Enhanced CNN Model for Brain Tumor Classification

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Summary
Brain tumor classification is an important process that allows doctors to plan treatment for patients based on the stages of the tumor. To improve classification performance, various CNN-based architectures are used for brain tumor classification. Existing methods for brain tumor segmentation suffer from overfitting and poor efficiency when dealing with large datasets. The enhanced CNN architecture proposed in this study is based on U-Net for brain tumor segmentation, RefineNet for pattern analysis, and SegNet architecture for brain tumor classification. The brain tumor benchmark dataset was used to evaluate the enhanced CNN model's efficiency. Based on the local and context information of the MRI image, the U-Net provides good segmentation. SegNet selects the most important features for classification while also reducing the trainable parameters. In the classification of brain tumors, the enhanced CNN method outperforms the existing methods. The enhanced CNN model has an accuracy of 96.85 percent, while the existing CNN with transfer learning has an accuracy of 94.82 percent.
Keywords:
Multi-classification, CNN model, Grid search technic, Hyper parameter optimization

1. Introduction

Brain cancer classification is an important task that requires the physician's knowledge and experience in order to select the best treatment for the patients. The automatic brain cancer classification system serves as a decision model for radiologists to identify tumors. For appropriate treatments, the current system's accuracy must be improved [1]. A brain tumor classification system can help a doctor determine the prognosis, aggressiveness, and growth of a brain tumor. Glioma, benign, and malignant brain tumors are the types of brain tumors that must be classified in order to assist doctors [2]. Recently, machine learning techniques have demonstrated significant performance on image analysis and provide nearly the same accuracy as trained specialists in the detection of brain tumors. Deep learning techniques significantly improve brain tumor detection and other medical image analysis [3]. Tumor diagnosis and treatment necessitates a number of factors, including the size and location of the tumor in the brain, as determined by Magnetic Resonance Imaging (MRI) [4]. MRI screening techniques are generally preferred by doctors for estimating tumor structure prior to and after treatment [5]. To detect and classify the tumor, various imaging techniques can be used, with MRI being the most commonly used non-invasive method. The MRI screening method does not use ionising radiationduring the scan, provides high resolution soft-tissue images, and employs imaging parameters to obtain various images [6, 7]. Deep learning methods based on Convolutional Neural Networks (CNN) have been successfully applied to brain tumor classification and have achieved successful classification performance. CNN-based methods have the advantage of not requiring a manually segmented portion of the tumor for classification and providing fully automated classification [8]. The most common issue with existing CNN-based brain tumor classification is poor performance in publicly available datasets [9, 10]. The enhanced CNN model is proposed in this study to improve the detection of brain tumors. The improved CNN model is built on three techniques: U-Net, RefineNet, and SegNet. The U-Net method is used for brain tumour segmentation, the RefineNet method for pattern analysis, and SegNet for classification. The analysis shows that the improved CNN model outperforms the existing method.

2. Literature Survey

Brain tumors are one of the most dangerous types of cancer, with a low survival rate. The early detection and classification of brain tumors aids in the effective treatment of the cancer. This section reviewed recent research on brain tumor classification.

Sajjad,*et al.* [11] proposed a large data augmentation method and a CNN-based model for brain tumor classification The tumor region is segmented from the image using CNN, and the data augmentation method is used to train the CNN model. The augmented data is used

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to fine-tune the pre-trained CNN model for brain tumor classification. The proposed CNN model is tested on the brain tumour dataset and performs better in classification. The over fitting problem of the CNN model must be addressed in order to improve the efficiency of brain tumor classification.

Anaraki,*et al*. [12] proposed Genetic Algorithm (GA) in CNN model for classification of brain tumors in MRI images To reduce the variance of prediction error, the CNN architecture is evolved using the GA method and bagging as an ensemble method. The results show that CNN with the GA method performs better in three-class classification. The developed CNN with GA method was evaluated using a brain tumor dataset. To train the CNN model for brain tumor classification, the data augmentation method is used. The effectiveness of the CNN model in brain tumor classification must be improved.

Swati, *et al*. [13] proposed block-wise transfer learning fine-tuning method for pre-trained CNN model On the T1-weighted contrast-enhanced MRI benchmark dataset, the developed method is tested. Under five-fold cross validation, the developed technique has a higher efficiency in brain tumor classification. In the classification of brain tumors, the developed method outperforms the existing method and CNN model. To analyses the performance of the developed method, it must be tested on standard MRI data.

Kaur and Gandhi, [14] developed various CNN models using transfer learning for brain tumor classification The performance of the brain tumor classification was tested using various CNN architectures. The brain tumor benchmark dataset was used to assess the model's performance. The pre-trained AlexNet with transfer learning outperforms the others in the analysis. The developed CNN-based method's efficiency in brain tumor classification must be increased.

Huang,*et al*. [15] proposed CNN-based method for MRI brain tumor classification with modified activation function The randomly generated graph algorithm is used to optimize the model's network structure. The generated graph is mapped into the neural network model using a network generator. When compared to other existing models, the proposed CNN-based model outperforms them. When compared to the ResNet, DenseNet, and MobileNet models, the developed method has lower test loss. To improve the performance of the brain tumor classification, the model's overfitting must be reduced.

3. Proposed Model

Automatic brain tumor classification for clinical applications aids in treatment selection. The enhanced CNN method was developed in this study to improve the performance of brain tumor classification. U-Net, RefineNet, and SegNet are the foundations of the enhanced CNN method. The brain tumor benchmark dataset was used to evaluate the effectiveness of the enhanced CNN method. The U-Net method is used to segment data based on local and contextual information. For pattern analysis, the RefineNet method is used, and for brain tumor classification, the SegNet method is used. The enhanced CNN method's overall block diagram is shown in

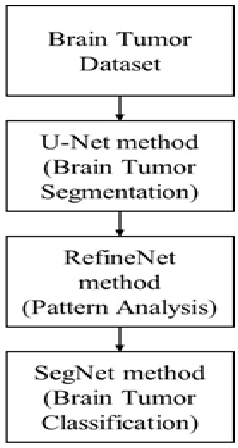


Figure 1. The block diagram of enhanced CNN method

3.1CNN based Model

In this study, three different Fully Connected Networks (FCNs) are used to classify brain tumors from MRI images. For the classification of brain tumors, three networks were used: U-Net, RefineNet, and SegNet. The U-Net method is used for segmentation, the RefineNet method is used for pattern analysis, and the SegNet method is used for classification. Networks are chosen based on various architectural functionalities, and the networks are evaluated in terms of brain tumor classification.

3.2 U-Net Method

The first architecture used in this research is U-Net [16] and this is applied for the brain tumor segmentation. Encoding and decoding part are present in U-Net architecture. Two convolution layers units are present in the encoding architecture. In encoding architecture, a 2 × 2 pooling (down-sampling) and rectification layer (ReLU) with stride are present. The feature channels are doubled at each down-sampling step. A 2 × 2 up-convolution layers are present in corresponding decoding architecture that reduces the feature channels halve. A ReLU with two 3 ×

3 convolutions, cropped feature map with a concatenation operator from encoding unit are also present in decoding layer. Finally, component feature vectors are mapped based on a 1 × 1 convolution for a segmentations. The soft-max energy function is computed based on the final feature map and combined with cross-entropy loss function. At each position, the soft-max deviation $(M_{\lambda(x)}(x))$ from one is used to penalizes the cross-entropy, as shown in Eq. (1).

$$\varepsilon = \sum_{k'=1} \log\left(M_{\lambda(x)}(x)\right), \tag{1}$$

Where each pixel true label is denoted as $\lambda : \Omega \rightarrow \{1,\dots,K\}$ at the position $x \in \Omega$, with $\Omega \subset Z^2$. The final segmentation is generated by networks soft-max layer as a probability map. The particular pixel value denotes the probability of the pixel belongs to the tumor or not. A large number of feature channels in network propagate context information to higher resolution layer and provide end-to-end training with limited training samples. The Keras library in TensorFlow framework is used to implement this network.

3.3 RefineNet Method

The second network architecture used in this study to extract the brain tumor pattern is the RefineNet [17]. RefineNet is a refinement network that uses a four-cascaded architecture, with each architecture made up of RefineNet units. Each unit is linked to the previous RefineNet block in the cascade as well as one Residual net output [18] block. Each RefineNet is made up of two Residual Convolution Units (RCU), which combine the high-resolution feature map and the outputs. The multi-path refinement architecture explicitly exploits the information during the down-sampling process to achieve long-range residual connections for high-resolution prediction. Fine-grained features from previous convolutions are used to directly refine the deeper layer, which captures high-level semantic features.To effectively capture rich background context, the network employs a chained residual pooling mechanism.

3.4 SegNet Method

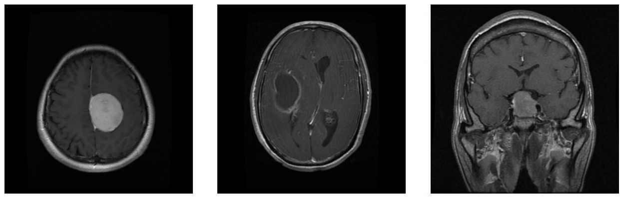
In this method, a fully convolutional encoder-decoder network called SegNet is used to classify brain tumours [19]. To segment the brain tumor, the softmax layer is redesigned. The entire network architecture is built around an encoder and decoder network. The network architecture of the encoder is made up of four stocks. A pooling layer with a 2 2 kernel size, stride 2, a ReLU layer, a batch normalization layer, and a convolutional layer are all included in each block. The up-sampling layer is located in the decode layer, which is similar to the encoder blocks. The convolution kernel size is set to 7 7 in the network for smooth labelling and to provide a wide context In this network, "indices pooling" is used. Experimental Design

Automatic brain tumor classification is the important process to select treatment for the patients. Various CNN architectures have been applied for the brain tumor classification and shows lower efficiency. In this research, enhanced CNN model has been proposed to increases the efficiency of classification of brain tumor. The dataset, metrics, parameter settings and system requirement to analysis the performance of enhanced CNN model is explained in this section.

4. Experimental Design

4.1. Dataset

The brain tumor benchmark dataset [20] is made up of 3064 MRI images from 233 patients. The image is 512512 pixels in size, with a 1 mm gap between each slice and a 6 mm slice thickness. The dataset contains three types of images: meningioma, glioma, and pituitary tumor. The Meningioma dataset contains 708 images, the Glioma dataset contains 1426 images, and the Pituitary tumor dataset contains 930 images. Meningioma, Glioma, and Pituitary tumor sampleimages are shown in Figure 2



(a) (b) (c)

Figure 2. The brain tumor benchmark dataset samples (a) Meningioma, (b) Glioma and (c) Pituitary tumor

4.2. Optimization of Hyper Parameters

Metrics: Theproposed enhanced CNN model's performance was evaluated using Accuracy, Sensitivity, and Specificity. The formulas for precision, sensitivity, and specificity are provided below. The True Positive is denoted as TP, the True Negative as TN, the False Positive as FP, and the False Negative as FN.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

5. Experimental Results

Brain tumor classification is an important step in determining the type of tumor and determining the best treatment. Several CNN-based architectures have been proposed for brain tumor classification, with the limitations of overfitting and lower efficiency. The enhanced CNN method was proposed in this study to improve the efficiency of brain tumor classification. The brain tumor benchmark dataset was used to assess the enhanced CNN method's performance in brain tumor classification.

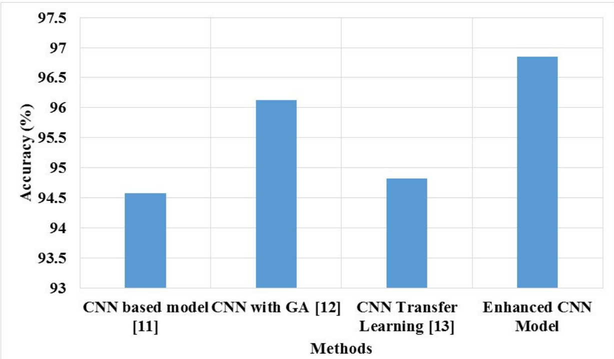


Figure 3. Accuracy of enhanced CNN method

As shown in Figure 3, the accuracy of the enhanced CNN model is measured and compared to the existing method. The analysis shows that the improved CNN model outperforms existing methods in terms of efficiency. The enhanced CNN U-Net architecture provides good segmentation based on local and contextual information. The SegNet architecture has the advantage of preserving important features in segmented images while also reducing the number of trainable parameters in decoders. The proposed enhanced-CNN method has an accuracy of 96.85 percent, while the existing CNN with GA method has an accuracy of 96.13 percent. The overfitting problem in CNN-based models [11] and CNN with transfer learning [13] has an impact on brain tumor classification performance.

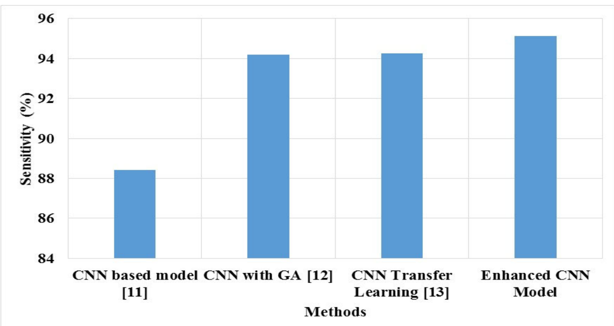


Figure 4. The sensitivity of enhanced CNN model

As shown in Figure 4, the sensitivity of the enhanced CNN model is measured in a brain tumor benchmark dataset and compared to the existing method. According to the results of the analysis, the enhanced CNN model has a higher sensitivity than the existing method. For segmentation based on local and contextual information, the enhanced CNN model employs U-Net. RefineNet is used to analyses brain tumor patterns, and SegNet is used to classify brain tumors. The SegNet method has the benefit of analyzing the important features in the segmented image while also reducing trainable parameters. The proposed enhanced-CNN model has a sensitivity of 95.12 percent, while the existing CNN with transfer learning has a sensitivity of 94.25 percent.

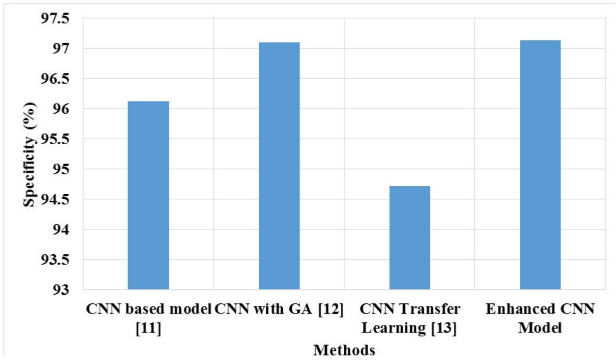


Figure 5. The specificity of enhanced CNN model

As shown in Figure 5, the specificity of the enhanced CNN model is measured in a brain tumor benchmark dataset and compared to existing methods. When compared to existing methods, the enhanced CNN model has a higher specificity. For brain tumor segmentation, the enhanced CNN model U-Net architecture employs local and contextual information. The SegNet architecture has the advantage of analyzing key features in segmented images while reducing the number of trainable parameters. In the classification of brain tumors, the CNN with GA method has the second highest specificity value. The proposed enhanced CNN model has a specificity of 97.14 percent, which is higher than the existing 97.1 percent specificity.

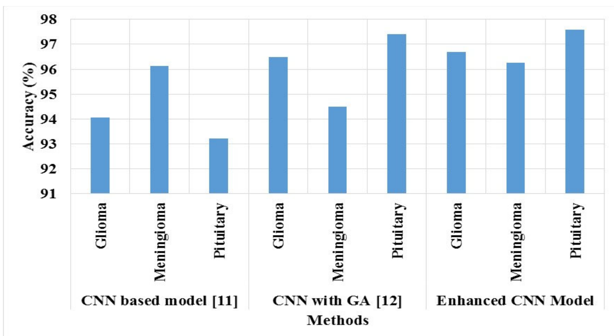


Figure 6. The accuracy of enhanced CNN model

Figure 6 depicts the enhanced CNN model accuracy for three classes in the brain tumor benchmark dataset. When compared to existing methods, the proposed enhanced CNN model has higher accuracy in three classes. The enhanced CNN model has a 96.6 percent accuracy in the Meningioma class and a 96.7 percent accuracy in the Glioma class. The CNN-based model has an accuracy of 96.14 percent in the Meningioma class and 94.05 percent in the Glioma class.

Table 1. Comparison analysis of enhanced CNN model

Methods	Accuracy	Sensitivity	Specificity
CNN based model [11]	94.58	88.41	96.12
CNN with GA [12]	96.13	94.2	97.1
CNN Transfer Learning [13]	94.82	94.25	94.71
Enhanced CNN Model	96.85	95.12	97.14

The proposed enhanced CNN model's accuracy, sensitivity, and specificity are measured and compared to existing methods, as shown in Table 1. In terms of accuracy, sensitivity, and specificity, the proposed enhanced CNN model outperforms existing methods. The enhanced CNN model has a 96.85 percent accuracy, while the existing CNN with transfer learning has a 94.82 percent accuracy. The enhanced CNN model has the advantage of segmenting and analyzing the important features for brain tumor classification using local and context information.

Table 2. Accuracy of enhanced CNN model for various classes

Methods	Class	Accuracy
CNN based model [11]	Glioma	94.05
	Meningioma	96.14
	Pituitary	93.21
CNN with GA [12]	Glioma	96.5
	Meningioma	94.5
	Pituitary	97.4
Enhanced CNN Model	Glioma	96.7
	Meningioma	96.26
	Pituitary	97.6

As shown in Table 2, the proposed enhanced CNN model accuracy is measured for three classes in datasets and compared to existing methods. When compared to existing methods, the enhanced CNN model is more accurate. The enhanced CNN model has the advantage of segmenting brain tumors using local and context information. In the Pituitary class, the enhanced CNN model has an accuracy of 97.6 percent, while the existing CNN-based model has an accuracy of 93.21 percent.

6. Conclusion

Automatic brain tumor classification is an important process for doctors to use when deciding on a treatment. Various CNN-based models for brain tumor classification have been proposed, and existing methods have the limitation of overfitting. In this study, an improved CNN model based on U-Net, RefineNet, and SegNet was proposed. The brain tumor benchmark dataset was used to evaluate the enhanced CNN model's efficiency. Based on local and contextual information, the enhanced CNN U-Net method provides good segmentation. When compared to existing methods, the enhanced CNN method outperforms them.The enhanced CNN method has the accuracy of 96.85 % and existing CNN based model has 94.58 % accuracy.

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