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Multi-modal fusion deep transfer learning for accurate brain tumor classification using magnetic resonance imaging images

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ABSTRACT

Early identification and treatment of brain tumors depend critically on accurate classification. Accurate brain tumor classification in medical imaging is essential for clinical decisions and individualized treatment plans. This paper introduces a novel method for classifying brain tumors called multimodal fusion deep transfer learning (MMFDTL) using original, contoured, and annotated magnetic resonance imaging (MRI) images to showcase its capabilities. The MMFDTL can capture complex tumor features frequently missed in analyzing individual modalities. The MMFDTL model employs three deep learning models for extracting features VGG16, Inception V3, and ResNet 50. The accuracy rate improves when combined with decision based multimodal fusion. It produces impressive outcomes of sensitivity 92.96%, specificity 98.54%, precision 93.60%, accuracy 98.80%, F1-score 93.26%, and kappa 91.86%. This research can improve medical imaging and brain tumor analysis through its multi modal fusion approach. It could give healthcare practitioners vital insights for personalized treatment plans and informed decision making.

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1. INTRODUCTION

Good diagnosis and treatment planning in medicine depends on classification of brain tumor. Determining treatment and developing an individual treatment plan based on each patient's needs requires the ability to distinguish different types of mental illness. Deep learning and image analysis techniques have advanced recently, opening new opportunities for boosting brain tumor classification accuracy. Brain tumors are an inherited disorder characterized by uncontrollably growing abnormal tissue. The timely and, at times, inaccurate detection of these tumors through manual methods is critical, whereas magnetic resonance imaging (MRI) detection is indispensable. To address this, the multi modal fusion deep transfer learning (MMFDTL) architecture combines multiple MRI modalities for comprehensive tumor analysis. Intelligent feature fusion is achieved by combining attention processes with specialized convolutional and fusion layers in an inventive way. We propose a MMFDTL technique based on the VGG16, InceptionV3, and ResNet50 models. Decision-based multimodal fusion for integration has improved the detection rate and yielded noteworthy outcomes. This approach can improve medical imaging and brain tumor analysis, facilitating better informed clinical decisions [1]-[3]. Brain tumor identification necessitates accurately separating malignant tissues from healthy brain structures. Segmentation of MRI images requires a lot of effort and time. Computer services provide effective solutions. To help doctors provide accurate diagnosis and classification, this article introduces tumor classification. The model plans to use deep learning techniques to provide brain diagnoses using medical data. Because this method connects information from many sources, the model can obtain a complete representation of the tumor and increase the accuracy of diagnosis. To improve patient outcomes and facilitate more accurate treatment planning, research aims to increase the effectiveness of psychiatric diagnosis [4]. The complexity of the data determines the model dependence of brain MR imaging. This study improves the understanding of the link between model performance and image features by examining the impact of data complexity on classification. Improving care and patient management can be facilitated by using test results that indicate the development of Alzheimer's disease and brain tumors [5]-[7].

Ottom *et al.* [8] proposed a new ZNet framework uses deep neural networks and data augmentation to segment brain tumors in MR images accurately. This method achieved high MCC of 0.81, F1-score of 0.81, pixel accuracy of 0.996, and dice coefficient of 0.96 in training, 0.92 in testing. ZNet works well in localizing and identifying tumors, allowing general application to other models and diseases. Asif *et al.* [9] explain a timely diagnosis of brain tumors requires accurate MRI classification. The efficient tumor classification in this work is achieved by using deep learning transfer models (Xception, NasNet, DenseNet121, InceptionResNetV2). The proposed convolutional neural network (CNN) model outperforms current techniques for accurate and quick brain tumor classification, achieving superior accuracy of 99.67% and performance based on Xception with ADAM optimization. Zhou *et al.* [10], MRI is essential for evaluating brain tumors. In order to increase robustness, a correlation model is used in this paper's innovative segmentation approach for missing modalities. It is more effective at handling absent modalities than state-of-the-art techniques, as demonstrated by tests conducted on BRATS datasets. Pereira *et al.* [11], aggressive brain tumors like gliomas require careful treatment planning. Automatic techniques are necessary since manual MRI segmentation takes a long time. Performance is improved by intensity normalization and augmentation, and this study suggests CNN-based segmentation with 3×3 kernels to boost architecture depth. The approach shows excellent segmentation performance in the BRATS 2013 and 2015 challenges. Zhou *et al.* [12], OM-Net uses a single-pass technique to handle the class imbalance problem in medical picture segmentation. Utilizing guided attention and correlations, it integrates activities into a deep model to achieve the best learning outcomes. OM-Net is effective at improving brain tumor segmentation, as evidenced by its performance on BRATS datasets and victories in challenges.

Zhou *et al.* [13], Through Bessel beam-based photoacoustic microscopy (PAM) and deep learning, clear images of hemoglobin concentration, oxygen saturation, and cerebral blood flow in living rats' brains can be improved. Compared to Gaussian beam PAM, high resolution decreases detection error, which may benefit cancer diagnosis and prognosis. Chen *et al.* [14] the model uses 3D CNNs to increase accuracy and combine previous experience with behavioral analysis of the electronic expert. It achieved 97.2% sensitivity and 86.3% accuracy on the Meme-CEUS dataset. Chang *et al.* [15] proposed a new MSCSC method. MSCSC is instrumental in general education, transferring scholarly work across various biomedical fields, obtaining specialized indicator filter banks, and sharing valuable knowledge across majors. Introducing a novel cascade CNN for genotype prediction and brain glioma segmentation, Liu *et al.* [16]. Combining multiple combinations and local optimization, our method achieves competitive genotype prediction (94.85% accuracy) and excellent segmentation accuracy (77.03% Dice) in MR images. Tupe-Waghmare *et al.* [17] and colleagues proposed a semi-supervised hierarchical multitask model provided the most accurate molecular marker prediction for high-grade gliomas. Leveraging multimodal MRI and unlabeled data, our method achieved 82.35% testing accuracy, leading to clinical interpretation from class to map to complete genetic analysis.

Figure 1 shows the changes in brain MRI. Original image to contour to annotated image that shows the distribution of MRI data for brain tumors. This transformation uses three levels of image processing to accurately and effectively differentiate brain tumor types, like gliomas, meningiomas, pituitary tumors, and no tumors. The morphological and structural characteristics of the brain are captured in this raw image, which is crucial information for further analysis. The outlines or contours of the brain tumors seen in the original MRI are then extracted using sophisticated image processing techniques in the contour image stage. By emphasizing the tumors' borders, this contour representation makes it easier to see how they are arranged spatially and what they seem like. Making annotated photographs is the last step. The tumor type, size, and other pertinent diagnostic information indicated thorough annotations applied by skilled radiologists or trained algorithms to the retrieved tumor patches on the contour pictures.

Combining these continuous changes increases the accuracy and efficiency of classifying brain tumors. By simplifying the analysis process, original MR images are converted into contoured images and annotations, providing doctors with additional information to make informed decisions. Furthermore, this approach sets the path for future developments in neuro-oncology clinical research, individualized therapy planning, and computer-aided diagnosis.

The paper's significant contributions are as follows:

- Increasing the quality of images by applying pre-processing techniques like sharpening, removing artifacts, and contrast enhancement.
- The novel MMF-DTL model for brain tumor classification has been introduced. It combines three deep learning techniques: VGG-16, ResNet 50, and Inception v3.
- Creating a user-friendly interface for the MMFDTL model expedites the diagnosis procedure and offers invaluable assistance in the ongoing scenario.

This article follows the following structure: 1. introduction, 2. method, 3. results and discussion, 4. conclusion.

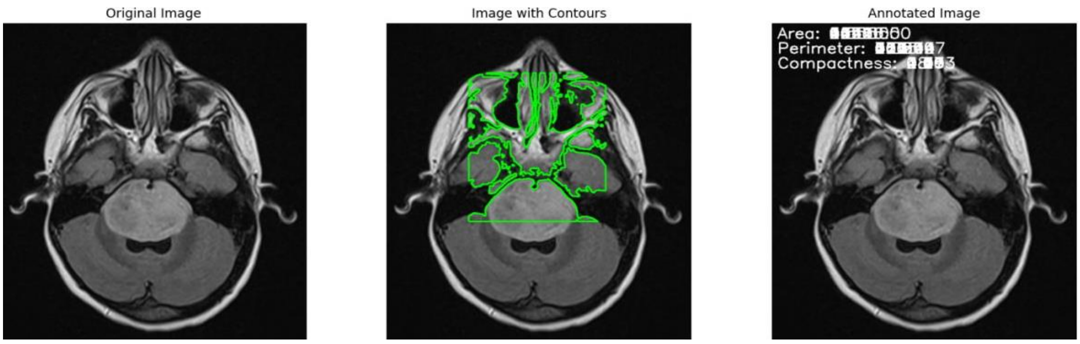

Figure 1. Sequential transformation of brain MRI: Original image to contour to annotated image

2. METHOD

A novel MMFDTL method was developed to identify and categorize brain tumor. Figure 2 shows the process of implementing this approach. It has different stages like preprocessing, feature extraction, fusion model, and classification.

2.1. Image preprocessing

MRI images are prepared carefully for annotation and contouring throughout the preprocessing phase. This critical stage guarantees the best possible data quality before being fed into the MMFDTL model for brain tumor identification and classification. Contrast enhancement techniques are utilized by highlighting pertinent elements in the pictures and improving the visibility of tumor boundaries and other essential details [18]. Carefully carried out artifact removal processes eliminate undesired noise or distortions that could make analysis more difficult. Image sharpening techniques are also utilized to improve the sharpness and clarity of contours to further assist in extracting complex tumor characteristics. This thorough preprocessing guarantees that the contoured and annotated MRI images are ready for efficient feature extraction and subsequent classification in the MMFDTL framework.

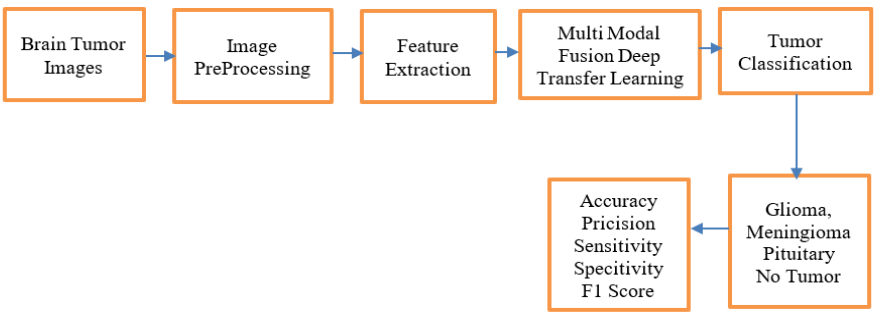

Figure 2. Proposed MMFDTL architecture

2.2. Images enhancing

Enhancing the contrast and emphasizing the unique features in an MRI image of a brain tumor is made possible through image enhancement techniques. Sharpening is achieved by convolving a particular kernel with the brain tumor MRI picture by applying a 2D filter model, which removes unnecessary noise. It can be helpful to apply a maximum filter, which calculates the mean of the pixel values inside a specified window. In particular, a 3×3 averaging filter kernel is frequently employed [19]. An organized method is used to apply image sharpening to an MRI of a brain tumor: each pixel in the image is placed in the center of a 3×3 window, and the values of each pixel inside this window are added together and divided by 9. All of the image's pixels go through this process, producing an improved image that successfully brings out the distinctive features of the brain tumor [20]. This sharpening procedure increases visibility and facilitates the precise study of the unique characteristics of the brain tumor.

2.3. Feature extraction

classification, and recognizing patterns. It involves transforming unprocessed information into a collection of relevant characteristics that capture the essence of the source material. By reducing the dimensionality of the data while retaining its vital information, feature extraction aims to improve its suitability for analysis or feeding into machine learning algorithms. For the feature extraction Noval MMFDTL technology is used to improve accuracy by combining VGG16, InceptionV3, and ResNet50 models.

2.3.1. VGG16

VGGNet-16, a robust deep CNN architecture, accomplishes brain tumor classification. Automatically extracting complex characteristics and patterns from brain tumor photos is highly successful by this architecture, consisting of 16 layers of convolutional and fully connected units in (1). VGGNet-16 ability to capture hierarchical representations is enhanced when it uses its depth, which improves its ability to distinguish between different kinds of brain tumors [21]. VGGNet-16 gains proficiency in precisely classifying brain tumors through intensive training, making a substantial contribution to medical imaging and facilitating accurate diagnosis and treatment plans.

$$j(w,b) = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\left\|k_{w,b}(x^i - y^j)\right\|2 + \frac{\lambda}{2}\sum_{(l=1)}^{n-1}\sum_{i=1}^{s}\sum_{1=1}^{s+1}\left(w_{ji}^{l}\right)^2 \tag{1}$$

2.3.2. Inception V3

Brain tumor classification is significantly improved using the Inception v3 CNN design. The sophisticated architecture of Inception v3, distinguished by parallel convolutional layers of different sizes, works well at extracting a wide range of features and patterns from brain tumor pictures. The scalability of this design makes it possible to analyze information effectively at different scales and accurately distinguish between different types of tumors [22]. By enabling accurate diagnosis and treatment plans, Inception v3 ability to categorize brain tumors is enhanced by extensive training. This provides significant benefits to medical imaging.

2.3.3. ResNet 50

Brain tumor categorization has advanced significantly using the ResNet 50 architecture. ResNet 50 deep residual learning architecture resolves gradient vanishing problems during deep neural network training, making extracting complex characteristics from brain tumor images easier [23]. The reliability and convergence of the model are enhanced by incorporating residual blocks and skip connections, which provide adequate gradient flow. Using ResNet 50 improves the ability to differentiate between different types of brain tumors, which fortifies medical imaging and makes it easier for clinicians to make educated decisions that lead to precise diagnoses and individualized treatment plans. In (2), the residue entry is represented by x, the weight associated with the residue is represented by y, and the value produced by the residue is represented by w.

$$W = f(x,y) + x \tag{2}$$

2.3.4. MMFDTL fusion

MMFDTL fusion technology leverages tumors and patterns by combining features of various deep transfer learning models such as VGG16, Inception V3, and ResNet 50. This fusion technique improves overall accuracy by harnessing the strengths of each model and combining their features [24]. The MMFDTL fusion method combines the power of multiple deep-learning models to classify tumor cells, thereby increasing the power and accuracy of image editing and enabling patients to make confident and informed medical decisions. This new method effectively captures complex tumor characteristics often missed when analyzing individual modalities by combining the power of original, contoured, and annotated MRI images. Modality-specific features are cleverly combined, and pertinent regions are highlighted thanks to a carefully thought-out architecture with specialized convolutional and fusion layers enhanced with attention methods in order to improve the accuracy, it also uses a multi-modal fusion process. This model uses VGG16, Inception V3, and ResNet50 for feature extraction [25], [26]. The resulting fusion model provides quality metrics such as sensitivity, specificity, accuracy, precision, F1-score, and Kappa. It suggests a path forward for improving brain tumor detection and classification precision in medical imaging and clinical practice [27].

A popular method for managing multiclass classification tasks is the softmax classification process, which entails using the feature vectors gathered from the earlier phases as input for the softmax classifier. In (3) illustrates how this classifier maps an input vector "i" into a higher-dimensional space with "N" dimensions, which corresponds to the number of output classes "K":

$$y_i = \frac{\exp\left(\theta_j^T i\right)}{\sum_{k=1}^{k} exp\ (\theta_k^T i)} \tag{3}$$

here, in (3), $\theta_k = [\theta_{k1}, \theta_{k2}, \theta_{k3} \dots \dots \dots . . \theta_{kn}]$ represents the weight vector associated with class "k," optimized by the algorithm. The output of this layer corresponds to the class probabilities in the brain tumor classification.

3. RESULTS AND DISCUSSION

The MMFDTL fusion technique introduces a comprehensive approach to enhance brain tumor classification accuracy. The MMFDTL method uses four types of tumors in the data sets (gliomas, meningiomas, pituitary tumors, and no-tumors) to plot original, contour, and histograms. Before the transformation, the original MRI pictures undergo necessary pre-processing stages like noise removal, denoising, and intensity normalization. Pre-processing methods like this guarantee data consistency while enhancing image quality. The original MRI images are processed using sophisticated techniques to create contour images. Histogram representation will be used for feature extraction in addition to contour and annotated images. Histograms provide information about the pixel intensity features of cancer by capturing the pixel intensity distributions within the regions affected by tumors. Annotated images with histogram representation result from the transformation process, which sequentially begins with the original MRI image and ends with a contour image. This sequential method makes possible practical and precise feature extraction for tumor classification. A comprehensive analysis uses multiple classification approaches on the altered images and their histogram representations. The study carefully compares different classification models to determine the best model to classify tumors.

Figure 3 Glioma dataset visualization selection based on Glioma-specific MRI imaging. The glioma collection has been selected carefully to cover various cancer types and grades. Tumour shapes and spatial properties can be more clearly visualized via contour images, drawing attention to glioma tumor boundaries. Following contour image production, expert radiologists or automated algorithms annotate the images with pertinent diagnostic information. Because the annotations provide information about the glioma tumors' location, size, and grade, the photos are very instructive for further investigations. Histogram representation will be used for feature extraction. The sequential method makes practical and precise feature extraction for glioma tumor classification possible.

Figure 4 meningioma dataset visualisation the selection process concentrates on a dataset, including meningioma tumor MRI scans. Carefully selected meningioma cases comprise the dataset, allowing for a thorough study. The accurate contours of meningioma tumors are brought to light by contour pictures, which improve the visualization of the tumor's boundaries and spatial features. The photos are helpful for further investigations since the annotations provide information about the meningioma tumors, including their location, size, and kind. The pixel intensity distributions within the meningioma tumor zones are captured by histograms, which provide insights into the pixel intensity properties of cancer. The purpose of classifying meningioma tumors is that this sequential method enables precise and efficient feature extraction.

Figure 5 Pituitary dataset visualisation focuses on a specific dataset comprising pituitary tumor MRI scans. The dataset is carefully chosen to ensure a representative sample of pituitary tumor cases for comprehensive analysis. Contour images highlight the boundaries of pituitary tumors, enabling better visualization of the tumor's spatial distribution and shape characteristics. Annotations provide detailed information about the pituitary tumors, including tumor type, size, and location, making the images informative for subsequent analysis. Histograms are constructed based on pixel intensity distributions, providing insights into the distribution of image intensities within the pituitary tumor regions. The entire process follows a sequential transformation, from the original MRI image to the contour image and finally to the annotated image with histogram representation. This sequential approach enables efficient and effective feature extraction for accurate pituitary tumor classification.

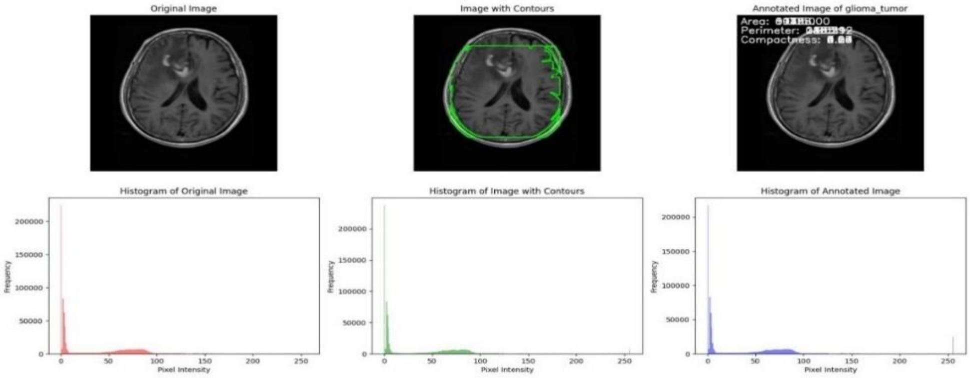

Figure 3. Transformation of glioma data set of original image to contour to annotated image with histogram representation

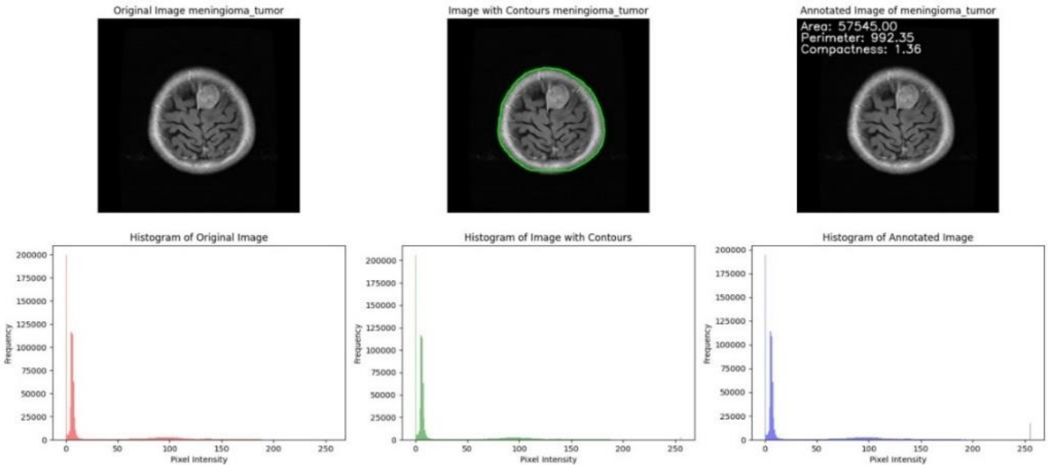

Figure 4. Transformation of meningioma data set of original image to contour to annotated image with histogram representation

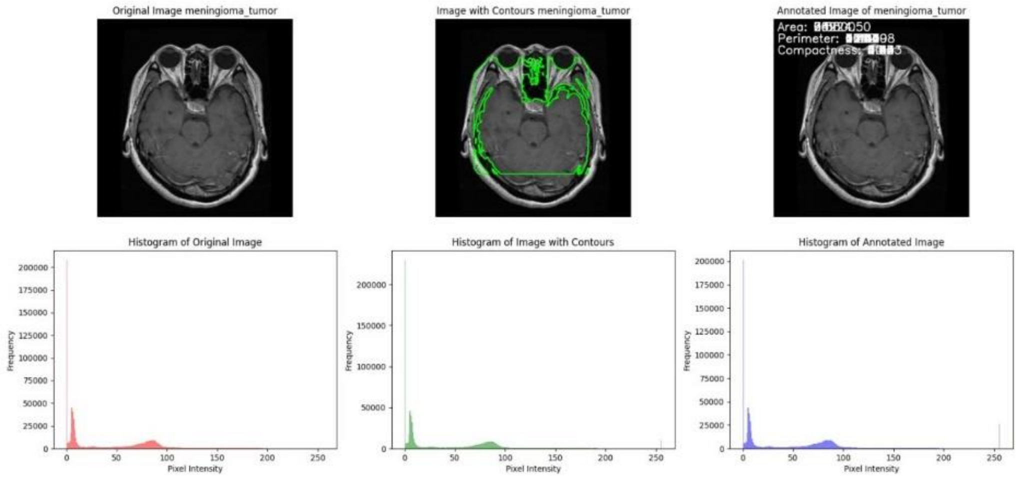

Figure 5. Transformation of pituarity data set of original image to contour to annotated image with histogram representation

Figure 6 represents the training and validation model accuracy of Figure 6(a) VGG16, Figure 6(b) ResNet 50, Figure 6(c) Inception V3, and Figure 6(d) MMFDTL. The x-axis represents epochs, and y-axis represent the accuracy. The accuracy ranges from 0.1 to 1, with 50 epochs, and the analysis shows significant improvements in training methods as the number of epochs increases. More importantly, Figure 6 shows the superior performance of the fusion model, which consistently achieves better accuracy than other models.

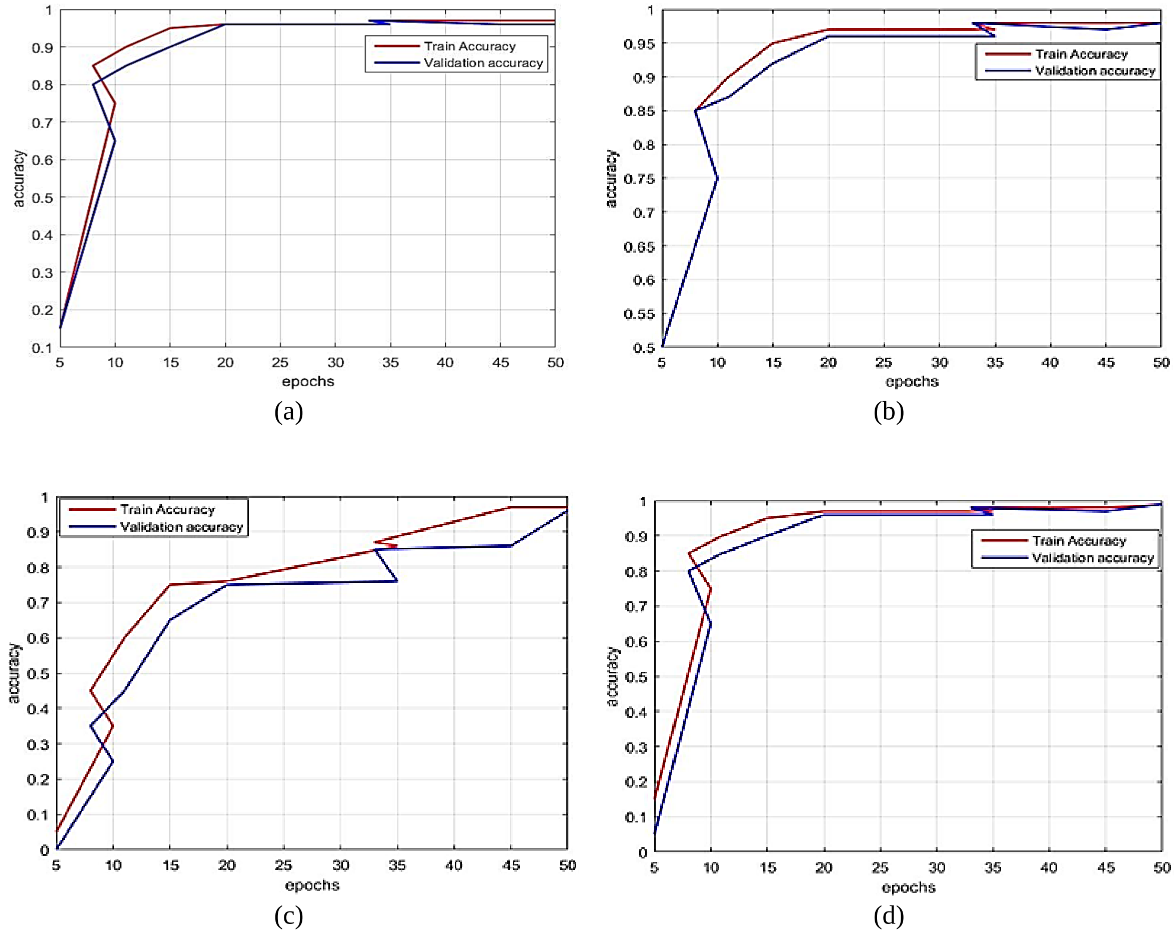

Figure 6. Displays the train and validation accuracy trends of: (a) VGG16, (b) ResNet 50, (c) Inception V3, and (d) MMFDTL

Figure 7 represents loss patterns of training and validation for Figure 7(a) VGG16, Figure 7(b) ResNet 50, Figure 7(c) Inception V3, and Figure 7(d) MMFDTL. The epoches are represented on x-axis, and the loss ranging from 0.1 to 1 over the 25 epochs are represented on y-axis. As the number of epochs increases, the value decreases more clearly, as seen in Figure 7. More importantly, the fusion method is effective and consistently achieves the minimum loss rates across the observations. Table 1 shows the predominance values in the confusion matrix, paying particular attention to the entries like true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

The evaluation is performed on a dataset with six classes in Table 2 comparison study with different models. The MMFDTL fusion model achieved a 92.96% sensitivity, 98.54% specificity, 93.60% precision, 98.80% accuracy, and 93.26% F1-score. The Inception V3 model, on the other hand, measured 94.49% sensitivity, 98.38% specificity, 87.28% precision, 98.00% accuracy, and 90.44% F1-score. The ResNet-50 model performed 88.13% sensitivity, 97.95% specificity, 84.07% precision, 97.04% accuracy, and 84.60% F1-score. The VGG16 model achieved a 86.94% sensitivity, 97.94% specificity, 82.46% precision, 96.79% accuracy, and 83.12% F1-score. From the above observation, it was observed that MMFDTL has better performance than other models. Compared to the other models depicted in Figure 8, these findings highlight the suggested fusion model's superior accuracy and performance of other critical criteria.

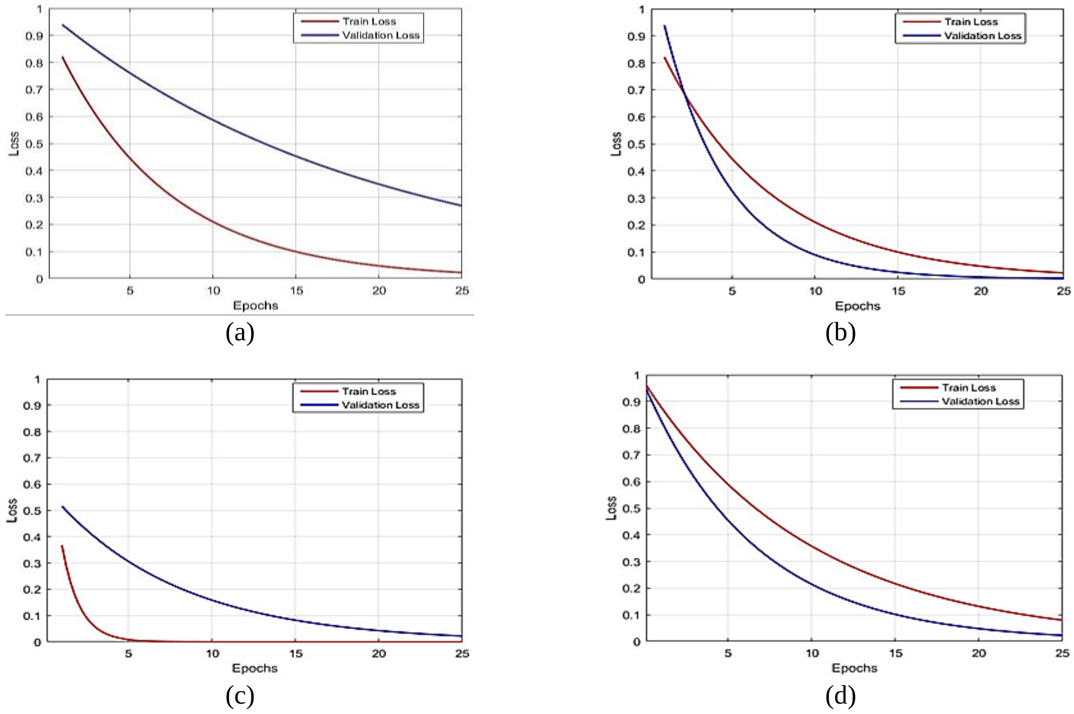

Figure 7. Illustrates the train and validation loss patterns of: (a) VGG16, (b) ResNet 50, (c) Inception V3, and (d) MMFDTL

Table 1. Analysis of the confusion matrix

Classes	VGG16 model						Classes	ResNet50 model					
	1	2	3	4	5	6		1	2	3	4	5	6
TP	10	201	27	15	7	17	TP	11	202	27	15	7	17
TN	267	76	250	262	270	260	TN	268	77	252	264	272	262
FP	7	2	13	5	0	1	FP	8	3	10	5	0	0
FN	5	19	0	0	4	0	FN	4	18	0	0	4	0
Classes	Inception V3 model						Classes	MMFDTL fusion model					
	1	2	3	4	5	6		1	2	3	4	5	6
TP	11	206	27	15	11	17	TP	9	215	27	15	11	17
TN	276	81	260	272	276	270	TN	285	79	267	279	283	277
FP	7	4	0	5	0	2	FP	5	6	0	0	0	0
FN	4	14	0	0	0	0	FN	6	5	0	0	0	0

Table 2. Comparative analysis of the various approaches to the proposed model

Methods	No. of classes	Sensitivity	Specificity	Precision	Accuracy	F-score
MMFDTL fusion	6	92.96	98.54	93.6	98.8	93.26
Inception V3	6	94.49	98.38	87.28	98	90.44
ResNet 50	6	88.13	97.95	84.07	97.04	84.6
VGG 16	6	86.94	97.94	82.46	96.79	83.12

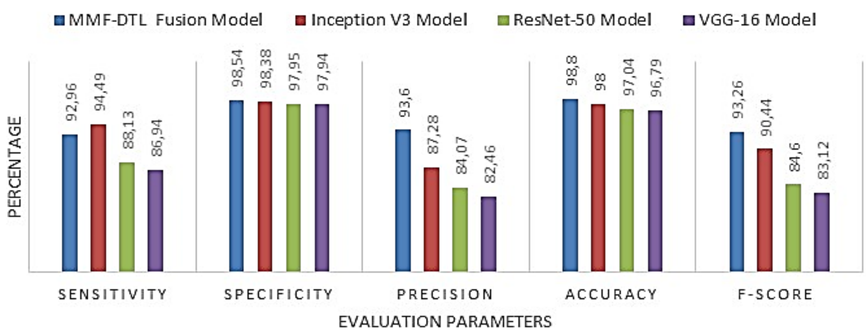

Figure 8. Comparative analysis of various approaches

4. CONCLUSION

In summary, brain tumors classificaiton is essential for suitable treatment planning in clinical practice. Brain tumor classification is essential for making informed clinical decisions and developing individualized treatment plans. Regarding brain tumor categorization, the suggested MMFDTL design offers a promising development. Using the combined strength of original, contoured, and annotated MRI images, the MMFDTL model can recognize complex tumor features frequently disregarded in separate modalities. Combining features with convolution and fusion techniques can improve the feature extraction ability of the model. The MMFDTL model showed an accuracy of 98.80%, precision of 93.60%, sensitivity of 92.96%, specificity of 98.54%, F1 score of 93.26%, and kappa of 91.86%. The new combination of different types of deep transform learning improves accuracy by combining VGG16, Inception v3, and ResNet 50 models. Comparative investigation confirms MMFDTL's superiority, demonstrated by several noteworthy metrics such as kappa, F-score, accuracy, precision, sensitivity, and specificity. It is possible to improve fusion efficacy by conducting additional optimization of the MMFDTL design by including sophisticated regularization techniques. Achieving even better performance involves investigating incorporating other deep learning models, like transformer-based architectures.

REFERENCES

[1] B. Anilkumar, N. P. Kumar, and K. Sowmya, "MR brain tumour classification using a deep ensemble learning technique," Jan. 2023, doi: 10.1109/ICNTE56631.2023.10146712.
[2] G. Karayegen and M. F. Aksahin, "Brain tumor prediction with deep learning and tumor volume calculation," Nov. 2021, doi: 10.1109/TIPTEKNO53239.2021.9632861.
[3] A. Banerjee and D. K. Atal, "Optimized deep learning technique for brain tumor segmenting, contouring, and detection," in *Proceedings of 4th International Conference on Cybernetics, Cognition and Machine Learning Applications, ICCCMLA 2022*, Oct. 2022, pp. 302–307, doi: 10.1109/ICCCMLA56841.2022.9989198.
[4] S. Solanki, U. P. Singh, S. S. Chouhan, and S. Jain, "Brain tumor detection and classification using intelligence techniques: an overview," *IEEE Access*, vol. 11, pp. 12870–12886, 2023, doi: 10.1109/ACCESS.2023.3242666.
[5] A. Kujur, Z. Raza, A. A. Khan, and C. Wechtaisong, "Data complexity based evaluation of the model dependence of brain MRI images for classification of brain tumor and alzheimer's disease," *IEEE Access*, vol. 10, pp. 112117–112133, 2022, doi: 10.1109/ACCESS.2022.3216393.
[6] J. P. Amorim, P. H. Abreu, A. Fernandez, M. Reyes, J. Santos, and M. H. Abreu, "Interpreting deep machine learning models: an easy guide for oncologists," *IEEE Reviews in Biomedical Engineering*, vol. 16, pp. 192–207, 2023, doi: 10.1109/RBME.2021.3131358.
[7] M. Ali, S. O. Gilani, A. Waris, K. Zafar, and M. Jamil, "Brain tumour image segmentation using deep networks," *IEEE Access*, vol. 8, pp. 153589–153598, 2020, doi: 10.1109/ACCESS.2020.3018160.
[8] M. A. Ottom, H. A. Rahman, and I. D. Dinov, "Znet: deep learning approach for 2D MRI brain tumor segmentation," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 10, pp. 1–8, 2022, doi: 10.1109/JTEHM.2022.3176737.
[9] S. Asif, W. Yi, Q. U. Ain, J. Hou, T. Yi, and J. Si, "Improving effectiveness of different deep transfer learning-based models for detecting brain tumors from MR images," *IEEE Access*, vol. 10, pp. 34716–34730, 2022, doi: 10.1109/ACCESS.2022.3153306.
[10] T. Zhou, S. Canu, P. Vera, and S. Ruan, "Latent correlation representation learning for brain tumor segmentation with missing MRI modalities," *IEEE Transactions on Image Processing*, vol. 30, pp. 4263–4274, 2021, doi: 10.1109/TIP.2021.3070752.
[11] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1240–1251, May 2016, doi: 10.1109/TMI.2016.2538465.
[12] C. Zhou, C. Ding, X. Wang, Z. Lu, and D. Tao, "One-pass multi-task networks with cross-task guided attention for brain tumor segmentation," *IEEE Transactions on Image Processing*, vol. 29, pp. 4516–4529, 2020, doi: 10.1109/TIP.2020.2973510.
[13] Y. Zhou, N. Sun, and S. Hu, "Deep learning-powered bessel-beam multiparametric photoacoustic microscopy," *IEEE Transactions on Medical Imaging*, vol. 41, no. 12, pp. 3544–3551, Dec. 2022, doi: 10.1109/TMI.2022.3188739.
[14] C. Chen, Y. Wang, J. Niu, X. Liu, Q. Li, and X. Gong, "Domain knowledge powered deep learning for breast cancer diagnosis based on contrast-enhanced ultrasound videos," *IEEE Transactions on Medical Imaging*, vol. 40, no. 9, pp. 2439–2451, Sep. 2021, doi: 10.1109/TMI.2021.3078370.
[15] H. Chang, J. Han, C. Zhong, A. M. Snijders, and J. H. Mao, "Unsupervised transfer learning via multi-scale convolutional sparse coding for biomedical applications," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 5, pp. 1182–1194, May 2018, doi: 10.1109/TPAMI.2017.2656884.
[16] J. Liu *et al.*, "A cascaded deep convolutional neural network for joint segmentation and genotype prediction of brainstem gliomas," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 9, pp. 1943–1952, Sep. 2018, doi: 10.1109/TBME.2018.2845706.
[17] P. Tupe-Waghmare *et al.*, "Comprehensive genomic subtyping of glioma using semi-supervised multi-task deep learning on Multimodal MRI," *IEEE Access*, vol. 9, pp. 167900–167910, 2021, doi: 10.1109/ACCESS.2021.3136293.
[18] N. Kesav and M. G. Jibukumar, "Multi-Channel CNN based image classification using SKIP connection and MSVM," *International Journal of Computers and Applications*, vol. 44, no. 10, pp. 981–990, Mar. 2022, doi: 10.1080/1206212X.2022.2047443.
[19] M. M. Islam, P. Barua, M. Rahman, T. Ahammed, L. Akter, and J. Uddin, "Transfer learning architectures with fine-tuning for brain tumor classification using magnetic resonance imaging," *Healthcare Analytics*, vol. 4, p. 100270, Dec. 2023, doi: 10.1016/j.health.2023.100270.
[20] P. Kanchanamala, K. G. Revathi, and M. B. J. Ananth, "Optimization-enabled hybrid deep learning for brain tumor detection and classification from MRI," *Biomedical Signal Processing and Control*, vol. 84, p. 104955, Jul. 2023, doi: 10.1016/j.bspc.2023.104955.
[21] H. Mzoughi *et al.*, "Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification," *Journal of Digital Imaging*, vol. 33, no. 4, pp. 903–915, May 2020, doi: 10.1007/s10278-020-00347-9.
[22] S. Divya, L. Padma Suresh, and A. John, "Enhanced deep-joint segmentation with deep learning networks of glioma tumor for multi-grade classification using MR images," *Pattern Analysis and Applications*, vol. 25, no. 4, pp. 891–911, Jul. 2022, doi: 10.1007/s10044-022-01064-5.

[23] S. Kumar and D. P. Mankame, “Optimization driven deep convolution neural network for brain tumor classification,” *Biocybernetics and Biomedical Engineering*, vol. 40, no. 3, pp. 1190–1204, Jul. 2020, doi: 10.1016/j.bbe.2020.05.009.
[24] G. Latif, “DeepTumor: framework for brain MR image classification, segmentation and tumor detection,” *Diagnostics*, vol. 12, no. 11, p. 2888, Nov. 2022, doi: 10.3390/diagnostics12112888.
[25] I. Javaid, S. Zhang, A. E. K. Isselmou, S. Kamhi, I. S. Ahmad, and U. Kulsum, “Brain tumor classification & segmentation by using advanced DNN, CNN & ResNet-50 neural networks,” *International Journal of Circuits, Systems and Signal Processing*, vol. 14, pp. 1011–1029, Dec. 2020, doi: 10.46300/9106.2020.14.129.
[26] R. Pillai, A. Sharma, N. Sharma, and R. Gupta, “Brain tumor classification using VGG 16, ResNet50, and inception V3 transfer learning models,” Mar. 2023, doi: 10.1109/INOCON57975.2023.10101252.
[27] S. Das, O. F. M. R. R. Aranya, and N. N. Labiba, “Brain tumor classification using convolutional neural network,” May 2019, doi: 10.1109/ICASERT.2019.8934603.

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