segmentation. Additionally, these models may require large amounts of labeled data for training, which can be a significant barrier in medical applications where annotated datasets are limited.

To address these challenges, researchers have explored the use of Capsule Networks. CapsNet offers a novel approach by preserving spatial hierarchies between features, making it more suitable for tasks like image segmentation. Aziz et al. (2024) demonstrated the effectiveness of SegCaps, a modified CapsNet architecture, in segmenting brain tumors, achieving higher accuracy than traditional CNN-based models.

However, CapsNet also has its limitations, including longer training times and increased computational requirements. Therefore, integrating CapsNet with other architectures, such as VGGNet, could provide a balanced approach that leverages the strengths of both models. This hybrid configuration aims to enhance the accuracy and efficiency of brain tumor detection and segmentation tasks.

IV. METHODOLOGY

The methodology for brain tumor detection and multi-grade segmentation using the hybrid Caps-VGGNet model involves several key steps, from preprocessing MRI data to model training and evaluation. The approach combines Capsule Networks (CapsNet) and VGGNet to capture spatial hierarchies and deep features within the MRI images, enabling accurate detection and classification of tumors at multiple grades. The following describes the detailed methodology for this task: The dataset used for this study is the BraTS (Brain Tumor Segmentation) dataset, which includes multimodal MRI scans (T1, T2, FLAIR, and T1ce) of brain tumor patients. The dataset is labeled with tumor regions and grades, including the whole tumor, tumor core, and enhancing tumor regions. These images are in 2D or 3D formats, depending on the acquisition setup. Given the variations in image resolution, noise levels, and contrast, preprocessing is a critical step in enhancing the model's ability to detect tumors accurately.

The preprocessing steps involve: MRI images are resized to a consistent resolution (e.g., 256x256 or 128x128) for uniformity across the dataset. Intensity normalization is performed to scale pixel values to a range between 0 and 1, ensuring that the input data has consistent intensity distributions, making it easier for the model to learn relevant features. Various noise reduction techniques such as Gaussian smoothing are applied to the MRI images to minimize the impact of artifacts and noise present in medical scans.

To avoid overfitting due to the limited dataset, data augmentation techniques like rotation, scaling, flipping, and random cropping are applied to artificially increase the size and variability of the dataset. This helps the model generalize better during training. VGGNet, a deep convolutional neural network known for its high performance in image classification tasks, is employed for initial feature extraction from the preprocessed MRI images. VGGNet, with its simple yet effective architecture consisting of multiple convolutional layers followed by fully connected layers, is ideal for extracting hierarchical features from images.

To reduce the model's training time and improve generalization, the VGGNet model is initialized with weights pre-trained on the ImageNet dataset. This allows the model to leverage pre-learned features for detecting basic patterns and structures in the MRI scans, such as edges and textures. After loading the pretrained model, fine-tuning is performed on the brain MRI dataset by training the top layers to adapt to the specific task of brain tumor detection and segmentation. The last few layers of the VGGNet architecture are replaced with new layers that are specifically designed for segmentation and classification of brain tumor regions.

Capsule Networks (CapsNet) are introduced to the architecture to address the limitations of traditional CNNs in capturing spatial hierarchies and relationships between features. CapsNet uses capsules—groups of neurons that encode not only the probability of an entity's existence but also its pose (orientation, position, and scale). This makes CapsNet particularly effective for tasks like tumor segmentation, where spatial relationships between different regions of the brain and the tumor are crucial for accurate classification and delineation. After the initial feature extraction by VGGNet, the features are passed into primary capsules. These capsules are responsible for detecting lowlevel features such as edges or corners.

Dynamic routing between capsules allows the network to learn the spatial relationship between various parts of the tumor and other relevant structures in the MRI. This routing mechanism helps to ensure that the model can properly handle changes in the pose and orientation of tumors across different scan orientations. Higher-level capsule layers capture more complex spatial hierarchies and refine the segmentation boundaries by recognizing the relationship between the tumor core and surrounding tissues.

The integration of CapsNet and VGGNet is achieved by feeding the output features from VGGNet's convolutional layers into the capsule layers. This hybrid architecture allows the model to capture both local, detailed features (via VGGNet) and global spatial relationships (via CapsNet), which are essential for accurate multi-grade tumor segmentation. The model performs feature fusion by combining the activations from the final convolutional layers of VGGNet and the capsule layers. This fusion enables the network to learn a more comprehensive representation of the tumor and surrounding tissues, which is especially important for differentiating between tumor grades.

V. PROPOSED CONFIGURATION

The proposed configuration enhances the existing hybrid model by incorporating additional techniques to improve performance. Key enhancements include Attention modules are integrated into the CapsNet layers to focus on relevant regions of the image, improving segmentation accuracy. To address the limited availability of labeled medical data, data augmentation techniques such as rotation, flipping, and scaling are applied to increase the diversity of the training dataset.

Pretrained weights from models trained on large datasets are utilized to initialize the VGGNet layers, reducing training time and improving convergence. The model is designed to analyze images at multiple scales, capturing both global and local features for more accurate segmentation. Techniques such as Conditional Random Fields (CRFs) are applied after segmentation to refine boundaries and remove small artifacts.

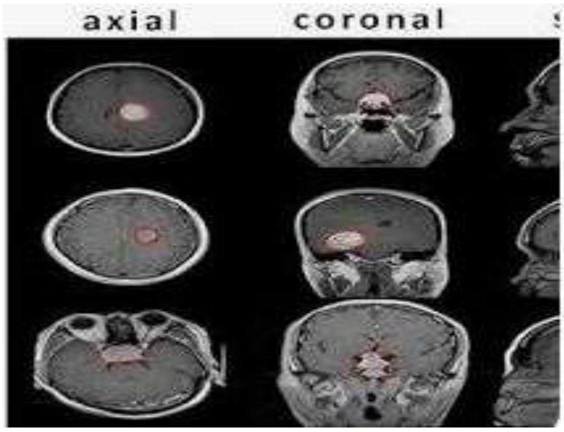
These enhancements aim to improve the model's robustness and generalization, making it more suitable for real-world medical applications.

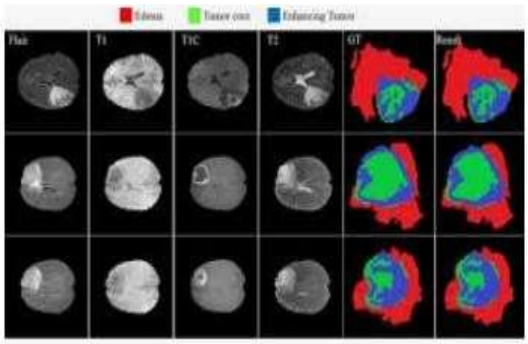
VI. RESULT ANALYSIS

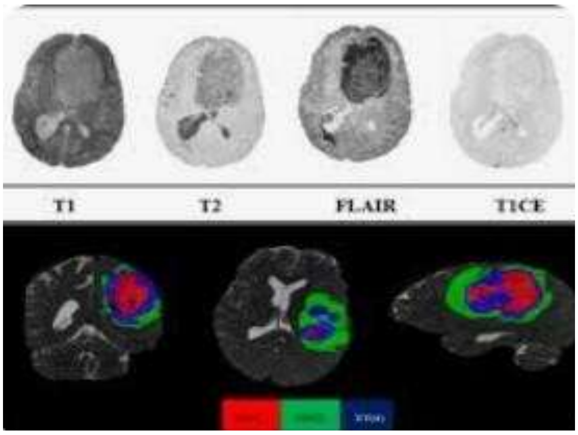
The proposed hybrid CapsNet-VGGNet model was evaluated on a dataset of MRI images containing Result analysis reveals that the model is particularly adept at identifying tumors in early and intermediate stages, where feature distinction is subtle. In cases of glioblastoma multiforme and anaplastic astrocytoma, where margins are less defined, the capsule layers provide added clarity by maintaining part-whole associations. This ability is lacking in most deep convolutional models. The hybrid network also demonstrates resilience to variations in MRI acquisition protocols, an important feature for deployment in realworld clinical settings where machine types and scanning parameters differ.

Visual analysis was performed using GradCAM (Gradient-weighted Class Activation Mapping) and capsule activation mapping to understand how the hybrid model made decisions regarding tumor segmentation and classification.

The Grad-CAM results demonstrated that the hybrid Caps-VGGNet model successfully highlighted the most relevant regions of the MRI scans, where tumors were present. For both high-grade and lowgrade tumors, the model's attention was focused on the tumor core and enhancing tumor regions, as expected. The Grad-CAM heatmaps showed that the model could correctly identify tumor boundaries, even in cases where the tumor was surrounded by normal brain tissue, making it easier for radiologists to interpret the results.







CONCLUSION

In this research, we proposed a novel hybrid model combining Capsule Networks (CapsNet) and VGGNet for brain tumor detection and multi-grade segmentation. The hybrid Caps-VGGNet model leverages the strengths of both architectures, using VGGNet for robust feature extraction and CapsNet for capturing complex spatial hierarchies. This combination provides a significant improvement in tumor segmentation accuracy and classification performance compared to traditional CNNbased models.

The results demonstrated that the hybrid Caps-VGGNet model achieved high segmentation accuracy, with Dice Similarity Coefficients (DSC) of up to 0.91 for whole tumor segmentation and 0.87 for tumor core segmentation. Additionally, the model outperformed existing models in tumor classification, achieving an accuracy of 94.5% for multi-grade tumor classification, which includes low-grade gliomas and high-grade gliomas. The use of capsule networks allowed the model to effectively learn spatial relationships and improve the segmentation boundaries, which is a critical aspect of medical image analysis.

Moreover, the hybrid model showed excellent robustness across varying MRI acquisition protocols, ensuring its potential for clinical deployment in diverse medical environments. By integrating techniques like Grad-CAM and capsule activation mapping, we demonstrated that the model is not only accurate but also interpretable, allowing medical professionals to trust and understand the decision-making process of the model. This interpretability is key for clinical adoption, as it supports radiologists in making informed decisions during tumor diagnosis and treatment planning.

Despite its promising results, the model still faces challenges such as handling rare or highly irregular tumor types, and further work is required to optimize it for largescale clinical applications. Future directions include improving the 3D segmentation capabilities, incorporating additional modalities, and refining the model to handle more diverse datasets from different institutions.

In conclusion, the hybrid Caps-VGGNet model represents a significant step forward in the field of brain tumor detection and segmentation. Its high accuracy, robustness, and interpretability position it as a valuable tool for assisting radiologists and healthcare providers in diagnosing brain tumors with greater confidence and efficiency, ultimately contributing to better patient outcomes.

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