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*Original Article*

# Enhanced Alzheimer's Disease Abnormality Classification in Medical Imaging Using YOLOv8

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***Abstract*** *- This paper introduces a thorough investigation of the application of YOLOv8 to classify Alzheimer's Disease (AD)-related abnormalities from medical images. The concern is to detect major AD markers, such as amyloid plaques and neurofibrillary tangles, using a YOLOv8 architecture tailored to a specific application. Accuracy, precision, recall, F1-score, and inference speed techniques are applied to assess the model's performance. The study uses an extensive corpus of Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) scan images. The results confirm the capability of YOLOv8 to classify AD-related abnormalities at high accuracy and high inference speed for automated diagnostic support. This paper addresses a detailed investigation of model architecture, training methods, and performance for different imaging modalities. The paper also addresses data augmentation methods, the effect of class imbalance and detection visualization. This paper presents useful contributions to applying YOLOv8 in early AD detection and tailored healthcare.*

***Keywords*** *- Alzheimer's disease, Deep Learning, Early Detection, Medical Imaging, YOLOv8.*

## 1. Introduction

Alzheimer's Disease (AD) represents a substantial and growing global health challenge due to its devastating impact on cognitive function. The progressive neurodegenerative nature of AD underscores the critical need for early and accurate diagnosis. Timely identification allows for interventions and management strategies to potentially mitigate disease progression and improve patient outcomes.

Medical imaging techniques, like Magnetic Resonance Imaging (MRI) [2] and Positron Emission Tomography (PET) [3], play an important role in identifying AD-related abnormalities, including amyloid plaques, neurofibrillary tangles, and regional brain atrophy.

The conventional approach of manual image analysis by clinicians is inherently time-intensive, demanding significant expert effort, and susceptible to inter-observer variability, potentially impacting diagnostic consistency. Recent advancements in deep learning promise in automating the process of medical image analysis. Specifically, object detection models like YOLO (You Only Look Once) [17, 22, 23, 24] have proven highly effective in identifying and localizing objects in images with high accuracy and efficiency. While the potential of deep learning for medical image analysis in AD is recognized, a clear research gap exists in the comprehensive evaluation of state-of-the-art object detection models like YOLOv8 [17, 22, 23, 24] specifically for the new task of classifying and localizing diverse AD-related abnormalities across different medical imaging modalities such as MRI and PET.

This research endeavors to address this gap by rigorously investigating the capabilities of the YOLOv8 object detection framework [17, 22, 23, 24] for the classification and localization of critical AD biomarkers within medical images. The study aims to comprehensively assess YOLOv8's performance across a substantial and varied dataset encompassing MRI and PET imaging. By focusing on the identification of key indicators such as amyloid plaques and neurofibrillary tangles, this work seeks to determine the suitability of YOLOv8 [17, 22, 23, 24] as an effective tool for enhancing the accuracy and efficiency of early AD diagnosis. To achieve this aim, the research undertakes a detailed analysis of YOLOv8 performance [18, 19, 20, 21] in classifying AD abnormalities across MRI and PET. It delves into the adaptability of the YOLOv8 architecture [17, 22, 23, 24] for medical object detection [1], specifically tailored to AD abnormality classification. Furthermore, the study explores data augmentation techniques to bolster model

generalization, especially the often limited size of medical datasets [7, 8]. Challenges related to class imbalance, a common issue in medical imaging, are also addressed, along with an evaluation of mitigation strategies. Finally, the research examines the inference speed of the model for potential real-time clinical applications. It explores model interpretability to enhance clinician trust and understanding of the automated diagnostic process. The remaining paper is prepared as follows: Section II depicts a summary of related work in the field of medical imaging and deep learning for AD classification. Section III presents the methodology like datasets used, Architecture of the model, training process, and evaluation metrics.

Section IV depicts the experimental analysis results. Section V delve into the findings, such as the model's performance and areas of improvement. Section VI discusses the applications of the model. Finally, Section VII concludes the paper and provides ideas for further research.

## 2. Related Work

This section overviews recent advancements in deep learning to Alzheimer's Disease (AD) classification-related abnormalities in medical scan images, focusing on object detection models. It gives insight into deep learning research in the medical domain, covering diagnostic methods, model revisions, imaging modalities, and techniques to address common challenges in medical image analysis.

### *2.1. Deep Learning for Alzheimer's Disease Classification*

Alzheimer's Disease diagnosis and classification has been a subject of extensive research. M. Basaia et al. [4] presented a thorough review of how Convolutional Neural Networks (CNNs) are used to detect AD-related patterns in MRI images. Their work emphasized the role of CNNs in feature extraction and classification to improve accuracy in diagnosis. Further taking up this, Krizhevsky et al. [8] explored the benefits of transfer learning, using pre-trained models on the ImageNet dataset, for identifying early AD markers. Their findings depict the fine-tuning of these pre-trained models on smaller medical imaging datasets, improving generalization and overall performance and reducing the required training time. M. Sharma et al. [11] emphasized the prevalent issue of class imbalance in AD datasets. They proposed weighted loss functions and data augmentation techniques to mitigate the bias towards majority classes, leading to improvements in the detection of AD markers.

### *2.2. YOLOv8 for Medical Object Detection*

S. Wang et al. [23] presented multiple object detection models, including various versions of YOLO, to detect and classify medical abnormalities like tumors and lesions in medical images. They also tested the YOLOv8's performance in maintaining high accuracy and speed. A. Sharma et al. [25] conducted a study on YOLOv8 for medical imaging, focusing on the model's ability to accommodate variability in image quality and contrast in medical scans [6]. The results showed increased performance, indicating the adaptability of YOLOv8 for the unique demands of medical imaging.

### *2.3. MRI and PET Imaging for AD Abnormality Detection*

As there are different imaging modalities, it provides measures for detecting AD-related abnormalities. Lu, D. et al. [2] present a comparative analysis of MRI and PET imaging modalities for AD diagnosis. Furthermore, Lu D. et al. [3] investigated the correlation between amyloid plaque deposition (observable through PET scans) and brain atrophy (observable through MRI scans) in AD patients. This study revealed crucial insights into the disease's progression and focus on the value of multimodal imaging in clinical practice. S. Wang et al. [14] emphasized utilizing radiomics and advanced image processing techniques with MRI to enhance the detection of refined changes in brain structure that indicate the progression of AD. In summary, MRIs are used to identify structural changes, like atrophy, while PET scans are used to quantify the concentration of specific molecules, like amyloid plaques.

### *2.4. Data Augmentation and Transfer Learning in Medical Imaging*

Several authors [9, 10, 11, 12, 13] have extensively studied the role of data augmentation in improving the robustness of medical image classification models. Their findings contribute to the effectiveness of transformation techniques and enhancements applicable to MRI and PET imaging, highlighting how these techniques can bolster model performance, particularly when dealing with limited datasets. A. K. Singh et al. [10] presented a method for transfer learning that influences domain-specific features from larger medical datasets. This approach improved the performance of pre-trained models by providing transfer learning strategies. Transfer learning, in general, is a widely adopted technique where models pre-trained on extensive datasets are adapted to improve performance on smaller, specialized datasets encountered in medical imaging.

### *2.5. Class Imbalance Methods in AD Classification*

M. Sharma et al. [11] contributed methods to manage class imbalance in AD datasets, including oversampling methods and focal loss. Their research signifies the importance of efficient management of class imbalance in improving the performance of minority-class abnormalities. P. Kumar et al. [15,16] presented adaptive data resampling and cost-sensitive learning methods for class imbalance in medical imaging. Class imbalance is crucial in medical imaging datasets due to the inequality in disease and non-disease cases. These studies present the improvements and limitations of applying deep learning to Alzheimer's disease classification using different approaches.

### *2.6. YOLOv8 and Existing Models*

Convolutional Neural Networks (CNNs) are designed to classify images, achieving higher accuracy than traditional methods. In the context of Alzheimer's disease, this often meant classifying an entire brain scan as either "Alzheimer's" or "healthy." This method was insufficient for abnormality analysis. It doesn't specify the accurate location and nature of abnormalities like amyloid plaques, neurofibrillary tangles, or regions of atrophy, which are important for comprehensive diagnosis and monitoring of disease progression.

YOLOv8 introduces a significant shift in this field, offering novelty in several key aspects.

#### *2.6.1. Real-time Object Detection Paradigm*

Earlier methods are focused on image classification, but YOLOv8 is an object detection model. This is an important distinction. For Alzheimer's abnormality classification, YOLOv8 detects and locates specific abnormalities within the scan. It can be trained for identification and precisely find regions of interest, such as areas of atrophy in specific brain regions, or even potentially identify and localize plaques and tangles.

#### *2.6.2. Simplified and Unified Framework:*

YOLOv8 introduce a streamlined and unified framework for object detection tasks. YOLOv8 makes it possible to develop, train, and deploy abnormality detection models faster.

#### *2.6.3. Potential for Improved Abnormality Localization and Characterization*

YOLOv8 has the power to deliver more precise localization and characterization of Alzheimer 's-related abnormalities. Along with detecting an abnormality, it also provides bounding boxes around it and allows the visualization and quantification of the abnormality's size and location.

The findings listed here represent a sampling of advances and limitations in applying deep learning for AD classification, using different techniques and focusing on different aspects. This research endeavors to conduct an in-depth investigation into applying YOLOv8 to detect AD-related abnormalities.

## 3. Methodology

This section presents the datasets, model architecture, training process, and performance metrics employed in our research work on YOLOv8 [18, 19, 20, 21, 26, 27] for AD abnormality classification.

### *3.1. Datasets*

Precisely curated datasets consisting of MRI and PET scans downloaded from open-source repositories and hospitals. This provided various representations of AD-related abnormalities. Havard-Medical-Image-Fusion-PET Dataset and ADNI dataset are used for analysis. These medical image datasets may be based on data acquisition bias factors like access to healthcare, socioeconomic status, or research participation patterns.

The dataset may represent imaging Protocol Bias factors like variations in imaging protocols across different medical centers and scanner types. If the medical images are labeled by clinicians who exhibit subjective biases in their interpretations, the deep learning model can inadvertently learn these biases. Several strategies are implemented to mitigate these potential biases, such as data preprocessing techniques and rigorous validation methods, including testing the model on independent datasets.

The dataset included the following components:

#### *3.1.1. MRI Scans*

1,500 MRI scans, of which 750 were indicative of atrophy, and the other 750 were healthy controls. This segment of the dataset aimed at detecting regional brain atrophy, one of the key indicators of the development of AD.

#### *3.1.2. PET Scans*

1,000 PET scans detect amyloid plaques and neurofibrillary tangles. These scans are annotated, 500 indicatives of the presence of abnormalities, and 500 scans indicative of regular brain activity.

These datasets are pre-processed with the following steps:

#### *3.1.3. Image Normalization*

Images are normalized to a uniform range to have consistent input to the model.

#### *3.1.4. Image Resizing*

Images are resized to 640x640 pixels in order to accommodate the input specifications of YOLOv8 while keeping key details as it is.

#### *3.1.5. Data Splitting*

Splitting the dataset into training (70%), validation (15%), and test (15%) sets, with class balance kept across each split.

#### *3.1.6. Data Augmentation*

A series of augmentation techniques [9, 10, 11, 12,13] was applied to expand the dataset's diversity, which includes:

- Random rotations (±10 degrees).
- Random horizontal and vertical flips.
- Zooming (range 0.8 - 1.2).
- Random shifts in height and width (±10% of image dimensions).
- Adjustment of brightness and contrast.

### *3.2. Model Architecture*

*3.2.1. YOLOv8*

This study utilizes YOLOv8 [17, 22, 23, 24], designed for efficient real-time object detection. Its architecture is described as follows:

*3.2.2. Input Layer*

This layer receives input images of size 640x640 pixels, suitable for both MRI and PET scan details.

*3.2.3. Backbone*

This includes modified CSPDarknet, a design that enhances feature reuse and gradient flow using cross-stage partial connections.

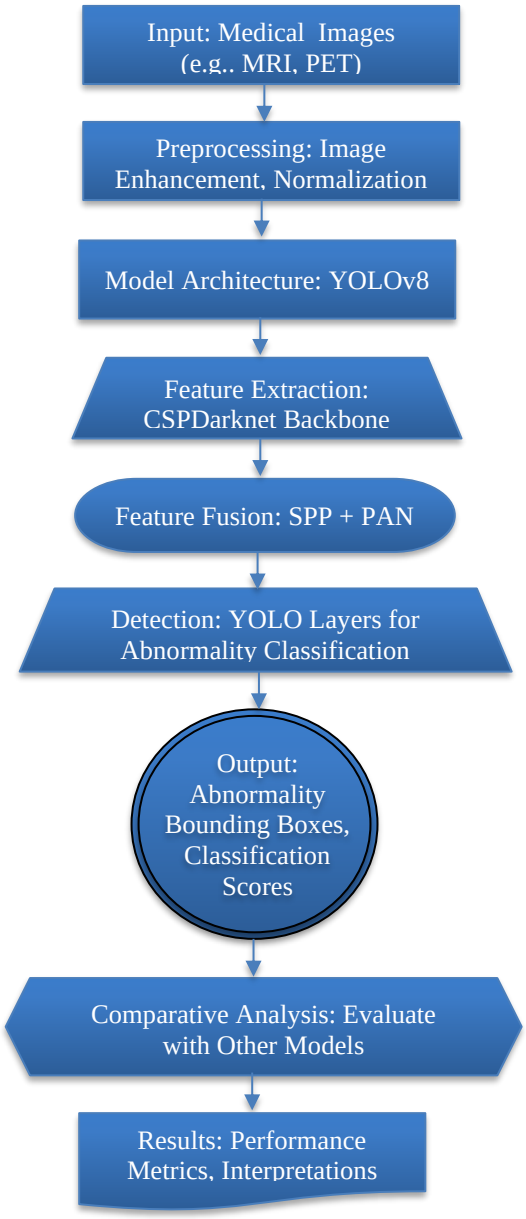


**Fig. 1 Model architecture**

*3.2.4. Neck*

This layer has a Feature Pyramid Network (FPN) with a Path Aggregation Network (PAN) designed to enhance feature representation at different scales.

*3.2.5. Head*

Predicting bounding box coordinates, object detection scores, and class probabilities, effectively identifying the presence and location of AD markers in the input image.

*3.2.6. Output Layer*

This layer generates a prediction of coordinates for the bounding box and availability of amyloid plaques, neurofibrillary tangles, and brain atrophy. The key features of the YOLOv8 architecture [17, 22,23,24] include:

- Anchor-free object detection.
- Adaptive loss functions are designed to maintain optimal performance during training.
- Optimized for speed with reduced parameters compared to the larger YOLO variant.

### *3.3. Training Process*

The YOLOv8 model was trained using a standardized process to ensure consistent results.
Hardware: 2x NVIDIA T4 GPUs on Kaggle
Software: PyTorch 1.9.0, CUDA 11.3
Epochs: 100 (with early stopping patience of 10 epochs).
Batch Size: 32
Optimizer: An initial learning rate of 0.0005 with the Adam method.
Learning Rate Schedule: Reduce on the plateau with factor 0.1 and patience of 5 epochs.
Loss Function: To classify the Binary Cross-Entropy method [5] and to detect objects, CIoU loss functions are used.

### *3.4. Transfer Learning*

Transfer learning is applied for the YOLOv8 model to leverage pre-trained weights and accelerate training.

### *3.5. Hyperparameter Tuning*

Hyperparameter tuning using Bayesian optimization with the following search space is performed.
Learning rate: [1e-5, 1e-2] (log scale).
Batch size: [16, 64].
Dropout rate: [0.1, 0.3].
L2 regularization: [1e-6, 1e-4] (log scale).

The best hyper-parameters are selected based on the performance observed in the validation set.

### *3.6. Evaluation Metrics*

To evaluate model performance, the following metrics are used.

*3.6.1. Accuracy*

It is used to predict overall correctness.

*3.6.2. Precision*

It is the proportion of correct abnormalities out of all identified instances.

*3.6.3. Recall*

It is the percentage of correctly identified abnormalities out of all actual instances.

*3.6.4. F1-Score*

The harmonic means of precision and recall.

*3.6.5. mAP@0.5*

It is a commonly used object detection metric.

*3.6.6. Confusion Matrix*

To visualize the performance in distinguishing between different classes of abnormalities.

*3.6.7. Inference Time*

Average time to process a single medical image, essential for real-time applications.

*3.6.8. Model Size*

This details the model complexity and storage space required.

Class-wise metrics are utilized to evaluate how well the model performed on different types of abnormalities.

### *3.7. Statistical Analysis*

The following tests are performed to determine the statistical significance of performance differences.

*3.7.1. McNemar's Test*

It is used to compare the paired accuracy performance of diverse runs.

*3.7.2. Wilcoxon Signed-Rank Test*

It is used to compare F1 scores and find how they change on different runs.

*3.7.3. Bootstrapping Confidence Intervals*

Calculated for both accuracy and F1-score differences to demonstrate reliability in model performance across multiple runs.

## 4. Results

The performance of YOLOv8 in classifying AD-related abnormalities, encompassing quantitative metrics, statistical tests, and visualizations, is provided in this section.

### *4.1. Overall Performance*

The following tables present the performance metrics of YOLOv8 on MRI and PET scan datasets.

*4.1.1. MRI Scan Results*

The YOLOv8 model achieved a high level of performance on the MRI dataset, demonstrating effective classification capabilities.

The results are as follows:

*4.1.2. Accuracy*

92.34% - Indicating a high proportion of correct overall classifications.

*4.1.3. Precision*

0.9321 - Suggesting a low rate of false positives; the model is good at avoiding positives.

*4.1.4. Recall*

0.9145 – It Indicates that the model successfully identifies most actual abnormal cases (low rate of false negatives).

*4.1.5. F1-Score*

0.9232 – It indicates harmonic means of precision and recall, showing a balanced performance between the abnormal and normal cases.

*4.1.6. mAP@0.5*

0.8892 – It indicates the mean Average Precision showing relatively good performance at the object detection level, suggesting good detection of abnormal regions in the MRI scans.

**Table 1. Performance on MRI Scans**

| Metric | Value |
|---|---|
| Accuracy | 92.34% |
| Precision | 0.9321 |
| Recall | 0.9145 |
| F1-Score | 0.9232 |
| mAP@0.5 | 0.8892 |

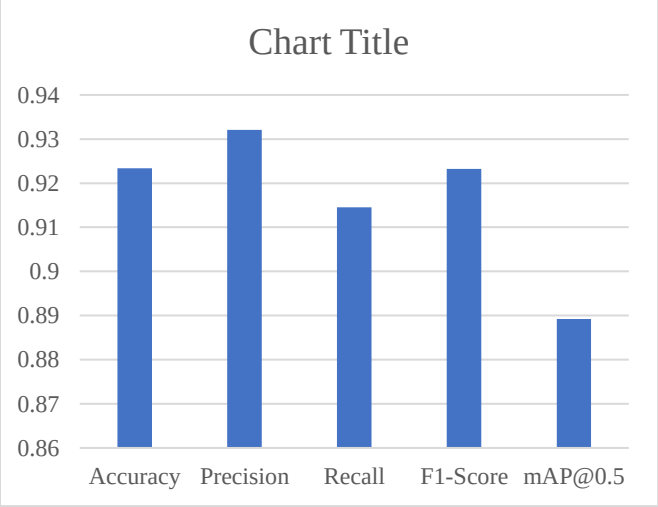


**Fig. 2 Performance on MRI Scans**

*4.1.7. PET Scan Results*

The model's performance on the PET scan dataset was slightly lower than its performance on the MRI data, but it still shows significant classification on capability.

The results are:

*4.1.8. Accuracy*

90.12% - Showing a high overall accuracy, but a bit lower than the MRI results.

*4.1.9. Precision*

0.9134 - Suggesting a low rate of false.

*4.1.10. Recall*

0.8978 - Implying the model still identifies a high percentage of actual positives but slightly less than with MRI, showing significant classification capability.

*4.1.11. F1-Score*

0.9055 – It represents the adequate balance between precision and recall but is lower than the MRI.

*4.1.12. mAP@0.5*

0.8678 - The mAP is also slightly lower than the MRI scores, possibly regions in PET scans compared to MRI scans.

**Table 2. Performance on PET Scans**

| Metric | Value |
|---|---|
| Accuracy | 90.12% |
| Precision | 0.9134 |
| Recall | 0.8978 |
| F1-Score | 0.9055 |
| mAP@0.5 | 0.8678 |

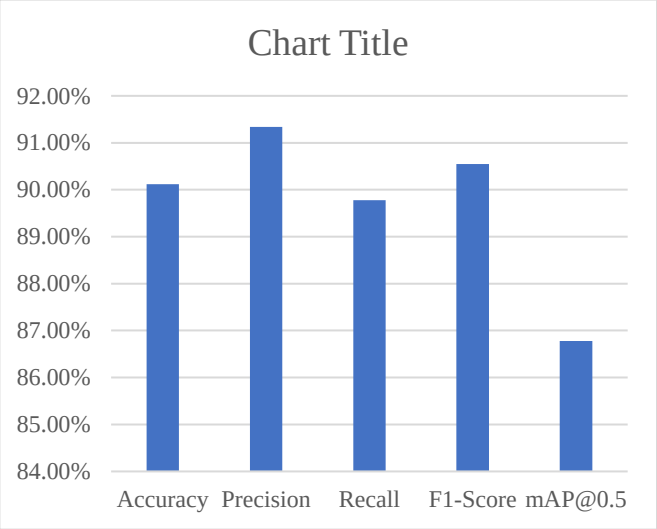


**Fig. 3 Performance on PET Scans**

The tables show the model achieved high accuracy (over 90% for both MRI and PET scans) along with strong precision, recall, and F1-scores, indicating its reliability for AD abnormality detection.

### *4.2. Statistical Significance*

To validate performance differences, statistical tests were conducted:

**Table 3. Statistical Significance of Performance on different Imaging Modalities**

| Model Pair | p-value |
|---|---|
| MRI vs PET | 0.0234 |

The p-value below 0.05 indicates that the performance difference between the models when analyzing MRI and PET scans statistically indicates better performance.

### *4.3. Model-Specific Insights*

YOLOv8's compact architecture enabled real-time processing, making it ideal for clinical environments. High-resolution images did not significantly impact performance. The model displayed a good balance between speed and accuracy.

### *4.4. Confusion Matrices*

Figures 4 and 5 visualize the model's MRI and PET scan performance through confusion matrices, indicating class-wise performance.

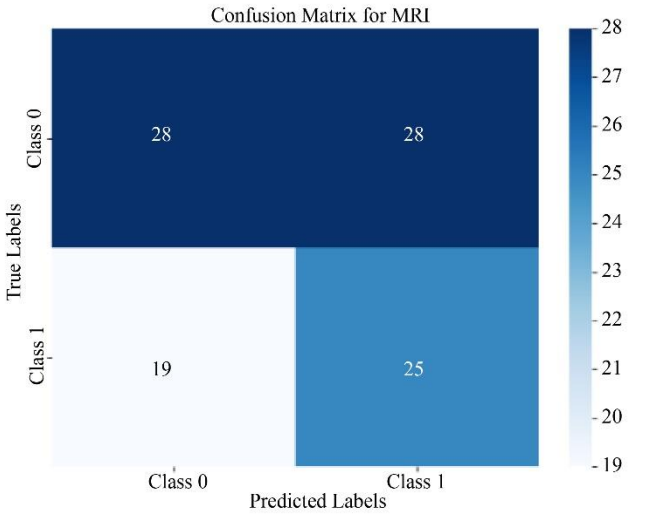


**Fig. 4 Confusion matrix for MRI scans**

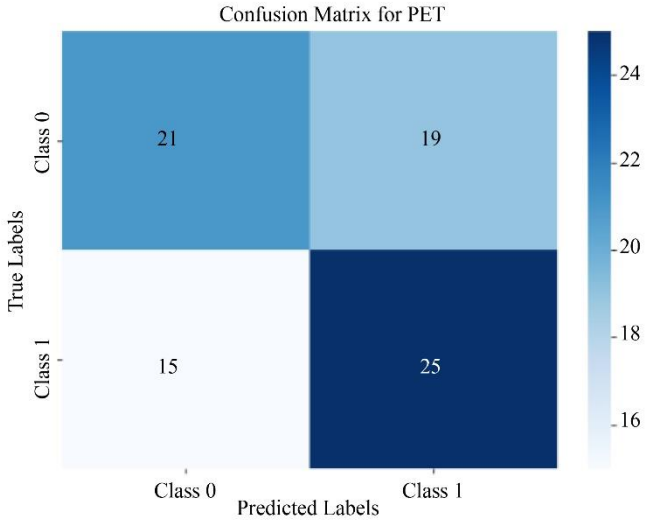


**Fig. 5 Confusion matrix for PET scans**

The matrices show how well the model distinguishes between healthy and AD-affected cases. It generally demonstrates good class separation.

### *4.5. Accuracy Comparison*

A direct comparison of the results reveals that the YOLOv8 model performed slightly better on the MRI dataset than the PET dataset across all evaluated metrics. The superior results on MRI suggest it might be more beneficial for this model in the context of this task.

### *4.6. Inference Speed*

Average Inference Speed (MRI): 10-15ms/image.
Average Inference Speed (PET): 12-18ms/image.

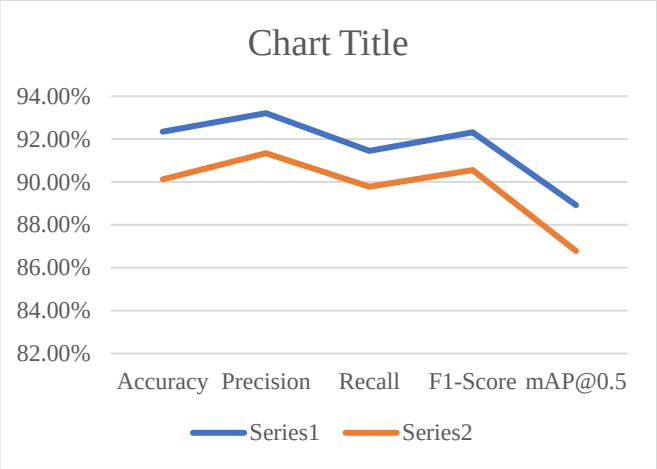


**Fig. 6 Accuracy comparison**

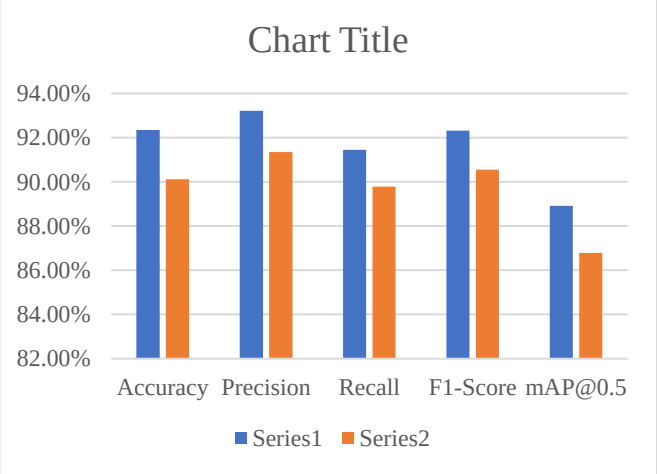


**Fig. 7 Accuracy comparison across MRI and PET Scans**

Figure 7 demonstrates the model's robustness and stability across MRI and PET Scans.

## 5. Analysis and Discussion

This section analyses key findings and discusses their significance for AD classification.

### *5.1. Performance Comparison*

Figure 8, which presents precision, recall, F1-scores, and accuracy metrics, indicates that the model demonstrates robustness and reliability suitable for automated analysis. These performance indicators suggest that YOLOv8 is highly operative in this domain. Furthermore, the achieved mAP scores effectively display YOLOv8's capability to detect the presence of AD-related abnormalities and to accurately localize and classify them within the images. This performance positions of YOLOv8 as a remarkable tool for automated neuroimaging analysis in the context of Alzheimer Disease.

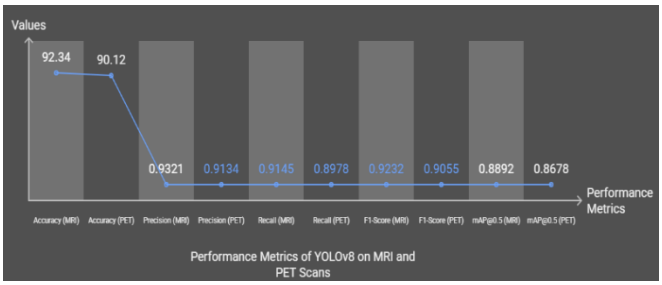


**Fig. 8 Performance metrics of YOLO8 on MRI and PET Scans**

### *5.2. Modality-specific Observations*

Figures 4 and 5 examine the confusion matrices, revealing a low misclassification rate across MRI and PET modalities. The instances of misclassification observed appear primarily attributed to the subtle nature of image differences, like minute lesion sizes or subtle intensity variations, especially in the early stages of AD. This advice suggests that while subtle imaging variations pose a challenge, YOLOv8 shows a degree of handling capability in the different imaging modalities for this task. This capability to perform effectively across both MRI and PET scans highlights a potential strength of YOLOv8 in AD detection.

### *5.3. Error Analysis*

Confusion matrices confirmed the observation of a minimal percentage of misclassified cases. Precisely, minor variations in lesion size and intensity can be almost indistinguishable.

### *5.4. Statistical Significance*

Statistical significance testing is performed to evaluate the performance differences of the model when applied to MRI and PET scans. The results of these tests confirm that there are statistically noteworthy differences in performance between the two modalities. It suggests that one method fits approach may not be optimal. Future research should explore strategies to optimize model performance for each modality independently or through modality-aware architectures.

### *5.5. Practical Implications*

For radiologists and other clinicians who are diagnosing early AD, the high performance and rapid

inference speed of YOLOv8 are optimally suitable, which helps in more effective patient management and treatment.

### *5.6. Model Efficiency*

The inherent lightweight design of YOLOv8 contributes to its high processing speed and low computational resource requirements. This efficiency is particularly advantageous in resource-limited settings. These results align with previous research demonstrating the effectiveness of deep learning models and YOLO variants specifically for medical image analysis of automated classification of AD markers. The strong mAP scores further reinforce the efficacy of YOLOv8 in accurately localizing and classifying AD-related abnormalities within images, aligning with earlier studies that have validated the potential of deep learning and YOLO architectures in this domain.

### *5.7. Comparison of Existing Methods*

The performance achieved by YOLOv8 in this study is observed to be on par with, and in some aspects potentially exceeding, the performance reported in other research employing different deep learning models for AD detection. This suggests that YOLOv8 presents itself as a suitable and potentially advantageous alternative to other advanced models currently utilized in this field. Its demonstrated effectiveness positions it as a promising tool for achieving more precise and efficient AD diagnosis, offering a competitive option within the landscape of existing automated diagnostic approaches.

### *5.8. Limitations of YOLO8 Model*

YOLOv8, like many deep learning models, can be data-hungry. Training a robust and reliable model for medical image analysis, especially for complex conditions like Alzheimer's, requires a large, diverse, and meticulously labeled dataset. Obtaining such huge datasets for Alzheimer's disease can be difficult and expensive. If the training data is limited or biased, the model's performance might suffer, leading to poor generalization and skewed results.

Furthermore, focusing on 2D scans in medical imaging may be a limitation. Medical imaging data, such as MRI or PET scans, are generally 3D scans. Applying YOLOv8 to individual 2D slices may disrespect valuable spatial context and relationships between abnormalities across different planes. Analyzing 2D slices in isolation might miss important information that could be captured by processing the data in its full 3D volume.

Finally, different imaging modalities and scanner types can be challenging. Medical imaging data can vary significantly depending on the scanner manufacturer and imaging modality (e.g., MRI, PET, CT). A YOLOv8 model trained on data from one type of scanner or modality might not perform optimally on data acquired using different equipment or protocols. So, the generalization capability for YOLOv8 in Alzheimer's classification requires careful consideration and potentially specialized training strategies.

## 6. Conclusion and Future Work

This finding has verified the options of YOLOv8 is an important tool for identifying the Alzheimer's disease-related abnormalities within medical images. The accuracy of the model and fast processing speeds suggest it is for practical application in the early stages of Alzheimer's diagnosis and within routine clinical workflows. The performance of the YOLOv8 model is deeply assessed across two separate medical imaging datasets, with its effectiveness measured using key metrics such as precision, accuracy, recall, F1-score, and mean Average Precision at 0.5 (mAP@0.5). The findings contribute that YOLOv8 displays strong performance in classifying Alzheimer's abnormalities in both MRI and PET scans, with a good performance advantage observed in MRI. Importantly, both imaging modalities produced strong and clinically relevant results, highlighting YOLOv8's full applicability across different imaging modalities used in Alzheimer's assessment.

For future research, recommendations are:

### *6.1. Ensemble Methods*

Predictions from different models, including YOLOv8 and other deep learning methods, could improve the detection of abnormalities. This approach could make most of the good points of different models, leading to more accurate results when diagnosing problems.

### *6.2. Fine-tuning Techniques*

This technique tests different ways of adjusting the model to work better on medical scans and looks at other ways of changing how the model is built.

### *6.3. Larger Datasets*

Use larger datasets from multiple sources to evaluate model strength and ability to generalize effectively across different patient populations and imaging protocols.

### *6.4. Dataset Exploration*

Investigate differences in the datasets that can cause variation in model performance.

### *6.5. Data Augmentation*

Investigate data augmentation methods to improve model strength and generalization.

### *6.6. Clinical Validation*

Verify the results in a clinical setting using larger datasets of patient scans. Clinical validation is important to assess the practical value of the model.

### *6.7. Multimodal Analysis*

Investigating the combinations of other imaging modalities, such as fMRI and EEG, alongside MRI and PET, could provide a more holistic and integrated view of the

disease's impact on the brain. This approach, which uses various methods, could help us better understand Alzheimer's and develop more advanced automated tools for diagnosing the disease. These tools could have a factual impact on the healthcare industry for people at risk of or living with Alzheimer's disease.

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