INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

OPEN ACCESS

Received: 07-04-2024

Accepted: 17-06-2024

Published: 19-07-2024

Citation: Ravindran V, Thiruvenkadam K, Thiyagarajan A (2024) MRI Brain Tumor Classification and Extraction using Deep Learning-Based Decision Level Image Fusion Technique. Indian Journal of Science and Technology 17(27): 2848-2857. https://doi.org/10.17485/IJST/v17i27.1138

* **Corresponding author**.

kalaiselvi.gri@ruraluniv.ac.in

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

MRI Brain Tumor Classification and Extraction using Deep Learning-Based Decision Level Image Fusion Technique

Vasanthi Ravindran[1], Kalaiselvi Thiruvenkadam[2]*, Anitha Thiyagarajan[3]

1 Research Scholar, Department of Computer Science and Applications,, The Gandhigram Rural Institute (Deemed to be University), Gandhigram, 624302, Tamil Nadu, India
2 Assistant Professor, Department of Computer Science and Applications, The Gandhigram Rural Institute (Deemed to be University),, Gandhigram, 624302, Tamil Nadu, India
3 Assistant Professor, School of Computational Intelligence, Joy University, Raja Nagar, Alaganeri, Near Kanyakumari, College Rd, Vaddakkankulam, 627116, Tamil Nadu, India

Abstract

Objectives: The proposed work emphasizes the tumor region extracted from the multimodal MRI brain scan by deep learning-based decision-level image fusion technique. **Methods:** Convolutional Neural Network (CNN) architectures such as AlexNet, ResNet50, and VGG16 perform brain tumor classification with multimodal MRI images Flair, T2, and T1c respectively. Flair images are fed to the AlexNet architecture, T2 images are fed to the ResNet50 architecture, and T1c images are fed to the VGG16 architecture to classify brain tumor images. The classification results from these architectures are fused together to perform the decision on the given inputs. If the inputs come under the decision of the tumor affected then the tumor portion will be extracted using the fusion of three images as a post-processing operation. **Findings:** The experiments are done using BraTS datasets an open-access brain tumor image analysis research repository. The three CNN architectures' performance is measured by accuracy and gives 0.87 for AlexNet, 0.91 for ResNet50, and 0.99 for VGG16. The extracted tumor region from the fused output image is compared with the ground truth image by metrics such as SSIM with 0.93, DC 0.96, and PSNR with 66.57. Better results are received for the proposed work in the evaluation analysis than the existing works. **Novelty:** Decision level image fusion limitedly experimented with Deep Learning techniques in state-of-art methods. In this proposed method, the decisions made based on the classification result of three CNN architectures.

Keywords: MRI; Brain tumor; Deep Learning; Convolutional Neural Network Architectures; Image Fusion; AlexNet; ResNet50; VGG16

1 Introduction

Medical imaging plays a vital role in medical diagnosis [1]. It is done by radiologist who acquires the images and produces the reports, and then these reports are referred by the physicians for their treatment plan. Medical imaging is the procedure to examine the human body for treatment in non-invasive manner [2]. Various types of medical imaging modalities are used such as X-ray radiography, Positron Emission Tomography (PET), Computed Tomography (CT), Single–Photon Emission Computed Tomography (SPECT), and Magnetic Resonance Imaging (MRI). These non-invasive techniques play a crucial role in brain tumor diagnosis. Among all these, MRI provides pertinent information of human body structure. It is a significant technique for brain tumor analysis in clinics.

Brain tumor is unwanted growth of cells. It will damage the brain tissue, and will disturb the work of the brain [3]. Brain tumors are categorized into two types, primary and secondary or metastatic. Initial growth of primary brain tumor is started from the brain tissue itself whereas metastatic brain tumor arise from other organs and it will affect the brain tissue. Low grade tumors, glioma and meningioma, are classified as benign type of tumors. High grade tumors, glioblastoma and astrocytoma, are classified as malignant [4]. The substructure of brain tumors consists of three parts such as edema, necrotic and active tumor. MRI produces images of human body tissues in non-invasive manner. This technique gives high quality anatomical image with functional information. Modalities of MRI are T1-weighted, T2-weighted, T2 and T1 weighted with gadolinium contrast enhancement (T1c) and Fluid Attenuated Inversion Recovery (FLAIR) as shown in Figure 1. These four types of modalities provide substructures of pathological details of the brain. In MRI multimodality images, each image type highlights a specific region of brain tumors. Healthy tissues of the brain are distinguished in T1. Edema regions appear brighter in T2 image. Tumor portion boundary is well distinguished from other regions in T1c. In Flair, water molecules are suppressed and edema region alone is displayed in a brighter manner [5]. By combining these modalities, a new image will be produced and thus image fusion is introduced here. So the fusion technique helps to combine all the segments of brain tumor in a single image and process them.

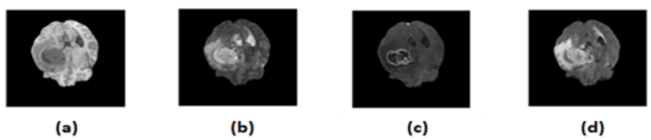

Fig 1. MRI Brain Tumor images: (a) T1 (b) T2 (c) T1c (d) Flair

Medical Image fusion is the process of integrating information from more than one image to generate a new image with suitable information [6]. Image fusion is categorized into three levels. First level is, pixel level image fusion, it integrates the raw data from the multiple images to produce a single image. Second level is, feature level fusion, it extracts the source image features to integrate and produce a more contextual informative image. Results from different algorithms are analyzed and fusion rule will be applied, and is referred as decision level image fusion [7].

Image fusion is categorized into two types, one is spatial and the other is frequency domain. The spatial domain is performed directly on the pixels of the image. In frequency domain method, decomposition of image by splitting and integrating the coefficients of the images are done based on the appropriate fusion rule [8]. Medical image fusion integrates the MRI multimodality brain tumor images to create a single image with detailed information. Now-a-days DL techniques are performed with image fusion techniques to classify the images, especially for brain tumor analysis [9].

1.1 Research Gap

In the literature different DL techniques are used for image classification, although some image fusion techniques are also mutually implemented with DL methods. However, most single modalities of the MRI images are used with any one of the CNN architectures to classify the tumor or non-tumor images. Therefore, there could be some lack of information in medical diagnosis, in order to overcome this multimodality of MRI brain tumor images may be used with CNN architectures. Hence, these CNN architectures are required to process the tumor types from multimodal MRI images, and finally the classification results will be used to decide and extract the tumor portion based on fusion rule. This resultant fused image will help the radiologist to analyze the tumor region with more features and use large volume of scans in less time with efficient manner.

The existing methods used for brain tumor classifications are discussed below:

Alqudah, A et.al, [3] proposed a new method to classify brain tumor images into three classes such as glioma, meningioma, and pituitary tumor. The experiment done to grade the brain tumor based on two scenarios are cropped tumor lesions and uncropped images. These images are processed by novel CNN architecture to classify the images. This model produced results with an accuracy of 99.93% and a sensitivity of 98.52%.

Adbd El Kader et.al, [8] developed a new differential deep CNN to classify the MRI brain tumor images. Some differential operators are used in the process. In the original CNN feature maps, additional feature maps are derived and applied. It suggests that these additional feature maps improve the proposed method's performance. The experiment was done with 25000 MRI brain images and this proposed model produced 99.25% accuracy.

Kaur et.al,[7] projected a novel method for brain tumor detection by image fusion techniques. First, MRI and Fluorodeoxyglucose images are taken as input images. To blur the image, the Guided filtering technique was applied. To sharpen the image, blurred and input images are subtracted. Finally, the average fusion technique was applied to merge both modalities. The resultant fused image is produced with the preserved edge which helps with brain tumor detection. The proposed technique is compared with existing techniques of multiresolution singular value decomposition technique (MSVD) and PCA. The evaluation analysis such as standard deviation, entropy, and PSNR gives better results for their method.

Padmini et al.[10] implemented a tumor detection algorithm that employs CNN and VGG16 deep learning techniques. In this strategy, the CNN model detects and differentiates between tumor types. The generated image from the CNN model will be fed into the VGG-16 model to determine the tumor's severity range. Later, the image will be classed as either tumor or non-tumor. The image will be enhanced again before being sent to the tumor Segmentation process. Finally, the output of the CNN model predicts the tumor's appearance via the prediction model.

Youis et al.[11] devised a tumor analysis approach utilizing deep learning techniques. They employed an ensemble learning methodology, CNN, and VGG16 to detect brain tumors using brain MRI data. In this approach, tumor zones are first eliminated using edge detection algorithm, and MRI images are classified as tumor or non-tumor using CNN. The validations were done using 253 brain images of MRI and evaluated the performance by accuracy metric with 97.16%.

In the proposed work, three architectures of CNN are used to classify the MRI multimodalities FLAIR, T2, and T1c images as tumor and non-tumor. After this classification, the result of three architectures is taken, only if the images are categorized as tumor. Then these three modalities are merged to produce a fused MRI brain tumor output image. Here, the fusion process is performed based on the decision-level image fusion. The fused MRI brain tumor output image is taken for the post-processing work to extract the tumor portion. To analyze the performance of the experiment, some evaluation metrics are used such as Dice Coefficient (DC), Structural Similarity Index Measure (SSIM), And Peak Signal to Noise Ratio (PSNR). Some of the DL models with fusion techniques are listed in Table 1 They do not fully utilize all three MRI multimodal scan images.

Table 1. Related Works for DL models with fusion techniques

S.No	Author	Year	Technique	Dataset	Performance Metric
1	Liu, Y et.al,[5]	2022	Pixel Level Image Fusion, CNN, V-Net architecture	Brats 2019 and 2020	DC- 0.8265 for 2019 and 0.8291 for 2020
2	Swarup, C et.al,[9]	2023	CNN - GoogleNet and AlexNet	RADHAMADHAB DALAI, July 1, 2021, "Brain Tumor Dataset", https://dx.doi.org/10.21227/2qfw-bf10.)	Accuracy : AlexNet - 98.95, GoogLeNet - 99.45
3	Sarkar et.al,[12]	2023	CNN- AlexNet with, BayesNet, sequential minimal optimization (SMO), Naïve Bayes (NB), and random forest (RF) classifiers	Kaggle dataset – 3600 images	Accuracy: BayesNet- 88.75% , NB 98.15, SMO,-86.25,RF- 100%
4	Younis, A[11]	2022	CNN, VGG16	Kaggle Dataset	Accuracy: CNN- 96%, VGG16 - 98.5%
5	Asiri, A[13]	2023	CNN	Kaggle Dataset	Accuracy -94.0%

This paper is structured as follows. The methodology of the proposed work is discussed in the second section. Third section three elaborates on materials and metrics. Quantitative analysis is discussed in section four. At last conclusion and future enhancement are described in section five.

2 Methodology

The proposed method procedure and architecture are shown in Figures 2 and 3 respectivly.

The proposed work starts with MRI brain tumor modalities. MRI produces four modalities and out of those, FLAIR, T2, and T1c are taken. Each modality is fed into three architectures of CNN, flair images are passed as input to AlexNet, T2 images into ResNet-50, and T1c images into VGG16 to classify the images.

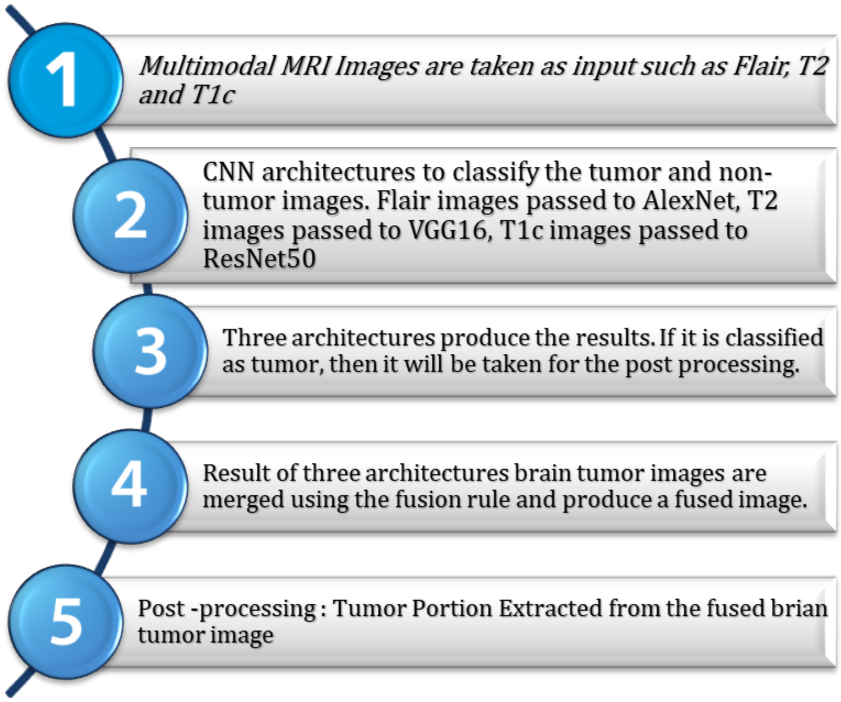

Fig 2. Proposed Method Procedure

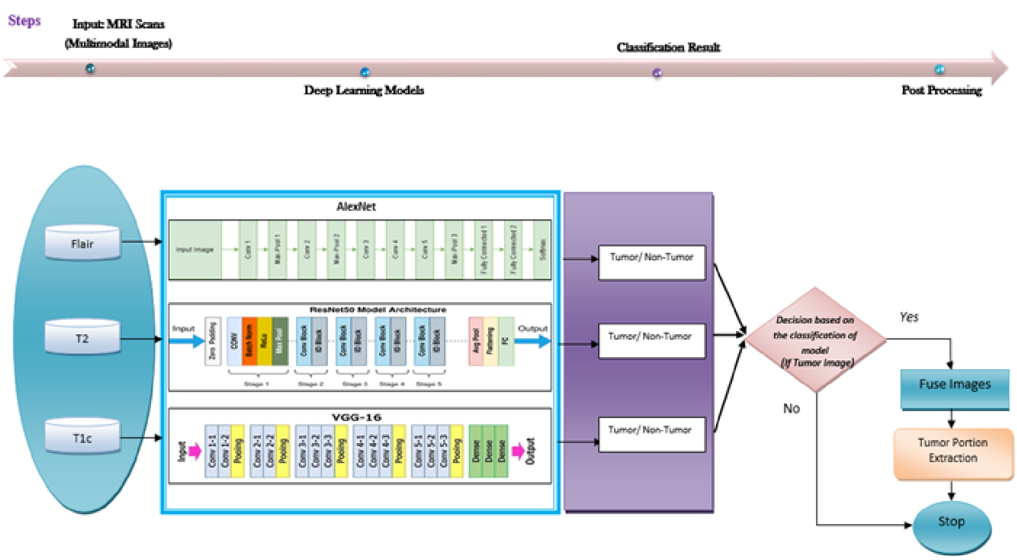

Fig 3. Proposed Method Framework

AlexNet is one of the CNN architecture [11,12], it consists of eight layers, five convolutional layers, and 3 fully connected layers. Convolutional layers are followed by the max pooling layer and the ReLU activation function is used. The architecture diagram of AlexNet is shown in Figure 4. In the experiment, MRI brain tumor FLAIR images are fed into this architecture with the ReLU activation function as shown in Equation (1).

$$f(x) = ReLU(x) = \begin{cases} 0, \; if \; x \leq 0 \\ x, \; if \; x > 0 \end{cases} \tag{1}$$

ReLU activates only the positive signals and deactivates the entire negative ones.

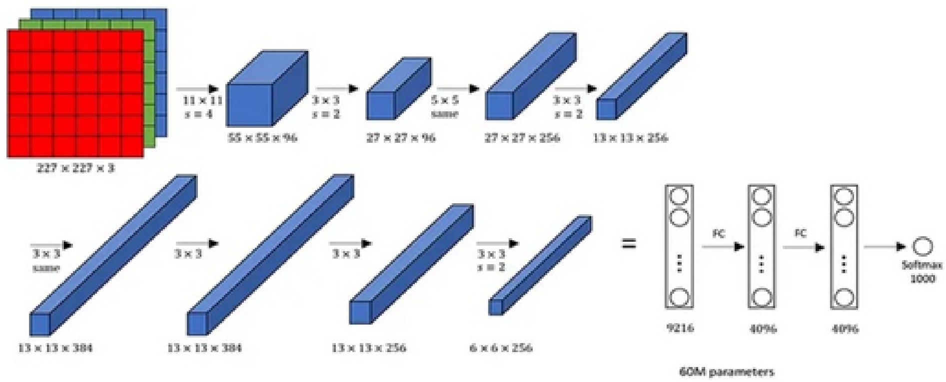

Fig 4. AlexNet Architecture

Visual geometry group (VGG), is one of the typical deep CNNs [10,14]. VGG network with 16 CNN layers refers to VGG16. It is formed with 13 convolutional layers and fully connected layers are three. It contains input layers, convolutional layers, hidden layers, and fully connected layers. This model takes the input size of 224 x 224. Convolution layers use 3x3 kernel size filters and additionally, 1x1 filters are used for linear transformation of the input. These layers are followed by a pooling layer to reduce the dimension of the feature maps of the input image. 64 filters are used for the first 2 convolutional layers; it will double to 128 for the next two convolutional layers, again double to 256 for the next three layers, and 512 filters for the next three layers. Finally, the fully connected layer ended with the softmax function. The architecture of VGG16 is shown in Figure 5. In the experiment, MRI brain tumor T1c images are fed into this architecture.

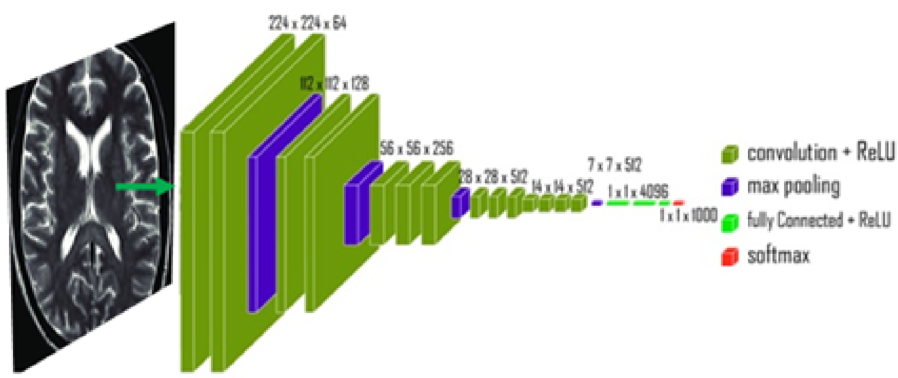

Fig 5. VGG16 Architecture

ResNet stands for residual network. It consists of 50 layers with residual blocks [15]. ResNet50 architecture has 48 convolutional layers, 1 maxpooling layer, 1 average pooling layer, and ended with fully connected layer. In the convolutional layer, during backpropagation weights would be changed, which causes decrease in the gradient value. To avoid this problem, skip connections are used by ResNet architecture. The architecture of ResNet50 is exposed in Figure 6.

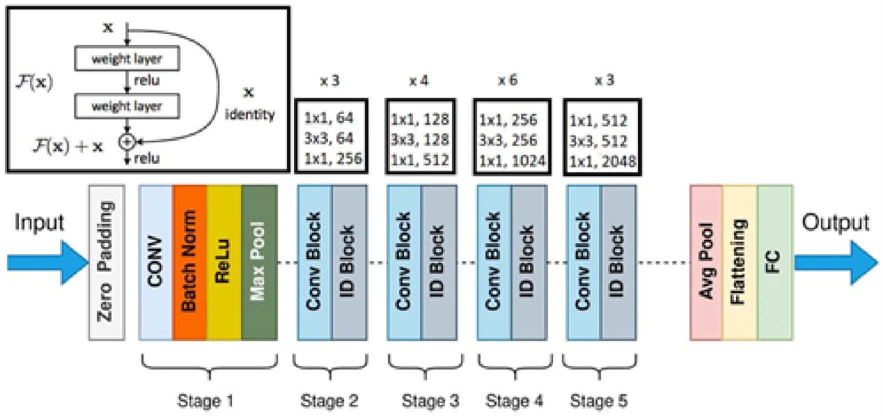

Fig 6. ResNet50 Architecture

In this network, the convolutional layer extracts the features from the source images. The maxpooling layer performs the operation of down sampling, and then it will be processed by residual blocks. Residual blocks are implemented with two convolutional layers with an activation function. The output features of the residual blocks are fetched by the fully connected layer and it will map the output. In the experiment, MRI brain tumor T2 images are fed into this architecture to classify the images.

If the classified image is a tumor, then it will process with the image fusion rule. After classification, each modality of tumor images is merged using the fusion rule to produce the fused image as displayed in Figure 7. Further, in post–processing work the tumor region is extracted, and binary transformation is applied to the output fused image that enhances the pixels, based on the threshold value as depicted in Figure 7. Then the tumor portion was extracted from the binary transformation image using the Largest Connected Component (LCC), displayed in Figure 8. Here, the fusion rule is applied to merge the multi modalities and the full structure of the tumor portion is extracted from the MRI brain tumor image without any feature loss. The experiment is evaluated by metrics that give better values for the proposed work.

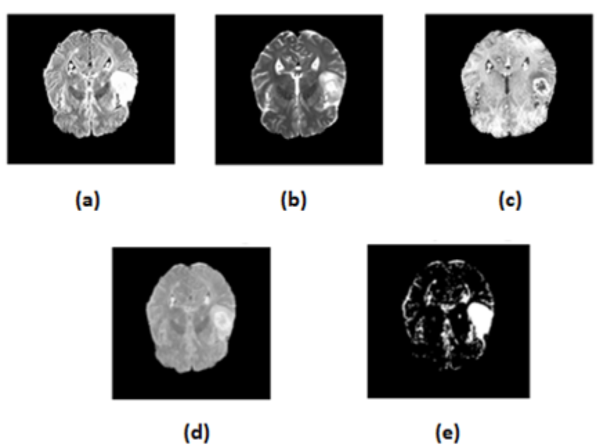

Fig 7. MRI multimodality images: a) Flair b) T2 c) T1c d) Fused output Image e) BinaryTransformation Image

Fig 8. Result of Post-processing Brain Tumor Extraction (a) Extracted Tumor Portion (b) Ground Truth Image

3 Material and Metrics

In this experiment, the BraTS dataset is used with 10 volumes of FLAIR, T2, and T1c. Each volume contains 155 images of brain scans. Each volume of modality has two classes of tumor and non-tumor images[16]. System configurations are 8 GB RAM, Intel(R) Core(TM), i5Processor, 64 bit, Windows 10, Python3.10. Quantitative analysis is done with metrics such as accuracy, PSNR, SSIM, and DC.

CNN architectures Alexnet, Resnet-50, and VGG16 are evaluated based on the accuracy metric. It calculates the number of correctly predicted values from the total number of predicted values[15,17]. It ranges from 0 to 1, if it is near to 1, then the model predicts correctly otherwise not. It is defined by the Equation (2),

$$Accuracy = \frac{no.\,of\ correctly\ predicted\ values}{total\ no.\,of\ predicted\ values} \tag{2}$$

The post-processing, tumor portion extraction work is evaluated by the metrics, PSNR calculates the ratio of maximum pixel intensity and noise value of the pixel[18], which is defined by the Equation (3),

$$PSNR = 10log_{10}\frac{R^2}{MSE} \tag{3}$$

A high PSNR value shows that the fused and ground truth images are closer with less distortion. Here, the fused image gray level value is represented by R, and the mean square error is represented by MSE, to calculate between the two images.

SSIM is a metric used to measure the similarity between the output fused image and the ground truth image[13]. The range of SSIM values is 0 to 1. SSIM gives the value near to 1 indicating that the images are nearly close to each other. It is defined by Equation (4) ,

$$SSIM_{(A,B,F)} = \frac{SSIM_{(A,F)} + SSIM_{(B,F)}}{2} \tag{4}$$

where, $SSIM_{(A,F)} = \frac{(2\mu_A\mu_F + C_1)(2\sigma_{AF} + C_2)}{(\mu_A^2 + \mu_F^2 + C_1)(\sigma_A^2 + \sigma_F^2 + C_2)}$

$$SSIM_{(B,F)} = \frac{(2\mu_B\mu_F + C_1)(2\sigma_{BF} + C_2)}{(\mu_B^2 + \mu_F^2 + C_1)(\sigma_B^2 + \sigma_F^2 + C_2)}$$

Where, F is the fused output image, A and B are input images. μ denotes the average value, σ indicates the variance, C_1 and C_2 are the constants.

DC value is used to calculate the similarity between two images[19]. Its value ranges between 0 and 1. It is calculated by the Equation (5).

$$Dice = \frac{2|X \cap Y|}{|X| + |Y|} \tag{5}$$

Where X is the output fused image and Y is the referenced image.

4 Results and Discussion

In the proposed method, 10 volumes of MRI multimodal images are taken and fed into CNN architectures such as AlexNet, ResNet50, and VGG16 respectively. Datasets are split into 60% for training and 40% for validation. The classification results of each architecture are shown in Figure 9. The performances of the three architectures are measured by accuracy and are shown in Figure 10. All these architectures produced 90% and above accuracy whereas VGG16 reached 99% accuracy. This is higher than other state-of-the-art methods(SOTM) as shown in Figure 11.

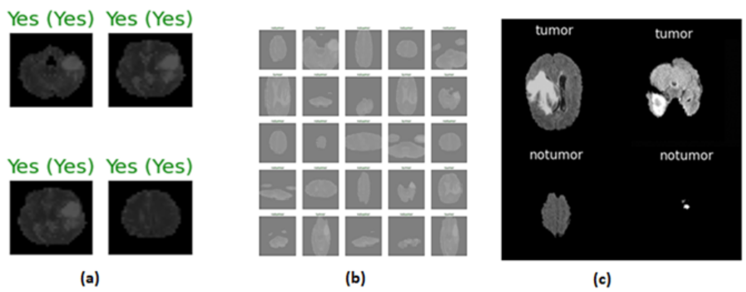

Fig 9. Classification Results a) Alexnet b) ResNet50 c) VGG16

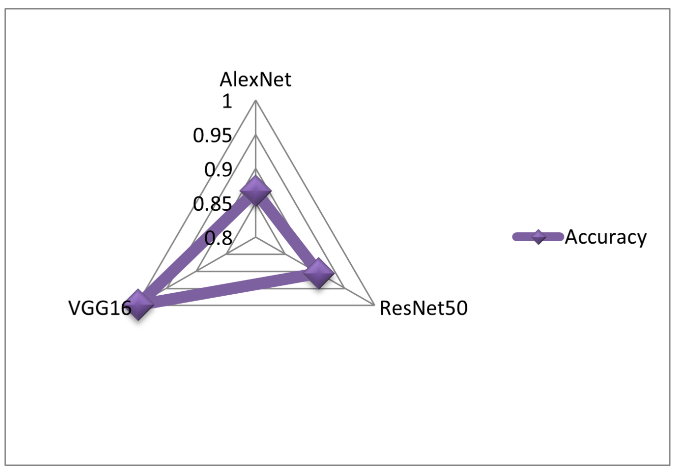

Fig 10. Accuracy value of Three CNN Architectures

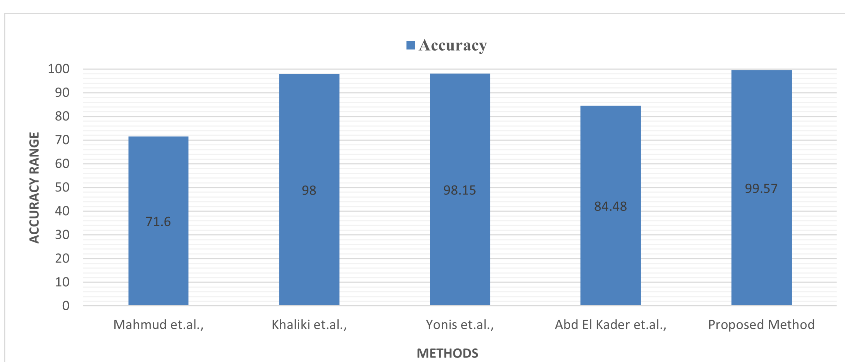

Fig 11. STOM for VGG16 is Compared with Proposed Work

Finally, in post-processing, the tumorous images chosen under the decision process of classification results are fused and the tumor portion is segregated. Ground truth image is compared with the extracted tumor portion. The average value of evaluation metrics is listed in Table 2. The values of SSIM and DC are nearer to 1 with higher PSNR values indicating that the fused output image is similar to the ground truth image.

Table 2. Evaluation Parameters of Extracted Tumor Portion

Vol Name	SSIM	DC	PSNR
BraTS19_CBICA_AAG_1	0.73	0.96	53.76
BraTS19_CBICA_AAB_1	0.87	0.95	63.85
BraTS19_CBICA_AAL_1	0.88	0.93	63.53
BraTS19_CBICA_AAP_1	0.97	0.98	66.59
BraTS19_CBICA_ABB_1	0.98	0.99	66.84
BraTS19_CBICA_ABE_1	0.97	0.98	70.92
BraTS19_CBICA_ABM_1	0.97	0.98	69.75
BraTS19_CBICA_ABN_1	0.96	0.91	66.70
BraTS19_CBICA_ABO_1	0.98	0.97	71.09
BraTS19_CBICA_ALU_1	0.99	0.98	71.94

5 Conclusion

MRI multimodal images FLAIR, T2, and T1c are fused based on the decision-level image fusion, the input images are chosen by the classification result of CNN. In previous literature, CNN processes the single modality dataset to classify the tumor images. In the proposed method, three modalities are merged based on the outcome of three architectures to get the tumor image. In the post-processing work, the tumor portion was extracted from the fused output image using the LCC approach. Further, extracted tumor region and ground truth image are similar and are evaluated by metrics such as SSIM with 0.93, PSNR 0.96, and DC with 66.57. DL model performances are analyzed by the accuracy metric gives an accuracy of 0.87 for AlexNet, 0.91 for ResNet50, and 0.99 for VGG16. Finally, the proposed method gives better accuracy than existing works. The experiment extracts the whole tumor portion, and the substructure of tumor regions will be segmented in the future by using other deep-learning architectures.

References

1) Anitha T, Kalaiselvi T. MRI Brain Tumor Classification Using Computational Intelligence Technique. *NeuroQuantology*. 2022;20(14). Available from: https://doi.org/10.4704/nq.2022.20.14.NQ880191.
2) Zhou SK, Greenspan H, Davatzikos C, Duncan JS, Van Ginneken B, Madabhushi A, et al. A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises. *Proceedings of the IEEE*. 2021;109(5). Available from: https://doi.org/10.1109/JPROC.2021.3054390.
3) Alqudah AM, Alquraan H, Qasmieh IA, Alqudah A, Sharu W. Brain tumor classification using deep learning technique–a comparison between cropped, uncropped, and segmented lesion images with different sizes. 2020. Available from: https://doi.org/10.30534/ijatcse/2019/155862019.
4) Ren T, Honey E, Rebala H, Sharma A, Chopra A, Kurt M. An Optimization Framework for Processing and Transfer Learning for the Brain Tumor Segmentation. 2024. Available from: https://doi.org/10.48550/arXiv.2402.07008.
5) Liu Y, Mu F, Shi Y, Cheng J, Li C, Chen X. Brain tumor segmentation in multimodal MRI via pixel-level and feature-level image fusion. *Frontiers in Neuroscience*. 2022;16. Available from: https://doi.org/10.3389/fnins.2022.1000587.
6) Tawfik N, Elnemr HA, Fakhr M, Dessouky MI, El-Samie FE. Survey study of multimodality medical image fusion methods. *Multimedia Tools and Applications*. 2021;80:6369–6396. Available from: https://doi.org/10.1007/s11042-020-08834-5.
7) Kaur H, Koundal D, Kadyan V, Kaur N, Polat K. Automated Multimodal image fusion for brain tumor detection. *Journal of Artificial Intelligence and Systems*. 2021;3(1):68–82. Available from: https://doi.org/10.33969/AIS.2021.31005.
8) Kader AE, Xu I, Shuai G, Saminu Z, Javaid S, Ahmad IS, et al. Differential deep convolutional neural network model for brain tumor classification. *Brain Sciences*. 2021;11(3):352–352. Available from: https://doi.org/10.3390/brainsci11030352.
9) Swarup C, Singh KU, Kumar A, Pandey SK, Singh T. Brain tumor detection using CNN, AlexNet & GoogLeNet ensembling learning approaches. *Electronic Research Archive*. 2023;31(5):2900–2924. Available from: https://doi.org/10.3934/era.2023146.
10) Padmini B, Johnson CS, Kumar A, Yadav B, G. Brain tumor detection by using CNN and Vgg-16. *Int Res J Modern Eng Technol Sci*. 2022;4(6):4840–4843. Available from: https://www.irjmets.com/uploadedfiles/paper/issue_6_june_2022/27282/final/fin_irjmets1656598281.pdf.
11) Younis A, Qiang L, Nyatega CO, Adamu MJ, Kawuwa HB. Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches. *Applied Sciences*. 2022;12(14). Available from: https://doi.org/10.3390/app12147282.
12) Sarkar A, Maniruzzaman M, Alahe MA, Ahmad M. An Effective and Novel Approach for Brain Tumor Classification Using AlexNet CNN Feature Extractor and Multiple Eminent Machine Learning Classifiers in MRIs. *Journal of Sensors*. 2023. Available from: https://doi.org/10.1155/2023/1224619.

13) Asiri AA, Shaf A, Ali T, Aamir M, Irfan M, Alqahtani S, et al. Brain tumor detection and classification using fine-tuned CNN with ResNet50 and U-Net model: A study on TCGA-LGG and TCIA dataset for MRI applications. *Life*. 2023;13(7):1449–1449. Available from: https://doi.org/10.3390/life13071449.
14) Atmakuri MK, Ram AG, Prasad VVKDV. Reliable image metrics-based brain tumor analysis using sensor deep learning technologies. *Measurement: Sensors*. 2023;29. Available from: https://doaj.org/article/cd0cfaaf0bf146d3b0e0c0832120b3d2.
15) Sriramakrishnan P, Kalaiselvi T, Padmapriya ST, Ramkumar S, Ponmozhi K. Online Brain Image Repositories for Brain Disease Detection. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*. 2019;(9):2278–3075. Available from: https://doi.org/10.35940/ijitee.B1134.1292S219.
16) Mahmud MI, Mamun M, Abdelgawad A. A deep analysis of brain tumor detection from mr images using deep learning networks. *Algorithms*. 2023;16(4):176–176. Available from: https://doi.org/10.3390/a16040176.
17) Kaur H, Koundal D, Kadyan V. Image Fusion Techniques: A Survey. *Archives of Computational Methods in Engineering*. 2021;28:4425–4447. Available from: https://dx.doi.org/10.1007/s11831-021-09540-7.
18) Khorasani A, Serej ND, Jalilian M, Shayganfar A, Tavakoli MB. Performance comparison of different medical image fusion algorithms for clinical glioma grade classification with advanced magnetic resonance imaging (MRI). *Scientific Reports*. 2023;13(1):17646–17646. Available from: https://doi.org/10.1038/s41598-023-43874-5.
19) Khaliki MZ, Başarslan MS. Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN. *Scientific Reports*. 2024;14(1). Available from: https://doi.org/10.1038/s41598-024-52823-9.