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TRANSFORMING BRAIN TUMOR DETECTION EMPOWERING MULTI-CLASS CLASSIFICATION WITH VISION TRANSFORMERS AND EFFICIENT NET V2

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ABSTRACT

Brain tumor detection is a crucial medical imaging task. In MRI images, accurate classification and detection of tumor sites in MRI play a crucial role in diagnosis and treatment success. In this study, we used the Brain Tumor MRI dataset for multi-class classification and detection. For classification we used advanced transfer learning models, such as EfficientNetV2, Vision Transformer ViT-B16, DenseNet121, and Xception. We also used ensemble averaging (average, weighted average, geometric mean) to improve prediction accuracy. We used several versions of YOLO (YOLOv5, YOLOv8, YOLOv9, and YOLOv11) with bounding box annotations in YOLO format to detect and localise tumors. We also applied explainable AI techniques such as Grad-CAM to generate heat maps of discriminative location of tumors that influence the model's predictions. Our experimental results indicate that DenseNet121 and Xception-based models had the highest accuracy (99.54%) for the classification of tumors among all the classifiers. YOLO v8 had the best detection accuracy, with a Map of 95.1%. This shows that the combination of the classification and detection models with interpretability methods is a good approach to achieve a robust and accurate brain tumor diagnosis. We also developed a web app using Flask to use the models. This allows users to upload MRI images and get information about the tumor location, class, and confidence through a user-friendly interface.

KEYWORDS: Efficientnetv2, Convolutional Neural Network (CNN), Brain Tumor Vision Transformers (ViT), Magnetic Resonance Imaging (MRI), Multilayer Perceptron (MLP).

INTRODUCTION

BTs are a diverse group of more than 200 unhealthy growths that start in the brain. The most common type of cancer is gliomas, which are derived from glial cells, and account for about 80% of all cancers [1]. The World Health Organization classifies gliomas into four grades, from low to high. This is crucial for determining treatment. But this grading process could be time consuming and requires great care. MRI is a non-invasive technology that

provides a lot of detail about brain structure. But it is difficult to comprehend, and it needs a lot of effort to grasp [2]. It is more difficult to detect brain tumors due to there being other types, such meningiomas and pituitary tumors. Pituitary tumors, which are tumors of the hormone regulating gland, can be benign (they do not effect bone growth) or malignant (they cause hormone imbalance and vision issues) [3]. It's important that they are detected and classified early because this affects the survival rate [4].

Recent advances in biomedical engineering and computer science have yielded some interesting technologies. Xu et al. [5] proposed a 3D-stacked inertial microfluidic device to isolate CTCs. They were able to separate tumor cells with high purity and

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efficiency, demonstrating the potential of integrated microfluidic analysis. At the same time, advanced ML techniques, including DL and VLLMs, are simplifying the detection of brain tumors. VLLMs use both images and text, allowing for a more comprehensive analysis of MRI images with clinical, and patient history data [6]. Self-supervised learning and attention mechanisms boost the quality of models, especially for rare types of tumors [7].

DL methods, such as CNNs and autoencoders have been widely used for classification, segmentation and prediction in medical images [8]. However, varying performances across the different data sets demonstrate that we need better designs [9]. ViTs area powerful approach for gathering complex spatial features in medical images. They can also be applied to other datasets and data types and can be up or down-scaled [10].

In this paper, we propose a ViT-based approach to automate the classification of brain tumors, into four classes: pituitary, glioma, malignant glioma and no-tumor. The architecture is based on hierarchical representations and attention mechanisms and is able to extract relevant features from MRI images, allowing for the classification of tumors. The aim of the method is to reduce the need for manual expert grading, improve the ability to detect problems early, and ease the way of planning treatment, all of which will lead to better treatment results for patients and, more importantly, provide a solution that can be used in clinical practice that can be modified and expanded as required.

LITERATURESURVEY

In recent research on BCI and brain tumor classification, there has been significant advancement in the use of DL and transformers and hybrid models for improving diagnostic accuracy and patient care. Li et al. [11] proposed a CVT-based asynchronous BCI for brain-controlled navigation of a robot. They are working on using a CVT to enhance asynchronous signal processing and enable precise navigation tasks through translating brain signals into robot actions. This approach demonstrates the need of incorporating complex neural network architectures in BCIs and the effectiveness of transformers in dealing with complex neural data. Moreover, Sietal. [12] built across-subject emotion recognition BCI that uses fNIRS and a DBJ Net. Their technique addresses the issue of individual interpretation of brain signals. It demonstrates that multi-modal DL models can learn small neural patterns, which facilitates emotion recognition for diverse individuals.

Kumar et al. [13] dealt with multi-class classification for brain tumor classification using residual network sand global average pooling. Their solution enhances the feature extraction process and simplifies the computations, thus making it scalable to classify different types of tumors in MRI scans. Similarly, Meshram et al. [14] investigated using Swin transformers for brain tumor detection. Swin transformer's hierarchical feature learning and self-attention mechanisms generate information about the local and global contexts. This approach outperforms convolutional methods, particularly multi-class classification. Ramakrishnan et al. [15] recently published a hybrid CNN with one API enhancement that offers a good balance between efficiency and accuracy in brain tumor classification. They demonstrated that for modern network designs, hardware-aware optimization

techniques can be used to significantly reduce inference time while keeping the accuracy of predictions. The model is thus suitable for clinical use.

Rastogi etal. [16] proposed a multi-branch DL model with inception blocks and five-fold cross-validation for multi-class brain tumor MRI classification. They have multiple branches in the network to learn different characteristics, which makes the network general and robust to different cancers. This is an example of how modular design may be applied in the medical imaging field. Meanwhile, Liu et al. [17] simulated FFPE staining of fresh brain tissue using a stimulated Raman Cycle GAN. This approach saves time and provides a high-quality visual representation of the tissue for diagnosis by allowing accurate visualization and assessment of brain tumor tissue without the use of conventional staining.

Tandele tal.[18] have shown that using AI-based feature extraction and classification techniques can improve the diagnosis of brain tumors through an artificial intelligence method for multi-class classification of MRI brain tumors. This highlights the potential of AI in classifying different types of tumors and thus early detection and treatment. Zhou et al. [19] proposed a VQ-GAN method to generate 3D brain tumor regions from MRI scans. This technique can be used to enhance the segmentation and visualizations of tumor

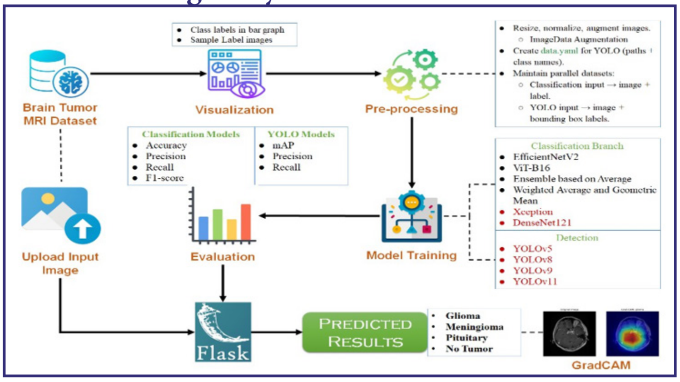
regions. This is crucial for surgical and medical treatment. Finally, Parshapa and Rani [20] reviewed the use of machine learning techniques to detect brain tumors. They examined many techniques to improve prediction accuracy, particularly with limited data, and discussed the importance of feature selection, hyper parameter tuning and cross-validation processes.

PROPOSEDSYSTEM

The novel method is a DL framework for automated multi-class brain tumor classification using MRI with the goal of improving diagnostic accuracy and streamlining clinical workflows. The proposedapproachusesEfficientNetV2

[26] and ViT-B16 [27] for efficient feature extraction and to capture long-range dependencies and global interactions respectively. Alternative architectures, such as Exception and DenseNet121, provide alternative feature representations for various tumors. YOLO models (YOLOv5, YOLOv8, YOLOv9 and YOLOv11) are used to detect and locate suspicious positions. Using a combination of techniques (average, weighted average, and geometric mean) for predictions improves them, and Grad-CAM helps explain AI images. The system also has a process for data preparation, training, testing and predictions. It has a web interface based on Flask for real-time MRI image analysis [28].

Fig. 1: System Architecture



Our system design integrates multiple DL models to automatically diagnose brain tumors from MRI scans. The method involves pre-processing the data, followed byfeatureextractionusingEfficientNetV2, Exception and DenseNet121. The Vision Transformer (ViT-B16) then takes into account the global context [29]. To detect tumors, we use YOLO models (YOLOv5, YOLOv8, YOLOv9 and YOLOv11) and combine their results using ensemble methods to improve accuracy. Grad-CAM lets us visualise images in an understandable way, and a Flask-based web app is used to upload images, predict tumors and classify them in real time; this is a fully integrated end-to-end system for diagnosing tumors [30].

A) Dataset Collection

The dataset includes 2,197 MRI images, 1,695 for training and 502 for testing. The classification branch is labeled with each image with its class, which corresponds to the type of tumor. The YOLO-based localization branch uses bounding box annotations in YOLO format (txt files) to detect and localize the tumors in the MRI scans. The data is carefully split into training, validation, and test sets to ensure that the classes in the dataset are equally represented and the model can be trained, evaluated and perform well at detecting tumors in multiple classes.

B) Image Processing

To ensure all MRI images have the same resolution and pixel value range, all images are resized and normalized. This makes it easier to train models. Also, they are converted into formats suitable for DL pipelines for classification, as well as YOLO-based detection. This preparation step guarantees that the models are able to learn relevant features from the tumor regions while maintaining their accuracy and reliability on a variety of MRI images. It also normalizes the input data and reduces the computational resources required.

C) Data Augmentation

Our dataset is augmented by rotation, horizontal and vertical flipping, zooming, and adjusting the brightness to improve model versatility and robustness. These augmentations increase the size of the dataset intentionally to ensure that the models are robust to changes in MRI orientation, size and intensity. Augmentation prevents overfitting, enhances feature extraction, and ensures that the classification and detection branches are robust in finding tumors in different imaging scenarios by training network on a range of scenarios.

D) Algorithms

EfficientNetV2: EfficientNetV2 identifies discriminative features in MRI images with a compound scaling of depth, width and resolution. Using pre-trained weights and fine-tuning, this allows efficient classification [21] of brain tumors in multiple classes with fast convergence.

Vision Transformer (ViT-B16): ViT-B16 employs multi-head self-attention and patch embedding to learn long-range dependencies in MRI images. It learns how regions of an image relate globally to each other to enhance the classification of subtle patterns [22] of brain tumors, while making the scans more robust.

Ensemble Methods: Averaging, weighted averaging or geometric mean is used to aggregate multiple models to reduce variance, reduce biases and combine complementary information. This makes multi-class tumor [23] predictions from MRI scans more reliable and robust.

Exception: Exception uses depth wise separable convolutions to extract spatial and semantic features from MRI scans [24]. This improves representation learning, convergence speed, and makes it easier to distinguish different types of tumors while requiring less computational resources.

$$O_{i,j,k}=\sum_{m,n} X_{i+m,j+n,c} W_{m,n,k} \qquad (1)$$

DenseNet121: DenseNet121 layers are connected to each other to promoter using features and flow of gradients. It uses both low- and high-level features in MRI images, which helps to classify the type of tumor [25], and makes classification more robust and interpretable.

$$x_l=H_l([x_0,x_1,\ldots,x_{l-1}]) \qquad (2)$$

YOLOv5: YOLOv5 efficiently detects and localized tumors in MRI scans by dividing the image into grids and simultaneously predicting the bounding boxes and class probabilities. This strikes a balance between speed and accuracy for quick tumor detection.

$$x=\sigma(t_x)+C_x, \qquad y=\sigma(t_y)+C_y (3)$$
$$w=p_w.e^{t_w}, \qquad h=p_h.e^{t_h} \qquad (4)$$

YOLOv8: YOLOv8 improves accuracy using a better backbone and multi-scale feature fusion to get precise tumor boundaries and variations to detect tumors of varying sizes in MRI and accurately find their location.

$$\mathcal{L}=\lambda_{box}\mathcal{L}_{box}+\lambda_{obj}\mathcal{L}_{obj}+\lambda_{cls}\mathcal{L}_{cls} (5)$$

YOLOv9:YOLOv9enhancesthebboxand feature representation accuracy to detect small and complex tumor shapes, while maintaining high accuracy. This helps doctors to localize tumors for clinical assessment.

$$\mathcal{L}_{YOLOv9}=\lambda_{box}\mathcal{L}_{box}+\lambda_{obj}\mathcal{L}_{obj}+$$
$$\lambda_{cls}\mathcal{L}_{cls}+\lambda_{dfl}+\mathcal{L}_{dfl} (6)$$

YOLOv11: Speed and real-time detection are the main focuses of YOLOv11. Its powerful backbone networks and anchor-free prediction allow it to predict tumors of any shape and size. This allows the easy and accurate detection of cancers to be investigated by MRI.

E) Integration of XAI and Flask Framework

The use of XAI and Flask makes for an DenseNet121: Flask allows anyone to easily use the web interface to connect to the model. The user can upload MRI scans, receive a diagnosis for the tumor type, observe the bounding box and the Grad-CAM visualization.

This link makes automated diagnostic processes more accessible, intuitive and manageable.

EXPERIMENTALRESULTS

Accuracy: A test is accurate if it can correctly diagnose patients with and without a disease. To determine how accurate a test is, we need to calculate the percentage of true positives and true negatives in all the instances we examined. This could be written as:

$$Accuracy=\frac{TP+TN}{TP+FP+TN+FN} \quad (7)$$

Precision: Precision is a measure of how many of the samples or instances that we labeled as positive were correct. So the formula to calculate the precision is:

$$Precision=\frac{True\ Positive}{True\ Positive+False\ Positive} \quad (8)$$

Recall: Recall is used to express the ability of a model to find all relevant samples to a class in machine learning. The recall formula is based on the number of true positives predicted of all the actual positives. This tells you how many instances of a particular class it finds.

$$Recall=\frac{TP}{TP+FN} \quad (9)$$

F1-Score: The F1 score is a measure of a ML model's performance. It's the sum of the accuracy and recall values of a model. The accuracy score is the number of times the prediction was correct on the entire data set.

$$F1Score=2*\frac{RecallXPrecision}{Recall+Precision}*100 \quad (10)$$

mAP: MAP is a measure of the effectiveness of a ranking. It takes into account the number of relevant suggestions, and their positions in the list. The MAP at K is the mean AP at K for all the users or queries.

$$mAP=\frac{1}{n}\sum_{k=1}^{k=n}AP_k \quad (11)$$

Table 1: PerformanceEvaluation–Classification

Model	Accuracy	Precision	Recall	F1-score	Error Rate
EfficientNetV2	0.988558	0.987758	0.988845	0.988268	0.011442
ViT-B16	0.985507	0.984658	0.985096	0.984758	0.014493
DenseNet121	0.995423	0.995132	0.995016	0.995057	0.004577
Xception41	0.995423	0.995089	0.995016	0.995043	0.004577
Ensemble (Avg)	0.992372	0.991831	0.992979	0.992374	0.007628
Ensemble (Weighted Avg)	0.991609	0.991038	0.992146	0.991553	0.008391
Ensemble (GeoMean)	0.992372	0.991831	0.992979	0.992374	0.007628

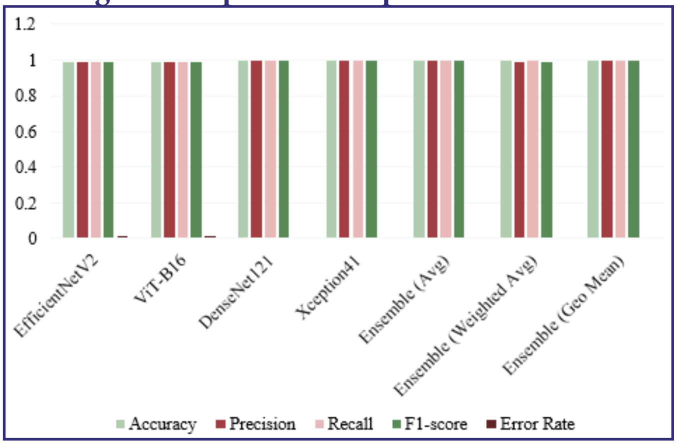
AsshowninTable1,the models with the highest accuracy were Dense Net 121 and Exception 41. Conversely, ensembles always produced reliable results.

Table 2: PerformanceEvaluation–Detection

MLModel	Precision	Recall	mAP
YOLOv5	0.915	0.904	0.944
YOLOv8	0.944	0.915	0.951
YOLOv9	0.911	0.888	0.947
YOLOv11	0.852	0.832	0.897

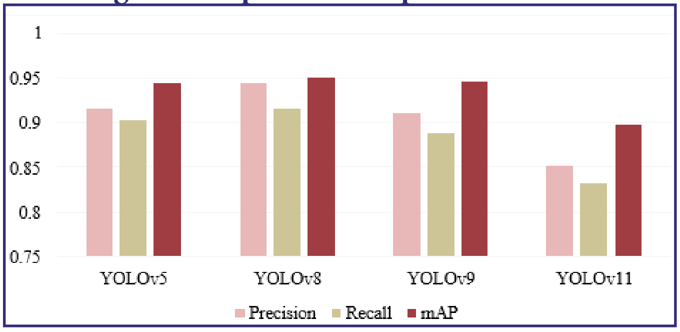
YOLOv 8 performs the best, according to table 2. It has better detection accuracy and reliability than previous YOLO versions.

Fig. 2: Comparison Graph-Classification



In fig. 2, DenseNet121 and Xception41 clearly perform better than others, because their bars are much higher than others. In contrast, ensemble methods have a well-rounded and consistent performance on all metrics, visually demonstrating reliability and overall performance.

Fig. 3: Comparison Graph– Detection



In fig.3, the bar of YOLOv8is obviously taller than the others, exhibiting better performance with good detection accuracy and stability than other YOLOs.

Fig. 4: Upload Input Image

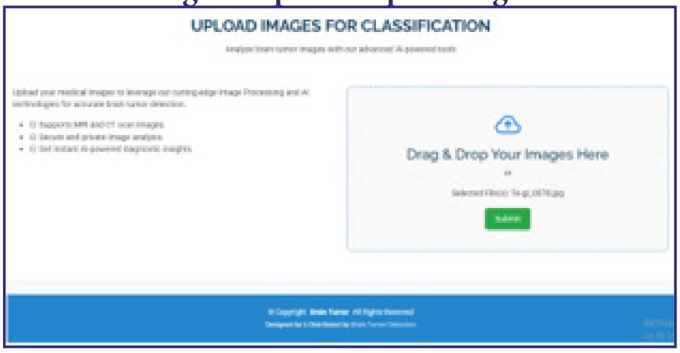


Fig.4 shows the input interface, in which users can upload brain images to get automatic results for multi-class brain tumor classification.

Fig. 5: Predicted Results

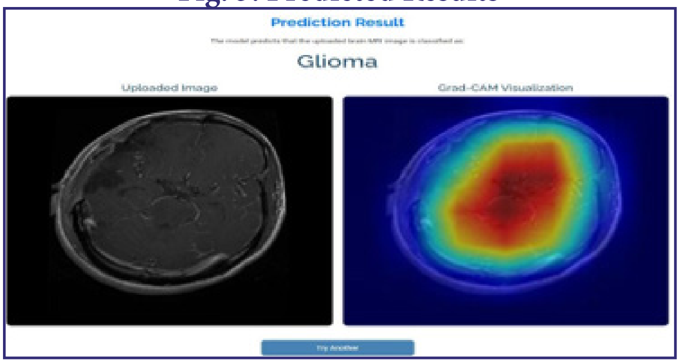


Fig. 5shows the output interface, where the output shows the expected tumor type is glioma. ItalsodisplaystheGrad-CAMimagethatshowsteregio nsofthetumorthatchangethemost.

Fig. 6: Upload Input Image

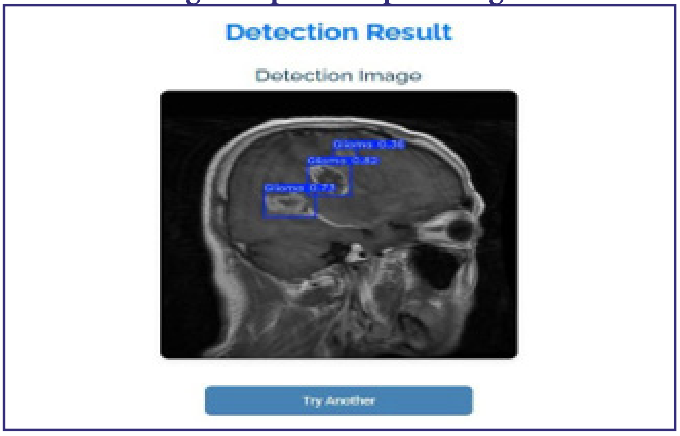


Fig. 6shows the detection interface, where users can upload MRI pictures of brain scans to automatically and precisely detect and display the tumor zones.

CONCLUSION

This study shows that classification and detection of brain tumors from MRI images using the state-of-the-art DL algorithms is effective. Dense Net121 and Exception were the top models with an accuracy of 99.54%, a precision of 99.51%, a recall of 99.50%, and an F1-score of 99.50%. So, they are the best models for multi-class tumor classification. YOLOv8 was the most accurate model to detect tumor regions in MRI scans. It had a mAP of 95.1%, a precision of 94.4%, and a recall of 91.5%. The use of Grad-CAM to make AI analyses explainable was also beneficial for the interpretability, as it generated heatmaps that focused on tumor regions, allowing clinicians to be more confident in the AI predictions. This study demonstrates the accuracy, speed and interpretability of diagnostic assistance by using both classification and detection frameworks in combination with interpretability techniques. In summary, the framework illustrate show DL methods can be used to improve the analysis of brain tumors by providing fast, accurate and transparent results to radiologists that can help them make better treatment plans.

Our future work will include expanding the dataset to include larger MRI datasets with more classes to increase the accuracy and utility of the classification model. Incorporating multimodal data (such CT and PET) might give you additional information for diagnosis and enhance classification. Further development of new transformer-based models and hybrid fusion techniques for more sophisticated DL models could improve classification accuracy.

We will also explore how to improve its computing efficiency and how to deploy in low resource settings, such as edge devices, to make it easier for real-time clinical use. Also, linking with electronic health record systems can assist in personalized predictions by integrating imaging data with other patient information, such as age, sex, and medical history for a more holistic approach to patient care.

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