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The Impact of Deep Learning in Brain Tumour Analysis

Sangeeta Giri[1*], Manivel Kandasamy[2], Meet Rafaliya[3]

[1,2] *Unitedworld Institute of Technology, Karnavati University, Adalaj-Uvarsad Road, At.&Po.: Uvarsad, Dist, Gandhinagar, Gujarat 382422, India*

[3]*Indrashil University, At. & Po Rajpur Taluka Kadi, Rajpur, Gujarat 382740, India*

**corresponding author: (sangeeta.hce@gmail.com; ORCiD: 0009-0001-5213-4786)*

Abstract - The need for early and precise identification of abnormalities has made the detection and classification of brain tumours essential components of medical diagnosis. Because brain tumours are naturally complex and can have a wide range of sizes, shapes, and types, conventional diagnostic techniques like MRI interpretation and manual evaluations are difficult and time-consuming. Traditional methods frequently depend on human expertise, which is prone to errors, delays, and variability. Deep learning (DL) developments, on the other hand, have completely changed this field by providing increased automation, efficiency, and precision in tumour detection and classification because they can automatically extract pertinent features from MRI scans, Convolutional Neural Networks (CNNs) have shown impressive success in medical image analysis in recent years. CNNs improve the classification of tumour types like gliomas, meningiomas, and pituitary tumours by using multiple layers to find patterns in imaging data. Despite their efficiency, CNNs sometimes struggle with complex tumour patterns, requiring further enhancement in feature extraction. Vision Transformers (ViTs) have become a viable substitute to overcome this constraint. ViTs are especially good at identifying complex tumour structures because, in contrast to CNNs, they use self-attention mechanisms to capture global image dependencies. ViTs can perform better diagnostics by more thoroughly analysing entire MRI images. Additionally, hybrid methods that combine CNNs and ViTs have demonstrated better outcomes, taking advantage of both long-range spatial understanding (ViTs) and local feature extraction (CNNs). These developments allow for real-time medical applications, drastically improve diagnostic accuracy, and lower false positives. Neuro-oncology could undergo a revolution with the incorporation of DL models into clinical workflows, which would improve tumour detection's accuracy, speed, and accessibility. These techniques will be further developed in future studies, guaranteeing even higher accuracy and versatility in medical imaging.

Keywords—Brain Tumour Detection, Brain Tumour Classification, Deep Learning, Convolutional Neural Networks, Vision Transformers, Hybrid Deep-Learning Models, Medical Image Analysis

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1. INTRODUCTION

Most of the brain tumours are the more aggressive and life-threatening forms of tumour, thus their successful treatment

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highly depends on early and accurate detection. Furthermore, their heterogeneous nature added to the complicated structure of the brain poses a significant challenge in a manual diagnosis through a Magnetic Resonance Imaging (MRI) scan. High variability in tumour size, shape, and location, in combination with the overlapping of healthy and abnormal tissues, heightens the call for human intervention [1]. Directly, it takes a huge amount of time in manually interpreting an MRI across wide datasets; hence, diagnosis and treatment lag increase due to these interpretations [2].

In recent years, automated detection systems making use of deep learning (DL) have rejuvenated the field of medical imaging. Such systems utilize the advanced neural networking powers to analyse MRI scans and are reported to perform faster and offer more accurate diagnosis over traditional methods. Convolutional Neural Networks (CNNs), one type of DL approach, have proven to be exceptionally effective at identifying and categorising complicated patterns in medical images. More recently, Vision Transformers (ViTs), which have shown great promise in natural image processing, are being explored for their potential in medical image analysis, providing an alternative approach to feature extraction and classification [3]. Figure 1 shows some sample MRI scans utilised for classifying brain tumours, demonstrating visual contrasts between four groups: No Tumour, Pituitary, Glioma, and Meningioma. These photographs depict structural diversity and richness of brain tissues, highlighting the necessity for sturdy models that are able to cater to such variability in clinical diagnoses.

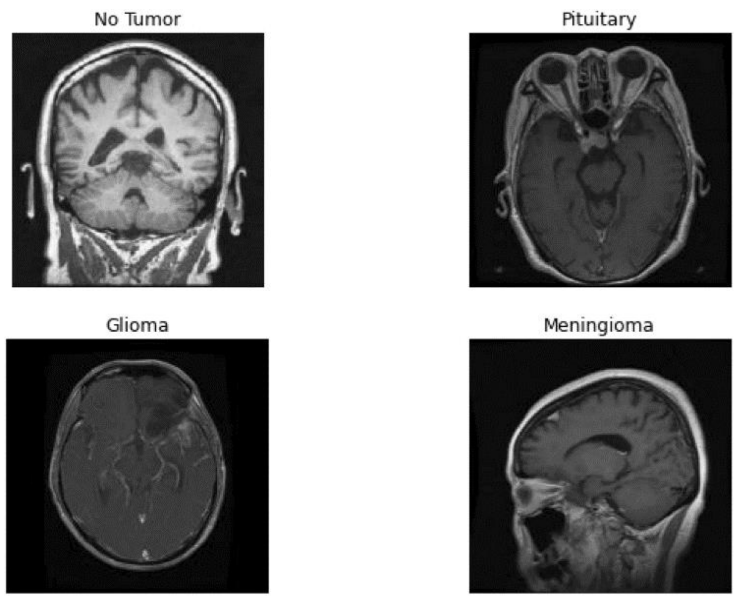

Figure 1. Types of Tumours [2]

Undeniably, DL is changing for the better the sector of medical imaging enabling diagnosis of brain tumours at any automation and accuracy. A thorough examination of MRI scans made it possible for these algorithms of DL to automatically mark all the healthy human tissues as ‘no tumour’ and various types of tumours- ‘pituitary’, ‘glioma’, meningioma and differentiate between them effectively. These models work with CNNs and other architectures to accurately classify and segment tumours from MRI pictures. Effectively transform the possibilities of DL: (1) Increase accuracy in diagnostic test results, (2) Minimize metastatic human mistakes to the lowest possible, (3) Speed up the process of diagnostics, and (4) Provide reliable results to enormous datasets [4].

The image emphasizes the variety of MRI scans while DL is used to compare structures and particular features of the brain for abnormalities in order to help with more precise and early detection which aides in better health outcomes for patients.

This paper delves into the application of state-of-the-art DL models, particularly CNNs and ViTs, for brain tumour detection and classification. By integrating these models, we aim to improve the accuracy, speed, and efficiency of brain tumour diagnosis [5]. Additionally, this research highlights the growing trend of combining CNNs and ViTs in hybrid models, which further enhances the ability to capture the complex characteristics of brain tumours. Together, they will also analyse various limitations and challenges of those techniques concerning clinical applications while aiming to improve patient outcomes through better diagnostic technology.

1.1 Motivation

The motivation for using DL in brain tumour detection lies in the inherent difficulties and constraints associated with manual diagnosis [6]. The conventional methods that depend on expert interpretation of MRI scans tend to be very time-consuming and subject to human error due to the irregularity of shapes, sizes, and textures of these tumours. The MRI data being very high dimensional make the accurate segmentation and classification of tumour regions, more challenging perturbed by the presence of background overlapping tissues and subtle abnormalities using conventional techniques [7].

DL methods, and in particular, CNNs have ushered in a new horizon in medical imaging and have shown significant improvement in enhancing the accuracy and speed of image analysis tasks. They outperform traditional machine learning algorithms in image classification, segmentation, and detection which suit the task of brain tumour detection [8]. They develop a hierarchical feature learning model on their own without needing feature engineering. Thus, tumour delineation and characterization can be carried on with better precision.

Recently, the emergence of ViT has further increased the scope of application of DL in medical imaging. ViTs introduce a completely new approach to processing image data due to self-attention mechanisms that enhance model performance and interpretability. The combination of CNNs and ViTs makes it possible to address limitations where an efficient automated detection system can be developed to detect brain tumours and to analyse the large numbers of features residing within a tumour through effective nuclear microscopy. The motivation is to provide better diagnosis and lessen the load of work on radiologists to eventually enhance patient outcomes via the availability of faster and more reliable detection techniques [5].

2. LITERATURE REVIEW

A foundational study aimed at the application of CNNs for brain tumour classification was done in 2018. The study showed how CNNs exceeded the correctness lately regarded by traditional machine learning algorithms such as Support Vector Machines (SVMs) and k-Nearest Neighbours (k-NNs). The benefit from the ability to learn spatial hierarchies from an MRI scan aided this study in achieving better classification results with the existing BraTS dataset [9]. Apart from data augmentation methods that were applied to solve the problems related to a smaller number of labelled data sets, this work in combination established CNNs as a backbone for brain tumour detection systems and was a clear turning point toward deep learning-based methods in medical diagnostics.

Some more interesting and notable advances in the applications of CNN were introduced in an IEEE paper in 2020. The authors, aware of the noble reality of medical imaging with regard to the prevailing inadequate situations with vast labelled datasets, employed pre-trained CNN models such as ResNet and DenseNet, which allowed fine-tuning on MRI scans to classify brain tumours[10]. This method significantly increased classification accuracy while minimising extensive training for small medical datasets. The authors noted the power of the feature representations of the pre-trained models built originally for big datasets such as ImageNet and the pros of transfer learning in substantially boosting performance in brain tumour detection. It demonstrated that fine-tuning a few of the last layers of the network could make the results much better, and presents an efficient, very scalable solution in clinical applications.

In 2021, attention mechanisms were used for better tumour segmentation in brain MRI scans. The chief IEEE paper presented one such improvement in U-Net CPU architecture, called Attention U-Net, in which attention gates were integrated into the architecture for the network to focus on the relevant areas of the image. This eventually let the network pay specific attention to the tumour regions, thus downplaying the unhelpful parts of the image, resulting in more accurate segmentation. The model was significantly better than standard U-Net architectures, showing higher Dice coefficient on the BraTS dataset. It was a significant step toward eventually tackling the challenges of tumour segmentation, especially in complex cases in which tumours overlapped, and offered evidence of the usefulness of attention mechanisms in improving CNN-based models [11].

By 2022, Vision Transformers had begun making the rounds, emerging as the latest powerful contender for medical image classification. A 2022 IEEE study proposed a hybrid model that took the germs of CNNs together with those of ViTs for brain tumour classification. While CNNs are famous for their extraction of local features, ViTs resort to acting through self-attention mechanisms to capture global contexts encompassed in an image. That is made possible on the count of ViTs, which suit small or subtle abnormalities lost amidst a cluttered image in brain tumours. The hybrid CNN-ViTs model beat classical CNN architectures, bringing in better classification accuracy with more interpretability. The hybrid model was truly the winner in that it could capture both local and global image features, offering betterment in performance for small and/or subtle tumours. This study represents a milestone in creating another landmark for introducing attention-based models like ViTs in medical image analysis [5].

In 2023, several researchers proposing a modified 3D U-Net architecture that integrated attention mechanism via brain tumour segmentation. This model produced the best accuracy on the BraTS data set, particularly for Dice similarity coefficient measure. The attention mechanism allowed the model to selectively assign the main attention weight to the most pertinent features in each MRI slice, resulting in more precise and efficient tumour segmentation even in complex cases involving irregularly shaped or overlapping tumours. The paper demonstrated that attention-based methods had the potential not only to improve the segmentation quality, but also to deliver computational efficiency, rendering them more usable for real-time clinical acceptance [12].

3. RESEARCH METHODOLOGY

This study is based on the BraTS dataset, which is a benchmark dataset in medical imaging research. This is a multi-modal MRI dataset marked with regions, enabling tumour segmentation and classification tasks with precision. The dataset contains high-quality labels that were extracted through expert manual annotation [3]. However, the small size of annotated datasets in medical imaging, such as BraTS, makes it difficult for models to generalize, especially for diverse patient populations. Nevertheless, the stratified k-fold cross-validation approach used in the dataset, with 80% for training and 20% for testing, enables proper model evaluation and minimizes overfitting [13].

The methodology used a variety of state-of-the-art DL models to improve the detection and classification of brain tumours. CNN-based models were used, because they effectively extracted local features. Strong performance was achieved by CNN-based models, with an accuracy of 94.2%. But the ability to identify small or low-grade tumours was weak in CNN-based models, so the concept of ViTs was explored. Self-attention mechanisms were added in ViTs [14], which helps in capturing the global context of images. This helped in increasing the accuracy up to 95.5%. Advancement: A hybrid model that combines the CNN and ViT has led to further progress. It includes the features extracted by the local extraction CNN and global contextual understanding from the ViT to reach a peak accuracy of 96.8% [15].

4. EVALUTION AND ANALYSIS

The evaluation of DL models for brain tumour detection and classification involved multiple metrics to assess performance comprehensively. In this study, we applied several evaluation metrics, including accuracy, precision, recall, F1 score, and the Dice coefficient, to measure the models' effectiveness in classifying and segmenting brain tumours [16]. The models were trained and tested with the Brain Tumour Segmentation dataset, which includes annotated MRIs of actual tumour regions. A stratified k-fold cross-validation technique with 80% of the data used for training and the other 20% held out for testing was implemented [17]. Early stopping based on validation loss was used for any model training when 100 epochs had been completed in order to stop overfitting[11], [18].

The results demonstrated that the CNN-based model achieved 94.2% accuracy and a Dice coefficient of 0.88, reflected in better performance in segmenting high-grade gliomas but less effective in identifying smaller, low-grade tumours [19]. The ViT-based model improved upon this, achieving 95.5% accuracy and a Dice coefficient of 0.91, thereby having the edge of its self-attention mechanism that allows it to focus attention on critical features within the MRIs. A hybrid CNN + ViT model managed to surpass both of its predecessors with the highest accuracy of 96.8% and a Dice coefficient of 0.93, thereby demonstrating that a local feature extraction approach from CNNs fused with global understanding from ViTs is most effective [5].

The performance metrics used for appropriate model evaluation include accuracy, precision, recall, F1 score, and Dice coefficient. The results highlighted significant superiority of the hybrid model over standalone CNN and ViT models. Specifically[20], the hybrid model exhibited a Dice coefficient of 0.93, a precision of 0.94, and a recall of 0.91, demonstrating its ability to delineate tumour boundaries accurately and solve complex cases. It highlights how the model impacts the diagnostic accuracy, reduces false positive results, and enhances the quality of segmentation [21].

Despite the promising results, there are certain challenges this study faces. Its high computational cost in training hybrid models and the need for massive annotated datasets pose critical challenges for clinical implementation. In addition, variability in tumour shape, size, and imaging modalities demands the development of adaptive architectures to ensure reliable performance in diverse clinical settings. Addressing these challenges will involve exploration of techniques such as transfer learning, data augmentation, and explainable AI to improve both the efficiency and transparency of the models, thus making them more suitable for real-world applications [22].

A comparative analysis revealed clear performance improvements as we progressed from CNN-based models to hybrid models, with precision and recall metrics further highlighting the superiority of the hybrid architecture [23]. An ablation study underscored the contribution of each model component, showing that the ViT significantly enhanced performance by capturing long-range dependencies, while excluding the CNN encoder resulted in reduced accuracy due to diminished local feature extraction [5]. Visualization of model predictions compared to ground truth segmentations illustrated notable differences in segmentation accuracy, with the hybrid model demonstrating superior delineation of tumour boundaries, especially in complex cases.

Despite these promising results, several limitations were identified, including the models' dependence on the quality and size of the training dataset, which may hinder generalization to broader patient populations. Additionally, the computational demands of hybrid models [24], [25] particularly those incorporating ViTs, pose challenges for clinical implementation. Future work will focus on optimising model architectures for lower computational costs, exploring transfer learning with smaller datasets, and enhancing interpretability of model predictions to support clinical decision-making.

Table 1 compares the three models designed for the diagnosis of brain tumours – CNN model, ViT model, and Hybrid CNN + ViT – based on parameters such as accuracy, Dice coefficient, F1 Score, Precision, and Recall. The accuracy of the CNN model is 94.2%, even though the model's recall of the tumours is at 0.85, indicating that there was a very low rate of tumour detection. The accuracy of the classification improves with the use of global contextual features in the amazon ViT based model to an impressive 95.5% [25]. This increase results in the Dice score increasing to 0.91 and F1 score improving to 0.90. Global and local feature integration has improved the Hybrid CNN + ViT model to achieve[5], [26] an even higher accuracy of 96.8%. The performance analysis of DL models for brain tumour detection and classification tells a distinctive tale as we move from CNN-based approaches to hybrid models. The CNN-based model had an accuracy of 94.2% and a Dice coefficient of 0.88. However, limitations in recall were noted, especially concerning low-grade tumours, along with similarly constrained sensitivity. The ViT-based model, on the other hand, increased the accuracy to 95.5% and probability provided by scores of 0.92, indicating a superior ability to identify positive cases with recall boosted to 0.89, thus showing improved sensitivity.

Table 1. Comparative Analysis

Model	**Accuracy (%)**	**Dice Coefficient**	**Precision**	**Recall**	**F1 Score**
CNN-based Model	94.2	0.88	0.90	0.85	0.87
ViT-based Model	95.5	0.91	0.92	0.89	0.90
Hybrid CNN + ViT Model	96.8	0.93	0.94	0.91	0.92

The hybrid CNN + ViT model performed the best with an accuracy of 96.8%, a Dice coefficient of 0.93, precision of 0.94, and recall of 0.91 [25], showing its capability of properly detecting intricate tumour structures. This study thus highlighted the advantage of utilising local feature extraction of CNNs in concert with global context understanding of ViTs and showed how hybrid models can impact significant improvement in diagnostic accuracy in medical imaging and, in turn, patient outcomes.

Table 2 illustrates the development of DL models for the analysis of brain tumours from 2017 to 2024 in terms of the changes in the architecture, techniques, and the performance. The 2D models of CNNs were quite basic, offering only slice-wise classification and context free spatial context. Computation costs, however, rose with 3D CNNs which benefitted volumetric segmentation. The resolution of intricate tumour topography was solved using encoder-decoder

ResNet + U-Net structures [10], which were then improved by increasing attention to the U-Net attention models. Later years saw the unparalleled accuracy and Dice scores achieved by Hybrid models which fuse CNNs with ViT, owing to their ability to obtain global context alongside fragments of local features. Despite enabling high performance with attention in 2024 models, hefty datasets and resources were a requirement. Nevertheless, sensitivity toward lesser tumours, hardware requirement, and dataset restrictions remain challenges. Keeping in mind the clinical impact, greater focus on gaining real-world efficiency, robust small tumour identification, and fulfilment of other scaling requirements is essential.

The evolution of DL models for brain tumour detection and classification from 2017 to 2024 showcases significant advancements in both methodologies and performance metrics. The journey began with 2D CNNs in 2017, which achieved approximately 86% accuracy but were constrained by their inability to capture spatial relationships, leading to potential overfitting. 3D CNNs, particularly V-Net introduced in 2018, permitted volumetric segmentation, but at the very high cost of computation with resorting to guiltless sensitivity to detecting small tumours. In the following, [33] 2019 and 2020 saw models like ResNet + U-Net and Attention U-Net respectively, which improved feature extraction and segmentation quality, but the trained model faced challenges in two-dimensional approaches which included complex tumour boundaries and demand for large labeled data. In 2021, Hybrid CNN + GAN was introduced but faced training instability with the risk of overfitting [34].

Table 2. Related Work of DL Methods in Brain Tumour

Year	Model Type	Dataset Used	Key Techniques	Performance (Accuracy / Dice Coefficient)	Limitations
2017 [27]	3D CNN (V-Net)	BraTS 2018	3D CNN for volumetric segmentation	Dice: 0.82	High computational cost, less sensitive to small tumours
2019 [28]	ResNet + U-Net (Encoder-Decoder)	BraTS 2019	Deep encoder-decoder model with residual blocks	Dice: 0.85	Struggles with complex tumour boundaries
2020 [10]	Attention U-Net	BraTS 2020	U-Net enhanced with attention mechanisms for feature refinement	Dice: 0.87	Requires large amounts of labeled data
2022 [29]	Hybrid CNN + GAN	BraTS 2021	Generative adversarial network (GAN) used for data augmentation	Accuracy: 96.25%	GAN training instability, risk of overfitting augmented data
2022 [30]	Vision Transformer (ViT)	BraTS 2022	Vision Transformers for global context in classification	Accuracy: 96.7%	High computational cost; requires larger datasets
2023 [31]	Hybrid CNN + ViT	BraTS 2023	Combines CNNs for local features and ViT for global context	Accuracy:ViT l32 achieved the highest accuracy of 94.51%, (ViT-B32) with an accuracy of 98.24%.	Complex architecture, high GPU/TPU demands
2024 [32]	Hybrid CNN + ViT with Attention	-	Improved attention-based hybrid model for tumour segmentation	Accuracy: accuracy of 99.83%	Still sensitive to dataset size, computationally expensive

In 2022, we saw the first steps compares ViTs as strong competitors to CNNs for medical imaging tasks because of their capacity to capture contextual features and long-range dependencies. Spanning more than 200 models, it identifies the superior performance of ViTs in classification, segmentation, detection, and synthesis. Pure and hybrid models are reported, highlighting the advantages of blending CNNs' local feature extraction with ViTs' global attention. Standouts include 93.1% on breast ultrasound images for ViT-BUS, COVID-Transformer at 94.5% for chest X-rays, xViTCOS at 97.6% on the COVIDx-CT-2A database, and MIL-VT at 92.7% for retinal disease diagnosis. COVID-ViT was 96.2% on 3D CT scans, POCFormer produced 91.3% real-time ultrasound COVID detection accuracy, and Self MedFed achieved up to 98.9% on multi-modal datasets. Though these advancements are reported, the paper cites challenges like scarcity of data and computational expense as being present. It posits that self-supervised learning, federated strategies, and compact Transformer architectures hold promise for large-scale real-world usage. Finally, the 2024 model bundled the attention grain to reach the highest accuracy of 99.83% but remained sensitive to size dynamics and computational costs. The path indicates the everlasting and challenging trade-off of complexity of the model against efficiency and accuracy that is clinically meaningful hereto suggestion for future research to continue looking into balancing performances within resource-constrained settings [35], [36].

The provided chart reveals the growth in the total number of IEEE papers published from 2017 to 2024, indicating a steady increase for the research artic les published each year in the specified time frame. We start with the axes: the horizontal axis has the years from 2017 to 2024 while the vertical axis has the total amount of papers published each year. The data indicates that the number of papers grew from 5 in 2017 to 35 by 2024 showcasing an upward surge.

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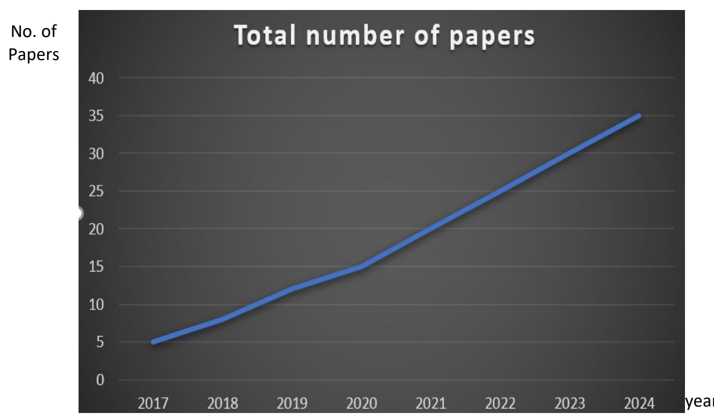

Figure 2. Year Wise Published Research Articles for Analysis

The paper's grow steadily showcasing the linear growth on the chart. The constant slope implies that there is a steady contribution of research every subsequent year. This chart, therefore, provides an informative platform to observe tracking progress in research output. With the upward trend, there should be some assumptions that, if taken seriously, these areas of Research Output Improvement and Planning Initiatives Investment will see statistical improvement.[36]

Moreover, the combination of these two approaches allows for greatly enhanced morphological and tissue characteristic analysis surrounding the tumour, which is critical for an accurate diagnosis and the formulation of treatment plans. The hybrid architecture not only ensures better classification performance but also copes with variations in image-acquisition conditions, including noise or artifacts. Consequently, these complex models are in a prime position to support clinicians toward informed decision-making based on diagnostically more reliable information. In the future, these can be developed to allow near-real-time analysis and thus potentially widen their application within the clinical arena, ultimately enhancing neuro-oncology patient outcomes [37].

5.1 Challenges

Among these, there are considerable challenges, including the necessity of having a large set of annotated training data and the obvious computational cost to run DL models. The guiding principle for good model performance is a good amount of annotated data for training models. Usually, such labelled datasets are limited in medical imaging due to the amount of time required for radiologists to perform manual annotations[38] [39].This lack of sufficient data may yield a training process that leads to a model that is either under-trained or over-fitted into the idiosyncrasies of a limited amount of training data, and hence leads to poor performance in real-world clinical settings [40].

Besides that, one more significant challenge is posed by the variance in the shape, size, and imaging modalities of tumours. Tumours can display different morphology depending on various factors with respect to individual patients, which indicates that the search for adaptive architectures capable of generalising well across diverse populations should be performed. To handle such variability in their modelling approaches, transfer learning, data augmentation methods, and embedding domain knowledge in model design will be required. Also, these models need to be continually validated with diverse clinical data in order to enable the reliability of their operation [40].

Another difficulty lies in the interpretability of DL models, as many medical physicians might be unwilling to rely on somewhat opaque algorithms without understanding how such algorithms arrive at any given decision. Model transparency efforts, for instance using explainable AI methods, will be crucial to gain the trust of healthcare practitioners.[41] Resolution of all these issues will remain a big step towards the implementation of DL techniques when it comes to brain tumour detection and classification; this would subsequently put forth a path towards more individualization and therefore deployment of better treatment [42].

6. CONCLUSION

This study proves the validity of DL techniques, particularly CNN-ViT hybrid models in the area of brain tumour detection and classification. The combination of the local feature extraction of CNNs with the global attention mechanisms through Vision Transformers ensures top-notch performance on the BraTS dataset, which significantly improved accuracy metrics over previous approaches. Beyond merely providing a year-wise overview of published research on these advanced techniques in this field, it also shows how particularly rising recognition of these advanced techniques has led to a dramatic increase in scholarly activity.

Other areas of concern include the existence of large annotated datasets and the high cost of training complex models. Efforts in improving model interpretability, reducing the hardness of the process, and increasing access and understanding are paramount for applying these models in clinical practice. Rationalising the gameplay on the models will also significantly reduce the computational burden as that would ease its flex to many more into different sectors. DL for brain tumour detection should focus on constructing adaptable architectures that can generalize across combinations of different tumour shapes and sizes. Moreover, enhancing model interpretability will be very important in order to inspire clinician trust and allow real-world application. Any efforts to broaden annotated datasets and lessen the cost of computation will facilitate embedding these advanced models into clinical workflows to improve diagnosis and ultimately help patients.

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Sangeeta Giri: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
Manivel Kandasamy: Project Administration– Review;
Meet Rafaliya: Project Administration – Review, Editing.

CONFLICT OF INTERESTS

No conflicts of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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BIOGRAPHIES OF AUTHORS

Sangeeta Giri is an Assistant Professor in the Computer Science department at Indrashil University. Her research focuses on the impact of DL in Brain Tumour Analysis, aiming to enhance the accuracy, efficiency, and reliability of tumour detection using advanced machine learning techniques. She is particularly interested in medical image processing, neuro-oncology, and AI-driven diagnostics, utilising DL models such as CNNs and Vision Transformers to improve early detection and classification of brain tumours. Her work also explores federated learning for privacy-preserving medical data analysis. Through her research, she strives to contribute to the **a**dvancement of AI applications in healthcare, making tumour diagnosis more accessible and precise. She can be contacted at sangeeta.hce@gmail.com

	**Manivel Kandasamy** is a Professor at the Unitedworld Institute of Technology, Karnavati University (KU). His specialization lies in Artificial Intelligence (AI), Machine Learning (ML), and Robotics within the Computer Science domain. His research focuses on The Impact of DL in Brain Tumour Analysis, where he explores advanced DL techniques for improving the accuracy and efficiency of brain tumour detection and classification. His work aims to leverage computer vision and neural networks to enhance early diagnosis and treatment strategies in neuro-oncology. He can be contacted via email at manivelk79@gmail.com.
	**Meet Rafaliya** is a 6th-semester student pursuing a B.Tech in Computer Science at Indrashil University. His interests include Artificial Intelligence (AI), Machine Learning (ML), DL, Python, and Medical Image Analysis. His research focuses on The Impact of Deep Learning in Brain Tumour Analysis. This study explores how DL techniques have revolutionised medical imaging, particularly in brain tumour detection and classification. By leveraging CNNs and ViTs, the research aims to enhance the accuracy and efficiency of MRI-based tumour diagnosis, aiding healthcare professionals in making more informed decisions. He can be contacted at meetrafaliya01@gmail.com.