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Transforming Brain Tumor Detection via Modified Detection Transformer Architectures for Enhanced Diagnostic Outcomes

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Abstract: Brain cancer, including gliomas, meningiomas, and pituitary tumors, is complex and difficult to diagnose and cure. Brain tumors account for 2% of cancer cases in India, affecting children and adults. Despite advances in imaging tools like MRI, CT, and PET, precise early detection improves results, especially in regions with limited specialist healthcare. This study uses a modified DETR (identification Transformer) model for brain tumor identification using real-time object detection and localization. DETR's advanced feature extraction and bounding box prediction enable precise brain tumor type identification. The proposed approach predicts tumor grades using a deep learning model trained on a large dataset of annotated medical images with a recall of 0.991, precision of 0.996, and F1 score of 0.995. This research combines the improved DETR model's real-time detection with standard imaging modalities to increase diagnosis accuracy, assessment time, and radiologists' decision-making. In India, brain cancer management is hindered by a lack of advanced diagnostic tools and high treatment costs. The updated DETR model's strengths are combined with neuro-oncology clinical procedures in this AI-driven method to improve brain cancer detection and patient outcomes.

Keywords: Brain Cancer; Gliomas and Meningiomas; Excess Hormones; Imaging Techniques; AI and ML; Healthcare Landscape; Malignant Brain Tumour; Brain Cancer Detection; Detection Transformer.

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1. Introduction

Brain cancer represents a complex and life-threatening group of conditions characterized by the abnormal growth of cells within the brain, leading to the formation of tumors. These tumors can be benign (non-cancerous) or malignant (cancerous), and their impact on the nervous system can vary depending on the type, size, and location within the brain. The diversity of brain tumors makes diagnosis and treatment particularly challenging, with each type presenting unique clinical manifestations and requiring specific therapeutic approaches. Among the numerous types of brain tumors, gliomas, meningiomas, and pituitary tumors are some of the most prevalent, collectively accounting for a significant portion of brain tumor cases worldwide. In India, these tumors constitute roughly 2% of all cancers, underscoring the need for improved detection and management strategies.

Gliomas are among the most aggressive forms of brain tumors, originating from glial cells, which are the supportive cells of the central nervous system. These tumors are not only the most common type of malignant brain tumors but also exhibit significant variability in terms of grade and behaviour. Gliomas are categorized into four grades based on the World Health Organization (WHO) classification, with Grades I and II being low-grade, relatively slow-growing tumors, and Grades III and IV, including glioblastoma multiforme (GBM), representing high-grade, rapidly growing, and more aggressive forms. The prognosis for patients with high-grade gliomas is generally poor, with survival rates remaining low despite advancements in surgical techniques, radiotherapy, and chemotherapy. Early and accurate detection of gliomas is crucial for improving patient outcomes, as these tumors can infiltrate surrounding brain tissue, complicating surgical removal and leading to high rates of recurrence.

Meningiomas, which arise from the meninges (the protective membranes surrounding the brain and spinal cord), represent another major type of brain tumor. Accounting for approximately 30% of all primary brain tumors, meningiomas are typically benign, but they can still pose significant risks to health due to their location and size. These tumors may exert pressure on surrounding brain structures, leading to symptoms such as headaches, seizures, and visual disturbances. Although the majority of meningiomas are slow-growing and have a favourable prognosis following surgical removal, atypical (Grade II) and anaplastic (Grade III) meningiomas have a higher potential for aggressive growth and recurrence, requiring additional therapeutic interventions like radiation therapy. The detection and treatment of meningiomas are primarily guided by imaging techniques, with magnetic resonance imaging (MRI) being the preferred modality due to its ability to provide detailed visualization of soft tissues.

Pituitary tumors develop in the pituitary gland, a small but crucial gland located at the brain's base, which regulates various hormones that control growth, metabolism, and reproductive functions. The majority of pituitary tumors are benign adenomas. Still, their effects can be profound due to hormone overproduction or the physical compression of nearby structures, such as the optic nerves, resulting in visual impairments. Pituitary adenomas are classified into functioning and non-functioning types, depending on whether they produce excess hormones. Functioning adenomas can lead to endocrine disorders such as Cushing's disease, acromegaly, or prolactinoma, while non-functioning adenomas may cause symptoms related to mass effect. Early detection through imaging and hormone-level tests is critical for managing pituitary tumors effectively, as untreated hormonal imbalances can lead to significant morbidity.

In India, the burden of brain cancer is increasing, with an estimated 28,000 to 30,000 new cases diagnosed annually. The incidence of brain tumors is noted to be higher in urban areas due to better access to diagnostic facilities and healthcare services. Brain tumors are also one of the leading causes of cancer-related mortality among children, making early diagnosis and intervention even more essential. Despite the advances in medical imaging techniques such as MRI, computed tomography (CT), and positron emission tomography (PET), which are used for detecting and characterizing brain tumors, several challenges persist. The lack of access to advanced diagnostic tools in rural areas, delays in seeking medical care, and the high cost of treatment are significant barriers that affect early detection and patient outcomes.

The advancements in artificial intelligence (AI) and machine learning (ML) technologies in medical imaging have brought new possibilities for enhancing brain tumor detection and classification. Techniques such as deep learning, particularly convolutional neural networks (CNNs), have shown remarkable potential in analyzing medical images, automatically detecting abnormalities, and differentiating between various types of brain tumors. These AI-based approaches can improve diagnostic accuracy and assist radiologists by providing automated image analysis, reducing the time required for manual assessment. Moreover, integrating AI with traditional imaging modalities can help predict the tumour's grade and aggressiveness, which is critical for treatment planning and prognosis.

This study aims to address the challenges associated with brain cancer detection by leveraging advanced detection methodologies, including machine learning algorithms (modified DETR) and medical imaging analysis, to improve the early identification and classification of gliomas, meningiomas, and pituitary tumors. The research focuses on developing AI-driven diagnostic tools that can analyze large datasets of medical images to detect and differentiate brain tumor types accurately. By integrating these advanced techniques with existing clinical workflows, this study seeks to enhance the precision of diagnosis, optimize treatment strategies, and ultimately improve patient outcomes in brain cancer care.

Brain cancer detection remains a complex challenge due to the diversity of tumour types and the limitations of current diagnostic methods. However, AI and ML offer promising avenues for revolutionizing brain cancer diagnostics, making it possible to detect tumours at an earlier stage, classify them with greater accuracy, and provide personalized treatment plans. This research aims to contribute to the growing field of AI in medical imaging, providing insights into how machine learning can be applied to improve brain tumor detection and management, with a particular focus on gliomas, meningiomas, and pituitary tumors in the context of India's healthcare landscape.

2. Literature Review

Khalighi et al. [1] emphasize that AI leverages imaging, histopathological analysis, and genomic data to enhance brain tumor detection, categorization, outcome prediction, and treatment planning. AI models have performed superior to traditional human evaluations, improving accuracy and specificity in diagnosing malignant brain tumors. By discerning molecular characteristics directly from imaging data, these models can reduce reliance on invasive diagnostics and expedite the time to critical molecular diagnoses, facilitating personalized treatment strategies that optimize clinical outcomes for glioma patients. The review also highlights challenges, such as the need for multimodal data integration, generative AI, and addressing racial and gender disparities in AI applications. Furthermore, ethical, legal, and social implications surrounding AI's integration into neuro-oncology are discussed, advocating for transparency and fairness to enhance patient care. Overall, the insights provided by Khalighi et al. [1] underscore AI's potential to revolutionize neuro-oncology, offering promising directions for future research and improving patient outcomes.

Mathivanan et al. [2] noted that recent advancements in artificial intelligence (AI), particularly deep learning methods, have significantly improved the accuracy of brain tumor diagnoses. These methods excel in processing large volumes of data, making them highly effective for medical imaging applications. Among various imaging modalities, magnetic resonance imaging (MRI) stands out as the gold standard for brain tumor diagnosis, surpassing computed tomography (CT), ultrasound, and X-ray imaging in efficacy. However, the complex structure of the brain presents ongoing diagnostic challenges. To address this, the study explores the potential of deep transfer learning architectures to enhance diagnostic accuracy. Transfer learning enables the repurposing of pre-trained models for new tasks, which is particularly useful in medical imaging, where labeled data is often limited. Four distinct transfer learning architectures were assessed: ResNet152, VGG19, DenseNet169, and MobileNetv3, utilizing a dataset from the Kaggle benchmark database. The researchers employed five-fold cross-validation for training and testing and applied image enhancement techniques to balance the dataset across four categories: pituitary tumors, normal cases, meningiomas, and gliomas. MobileNetv3 achieved the highest accuracy of 99.75%, significantly outperforming other existing methods and demonstrating the transformative potential of deep transfer learning architectures in revolutionizing brain tumor diagnosis.

Mehrotra et al. [3] highlight that the standard diagnosis of brain tumors (BTs) relies on histological examination of biopsy samples, a method that is invasive and error-prone. This underscores the need for automated tumor detection. In the U.S., approximately 0.7 million individuals currently have primary brain tumors, and this number is expected to rise. Efficiently categorizing magnetic resonance (MR) brain images as normal or pathological can alleviate the burden on radiologists. The authors present a framework that combines discrete wavelet transform (DWT), deep convolutional networks (DCN), and machine learning (ML) for BT identification. DWT extracts important features from MR images, while DCN captures deep features, enhancing tumor detection. Their model achieves an impressive 99.5% accuracy and an area under the curve (AUC) of 1, surpassing several existing methods. This framework offers valuable support for radiologists and medical professionals in diagnosing brain tumors.

Pacal [4] emphasizes the importance of timely and accurate brain tumor diagnosis due to serious health implications. Poor imaging quality, data integrity issues, and diverse tumor types hinder precise detection. Rapid identification is crucial for patient safety, and deep learning systems can aid radiologists in making swift diagnoses. This study presents an advanced deep learning approach using the Swin Transformer, featuring a Hybrid Shifted Windows Multi-Head Self-Attention module (HSW-MSA) and a rescaled model to enhance classification accuracy and reduce memory usage. The traditional multi-layer perceptron (MLP) is replaced with a Residual-based MLP (ResMLP) to improve accuracy and training speed. The Proposed-Swin model is evaluated on a publicly available brain MRI dataset with four classes, employing transfer learning and data augmentation for robust training. Remarkably, it achieves an accuracy of 99.92%, surpassing previous models. This method highlights the effectiveness of the Swin Transformer with HSW-MSA and ResMLP in improving brain tumor diagnosis, providing valuable support to radiologists, and enhancing patient outcomes.

Khaliki and Başarslan [5] underscore the critical role of health, particularly brain health, in human well-being. They emphasize that magnetic resonance imaging (MRI) is essential for diagnosing brain conditions and provides substantial data that can be harnessed for artificial intelligence (AI) applications. Their study focuses on classifying various brain tumors, including glioma, meningioma, and pituitary tumors, using MRI scans. The authors employed Convolutional Neural Networks (CNNs) and advanced CNN-based architectures such as Inception-V3, EfficientNetB4, and VGG19 to achieve this. They utilized F-score, recall, precision, and accuracy metrics to evaluate model performance. The results indicated that the VGG16 model achieved the highest accuracy at 98%, accompanied by an F-score of 97%, an Area under the Curve (AUC) of 99%, a recall rate of 98%, and a precision of 98%. These findings highlight the significance of CNN architectures and transfer learning methods in enhancing the early diagnosis and rapid treatment of brain tumors, significantly contributing to improved patient outcomes.

Anantharajan et al. [6] describe brain tumors as abnormal cell growths that can become cancerous, highlighting the importance of early diagnosis and timely treatment for improving patient outcomes. They note that Magnetic Resonance Imaging (MRI) is the primary method for detecting brain tumors, but accurate identification and segmentation depend on the radiologists' skills, making the process labour-intensive. The authors propose a novel detection method that combines deep learning (DL) and machine learning (ML) approaches to address challenges in traditional imaging techniques. Their method begins with preprocessing MRI images using an Adaptive Contrast Enhancement Algorithm (ACEA) and a median filter, followed by fuzzy c-means clustering for segmentation. Features such as energy, mean, entropy, and contrast are extracted with the Gray-Level Co-Occurrence Matrix (GLCM), and abnormal tissues are classified using an Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifier. The results show high accuracy (97.93%), sensitivity (92%), and specificity (98%) in differentiating normal from abnormal tissues, demonstrating the potential of their approach to enhancing brain tumor detection.

Poornam and Angelina [7] emphasize the importance of brain tumor detection and classification for guiding treatment plans. Magnetic resonance imaging (MRI) is preferred due to its high quality and lack of ionizing radiation. However, the increasing volume of MRI data makes manual processing time-consuming and prone to errors. To address these challenges, the authors propose the "Vision Transformer with Attention and Linear Transformation module (VITALT)," which integrates the Vision Transformer (ViT), Split Bidirectional Feature Pyramid Network (S-BiFPN), and Linear Transformation Module (LTM) for effective feature extraction from complex brain structures. The method begins with preprocessing steps to reduce training inaccuracies, followed by dividing images into patches for high-dimensional embedding, enabling the ViT to learn relationships and capture features. The S-BiFPN enhances prediction accuracy by fusing multi-scale spatial features, while the LTM identifies key characteristics for classification. Experimental results on four benchmark datasets demonstrate the VITALT system's reliability, achieving accuracies of 99.08%, 98.97%, 98.82%, and 99.15%. This high accuracy highlights the system's potential in medical imaging.

Shamshad et al. [8] highlight brain tumors as a significant health concern, projected to increase by 5% annually per the World Health Organization. This study evaluates transfer learning methods for identifying brain tumor types, focusing on the need for prompt diagnosis. The authors use MRI datasets' pre-trained models such as VGG-16, VGG-19, Inception-v3, ResNet-50, DenseNet, and MobileNet to enhance classification accuracy and efficiency. The evaluation framework includes metrics like confusion matrices, ROC curves, and Area under the Curve (AUC) for each method. The methodology serves as a guide for implementing and assessing deep learning models for brain tumor classification. Notably, VGG-16 achieves the highest accuracy at 97% while reducing processing time by 22% compared to previous approaches.

Aljohani et al. [9] highlight the necessity of classifying brain tumors to determine their severity and treatment. Their framework employs Artificial Intelligence in medical imaging, achieving high accuracy in classifying brain tumors using Convolutional Neural Networks (CNN), pre-trained models, and the Manta Ray Foraging Optimization (MRFO) algorithm on X-ray and MRI images. The MRFO optimizes the hyperparameters of the CNN and Transfer Learning (TL) models, enhancing performance. The study utilizes two Kaggle datasets: one for X-ray images with two classes and another for three classes of contrast-enhanced T1-weighted MRIs. Patients are first classified as "Healthy" or "Tumor," with subsequent MRI scans identifying tumor types (meningioma, pituitary, or glioma). The VGG16 pre-trained model outperforms others in the two-class dataset, while Xception excels in the three-class dataset. A review of misclassifications aids in correcting errors. The framework achieves 99.96% accuracy for X-rays and 98.64% for T1-weighted MRIs, surpassing most current deep-learning models.

Mahmoud et al. [10] examine how brain tumors can affect facial symmetry based on their location and size. Tumors impacting facial muscles may cause noticeable asymmetry, while some tumors may not affect appearance, and early-stage changes can be subtle. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), are utilized to classify brain tumors as benign or malignant by analyzing MRI scans. Manual analysis of these images is time-consuming and prone to errors. The authors trained CNN models to detect glioma, meningioma, and pituitary tumors, using the Aquila Optimizer (AQO) for dataset modification, with 80% for training and 20% for testing. The VGG-16, VGG-19, and Inception-V3 architectures were optimized with AQO, achieving the highest accuracy of 98.95% with the VGG-19 model.

Mohammed et al. [11] highlight the importance of early diagnosis for brain tumors, which have a low survival rate due to their heterogeneous nature. Analyzing complex Magnetic Resonance (MR) images is time-consuming and requires skilled experts. This study presents four AI systems combining machine learning, deep learning, and hybrid approaches. The first system uses artificial neural networks (ANN) and feedforward neural networks (FFNN) with features from local binary patterns (LBP), grey-level co-occurrence matrix (GLCM), and discrete wavelet transform (DWT). The second employs pre-trained GoogLeNet and ResNet-50 models, while the third integrates convolutional neural networks with support vector machines. The fourth merges features from GoogLeNet and ResNet-50 with LBP, GLCM, and DWT for classification using ANN and FFNN, achieving an accuracy of 99.9%, precision of 99.84%, sensitivity of 99.95%, specificity of 99.85%, and an AUC of 99.9%.

Babu Vimala et al. [12] highlight the importance of accurately classifying brain tumor types for timely diagnosis. They use Magnetic Resonance Imaging (MRI) and a transfer learning approach with EfficientNets to classify tumors into glioma, meningioma, and pituitary tumors, utilizing the CE-MRI Figshare dataset. The method involves initializing models EfficientNetB0 to EfficientNetB4 with ImageNet weights and adding layers for classification. Tests evaluate the robustness of the fine-tuned models, while data augmentation and Grad-CAM visualization are used to assess the accuracy and highlight tumour locations. EfficientNetB2 achieved notable performance with test accuracy of 99.06%, precision of 98.73%, recall of 99.13%, and an F1-score of 98.79%.

Aamir et al. [13] introduce the need for accurate and rapid brain tumor detection to expedite patient rehabilitation. Given the variation in tumor size, shape, and appearance, manual diagnosis by radiologists can be inefficient and prone to error. This study introduces a streamlined approach using MRI imaging, which enhances image quality through a low-complexity algorithm. Morphological analysis filters out non-tumour regions, while segmentation and clustering techniques identify high-quality tumor areas. Multiple deep neural networks extract features from these regions, and an adaptive fusion network creates a hybrid feature vector for classification using multi-class SVM. By augmenting training data to minimize overfitting, the system achieves an accuracy of approximately 98.98%, enhancing the resilience and automation of the diagnostic process.

Sharma et al. [14] highlight that brain tumors arise from uncontrolled cell growth and can be fatal if not diagnosed early. Accurate classification and segmentation are challenging due to tumor size, shape, and location variations. Computer-aided diagnosis significantly aids radiologists in assessing MRI images, as brain tumors are associated with reduced life expectancy at higher grades. This study introduces a model that uses the histogram of gradients (HOG) features from MRI images for tumor detection. A feature optimization approach extracts intuitive features, while a Modified ResNet50 model employs HOG for accurate deep feature extraction. The model maintains computational efficiency and integrates augmentation and feature extraction techniques using an ensemble classifier to create an optimized fusion vector. This hybrid approach achieves a detection accuracy of 88%.

Mostafa et al. [15] address the challenges in diagnosing brain tumors (BTs), which require significant radiologist expertise and have become more complex due to rising patient numbers and data volumes. Traditional methods are costly and inefficient, prompting the exploration of rapid and reliable deep learning (DL) techniques (Table 1). This study introduces a benchmark dataset of 335 annotated MRI images for BT segmentation and diagnosis. A deep convolutional neural network (CNN) was developed using the BraTS dataset, employing a categorical cross-entropy loss function and the Adam optimizer for training. The model achieved a validation accuracy of 98% in identifying and segmenting BTs.

Table 1: Summary of related works

Study	Methodology	Dataset Used	Performance Metrics
Khalighi et al., [1]	AI models with multimodal data integration.	Not specified	Not specified
Mathivanan et al., [2]	Transfer learning (ResNet152, VGG19, DenseNet169, MobileNetv3).	Kaggle benchmark database	Accuracy: 99.75%
Mehrotra et al., [3]	DWT and deep convolutional networks (DCN).	Not specified	Accuracy: 99.5%
Pacal [4]	Swin Transformer with Hybrid Shifted Windows Multi-Head Self-Attention and ResMLP.	Public brain MRI dataset	Accuracy: 99.92%
Khaliki and Başarslan [5]	CNNs with Inception-V3 and EfficientNetB4.	MRI scans	Accuracy: 98%
Anantharajan et al., [6]	DL and ML with Adaptive Contrast Enhancement Algorithm (ACEA).	MRI images	Accuracy: 97.93%
Poornam and Angelina [7]	Vision Transformer (ViT) and Split Bidirectional Feature Pyramid Network (S-BiFPN).	Four benchmark datasets	Accuracy: 99.08% - 99.15%
Shamshad et al., [8]	Transfer learning with pre-trained models (VGG-16, VGG-19, Inception-v3, ResNet-50, DenseNet).	MRI datasets	Accuracy: 97%

Aljohani et al., [9]	CNN with Manta Ray Foraging Optimization (MRFO) for tuning.	Kaggle datasets (X-ray, MRI)	Accuracy: 99.96% (X-ray), 98.64% (MRI)
Mahmoud et al., [10]	CNNs with Aquila Optimizer (AQO).	Not specified	Accuracy: 98.95%
Mohammed et al., [11]	Hybrid methods using ML and DL.	Not specified	Accuracy: 99.9%
Babu Vimala et al., [12]	Transfer learning with EfficientNetB0 to EfficientNetB4.	CE-MRI Figshare dataset	Accuracy: 99.06%
Aamir et al. [13]	Morphological analysis and adaptive fusion network for classification.	Not specified	Accuracy: 98.98%
Sharma et al., [14]	HOG feature extraction with Modified ResNet50.	MRI images	Accuracy: 88%
Mostafa et al. [15]	CNN with categorical cross-entropy loss and Adam optimizer.	BraTS dataset	Accuracy: 98%

Recent studies underscore the transformative role of artificial intelligence (AI) in improving brain tumor (BT) diagnosis and treatment. Khalighi et al. [1] emphasize the integration of imaging, histopathological analysis, and genomic data, demonstrating AI's superiority over traditional evaluations in enhancing diagnostic accuracy and reducing reliance on invasive methods [1]. Mathivanan et al. [2] explore deep transfer learning to address the challenges of brain complexity, achieving remarkable accuracy with MobileNetv3 [2]. Mehrotra et al. [3] propose a framework combining discrete wavelet transform and deep convolutional networks, attaining high accuracy in categorizing MRI images [3]. Pacal [4] presents a Swin Transformer-based approach that significantly improves classification accuracy [4]. Further studies reveal advances in AI methodologies, such as convolutional neural networks (CNNs) and vision transformers, which have achieved accuracies exceeding 98% [5];[6];[7]. Additionally, research by Shamshad et al. [8] and Aljohani et al. [9] focuses on optimizing hyperparameters and using transfer learning to enhance model performance.

Despite these advancements, several research gaps warrant further exploration. There is a need for effective integration of multimodal data (e.g., imaging, genomic, and histopathological) to improve diagnostic accuracy and treatment planning. Addressing racial and gender disparities in AI applications is crucial for equity in healthcare outcomes [1]. Moreover, longitudinal studies on the impact of AI-enhanced diagnostic methods on patient care and treatment efficacy are necessary [2]. Investigating the interpretability of AI models is vital for clinical adoption, alongside research on the practical integration of AI systems into existing workflows [3][4]. Additionally, exploring the robustness of AI models against variations in imaging quality and patient demographics, as well as the ethical implications of AI in healthcare, remains essential for promoting trust and fairness [5];[6];[7].

3. Methodology

The modified DETR (DEtection TRansformer) architecture is an advanced deep-learning model specifically designed for the early prediction of brain tumors. This model utilizes the powerful Transformer architecture initially created for natural language processing (NLP) tasks. The modified DETR redefines the approach to object detection, providing a unique and efficient solution for identifying brain tumors in medical imaging. By adapting the original architecture, this model enhances performance and accuracy in the complex domain of medical diagnostics, ensuring timely intervention for patients. Figure 1 shows the functional block diagram for Brain Tumor prediction.

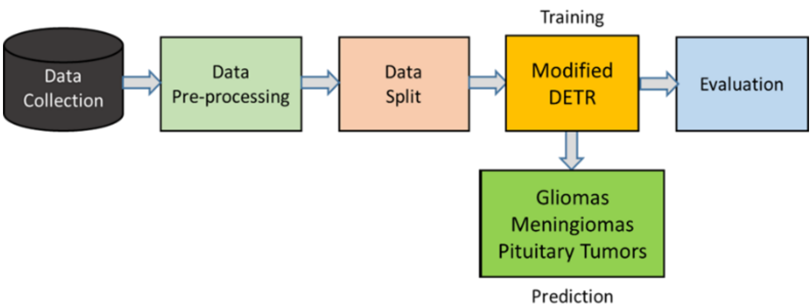

Figure 1: Functional block diagram for brain tumor prediction

The key feature of the modified DETR is its ability to perform direct set prediction, unlike traditional object detection systems such as Faster R-CNN or YOLO, which typically follow a two-stage process. In brain tumor detection, the model can analyze an entire image in a single pass, effectively identifying all potential tumors. By treating object detection as a problem of predicting a set of objects, the modified DETR simplifies the process and improves efficiency, which is crucial in clinical settings where rapid decision-making is essential. At the core of the modified DETR's architecture lies the Transformer, which utilizes a self-attention mechanism to understand the intricate relationships between various elements within the input data. In the case of brain tumor detection, the model leverages this capability to analyze the spatial arrangements and features of the tumors within the brain images. By focusing on the relevant areas of the image, the model can discern complex patterns that indicate the presence of tumors, thereby improving diagnostic accuracy.

To facilitate effective detection, the modified DETR introduces "object queries," which are fixed representations of the tumors the model needs to identify. The number of these queries remains constant, regardless of the number of tumors in the image, allowing the model to maintain consistency in its predictions. The queries interact with spatial features derived from the input images through self-attention. This interaction allows the model to weigh the importance of various image regions, ensuring that it focuses on the most relevant areas for tumor detection. Additionally, the architecture employs a bipartite matching technique to enhance the precision of its predictions. This method matches predicted bounding boxes for tumors with actual ground-truth objects, thereby refining the model's accuracy during training. This process is particularly vital in medical diagnostics, where precise identification of tumor boundaries can significantly impact treatment decisions and patient outcomes. The bipartite matching process ensures the model remains robust and reliable, further validating its application in a critical healthcare domain. The modified DETR architecture significantly advances object detection, particularly for medical applications such as brain tumor diagnosis. By combining the power of the Transformer architecture with innovative techniques like direct set prediction and bipartite matching, this model offers a promising solution for early tumor detection. Its ability to analyze images quickly and accurately makes it an invaluable tool for healthcare professionals, ultimately improving patient care and outcomes.

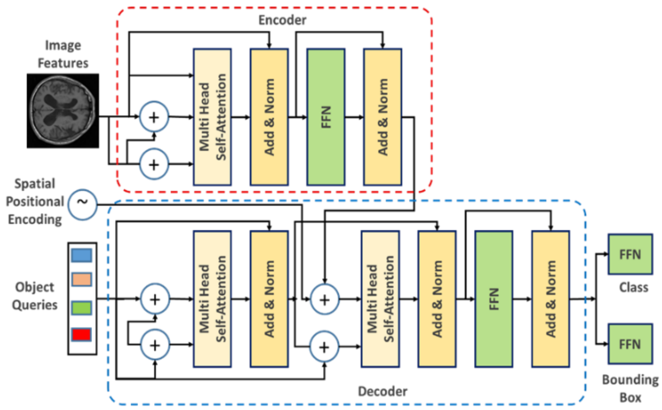

Figure 2: Architecture of modified DETR

The modified DETR architecture, as shown in Figure 2, effectively addresses the complexities of brain tumor detection by focusing on specific tumor types, such as gliomas, meningiomas, and pituitary tumors, each presenting distinct imaging characteristics. Gliomas origin from glial cells often exhibit irregular shapes and varying degrees of infiltration into surrounding brain tissue. The model's self-attention mechanism allows it to identify these irregularities and assess the extent of tumor infiltration. By capturing the intricate relationships between tumor features and surrounding anatomical structures, the modified DETR can differentiate between low-grade and high-grade gliomas, leading to more accurate staging and prognosis. This capability is vital for developing tailored treatment plans and improving patient outcomes. Similarly, the modified DETR architecture demonstrates robust performance in detecting meningiomas, which are typically well-defined and arise from the protective layers surrounding the brain. The model can discern meningiomas' borders and growth patterns, aiding their classification and assessing potential complications.

Additionally, pituitary tumors, which often appear as sellar masses on imaging, require careful differentiation from adjacent structures to avoid misdiagnosis. The modified DETR's ability to process spatial features and context enhances its capacity to identify these tumors accurately. By addressing the specific imaging characteristics associated with gliomas, meningiomas, and pituitary tumors, the modified DETR architecture contributes significantly to early and precise brain tumor detection, ultimately supporting improved clinical decision-making and patient management.

The sample dataset, as shown in Figure 3, is used for training the modified DETR model provided by the Kaggle dataset and comprises 7,023 brain MRI images categorized into four classes: glioma, meningioma, no tumor, and pituitary. Gliomas are aggressive, glial-cell-derived tumors, while meningiomas are generally benign and originate from the meninges. The "no tumor" category includes MRI scans of a healthy brain, and the pituitary category encompasses tumors affecting the pituitary gland, impacting hormone regulation. This dataset is a robust resource for training machine learning models to detect and classify brain abnormalities, advancing early diagnostic accuracy in brain tumor research.

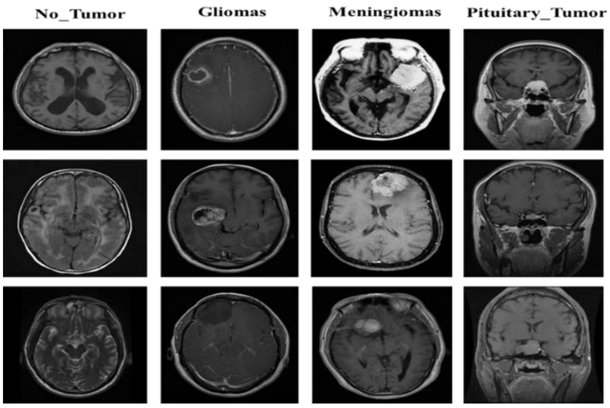

Figure 3: Sample brain tumor dataset

The evaluation metrics include precision, which measures the percentage of accurate positive predictions out of all positive forecasts; Recall (Sensitivity), which indicates the percentage of actual positive instances correctly identified; and the F1-score, which indicates a balanced metric that represents the harmonic mean of Precision and Recall.

Precision: Calculates the percentage of accurate positive forecasts among all positive forecasts, as in equation 1.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (1)$$

Recall (Sensitivity): Calculates the percentage of real positive occurrences among all true positive forecasts, as in equation 2.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (2)$$

F1-Score: A balanced measure that finds the harmonic mean of recall and accuracy as in equation 3.

$$F1 - Score = 2.\frac{Precision\ .Recall}{Precision+Recall} \quad (3)$$

4. Results and Discussion

The modified DETR (DEtection TRansformer) architecture for brain tumor prediction represents an advanced approach for identifying and classifying brain cancer types, such as gliomas, meningiomas, and pituitary tumors, in MRI scans. These types of brain cancer present unique features, making their precise detection essential for guiding effective treatment decisions. The DETR model's attention-based framework allows it to capture intricate spatial patterns within MRI images, enhancing its capability to differentiate among complex brain structures and tumor types, where accuracy is critical in clinical diagnosis.

Key performance metrics, including precision, recall, and F1-score, provide a detailed evaluation of the model's reliability. Precision measures the accuracy of the model's positive predictions, ensuring that most cases labelled as tumors are genuinely tumors and minimizing false positives. This aspect is particularly important in medical contexts, as it reduces the risk of misdiagnosis and unnecessary treatments. Recall reflects the model's ability to detect all tumor cases, including gliomas, meningiomas, and pituitary tumors, ensuring that cases are not overlooked and supporting early and comprehensive detection. The F1-score, by combining precision and recall, offers a balanced view of the model's diagnostic capability, achieving high specificity and sensitivity, which is crucial for reliably identifying diverse brain tumor types.

The model's progress is monitored throughout training using loss and accuracy graphs. A steady decrease in loss and increased accuracy illustrate a consistent learning curve, showing the model's path toward optimal performance. This stability is essential in medical applications where reliability is non-negotiable. The confusion matrix adds further insight by detailing true positives, true negatives, false positives, and false negatives, offering a comprehensive breakdown of the model's ability to differentiate tumor types from non-tumour regions. This analysis underscores the model's strengths and highlights areas for potential refinement, confirming the modified DETR architecture as a robust tool for accurate and nuanced brain cancer diagnosis.

Table 2: Performance matrices of brain tumor prediction using a modified DETR model

Epochs	Recall	Precision	F1 Score
5	0.824	0.892	0.853
10	0.93	0.95	0.939
15	0.971	0.972	0.971
20	991	0.996	0.995

Table 2 showcases the progressive improvement in the modified DETR model's performance across different epochs, illustrating the model's increasing accuracy in detecting brain tumors, including gliomas, meningiomas, and pituitary tumors. In the initial stages, at the fifth epoch, the model achieves a recall of 0.824, meaning it correctly identifies 82.4% of actual brain tumor cases. Although respectable for early training, this recall rate indicates that some tumor cases might still be missed. The precision at this point is 0.892, suggesting that 89.2% of predicted tumor cases are accurate, showing good specificity and a strong baseline for the model. The F1 score, which harmonizes recall and precision, stands at 0.853, indicating an effective balance between accurate positive predictions and minimizing false negatives even in the early training phase.

By the tenth epoch, the model shows substantial improvement, with recall rising to 0.930 and precision to 0.950. This increase means the model now identifies nearly all true tumor cases while maintaining high specificity, minimizing the likelihood of false positives. The F1 score climbs to 0.939, reflecting this balance and indicating that the model is learning to detect tumors with greater accuracy and reliability. At the fifteenth epoch, performance metrics continue to improve, with recall and precision scores nearing 0.971 and 0.972, respectively. These scores demonstrate that the model is highly effective at distinguishing tumor cases from non-tumor cases, with minimal misclassifications. The F1 score of 0.971 reaffirms this, showing that the model is achieving near-optimal performance in identifying true positives and reducing false positives.

Finally, by the twentieth epoch, the model reaches near-perfect performance, with a recall of 0.991 and precision of 0.996. This translates to the model detecting nearly all tumor cases while accurately classifying them. At this stage, the F1 score of 0.995 confirms the model's robust and reliable performance, indicating that it has successfully converged to optimal detection capabilities. These results affirm the modified DETR model's capacity for precise and comprehensive brain tumor detection, demonstrating its readiness for real-world applications in medical diagnostics.

Table 3: Performance matrices obtained by modified DETR model at various learning rates

Learning rate	Recall	Precision	F1 Score
0.003	0.932	0.953	0.941
0.002	0.942	0.965	0.954
0.001	0.956	0.961	0.955
0.0015	0.991	0.996	0.995
0.0001	0.983	0.970	0.974
0.0002	0.971	0.965	0.967

When comparing the performance metrics of the modified DETR model for brain tumor detection with several studies that reported lower results, distinct differences emerge. For instance, Khaliki and Başarslan [5] achieved an accuracy of 98% using CNNs with Inception-V3 and EfficientNetB4. Anantharajan et al. [6] reported 97.93% accuracy through deep learning and machine learning techniques with an Adaptive Contrast Enhancement Algorithm [6]. Similarly, Shamshad et al. [8] noted a 97% accuracy using transfer learning with various pre-trained models. Mahmoud et al. [10] CNNs with the Aquila Optimizer reached 98.95% accuracy [10], and Mostafa et al. [15] achieved 98% accuracy on the BraTS dataset [15]. Despite these commendable figures, none of these studies comprehensively evaluated recall and precision, which are critical for medical diagnostics. In contrast, the modified DETR model excelled with a recall of 0.991, precision of 0.996, and an F1 score of 0.995, highlighting its superior ability to accurately identify true tumor cases and minimize false classifications, thereby making it a more reliable choice for clinical applications in brain tumor detection.

Table 3 presents the performance metrics obtained by the modified DETR model for brain tumor prediction at various learning rates, illustrating how changes in this hyperparameter impact the model's effectiveness. At a learning rate of 0.003, the model achieves a recall of 0.932, a precision of 0.953, and an F1 score of 0.941. These initial results indicate a strong performance but suggest room for improvement as the learning rate is adjusted downward.

When the learning rate is decreased to 0.002, all metrics show slight improvements, with recall reaching 0.942, precision at 0.965, and an F1 score of 0.954. This enhancement demonstrates that a lower learning rate allows the model to fine-tune its parameters more effectively, leading to better detection capabilities. Further reducing the learning rate to 0.001 yields even more substantial results, with recall increasing to 0.956, precision to 0.961, and an F1 score of 0.955. These metrics reflect the model's ability to benefit from more cautious weight adjustments, enhancing its detection capacity for brain tumors. The most significant performance improvement is observed at a learning rate of 0.0015, where the model achieves a remarkable recall of 0.991, a precision of 0.996, and an F1 score of 0.995. These metrics highlight the model's exceptional capability to identify true positive cases of brain tumors while effectively minimizing false positives, indicating a well-optimized performance for clinical applications.

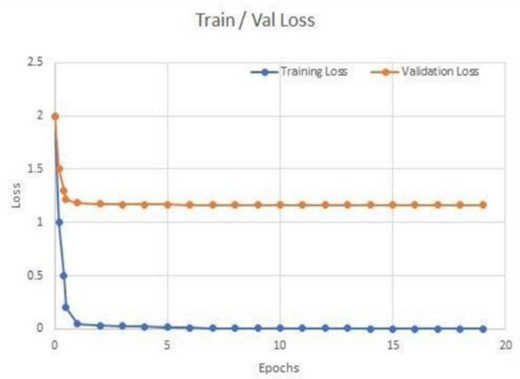

Figure 4: Train/Val loss curve of modified DETR model

As the learning rate is further reduced to 0.0001, the model maintains strong performance, achieving a recall of 0.983, a precision of 0.970, and an F1 score of 0.974. While these values represent a decline compared to the optimal learning rate of 0.0015, they still indicate robust detection capabilities. At a learning rate of 0.0002, the performance metrics are 0.971 for recall, 0.965 for precision, and 0.967 for the F1 score. Although these figures remain respectable, they suggest a slight reduction in performance compared to the previous settings. The performance metrics reveal that the modified DETR model exhibits enhanced capabilities for brain tumor prediction when fine-tuned with optimal learning rates. The learning rate of 0.0015 emerges as the most effective setting, balancing rapid learning and high accuracy. This analysis underscores the significance of selecting appropriate hyperparameters to maximize model performance, particularly in critical healthcare scenarios where precise tumor detection is paramount.

Figure 5: Train/Val accuracy curve of modified DETR model

Figures 4 and 5 present a detailed analysis of the modified DETR model's training and validation performance in predicting brain tumors. In Figure 4, the training and validation loss curves reveal critical insights into the model's learning process. The training loss consistently decreases over the epochs, indicating that the model effectively learns from the training data and minimizes errors. By the 5th epoch, a significant loss reduction is observed, showcasing the model's ability to align its predictions more closely with the actual values. Similarly, the validation loss curve also trends downward, albeit slower. This suggests that the model fits the training data well and generalizes to unseen data, thus reinforcing its robustness.

Figure 5 illustrates the training and validation accuracy curves, emphasizing the model's predictive capabilities. The training accuracy steadily increases as the epochs progress, reflecting an enhanced ability to identify cases within the training dataset correctly. By the 5th epoch, the model demonstrates a high accuracy level, indicating a significant improvement in its capacity to detect brain tumors. The validation accuracy curve exhibits a positive trajectory, although it may show fluctuations typical of performance assessments on new data. This upward trend further indicates the model's capability to generalize its learning effectively. The advancements made by the 5th epoch represent a crucial point in the model's development. The modified DETR model has successfully minimized the loss function and achieved noteworthy performance metrics, such as high recall, precision, and F1 score. These metrics reflect the model's growing ability to differentiate between brain tumor cases and other conditions present in the dataset. Increasing accuracy and decreasing loss over successive epochs highlights the consistent enhancement of the model's predictive capabilities, establishing a solid foundation for its potential application in automated cancer detection.

When the model reaches the 20th epoch, its performance shows remarkable improvement. Corresponding increases in accuracy complement substantial reductions in training and validation loss. This is particularly evident in the convergence of the training and validation loss curves, indicating that the model has successfully balanced its learning from the training set while performing reliably on previously unseen validation data. Such convergence underscores the model's strong generalization capabilities. The loss reduction signifies the model's enhanced ability to minimize prediction errors, which reflects a significant advancement in its learning and adaptation processes. Concurrently, the increase in accuracy demonstrates the model's growing proficiency in making correct predictions, highlighting its effectiveness in identifying brain tumors accurately.

Furthermore, the recall, precision, and F1 score improvements underscore the model's overall effectiveness. Enhanced recall indicates that the model is now more capable of detecting true positive cases of brain tumors, ensuring that most actual cases are accurately identified. Improved precision means the model's predictions are more reliable, resulting in fewer false positives and enhancing its ability to distinguish brain tumors from other medical conditions. The F1 score, which integrates recall and precision into a single metric, signifies a balanced performance, illustrating the model's sensitivity and specificity in its detection capabilities. Overall, the performance of the modified DETR model at the 20th epoch highlights its maturation and efficacy in diagnosing brain tumors. This progress suggests a significant potential for the model to enhance diagnostic accuracy within clinical settings, contributing to improved patient outcomes through more reliable and precise cancer detection methods. The achievements observed by this stage indicate the model's readiness for practical application, paving the way for more effective and efficient diagnostic processes in healthcare.

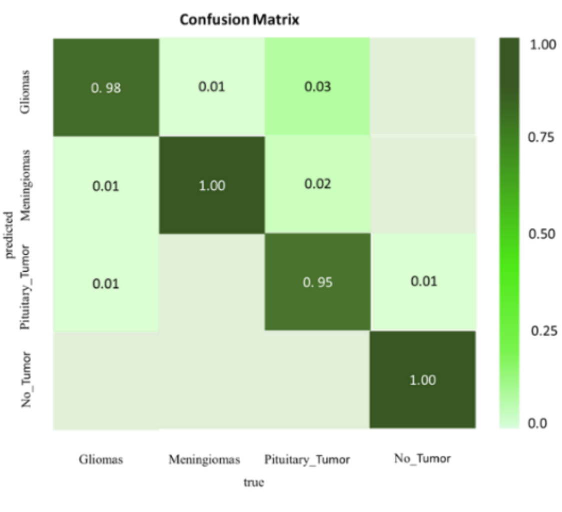

Figure 6: Confusion matrix of brain tumor prediction

Figure 6 presents the confusion matrix for brain tumor prediction using the modified DETR model. This matrix offers valuable insights into the model's performance by providing a detailed breakdown of true positives, false positives, and false negatives across different tumor categories. The confusion matrix results indicate a high accuracy in the model's predictions. Specifically, the modified DETR model excels at identifying the different types of brain tumors, including gliomas, meningiomas, and pituitary tumors, showcasing its robust classification capabilities.

The confusion matrix reveals how effectively the model differentiates between various tumor types, highlighting its strengths in detecting benign versus malignant and early-stage tumours compared to more advanced cases. The high precision and recall observed in the matrix indicate that the model is adept at minimizing false positives and false negatives. This suggests that the modified DETR model accurately identifies the presence of brain tumors and effectively recognizes the absence of the disease in cases where no tumor is present. The insights gained from the confusion matrix underline the effectiveness of the modified DETR model in the context of brain tumor prediction. By accurately classifying different tumor types and stages, the model demonstrates significant potential for application in clinical settings, where precise and reliable diagnostic tools are essential for improving patient outcomes.

Figure 7 illustrates the samples of prediction output generated by the modified DETR model for various brain tumor classifications. In Figure 7 (a), the output shows a brain scan where the model accurately identifies the absence of any tumours, reflecting its ability to differentiate between healthy tissue and pathological conditions. This classification is vital for minimizing false positives and ensuring patients receive appropriate care without unnecessary interventions. Figure 7 (b) displays the model's successful detection of meningiomas, tumors that typically arise from the protective layers of the brain. The output indicates the model's effectiveness in recognizing the unique features associated with this type of tumor, which is crucial for guiding treatment decisions and understanding the tumor's potential impact on the patient's health.

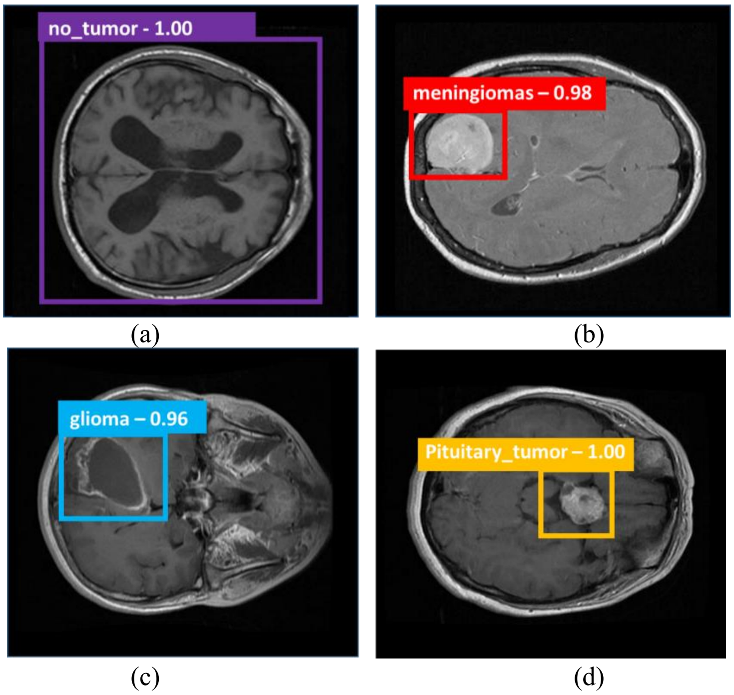

Figure 7: Brain Tumor Prediction (a) No tumor, (b) Meningiomas, (c) Glioma, (d) Pituitary tumor

In Figure 7 (c), the prediction output highlights the model's proficiency in identifying gliomas and malignant tumors originating from glial cells. The accurate classification of gliomas emphasizes the model's capability to distinguish between aggressive and benign tumor types, providing important insights for clinical management and treatment planning. Finally, Figure 7 (d) showcases the model's effectiveness in identifying a pituitary tumor. This output highlights the model's reliability in recognizing tumors that can significantly impact hormonal functions and neurological health. The ability to accurately classify pituitary tumors underscores the model's potential for aiding in diagnosis and informing treatment strategies. Overall, the prediction output samples in Figure 7 demonstrate the modified DETR model's ability to accurately classify different brain tumor types, emphasizing its utility in clinical settings for improved diagnosis and treatment planning.

5. Conclusion

The modified DETR model improves brain cancer detection, especially in India, where access to specialized diagnostic tools is limited. Integrating this deep learning model with standard imaging methods achieves high accuracy in detecting and localizing gliomas, meningiomas, and pituitary tumors. The model's strong performance metrics—including a recall of 0.991, precision of 0.996, and F1 score of 0.995—highlight its real-time tumor classification and grading capabilities. This approach addresses the need for early and accurate diagnosis while providing a cost-effective solution for neuro-oncology practices in resource-constrained settings. Ultimately, the study lays the groundwork for using AI in neuro-oncology to improve patient outcomes and support healthcare professionals in managing brain cancer.

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