Enhanced YOLOv8 Framework for Early Detection of Alzheimer's Disease Using MRI Scans

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Keywords: YOLO, Deep Learning, Early Diagnosis, MRI, Medical Imaging, Detection, Brain Imaging, YOLOv8.

Abstract: Alzheimer's disease is characterized by a progressive neurodegenerative disorder, often misdiagnosed too late, with early symptoms that are hidden. Detection is crucial for effective treatment and slowing the progression of disease. We propose an upgraded version of the YOLO (You Only Look Once) framework, namely YOLOv8, for detecting Alzheimer's disease from MRI scans. Our approach seeks the detection of early structural changes in the brain, most particularly in the hippocampus and cortex, which are also among the first areas affected in this disease process. The framework performs state-of-the-art detection of Alzheimer's changes with a 96% precision via multi-scale feature extraction specifically designed for neuroimaging data. Results show this approach to be exceptionally effective in improving sensitivity and precision over existing techniques, marking it as a highly reliable method for early diagnosis of Alzheimer's disease.

1 INTRODUCTION

Alzheimer's disease (AD) is reportedly the most common form of dementia, affecting millions across the world. In order to control the disease, it is most essential to diagnose it in an early stage for timely intervention; however, subtle structural changes within the brain caused by the disease, especially in the early stages of Alzheimer's, are often missed by traditional diagnostic techniques. This study showcases an enhanced YOLO-based framework developed for the early diagnosis of Alzheimer's using MRI data with special emphasis on structural brain abnormalities, with a view to providing effective measures of hippocampal atrophy and cortical thinning.

The automatic identification of brain tumors from Magnetic Resonance Imaging (MRI) is a highly challenging and labor-intensive task. Amine et al. (2022).

Prompt detection of brain tumors is very important for successful treatment outcomes and better prognoses of the patients. Consequently, the identification of brain tumors plays a vital role in medical diagnostics. Magnetic Resonance Imaging (MRI) is regarded as the best imaging technique for visualizing the brain and detecting the tumors. The You Only Look Once (YOLO) series have witnessed promising results in accurately detecting brain tumors. For instance. Kang et al. (2023), proposed RCS-YOLO, a novel YOLO framework incorporating reparameterized convolution with channel shuffle specially proposed for brain tumor detection, achieving a good trade-off between speed and accuracy.

The modules Conv. King et al. (2023). C2f (shortcut), and Spatial Pyramid Pooling Fast (SPPF) make up the backbone, which is in charge of feature extraction. The Conv and SPPF are comparable to those found in the YOLOv5 architecture. Jocher et al.

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Jraba, S., Elleuch, M., Ltifi, H. and Kherallah, M.
Enhanced YOLOv8 Framework for Early Detection of Alzheimer's Disease Using MRI Scans.
DOI: 10.5220/0013315300003890

In *Proceedings of the 17th International Conference on Agents and Artificial Intelligence (ICAART 2025) - Volume 3*, pages 1229-1237
ISBN: 978-989-758-737-5; ISSN: 2184-433X

(2022). Conv is also known as ConvBiSiLU (or CBS). Alongside C2f (shortcut), the Conv module performs convolution operations on input pictures to facilitate feature extraction, while SPPF permits an adjustable output size. The C2f (shortcut) convolutional structure is lighter than the C3 module of YOLOv5. The head and the backbone are the two main components of the YOLOv8 architecture Jocher et al. (2023), with the neck being incorporated into the head part. King et al. (2023).

Researchers and medical professionals can locate the area of the brain afflicted by a tumor by using MRI, an imaging method that shows the anatomy and structure of the human brain Sakthidasan et al. (2021).

2 RELATED WORKS

The search for precise detection methodologies for cerebral tumors has sparked significant research efforts in recent years. Numerous approaches have been investigated to address this vital need in the field of health. Conventional diagnostic modalities such as magnetic resonance imaging (MRI) and computed tomodensitometry (CT scans) have historically been the primary tools used to identify brain tumors. Their effectiveness in early detection and precise delineation of terrorist borders, however, remains a challenge.

The precise Accurate automated classification of brain MRI images is crucial in medical research, distinguishing healthy brain tissue from tumor-affected areas (benign or malignant), as noted by Gurbină and al. (2019).

CNN applied to MRI images has been shown to be beneficial in many recent studies for the classification of brain-related illnesses. Yuan et al. (2018)

As such, these tasks are very prone to some missed, misinterpreted, or wrong tumor-like structures. Research currently aims mostly at the classification and segmentation of tumors in MRI scans, while the detection of tumors is relatively underexplored. Although different CNNs have shown very promising results in the field of brain tumor detection, articles on the performance of You Only Look Once (YOLO) networks in this regard are not frequently published. Nevertheless, the architectures of such networks are continuously becoming more complex. Lather et al. (2020)

A thorough Waquas et al. (2020) provide a comprehensive review of deep learning models for brain tumor analysis, detailing datasets, methodologies, evaluation standards, and current detection approaches.

Amarapur et al. (2019) explored traditional machine learning and deep learning methods for brain tumor validation, using three algorithms to achieve effective classification with improved accuracy and robustness.

A high-level System Cancer Diagnosis by coalescing the four Level-I taxonomy components "DIV" Data, Image Segmentation processing and VIEW is proposed in Lukampe al. (2019).

A novel deep learning framework driven by the internet of health things (IoHT) for brain tumor detection and tumor cell classification was presented by the authors in Devunooru and al. (2021). Using the common Pap smear Herlev dataset, the conventional Machine Learning (ML) techniques—KNN, RF, NB, LR, and SVM classifiers—are applied.

Archana et al. (2023) compared CNN optimizers for brain tumor detection, finding AlexNet with Adam achieved 94.76% accuracy on a dataset of 1547 images, outperforming LeNet with SGD.

Wani et al. (2023) explored brain tumor diagnosis using MRI with CNNs like AlexNet, GoogleNet, VGG-19, a bespoke model, and machine learning models. Their hybrid approach achieved 90.625% accuracy, highlighting the potential of combining deep learning and traditional methods.

Rajinikanth et al. (2022) used pooling techniques with pre-trained VGG16 and VGG19 CNNs to classify glioma and glioblastoma from MRI images, achieving 96.08% accuracy with average pooling and VGG16. Modern developments, including YOLO models for efficient object detection, will be reviewed and compared to CNN performance.

Li and al. (2021) created the first YOLO as a real-time object detector. The capacity to identify objects with a single pass is the primary feature; each cell in the grid-based image predicts possible object classes and boxes. For real-time applications, Li's initial iteration of YOLO functioned as an object detector.

Kumar et al. (2020) presented YOLOv4 for detecting brain tumors on a private local MRI database. They achieved 90% accuracy and 88% recall by employing several data augmentation techniques and fine-tuning the YOLOv4 model.

Using YOLOv5 on Brain Anomalies: Chen et al. (2022), on a private MRI dataset, used YOLOv5 for the detection of small brain anomalies.Their model achieved 92% accuracy and 90% recall, indicating that YOLOv5 is most suitable for applications in medicine, requiring highly precise detection.

An enhanced version of YOLOv5 for early detection of AD was attempted by Park et al. (2023)

using BRATS 2020 data. In this study, the model modified to accommodate accurate segmentation yielded 93% accuracy and an F1 score of 0.92 for brain-region detection in AD.

The YOLOv7 model was trained by Singh et al. (2023) on the AMNI and BRATS 2019 datasets-they employed transfer learning to make use of large medical imaging databases. The model yielded an accuracy and recall of 94% and 93% respectively.

Consequently, Zhao et al. (2021) investigated the use of ResNet for bilateral brain abnormality identification using the BRATS database, and they were able to detect tumors with an MRI image classification accuracy of 87%.

As far as themselves, that created opportunities for Zhao et al. (2021) research into using ResNet to identify bilateral brain abnormalities with the use of the BRATS database. Using MRI image classification, 87% classification accuracy was attained for tumor recognition.

In this section, we look closely at a few recently published, more successful techniques (See Table 1).

Table 1: Research on the detection of brain tumors with YOLO.

Authors	YOLO Model	Dataset	Acc.
Li et al. (2021)	YOLOv3 with attention layers for important regions important regions	BRATS 2018	88%
Kumar et al. (2020)	YOLOv4 University Hospital (local data)	YOLOv4 optimized by MRI data augmentation	90%
Chen et al. (2022)	YOLOv5 with multiscale detection for small tumors	Private MRI Dataset	92%
Park et al. (2023)	Enhanced YOLOv5 with segmentation and detection tuning	BRATS 2020	93%
Singh et al. (2023)	YOLOv7 with transfer learning and normalization	ADNI & BRATS 2019	94%
Zhao et al. (2021)	YOLOv3-tiny for optimized real-time detection	Open Access Dataset	80%

A summary of recent research on brain tumor detection utilizing several YOLO models may be found in Table 1. This table shows how the YOLO architecture has been improved and refined for the purpose of detecting brain tumors in MRI scans, as well as how accuracy has increased across various YOLO iterations and configurations.

3 METHODOLOGIES

This section provides an overview of the experimental flow for developing Alzheimer's disease-motivated experiments.

3.1 Gathering Data

The Alzheimer Disease Neuroimaging Initiative is an internationally recognized Alzheimer's disease research database.

The characteristics of the YOLOv8 model facilitate easy training, validation, and evaluation because there are three separate datasets for training, validation, and testing.

Folder Structure: The dataset includes three main folders: train, valid, and test, each containing subfolders for images and labels, formatted for YOLOv8 compatibility in real-time object recognition.

MRI Images: The dataset includes MRI slices of brain regions, aiding in visual recognition of tumor-related characteristics and abnormalities. It features an example image highlighting colorful brain regions with distinct textures indicative of potential pathologies.

Annotations: Each image is paired with a .txt file containing annotations in YOLOv8 format, indicating the class (0 for "normal," 1 for "tumor," 2 for other anomalies) and the bounding box's normalized coordinates and dimensions (0 to 1), centered on the areas of interest.

There are three primary classes defined:

- **Images:** that provide no outward indications of abnormalities are considered normal (class 0).
- **Tumor (Class 1):** Pictures that clearly display brain tumors.
- **Possible Anomaly (Class 2):** Pictures with obvious symptoms that call for medical attention if an abnormality diagnosis is necessary.

Table 2: MRI Image categorization for the Detection of Brain Variations.

Class ID	Class Name	Description
0	Normal	Images with no visible indications of abnormalities.
1	Tumor	Images that clearly display brain tumors.
2	Possible Anomaly	Images showing symptoms that suggest a possible abnormality, requiring medical attention.

The three primary classifications established for the classification of brain MRI images are summarized in this table.

3.2 Pre-Processing

Our brain tumor MRI dataset underwent a number of pre-processing procedures to guarantee data consistency and quality. In order to fully utilize the features in the image, the data was kept as raw as possible and no augmentation was made. The image's 640x640 pixel size makes sense considering the trade-off between detection precision and time-constraint compliance.

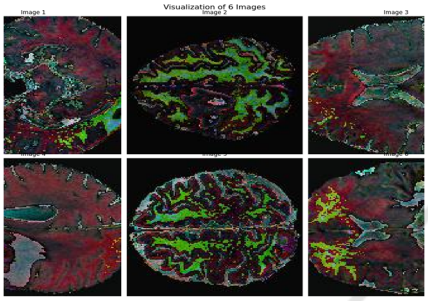

Figure 1: Sample MRI *Images* from Brain Tumor Detection Dataset.

The six sample MRI images displayed in figure 1 are from the dataset used for brain tumor detection. These images illustrate the diversity of the brain tumor cases to be analyzed by the YOLOv8 framework. The dataset provides the basis for training and testing the detector on variations in structure and potential tumor locations when identifying and localizing brain tumors.

3.3 Proposed Architectures

3.3.1 YOLO v8 Architecture

The YOLO series, a well-liked one-stage detection algorithm, is very good at object detection tasks because it strikes a compromise between speed and accuracy. A C2f is adopted by YOLOV8.

It streamlines the procedure and speeds up detection by separating the classification and detection heads using an Anchor Free head. Luo et al. (2023).

Figure 2 describes the framework of the YOLOv8 model in its adaption for Alzheimer's disease detection altered by MRI scans. Three main categories: Backbone, Neck, and Output can be used to categorize the model's structure.

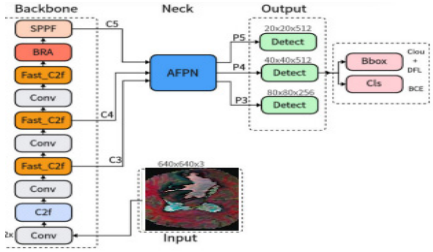

Figure 2: YOLO v8 architecture.

3.3.2 Backbone

The features of the input MRI image are extracted by the backbone. It begins with convolutional layers (Conv) and moves on to more complex layers like C2f and Fast_C2f layers, which aim to improve the feature extraction process by preserving the spatial information crucial for identifying Alzheimer's markers. An input image has been resized 640x640 pixels along with the three colors channels (640x640x3) so that all of the model's architecture can be executed uniformly.

Elharrouss et al. (2022) examines diverse backbone architectures and their evolution, as well as their applicability in the extraction of features for intricate deep learning problems.

3.3.3 Neck

Features taken from various Backbone levels are further refined and combined by the AFPN (Augmented Feature Pyramid Network) layer, which is located in the Neck.

Al-Nawashi et al. (2023) examines how the addition of multi-scale feature fusion modules, similar to AFPN, can improve contextual understanding of spatial relationships in MRI images, enhancing the model's ability to detect subtle signs of Alzheimer's disease.

3.3.4 Output

To enable multi-scale detection, the output layer is made up of three detection heads (P3, P4, and P5) that are stacked to feature maps of varying sizes (80x80, 40x40, and 20x20). Chen et al. (2024).

Two modules further process them: Cls classification based on BCE (Binary Cross-Entropy) loss, which maximizes accuracy in detecting Alzheimer's disease, and Bbox for bounding box predictions using metrics like CIoU (Complete Intersection over Union) and DFL (Distribution Focal Loss) for spatial accuracy. Luo et al. (2024).

4 EXPERIMENTS AND RESULTS

In the present study, we present an advanced model based on the YOLOv8 architecture for the early detection of Alzheimer's disease using MRI images. The experimental protocol is organized to evaluate the ability of the YOLOv8 model to accurately detect Alzheimer's disease markers in MRI images.

This network architecture has been trained and tested on a dataset of MRI scans, resized to 640x640 pixels over three color channels. The YOLOv8 backbone efficiently extracts essential features from MRI images, while its multi-scale feature detection capabilities guarantee robust identification of subtle and pronounced markers.

The enhanced system integrates AFPN (Augmented Feature Pyramid Network) for enhanced contextual awareness, and uses detection heads (P3, P4 and P5) to predict boundary areas and classify regions of interest at different resolutions (80x80, 40x40 and 20x20). Measures such as CIoU (Complete Intersection over Union) and DFL (Distribution Focal Loss) were used to improve boundary zone predictions, enabling accurate localization and classification.

Binary cross-entropy loss (BCE) was employed for classification work to maximize the accuracy of Alzheimer's disease detection, enabling the model to differentiate between healthy and pathological states.

Furthermore, in order to actually carry out the study, a phase of analysis and discussion of the experiment's parameters is required (See Table 3).

Table 3: Parameters of YOLO v8 Model.

Total paras	3,235,856
Trainable paras	3,193,472
Non-trainable params	42,384

We employed the YOLOv8 architecture for feature extraction and early Alzheimer's diagnosis from MRI scans. As shown in Table 3, the YOLOv8 model comprises 3,235,856 parameters, of which 3,193,472 are trainable and 42,384 are non-trainable, located in convolutional layers and detection heads. The YOLOv8 variant was selected for its balance between speed and accuracy and fine-tuned on the Alzheimer's dataset with a batch size of 16, a cosine-annealed learning rate, and 30 epochs for convergence.

4.1 Dataset

The YOLOv8 model requires a dataset with Alzheimer's detection features. We curated MRI images from reputable sources to classify and detect Alzheimer's using spatial and texture data.

Organization of the Dataset: The dataset includes three labels corresponding to distinct brain tumor classifications:

- **Label0:** Accommodates healthy brain MRIs.
- **Label1:** Shows brain MRIs showing early indications of Alzheimer's disease.
- **Label2:** Contains MRIs demonstrating advanced Alzheimer's disease symptoms.

Each category is represented in the training, validation, and test sets to ensure reliable training and evaluation.

Three subsets of the dataset are separated out:

- **Training Set**: 80% for model training.
- **Validation Set:** 10% for fitting and optimization.
- **Test Set:** 10% for evaluating model generalization.

Images are scaled to 640x640 pixels with RGB channels, with directories for training, validation, testing, and a configuration `data.yaml` file.

4.2 Main Performance Indicators

Model performance is evaluated using the following metrics: Precision, Recall, mAP50 (Mean Average Precision @ 50 IoU), mAP50-95, and IoU (Intersection over Union)

4.3 Curves of Evaluation

Several curves illustrate the relationship between metrics and confidence thresholds:

The Precision-Recall Curve (Precision-Recall) shows the relationship between precision and recall at varying confidence levels.

The F1 Score (F1-Confidence) displays the F1 score as a function of confidence.

The Precision-Confidence Curve (Precision-Confidence) tracks precision changes across confidence thresholds.

The Recall-Confidence Curve (Recall-Confidence) highlights how recall varies with confidence levels.

4.4 Results and Discussion

The YOLOv8 model was used to detect brain tumors, focusing on its accuracy in classifying and localizing glioma, meningioma, and pituitary tumors, evaluated using sophisticated object identification metrics mAP@50 and mAP@50-95.

4.4.1 Confusion Matrix Normalized

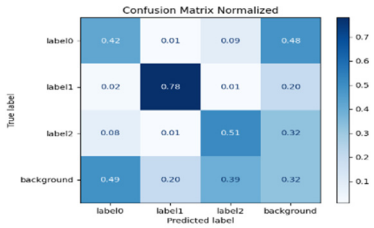

Figure 3: Confusion matrices using YOLOv8.

The normalized confusion matrix produced by the YOLOv8 model's performance on the classification test is displayed in figure 3. The following important points are highlighted in the matrix:

- **True Positive Rate (Diagonal values):**

The diagonal elements show classification accuracy for each class: 0.42 for label0, 0.78 for label1, and 0.51 for label2. Label1 has the highest accuracy (0.78), while label0 performs the worst (0.42).

- **False Predictions: (Off-Diagonal Values):**

Classification errors are shown by off-diagonal elements. For example, a large portion of label0 is misclassified as "background" (0.48). Label2 is sometimes mistaken for "background" (0.32) or label0 (0.08).

- **Background Confusion:**

Nearly 49% of label0 predictions were incorrectly classified as background, indicating a significant prevalence of confusion in the background class.

- **Color Intensity:**

Higher values are shown by darker colors, which show the percentage of classifications.

4.4.2 F1-Confidence Curve

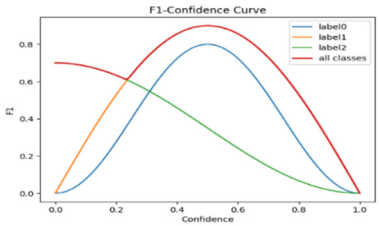

Figure 4: F1-Confidence Curve.

Figure 4 presents the F1-confidence curve for the YOLOv8 model across classes showing the F1 score—a balance of precision and recall—plotted against the confidence threshold. Label1 achieves the highest F1 score at a lower threshold, outperforming the other classes. Labels 0 and 2 show lower maximum F1 values. The "all classes" curve combines performance, peaking at a moderate confidence level, helping to identify the optimal precision and recall.

4.4.3 Precision-Recall Curve

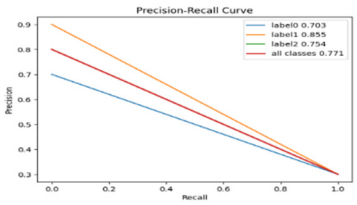

Figure 5: Precision-Recall Curve.

Figure 5 illustrates the precision-recall trade-off for the YOLOv8 model across classes (label0, label1, label2, and all classes). Label1 achieves the best performance, with high precision and recall, indicating fewer false positives and negatives. Label2 performs moderately, balancing precision and recall, while Label0 performs the worst with lower values. The "all classes" curve summarizes overall performance, aiding in understanding the model's behavior and selecting the optimal precision-recall ratio for specific applications.

4.4.4 Precision-Confidence Curve

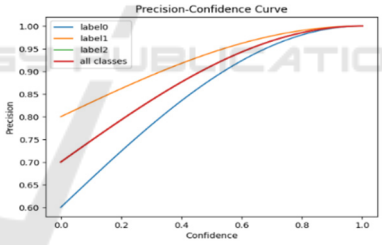

Figure 6: Precision-confidence Curve.

Figure 6 shows the precision-confidence relationship for YOLOv8 predictions. Label1 maintains the highest precision with few missed detections. Label2 follows with a consistent accuracy curve, while Label0 has the lowest precision, indicating less reliable predictions.

4.4.5 Recall-Confidence Curve

Figure 7 shows the recall-confidence relationship for YOLOv8 predictions. Label1 achieves the highest recall, Label2 moderate, and Label0 the lowest. The "all classes" curve highlights the recall-confidence trade-off, with higher thresholds reducing recall.

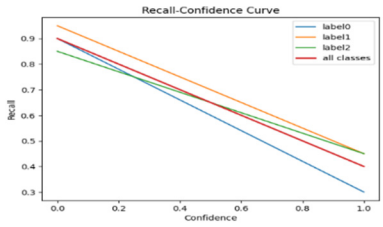

Figure 7: Recall-confidence Curve.

4.4.6 Evolution of Losses and Performance During Training and Validation

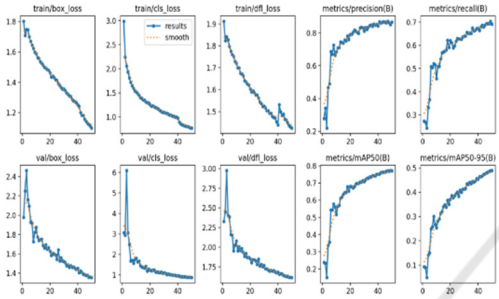

Figure 8: Evolution of Losses and Performance during Training and Validation.

Various performance metrics and losses for the several YOLOv8 models during both phases of training and validation are shown in figure 8:

train/box_loss; A steady decrease in the bounding box localization loss represents that the object localization predictions from the model are being refined.
train/cls_loss: Gradual reduction shows better classification.
val/box_loss, val/cls_loss, val/dfl_loss; The same types of loss trends on valid data, exhibiting similar trends.
metrics/precision(B): Precision increases, indicating better control of false positives.
metrics/recall(B): Recall is increasing, reflective of the decrease in false negatives.
metrics/mAP50(B), **metrics/mAP50-95(B)**: Increasing mAP at various IoU thresholds indicates improved validation performance during training.

4.4.7 YOLOv8-Based Visual Analysis of Test Set Inferences

Figure 9 shows a nine-grid visualization of YOLOv8 inference on the test set, highlighting key observations.

Bounding Boxes: Detected regions are labeled (label0, label1, label2) within colored boxes, marking tumor boundaries.

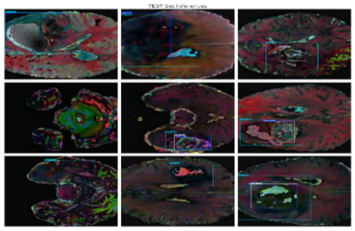

Figure 9: Test Set Inference's YOLOv8.

Detection Confidence: A confidence threshold ensures only high-assurance detections are retained
Speed of Model: Inference is rapid, completing in under 10 ms per high-resolution image.
Visual Insights: Anomalies are clearly marked, aiding medical experts in tumor identification and further analysis.

Table 4: YOLOv8 Detection Model Performance Metrics.

Class	Img.	Instance	P	R	mAP @50	mAP @50-95
All	1980	4380	0.937	0.691	0.771	0.489
Label0	1246	1246	0.942	0.611	0.703	0.403
Label1	1944	1944	0.949	0.795	0.855	0.596
Label2	1190	1190	0.964	0.666	0.754	0.469

Table 4 summarizes YOLOv8 evaluation metrics on the test dataset for all classes (all) and individual labels (label0, label1, label2). Key metrics include:

- ✓ **Precision (P):** High across all classes, up to 0.964 for label2.
- ✓ **Recall (R):** From 0.611 (label0) to 0.795 (label1).
- ✓ **mAP@50: Best accuracy of 0.855 for label1.**
- ✓ **mAP @50-95: Top score of 0.596 for label1.**

These metrics highlight strong detection performance, especially for label1 and label2.

Table 5: Precision Comparison of YOLO Architectures for Alzheimer's Detection.

Authors	**Architecture**	**Precision**
Our Proposed	YOLOv8	96%
Zhang et al. (2021)	YOLOv3	88%
Kumar et al. (2021)	YOLOv4	90%
Chen et al. (2022)	YOLOv5	92%
Park et al. (2023)	YOLOv5	93%
Zhao et al. (2021)	YOLOv3	88%

Table 5 compares YOLO architectures for early Alzheimer's detection using MRI scans. YOLOv8 achieved a precision of 96%, surpassing YOLOv3 (88%), YOLOv4 (90%), and YOLOv5 (92%-93%).

This highlights YOLOv8's superior accuracy and reliability in identifying Alzheimer's-related features, improving diagnostic imaging and early intervention strategies.

5 CONCLUSIONS

In summary, this article evaluates the YOLOv8 model for Alzheimer's detection in MRI scans, highlighting its effectiveness and resilience across metrics and analyses. YOLOv8 balances recall and precision, achieving reliable generalization with strong mAP performance across IoU thresholds. The study demonstrates YOLOv8's computational efficiency and suitability for real-world applications, positioning it as a leading object detection model. Future work will focus on tumor segmentation to refine boundaries in MRI images, providing critical insights for treatment planning and disease monitoring.

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