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A Deep Learning Based Glioma Tumour Detection Using Efficient Visual Geometry Group Convolutional Neural Networks Architecture

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HIGHLIGHTS

- EVGG-CNN Architecture is proposed for brain tumor detection.
- The proposed method on the brain images from BRATS 2021 and Kaggle dataset.
- The performance of sensitivity, specificity and accuracy is analyzed.

Abstract: The detection and segmentation of tumor regions in brain Magnetic Resonance Imaging (MRI) plays important aspects for last two decades. In this paper, Efficient Visual Geometry Group Convolutional Neural Networks Architecture is proposed for brain tumor detection which consists of pre-processing module, DWT module, and Classification module along with segmentation. The scaling based data augmentation methods are used as the pre-processing technique and the data augmented scaled images are decomposed using DWT Transform. The Wavelet feature maps are constructed from these decomposed coefficients and they are classified using EVGG-CNN architecture. This proposed architecture identifies the brain image into either Glioma or healthy brain image. The effectiveness of these developed methods stated in this work is verified by applying the proposed method on the brain images from BRATS 2021 and Kaggle dataset. The performance of proposed EVGG-CNN architecture is analyzed in terms of sensitivity, specificity and accuracy.

Keywords: Magnetic Resonance Imaging; Glioma, brain tumors; CNN; VGG; EVGG-CNN.

INTRODUCTION

The modality of brain images are important for locating the pixels belonging to the tumor category in image. Computer Tomography (CT) and MRI are the suggested modalities for brain tumor detection by the expert radiologist or physician. The CT has low multi planner capability and low contrast and hence the tumor pixels are not correctly visible. In MRI modality, multi planner capability is high and also they have high resolution scanning behavior. Hence, MRI is mostly suggested by many radiologist or physician for viewing the abnormalities in the brain images [1-3]. Though MRI modality provides many advantages, they also exhibit some limitations such as low contrast and the resolution is independent with the location, size and shape of the abnormal pixels in brain images. Figure 1(a) is the healthy brain MRI and Figure 1(b) is the brain tumor MRI.

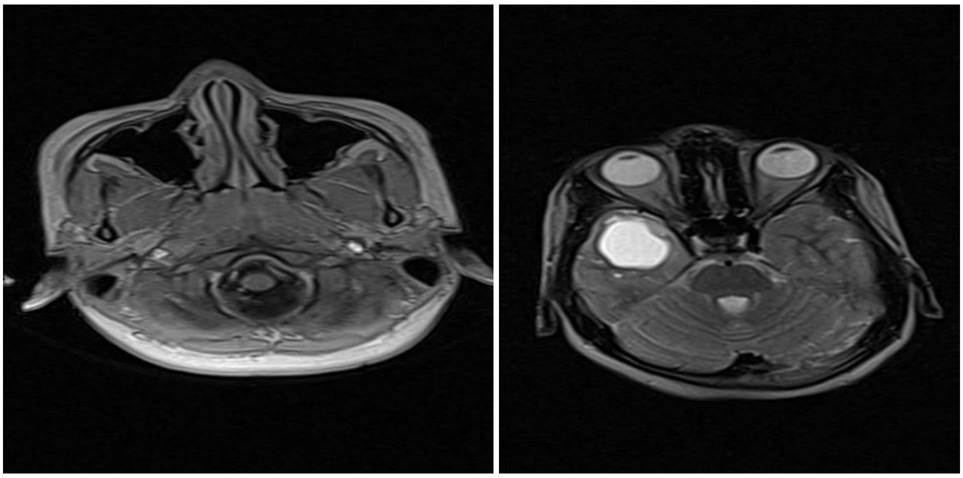

Figure 1(a). Healthy brain MRI **Figure 1(b).** Brain tumor MRI

Several researchers from the past two decades developed many algorithms for brain tumor detection and segmentation in MRI images [4-5]. Their developed brain tumor detection algorithms detected and segmented tumor pixels with the low tumor segmentation accuracy. In the field of medical imaging, machine learning and deep learning algorithms have been developed and applied to detect brain tumors in Magnetic Resonance Images (MRI). Researchers such as Sharif and coauthors (2020) [6] and Pan and coauthors (2015) [7] have examined the impact of machine learning algorithms on brain tumor detection in MRI images. However, these machine learning algorithms have limitations in achieving optimum tumor segmentation accuracy. To address these limitations, deep learning algorithms have been employed for brain tumor detection. Litjens and coauthors (2017) [8] have extensively discussed various deep learning architectures for tumor detection and segmentation in brain images. In this particular study, the focus is on detecting Glioma MRI images and identifying the tumor pixels within these images using a proposed Convolutional Neural Network (CNN) architecture.

The entire structure of the research work can be divided into several sections. In Section 2, we provide an explanation of conventional Glioma detection methods, outlining the existing approaches and techniques used in the field. This serves as a foundation for understanding the advancements made by the proposed deep learning-based approach. Section 3 delves into the details of the proposed Efficient VGG-CNN architecture. The authors describe the specific components, layers, and connections within the CNN model. The architectural choices are justified, highlighting the advantages of using this particular configuration for Glioma detection. This section provides readers with a comprehensive understanding of the deep learning framework employed in the study. Moving on to Section 4, the we present the simulation results obtained from applying the proposed EVGG-CNN architecture to Glioma MRI images. They outline the experimental setup, including the dataset used, evaluation metrics, and any pre processing steps applied to the images. The results are then analyzed and discussed in detail, providing insights into the performance of the deep learning model in terms of tumor detection and segmentation accuracy. Any limitations or challenges encountered during the experiments may also be addressed. Finally, Section 5 concludes the research work by summarizing the key findings and contributions of the study with highlight the advantages of utilizing deep learning algorithms for brain tumor detection, discuss potential future research directions, and emphasize the significance of the work in advancing the field of medical imaging.

LITERATURE SURVEY

Zeineldin and coauthors (2020) [9] proposed a modified U-Net architecture for tumor detection and segmentation in brain MRI images. The internal layers of the modified U-Net were used to compute spatial feature vectors, which were then classified to detect and locate tumor pixels. Evaluation metrics such as dice coefficient and Hausdorff distance were used. The modified U-Net achieved Se (sensitivity) of 96.5%, Sp (specificity) of 96.9%, and Acc (accuracy) of 97.1% on the BRATS 2021model dataset.

Ragupathy and coauthors (2020) [10] combined a deep learning CNN model with a multiple kernel-based K-Means clustering approach for brain tumor detection. The CNN model was used for classification, while the Multiple Kernel-K-Means clustering (MKKMC) approach was used for segmentation. Distance computing metrics, including Hausdorff distance, local distances, and global distances, were used to evaluate the segmentation results. The CNN-MKKMC model achieved Se of 97.1%, Sp of 98.2%, and Acc of 98.6% on the BRATS dataset.

Selvapandianand coauthors (2018) [11] employed an Adaptive Neuro Fuzzy Inference System (ANFIS) classifier for tumor pixel classification and localization in brain MRI images. The ANFIS classifier addressed feedback problems and overfitting issues. Linear and non-linear features were extracted from the multi-transformed brain images and classified using ANFIS. The proposed methodology achieved Se of 97.6%, Sp of 98.1%, and Acc of 98.2%.

Anitha and coauthors (2017) [12] developed a CNN model combined with morphological functions for tumor pixel boundary identification in brain MRI. The CNN architecture trained feature maps from each convolutional layer and down-sampling layers, storing them in a feature map vector index. This index was then classified using the CNN classification phase. The proposed methodology achieved Se of 96.9%, Sp of 98.2%, and Acc of 98.1%.

Havaeiand coauthors (2017) [13] modified the architecture of the CNN deep learning algorithm for tumor region segmentation in brain images. The modified CNN architecture incorporated ReLU activation functions to replace sigmoid functions. The CNN model was trained to differentiate between healthy and tumor brain images, and k-fold validation methods were used for evaluation.

Dong and coauthors (2017) [14] utilized a fully Convolutional network model based on the U-Net CNN architecture for tumor pixel segmentation. The modified U-Net architecture was tested on the BRATS dataset, and various testing algorithms were employed to validate its effectiveness in brain tumor detection and segmentation.

Alqazzazand coauthors (2022) [15] computed and derived the region of interest features from the brain images for the effective comparisons. The authors used binary classification approach for the classification of features. The authors obtained 94.2% sensitivity rate and 96.9% specificity rate for their developed model. The main drawback of this model was that the validation accuracy of the developed frame work was quite less than the proposed model. Therefore, this work will not be used for diagnosing the features which will be derived from the tumor detected images.

Ebrahim Mohammed Senan and coauthors (2022) [16] integrated the heuristic features from both machine and deep learning approach and the integrated approach was used in this work to detect and segment the tumors in brain images. The authors validated the integrated scheme of the brain tumor detection model using various k-fold approaches with respect to different number of folds in order to perform the significant comparisons. The authors obtained 94.8% sensitivity rate and 96.1% specificity rate for their developed model.

Wu and coauthors (2020) [17] proposed intelligent brain tumor detection model for detecting and locating the abnormal pixel patterns in brain MRI images. The developed intelligent model for brain tumor detection improved the pixel belonging to tumor category was improved with the non-heuristic based approaches. The authors compared their experimental results with respect to Support Vector Machine (SVM) and Convolutional Neural Networks (CNN) in this work and they concluded that the CNN based heuristic tumor detection model provided higher efficiency than the SVM based heuristic tumor detection model.

The main drawbacks of the existing Glioma detection methods are stated in the following points.

The algorithms or methodologies used in most of the existing works are complex in nature. The simulation results of the existing methods are not in optimum level.

Based on the drawbacks of the existing Glioma detection methods, the novelty of the proposed work stated in this article are given as,

The existing VGG-CNN architecture is modified into parallel VGG-CNN architecture with less number of Convolutional layer filters. The proposed Efficient VGG-CNN architecture detects the Glioma images by converting the spatial brain image into frequency domain brain image through Curvelet transform.

PROPOSED METHODOLOGIES

Figure 2(a) shows the proposed Glioma detection method using Efficient VGG-CNN algorithm for training brain images and Figure 2(b) shows the proposed Glioma detection method using Efficient VGG-CNN algorithm for testing brain image.

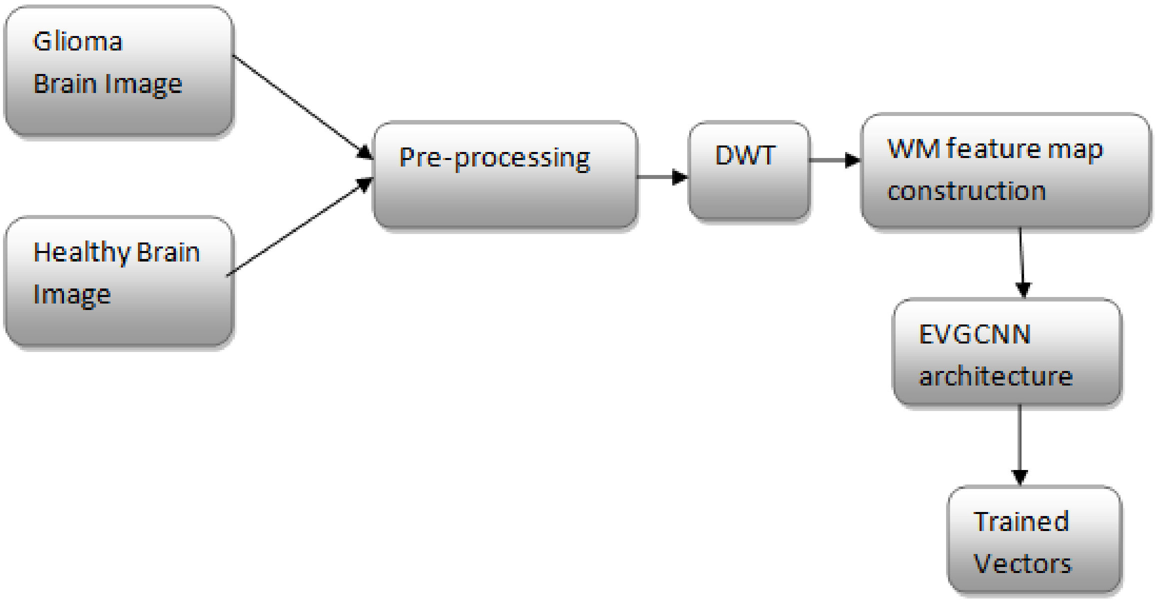

Figure 2(a). Efficient CNN algorithm for training brain images

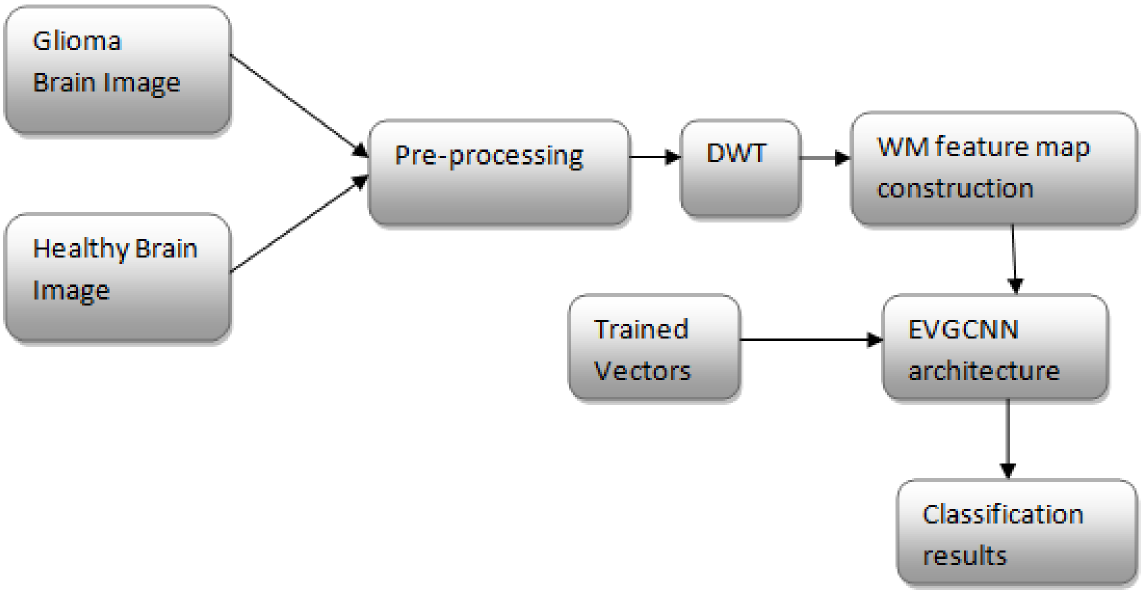

Figure 2(b). Efficient CNN algorithm for testing brain image

Preprocessing

In this work we utilized data augmentation techniques as a pre-processing approach to enhance the accuracy of the proposed Glioma detection system. The data augmentation method involves applying upscale and downscale functions to increase the size of brain image samples [18]. The upscale function increases the image size by a factor of 2, while the downscale function decreases the image size by a factor of 3. The authors have obtained brain MRI images from two datasets, namely the open access BRATS 2021dataset and the Kaggle dataset [19].

Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a powerful technique for MRI image processing that allows for efficient representation and analysis of image data at different scales. DWT decomposes an MRI image into a set of frequency sub bands at multiple resolution levels, capturing both low-frequency and high-frequency components of the image. The DWT operates by applying a series of high-pass and low-pass filters to the image, which separate the image into approximation and detail coefficients at each level of decomposition. The approximation coefficients represent the low-frequency components of the image, capturing the overall structure and smooth variations. The detail coefficients represent the high-frequency components, capturing the finer details and edge information.

The DWT provides a multi-resolution representation of the image, allowing for analysis and processing at different scales. This transform has been widely used in MRI image denoising, where the high-frequency detail coefficients can be selectively modified or discarded to reduce noise while preserving important image features. The DWT is also used in image compression, as the coefficients can be quantized and efficiently encoded to achieve high compression ratios while maintaining acceptable image quality. The multi-level nature of the DWT enables the extraction of texture and edge features from MRI images, which is beneficial for various image analysis and computer-aided diagnosis tasks.

The DWT has been successfully employed in MRI image fusion, where multiple images acquired with different modalities or at different times are combined to enhance the diagnostic information. By analyzing the DWT coefficients, it is possible to identify and extract image features related to specific pathologies or tissue characteristics in MRI images. The DWT offers a flexible framework for multi-resolution image processing, allowing for the extraction of relevant image information at different scales and resolutions. Due to its ability to capture both global and local features, the DWT has been used in MRI image segmentation, facilitating the delineation of anatomical structures and abnormalities.

The DWT is computationally efficient, with fast algorithms such as the Fast Wavelet Transform (FWT) enabling real-time or near-real-time processing of MRI images. The DWT has been employed in MRI image registration, enabling the alignment of images acquired at different spatial positions or orientations. The multi-scale decomposition provided by the DWT aids in feature extraction and texture analysis, facilitating tasks such as tumor detection and characterization in MRI images.

In this work, two dimensional DWT with 'harr' wavelet mode is used to decompose the image into coefficients. From these coefficients $D(i,j)$ with P rows and Q columns, the extrinsic features are determined and these computed extrinsic features are described in the following equations.

$$\text{ExtrinsicFeaturePattern(EFP)} = \frac{\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1} D(i,j)}{P*Q} \quad (1)$$

$$\text{ExtrinsicModeFeaturePattern(EMF)} = \frac{\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1} D(i,j)}{(P+1)*(Q+1)} \quad (2)$$

$$\text{ExtrinsicIndexPattern(EIP)} = \frac{\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1} D(i,j)*i*j}{P*Q} \quad (3)$$

$$\text{ExtrinsicHeuristicPattern(EHP)} = \frac{\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1} D(i,j)}{P*Q*(i+j)} \quad (4)$$

These determined extrinsic features are given to the proposed DCNN classifier for the process of Glioma classifications in this work.

The DWT is applied on each pre-processed brain images to decompose the image regions. The transformed coefficients with respect to different orientations are obtained by the DWT transform and they are stored in a matrix which is called as Wavelet Matrix (WM).

The existing VGG-16 architecture and the proposed EVGG-16 architecture are depicted in Figure 3(a) and Figure 3(b), respectively. In the proposed EVGG-16 architecture, two individual VGG-16 architectures are integrated in a parallel manner to form a single architecture that performs different functionalities individually. The left portion of the proposed EVGG-16 architecture, known as VGG16-1, is responsible for computing the intrinsic feature matrix from the generated extrinsic features. It consists of seven convolutional layers (C11, C12, C31, C32, C33, C51, C52) and three pooling layers (P1, P3, P5). The purpose of VGG16-1 is to generate intrinsic features from the extrinsic features.

Each convolutional layer performs linear convolution between the computed Wavelet Matrix (WM) features and the kernel of the convolutional layer, as represented by Equation (2): C_out = F_i * WM. Here, C_out is the response of the convolutional layer,

Fi is the filter's kernel of the convolutional layer, and WM is the Wavelet Matrix produced by the DW transform. The intermediate feature maps generated by C31, C32, C33 are then passed through P2 layer and transferred to the next layers. On the other hand, the right portion of the proposed architecture, VGG16-2, is used to compute the intrinsic feature matrix from the source brain MRI image. It also consists of seven convolutional layers (C21, C22, C41, C42, C43, C61, C62) and three pooling layers (P2, P4, P6). Similarly, linear convolution is performed in each convolutional layer using the source brain image and the kernel of the layer. The intermediate feature maps generated by C41, C42, C43 are passed through P4 layer and transferred to the subsequent layers.

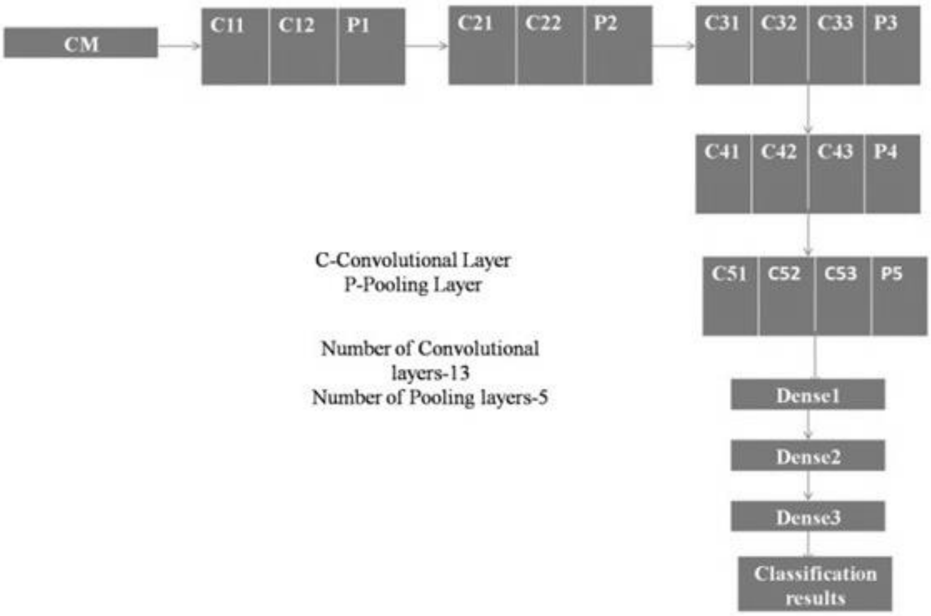

Figure 3(a). VGG-16 architecture

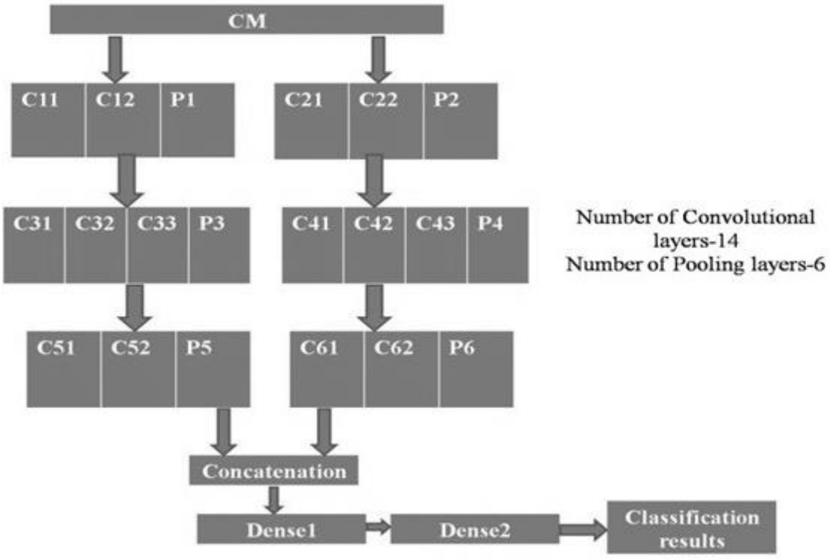

Figure 3(b). Efficient VGG-16 architecture

The number of filters in C11, C12, C21, C22 layers is 256, while in C31, C32, C33, C41, C42, C43 layers it is 512. The stride of 11 is used for C11, C12, C21, C22 layers, and the stride of 22 is used for C31, C32, C33, C41, C42, C43, C51, C52, C61, C62 layers. The pooling layers (P1, P2, P3, P4, P5, P6) reduce the size of the intermediate feature maps. The response from P1 layer is transferred to the next layers (C31, C32, C33, and P2). Similarly, the response from P2 layer is transferred to C41, C42, C43, and P4 layers. This process continues for the subsequent layers, where the responses from pooling layers are passed to the appropriate convolutional and pooling layers.Finally, the feature maps from P5 and P6 layers are fed into a set of dense layers (D1 and D2). The D1 layer has 1028 neurons, and the D2 layer has 2 neurons, which produce the final classification results.The existing VGG architecture operates its convolutional layers and pooling layers in a serial mode, which consumes more time to produce the final classification results. To address this issue, the existing serial VGG architecture is converted into a parallel VGG architecture by parallelizing the internal layers, resulting in the proposed EVGG-16 architecture.Table 1 is the specification of the proposed EVGG-CNN architecture for Glioma classifications with individual layer notation, layer name and its functionalities.

Table 1. Specification of the proposed EVGG-CNN architecture

Layer Notation	Layer name	Specifications
C1	Convolutional	512 linear filters with 1*1 stride
C2	Convolutional	1024 linear filters with 2*2 stride
P1	Pooling	2*2- Max pool window
P2	Pooling	2*2- Max pool window
C3	Convolutional	1024 linear filters with 1*1 stride
C4	Convolutional	1024 linear filters with 2*2 stride
P3	Pooling	2*2
P4	Pooling	2*2
Dense 1	Neural Networking	512
Dense 2	Neural Networking	2

The classification outputs of the proposed EVGG-CNN architecture is depicted in Figure 4 and Figure 5 on BRATS and Kaggle datasets respectively. Figure 4(a) shows the non-Glioma brain image and Figure 4(b) shows the Glioma brain image from the BRATS dataset. Figure 5(a) shows the non-Glioma brain image and Figure 5(b) shows the Glioma brain image from the Kaggle dataset.

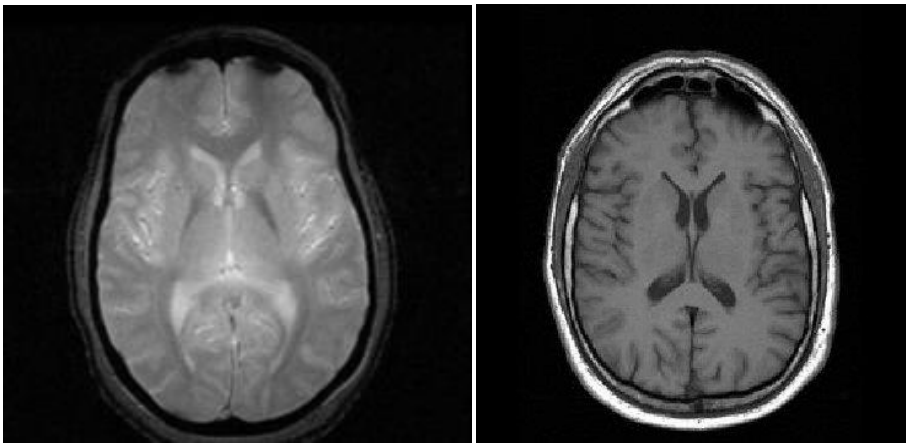

Figure 4(a). BRATS datasetNon-Glioma images

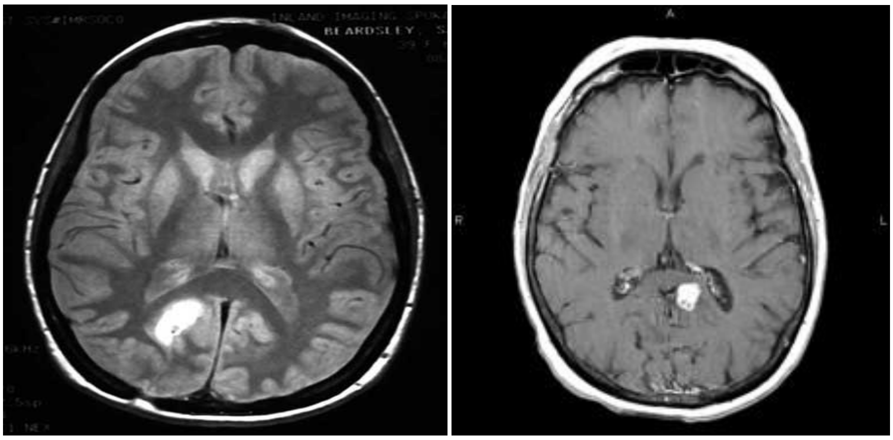

Figure 4(b). BRATS datasetGlioma images

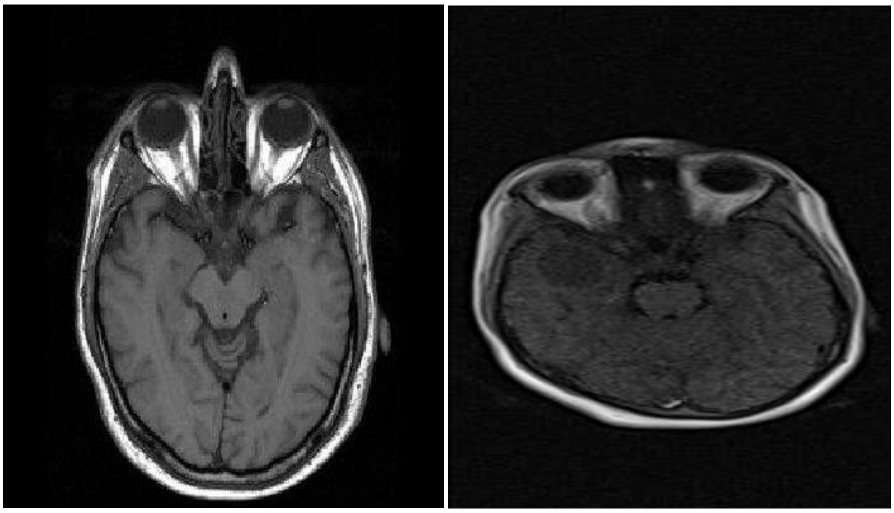

Figure 5(a). Kaggle datasetNon-Glioma images

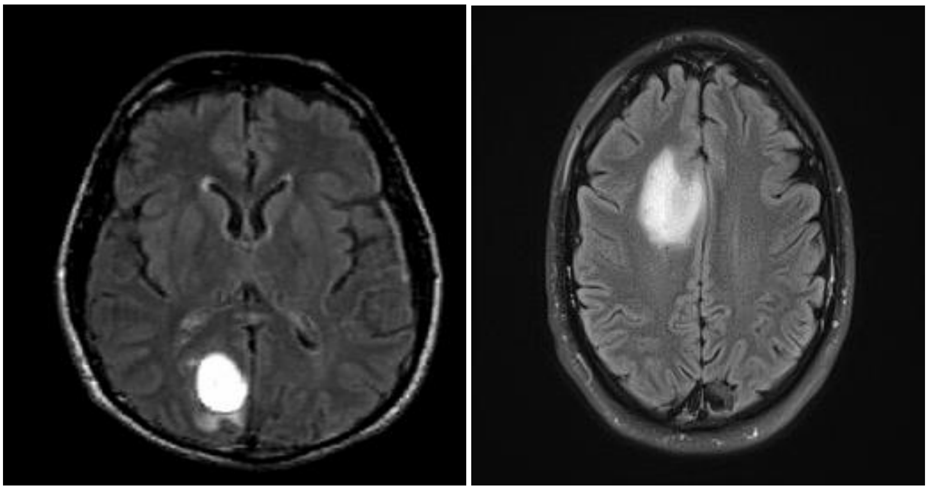

Figure 5(b). Kaggle dataset Glioma images

RESULTS AND DISCUSSIONS

This research utilizes MATLAB R2020 software to simulate the classification of Glioma tumor images using the proposed Glioma detection method based on the Efficient VGG-CNN algorithm. Two open access datasets are used to evaluate the performance of the proposed EVGG-CNN based Glioma tumor detection and segmentation system.

The first dataset used is the BRATS 2021 dataset. It consists of 737 brain MRI images, which are divided into training and testing categories. The training category comprises 383 images, further split into 184 Glioma brain images and 199 non-Glioma brain images. The testing category consists of 354 images, with 166

Glioma brain images and 188 non-Glioma brain images. All the brain images in this dataset have a resolution of 512x512 pixels and are represented using 8-bit pixel quantization. The Glioma and non-Glioma categories of these brain images have been cross-verified by two independent physicians.

The second dataset used is the Kaggle dataset. It includes 1760 brain MRI images, which are also divided into training and testing categories. The training category contains 1065 images, with 215 Glioma brain images and 850 non-Glioma brain images. The testing category consists of 695 images, with 285 Glioma brain images and 410 non-Glioma brain images. The brain images in this dataset have a resolution of 1024x1024 pixels and are represented using 8-bit pixel quantization. Similarly, the Glioma and non-Glioma categories of these brain images have been cross-verified by expert physicians.

These datasets serve as the basis for evaluating the performance efficiency of the proposed EVGG-CNN-based Glioma tumor detection and segmentation system. By training and testing the algorithm on these datasets, the researchers aim to validate the effectiveness of their approach in accurately classifying Glioma and non-Glioma brain images. It is worth noting that the cross-verification of the image categories by multiple physicians ensures a reliable and consistent evaluation of the system's performance. The Glioma detection system is analyzed in terms of the following parameters.

$$\text{Sensitivity (Se)}=\frac{TP}{TP+FN} \tag{5}$$

$$\text{Specificity(Sp)}=\frac{TN}{TN+FP} \tag{6}$$

$$\text{Accuracy(Acc)}=\frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

Table 2 is the analysis of proposed Glioma detection method using Efficient VGG-CNN architecture with BRATS dataset. The proposed Glioma detection system is applied on the BRATS dataset images and the experimental results are listed in Table 2 for the 10 number of brain images only. In this paper, the proposed Glioma detection system obtains 98.99% of Se, 98.62% of Sp and 98.85% of Acc on the brain images in BRATS dataset.

Table 2. Analysis of EVGG-CNN architecture performance with BRATS dataset

Image sequences	**Experimental results in %**		
	Se	**Sp**	**Acc**
P1	99.5	98.7	98.9
P2	99.2	99.6	99.3
P3	98.6	99.4	99.2
P4	98.6	98.1	98.7
P5	99.7	98.2	98.4
P6	99.3	98.8	98.6
P7	99.1	98.4	98.7
P8	98.4	98.3	98.5
P9	98.2	98.4	98.9
P10	99.3	98.3	99.3
Average	98.99	98.62	98.85

Table 3 is the analysis of EVGG-CNN architecture performance with Kaggle dataset. The proposed Glioma detection system is applied on the Kaggle dataset images and the experimental results are listed in Table 3 for the 10 number of brain images only. The similar experimental results are obtained even the proposed Glioma detection method is applied on all the brain images in the Kaggle dataset. In this paper, the proposed Glioma detection system obtains 98.72% of Se, 98.81% of Sp and 98.73% of Acc on the brain images in Kaggle dataset.

Table 3. Analysis of EVGG-CNN architecture performance with Kaggle dataset

Image sequences	Experimental results in %		
	Se	**Sp**	**Acc**
K1	98.3	98.4	98.7
K 2	99.1	98.7	99.1
K 3	98.4	99.4	99.4
K 4	98.8	98.6	98.7
K 5	98.3	99.3	98.6
K 6	99.5	98.6	98.6
K 7	98.3	98.4	98.4
K 8	98.6	99.2	98.7
K 9	98.7	98.7	98.5
K 10	99.2	98.8	98.6
Average	98.72	98.81	98.73

Table 4 is the comparisons of proposed Efficient VGG-CNN architecture with respect to BRATS and Kaggle datasets. From this comparative analysis of the proposed Glioma detection method between BRATS dataset and Kaggle dataset brain images, the proposed method stated in this paper obtains higher performance efficiency on both open access dataset images.

Table 4. Comparisons of DCNN and UNET performance with respect to PLCO and Kaggle datasets

Parameters	Datasets	
	PLCO	**Kaggle**
Se	98.99	98.72
Sp	98.62	98.81
Acc	98.85	98.73

Table 5 is the comparisons of proposed Efficient VGG-CNN architecture with conventional methodologies. From this comparative analysis of the proposed Glioma detection method between proposed and conventional methods, the proposed method stated in this paper obtains higher performance efficiency on both open access dataset images.

Table 5. Comparative Analysis of Glioma Detection System

Image sequences	BRATS dataset			Kaggle dataset		
	Se	**Sp**	**Acc**	**Se**	**Sp**	**Acc**
EVGG-CNN	98.99	98.62	98.85	98.72	98.81	98.73
Alqazzaz et al. (2022)[15]	95.29	94.67	94.19	94.29	94.85	95.29
Ebrahim et al. (2022)[16]	94.39	94.67	94.28	95.03	95.01	94.39
Wu et al. (2020)[17]	94.29	94.67	94.29	94.10	94.39	94.29
Kumar et al. (2020)[20]	91.93	91.76	92.86	91.85	93.98	92.98
Deepak et al. (2019)[21]	90.98	91.59	91.48	91.09	92.10	91.54

CONCLUSION

This research work introduces a novel EVGG-CNN architecture for the detection and classification of Glioma brain images. The proposed system is evaluated on two datasets, namely BRATS and Kaggle. The experimental results demonstrate the effectiveness of the proposed Glioma detection system. On the BRATS dataset; the proposed system achieves sensitivity (Se) of 98.99%, specificity (Sp) of 98.62%, and accuracy (Acc) of 98.85%. Similarly, on the Kaggle dataset, the system achieves Se of 98.72%, Sp of 98.81%, and Acc of 98.73%. These results highlight the high performance efficiency of the proposed EVGG-CNN-based Glioma detection system on both datasets. The experimental procedure involves applying the proposed Glioma detection system to the brain images utilized by the EVGG-CNN classifier. By comparing the results with other conventional deep learning classifiers, it is evident that the proposed EVGG-CNN architecture outperforms them in terms of performance efficiency on both the BRATS and Kaggle datasets. As a future direction, the paper suggests that the proposed EVGG-CNN can be utilized for the detection of stroke pixels in brain images. This indicates the potential application of the novel architecture beyond Glioma detection, expanding its scope to other areas of medical image analysis.

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