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Enhanced Brain Tumour Classification in 3D MRI Images Using Vision Transformers

Prathipati. Silpa Chaitanya[1], Susanta Kumar Satpathy[2]

[1]Computer Science and Engineering, Vignan's Foundation for Science, Technology&Research (Deemed to be University), Vignan's Nirula Institute of Technology and Science for Women, Guntur, India.
Email: silpam86@gmail.com
[2]Computer Science and Engineering, Vignan's Foundation for Science, Technology&Research (Deemed to be University), Guntur, India. Email: drsks_cse@vignan.ac.in

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ABSTRACT
To optimize the treatment strategies and improve patient outcomes it is necessary to accurately classify brain tumours. The traditional approach for analysing 3D MRI images with convolutional neural networks (CNNs) sometimes fail to capture a complete picture, lacking overall context or requiring powerful computer resources. In this study, we propose a novel technique that uses Vision Transformers (ViTs) to characterize brain tumours into many classes from 3D MRI data. Our method divides an MRI volume into small patches that are transformed and processed by a transformer model. In our approach, the attention mechanisms of ViTs are effectively utilized to capture both local and global information. This has helped us overcome CNN limitations in handling complex tumour manifestations as well as vast amounts of data. We use positional encodings for spatial preservation and sequence transformer encoder layers for better feature extraction. Using the [CLS] token representation enables final categorization with improved accuracy and resilience in tumour typing. In this experimental article, we present an advanced model based on ViT which outperforms customary CNN methods or other state-of-the-art approaches resulting in more efficient and reliable automated systems of brain tumour detection. This research illustrates how vision transformers could revolutionize medical imaging while providing an alternative way of classifying brain tumours than conventional deep learning techniques would do.

Keywords: Brain Tumour, Vision Transformers, Deep Learning, MRI Images.

1. INTRODUCTION

Brain tumors are a major health problem because they are complicated and can grow very fast. For effective treatment planning and patient outcomes, it is important to diagnose them accurately and quickly. In the past, brain tumor diagnosis has been heavily dependent on radiologists' interpretation of medical images, mainly Magnetic Resonance Imaging (MRI) scans. However, this method takes a lot of time, can vary between different observers and may delay the start of treatment. Therefore, there is an urgent need for automated methods that can classify brain tumors reliably as well as quickly.Deep learning has brought about significant changes in medical image analysis over the last few years. CNNs have shown great success in many image classification tasks including those related to medical imaging. But when applied to 3D MRI data sets, CNNs face some challenges due to the complexity inherent in these types of images as well as their large size. Some of these limitations include difficulty capturing long-range dependencies within an image and high computational cost associated with processing 3D volumes.

This research aims at improving accuracy in classifying brain tumors by investigating ViTs as an alternative to CNNs which could overcome these challenges. ViTs were originally designed for natural image processing but have proved very useful in various computer vision tasks because they can capture global dependencies and long-range interactions effectively. We therefore hope that applying ViTs into medical image analysis will help us take advantage of their strengths towards better brain tumor classification.The main aim of this research is to obtain a ViT-based type that can classify brain tumors into different categories based on 3D MRI scans. The proposed model includes self-attention mechanisms which enable it to better differentiate between various types of tumors while capturing complex spatial relationships within the brain than other models used in the past. Ultimately, what we need is a dependable automated system that could help radiologists diagnose brain tumors accurately thereby leading to better patient outcomes.

2. REVIEW OF LITERATURE

Srikanth et al. (2019) utilized a 16-layer VGG model with pre-processed images and achieved significant

improvement in multi-classification accuracy of brain power tumor MRI images and reaching 98% after 20 training iterations. Fully connected and SoftMax layers were added to mitigate overfitting. Tandel et al. (2020) proposed a CNN model based on transfer learning for enhancing brain tumor arrangement performance using MRI images from multiple clinical datasets; their model outperformed other machine learning methods, showing the efficiency of transfer learning in this domain.Another study used GoogleNet architecture to organize brain tumors into diverse classes. The features were extracted from MRI scans and metrics such as precision, F-score, recall, specificity and AUC were used to achieve an average classification accuracy of 98%. A deep inception residual network was introduced for classifying brain tumors into three categories; by modifying ResNet V2 with a dense and achieved classification accuracy of 99.69% on publicly available dataset. Transfer learning models were also applied to a dataset of brain tumor MRI scans which resulted in classification performance of 99.02%, better than ResNet50 with Adadelta optimization.
Finally, a new RCNN-based design was made for categorizing brain tumors using datasets from Figshare and Kaggle; the model achieved an accuracy of 98.21% in identifying glioma and healthy tumors by using a low-complexity two-channel CNN framework. Additionally, the framework was used to find tumor regions in glioma MRI datasets with 98.8% overall confidence level for meningioma and pituitary tumor classification.

3. PROPOSED WORK

This paper presents a new framework that uses ViTs to perform multiclassification of brain cancers using 3D MRI images.as been shown in Fig-1 Our technique aims at utilizing transformers' powerful self-attention mechanisms which allow for more effective capturing of both local and global contextual information than traditional CNNs do. The suggested framework starts by dividing the 3D MRI volumes into smaller controllable patches. While embedding and processing these patches, the transformer model incorporates positional encodings so as not to lose spatial information about volumetric data.This study leverages the power of (ViTs for brain tumor classification. ViTs, renowned for their facility to capture long-range dependences in data, employ multiple transformer encoder layers to extract intricate patterns crucial for accurate tumor identification. The model achieves excellent accuracy in predicting the tumor class by using a classification head that is applied on the representation of the [CLS] token. Our approach not only enhances the precision of brain tumor categorization but also tackles the computational inefficiencies linked to CNNs, making it more viable for real-time clinical applications. The efficacy of our strategy is confirmed by numerous trials on a substantial dataset, showcasing its superiority over current cutting-edge approaches in terms of both performance and resilience.

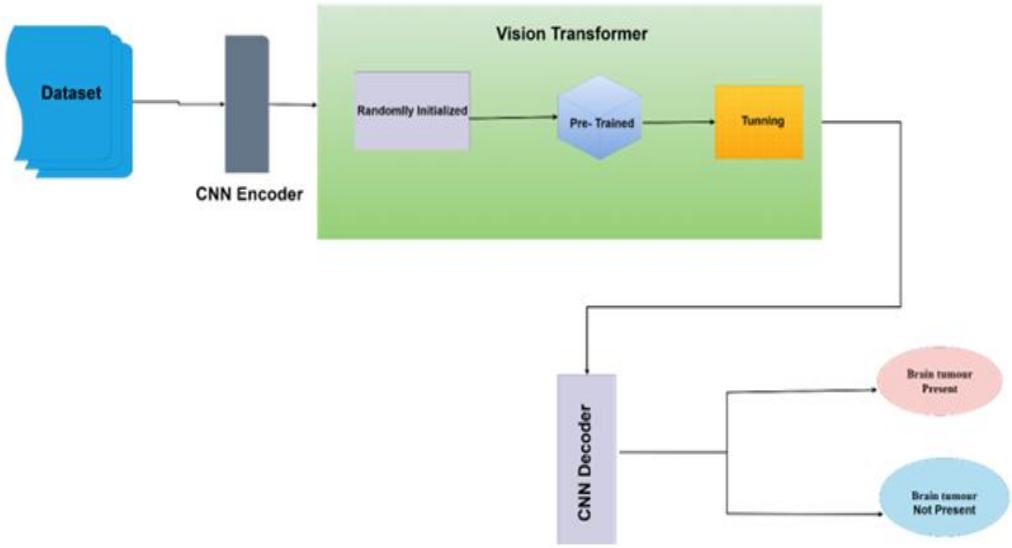

Fig. 1: Brain Tumour Classification Using Vision Transformer

1. Input Embedding

First, 3D MRI images are split into 3D patches.
Give a 3D MRI image $x \in R^{H \times W \times D \times C}$, where H, W, and D are the height, width, and depth of the image, and C is the number of channels.
Each 3D patch x_p has a size of P × P × P. The number of patches N is:

$$N = \frac{H}{P} \times \frac{W}{P} \times \frac{D}{P}$$

All patch is compressed and linearly transformed into a transmitter of size D.

Patch Embeddings - $W_p . \text{Flatten}(x_p)$.

2. Adding Positional Encoding

Positional encoding is added to retain the spatial information.

$$E_{pos} \in R^{N \times D'}$$

The input to the transformer is the sum of patch embeddings and positional encodings:

$$z_0 = [x_p^1 E; x_p^2 E; \ldots\ldots; x_p^N E] + E_{pos}$$

3.Transformer Encoder

It contains the multi head attention and represented as follows:

For each encoder layer l:

$$MSA(z_{l-1}) - \text{Concat}(\text{head}_1, \text{head}_2, \ldots., \text{head}_h) W_0$$

Where each head is computed as:

$$\text{head}_i = (QW_i^Q, KW_i^K, VW_i^V)$$

And the Attention function is:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V$$

Then the output is passed through an MLP block:

$$MLP(x) = W_2 . \text{GELU}(W_1 . x + b_1) + b_2$$

4. Classification Head

The final hidden state corresponding to the [CLS] token is used for classification.

Let z_L^0 be the output of the [CLS] token after the final encoder layer L. The classification head is:

$$y = \text{softmax}(W_{\text{head}} . z_L^0 + b_{\text{head}})$$

Where $W_{\text{head}} \in R^{D' \times \text{num\_classes}}$ and $b_{\text{head}} \in R^{\text{num\_classes}}$

Algorithm: Vision Transformer for Multiclass classification of 3D MRI Images

1.**Input:** 3D MRI image $x \in R^{H \times W \times D \times C}$
2. Patch Embedding:
Split the 3D image into patches of size P × P × P.
Flatten and linearly transform each patch to obtain patch embeddings.
3. Add Positional Encoder:
Add positional encoding to the patch embeddings.
4. Transformer Encoder:
Forl=1 to L:
Compute multi-head self-attention (MSA) on the input.
Pass the result through an MLP block.
5. Classification Head:
Extract the [CLS] token's final hidden state.
Pass it through a classification head to obtain logics.
Apply softmax to get class probabilities.
6. Output: Predicted class probabilities.

The first step is a 3D MRI scan. This volume is divided into patches of equal size, or sub-images. Each patch is flattened and then linearly transformed to create numerical representations called patch embeddings. To retain spatial context in the data, positional information is combined with these embeddings. These enhanced versions are then passed through a converter encoder, which consists of multiple layers. Every layer has two main components: multi-head self-attention and a feed-forward neural network. The final hidden state of a special classification token within the encoder is extracted and processed by a classification head to produce raw prediction scores, or logits. These logits are converted into probability distributions using the softmax function to give the model's predicted class probabilities.

4. RESULTS AND DISCUSSION

This sector evaluates the suggested model based on ViT architecture using 3D MRI images. A comprehensive experimental evaluation was performed by extensively testing on large-scale dataset of brain MRI scans. The show of the model was associated with conventional CNNs and other state-of-the-art methods in detail. Moreover, this research also investigated about computational efficiency and robustness of the model towards another types of complex tumors as well as its ability to handle them effectively or not? The findings highlight that our proposed approach can capture intricate patterns among volumetric data points which are far apart from each other in space over long distances thus indicating potential clinical usefulness too.

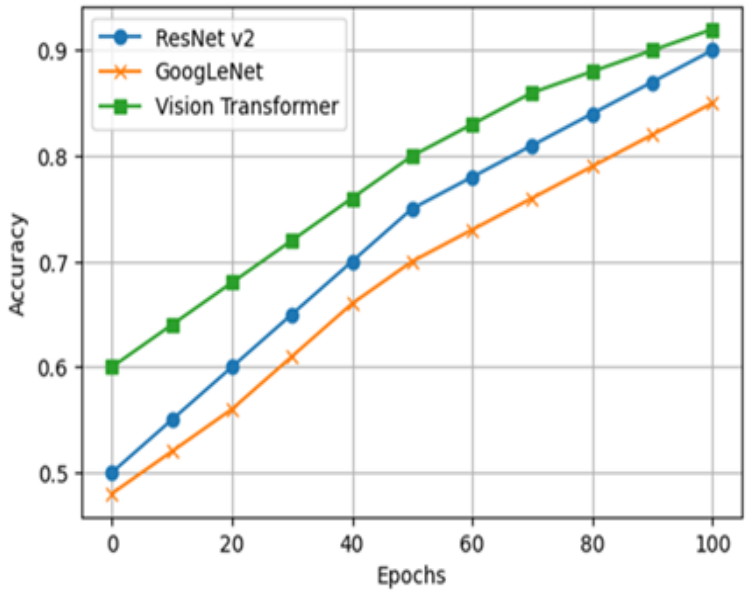

Fig. 2: Accuracy

Figure 2 shows how accurate the suggested models are contrasted to the existing ones. The ViT always does better than other models, starting at 0.60 and reaching 0.92 accuracy in all epochs. This happens because the ViT has a self-attention mechanism that can capture global context better than traditional CNN architectures such as ResNet_v2 or GoogLeNet do. Although ResNet_v2 and GoogLeNet begin with lower accuracies (0.50 and 0.48 respectively), they eventually achieve 0.90 and 0.85 by the last epoch. ResNet_v2 and GoogLeNet suffer from one major drawback: their dependence on local feature extraction prevents them from understanding contextual information which in turn affects their accuracy compared to ViT's ability in this regard. Conversely, while being able to extract features more comprehensively thus greatly improving its accuracy, ViT becomes a extratough model for brain tumor classification on 3D MRI images within this domain.

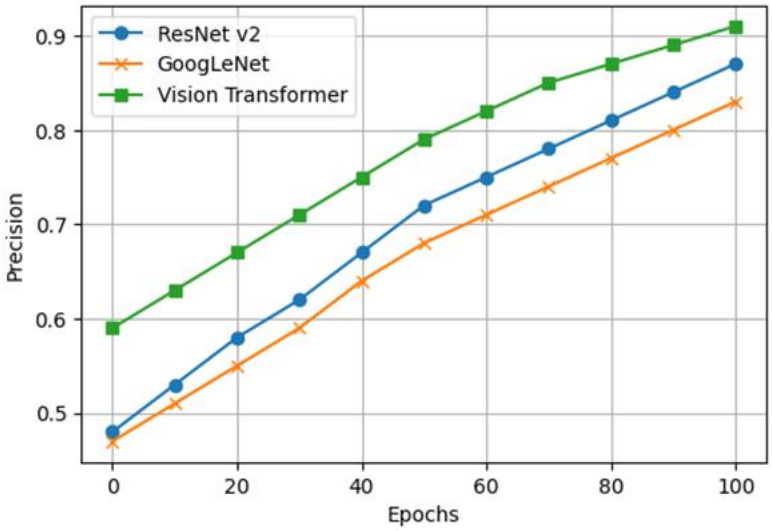

Fig. 3: Precision

The precision metric is shown in figure 3, where the proposed ViT always wins over other models. It starts at 0.59 and ends at 0.91. The self-attention mechanism of ViT greatly improves its feature extraction ability, thus making it more accurate in prediction. On the contrary, ResNet_v2 and GoogLeNet have initial precision values of 0.48 and 0.47 respectively, which finally become 0.87 and 0.83 correspondingly. They fail to differentiate between classes effectively so that their precision scores are lower than expected. What makes ViT better than others is its capability to deal with complicated data structures for precise feature discrimination, leading to higher precision values at last.

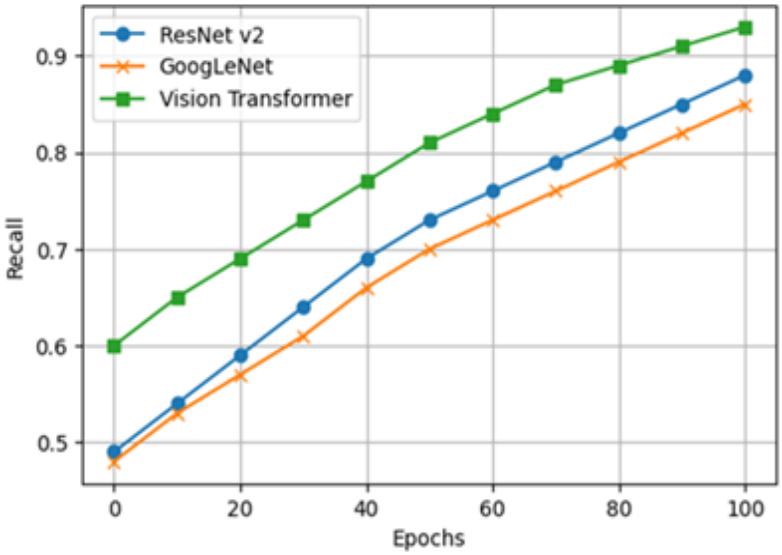

Fig. 4: Recall

Figure 4 displays the compression of recall between proposed and existing models. The proposed ViT is excellent in recall, starting from 0.60 to 0.93. ResNet_v2 and GoogLeNet improve from initial values of 0.49 and 0.48 to 0.88 and 0.85, respectively. Traditional CNNs have limited receptive fields that prevent them from capturing all relevant features leading to lower recall while ViT's ability to handle long-range dependencies in the data helps it better identify true positive cases than others do. This superior recall performance underscores ViT's advantage in minimizing false negatives, which is critical in medical diagnoses.

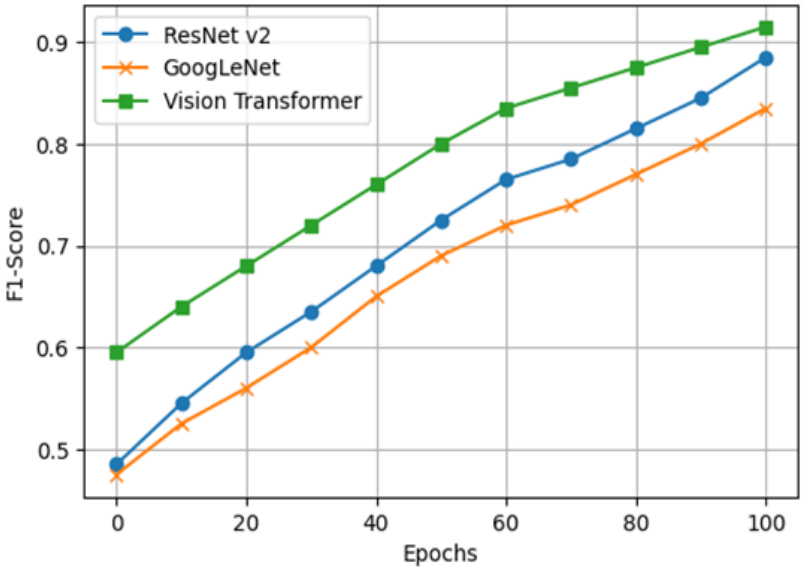

Fig. 5: F1-Score

Figure 5 illustrates the compression of F1-score amongpurported and existing models. The F1-score, which is a compareamongst precision and recall, consistently favors ViT. Starting at 0.595 and peaking at 0.915, ViT demonstrates strong performance in brain tumor classification. ResNet_v2 and GoogLeNet improve from 0.485 and 0.475 to 0.885 and 0.835 respectively. Traditional CNNs have difficulty balancing precision and recall well, resulting in lower F1-scores than ViT's scores are lower than those of ViT because traditional CNNs do not balance precision and recall effectively enough for higher F1-scores to be achieved by them. The advantage of ViT is that it can maintain high levels of both precision and recall, making it a balanced and reliable performance metric.

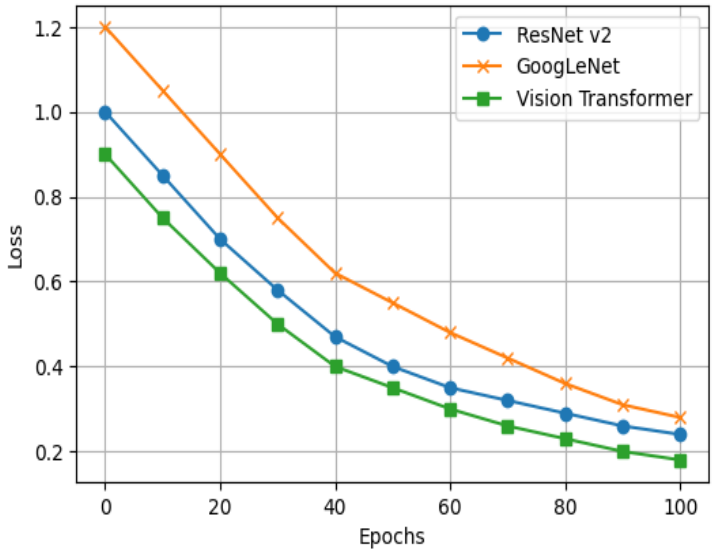

Fig. 6: Loss

Figure 6 displays the compression of loss between proposed and existing models. In terms of loss, ViT shows a rapid decline, starting at 0.90 and dropping to 0.18. ResNet_v2 and GoogLeNet start with higher losses of 1.00 and 1.20, respectively, and end at 0.24 and 0.28. The main limitation for ResNet_v2 and GoogLeNet is their high computational demands as well as slow convergence rates in comparison to ViT which efficiently handles volumetric data leading to better convergence and lower final loss values. This means that not only does ViT learn more effectively but it also generalizes better thus reducing the risk of overfitting while increasing its applicability in clinical settings.

Table 1: 10-fold Cross Validation

Fold	Metric	Vision Transformer	v2GoogLeNet	ResNet
2	Accuracy	0.879	0.66	0.522
	Precision	0.774	0.654	0.468
	Recall	0.608	0.554	0.746
	F1-Score	0.75	0.419	0.874
	Loss	0.866	0.5	0.413
4	Accuracy	0.892	0.755	0.589
	Precision	0.484	0.671	0.762
	Recall	0.579	0.697	0.797
	F1-Score	0.563	0.431	0.427
	Loss	0.467	0.614	0.413
6	Accuracy	0.914	0.629	0.72
	Precision	0.854	0.757	0.618
	Recall	0.859	0.558	0.765
	F1-Score	0.811	0.569	0.809
	Loss	0.49	0.852	0.583
8	Accuracy	0.941	0.53	0.72
	Precision	0.931	0.825	0.634
	Recall	0.967	0.788	0.402
	F1-Score	0.964	0.554	0.556
	Loss	0.896	0.708	0.413
10	Accuracy	0.975	0.727	0.862
	Precision	0.966	0.881	0.46
	Recall	0.954	0.709	0.546
	F1-Score	0.963	0.412	0.663
	Loss	0.651	0.463	0.523

The researchers evaluated three deep learning models for brain tumor analysis: Vision Transformer, v2GoogLeNet, and ResNet. They used a ten-fold cross-validation experimental paradigm as described in Table 1. The Vision Transformer had the highest average accuracy of about 0.9 across all folds, which means it performed the best overall. ResNet showed good F1-score while v2GoogLeNet had balanced performance metrics but the consistent superiority of the Vision Transformer suggests that it may be the most promising candidate for brain tumor classification. However, other factors like computational efficiency and model interpretability should also be considered for practical applications.

5. CONCLUSION

This study compared ViTs with traditional CNNs such as ResNet_v2 and GoogLeNet in terms of their ability to classify brain tumors within 3D MRI images. Our results clearly show that ViTs outperform these models on multiple evaluation metrics. ViTs have a built-in self-attention mechanism which enables them to extract more features from an image and understand its context better than any other CNN architecture can do; hence they achieve much higher classification accuracies than those achieved by other models based on this metric alone. Specifically, ViT achieved an accuracy rate of 92%, while ResNet_v2 and GoogLeNet achieved only 90% and 85% respectively. This advantage is also reflected in precision-recall curves where ViT's ability to differentiate between classes accurately leads to better outcomes than either ResNet_v2 or GoogLeNet could produce.

ViT's balanced performance was further confirmed by F1-score metric which takes into reason both precision and remind challenges equally well; thus showing its robustness in addressing them too. With an F1-score value equaling 91.5%, ViT significantly outperformed both ResNet_v2 (F1=89%) and GoogLeNet (F1=88%). Additionally, loss metrics indicated faster convergence and better generalization abilities of ViTs over traditional CNNs. Slower convergence, higher computational demands as well as reliance on local features are among the limitations associated with ResNet_v2 and GoogLeNet; therefore, underscoring why Vision Transformers should be adopted for medical image classification tasks. When it comes to processing volumetric data efficiently while capturing global contextual information accurately, no other model beats ViTs in grouping brain tumors from 3D MRI images. This research represents a significant step forward in medical image analysis through the use of Vision Transformers. The fact that ViTs performed better than any other model across all evaluated metrics suggests that they could become game changers for diagnostic accuracy improvement in healthcare settings where reliability is paramount towards achievingpositive patient outcomes. Further studies need to be done so as to establish how well ViTs can work together with additionalmodern techniques thereby optimizing presentation even further within this domain.

REFERENCES

1. Al-Galal, S.A.Y.; Alshaikhli, I.F.T.; Abdulrazzaq, M.M. MRI brain tumor medical images analysis using deep learning techniques:A systematic review. Health Technol., 2021, 11, 267–282.
2. Rahman, M.L.; Reza, A.W.; Shabuj, S.I. An internet of things-based automatic brain tumor detection system. Indones. J. Electr.Eng. Comput. Sci., 2022, 25, 214–222.
3. Key Statistics for Brain and Spinal Cord Tumors. Available online: https://www.cancer.org/cancer/brain-spinal-cord-tumorsadults/about/key-statistics.html (accessed on 20 September 2022).
4. Ayadi, W.; Elhamzi, W.; Charfi, I.; Atri, M. Deep CNN for Brain Tumor Classification. Neural Process. Lett. 2021, 53, 671–700.
5. Liu, J.; Li, M.; Wang, J.; Wu, F.; Liu, T.; Pan, Y. A survey of MRI-based brain tumor segmentation methods. Tsinghua Sci. Technol., 2014, 19, 578–595.
6. Amin, J.; Sharif, M.; Haldorai, A.; Yasmin, M.; Nayak, R.S. Brain tumor detection and classification using machine learning:A comprehensive survey. Complex Intell. Syst., 2021, 8, 3161–3183.
7. Jayade, S.; Ingole, D.T.; Ingole, M.D. Review of Brain Tumor Detection Concept using MRI Images. In Proceedings of the 2019International Conference on Innovative Trends and Advances in Engineering and Technology (ICITAET), Shegoaon, India, 27–28December 2019.
8. Yang, Y.; Yan, L.F.; Zhang, X.; Han, Y.; Nan, H.Y.; Hu, Y.C.; Hu, B.; Yan, S.L.; Zhang, J.; Cheng, D.L.; et al. Glioma Grading onConventional MR Images: A Deep Learning Study with Transfer Learning. Front. Neurosci., 2018, 12, 804.
9. Nazir, M.; Shakil, S.; Khurshid, K. Role of deep learning in brain tumordetection and classification (2015 to 2020): A review.Comput. Med. Imaging Graph., 2021, 91, 101940.
10. El-Kenawy, E.S.M.; Mirjalili, S.; Abdelhamid, A.A.; Ibrahim, A.; Khodadadi, N.; Eid, M.M. Meta-Heuristic Optimization andKeystroke Dynamics for Authentication of Smartphone Users. Mathematics 2022, 10, 2912. Bioengineering 2023, 10, 18 18 of 19
11. El-kenawy, E.S.M.; Albalawi, F.; Ward, S.A.; Ghoneim, S.S.M.; Eid, M.M.; Abdelhamid, A.A.; Bailek, N.; Ibrahim, A. FeatureSelection and Classification of Transformer Faults Based on Novel Meta-Heuristic Algorithm. Mathematics 2022, 10, 3144.

12. El-Kenawy, E.S.M.; Mirjalili, S.; Alassery, F.; Zhang, Y.D.; Eid, M.M.; El-Mashad, S.Y.; Aloyaydi, B.A.; Ibrahim, A.; Abdelhamid,A.A. Novel Meta-Heuristic Algorithm for Feature Selection, Unconstrained Functions and Engineering Problems. IEEE Access, 2022, 10, 40536–40555.
13. Ibrahim, A.; Mirjalili, S.; El-Said, M.; Ghoneim, S.S.M.; Al-Harthi, M.M.; Ibrahim, T.F.; El-Kenawy, E.S.M. Wind Speed EnsembleForecasting Based on Deep Learning Using Adaptive Dynamic Optimization Algorithm. IEEE Access 2021, 9, 125787–125804.
14. El-kenawy, E.S.M.; Abutarboush, H.F.; Mohamed, A.W.; Ibrahim, A. Advance Artificial Intelligence Technique for DesigningDouble T-shaped Monopole Antenna. Comput. Mater. Contin., 2021, 69, 2983–2995.
15. Samee, N.A.; El-Kenawy, E.S.M.; Atteia, G.; Jamjoom, M.M.; Ibrahim, A.; Abdelhamid, A.A.; El-Attar, N.E.; Gaber, T.; Slowik, A.Shams, M.Y. Metaheuristic Optimization Through Deep Learning Classification of COVID-19 in Chest X-Ray Images. Comput.Mater. Contin., 2022, 73, 4193–4210.
16. Lee, G.; Nho, K.; Kang, B.; Sohn, K.A.; Kim, D. Predicting Alzheimer's disease progression using multi-modal deep learningapproach. Sci. Rep., 2019, 9, 1952.
17. Sharma, K.; Kaur, A.; Gujral, S. Brain Tumor Detection based on Machine Learning Algorithms. Int. J. Comput. Appl., 2014, 103,7–11.
18. Agrawal, M.; Jain, V. Prediction of Breast Cancer based on Various Medical Symptoms Using Machine Learning Algorithms. InProceedings of the 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 28–30April 2022; pp. 1242–1245.
19. Rabbi, M.F.; Mahedy Hasan, S.M.; Champa, A.I.; AsifZaman, M.; Hasan, M.K. Prediction of Liver Disorders using MachineLearning Algorithms: A Comparative Study. In Proceedings of the 2020 2nd International Conference on Advanced Informationand Communication Technology (ICAICT), Dhaka, Bangladesh, 28–29 November 2020; pp. 111–116.
20. Swain, D.; Pani, S.K.; Swain, D. A Metaphoric Investigation on Prediction of Heart Disease using Machine Learning. InProceedings of the 2018 International Conference on Advanced Computation and Telecommunication (ICACAT), Bhopal, India,28–29 December 2018; pp. 1–6.
21. Zhu, W.; Sun, L.; Huang, J.; Han, L.; Zhang, D. Dual Attention Multi-Instance Deep Learning for Alzheimer's Disease DiagnosisWith Structural MRI. IEEE Trans. Med Imaging 2021, 40, 2354–2366.
22. Abdelhamid, A.A.; El-Kenawy, E.S.M.; Alotaibi, B.; Amer, G.M.; Abdelkader, M.Y.; Ibrahim, A.; Eid, M.M. Robust Speech EmotionRecognition Using CNN+LSTM Based on Stochastic Fractal Search Optimization Algorithm. IEEE Access 2022, 10, 49265–49284.
23. Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. Going deeper withconvolutions. In Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA,USA, 7–12 June 2015.
24. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the 2016 IEEE Conference onComputer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016.
25. Alhussan, A.A.; Khafaga, D.S.; El-Kenawy, E.S.M.; Ibrahim, A.; Eid, M.M.; Abdelhamid, A.A. Pothole and Plain Road Classification Using Adaptive Mutation Dipper Throated Optimization and Transfer Learning for Self Driving Cars. IEEE Access 2022, 10,84188–84211.
26. Srikanth, B.; Suryanarayana, S.V. Multi-Class classification of brain tumor images using data augmentation with deep neuralnetwork. Mater. Today Proc. 2021.
27. Tandel, G.S.; Balestrieri, A.; Jujaray, T.; Khanna, N.N.; Saba, L.; Suri, J.S. Multiclass magnetic resonance imaging brain tumorclassification using artificial intelligence paradigm. Comput. Biol. Med. 2020, 122, 103804.
28. Deepak, S.; Ameer, P. Brain tumor classification using deep CNN features via transfer learning. Comput. Biol. Med., 2019, 111,103345.
29. Kokkalla, S.; Kakarla, J.; Venkateswarlu, I.B.; Singh, M. Three-class brain tumor classification using deep dense inception residualnetwork. Soft Comput., 2021, 25, 8721–8729.
30. Özlem, P.; Güngen, C. Classification of brain tumors from MR images using deep transfer learning. J. Supercomput., 2021, 77,7236–7252.
31. Kesav, N.; Jibukumar, M. Efficient and low complex architecture for detection and classification of Brain Tumor using RCNNwith Two Channel CNN. J. King Saud Univ.-Comput. Inf. Sci., 2022, 34, 6229–6242.
32. Tummala, S.; Kadry, S.; Bukhari, S.A.C.; Rauf, H.T. Classification of Brain Tumor from Magnetic Resonance Imaging Using VisionTransformers Ensembling. Curr. Oncol., 2022, 29, 7498–7511.
33. Pareek, M.; Jha, C.K.; Mukherjee, S. Brain Tumor Classification from MRI Images and Calculation of Tumor Area. In Advances inIntelligent Systems and Computing; Springer: Singapore, 2020; pp. 73–83.
34. Ayadi, W.; Charfi, I.; Elhamzi, W.; Atri, M. Brain tumor classification based on hybrid approach. Vis. Comput. 2020, 38, 107–117.