International Journal of Education, Modern Management, Applied Science & Social Science (IJEMMASSS)
e-ISSN :2581-9925, Impact Factor (Cosmos: 7.555&I2OR: 5.105), Volume 08, No. 01(II), January- March, 2026, pp. 292-300

AI Innovations in Early-Stage Brain Cancer Detection: A Review of Recent Advances

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Citation: Sharma, D., & Rustagi, T.(2026). AI Innovations in Early-Stage Brain Cancer Detection: A Review of Recent Advances. International Journal of Education, Modern Management, Applied Science & Social Science, 08(01(II)), 292–300. https://doi.org/10.62823/IJEMMASSS/8.1(II).8887

ABSTRACT

Amongst the many different forms of cancers, the brain cancer is undoubtedly one of the hardest cancers to detect in its early stages due to issues arising from early diagnosis of cancers using medical images. Even though they play an essential role in diagnosing, traditional diagnosis methods tend to be inconsistent, subjective, and lead to many late diagnoses at last. The AI sector has done quite some good in early diagnosis of brain tumors through deep learning in recent years, making the process faster and more accurate by using effective medical image processing. Some of the significant models that can be used include EfficientNetV2S, EfficientNetB7, U-Net, YOLOv5, and efficient deep Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs). All these models use powerful algorithms like transfer learning and object detection amongst others with high efficiency and accuracy. Further, cutting-edge research is devoted to techniques for better generalisation and these include federated learning, where distributed datasets can be used to train a model, and Explainable AI (XAI), which addresses model interpretability for clinical applications. Currently, there is a major interest in using AI-driven innovations as a tool that could revolutionize the diagnosis of brain cancer by providing more precise and reliable tools for improving detection time, more personalized treatment options, and better survival rates as the number of brain cancer cases keeps on increasing around the world.

***Keywords**: Artificial Intelligence, Brain Cancer Detection, Deep Learning, Vision Transformers (ViTs), Medical Imaging, Clinical AI Integration.*

Introduction

Brain tumors are one of the most life-threatening and malignant form of cancer with high morbidity and mortality rate. Early Detection is important in improving patients' survival rates, as timely treatment and intervention are possible. Still, early diagnosis of brain tumors is difficult because the brain has inherently complex tissue and tiny tumors often are not easily identified on medical imaging. Although commonly used, conventional diagnosis systems like magnetic resonance imaging (MRI) or computed tomography (CT) typically require manual procedures.

Interpretation, a Process that may Lead to Subjectivity and Variability in Clinicians

Artificial Intelligence (AI), particularly Deep Learning (DL), has become increasingly creative and interestingly innovative when used in medical imaging within the last few years. Artificial Intelligence technology has great potential to increase the effectiveness of brain tumour diagnosis and classification, which gives us an objective and standardized approach to diagnosing illnesses. An AI system is capable of analysing past data of medical imaging and detecting trends, making it possible to give more precise diagnosis of tumours in comparison to the conventional methods.

The rapidly evolving AI-based technologies, such as Deep CNNs, Vision Transformers (ViTs), hybrid architectures among others have proven to be very efficient in achieving the goal of increasing the accuracy of tumor detection, segmentation, and classification. The algorithms incorporated in these models are capable of detecting complex structure patterns in medical imaging, allowing for the detection of any early stage cancers that can easily go undetected with a naked eye. Also, AI algorithms like EfficientNet, U-Net, and YOLOv5 have proven to be very effective in dealing with the imaging challenges such as noise, distortions and varied sizes and shapes of tumors.

The objective of this review paper is to obtain and elaborate the understanding of recent advances in the domain of AI detection of brain tumors in their initial phases. The aim of this research paper is to study these breakthroughs and emphasize on the future that holds much potential for the application of AI towards the diagnosis of brain tumors in a better way.

Overview of AI in Medical Imaging

In terms of medical image recognition and classification, artificial intelligence and especially deep learning technology can help in achieving efficient and powerful processing of the vast amounts of complicated medical data. Diagnostic techniques, although they may be effective, can hardly cope with tasks that require manual data interpretation. Due to its effectiveness, however, diagnostic technique cannot compete with manual interpretation of data, which may result in inconsistency. In contrast, technologies like AI, which can successfully work with high-dimensional medical images, such as MRI and computed.

The use of CT scanning significantly increased the reliability, consistency, and effectiveness of diagnosing.

One of the strengths of the use of artificial intelligence in the area of imaging in medicine lies in the ability to distinguish patterns and features that are hard for humans to spot, even at the very beginning of the development of the disease. AI systems are capable of identifying abnormalities and classifying the region of interest and tumor using deep learning algorithms like CNNs and ViT. The importance of AI cannot be understated for detecting and classifying brain tumors.

There is proof that artificial intelligence-based models perform better and provide better results compared to the conventional models used. This will mean less time is taken during diagnoses and prompt treatment intervention measures can be applied. The AI models are capable of solving issues in medical imaging like noise in images and different images qualities and tumor morphology. The future of artificial intelligence in the health sector diagnostics looks bright.

Recent Advances in AI Models / Deep Learning Techniques for Brain Tumor Detection

- **EfficientNetV2S**

EfficientNetV2S is a downsized variant of the EfficientNetV2 network that aims to be efficient and fast, providing a compromise between performance and size.

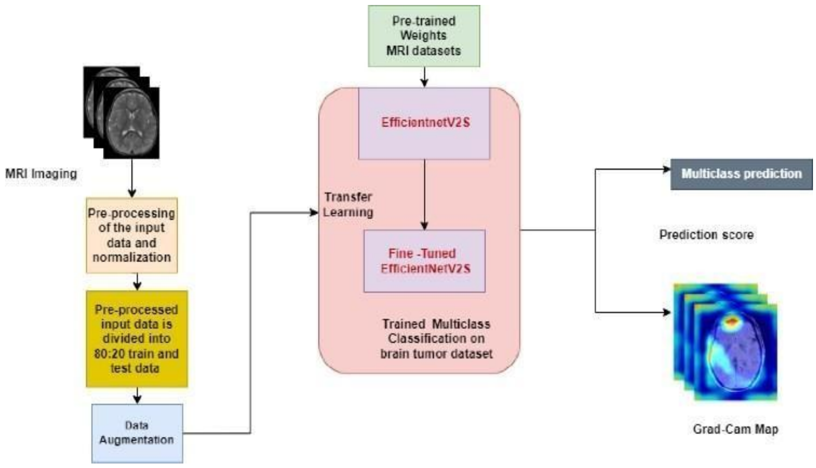

Figure 1: Proposed Framework for Brain Tumor Detection using EfficientNetV2S with Grad-CAM Visualization and Transfer Learning (Figure taken from [1])

Speaking specifically about the problem of brain tumor detection, the EfficientNetV2S architecture achieves a remarkable test accuracy of 98.35%, surpassing many classical algorithms and even modern deep learning approaches.[1]

EfficientNetV2S can be considered a breakthrough in artificial intelligence applications for healthcare, providing a powerful solution for detecting brain tumors with high efficie.

- **EfficientNetB7**

The EfficientNetB7 model represents the latest innovation in Deep Learning model architecture where the objective is to scale up accuracy while ensuring high efficiency. The EfficientNetB7 model represents the largest and most robust member of the EfficientNet architecture family, which has made great strides in achieving both accuracy and lower complexity.

An important innovation that comes with the EfficientNetB7 model is the improved level of accuracy when compared with existing architectures despite using significantly fewer parameters in the model. This model has become a new benchmark for accuracy, scoring 84.3% top-1 accuracy on the ImageNet dataset.[2] Moreover, the EfficientNetB7 model is 8.4 times smaller and 6.1 times faster than previous convolutional networks.

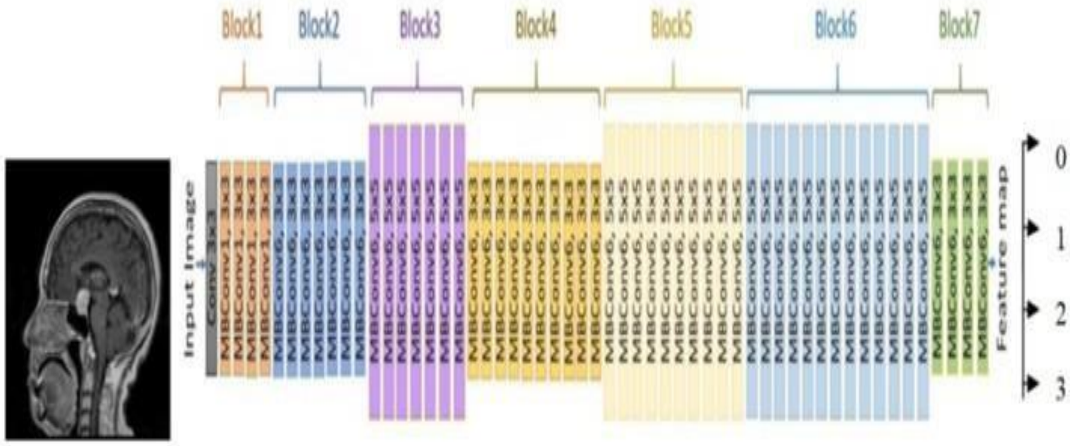

Figure 2: Brain Tumor Classification Framework using EfficientNetB7. (Figure taken from [3]).

Especially in detecting brain tumors, it has been noted that EfficientNetB7 performs exceedingly well when working with high dimensional MRIs and CT scans. The design of the architecture is transferable in nature, and thus it is suitable for use in different medical imaging applications.

- **YOLOv5**

The YOLOv5 is a state-of-the-art detection algorithm that offers high performance in terms of speed and accuracy, making it suitable for deployment in real-time applications. As the name implies, YOLOv5 is an advanced iteration of YOLOv3 and YOLOv4, whose developments and improvements in the architecture enable more effective object detection, shorter inference times, and better usability of the model. YOLOv5, which can offer excellent performance for detecting brain tumors, proves to be highly efficient in dealing with such a task. When tested on a special dataset designed specifically for brain tumors, YOLOv5 achieved impressive precision and recall scores, being rated at 83.5% and 86%, respectively. The results are far more favorable than those obtained using any other detection algorithm in terms of accuracy and computational efficiency.[4]

In addition to that, YOLOv5 performs well when used in conjunction with transfer learning methods, making it possible to adapt it to smaller datasets that are specific to particular domains without going through retraining processes. This makes YOLOv5 an excellent choice for application in medicine, especially when considering the limited amount of available data.

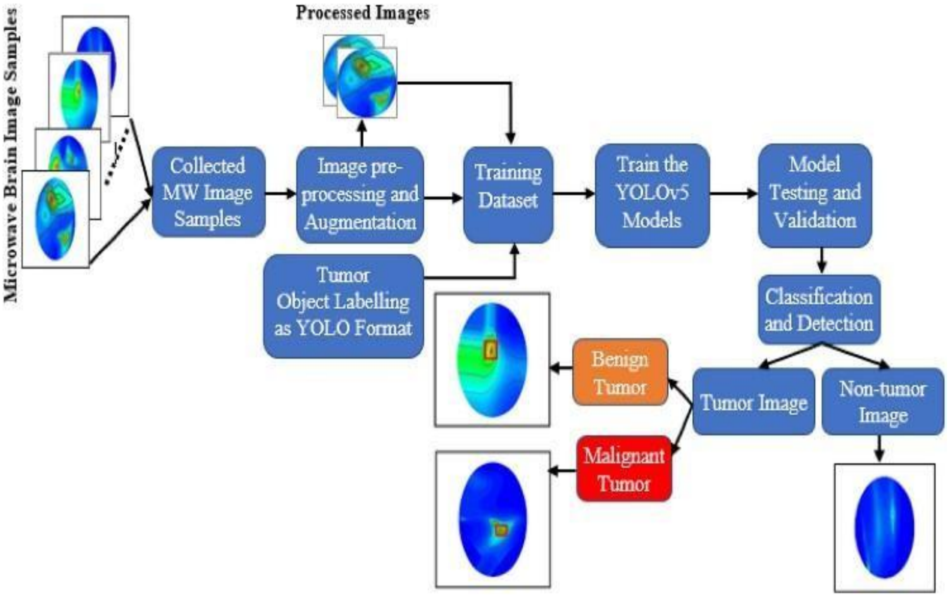

Figure 3: MRI Brain Tumor Detection Using YOLO Model with Real-Time Object Localization. (Figure taken from [5])

- **U-Net**

U-net architecture which was created to aid in biomedical image segmentation proves highly accurate in detecting brain tumors. The U-net is a CNN architecture which employs an encoder and decoder model to carry out segmentations on medical images. The design of the U-net architecture which involves the use of a contracting path that captures context and an expanding path which helps to precisely locate objects makes the algorithm fit to segment brain tumors through MRIs. It achieved high levels of accuracy in its performance, recording a dice coefficient of 0.9815, 0.9844, 0.9804, and 0.9954 respectively in four different sets of data from BraTS 2018 database.[7] These results show how the algorithm can successfully segment brain tumors accurately. U-net was highly successful in achieving high Dice coefficients (Metric for measuring similarity between predicted and ground truth segmentations.)[6]

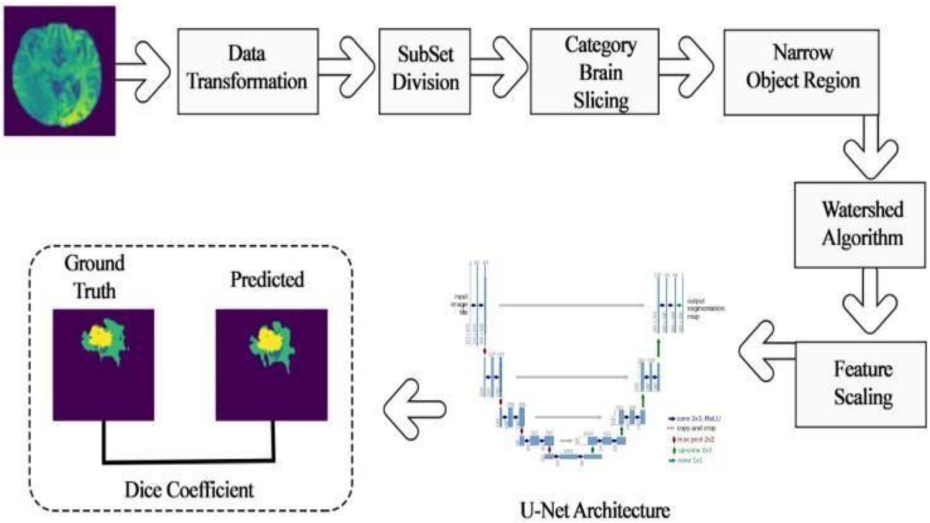

Figure 4: Architecture of Deep Learning Model for Tumor Detection in Medical Imaging. (Figure taken from [7]).

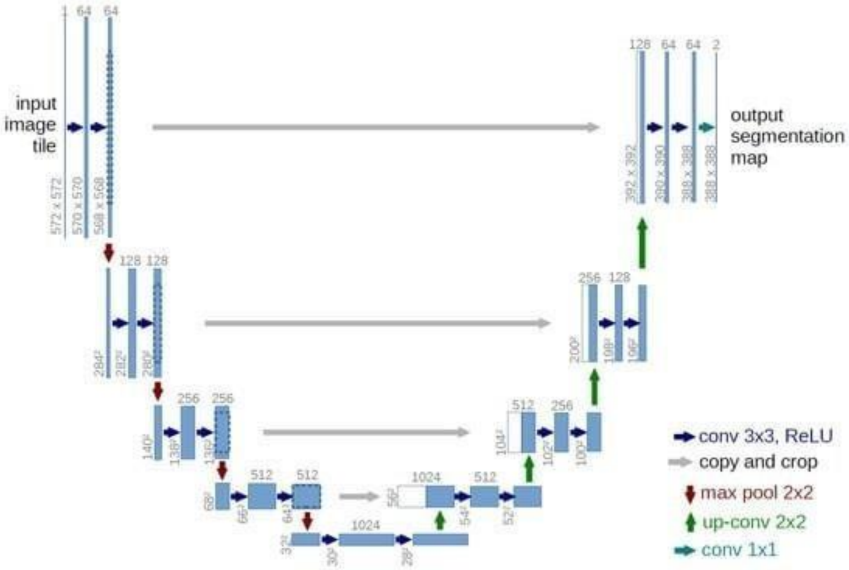

Figure 5: U-Net Architecture for Tumor Segmentation at 32 × 32 Pixel Resolution (Figure taken from [6])

- **DCT-CNN-ResNet50**

The DCT-CNN-ResNet50 model is an advanced architecture combining Discrete Cosine Transform (DCT) for image enhancement, a Convolutional Neural Network (CNN) for feature extraction, and ResNet50 for classification. This model was developed to improve the accuracy of brain tumor classification in MRI images, particularly for low-resolution images. By integrating super-resolution techniques, the model achieved a high classification accuracy of 98.14%, demonstrating its effectiveness in distinguishing between tumor and non-tumor tissues.[8]

The DCT-CNN-ResNet50 architecture for classifying brain tumors achieved an accuracy of 98.14% when tested on MRI images, according to the paper. This high accuracy is attributed to the combination of super-resolution, convolutional neural network (CNN), and ResNet50 architecture.[9]

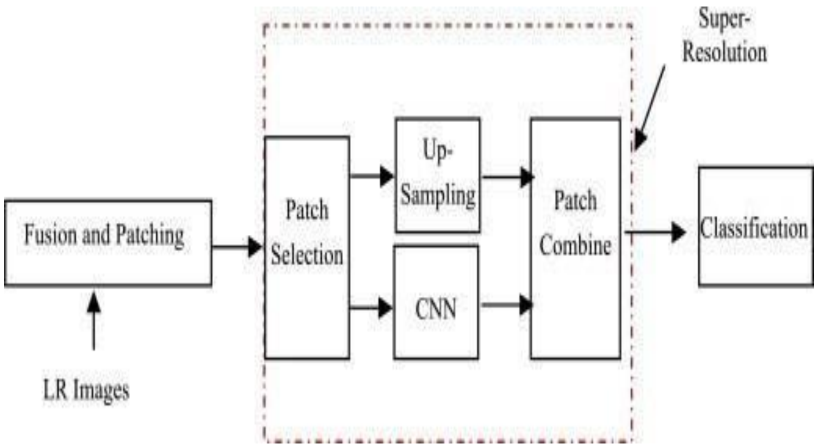

Figure 6: DCT-CNN-ResNet50 Framework for Brain Tumor Classification. (Figure taken from [8])

- **Deep Convolutional Neural Networks(CNN)**

Deep convolutional networks generally involve several well-known models, each with specific architectures and features designed for various tasks. The deep convolutional networks discussed are likely: the two models utilized are:

- **23-Layer CNN:** This custom deep convolutional neural network features 23 layers, designed specifically for feature extraction and classification of brain tumors from MRI images. Its depth allows for capturing intricate details in the data.
- **VGG16:** This well-established model is used for its proven ability to learn hierarchical features with its 16-layer architecture, providing robust performance in image classification tasks including brain tumor detection.

These models are used to leverage their strengths in feature extraction and classification to achieve high accuracy in brain tumor detection. By combining the VGG16 architecture with their custom 23-layer CNN model. Their experimental results show that this combined approach achieves impressive classification accuracies of up to 97.8% and 100% on their datasets, surpassing the performance of existing state-of-the-art models in brain tumor detection.

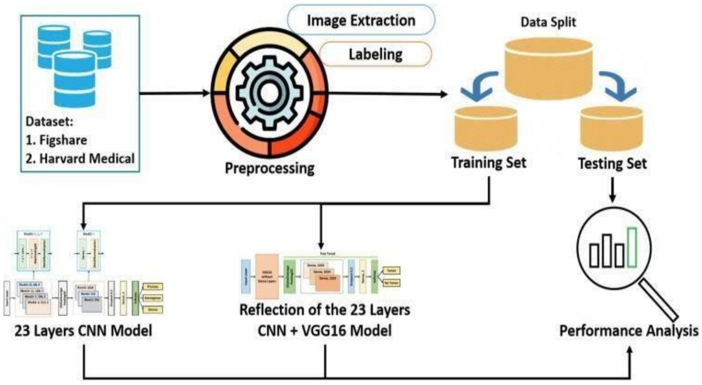

Figure 7: Proposed Deep Convolutional Neural Network (CNN) Architecture for Brain Tumor Detection. [Figure taken from [9]]

- **Vision Transformers (ViTs)**

Transformers apply self-attention processes for the analysis of images. While ViTs have exhibited success in image recognition, they still struggle in the case of medical imaging due to heavy computation requirements and large data samples. Nonetheless, ViTs can be considered promising for brain tumor classification if provided with enough training data; recent research indicates that these models may compete with CNNs in brain tumor classification accuracy. Specifically, several ViT models are trained using MRI data sets to identify different kinds of brain tumors. The classification results are aggregated using ensemble approaches to enhance the quality of the predictions. The particular variant of a transformer model utilized in this case study is ViT, customized for use in medical imaging. The model was highly successful at brain tumor classification, outperforming other approaches currently being employed. The accuracy of brain tumor identification with transformers is 98.7%.[10]

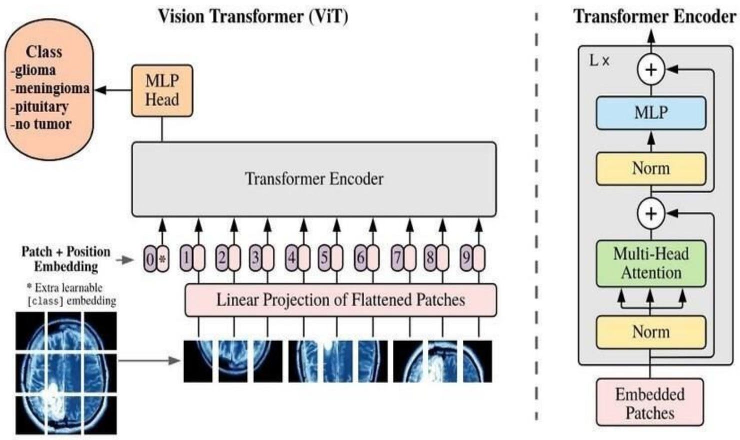

Figure 8: Vision Transformer (ViT) Architecture for Brain Tumor Classification. (Figure taken from [11])

Best Performing AI Techniques

In terms of the best AI algorithms among those analyzed, it can be stated that both EfficientNetV2S and ViTs demonstrate excellent performance when used for detecting brain tumors. The former algorithm demonstrates impressive results due to its high efficiency, accuracy, and speed, since its accuracy is 98.35%. It means that the algorithm can be used in the medical practice where timely diagnosis is required. ViTs, with their accuracy being equal to 98.7%, show high efficiency due to the use of the self-attention approach, which allows for solving problems with large datasets.

Challenges in AI-Based Brain Tumor Detection

Although progress has been made, there are still a number of issues to overcome when creating and implementing AI models for brain tumor detection.

- **Data Scarcity**

Access to large size annotated datasets is one of the largest challenges. For AI models, particularly in medical imaging, a large amount of data are required for effective training. However, given privacy concerns and the need for qualified professionals to assist in collecting and tagging the data, it is difficult to collect, pool and label sufficient high quality data. This data deficiency may result in overfitting, in which the model may work well on the training data but not so well on new, unseen data.

- **Model Generalization**

Generalization of the model is another important aspect that needs to be addressed. There are a number of AI algorithms which have their training and testing data from a particular location or from a particular type of scanner. This may cause the model to be ineffective when applied to data from other sources, or to patients of different demographic makeup. Due to this, if these models through these aforementioned ways are deployed in real-world clinical scenarios, the precision of these models may suffer if the input data deviates from the one the models were trained with.

- **Computational Complexity**

The models in deep learning, particularly those that are substantial such as CNNs (Convolutional Neuronal Network), can be quite heavy in resources. They have heavy demands for computer systems, memory needs and require powerful processors and able to fit a lot of memory, which can pose a challenge in clinical settings particularly for clinics which maybe resource constrained. The high computational expense involved can retard the use of such sophisticated models.

- **Variability in Areas of Imaging Techniques**

Variability in the data can be caused by different imaging technologies and protocols. For example, the images that are captured with different MRI machines or MRI settings, may also look different, even if the same tumour is being scanned. This can produce significant variations, which can make it difficult for AI models to deliver accurate results in different imaging environments.

- **Explainability of Models**

Often, AI models, especially deep learning models, are 'black boxes' and it can be difficult to see how the models make their predictions. For informed choices it is crucial to understand the rationale behind a model's decision in clinical practice. Transparency of AI model actions can be a huge challenge to applying AI models in clinical practice.

- **Successful Program Integration within Clinical Workflow**

The challenge is to fit AI tools into the current clinical workflows. These tools must be easy to use, compatible with existing tools and systems, and offer benefits without creating disruption to the day to day activities. Proper integration is crucial to ensure that AI models are effectively used in clinical settings.

- **Reflection is Enabled by Continual Learning, Adaptation, and Reflection**

Medical imaging and the features of the tumor are always changing. AI models need to be regularly updated to keep up

In the face of the new imaging technology, tumour types and treatment methods. Continuous learning and adaptation are essential to keep AI models up-to-date and accurate in the long run.

Future Directions and Clinical Implementation

Improvements for this include having more powerful models that are able to be generalizable across other datasets and imaging modalities.

- **Incorporate into the Clinical Workflow**

In order for AI tools to be efficiently used, they need to seamlessly integrate into current processes. The tools should be not only easy to operate but also available and provide tangible outcomes without hindering the daily maintenance of such. Instead of replacing radiologists, the AI tools should act as a puzzle piece among humans, aiding in making decisions.

- **Real-Time Tumor Detection**

Computational efficiency, in turn, will result in better models for detecting and segmenting tumors that work faster. The development of an efficient architecture of a neural network that will maintain its accuracy while being fast enough to be utilized in real time, for example, helping radiologists when analyzing MRIs or in surgeries, is crucial in order to apply the model into practice.

- **Multimodal Approaches**

For future reference, various types of data can be used for the model including the use of MR imaging in addition to patient history or any other medical documentation and the use of genomics data. There is also a possibility that multimodal approaches will yield more comprehensive details on the condition of brain tumors.

- **Federated Learning**

By adopting the concept of federated learning, data distributed across several sources will be able to train AI models without transferring or consolidating the data. This would allow both the institutions to pool their resources in terms of accessing data and maintain confidentiality for patients, tackling the issue of data scarcity. Federated Learning could help make AI models more robust and accurate in detecting brain tumors among other things.

- **Explainable AI (XAI) Techniques. Explainable AI (XAI) Techniques**

There has been an increasing interest in the interpretability of the AI algorithms being developed. In the future, XAI will focus on explaining the results of queries of AI systems through increased transparency in order to allow the user to understand how the AI system arrived at its particular prediction.

- **The Training and Education of Clinicians. Clinician Training and Education**

In order to make sure that the application of AI technology is utilized effectively in the healthcare field, there should be a requirement for clinicians to receive proper training about the technology as well as how to evaluate the model's performance and to remain cognizant of its limitations.

Conclusion

Over the last couple of years, AI has become a focal point of rapid developments in early stage identification of brain cancers. Deep learning models such as Deep CNN, U-Net, and ViT have greatly improved the accuracy and efficiency of brain tumor detection and classification, creating more chances for early diagnosis and treatment. EfficientNetB7, EfficientNetV2S, YOLOv5, and other hybrid models, such as DCT-CNN-ResNet50, took this further still, demonstrating superior performance and the ability to process complex medical imaging datasets in practical applications.

Despite these developments, there are issues which require to be resolved in order for AI models to be adopted clinically. This was definitely impressive, although there were still some issues which needed to be overcome if AI models were to be widely used in practice. Issues such as data limitation, model generalisability, computational requirements, and the need for explainable AI still persist. In the future, these should be solved by increasing dataset size, making the models more computationally efficient, and improving their interpretability.

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