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Brain Tumor Detection using VGG-Net Model

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ABSTRACT: In order to diagnose and plan for treatment of brain cancer, brain tumor detection and segmentation are essential. The VGG Net Model is a revolutionary method for brain tumor identification that is presented in this paper. The accuracy was greatly increased by using the powerful feature extraction capabilities of VGG Net. A large dataset of brain MRI images is used to train and validate the suggested model, which shows excellent performance in differentiating between tumor grades. According to experimental data, Net Model outperforms other cutting-edge techniques and conventional neural networks (CNNs) in terms detection accuracy. This work offers a promising tool for clinical applications and advances automated brain tumor diagnosis.

KEYWORDS: Convolutional neural networks (CNNs), VGGNet,

I. INTRODUCTION

Because brain tumors have high rates of morbidity and mortality, they pose a serious medical challenge. For better patient outcomes and efficient treatment planning, early and accurate detection must be followed by exact segmentation. Because of its superior soft tissue contrast and comprehensive anatomical visualization, magnetic resonance imaging (MRI) is the gold standard for diagnosing brain tumors. However, radiologists' human interpretation of MRI scans takes a lot of time and is subject to error, which emphasizes the need for automated, dependable, and effective techniques to support diagnosis.

Convolutional neural networks (CNNs), a type of deep learning approach, have demonstrated significant promise in medical image processing in recent years. The well-known CNN architecture VGGNet is a promising contender for brain tumor detection applications because of its exceptional performance in extracting high-level characteristics from images. Despite their effectiveness, CNNs like VGG Net frequently fail.

In order to overcome these drawbacks, we suggest a hybrid model that combines VGGNet with capsule networks, which are renowned for their capacity to maintain spatial hierarchies and enhance feature extraction resilience. A deeper comprehension of the spatial relationships and transformations within the data is ensured by the employment of dynamic routing techniques in capsule networks. Our Hybrid Caps VGG Net Model seeks to improve brain tumor detection accuracy and offer more thorough and dependable multi-grade segmentation by fusing the advantages of VGGNet and capsule networks.

The first step in the hybrid model's methodical workflow is data preparation, which standardizes and enhances the MRI images. The capsule network layer then processes the deep data that VGGNet has extracted to capture intricate spatial hierarchies.

A segmentation head uses the generated feature maps to identify tumors and categorize them into different grades. This approach meets the crucial requirements of both detection and segmentation tasks by utilizing the strong feature extraction capabilities of VGGNet and the spatial awareness of capsule networks.

This study uses a dataset of brain MRI scans to provide a thorough assessment of the Hybrid Caps VGG Net Model. Compared to conventional CNN-based methods, our experimental results show notable gains in detection accuracy and segmentation quality.

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II. RELATED WORK

The work related to the brain tumor detection is presented in the table 1

TABLE 1: Literature review

SLNO.	AUTHORS	TITLE AND YEAR OF PUBLICATION	OBSERVATION
1	G.Hemanth, M.Janardhan, and L.Sujihelen	Design and implementing brain tumor detection using machine learning approach, in Proc. 3rd Int. Conf. Trends Electron. In format. (ICOEI), Apr. 2019	MODEL: CNNNADE. TARGET: Binary Grading ACC: 0.955 LOSS: 0.174
2	G.Garg And R.Garg	Brain tumor detection and classification based on hybrid ensemble classifier, 2021	MODEL: KNN-RF TARGET: Multi Grade ACC: 0.952 LOSS: 0.221
3	G. A. Amran, & Et al	Brain tumor classification and detection using hybrid deep tumor network, Oct- 2022	MODEL: Google Net- Res Net TARGET: Tumor ACC: 0.932 LOSS: 0.233
4	M.Rajand V.Singh	Brain tumor detection using hybrid approach of fish school search using SVM, in Proc. IEEE 6th Int. Conf. Comput. Commun. Autom. (ICCCA), Dec. 2021	MODEL: PSO-SVM TARGET: Binary ACC: 0.917 LOSS: 0.266
5	X.Kong, G.Sun, Q.Wu, J.Liu, and F.Lin	Hybrid pyramid U-Net model for brain tumor segmentation, in Intelligent Information Processing IX. Nanning, China: Springer, 2018.	MODEL: HPU-NET TARGET: Binary ACC: 0.917 LOSS: 0.347
6	I.A.ElKader, G.Xu, Z.Shuai, and S. Saminu,	Brain tumor detection and classification by hybrid CNN-DWA model using MR images, Current Med. Imag. Formerly Current Med. Imag. Rev, Oct. 2021.	MODEL: CNN-DWA TARGET: Multi-grading ACC: 0.923 LOSS: 0.293
7	M. R.Devi, S.Sainath, and P.Pappula,	Brain tumor detection using hybrid neural network based on VGGNet-19 and DenseNet, in Proc. Smart Syst. (ICSSIT), Jan. 2022	MODEL: VGGNet-ResNet TARGET: Multi-grading ACC: 0.930 LOSS: 0.248

2.1 SUMMARY OF LITERATURE REVIEW

In medical imaging, brain tumor detection and segmentation are crucial jobs, and deep learning-based methods have recently demonstrated encouraging outcomes. The hybrid Caps-VGGNet model is a new method that combines the advantages of VGGNet and Capsule Networks (CapsNet) to perform multi-grade segmentation and accurate brain tumor identification.

Based on CE-MRI images from the Brats-2020 and Brats-2019 datasets, the study presents a novel hybrid system that

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detects, extracts radiomic characteristics, and classifies brain cancer using deep learning approaches. To improve the quality of the photos, preprocessing techniques were used, such as distance image enhancing techniques. Accurate brain cancer categorization and early detection were made possible by the optimization of transfer learning-based architectures to extract complicated characteristics from the images. The suggested method uses a CNN-based hybrid architecture with a Soft max classifier.

III. PROBLEM STATEMENT

Worldwide, brain tumors are a common type of tumor. Due to incorrect and delayed diagnosis, this disease is now the leading cause of death. The present approaches to brain tumor diagnosis are less efficient when it comes to meeting the needs of larger datasets. Larger datasets require more processing time, which slows down system performance. To address this problem, the Caps-VGGNet model—which combines the Caps Net model with the transfer learning-based VGGNet architecture—is suggested. The models' performance is evaluated based on their sensitivity, specificity, and accuracy..

IV. PROPOSED SYSTEM

We suggest a Hybrid Caps VGGNet Model that combines the advantages of both VGGNet and capsule networks to overcome the difficulties in brain tumor identification and multi-grade segmentation. Capsule networks improve the model's capacity to preserve positional links between features and capture spatial hierarchies, while VGGNet's deep architecture offers reliable feature extraction. By combining these two designs, our hybrid technique produces a model that can accurately identify and segment brain tumors. The model is intended to interpret MRI pictures of the brain, identifying important features and differentiating between tumor grades. Using sophisticated data augmentation methods and optimization algorithms, we train and verify the Hybrid Caps VGGNet Model using an extensive dataset in order to enhance its performance and generalization. The suggested model seeks to surpass current.

OBJECTIVES

1. To separate the different tumor regions from the brain MRI scans.
2. To integrate the Caps Net model with the VGG Net model by adding the layers of VGG Net to address the challenge of brain tumor segmentation.
3. To achieve accurate detection and segmentation of brain tumors with varying grades and sizes.

V. METHODOLOGY

DATASET: We used the BraTs 2020 dataset. In BraTs 2020, the division of characteristically diverse (by all accounts, shape, and histology) brain cancers—specifically, gliomas—is the main focus, and multi-institution pre-employable X-ray checks are used. Furthermore, BraTS'20 focuses on patient expectations, significant endurance, and the differentiation between pseudo progression and actual cancer recurrence through integrative analyses of radiomic elements and AI computations in order to identify the clinical relevance of this division task. The BRATS19 datasets HGG (High Grade Glioma) and LGG (Low-Grade Glioma), which were obtained from The Cancer Genome Atlas (TCGA), were used to evaluate the benchmark that was presented in addition to the BRATS20 dataset. MRI images and clinical information from patients with high- and low-grade gliomas are included in these databases.

ALGORITHM:

Step1- Input MRI image: The process starts by inputting an MRI image from a dataset.

Step2-Pre-processing: The image undergoes pre-processing to improve its quality for segmentation. This may involve steps like noise intensity normalization.

Step3-Feature extraction: Features are extracted from the pre-processed image. These features may be based on Gray level co-occurrence Matrix (GLCM) .

Step 4-Segmentation: The image is segmented in to different regions using a CNN based algorithm.

Step 5-Tumor identification: The segmented regions are analyzed to identify the presence of a tumor.

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Step 6-Output: If a tumor is identified, its location is marked on the image. The final output is the segmented image with the identified tumor.

VI. RESULTS & DISCUSSION

The following results re obtained from the proposed work and are presented in the following section On providing dataset containing raw brain images, we observe the following result.

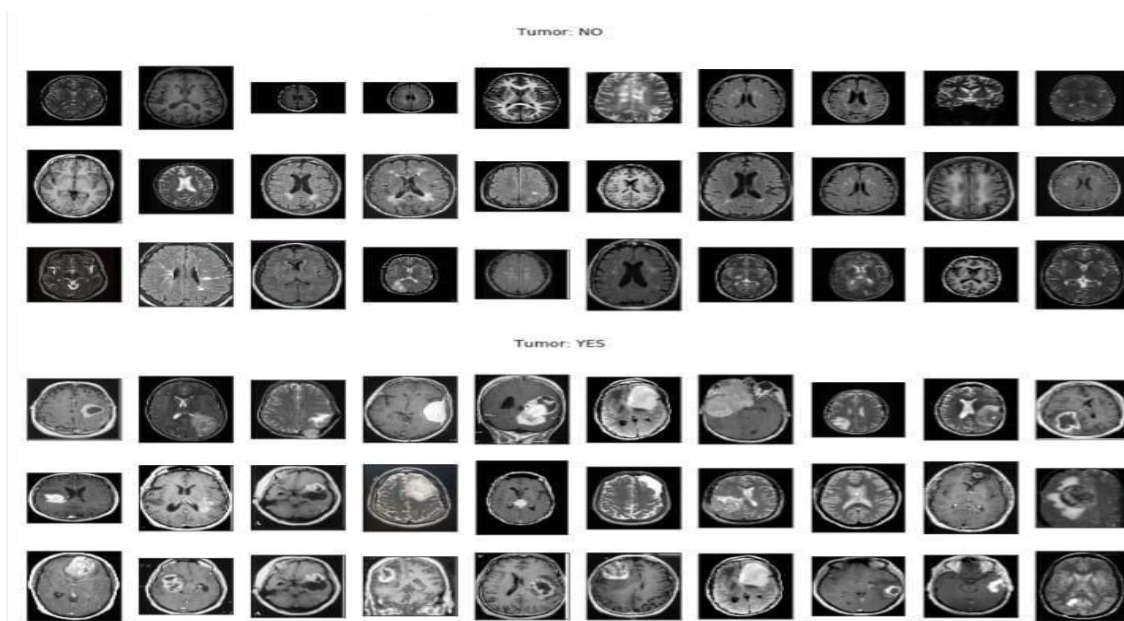


Figure.1: Shows the presence of Tumor or not An abnormal cell development in the brain is called a brain tumor. It may be benign (not cancerous) or malignant (cancerous). The size, location, and kind of a brain tumor all affect its symptoms. Think of your brain as a sophisticated metropolis with many neighborhoods cooperating to maintain order. A brain tumor can cause issues and disturb the regular flow of traffic, much like an unwelcome construction site.

Preprocessing of images:

Brain noise removal: The initial step is to remove noise present in the dataset which is removed by doing preprocessing and results of the are shown in the following figures.



Figure 2.1:Original image



Figure.2.2:Blurred image

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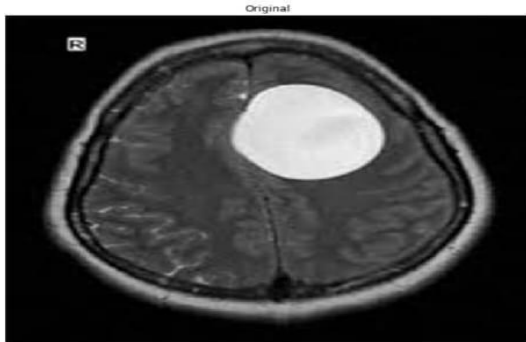


Figure 2.3: Original image

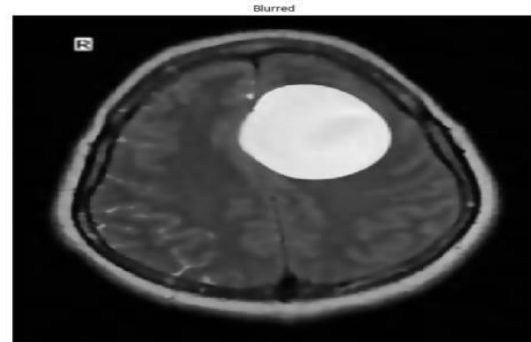


Figure.2.3: Blurred image

Preprocessing it is also a critical step in brain tumor detection that involves preparing the raw image data for subsequently sis and processing. Its goal is to enhance image quality, reduce noise, and extract relevant information, ultimately improving the accuracy and efficiency of tumor detection.

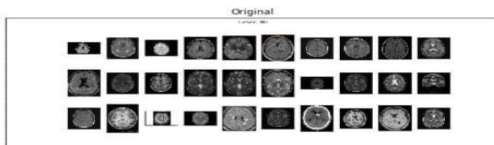


Fig.2.4: Original image

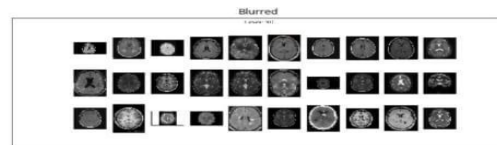


Fig.2.4: Blurred image



Figure 2.5: Brain MRI

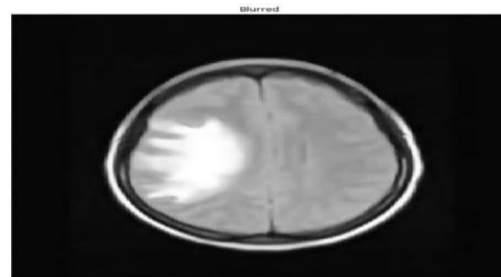


Figure 2.5 :Fuzzy C Means cluster



Figure 2.6: Identify tumor on MRI by position of tumor

Steps Involved:

1. **Image Preprocessing:** The original brain MRI image undergoes preprocessing steps to enhance contrast, reduce noise, and improve image quality.
2. **Cluster Initialization:** The FCM algorithm randomly initializes cluster centers.
3. **Membership Calculation:** Each pixel in the image is assigned membership values to all clusters based on its similarity to the cluster centers.

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4. **Cluster Center Update:** The cluster centers are recalculated based on the membership values of the pixels.
5. **Iteration:** Steps 3 and 4 are repeated until convergence, i.e., when the cluster centers no longer change significantly.
6. **Segmentation:** Pixels with the highest membership value to a specific cluster are assigned to that cluster, creating the segmented image.

Interpretation of Results:

The algorithm has successfully identified the tumor boundary, separating it from the surrounding brain tissue. However, it's important to note that the accuracy of segmentation can be influenced by various factors, including image quality, tumor characteristics. The comparisons of the results are presented in the table 2 and figure 3.

Table 2: Comparisons of the results

SLNO	Model	Accuracy (%)	Loss
1.	Proposed	0.9476	0.5004
2.	Ref[8]	0.917	0.266
3.	Ref[9]	0.930	0.248
4.	Ref[10]	0.932	0.233
5.	Ref[02]	0.917	0.347

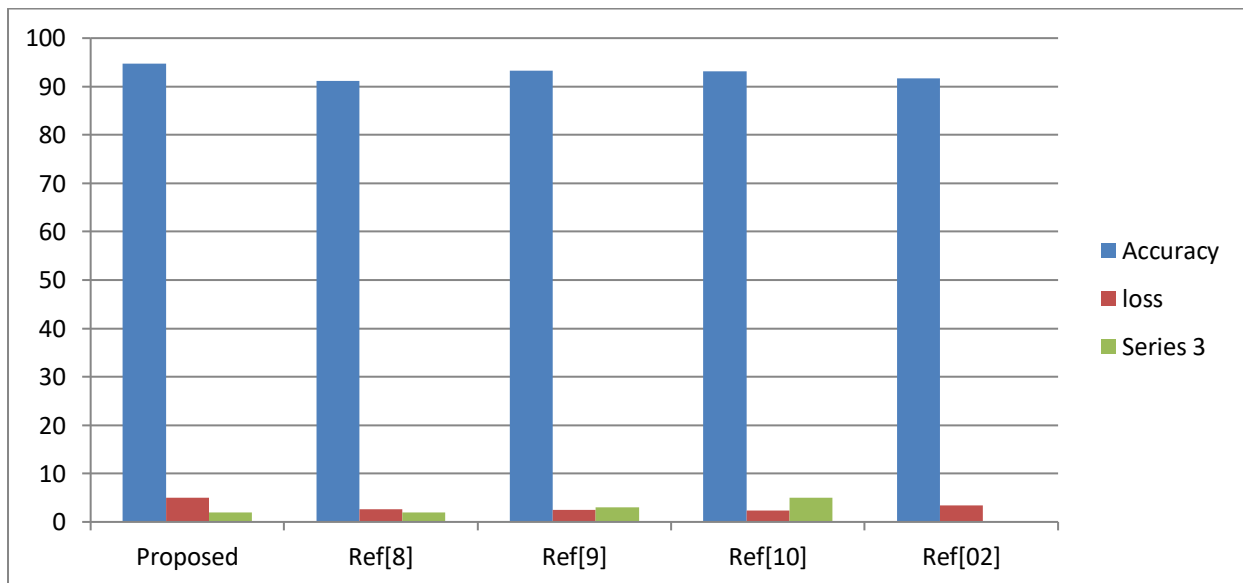


Figure 3: Comparison of the results

From the above table it is clear that accuracy is better than previous researchers and due to large dataset loss has been increased.

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VII. CONCLUSION

The hybrid CAPS-VGGNet model has shown its effectiveness in accurately detecting and segmenting brain tumors of different grades, paving the way for more personalized and effective treatment planning and results are shown that better as compared to previous state of art work. In the proposed work the accuracy is about 94.76% and with a loss of 5.004 and which is due to large data set.

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