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Brain Tumor Identification using Dilated U-Net based CNN

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Abstract

The identification of brain tumor consumes time and therefore it is important to develop an automated system using an imaging technique. The classification of brain tumor into benign or malignant is performed by using Magnetic Resonance Image (MRI). From the MRI based brain tumor images, the extraction of features is essential for pattern recognition that determines the object based on the color, names, shapes, or more. Therefore, the classifiers are dependent on the strength of features such as shape, color, etc., Yet, the classifiers are dependent on the features that are extracted using deep learning classifiers which are dependent on the features that were extracted. The deep learning algorithm in the medical domain showed interest in the computer vision researchers which consumed time during the process of execution. The proposed Dilated U-Net model expands the receptive field for the extraction of multi scale context information. Based on the high resolution conditions, the large scale feature maps and high-resolution conditions are generated using large scale feature maps. It provides rich spatial information that was applied for performing semantic segmentation. Semantic image segmentation is achieved using a U-Net as it adds an expansive path to generate classifications of the pixels belonging to features found in the source image. The existing Kernel based SVM model obtained accuracy of 99.15%, Non-Dominated Sorted Genetic Algorithm-Convolutional Neural Network (NSGA -CNN) obtained accuracy of 99%, Deep Elman Neural network with adaptive fuzzy clustering obtained accuracy of 98%, 3D Context Deep Supervised U-Net obtained accuracy of 92%. Whereas, the proposed Dilated U-Net-based CNN model obtained accuracy of 99.5% better when compared with the existing models.

Keywords: Brain Tumor, Deep Learning Classifiers, Dilated U-Net CNN Model, Magnetic Resonance Image.

1 Introduction

Brain is an important part of the whole nervous system as it can control and coordinate the whole body [1]. The abnormal cells in the brain are referred to as brain tumors which threaten the life of an individual if it is untreated [2]. Thus, the tumors are classified into two major types such as primary tumors and secondary tumors [3]. The malignant tumor primarily starts to grow inside the brain yet the secondary malignant tumor initiates in other organs that might spread towards the brain through metastasis [4]. The human body suffers from a brain tumor and a malignant tumor which is highly intimidating if untreated [5]. Thus, the brain tumors were unknown and complete medical history was required to be evaluated to show risk for the occurrence [6]. The segmentation of brain tumor is important in diagnosis and helps to plan the cancer treatment that detects the stages of tumor such as Low-grade (LGG) and High-Grade Gliomas (HGG) [7]. The specialists have the option of using Computed Tomography (CT), Ultrasound, Magnetic Resonance Imaging (MRI) for screening the patients [8]. The MRI image is an impressive technology that shows various modalities as it is non-invasive which obtained a better representation of internal tumor information [9]. The manual classification of brain tumors shows vulnerability with respect to formidable tasks, time consumption, and error [10]. Therefore, deep learning models are used to classify brain tumor based on MR data [11]. The model operated fast and obtained higher accuracy showed treatment for the patients [12]. The MRI segmentation is done based on the learning strategies and recognizes the patterns successfully for analyzing the brain images. The density-based function is used for selecting the functions as it considers the parametric model [13].

The existing models such as Convolution Neural Network (CNN), Fully Convolutional Neural Network (FCNN), Cascaded Neural Network, Auto Encoder, DeconvNets, 3D CNN were used for the detection of brain tumor based on MR image analysis. The low resolution channels or the images were required for reducing the computational complexity without any alteration in the accuracy factor. The significant difference between deep learning and artificial neural network is that it does have several layers for computation where excellent classification is performed for the medical images better compared to the existing models. In the present research work, the proposed process of semantic segmentation is deepened that has the spatial information present in the feature map that reduces the time. The main objective is to extract information from image's edge when the convolution layer deepens and shows higher semantics. The spatial information is lost and the dilated convolution preserves the spatial information and the dilated convolution preserves it as much as that showed improvement in terms of accuracy for segmentation prediction.

The research paper is given as follows: Section 2 explains the existing models under the literature review. Section 3 explains the various steps involved in the proposed method. Section 4 describes the results and discussion of the proposed method. The conclusion and future work of this research paper is given in Section 5.

2 Literature Review

The existing methodologies involved in brain tumor classification are given as follows:

A Novel Residual Mobile U-Net Model for Brain Tumor Segmentation from MR Images was shown by Muhammad Usman Saeed et al. [14]. A hybrid deep learning model called RMU-Net is suggested to achieve end-to-end brain tumor segmentation. Remaining blocks are added to MobileNetV2's design in order to master intricate characteristics. The suggested technique uses this modified version of Mobile Net V2 as an encoder and U-up Net's sampling layers as the decoder. The suggested technique improves with much less computational time and expense. Even though, RMU-training Net's needs a considerable portion of manually labeled brain tumor data.

Multi-encoder net (ME-Net) framework has been demonstrated by Wenbo Zhang et al [15] for segmenting brain tumors. This model suggestively advances model presentation whereas reducing the difficulty of feature extraction. Additionally, a new loss function named Categorical Dice was added, and different weights were simultaneously assigned for various segmented regions, which resolved the voxel imbalance issue. This architecture simultaneously processes many input images and extract particular features. Finally, one of the issues was that better data improvement methods have not yet been established.

Champakamala Sundar Rao and Karunakara [16] developed a Kernel based SVM model with Social Ski Driver (SSD) for the detection of brain tumor. An efficient brain tumor detection was important that uses a binomial thresholding approach for segmentation. From the segmented region, the features were fused and were undergone for feature selection using Harris Hawk's Optimization (HHO). The proposed KSVM-SSD performed an effective and accurate results classification that classified as benign or malignant and the SSD optimization further helped to find the tumor as high, medium, or low. The optimization algorithm was sensitive to the data features which were irrelevant during feature occurrences.

Muhammad Irfan Sharif et al. [17] developed an improved framework to detect the brain tumor using MRI based on CNN and YOLOv2 models. The features were extracted from the inceptionv3 model for pre-training the informative features. From the extracted features, the non-dominated sorted genetic algorithm (NSGA) was used for the selection of features. The features were optimized by forwarding to the classifier at the depth concatenation mixed 4 layers which is then supplied to YOLOv2. However, at the segmentation stage, the disease severity levels were not identified.

Sakthidasan Sankaran et al. [18] developed fuzzy clustering approach adaptively with a deep Elman Neural Network to perform segmentation and clustering for identifying the brain tumor grade. The regions from the tumor were segmented using an adaptive Fuzzy Tsallis Entropy (FTE) clustering with Cuckoo Search Optimization (ICS). Initially, the images were undergone for the process of pre-processing by using the anisotropic diffusion and non-parametric region based model for the noise and skull removal. The deep Elman neural network (DENN) was used for categorizing the brain tumor that was developed and classified as a brain tumor. The model used more than one classifier which examined robustness to improve the accuracy of large database that consisted of medical images.

Mingquan Lin et al [19] developed a Fully Automated Segmentation with 3D Context Deep Supervised U-Net model to segment the brain tumor. The multipara metrics from the brain tumor images were evaluated using the 3D context deep supervised U-Net model. The developed approach enlarged the receptive field effectively using the CNN model. This improved the segmentation accuracy of brain tumor regions. The tumor volume generated by the proposed method was compared with the Pearson analysis and Bland Altman plots. However, the 3D CNN network required GPU for processing large images which took a long time for network training.

Ahmet Ilhan et al. [20] developed a U-Net based model for the classification of brain tumor images based on non-parametric localization. The developed model used an efficient approach for the segmentation of brain tumors based on tumor localization using deep learning architecture. The histogram based non-parametric tumor localization approach was applied to modify the localized regions which increase the virtual appearance of low-contrast tumors indistinctly. The tumorous regions show better performances for the deep learning models which effectively segmented the trained and untrained datasets without any requirement for augmented data.

3 Proposed Method

Figure 1 shows the block diagram of the proposed research work that consists of BRATS 2020 dataset that are processed for pre-processing. The obtained pre-processed images are undergone for segmentation of the BRATS image dataset. The segmented images are classified into benign or malignant based on the segmented image.

3.1 BraTS 2020 Dataset

The BraTS Dataset mainly focuses on the evaluation state based on the state of art techniques. The segmentation of brain tumors is performed with respect to the multi modal MRI scans. The distinction between the pseudoprogression and recurrence of a true tumor through integrative analysis is performed based on the random features. There are totally 335 images from the BRATS 2020 dataset. Among the total number of images, 76 images are from Low Grade Glioma (LGG) and the leftover 259 images are from High Grade Glioma (HGG) type of image. The MRI scans are focusing mainly on 3 major tasks segmentation, intrinsic heterogeneous image based on shape and appearance, and histology images for the patient survival prediction.

3.2 Preprocessing

The MR images are undergone for Resizing the pixels. During resizing the images are cropped but also to manipulate the pixels for reducing the file size. The process of resizing images has become better than adjusted the file and picture size from a particular image which is expressed in equation (1).

$$RI = imresize(I, [W, H]) \tag{1}$$

Where I shows the input image along with height $(H)$and width (W), which is given as input to the further processing. Here, the dimension of the image is (240×240×155). The normalizing process considerably improves the image quality and is more effective at reducing impulse and machine noises. In this research, color images are successfully converted to grayscale images. The following equation (2) is used to conduct grayscale image normalization:

$$I_N = (I - Min) \times \frac{newMax - newMin}{Max - Min} + \ newMin \tag{2}$$

An n-dimensional grayscale image I is represented with intensity values among (Min, Max) which is converted through normalization into a new image I_N with intensity values among $(newMin, newMax)$. The block diagram of the proposed research work is displayed in figure 1.

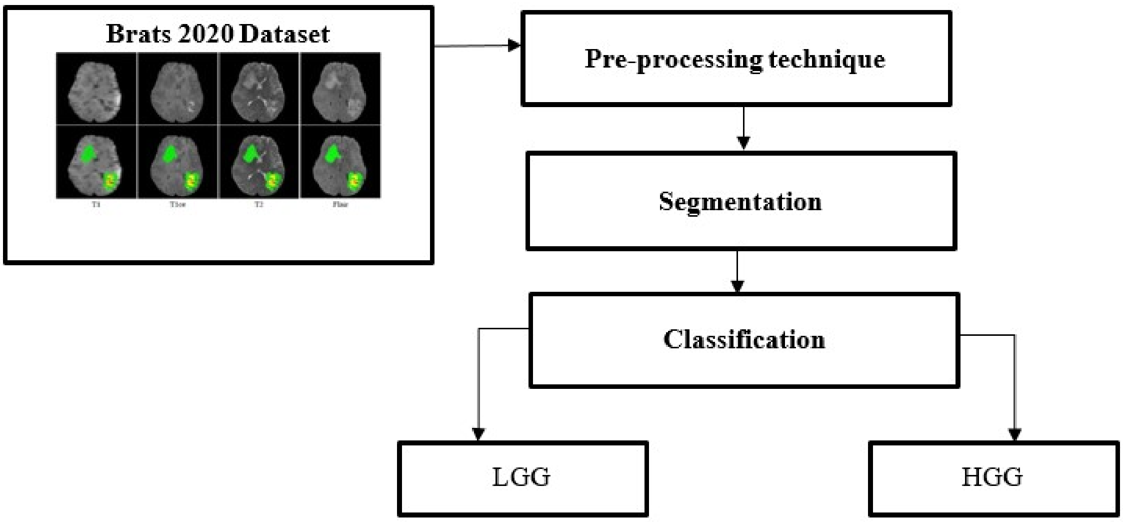

Figure 1: Block diagram of the proposed research work

The process of normalization is performed for the dataset where the process of normalization gets rid of irregularities makes more difficult for data interpretation. The process of normalization includes deleting data, updating existing information, or adding information where anomalies arise. The process of data augmentation is performed for data analysis to increase the data amount by adding the modified copies that are existing. The new synthetic data is created from the existing data. The regularized process helps to reduce the overfitting of the machine learning model for training and the batch wise data loading is performed. The input image and its predicted output image are illustrated in figure 2 and 3 respectively.

3.3 Segmentation using Dilated U-Net model

The initialization of U-Net model is performed where the modern image classification is performed that uses a series of pooling to improve the context information. The operation of pooling is effectively increasing the neural network receptive field which is benefitted for computer vision tasks at a

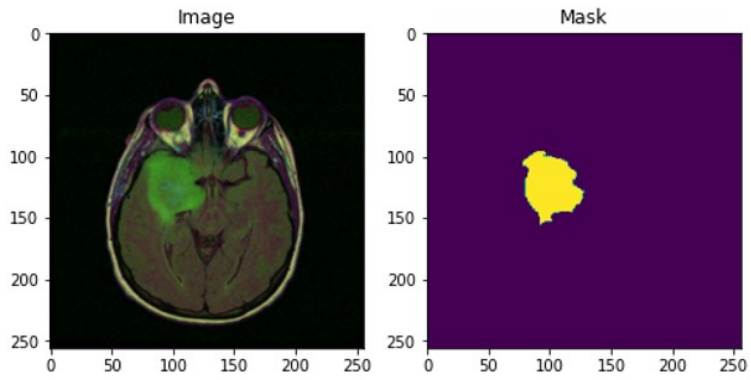

Figure 2: Input image

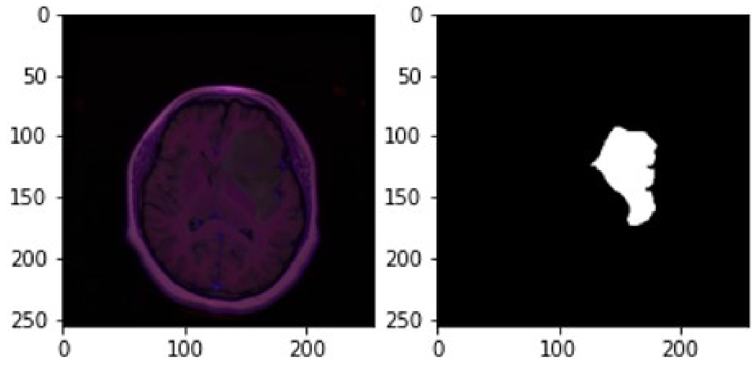

Figure 3: Predicted output image

high level. Yet, the pooling operation overcomes the degradation problem during picture resolution. Therefore, the pooling operation is performed which gives irreversible results with spatial information loss when the results with non-reconstruction of a small object are obtained. The U-Net model is used in the medical field and has implemented consecutively four 4 times based on the down sampling operations. However, due to the encoder-decoder architectures the low level feature maps are used for unsampling or decoding based on the invariance translation compromises. Thus, violating translation invariance at the segmentation maps shows relatively low resolution because of the pooling layer presence in the encoder stage. Therefore, the pooling layer preserves the high spatial resolution yet the convolution is rather operating locally and the U-Net based model without pooling is not able to learn the image holistic features.

The dilated convolutions or atrous convolutions provide the potential solution for overcoming the problem that is capable of providing and capturing the global context information. This is performed without decreasing the segmentation map resolution. The Dense CNN model works based on the Convolution layer fact that collects the larger neighborhood information. The CNNs are working based on the convolutional layer that collects the information from the larger neighborhood around every pixel. From the upper layers of the network, the features from each pixel holds the information of the large region of an image. The results from the experiments show that the learning is performed and each of the pixel information is localized in each of the networks. The Dilated convolution changes the rule based on the same size of kernels as it is having convolutional layers which cannot spread over a larger image area. The normal convolutions use zero padding approach for the dilated convolutions as it preserves the resolution exponentially which increases the receptive field of the kernel. Thus, global information is exchanged among the layers without sacrificing resolution. The dilated convolution replaces the pooling layers and striding layers' functionality in the networks. The Convolution layers are replaced after the pooling operation is dilated with convolution made up the loss of weight after sharing. The training of the model performed and the prediction of masks are performed. The general U-Net based convolution is stated in below equation (3),

$$(I \times w)(p) \sum_{s} I[p+s]w[s] \tag{3}$$

The simple convolution operation can be generalized dilated convolution (dl) which is expressed in equation (4)

$$(I \times dlw)(p) \sum_{s} I[p+dls]w[s] \tag{4}$$

The predicted output of the image is shown in figure 4. While in the figure 5, Predicted output mask is displayed. The augmentation output is presented in figure 6.

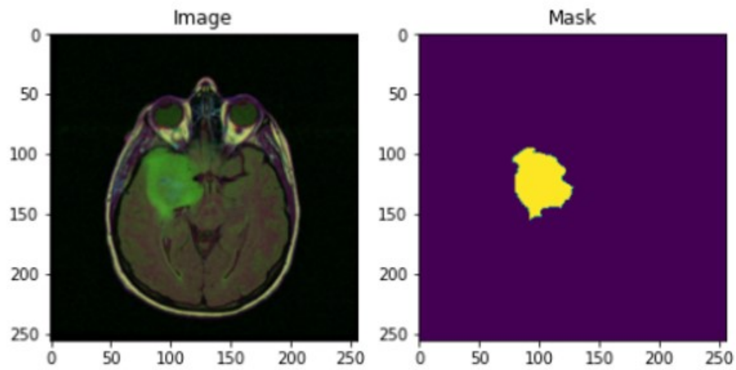

Figure 4: Predicted Output

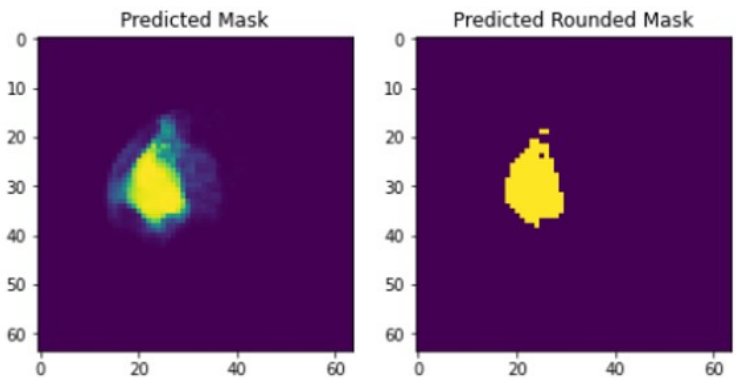

Figure 5: Predicted output mask

Pseudo code

INPUT:

Let the labeled data is represented as $\tilde{X} = X^{(1)}, X^{(2)}, \ldots, X^{(K)}$

Preprocessing:

Deleting data, updating existing information, or adding information

Obtained Labeled training data

$\tilde{X} = X^{(1)}, X^{(2)}, \ldots, X^{(K)}$, where K is called as the total number of classes

CNN $\leftarrow \tilde{X}$; % which is known as the training data which are sent to CNN for extraction of feature vectors

$\tilde{F} = \left\{F^{(1)}, F^{(2)}, \ldots, F^{(K)}\right\}$ % extracted the features which are mapped for high dimensional space

Classification:

INPUT: $\hat{x}$ is known as a classified image

OUTPUT: The $\hat{x}$ class that belongs

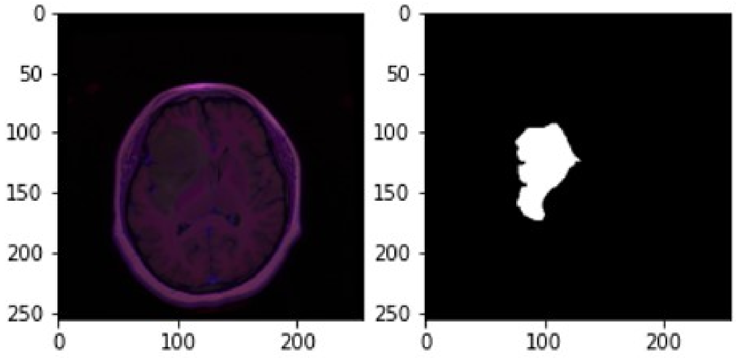

Figure 6: Augmentation Output

Figure 7 shows the proposed dilated based U-Net models architecture.

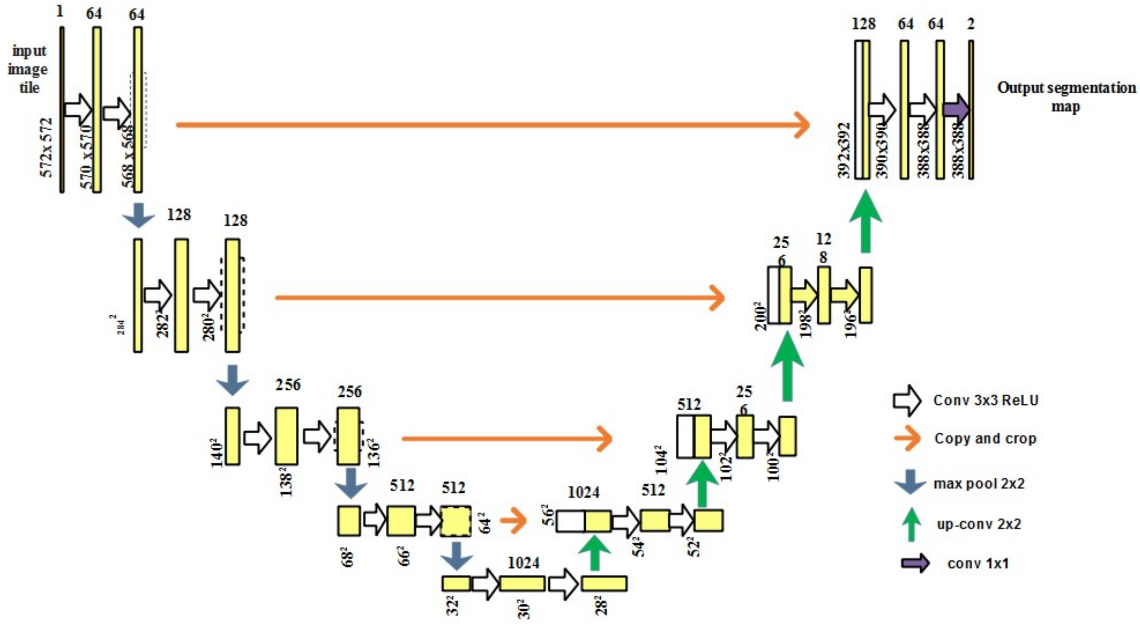

Figure 7: The architecture of proposed dilated based U-Net model

4 Results and Discussion

The results obtained by the proposed method are evaluated in terms of accuracy, F-score, precision, and recall of the model. The developed model worked on the imbalanced MRI datasets to evaluate the effectiveness. This research analyzed the Imbalanced MRI data which have an uneven distribution of observations across the target class, i.e., one class label has a high number of observations while the other has a low number. Due to this reason, the conventional method of classification and model accuracy estimation is not valuable in the case of imbalanced data. On the whole, the metrics are dependent on the class imbalance and there is an improvement in the overall performances that are concerned with the class counts. The results were obtained by the proposed method by conducting it in an Intel Core i7 processor with 2 GHz CPU utilization time working with 48 GB of RAM. The present research work feeds the training data to the classifier that evaluates the testing data. The performances are evaluated in terms of accuracy, precision, recall, and F-measure.

Accuracy

The performance measure accuracy is called the ratio of correctly predicted observations to the overall observations. The accuracy term is calculated using the Equation (5)

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{5}$$

Precision

The precision is expressed as the number of total data samples that are predicted to the overall observations that are false with respect to the actual number with false observations. The Precision term is defined as shown in the Equation (6).

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

Recall

Recall is known as the actual number of traditional false observations that are considered as the ratio of totally predicted false observations. The recall is expressed as shown in Equation (7).

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

F1-Measure

The F1 measure is known as the harmonic mean of the recall and precision which are evaluated by Equation (8).

$$F1-measure = \frac{2 * \text{ Precision } * \text{ Recall}}{\text{Precision } + \text{ Recall}} \tag{8}$$

Dice Coefficient

The equation for dice coefficient is expressed in Equation (9).

$$DICE = \frac{2TP}{2TP+FP+FN} \tag{9}$$

4.1 Quantitative Analysis

Table 1 shows the results obtained by the proposed Dilated U-Net based CNN model. The results were obtained by the proposed Dilated U-net based CNN model in terms of accuracy of 99.5%, F-score of 69%, and Dice Coefficient of 0.015. The proposed dilated U-Net based approach obtained the accuracy of 99.47%, F-score of 69%, Dice Coefficient of 0.015. The proposed Dilated U-Net based CNN model that would not classify whether the infection is present or not but also identifies the infected area. The proposed Dilated U-Net based CNN model obtained better accuracy of 99.47%, F-score of 69%, and dice coefficient of 93.49%. While the existing RMU-Net [14] and ME-Net [15] has attained the dice coefficient of 91.35% and 88% respectively. The dilated based U-Net model can extract the edge-based features accurately during segmentation and thus obtained better values of results. The overall training time for the execution process is 14 mins and 24 seconds. But the running time taken per image is 0.11 seconds.

Table 1: Results obtained for the proposed Dilated U-Net based CNN and Existing model

Parameters	RMU-Net model [14]	ME-Net model [15]	Proposed Dilated U-Net based CNN model
Accuracy (%)	-	-	99.47
F-score (%)	-	-	69
Dice Coefficient (%)	91.35	88	93.49

Deep Neural Network (DNN) needs a large amount of data thus obtained accuracy of 95.42% and F-score of 65.32%. Similarly, the dilated CNN model needs large number of datasets to process and train the neural network that obtained the accuracy of 97.54% and F-score of 67.32%. Also, the image derived limited the information related to location with standard or specific distance among the object and region that obtained the accuracy of 98.02% and F-score 67.87%. Whereas, the proposed Dilated U-Net based CNN model obtained an accuracy of 99.5% and F-score of 69%. Also, the U-Net allows for the use of global location and context as the larger receptive field with no loss of convergence.

Table 2: Results obtained for the proposed Dilated U-Net based CNN model with the existing classifiers

Classifiers	Accuracy (%)	F-score (%)
DNN	95.42	65.32
Dilated CNN	97.54	67.32
U-Net	98.02	67.87
Dilated U-Net based CNN	99.5	69

The model shows efficient computation and provides larger convergence. With the U-net model, the dilated CNN extracts the image which is derived with information and a standard type of shape and distance among the object and the region is also determined. Figure 7 presented the results which is obtained for the proposed dilated based U-Net model in terms of accuracy and f-score.

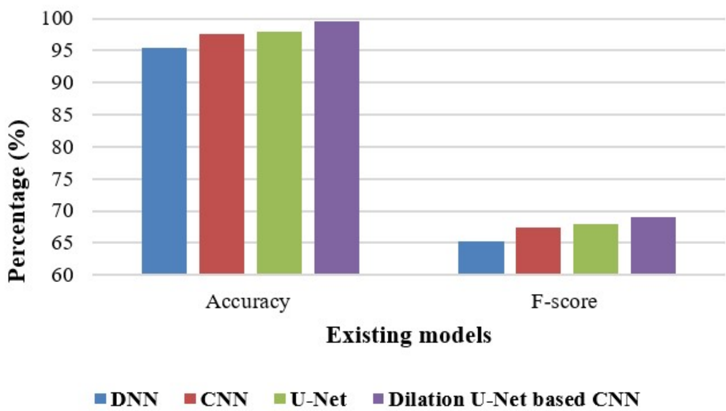

Figure 8: The results obtained for the proposed dilated based U-Net model in terms of accuracy and f-score

4.2 Comparative Analysis

Table 3 shows the comparative analysis where the comparison of the existing with the proposed model is performed. The existing optimization approaches were sensitive to data features as it was having irrelevant features and obtained an accuracy of 99.15% [16]. At the segmentation stage, the severity levels of diseases were not identified which showed an accuracy of 99% [17]. The large database consisted of medical images showed improvement in accuracy and thus showed 98% [18]. The developed model used more than one classifier for examining the robust mechanisms to improve the accuracy for large database which consisted of medical images obtained 92% of accuracy [19]. Also, tumorous regions showed performance better using the deep learning models which effectively segmented the untrained and trained datasets without using augmented data requirements and obtained 99.4% of accuracy [20]. Whereas, the proposed Dilated based U-Net model obtained better accuracy of 99.5% when compared to the existing models.

Table 3: Comparative analysis

Authors	Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
Champakamala Sundar Rao and K. Karunakara [16]	Kernel based SVM	99.15	98.53	-
Muhammad Irfan Sharif [17]	Non-Dominated Sorted Genetic Algorithm (NSGA) Convolutional Neural Network	99	95	95
K. Sakthidasan Sankaran [18]	Deep Elman Neural network with adaptive fuzzy clustering	98	97	98
Mingquan Lin [19]	3D Context Deep Supervised U-Net	92	-	-
Ahmet Ilhan [20]	Nonparametric Localization And Enhancement Methods with U-Net	99.4	92.19	99.75
Proposed	Dilated U-Net based CNN	99.5	99.52	99.81

While considering the other performance metrics such as sensitivity and specificity, the proposed method attains better when compared with existing methods ([16]-[20]) which is stated in table 3. The proposed method achieves the sensitivity of 99.52% and specificity of 99.81% which is superior than state of the art methods.

5 Conclusion

In the present research work, the proposed process of semantic segmentation is deepened that has spatial information in the feature map which reduces the critical time. Automated multi-modal classification is used as a deep learning approach to classify the brain tumor. The main aim is to extract the information of an image's edge when the convolution layer deepens and shows higher semantics. The spatial information is lost and the dilated convolution preserves as much as to use convolution that showed improvement in terms of accuracy for segmentation prediction. The existing Kernel based SVM model obtained 99.15% of accuracy, Non-Dominated Sorted Genetic Algorithm (NSGA) Convolutional Neural Network obtained accuracy of 99%, Deep Elman Neural network with adaptive fuzzy clustering accuracy of 98%, 3D Context Deep Supervised U-Net obtained accuracy of 92%, Nonparametric Localization and Enhancement Methods with U-Net obtained accuracy of 99.4%. Whereas, the proposed Dilated U-Net based CNN model obtained accuracy of 99.5% when compared with the existing models. However, in the future, it is required to detect brain tumors accurately based on real patient data with any medium. The deep features and handcrafted features were required to be fused for improving the results of classification.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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