An Efficient Convolutional Neural Network Model for Brain MRI Segmentation

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Abstract: Medical image analysis is a very interesting research area, and it is a significant challenge for researchers. Due to the complexity of the brain structure, accurate diagnosis of brain tumors is extremely difficult. In recent years, research focused on medical image processing to solve this problem by relying on deep learning techniques, and it has achieved good results in this field. This paper proposes an efficient convolutional neural network model for MR brain image segmentation and analysis. The novel model consists of segmentation efficient-CNN and pre-efficient-CNN blocks for dataset diminution and improvement blocks. The unique efficient-CNN is specially designed according to the model proposed by ASCNN (application) CNN-specific) to perform unidirectional and transverse feature extraction and tumor and pixel classification. The recommended Full-ReLU activation feature halves the number of cores in a high-coil filtered winding layer without reducing process quality. In this specific efficient-CNN consists of 8 convolutional layers and 110 kernels. The experiment results were done using the MR brain database from the Arizona university, including eluding with and without tumor images. The proposal model achieved an accuracy of 97.2% to 98%, which proves the efficiency of the model and its ability to assist in the early diagnosis of brain tumors with sufficient accuracy to support the doctors' decision during diagnosis.

Key Words: - Brain Tumor, MRI databases, Medical Image, CNN Model and accuracy.

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1 Introduction

The brain is one of the most complex mechanisms in humans. The body is composed of billions of cells. Brain tumors can be expressed as follows:

Tissues that are in places that should not be in our brains, or each substance grows uncontrollably where it should not be. Early and correct detection of brain tumors is essential in this cancer species; it is a killer [1]. In this work, the classification process was performed using MRI images. The network must form an extensive network before performing this procedure. In this article, deep learning methods can yield positive results in large databases. Thanks to computer-aided systems, experts can diagnose the disease. In this way, errors with traditional methods can be avoided [2]. There are studies in the literature that use different models and architectures [3].

Isselmou et al. [4] proposed a hybrid convolutional neural network with fuzzy c-means algorithm for brain tumor detection and analysis. Their proposed model combined a new deep learning algorithm with the traditional method. Their model provides good results in brain tumor detection using MRI images and good performance during the analysis step.

Isselmou et al. [5] suggested a differential convolutional neural network model for brain tumor classification using MR big data. The new differential model innovative is added two layers and one operator in the original architecture of the convolutional neural network. The model has shown excellent classification of the brain tumors as yes/no tumor using massive data and obtained outstanding overall achievement during training and testing stages without any technical problems or data balance.

Guizhi Xu et al. [6] created a deep wavelet transform model for brain tumor detection and classification using different MRI BRATS databases. The model uses 4-connected for thresholding cluster pixels in the input MR databases, two layers to provide slices images segmentation and 200 units in the first layer and 400 units in the second layer. The model gives excellent results and ability about brain classification and segmentation data and good performance analysis using FNR and FPR values.

Guizhi Xu et al. [7] suggested a hybrid convolutional neural network with a deep watershed auto-encoder for brain tumor detection and analysis. The hybrid model training and testing using BRATS MR extensive databases. The model is based on a complex matrix combined convolutional neural network and a deep watershed auto-encoder to provide excellent detection and classification of big data achieved excellent performance using different values.

Ahmet Çinar et al. [8] proposed a hybrid convolutional neural network architecture for brain tumor detection on MR images. The model used resnet50 architecture. They removed the last layers of the Resnet50 model and added 8 new layers. The model produced an excellent performance based on accuracy value.

Khan, M.A ET at [9] presents multiple automated models based on deep learning for brain tumor classification using T1-T2 weight and FLAIR images. The model includes five steps; In the first step; is applying linear contrast stretching based on edge-based histogram equalization and discrete cosine transform (DCT). In the second step, they performed deep learning feature extraction by using transfer learning, two pre-trained convolutional neural networks (CNN) models, namely VGG16 and VGG19. The third step implemented a correntropy-based joint learning approach with the extreme learning machine (ELM) to choose the best features. In the fourth step, they fused the partial least square (PLS)-based robust covariant features in one matrix. The fed to ELM for the last classific in the fifth station. In the fifth step, The multiple models obtained good performance based on accuracy value.

Tanzila Saba et al. [10] proposed a grab cut model used to precisely distribute actual lesion symptoms. At the same time, the VGG-19 optical engineering set is tuned explicitly for function and then sequenced by a sequence-based approach to manual features (shape and texture). These characteristics are optimized by entropy for accurate and fast classification and provide fusion vectors to the classifier. The model was tested using medical image computing and computer-assisted intervention (MICCAI) database and obtained good performance based on dice similarity coefficient (DSC) value achievement.

Hemanth, D.J et al. [11] presented a modified deep convolutional neural network model for brain tumor classification. The second objective of the work is to reduce the complexity of the original convolutional neural network architecture. Suitable, the training algorithm is adjusted to reduce the number of parameter adjustments. The proposed modifications method eliminates changing the weight in the fully connected layer. Instead, use a simple mapping process to find the weights of this fully connected layer. Thus, the proposed method considerably reduces the complexity of the calculation. The model training uses different

MR brain abnormal images and gives a good performance.

2 Databases or Materials

This paper used 6000 MR brain images from the Arizona university website for the brain database. The database consists of 4000 MR brain images with tumor, and 2000 MR brain images without tumor figure 1 represent sample with tumor, and figure 2 denotes sample without tumor.

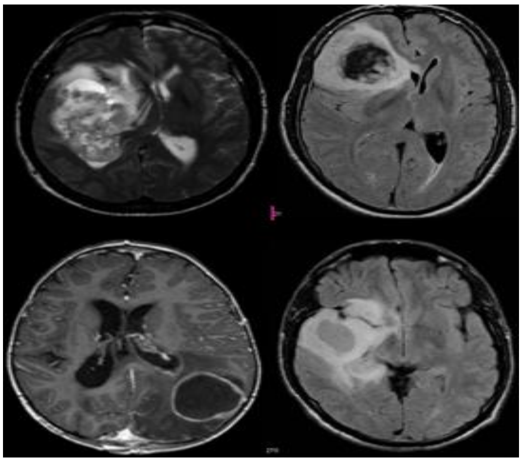

Figure 1: Sample of MR Brain Images with Tumor.

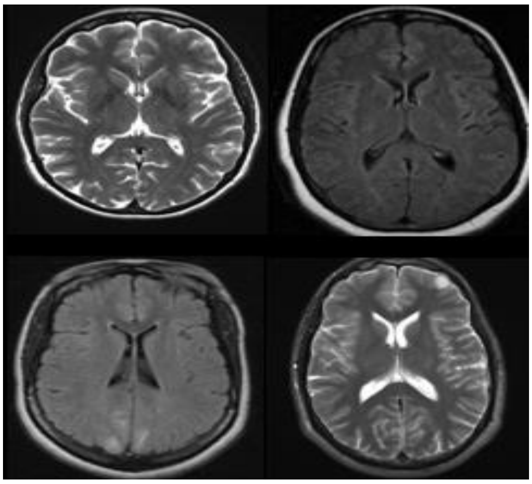

Figure 2: Sample of MR Brain Images with Tumor.

3 Method of the Proposed Model

Each MR image is displayed as input for a hash system with four different 3D MRI images road. Because all 3D image voxels are cut into 2D segments, which become images of 3D pixels in a 2D chip. In the system proposed by efficient CNN, brain tumors with 3D images are fragmented. This is done by dividing these 2D slides.

The proposed model uses the most important data partition that occurs in CNNs. There are efficient CNN and post-efficient CNN blocks to reduce CNN, designed to improve CNN computing efficiency. In addition, by doing so, the system will have a higher degree of certainty, less Randomness, and better replication. The final step is output consisting of segmentation, classification slices results, and the overall performance of the efficient-CNN model—the stages of the proposed efficient-CNN model is illustrated in figure 3.

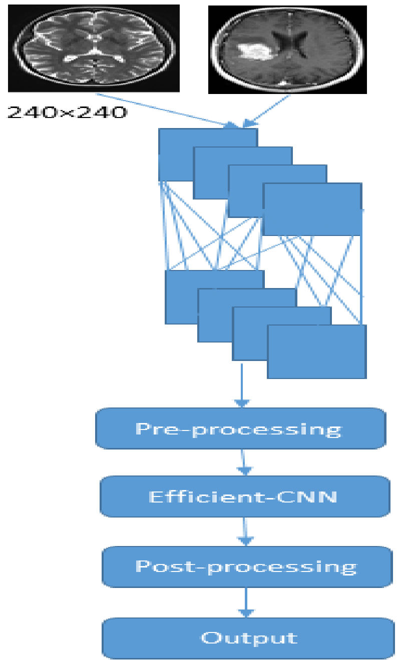

Figure 3: Schematic explaining the stages of the proposed efficient-CNN model.

3.1 Pre-efficient-CNN

The 3D images entered from commonly used datasets, such as the University of Arizona Brain Site Database, are 240×240×155 in size and are generated through late-× acquisition registrations. Predictive CNN's simplify CNN calculations by reducing the amount of 3D image data. Specifically, this is done by detecting and removing tumor-free fragments from brain images.

$$SSIM = (x, y)[(x, y)]^{\alpha}.[c(x, y)]^{\beta}.[s(x, y)]^{\gamma} \quad (1)$$

Where

$$l(x,y) = \frac{2\mu_x, \mu_{y+c_1}}{\mu_x^2 + \mu_y^2 + c_1}, c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}, s(x,y) = \frac{\sigma_{x,y+c_3}}{\sigma_x\sigma_y + c_3}$$

3.2 Convolutional Neural Network (CNN)

Given that the results proposed by CNN are an essential function of retail, the quality of the treatment determines the overall performance of the whole system. In order not to compromise the quality of processing while reducing the amount of computation, CNNs must be designed on demand, not just to support and modify existing networks. All calculation elements are necessary and fair enough to process input data for specific brain fragmentation tasks. In addition, a new activation feature called Full-ReLU (Fully Corrected Linear Unit) is used in some layers to help create it.

More efficient computing. The new Full-ReLU activation feature is presented in section 3.2.1.

3.2.1 Full-ReLU – a novel activation function

The activation feature performs a nonlinear transformation in the wrapper layer. ReLU (Correction Linear Unit), defined as $f(x) = \max(0, x)$ is probably the most commonly used activation function in CNN designs. However, they are not perfect. In the case of high eddy current filtration, a single escape process can produce a series of positive and negative elements that represent signal differences in opposite directions. If ReLU applies to these projects, negatives will be eliminated, resulting in a loss of information.

It is derived from a data set $[X]$ in two groups 2, namely $[X_P]$ and $[X_n]$ and it is mathematically expressed as follows:

$$\begin{cases} x_{p\,ij} = \max(0, x_{i\,j}) \\ x_{n\,ij} = |\min(0, x_{ij}) \end{cases} \quad (2)$$

3.3 Post Efficient-CNN

After being ranked by CNN, the post-CNN block is placed Identifies pixels that have been incorrectly classified as positive. Identification depends on whether the brain tumor and its tumor amplify basic (if any) is a 3D object, and the surface of each entity must be Found in several consecutive slides.

The thickness of the entire tumor that can be detected is considered at least 1/25 of the diameter of the brain. If the 3D brain image consists of 150 slices, this thickness corresponds to at least seven consecutive cuts. As a whole, tumor areas appear in less than seven successive segments, with pixels in this area can be misclassified and reclassified as tumor-free pixels.

In short, efficient CNNs are explicitly based on Features brain images, along with pre-and after CNN's functions accurate and effective blocking and fragmentation of brain tumors he has a very low account cost.

4 Experimental Results and Analysis

In this work, the experiments were done on a Jupiter notebook environment using Lenovo workstation 16G. The experiments results consist following steps:

4.1 MR Databases processed

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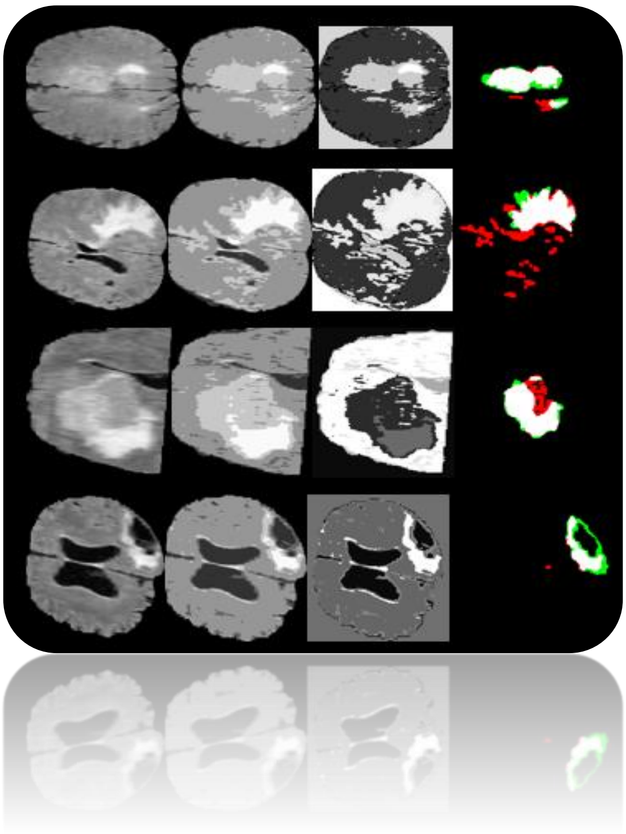

Figure 4: Results of MR Database processing based on efficient-CNN Model.

In the MR database process section, we presented the result of brain tumor detection using the efficient-CNN model in figure 4. It shows the ability of the proposed model to segment MR images and detect the area of tumor in each image.

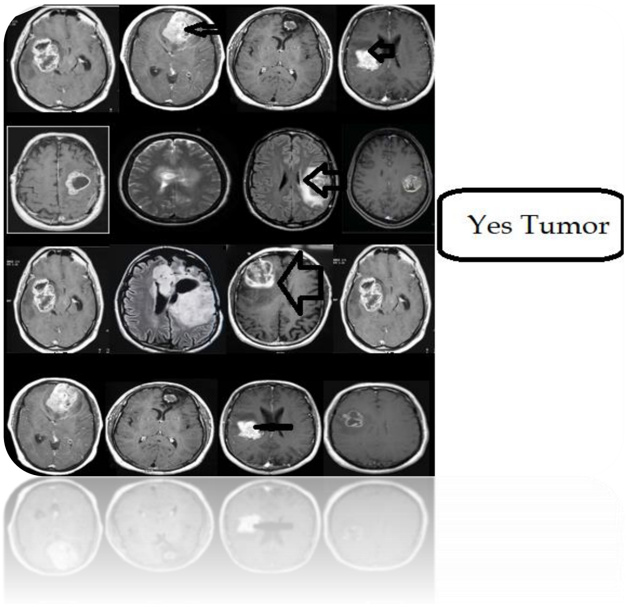

Figure 5: Results of classification as yes Tumor based on Efficient-CNN Model.

Figure 5 denotes the efficient-CNN model's classification results as yes tumor commend. The process gives excellent results and proves the proposed model's capacity to classify the MR database as a brain tumor dataset.

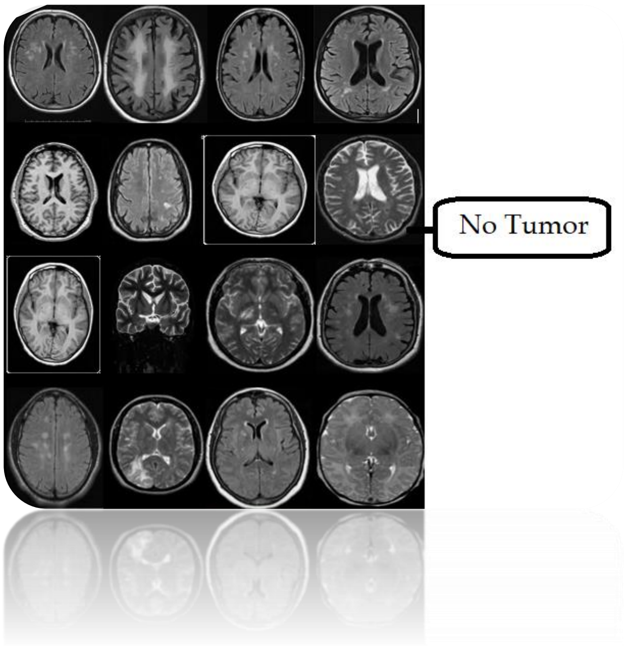

Figure 6: Results of classification as No Tumor based on Efficient-CNN Model.

Figure 6 represents the results of classification based on the efficient-CNN model as no tumor commend. The results have shown good classification results as MR database without tumor. From the section on MR databases, we can see the great abilities of the proposed model during segmentation, detection Tumor, and classification of no or yes tumor.

4.2 Evaluation of Efficient-CNN Model

The evaluation of the efficient-CNN model is based on a comparison with five existing machine learning models such as CNN, DNN, ANN, KNN, and Multi-SVM, using the following values: accuracy, sensitivity, dice score, and false discovery rate (FDR) values.

$$Accuracy = \frac{\propto+\beta}{\propto+\beta+\gamma+\xi} \quad (3)$$

$$Sensitivity\ or\ True\ Positive\ Rate$$

$$TPR = \frac{\alpha}{\alpha+\xi} \quad (4)$$

$$Dice\ Score\ Dice$$

$$(P_1\ ,T_1) = \frac{P_1 \cap T_1}{(P_1+T_1)/2} \quad (5)$$

$$False\ Discovery\ Rate$$

$$FDR(P_1, T_1) = \frac{P_1 - (P_1 \cap T_1)}{P_1} \quad (6)$$

Figure 7 denotes the accuracy value results of the proposed model, and it shows a good achievement during the training and testing steps.

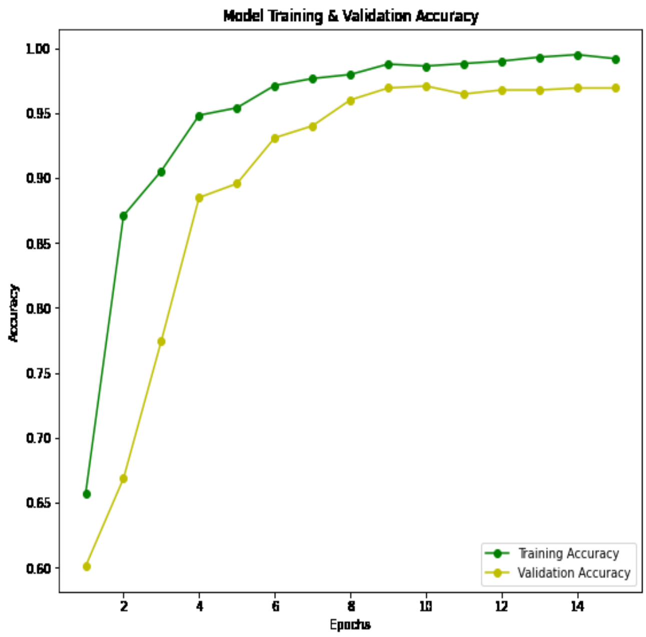

Figure 7: Results of accuracy value using Efficient-CNN Model

Figure 8 represents the loss validation value results of a proposed model during training and testing steps, and it achieved an excellent loss value result.

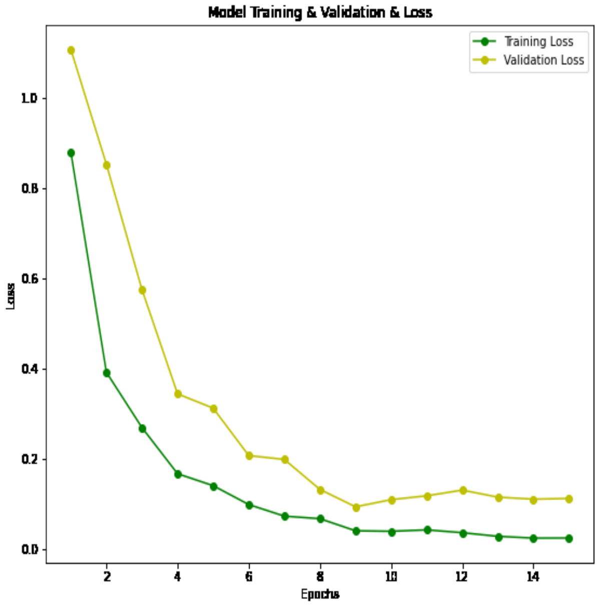

Figure 8: Results of loss validation value using Efficient-CNN Model.

Table .1 Comparison between Efficient-CNN Model Performance with existing Model.

Model	Accuracy%	Sensitivity%	Dice Score	FDR
CNN [12]	94	92.5	0.46	0.52
DNN [13]	91.4	93.2	0.51	0.61
ANN [14]	88	62	0.68	0.56
KNN [15]	78	46	0.55	0.52
Multi-SVM [16]	84	55	0.6	0.56
Efficient-CNN	**97.2**	**95.5**	**0.31**	**0.47**

Table 1 compares the efficient-CNN model with existing models such as CNN, DNN, ANN, KNN, and Multi-SVM using four metrics values. The convolutional neural network (CNN) model produced an accuracy of 94%, sensitivity of 92.5%, dice score of 0.46, and FDR of 0.52. The deep neural network model obtains an accuracy of 91.4%, sensitivity of 93.2%, dice score of 0.51, and FDR of 0.61. The artificial neural network model achieved an accuracy of 88%, sensitivity of 62%, dice score of 0.68, and FDR of 0.56. K-neural network model gives an accuracy of 78%, sensitivity of 46%, dice score of 0.55, and FDR of 0.52. The multi-SVM model obtains an accuracy of 84%, a sensitivity of 55%, a dice score of 0.6, and an FDR OF 0.56. The efficient-CNN model gives an accuracy of 97.7.2%, a sensitivity of 95.5%, a dice score of 0.31, and an FDR of 0.47. According to an analysis of existing model performance using accuracy, sensitivity, dice score, and false discovery rate (FDR), the efficient-CNN model achieved better overall performance than CNN, DNN, ANN, KNN, and Multi-SVM models.

5 Conclusion

Due to the excellent achievement of the deep learning model in the medical image analysis field, we proposed an efficient-CNN model with a new structure and innovated for brain tumor detection and classification with high performance. The proposed model shows excellent results during the MR database process, detects the tumor area in different images, and classifies the database as yes/no tumor effectiveness (see section 4.1). The evaluation stage of the proposed model shows excellent overall performance, such as accuracy of 97.2 to 98%, a sensitivity of 95.5%, and a dice score of 0.31 and FDR of 0.47, which are better than existing models. Based on the high performance of the efficient-CNN model, we strongly recommend using it as a computer brain aide technique for early brain tumor detection and reducing the number of deaths. We will add more layers in future work and make the model deeper.

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Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Isselmou Abd El Kader: Created the Model, Writing, Experiments simulation and analysis.
Guizhi Xu: Review& editing.
Zhang Shuai: Technical Review.
El maalouma Sidi Brahim: Writing Methodology.
Sani Saminu: Formatting.

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