Intra Fusion Based CNN Technique for MRI Multimodal Brain Tumor Classification and Segmentation

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Abstract. The proposed work segment the tumor portion with substructure from MRI Multimodal brain tumor images using image fusion techniques. The preprocessing work is done by using Piece-wise linear transformation, to enhance the tumor region. The proposed work classify the brain tumor image as tumor or non-tumor by convolutional neural network (CNN) model, then extracts the whole tumor portion by largest connected component (LCC) and finally segments the substructures. The segmented substructure of tumor portion is validated with ground truth in qualitative and quantitative analysis. The experiments are done using BraTS datasets and performance metrics such as structural similarity index measure (SSIM), accuracy, dice coefficient (DC), and peak signal to noise ratio (PSNR). This metrics are used to validate the shape of the tumor portion. The metrics gives better results for the proposed work.

Keywords: Deep Learning, Convolutional Neural Network, Image Fusion, Piece - wise linear transformation, MRI, Brain Tumor, Substructure Segmentation, Morphological Operation.

1 Introduction

In medical diagnosis, medical image plays a crucial role to analysis the defects in the human body. The most popular imaging techniques are magnetic resonance imaging (MRI), Computed tomography (CT) and X-rays[1]. In brain tumor analysis, MRI is the most admired technique for segmentation and detection of tumor.

The unwanted growths of cells are formed in the brain are tends to brain tumor. Primary and secondary are two categories [2]. The MRI brain tissues are gray matter (GM), white matter (WM), cerebrospinal fluid (CSF). Flair, T1,T2 and T1c are the four modalities produced by MRI as shown in Figure 1.

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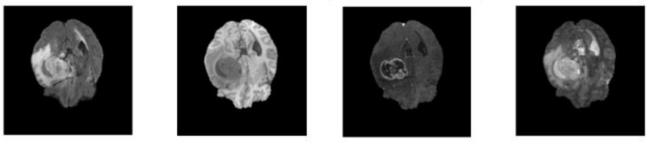

Fig 1. MRI Multimodality of Brain Tumor image a) Flair b) T1 c) T1c d) T2

Tumor portion in these four modalities are emerge with different intensities. To combine these intensities of four modalities and provide more informative MRI brain tumor image, image fusion is introduced in this process. The method of combining different images that will produce single image with good quality is referred as image fusion [3].

Two domains are performed in image fusion. One is spatial and another one is frequency domain. Thus, in medical diagnosis for brain tumor, MRI produces four modalities with different information. It leads to make the treatment process more difficult. To overcome this medical image fusion is applied, which will merge the different modalities of the MRI medical imaging to give an output fused medical image.

Now a days, in the field of AI, deep learning (DL) is a recent developments of research, helps to analyze the brain cancer, its causes[5]. In DL, various segmentation and classification techniques are available, among that CNN is the most flexible architecture to classify the images and will produce the accurate result.

In the proposed method, preprocessing work is done with four modalities of MRI brain tumor images are merged in the combination of Flair + T1c, Flair+T2+T1c and T1+T2+T1c+Flair using image intra fusion rule Then the classification of tumor and non tumor process is performed by CNN architecture with good accuracy. After that, the tumor portion and its substructures are segmented using morphological operations. Then the ground truth image is compared with output fused segmented image using evaluation metrics are SSIM, PSNR and dice - co-efficient (DC). The intra fusion technique proposed work produce better results both in qualitative and quantitative analysis.

This paper structured as follows. Literature survey based on brain tumor segmentation techniques are described in second section. Methodology expressed in third section. Materials and metrics are discussed in fourth section. Performance evaluation and results expressed in section five. Finally, conclusion of the work and future enhancement are expressed in section six.

2 Literature Review

Kaur et.al, [11] proposed a new method using multimodal image fusion techniques for brain tumor detection using. Here they used the modalities are MRI and Flurodeoxyglucose images.

In the proposed work, pixel level image fusion techniques were used. Here they described that the PCA techniques produced the result with blurred edges and result obtained from MSVD was blurred, the content information also less. When compared to other techniques proposed method was give good edge details and content information. The evaluation parameters was used for evaluation are , structural similarity index metric, standard deviation (SD with 0.2), entropy (EN with 4), Mutual Information, PSNR with 36.651. Thus the work gives good result when compared to PCA.

Nandhini et.al [3], proposed a method for tumor segmentation. Here they used positron emission tomography (PET) and MRI images of brain tumor In this paper, they illustrated that the PET image gives functional information of the brain and the MRI produced the brain tissues. The novel method produces the result to locate the tumor portion for medical diagnosis. The experiment was done using PET and MRI images in 256 X 256 sizes. Datasets were taken from med.harvard.edu database. Evaluation metrics SSIM, MI were used and produced the results 0.8551 and 2.8059 respectively.

Chandrashekar et.al [6] proposed a new using non – subsampled contourlet transform (NSCT) and sparse representation (SR). Modalities are taken here was CT and MRI brain images. They proposed a technique for fusion with NSCT and SR. The proposed result of fused CT and MRI images gives better quality. The experiments were done using radiopedia brain tumor datasets. Performance evaluation metrics used here are standard deviation, Entropy, phase congruency, Execution Time, PSNR, universal image quality index. The authors conclude that the proposed technique produce better and improved result with 7.23%, *%, 0.01% and 6.9% for PSNR, SSIM, PC and UIQI respectively.

3 Methodology

The proposed intra fusion segmentation of multimodal MRI brain tumor region with substructure is implemented by the following steps.

Step 1:

• Input the Flair image which is one of the multimodal MRI brain tumor image, process with Piece - Wise Linear Transformation and produce contrast brain tumor image.

• Contrast brain tumor Flair image is combined with other modalities T1,T1c,T2

• Fusion rule is applied to the combinations Flair+T1c, Flair+T1+T2+T1c, Flair+T2+T1c

• Among the three combinaions, Flair+T2+T1c selected. It gives better fused image with good contrast of tumor portion

• The fused images processed with CNN model to classify the tumor and non-tumor images.

• After classification, whole tumor extracted from the MRI brain tumor image using largest connected componentes (LCC).

• From the resultant MRI fused brain tumor image , substructure of tumor portion such as Edema, Necrosis and Enhancing Tumor are segmented using morphological operations.

• Output is fused segmented gray image with substructure

The work started with MRI multimodal brain tumor images Flair, T1, T1c, and T2, are appear with different intensities and different structures of tumor region as shown in figure 4. Pre-processing work is done with Flair image processed by Piece – Wise Linear Transformation to increases the contrast of tumor portion and distinguish from other tissue as shown in figure 2. Then the enhanced flair image and other modalities are fused by Pixel level image fusion rule to produce a high quality and enhanced structure of tumor portion. These modalities are merged based on the combinations such Flair+T1c, Flair+T1+T2+T1c, Flair+T2+T1c. Here Flair+T2+T1c produce the grayscale output fused brain tumor image with good structure of tumor region with substructure as shown in Figure 3(a). Therefore Flair+T2+T1c combination is taken for post-processing. The fused images are processed with CNN to classify the tumor or non-tumor image. In CNN model five layers are used, each layer consist of convolutional layer, max pooling layer with ReLu activation function and the model end with dropout and fully connected layer. Compilation of CNN is done by Adam optimizer. This model produces better accuracy for the proposed method. If the output of CNN model for MRI fused image is tumor, then binary threshold transformation is applied to segregate the whole tumor portion from other pixel of the image as displayed in Figure 3(b). Then the threshold image is processed with LCC to extract the tumor region, is shown in Figure 3(c), then it produce the whole tumor region is displayed in Figure 3(d). Based on the morphological operations, tumor region substructure are segmented as Enhancing Tumor, Edema, and Necrosis are presented in Figure 4 (a),(b)and (c) .

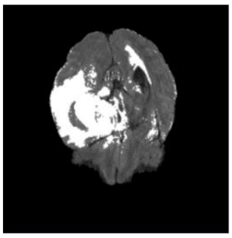

Figure 2. Flair with Piece - Wise Linear Transformation

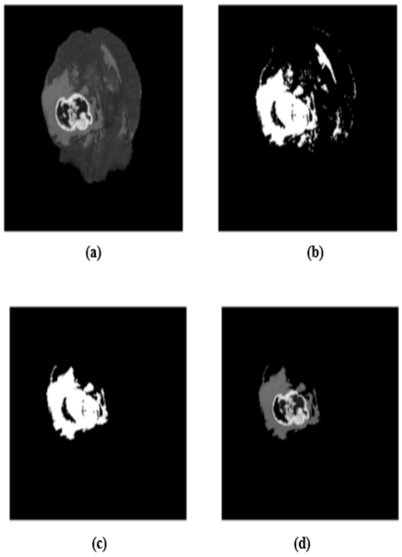

Fig 3. (a) Fused Output Image (b) Threshold Binary Image (c) Segmented Tumor Portion (d) Whole Tumor region

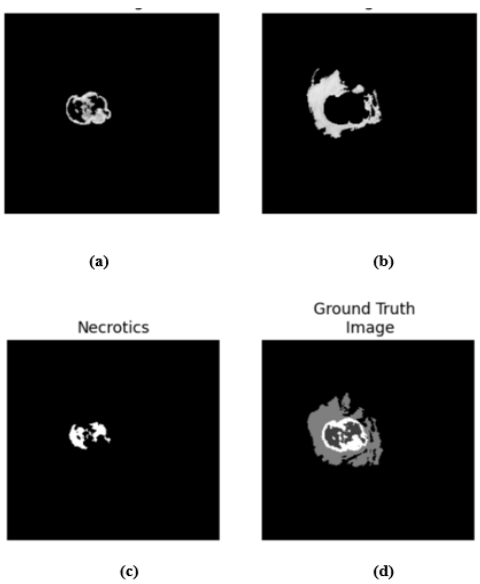

Fig 4. (a) Enhancing Tumor (b) Edema (c) Necrotics (d) Ground Truth Image

Finally, similarity measures are done by the metrics DC,SSIM and PSNR between output fused segmented image and ground truth image. Proposed method produce good results in the quantitative analysis when compared to other existing methods.

4 Material and Metrics

BraTS publicly available dataset is used in this experiment [4]. Dataset contains11 volumes, Flair, T1, T1c, and T2 of each modality have 135 images in these volumes. The preprocessing work intra fusion method produced the fused images of each volume is 4890 images. The experiments are done in the device with configuration: Intel(R) Core(TM), 64 bit, Windows 10, i5Processor, 8 GB RAM, Python3.10. The evaluation metrics PSNR, SSIM and DC, are used here for evaluation and results are shown in section five. CNN model performance is measured by accuracy.

5 Results and Discussions

The preprocessing work was done with pixel level intra fusion method, using MRI multimodality brain tumor images. These images are fused based on the combinations Flair +T1c, Flair + T1c +T2 and Flair+T2+T1c+T1. To evaluate the CNN model, accuracy metric is used for each epochs. In the experiment, CNN model implemented with 50 epochs, the model give better accuracy upto 90% - 98.9 % .

The evaluation metrics PSNR, SSIM and DC are calculated for each volume. The proposed work compared with existing method listed in Table 1. This expressed that the proposed intra fusion brain tumor classification gives better accuracy result when compared to other CNN based image fusion techniques.

Table 1. Proposed Method Compared with Existing Method

Existing Methods	Accuracy
Fuzzy C Means with Gaussian mixture model – CNN [7]	96.5
CNN [8]	92
Transfer Learning based DCNN Model [9]	98.93
Image fusion with CNN[10]	98.18
Proposed Intra fusion with CNN classification	**98.97**

6 Conclusion

In this work multimodality of MRI brain tumor images are fused using pixel level fusion rule. The output of this preprocessing work produce the fused image is implemented with the CNN model with five layers and dropout to categorize the image as tumor and non-tumor images of MRI. Finally, in the classified brain tumor image tumor portion is extracted and tumor regions are segmented using morphological operation. Thus the experiment is analyzed by the metrics such as DC, PSNR and SSIM. CNN model evaluated by the validation accuracy, it gives better accuracy result with 98.9%. In future, there is intent to segment the tumor regions using other deep learning techniques.

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