Indonesian Journal of Electrical Engineering and Computer Science
Vol. 33, No. 3, March 2024, pp. 1405~1415
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v33.i3.pp1405-1415

Deep transfer learning model for brain tumor segmentation and classification using UNet and chopped VGGNet

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Article Info

Article history:

Received Oct 5, 2023
Revised Nov 7, 2023
Accepted Dec 13, 2023

Keywords:

Brain tumor
Classification
Deep learning
Segmentation
Transfer learning

ABSTRACT

Brain tumors (BT) are a leading cause of cancer-related mortality worldwide, underscoring the critical need for early and precise detection to improve patient survival rates. Computer-aided diagnosis (CAD) plays a pivotal role in early BT detection by providing medical experts with valuable information image analysis. Various researchers have developed distinct methodologies, drawing from both machine and deep learning approaches. ML relies on manual feature analysis, which entails a time-intensive procedure of selecting an optimal feature extractor and necessitates domain experts with a deep understanding of feature selection. Conversely, deep learning methods exhibit superior performance compared to ML owing to their end-to-end, automated, high-level, and robust attribute mining capabilities. In this study introduced an innovative two-stage framework designed for the automatic classification of BT. In the initial stage, utilize U-Net models to conduct BT segmentation as part of the pre-processing step. Subsequently, in the second stage, utilize the improved BT images as input for a transfer learning-based model known as visual geometry group neural network (VGGNet), which excels in BT classification. The experimental analysis shows that the proposed approach has reported the average classification accuracy as 98.6%, 98.76%, and 99.45% for Meningioma, Glioma, and Pituitary BTs, respectively.

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1. INTRODUCTION

Brain tumors (BTs) are characterized by the uncontrolled increase of abnormal brain cells [1]. Brain tumors encompass a diverse category of prevalent intracranial tumors, which carry substantial burdens of mortality and morbidity [2], [3]. Statistics from the period spanning 2014 to 2018 indicate reported annual mortality rates of 5.4 per 100,000 for men and 3.6 per 100,000 for women [4]. The primary diagnostic methods used to identify and evaluate BTs include magnetic resonance imaging (MRI) and computer tomography (CT) scans [5], [6]. Early detection and accurate classification of BTs are paramount as they inform the development of tailored treatment strategies rooted in MRI and other imaging modalities [7]. A fundamental challenge in BT detection lies in the effective delineation of abnormal tissue from the surrounding healthy brain matter and is compounded by variations in tumor size, shape, and location,

rendering BT detection an ongoing and dynamic problem. The principles of medical image processing play a pivotal role in the analysis of BTs, encompassing tasks such as classification, segmentation, and detection [8], [9]. To aid radiologists and enhance BT classification, contemporary computer-aided diagnosis systems have emerged within the field of biomedical image processing [10]. It is imperative to recognize that BTs constitute a hazardous disease, with high-grade tumors particularly associated with shortened life expectancies. In this context, the accurate diagnosis of BTs assumes a pivotal role in treatment planning and has profound implications for the patient's overall quality of life [11].

The gold standard for diagnosing and grading tumors involves the pathological evaluation of tissue samples. Nevertheless, there is a strong desire for a non-invasive tool capable of precisely classifying the various types of tumors and estimating their grades [12]. While there exist several non-invasive imaging modalities for visualizing brain tumors, including computed tomography (CT), positron emission tomography PET, and MRI, MRI remains the clinical standard of care [13]. MRI offers comprehensive insights into various aspects of brain lesions, including their location, size, extent, morphological characteristics, relationships with adjacent structures, and associated mass effects. MRI can also provide valuable information about microstructural attributes such as lesion cellularity, architecture, and patterns [14]–[16].

In recent years, radiologists have extensively employed computer-aided diagnosis (CAD) systems, primarily based on machine learning (ML) methodologies [17]. Initially, the earliest tumor prediction models utilized feature representations, such as wavelet features, in conjunction with ML algorithms to distinguish between normal and pathological tumors. Subsequent models have evolved to incorporate a diverse set of features, encompassing boundary, texture, and form characteristics, which collectively form high-dimensional feature maps [18]. Usman and Rajpoot [19] have harnessed the intensity, and wavelet attributes of brain MRI images and employed an ensemble classification approach. support vector machine (SVM) classifiers and deep neural networks have been deployed for the classification of brain tumors [20]. However, convolutional neural network (CNN) has rapidly superseded traditional machine-learning techniques across a wide range of application domains. The convolutional layer plays a pivotal role in optimal feature extraction from input images, employing various filters to discern edges, colors, shapes, and more. Subsequently, the extracted feature maps undergo dimensionality reduction through operations in the pooling layer [21]. In the fully connected (FC) layer, each neuron from the preceding layer is intricately connected to the neurons in the subsequent layer. Finally, the output layer takes responsibility for class prediction by assigning labels to each respective class. Figure 1 depicts the general architecture of CNN. Transfer learning is commonly implemented through the utilization of pre-trained models like VGG, GoogLeNet, and AlexNet, [22], [23] which have undergone extensive training on the expansive ImageNet benchmark dataset. Therefore, this work presents a novel transfer learning approach by using visual geometry group neural network (VGGNet) architecture where the last layers of VGGNet are modified to obtain the classification outcome for brain tumor images.

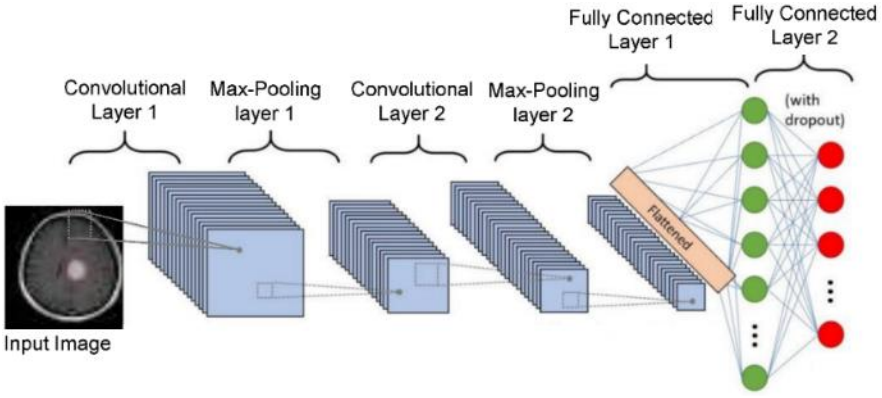

Figure 1. The general architecture of CNN

2. PROPOSED METHOD

The proposed model for brain tumor segmentation and classification using transfer learning involves the following steps:

- Finding the gaps or drawbacks of the deep learning techniques. In recent years, deep learning techniques, particularly transfer learning, have shown significant promise in medical image segmentation tasks. Despite the advancements in deep learning, developing an accurate and reliable brain tumor segmentation model remains a challenge. The existing models often struggle with the complexities of diverse tumor shapes, sizes, locations, and imaging modalities. Additionally, the shortage of annotated medical imaging data hampers the training of deep neural networks, leading to suboptimal performance.
- To overcome the limitations of deep learning methods, the proposed model aims to develop a robust and efficient brain tumor segmentation system utilizing transfer learning techniques where pre-trained models are fine-tuned on specific tasks and can leverage the knowledge learned from vast datasets in unrelated domains. The proposed model aims to achieve it by following. i) Pretrained convolutional layers: By utilizing pretrained VGGNet layers, the model benefits from the features learned during training on large-scale datasets like ImageNet. This transfer learning approach allows the model to leverage knowledge from general image patterns, enhancing its ability to extract relevant features from brain tumor images. ii) Fine-tuning strategies: Fine-tuning pretrained VGGNet layers enables the model to adapt its learned features to the specific characteristics of brain tumor images. This fine-tuning process optimizes feature extraction for improved classification accuracy.
- By Leveraging the pre-trained model for robust feature extraction, addressing the issue of training data scarcity, and improving the convergence Transfer learning involves the application of previously acquired knowledge to enhance the performance of a new classification task. This is achieved by fine-tuning an existing model using a smaller dataset that is tailored to the specific objectives of the study. This work presents a novel transfer learning approach by using VGGNet architecture where the last layers of VGGNet are modified to obtain the classification outcome for brain tumor images.

This work focuses on the transfer learning mechanism and presents a new transfer learning scheme that leverages VGGNet architectures for feature extraction and learning. The main aim of this work is to address several challenges such as: achieving improved segmentation accuracy, handling the variable characteristics of tumors, and presenting a generalized and scalable model for brain tumor segmentation.

2.1. Importance of transfer learning

Transfer learning's significance has grown considerably owing to its manifold benefits, all of which synergistically contribute to achieving more precise and efficient outcomes in segmentation tasks:

- Limited dataset: transfer learning offers researchers the invaluable opportunity to harness pre-trained models on more extensive and diverse datasets, thereby facilitating the transference of knowledge acquired from these datasets to the specialized domain of brain tumor segmentation.
- Computation resources: transfer learning mitigates resource demands by commencing with pre-trained models. This not only curtails the necessity for substantial computational resources but also expedites the development process.
- Generalized process: by acquiring valuable insights from analogous tasks, the model becomes more adept at discerning critical patterns and variations, thus bolstering its resilience in dealing with diverse tumor types, sizes, and imaging circumstances.
- Adaptability to different modalities: this work focuses on the transfer learning mechanism and presents a new transfer learning scheme that leverages VGGNet architectures for feature extraction and learning.

Transfer learning emerges as a potent technique within the realm of medical image analysis, with a particular application in tasks such as brain tumor segmentation. Its significance has grown considerably owing to its manifold benefits, all of which synergistically contribute to achieving more precise and efficient outcomes in segmentation tasks.

3. METHOD

The proposed deep learning architecture is based on the VGGNet which is popular deep learning-based approach and widely adopted in various real-time computer vision-based applications for classification and recognition tasks. The important characteristics of this architecture are as follows:

- Depth: VGGNet is characterized by its deep architecture. It consists of 16 or 19 weight layers (depending on the variant), making it one of the first CNNs to demonstrate the importance of depth in improving model performance. The deeper network allows it to learn more complex and abstract features from images.
- Convolutional layers: VGGNet predominantly employs 3x3 convolutional layers with a stride of 1 and maintains the input image's spatial dimensions through the use of same padding. This consistent utilization of small convolutional filters allows the network to effectively capture both local and global features.

- Max-pooling layers: Following each group of convolutional layers, VGGNet incorporates max-pooling layers with 2×2 windows and a stride of 2. This max-pooling operation diminishes the spatial dimensions of the feature maps while preserving the most crucial information.
- Fully connected layers: VGGNet wraps up its architecture with one or more fully connected layers, which are subsequently followed by a softmax activation layer used for classification purposes. These fully connected layers play a critical role in generating the ultimate predictions by leveraging the features acquired through the convolutional layers.
- Configurations: there are two commonly used VGGNet configurations: VGG16 and VGG19. VGG16 consists of 16 weight layers which include 13 layers for convolutional operation and 3 layers for FC layers, while VGG19 has 19 weight layers where 16 layers are used for convolutional operations and 3 layers are used as fully convolutional networks (FCN). The VGG16 model is a bit more popular and widely used.

This method introduced an innovative framework designed for the segmentation, classification, and grading of brain tumors utilizing a deep learning-based model. Our approach leverages publicly available datasets and employs pre-processing techniques, including image resizing and contrast enhancement, to enhance the quality of the input images. To mitigate the influence of retinal biomarkers on brain tumor classification, a UNet-based segmentation model into the pre-processing pipeline is used. This process results in an improved brain tumor image after pre-processing and segmentation. Finally, a transfer learning based VGGNet model to classify the enhanced image dataset for brain tumor classification. Generally, this work resizes all images into a uniform size of 256*256. Moreover, directly resizing the brain images is not a practical approach, as it may lead to the loss of significant information. Instead, this work opted for a bicubic interpolation operation to resize the images while preserving their aspect ratio. Additionally, enhanced the quality of the brain tumor images by applying a histogram equalization approach. Figure 2 depicts the overall architecture of the proposed deep transfer learning-based system for BT image classification.

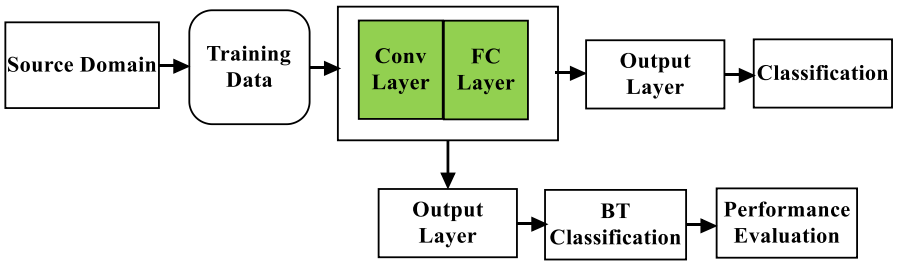

Figure 2. Overall architecture of transfer learning scheme for BT classification

This work employed a UNet-based architecture for the segmentation task. The UNet architecture is a CNN design specifically crafted for image segmentation, particularly within the realm of medical image analysis. It has gained widespread popularity as an effective framework for a range of image segmentation tasks. This comprehensive architecture is distinguished by its dual pathways: a contracting and an expanding path, enabling it to capture intricate details while preserving spatial information. The basic details of UNet are as follows:

- Contracting path (encoder): this segment of the network comprises multiple convolutional layers that are succeeded by max-pooling layers. The objective of this pathway is to progressively diminish the spatial dimensions of the input image while concurrently augmenting the quantity of feature channels. This process aids in the extraction of abstract features and patterns from the input image.
- Bottleneck: at the center of the U-Net architecture, there's a bottleneck layer consisting of multiple convolutional layers. This layer acts as a bridge between the contracting and expanding paths.
- Expanding path (decoder): this part of the network consists of up-sampling layers to gradually upsurge the spatial dimensions of the feature map. It also includes skip connections that concatenate feature maps from the contracting path to the expanding path. These skip connections help the network recover spatial information and handle fine details.
- Output layer: the final layer of the network typically consists of a 1×1 convolutional layer followed by a suitable activation function (e.g., sigmoid for binary segmentation or softmax for multi-class segmentation). This layer produces the segmentation mask that indicates the class of each pixel in the input image.

The U-Net architecture is particularly effective for medical image segmentation tasks, such as segmenting organs, tumors, or other structures within medical images like MRI or CT scans. Its ability to capture fine details while maintaining spatial information makes it well-suited for these tasks.

3.1. Transfer learning model for tumor classification

This section describes the proposed deep transfer learning approach for brain tumor classification. Generally, performing CNN-based classification with a restricted medical dataset size and initiating network training from scratch is a difficult task. To address these constraints, the prevalent approach in medical image classification involves the utilization of transfer learning-based models. These models effectively transfer knowledge acquired from one task to another identical task. VGGNet plays an important role in transfer learning applications. This model is specifically tailored for natural image classification, having undergone training on the ImageNet dataset which comprises approximately 14 million images spanning 1000 distinct categories. Transfer learning (TL) is employed with the aim of enhancing network performance, regardless of the specific dataset in the target domain. TL-based models have exhibited noteworthy success across diverse medical image classification tasks, such as the detection of cataracts, the classification of breast cancer, and the diagnosis of glaucoma. In this manuscript, introduced a VGGNet model for brain tumor classification, which is based on transfer learning techniques. Furthermore, this work extends the experimental framework to encompass the identification of glioma grading.

The schematic representation of the proposed architectural framework is depicted in Figure 3. This architectural design comprises a total of seven convolutional layers, interspersed with three pooling layers, and incorporates the ReLU activation function, which is initiated after the initial input computation. The pooling layers play a pivotal role by introducing up-sampling operations, thereby reducing the image dimensions post each convolutional layer operation. To enhance the VGG16 baseline architecture, three additional dense layers are incorporated, each endowed with 128 neurons and activated by the ReLU function. Notably, within the architecture, only the three convolutional layers situated in the final block are configured to be trainable, while the remainder of the blocks remain frozen in their weights and biases. Preceding the final classification layer, two dense layers are employed for the purpose of flattening the retinal image. Subsequently, a softmax classifier is employed in the final layer, producing an output layer characterized by four neurons. To mitigate the risk of overfitting, a dropout layer is introduced after the dense layers. Moreover, batch normalization is applied to expedite the training process and counteract overfitting by effectively reducing the overall network parameters. Additionally, global average pooling (GAP), as proposed by Lin *et al* [24]. is employed to further facilitate expedited training and to curtail overfitting by reducing the network's parameter count.

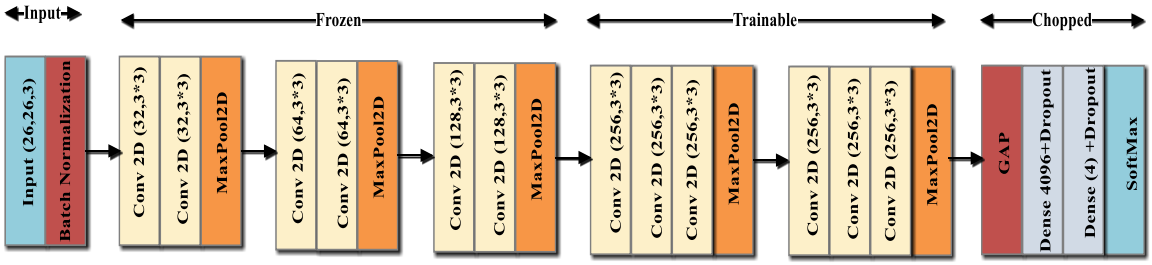

Figure 3. Architecture of proposed VGGNet

During the training process, it is employed the categorical cross-entropy loss function to assess the loss value. This particular loss function relies on the probabilities of activations in the output layer and their alignment with the respective target class. This can be expressed as in (1).

$$\mathcal{L}(p,\hat{p}) = -\sum_{i=0}^{A}\sum_{j=0}^{B}\left(p_{ij} * \log\left(\hat{p}_{ij}\right)\right) \quad (1)$$

Where $\mathcal{L}(p,\hat{p})$ represents the comparison between the distribution of prediction and ground truth, respectively. A denotes the number of samples and B represents the number of labels, y_{ij} represents the actual value and p_{ij} represents the predicted value.

4. RESULTS AND DISCUSSION

This section showcases the results of the proposed approach and compares its performance with existing classification methods. The first subsection provides details about the experimental settings used in this study for classification, followed by a description of the dataset details in the next subsection. After that, we explain the performance measurement parameters, and finally, we present a comparative study.

4.1. Experiment details and configuration

The hardware configuration for the proposed model comprises an Intel 10th Generation Core i7 processor, 16 GB of RAM, and a GP2060 GPU. To realize the model, this work employs the publicly available Python library, Keras, in conjunction with TensorFlow. During the training phase, the model undergoes 200 epochs, with 70% of the dataset utilized for training purposes, while the remaining 30% is allocated for model testing. For optimization, the Adam optimizer is chosen, and the categorical cross-entropy loss function is employed. Additional hyperparameter settings encompass a momentum value of 0.9, a batch size of 64, and a learning rate of 0.001. These hyperparameter configurations are summarized in Table 1.

Table 1. Parameters for VGGNet

Parameter name	Considered value
Batch size	64
Optimizer	Adam
Loss function	Cross Entropy
Dropout	0.5
Epoch	200
Train –Test Ratio	70%-30%

4.2. Dataset details

The evaluation of the proposed model's performance was conducted using the publicly available brain tumor dataset, as presented by Cheng *et al* [25] in their work. The dataset encompasses clinical data from 233 patients and comprises a total of 3,064 T1-weighted enhanced contrast brain MRI scans, each having a resolution of 512×512 pixels per image and a voxel spacing of 0.49×0.49 mm². Notably, this dataset encompasses three distinct categories of brain tumors, namely pituitary, meningioma, and glioma, which are imaged from three different anatomical planes: axial, coronal, and sagittal views. Figure 4 depicts some sample images from this dataset. Specifically, the dataset contains 930 instances of Pituitary tumors, 708 instances of Meningioma tumors, and 1,426 instances of glioma tumors. Table 2 demonstrates the details of this dataset.

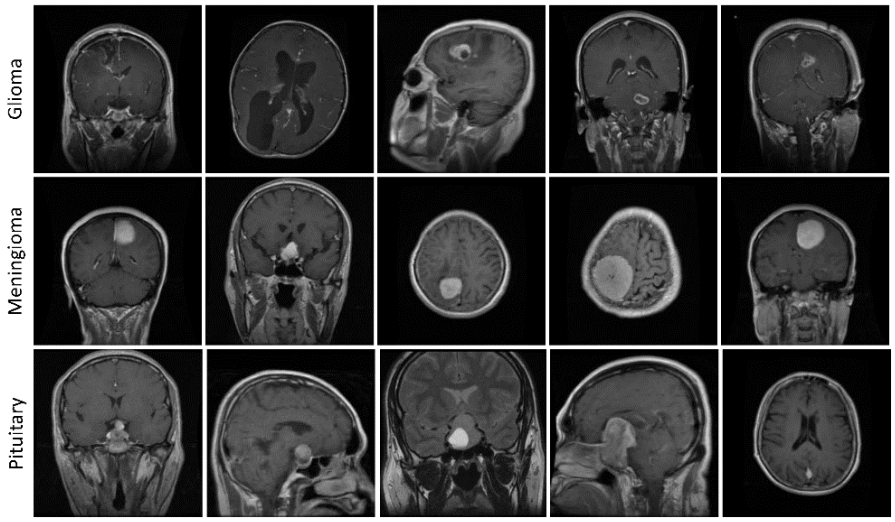

Figure 4. Sample images

Table 2. Dataset details

Category of tumor	Patients in each category	Total image count	Different views of MRI
Glioma	89	1426	Sagittal View:495 Axial View=494 Coronal View:437
Meningioma	82	708	Coronal View:268 Sagittal View:231 Axial View=209
Pituitary	62	930	Sagittal View:495 Axial View=494 Coronal View:319
overall	233	3064	Sagittal:1046 Coronal:1024 Axial View=994

4.3. Performance measurement parameters

This subsection describes the various performance measurement parameters which are used to evaluate the overall performance of the proposed model. The performance of the classification model is evaluated by estimating the confusion matrix which is a representation of total true positive, false positive, true negative, and false negative samples. The confusion matrix consists of count of instances which are predicted accurately and misclassified instances. Table 3 shows a sample representation of three class confusion matrix.

Table 3. Confusion matrix representation

	Predicted Lesion Class			
	Lesion class 1	Lesion class 2	Lesion class 3	FN
Actual lesion class	T_{11}	T_{12}	T_{13}	$(T_{12} + T_{11})$
	T_{21}	T_{22}	T_{23}	$(T_{21} + T_{23})$
	T_{31}	T_{32}	T_{33}	$(T_{31} + T_{32})$
FP	$(T_{21} + T_{31})$	$(T_{12} + T_{32})$	$(T_{13} + T_{33})$	
TP	T_{11}	T_{22}	T_{33}	

True positive (TP): it shows that the classifier correctly predicts the positive class from the given test set. True negative (TN): it shows that the classifier model correctly predicts the negative class from the given test set. The true negative and true positive values show the accuracy of the classifier. However, these categories should match the actual values of TP and TN. False positive (FP): denotes the classifier model incorrectly predicts the positive class. False negative (FN): denotes that the classifier mistakenly predicted the negative class. Table 4 shows the various parameters used to evaluate the performance of the proposed work.

Table 4. Performance evaluation parameters

Parameter	Computation formula
Accuracy	$\frac{Tp + TN}{Tp + TN + Fp + FN}$
Recall	$\frac{Tp}{Tp + TN}$
Precision	$\frac{Tp}{Tp + Fp}$
F-Measure	$\frac{2 \times P \times Senstivity}{P \times Senstivity}$

4.4. Comparative analysis

This section presents the comparative analysis of the proposed approach for the aforementioned dataset. In order to measure the performance of the proposed approach, first used varied learning rate and employed different optimizer schemes to identify the best suitable optimizer. Table 5 shows the outcome of different optimizers at different learning rates.

According to this experiment, the proposed approach obtained the highest classification accuracy as 98.50 for learning rate 0.001 by using the Adam optimizer. Therefore, adopted the Adam optimizer with learning rate 0.001 in this work. Further, this work focuses on identifying the suitable number of iterations

therefore experimented for different number of epochs and measured the overall accuracy of the system for varied number of epochs. Table 6 depicts the obtained performance for this experiment scenario.

Table 5. Accuracy measurement for varied learning rates for different optimizers

Optimizer	Learning rate					
	0.1	0.01	0.001	0.002	0.003	0.004
Adam	88.50	92.50	98.85	91.70	95.20	96.50
SGD	87.80	75.10	88.4	81.45	85.20	91.20
Adadelta	68.50	86.50	75.21	82.10	83.60	93.65
RMSprop	83.58	82.30	76.86	81.70	80.50	80.55
Adagrad	85.10	91.10	79.85	90.30	91.20	81.58

Table 6. Overall accuracy analysis for varied number of Epochs

Number of epochs	10	20	30	40
Overall accuracy	97.30	98.25	98.51	98.80

According to this experiment, the highest accuracy of the proposed model is reported for the 40 epochs as 98.80 whereas the lowest accuracy is reported for the 10 epochs as 97.30. Similarly, simulate the proposed model to identify the best dropout rate to obtain the high accuracy. Table 7 shows the obtained performance for varied dropout rates.

Table 7. Overall accuracy analysis for varied dropout rates

Number of epochs	0.1	0.3	0.5	0.7
Overall accuracy	98.35	98.10	98.45	98.80

Based on these experiments, adopted the best suitable parameters for the proposed approach. Based on these parameters, this work has simulated the proposed model and measured the overall performance, and compared its performance with existing mechanisms. First, obtained the confusion matrix which shows that the proposed model accurately classifies 3,015 images correctly and 49 images are wrongly classified. Table 8 depicts the obtained confusion matrix for brain tumor classification. Based on this matrix, evaluated the performance for each class in terms of accuracy, precision, recall, F1-score and specificity Table 9 shows the obtained performance corresponding to each class.

Table 8. Confusion matrix

		Predicted Value		
Actual value	Class	Meningioma	Glioma	Pituitary
	Meningioma	693	6	9
	Glioma	26	1400	2
	Pituitary	2	4	922

Table 9. Classification performance for different types of tumors

Type of tumor	Accuracy	Sensitivity (Recall)	Precision	F1-score
Meningioma	98.6%	.96	.98	.97
Glioma	98.76%	.99	.98	.99
Pituitary	99.45%	.99	.99	.99

The study reports that the Pituitary tumor has the highest classification accuracy of 99.45%, while the average accuracy of all tumors is 98.4%. Meningioma and Glioma also showed high overall accuracy rates of 98.6% and 98.76%, respectively. The obtained performance is visually represented in Figure 5. Furthermore, compared the performance of our mechanism with various existing methods. Table 10 illustrates the comparative analysis for brain tumor classification.

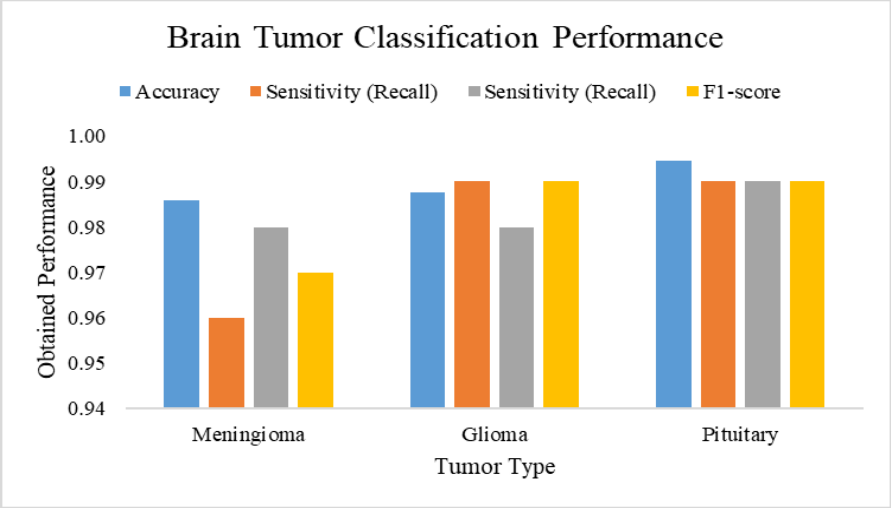

Figure 5. Brain tumor classification performance

Based on this comparative analysis, it's clear that utilizing CNN-based feature extraction has significantly improved overall accuracy. While state-of-the-art methods have also employed CNN-based approaches, they have struggled with issues such as high computational complexity, training loss, and excessive resource consumption. In contrast, the proposed approach leverages transfer learning to extract robust features and efficiently use them for training the CNN model.

Table 10. Comparative analysis of classification performance

Method	Feature	Accuracy
BoW SVM [25]	BOW	91.28
NN [26]	DWT Gabor	91.9
Pre-processing SVM [27]	2 D DWT with Daubechies wavelet	86
ConvNet 64×64 [28]	CNN	84.52
ConvNet 256×256 [29]	CNN	90.26
CapsNet [30]	CNN	86.56
Holistic RNN [31]	Dense CNN	92.13
ELM [32]	CNN	93.68
Different ConvNet [33]	Model based	84.19
GAN ConvNet [34]	CNN	93.1
GA+CNN [35]	CNN	94.2
CapsNet [36]	CNN	94.74
VGGNet transfer learning [Proposed]	CNN	98.95

5. CONCLUSION

Brain tumor detection and classification play an important role in this field of biomedical image processing. The traditional CAD systems rely on traditional machine learning algorithms which suffer from several issues related to their performances. The current research advancements have introduced the deep learning-based approach to overcome the issues. In this work, adopted deep learning approach along with the transfer learning concept where VGGNet model is used as pre-trained network. Also, modified the final layers of the VGGNet to obtain the desired classification accuracy. the performance of the proposed approach is measured in terms of accuracy, sensitivity (recall), precision, and F1-score which are obtained as 98.93%, 0.98%, 0.9833, and 0.9833, respectively.

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