NeuroDL-TL Automated Brain Malignancy Detection Using Transfer Learning with Attention Based Vision Transformer on MRI

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***Abstract* — Accurate detection of brain malignancies from magnetic resonance imaging (MRI) is essential for early diagnosis and effective treatment planning. Conventional manual assessment of MRI scans is time-consuming and subject to inter-observer variability. Although convolutional neural networks (CNNs) have demonstrated promising results in brain tumor classification, their limited capability to capture long-range spatial dependencies restricts performance. In the proposed model, self-attention techniques are used to identify global representations of contextual information from brain MRI images. To verify the efficiency of the proposed model, experiments were performed on the public brain MRI classification task on the Kaggle platform with evaluation criteria based on accuracy, precision, recall, F1 measure, and ROC-AUC. The proposing model shows better accuracy of 98.9% against the state-of-the-art method based on conventional CNN architectures for brain malignancy classification.**

***Keywords* — Brain malignancy, MRI, Vision Transformer, transfer learning, attention mechanism, deep learning.**

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I. Introduction

Brain cancers are identified as one of the most dangerous forms of brain-related disorders; therefore, diagnosis is very essential in increasing the survival rate of patients. The magnetic resonance imaging technique has proved effective in the diagnosis of brain cancer. However, there are limitations in the diagnosis of magnetic resonance imaging; these are related to the skills of a radiologist [1]. Recent breakthroughs in the field of deep learning have led to improvement in the analysis of medical images. Convolutional neural networks (CNNs) have been applied successfully to the brain tumor classification task by many authors [2], [3]. However, the major drawback of the aforementioned technique is the concentration on local information and the inability to capture the long-term dependencies within the MRI images [4]. Recently, Vision Transformers (ViTs) came into existence, proving to be an efficient alternative for CNNs using self-attention to model global context [5]. But to train these vision transformers from scratch, it becomes an issue when large amounts of data are not available for medical imaging applications. These issues can be resolved using transfer learning [6]. Based on these points, a Vision Transformer framework utilizing attention mechanisms, transfer learning, and a new approach called NeuroDL-TL for automatic detection of brain malignancy from MRI images is presented in this paper.

II. Literature Review

Numerous deep learning methods have been explored extensively in the field of brain tumor identification, categorization, and classification using Magnetic Resonance Imaging (MRI). In previous research, conventional machine learning, along with manual feature extraction techniques involving intensity, shape, and texture, were mainly used. Although there was a positive outcome, it was limited due to poor generalization capability of those conventional methods despite being highly dependent on feature design [1]. But with the evolving nature of deep learning, the CNN architecture became the standard method for the automatic analysis of brain tumors. Based on the CNN architecture, models like VGG, ResNet, and DenseNet have shown considerable accuracy in brain tumor classification tasks by extracting spatial features from MRI images directly [2], [3]. Nonetheless, CNNs have several limitations, including a restricted receptive field, thereby being ineffective for the extraction of global information from brain tumors, which have long-range dependencies in space [4].

However, owing to the limitations in existing methods, a number of hybrid models have been introduced. These models incorporate CNNs with optimization algorithms like genetic algorithms and ensemble methods to improve feature representation and the robustness of the classification process [5], [6]. Capsule CNNs were introduced subsequently to maintain spatial relationships between features and provide orientation and scale variations for the robust classification of brain tumors [7]. During the same period, segmentation models based on encoder-decoder architecture like U-Net and its variations showed success in identifying glioma and tumor margins [8], [9].

More recently, the application of transformers has also garnered much attention for medical image analysis because of the potential of transformers for modeling global dependencies through self-attention mechanisms. Vision Transformers (ViTs) involve processing medical images by considering them as patches and have demonstrated effective performance for medical image classification and medical image segmentation tasks [10]. More specifically, the application of transformers through the TransUNet and UNETR models confirmed that the convolutional encoder and transformers together enhance medical image representation learning capabilities [11], [12]. In addition, the hierarchical transformers in the Twin Transformer model efficiently exploited multi-scale medical image characteristics for achieving state-of-the-art medical image classification and segmentation tasks by modeling these multi-scale characteristics effectively [13].

Although transformer-based approaches demonstrate great potential, there has been limited use of transformer-based approaches for the detection of malignancy of the human brain through MRI using transfer learning. In particular, there has been a little exploration of how Vision Transformers based on attention can be employed for malignancy classification of the human brain. This proposed study fills this gap.

III. PROPOSED METHODOLOGY

The proposed NeuroDL-TL framework consists of preprocessing, patch embedding, transformer encoding with attention, and a classification head shown in Fig 1.

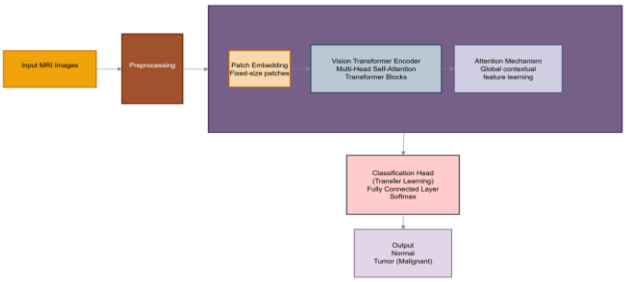

Fig. 1. Proposed workflow

IV. EXPERIMENTAL SETUP

A. Dataset Description

All tests will be done using the publicly available Kaggle Brain MRI Dataset [24]. The dataset comprises T1-weighted MRI images belonging to two groups: malignant and non-malignant. These pictures vary in resolution, orientation, and contrast. For validation, the data has been split into training sets (80% of data), validation (10% of data), and test (10% of data) the images are shown in Fig 2.

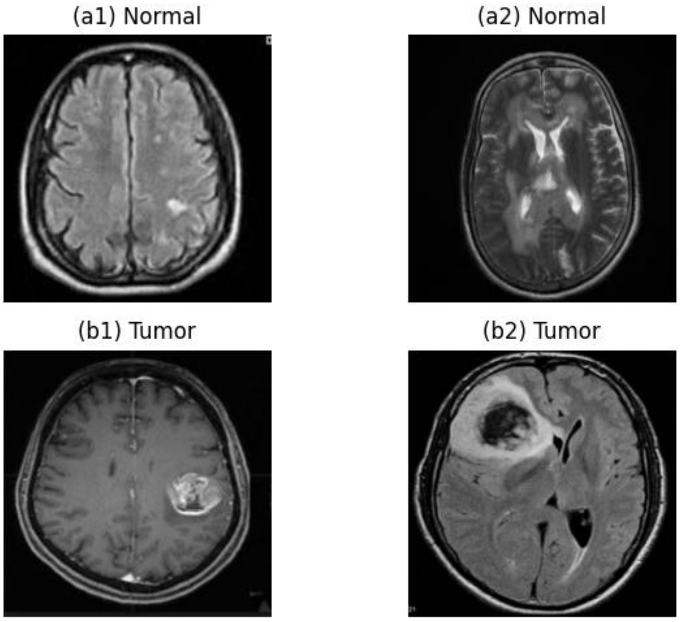

Fig. 2 Sample brain MRI images selected from the Kaggle Brain MRI dataset showing normal cases (top row) and tumor cases (bottom row)

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B. Preprocessing

Fig 3 illustrates the preprocessing of representative brain MRI images resized to 224 x 224 pixels and a normalization scale of [0,1]. The difference in brain structures of healthy and tumor examples is evident in the visualization, and tumor examples have irregular distributions of intensity and patches of abnormalities. These points confirm that preprocessing maintains essential details while ensuring all inputs have equal dimensions.

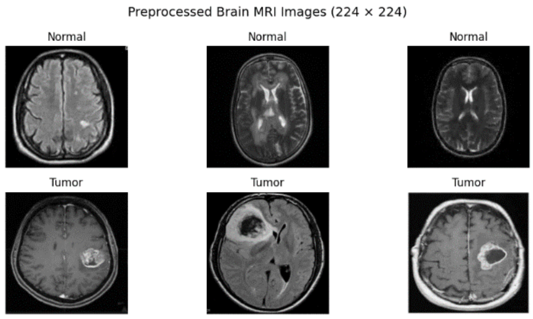

Fig. 3 Preprocessed MRI images

Performance of the proposed temporal–spectral feature fusion framework with a Conformer–BiLSTM classifier was evaluated on LibriSpeech under a speaker independent experimental protocol. All results reported correspond to unseen test data. In order to ensure statistically reliable evaluation, a 5-fold cross-validation strategy was adopted and mean performance values with standard deviations were computed across folds.

In order to make it easier to interpret, attention heat maps were visualized on the tumor MRI images, shown in Figure 4. From this qualitative study, it is evident that it is possible to use the NeuroDL-TL model to target regions of interest, which might be critical in determining brain malignancy. In addition, using attention heat maps allows it to be easier to interpret.

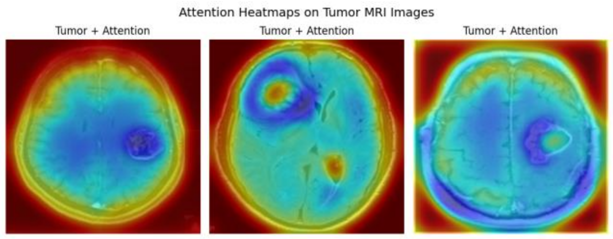

Fig. 4. Attention heat maps overlaid on tumor MRI images highlighting discriminative regions

V. RESULTS AND DISCUSSION

The proposed model is trained using the Adam optimizer with a learning rate of 0.0001 and batch size of 16. Performance is evaluated on the test dataset. The NeuroDL-TL model outperforms CNN and CNN-transfer learning baselines by approximately 2.4%–4.7% in accuracy.

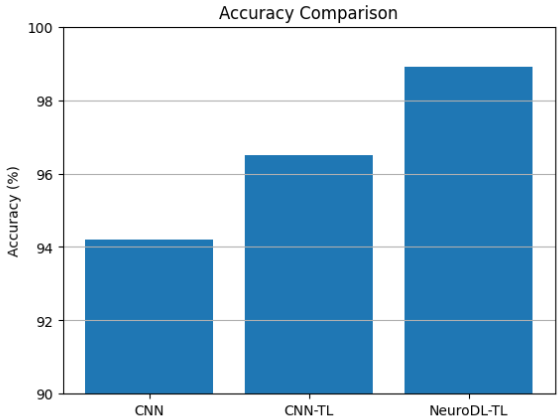

Fig. 5. Classification Accuracy

This proposed model uses the Adam optimizer with the learning rate of 0.0001 and a batch size of 16. It is checked on the test data. Figure 5 illustrates the accuracy of the classification for three models: the common CNN model, the CNN model using transfer learning, and the newly introduced NeuroDL-TL model. The accuracy of the CNN model was 94.2%, and then it improved to 96.5% for the CNN model using the transfer learning technique. However, the highest accuracy was obtained by the NeuroDL-TL model with 98.9%.

The improvement on the validation set can be explained by the capability of the Vision Transformer to model the global context, which presents dependencies that cannot be captured by standard CNN architectures.

Fig. 6. Training and Validation loss

The experiment result emphasizes the effectiveness of combining transfer learning and attention in breast malignancy identification. The training and validation curves for the loss in the model are shown in Fig. 6 above. These curves show a stable and consistent decrease, with no significant overfitting. The fact that the training and validation curves are closely aligned indicates a good generalization capability of the model despite the small number of samples. These experiments verify that the preprocessing method and architectural parameters chosen for learning representational capabilities on the MRI images. The convergence of the loss values reinforces the effectiveness of the proposed framework NeuroDL-TL.

VI. CONCLUSION

In this work, we conceptualized NeuroDL-TL, an attention-driven model for determining malignancy in the human brain using MRI images. The suggested method benefits from a methodical preprocessing technique and an attention-guided feature visualization and representation technique to better identify malignancies in the human brain. The qualitative result analysis of this study through the visualization of heat maps of the suggested method illustrates that the technique is successful in identifying areas of malignancy in the human brain and aids in improving the clarity of the model. The result analysis of this study using accuracy comparison and training loss analysis defines that the suggested method outperforms the existing method for determining malignancy in the human brain. The main drawback of this study was that it was conducted on a small set of samples for validation purposes; therefore, it is recommended that it should be conducted in the future using a large set of samples.

REFERENCES

[1] J. S. Paul, A. J. Plassard, B. A. Landman, and D. Fabbri, "Deep learning for brain tumor classification," in *Proc. SPIE Medical Imaging: Biomedical Applications in Molecular, Structural, and Functional Imaging*, vol. 10137, 2017, p. 1013710.

[2] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Med. Image Anal.*, vol. 42, pp. 60–88, 2017.

[3] K. Machhale, H. Nandpuru, V. Kapur, and L. Kosta, "MRI brain cancer classification using hybrid classifier," in *Proc. IEEE Int. Conf. Electron. Comput. Technol.*, 2015, pp. 60–65.

[4] M. Shasidhar, V. S. Raja, and B. V. Kumar, "MRI brain tumor segmentation using modified FCM algorithm," *Int. J. Comput. Appl.*, vol. 54, no. 1, pp. 13–17, 2012.

[5] S. Bauer, R. Wiest, L.-P. Nolte, and M. Reyes, "A survey of MRI-based medical image analysis for brain tumor studies," *Phys. Med. Biol.*, vol. 58, no. 13, pp. R97–R129, 2013.

[6] H. Dong, G. Yang, F. Liu, Y. Mo, and Y. Guo, "Automatic brain tumor detection and segmentation using U-Net," in *Proc. MICCAI*, 2017, pp. 506–514.

[7] P. Afshar, A. Mohammadi, and K. N. Plataniotis, "Brain tumor type classification via capsule networks," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, 2018, pp. 3129–3133.

[8] A. K. Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification using genetic algorithm and convolutional neural network," *Biomed. Signal Process. Control*, vol. 36, pp. 63–74, 2017.

[9] R. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.

[10] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. MICCAI*, 2015, pp. 234–241.

[11] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst. (NeurIPS)*, 2012, pp. 1097–1105.

[13] S. Pan and Q. Yang, "A survey on transfer learning," *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 10, pp. 1345–1359, 2010.

[14] A. Dosovitskiy *et al.*, "An image is worth 16×16 words: Transformers for image recognition at scale," in *Proc. Int. Conf. Learn. Representations (ICLR)*, 2021.

[15] Z. Liu *et al.*, "Swin Transformer: Hierarchical vision transformer using shifted windows," in *Proc. IEEE/CVF Int. Conf. Comput. Vision (ICCV)*, 2021, pp. 10012–10022.

[16] J. Chen *et al.*, "TransUNet: Transformers make strong encoders for medical image segmentation," *Med. Image Anal.*, vol. 73, 2021, Art. no. 102055.

[17] D. Esteva *et al.*, "A guide to deep learning in healthcare," *Nat. Med.*, vol. 25, no. 1, pp. 24–29, 2019.

[18] S. Minaee *et al.*, "Image segmentation using deep learning: A survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 44, no. 7, pp. 3523–3542, 2022.

[19] Y. Zhou *et al.*, "UNet++: A nested U-Net architecture for medical image segmentation," *IEEE Trans. Med. Imaging*, vol. 39, no. 6, pp. 1856–1867, 2020.

[20] A. Isensee *et al.*, "nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation," *Nat. Methods*, vol. 18, no. 2, pp. 203–211, 2021.

[21] M. Hatamizadeh *et al.*, "UNETR: Transformers for 3D medical image segmentation," in *Proc. IEEE/CVF Conf. Comput. Vision Pattern Recognit. (CVPR)*, 2022, pp. 574–584.

[22] J. Ma *et al.*, "Segment anything in medical images," *IEEE J. Biomed. Health Inform.*, vol. 26, no. 10, pp. 4965–4977, 2022.

[23] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit. (CVPR)*, 2016, pp. 770–778.

[24] Kaggle, "Brain MRI Images for Brain Tumor Detection," 2020. [Online]. Available: https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection.

[25] R. Verma, A. Zacharaki, and C. Davatzikos, "Multimodal segmentation and classification of brain tumors," *IEEE Trans. Med. Imaging*, vol. 31, no. 9, pp. 1819–1831, 2012.