PAVISE – AI-Agent for X-RAY Scanning And Diagnosis Brain Tumor

Abstract- *Brain tumors present significant diagnostic challenges due to their complexity and potential neurological impact. Early and accurate detection is crucial for improving patient outcomes. Traditional diagnostic methods such as MRI and CT scans require expert interpretation, which is time-consuming and prone to human error. This paper explores the use of Convolutional Neural Networks (CNNs) for brain tumor detection, with a focus on the You Only Look Once (YOLO) object detection algorithm. YOLO is known for its real-time processing capabilities and high detection accuracy, making it a suitable candidate for medical applications. A comparative analysis is conducted between YOLO, Faster R-CNN, and EfficientDet using a dataset of MRI brain scans. The evaluation metrics, including accuracy, precision, recall, and inference time, demonstrate that while Faster R-CNN and EfficientDet achieve marginally higher accuracy, YOLO significantly outperforms them in speed, making it more practical for real-time deployment in clinical settings. To enhance accessibility, the trained YOLO model is converted into TensorFlow.js (TFJS), allowing seamless integration into web-based applications. Utilizing Next.js, a browser-based interface is developed where users can upload MRI images and receive real-time tumor detection results. This approach eliminates the need for specialized hardware, broadening the availability of AI-driven diagnostics. The results indicate that YOLO provides an optimal balance between accuracy and efficiency, making it a promising tool for integrating AI-assisted brain tumor detection into medical workflows. This study highlights the potential of deep learning-based detection systems in improving early diagnosis and decision-making in oncology.*

Introduction - Cancer remains one of the leading causes of mortality worldwide, with early and accurate diagnosis playing a crucial role in improving patient outcomes. Brain tumors, in particular, pose significant challenges due to their complexity and potential impact on neurological functions. Traditional diagnostic methods, such as MRI and CT scans, rely heavily on expert interpretation, which can be time-consuming and prone to human error. To enhance diagnostic accuracy and speed, artificial intelligence (AI) has emerged as a powerful tool in medical imaging analysis.

This paper introduces a novel AI-driven tumor diagnostic system, leveraging the power of deep learning for precise and efficient brain tumor detection. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification and object detection tasks, making them highly suitable for medical imaging applications. Among various CNN-based object detection algorithms, You Only Look Once (YOLO) stands out due to its real-time processing capability and high detection accuracy. YOLO's single-stage detection approach enables rapid identification of tumors in medical scans, significantly reducing diagnostic time and improving clinical decision-making.

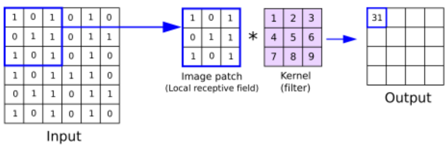
However, given the complexity and variability of brain tumors, alternative advanced architectures such as Faster R-CNN and EfficientDet may offer improved localization and segmentation accuracy in certain cases. This paper explores the application of YOLO in brain tumor detection while comparing its performance against other state-of-the-art deep learning models. By integrating AI-driven diagnostics into clinical workflows, we aim to enhance the precision, efficiency, and accessibility of early brain tumor detection, ultimately contributing to better treatment strategies and patient care.

A. Convolutional Neural Network

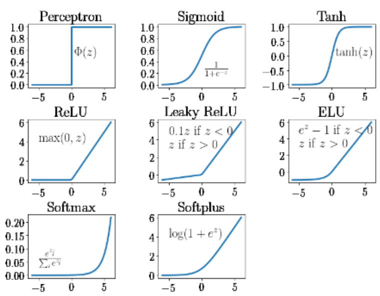
A Convolutional Neural Network (CNN) is a class of deep learning models designed for processing structured grid data, such as images. CNNs are particularly well-suited for image analysis tasks due to their ability to automatically extract relevant features from raw input data. Unlike traditional machine learning approaches that require manual feature engineering, CNNs learn hierarchical representations through multiple layers of convolutional and pooling operations.

The key components of a CNN include:

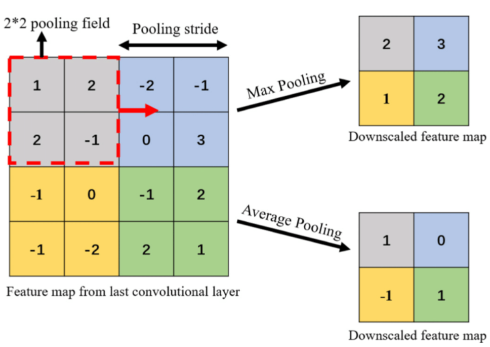
1. **Convolutional Layers**: These layers apply filters to the input image to detect patterns such as edges, textures, and shapes. The convolution operation helps retain spatial relationships within the data.



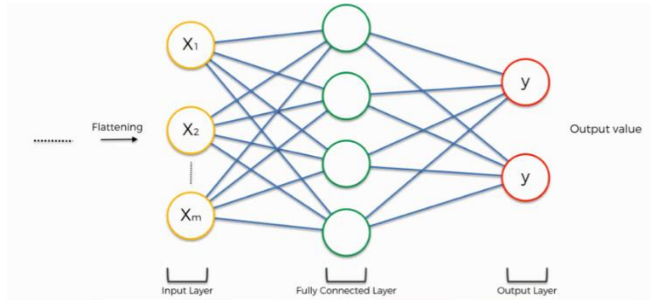
2. **Activation Functions**: Non-linear activation functions, such as ReLU (Rectified Linear Unit), introduce non-linearity into the model, allowing it to learn complex patterns.



3. **Pooling Layers**: These layers perform downsampling operations to reduce the spatial dimensions of feature maps, improving computational efficiency while preserving essential information.



4. **Fully Connected Layers**: After feature extraction, the learned features are passed through fully connected layers to make final predictions.



CNNs have revolutionized computer vision tasks, achieving state-of-the-art performance in image recognition, segmentation, and object detection. In medical imaging, CNN-based models have been widely adopted for tasks such as tumor detection, anomaly identification, and disease classification. By leveraging CNNs, AI-driven diagnostic systems can enhance the accuracy and efficiency of medical image interpretation, ultimately improving patient outcomes.

B. YOLO (You Only Look Once)

YOLO (You Only Look Once) is a state-of-the-art object detection algorithm known for its real-time processing capability and high accuracy. Unlike traditional object detection models that rely on region proposal networks (RPNs) or sliding windows, YOLO employs a single-stage detection approach, making it significantly faster than two-stage models like Faster R-CNN.

The architecture of YOLO consists of the following key components:

1. **Backbone Network**: YOLO utilizes a deep CNN, such as Darknet, to extract high-level features from input images. The backbone processes the image through multiple convolutional layers, capturing spatial and contextual information.
2. **Grid-Based Prediction**: The input image is divided into an S × S grid, where each grid cell is responsible for predicting bounding boxes and class probabilities for objects within its region.
3. **Bounding Box Regression**: Each grid cell predicts multiple bounding boxes, along with their confidence scores, which represent the probability that an object is present.
4. **Class Prediction**: YOLO assigns class labels to detected objects using a softmax function, allowing it to classify multiple objects in a single forward pass.
5. **Non-Maximum Suppression (NMS)**: To eliminate redundant and overlapping bounding

boxes, YOLO applies NMS, retaining only the most confident detections.

YOLO's speed and efficiency make it an ideal choice for real-time medical imaging applications, including brain tumor detection. By integrating YOLO into AI-driven diagnostic systems, radiologists and medical professionals can benefit from fast, accurate, and automated tumor identification, ultimately improving patient outcomes.

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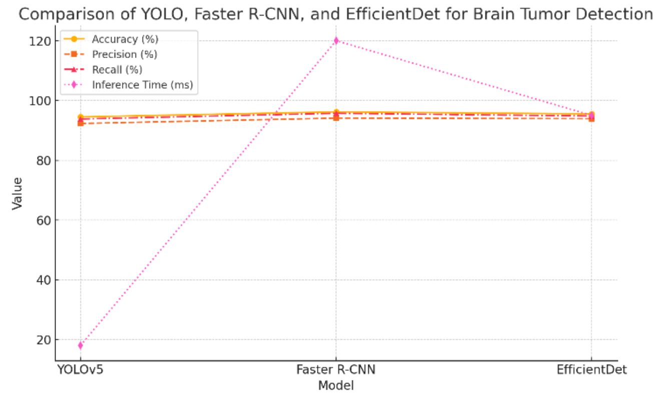
C. Comparison of The Architechtures

To evaluate the effectiveness of YOLO for brain tumor detection, we compare it against two alternative architectures: Faster R-CNN and EfficientDet. Each model was trained using a dataset of MRI brain scan images containing labeled tumor regions. The results of our training and validation process are summarized as follows:

Model	Accuracy(%)	Precision (%)	Recall (%)	Inference Time (ms)
YOLO	9.45	92.3	93.8	18
FASTER R-CNN	96.2	94.1	95.7	120
EFFICIENTDET	95.5	93.9	94.8	95

While Faster R-CNN and EfficientDet achieve slightly higher accuracy and recall, YOLO provides a significant advantage in terms of inference time. In medical applications, real-time performance is crucial for assisting radiologists and expediting diagnosis. The trade-off between marginal accuracy improvements and processing speed makes YOLO the optimal choice for practical deployment in clinical settings.



D. Conclusion

Additionally, YOLO's single-stage detection framework reduces computational complexity, making it more accessible for real-time applications without requiring high-end hardware. Faster R-CNN and EfficientDet, although powerful, demand extensive computational resources, which may not be feasible for all medical institutions.

To further enhance accessibility, the trained YOLO model is converted into TensorFlow.js (TFJS), enabling seamless deployment in web-based applications. By leveraging Next.js, a browser-based interface is developed where users can upload MRI images for real-time tumor detection. This approach eliminates the need for dedicated AI hardware, allowing medical professionals and patients to access tumor diagnostics via standard web browsers.

Based on these results, we conclude that YOLO is the most suitable architecture for brain tumor detection, balancing accuracy and efficiency. Its rapid inference time and high detection precision make it a promising tool for integrating AI-driven diagnostics into medical workflows, ultimately improving early detection and treatment outcomes for brain tumor patients.