A Comparative Study of Deep Learning Techniques for Alzheimer's disease Detection in Medical Radiography

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Abstract
Alzheimer's disease is a brain disorder that worsens over time and affects millions of people around the world. It leads to a gradual deterioration in memory, thinking ability, and behavioral and social skills until the person loses his ability to adapt to society. Technological progress in medical imaging and the use of artificial intelligence, has provided the possibility of detecting Alzheimer's disease through medical images such as magnetic resonance imaging (MRI). However, Deep learning algorithms, especially convolutional neural networks (CNNs), have shown great success in analyzing medical images for disease diagnosis and classification. Where CNNs can recognize patterns and objects from images, which makes them ideally suited for this study. In this paper, we proposed to compare the performances of Alzheimer's disease detection by using two deep learning methods: You Only Look Once (YOLO), a CNN-enabled object recognition algorithm, and Visual Geometry Group (VGG16) which is a type of deep convolutional neural network primarily used for image classification. We will compare our results using these modern models Instead of using CNN only like the previous research. In addition, the results showed different levels of accuracy for the various versions of YOLO and the VGG16 model. YOLO v5 reached 56.4% accuracy at 50 epochs and 61.5% accuracy at 100 epochs. YOLO v8, which is for classification, reached 84% accuracy overall at 100 epochs. YOLO v9, which is for object detection overall accuracy of 84.6%. The VGG16 model reached 99% accuracy for training after 25 epochs but only 78% accuracy for testing. Hence, the best model overall is YOLO v9, with the highest overall accuracy of 86.1%.

Keywords:
convolutional neural network (CNN), Alzheimer's disease, MRI dataset, YOLO, VGG16.

1. Introduction

Alzheimer's disease is a neurodegenerative disorder that has affected millions of people in the world. The global prevalence of dementia is reported to be as high as 24 million and is predicted to increase 4 times by the year 2050 [1]. These numbers show how crucial early detection is for Alzheimer's disease. With the help of machine learning algorithms, we focus on improving the patient's quality of life and the doctor's diagnoses since machine learning algorithm techniques are increasingly being used in disease prediction and visualization [2] which improved the healthcare industry in many ways. we aim to explore multiple algorithms in the classification of Alzheimer's disease to compare the limitations and strengths including the accuracy rate to see which gives a better performance. As for the dataset, the MRI data was used to perform this study [3]. MRI is an effective instrument, widely recognized for diagnosing various diseases including neurological disorders [4]. MRI dataset is classified into four classes: Mild demented, Moderate demented, Non-demented, and Very mild demented. Furthermore, the machine learning algorithms used in this study were several versions of YOLO (You Only Look Once) and VGG16 (Visual Geometry Group). For the YOLO algorithms, we investigated YOLOv5, YOLOv8, and YOLOv9 which are widely used for object detection and classification images. They are known for their great speed and accuracy [5]. VGG16 has been highly successful in image classification. The VGG-16's deep convolutional layers allow for the extraction of powerful features, making it a suitable choice for transfer learning tasks in image classification [6].

Moreover, in this research, we aim to investigate the new modern techniques in the field of image classification and object detection and provide a full comparison between the versions of YOLO and VGG16 by developing an AI model to detect the level of Alzheimer's disease using the following steps:

- Review previous research in the field of image classification and object detection.
- Highlight the new versions and techniques of object classification and detection algorithms.
- Search for a dataset of MRI from Kaggle.
- Add labels (classes) by annotating the images in roboflow [7].
- Train and test the models (YOLOv9, YOLOv8, YOLOv5, and VGG 16) to classify and detect the images.

Manuscript received May 5, 2024
Manuscript revised May 20, 2024
https://doi.org/10.22937/IJCSNS.2024.24.5.6

- Evaluate the accuracy and compare the results.

This study compared four Machine Learning models to determine the best approach for early detection of Alzheimer's disease. Therefore, the YOLOv9 model showed the highest accuracy of 84.6% at 50 epochs for all classes of the dataset.

2. Literature Review

In this section, we will review the literature reviews related to the discovery of Alzheimer’s disease using modern technologies. Research has been arranged from newest to oldest, starting from 2024 to 2017:

Firstly, Sorour and colleagues [8] suggested using advanced deep learning (DL) techniques to detect Alzheimer's disease at an early stage. They worked with brain MRI images to create and test the model, which involved several stages such as preprocessing, DL model learning, and evaluation. They presented five DL models for automatic feature extraction and binary classification. These models were split into two groups: ones without Data Augmentation (without-Aug), like CNN-without-AUG, and ones with Data Augmentation (with-Aug), including CNNs-with-Aug, CNNs LSTM-with-Aug, CNNs SVM-with-Aug, and Transfer learning using VGG16-SVM-with-Aug. Their aim was to develop a model with high detection accuracy, recall, precision, F1 score, training time, and testing time. The dataset used to evaluate the proposed method showed strong results, with the experiment indicating that CNN-LSTM performed the best, achieving an accuracy rate of 99.92%. These findings set the stage for future DL-based research in AD detection.

Moving on, El-Assy et al [9] discussed Alzheimer's disease (AD) as a severe neurological condition that requires an accurate diagnosis for proper management and treatment. They introduced a CNN model using MRI data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset to classify AD. The CNN consisted of two different models with distinct filter sizes and pooling layers, combining in a classification layer to address the multi-class problem across three, four, and five categories. The suggested CNN model achieved high accuracies of 99.43%, 99.57%, and 99.13% for these categories, highlighting the network's effectiveness in identifying important features from MRI images. By leveraging the hierarchical structure of convolutional layers, pooling layers, and fully connected layers, the network extracted both local and global patterns from the data. The reported accuracy demonstrates the potential of using CNN architecture to support medical professionals and researchers in making well-informed decisions about AD patients.

Moreover, Aleid A et al. [10] introduced multilevel thresholding segmentation as a method of early diagnosis for brain tumors using MRI images. The method employs classical picture processing techniques such as edge-based segmentation and morphology operation to properly segment the brain tumors. A particular feature of that study is the comparison of the proposed network and deep learning methods with the multilevel thresholding approach. Adequate importance is paid to both accuracy and execution time. This document points to the relevance of segmentation quality during medical image analysis as well as reminds us about early tumor diagnosis in brain MRI for better precision. Thus, the investigation of the multilevel thresholding segmentation technique is shown as an efficient method for the timely detection of brain tumors.

Also, Al Shehri W. [11] presented cognition diagnosis methods that are analyzed mostly focused on neural networks: DenseNet-169 and ResNet-50 based on deep convolutional neural network (DCNN). They found DensNet-169 to be the best in the data training section as well as in the testing data collection stage. Hence, it may be a viable option in the Practical application. It is very eloquent of this article that it talks about medical imaging techniques and how automation in diagnosis is very sophisticated. Assessment results of DenseNet-169 models no principally confirm that it is useful for disease management, and also, they are applicable in the creation of a novel framework with the ability of further data utilization. Nevertheless, at the end of the day, deep learning in this context is solely the solvent to two complex problems - differential diagnosis and classification of Alzheimer’s disease, as a result, justifies the utility and efficiency of deep learning in the rapid and accurate diagnosis.

Meanwhile, Yousry A. et al. [12] presented a classification of Alzheimer's disease (AD) based on a convolutional neural networks (CNN) framework. which aimed to develop a deep learning framework for the accurate classification of AD using brain MRI scans. The dataset used in the study was the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset and the proposed framework achieved impressive classification accuracies with 99.6% for AD vs. Cognitively Normal (CN) binary classification, 99.8% for another binary classification task, and 97.8% for multi-class classification. These results indicate a very good performance of the presented neural network model because it can make a very precise diagnosis of AD patients. For future work, the paper suggested testing out the framework using larger datasets and unexplored additional biomarkers for a more accurate classification of AD.

Additionally, Sarraf S. et al. [13] used the convolutional neural network to classify Alzheimer's brain from a normal healthy brain with CNN and the architecture LetNet-5, they classified structural MRI data of Alzheimer's subjects from normal controls and accuracy of test dataset on the trained dataset reached 98.84. The authors extracted the invariant features using CNN and then used the deep learning classification which made this method powerful and helped differentiate clinical data from healthy data in MRI.

Furthermore, Salehi A. et al. [14] mentioned the application of MRI to early diagnosis and classification of Alzheimer's disease by a Convolutional Neural Network (CNN). The model was evolved to diagnose AD and help both doctors and patients save cost and time. By using a dataset consisting of 1512 AD, 2633 normal, and 2480 mild cases, the model achieved excellent results with 99% accuracy which showed that the CNN algorithm was successful for this case. The last part of the paper recommends improving the results of the CNN model by adding huge MRI scan images as input and testing other more powerful deep learning algorithms to increase the accuracy of the model.

Ebrahim D. et al. [15] propose using deep learning, specifically convolutional neural networks (CNN), for early detection of Alzheimer's disease (AD). Specifically, VGG-16, to extract and classify features in the early detection of Alzheimer's disease, using neuroimaging MRI images from the Kaggle website. associated with Alzheimer's disease to train a CNN model. The best accuracy obtained from the algorithm when splitting data into 20% testing data and 80% training data at this accuracy of training 97.49% and testing 95.31%.

In the same context, Shrikant P. et al [16]. proposed to apply image processing techniques for early detection of Alzheimer's disease. They stress the importance of early screening, by image processing techniques, specifically segmentation magnetic resonance imaging (MRI) of the brain, to identify affected areas such as the hippocampus and brain volume. By comparing the regions identified in a brain MRI of those with Alzheimer's disease, healthy individuals, and those with mild cognitive impairment (MCI), the results were 91.6%.

Finally, Nawaz A. et al. [17] described Alzheimer's disease (AD) as a progressive and incurable disease that causes patients to lose their memory, and then they assured the benefit of the early detection of the disease and how there were so many proposed methods and techniques that focused on the fast and accurate detection and so they did in this paper, with the two-dimensional deep convolutional neural network (2D-DCNN). Their model classified the MRI dataset into three stages, first the normal health control (NC), then mild cognitive impairment (MCI), and the last stage Alzheimer's disease. The accuracy rate of the model reached 99.89% with the imbalanced three-dimensional MRI dataset. The model showed a big improvement in terms of accuracy. Finally, the authors mentioned that an accurate detection of AD is not possible until the patient's initial stage of dementia is converted to MCI which is the second stage that leads up to AD.

The existing literature on Alzheimer's disease mainly focused on using convolutional neural network features and has already shown results with high accuracy. However, there is still a research gap regarding the lack of modern techniques that use convolutional neural networks, such as You Only Look Once (YOLO), which consists of many versions, the latest of which is the ninth version, Yolo can detect objects with images or classification as well. This research gap represents a crucial area for further research that deserves attention in comparing the use of Yolo versions to detect Alzheimer’s disease and comparing them to the results in previous research.

3. Data Collection

In this research, we propose to compare Alzheimer's disease detection with previous research results by exploiting the features of You Only Look Once (YOLO), a CNN-enabled object recognition algorithm. The dataset was collected from Kaggle [3], where we used images of magnetic resonance imaging and brain imaging technology (MRI), with a total of 500 divided into 80%, 10%, and 10% for training, validation, and testing images. The data was labeled into four classes of images, both in training and in a testing set:

- Mild Demented
- Moderate Demented
- Non-Demented
- Very Mild Demented

The data was divided into 3 parts: testing, training, and validation. The train data contained 400, and the test and validation data each contained 50 pictures labeled with the same classes. The images were labeled as 150 images. Mild Demented, 64 images Moderate Demented, 178 images Non-Demented, and

107 images Very Mild Demented. judging by the image dimensions (axial plane: 176 x 208) and the names of the classes this dataset is based on OASIS. But there are four different datasets in OASIS and depending on the number of images at Kaggle, this dataset may be based on OASIS 1 or merged with other datasets. The bulk of the downloads are files in .hdr and .img formats. OASIS 1 also contains .gif images of axial, coronal, and sagittal planes for each of the cases, and it seems that its axial planes are taken from OASIS that were included in this Kaggle dataset.

4. Methodology

A. Yolo Algorithms

YOLO, which stands for "You Only Look Once", is famous for its object detection characteristic [18]. Its goal is to predict the location of bounding boxes around objects in an image, along with the probabilities of those objects belonging to certain classes. During testing, YOLO analyzes the entire image and uses global context to make predictions. This approach makes YOLO very fast, making it ideal for real-time applications.

1) YOLOv9

YOLOv9 is the latest version of YOLO, and it provides exceptional performance in real-time object detection. YOLOv9 primarily focuses on the design of programmable gradient information (PGI) and generalized ELAN (GELAN) [19], which effectively addresses issues related to information loss and computational efficiency.

2) YOLOv8

YOLOv8 is a model within the YOLO series known for its speed, accuracy, and ease of use. It comes with built-in support for object detection and classification tasks. YOLOv8 can be accessed through the Python package and includes a specialized model called "yolov8n-cls.pt" that is designed specifically for classification purposes.

3) YOLOv5

Yolov5 is the most commonly used model of the You Only Look Once (YOLO) family. The design of YOLOv5 exhibits improved efficiency compared to its predecessors, resulting in improved accuracy and speed for object recognition Meanwhile, the architectural components of YOLOv5 include a backbone network, a neck network, and a head network [20]. This research utilized object detection with the "yolo5vs.pt" model, using a dataset of 500 images for four categories (Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented).

B. VGG16

VGG16 is well-known for its robust performance in tasks like image classification and object recognition within computer vision. It's a deep convolutional neural network primarily used for image classification. Its structure typically consists of several layers of convolution followed by pooling layers, gradually increasing in depth. These layers are then connected to fully connected layers for final classification. The final layer often utilizes a SoftMax activation function to categorize images into different classes, such as disease stages.

C. Training Methodology

This study aims to compare previous studies' results with new results of the detection of Alzheimer's disease by using the features of You Only Look Once (YOLO), a CNN-powered object recognition algorithm. In addition, VGG-16 was also used to perform the same task. The study compared the results from both models to determine which performed better. Table 1 portrays the training settings.

Table 1: Training Settings for the Models

Model	Hyperparameters	Value
Yolov5s	Epochs	50 – 100
	batch size	16
	Learning rate	0.01
Yolov8n	Epochs	5 -100
	batch size	16
	Learning rate	0.01
Yolov9	Epochs	50-100
	batch size	8
	Learning rate	0.01
VGG-16	Epochs	25
	batch size	10
	Learning rate	0.01

The models used in this study include yolo5vs.pt, yolo8n-cls.plt, yolov9 (object detection), and VGG-16. These models were trained using a dataset of 500 images and a set of hyperparameters that included epochs varying from 5 to 100 and batch sizes of 16 for Yolov5s, 16 for Yolov8n, 8 for Yolov9, and 10 for VGG-16.

D. Training Environment

For training the models we chose Google Colab to run the Python code and enable the use of advanced computational power, like GPUs to suit our training needs for both YOLO and VGG 16.

E. Evaluation

Several evaluations, such as precision (P), recall (R), and mAP, were applied in yolov5 and yolov9c to evaluate the model's performance and ability in the detection. The accuracy was evaluated using the Top-N approach in YOLOv8n-cls for classification. And clarifying the loss for both training and testing. Finally, the accuracy was calculated for all these models.

These metrics provide comprehensive knowledge about the accuracy and reliability of the model in detecting Alzheimer's disease. These metrics are calculated using a confusion matrix consisting of four parts:

1. True Positive (TP) – This occurs when the model rightly identifies a positive case. Specifically, the actual class is positive, and the model predicts it as positive.
2. True Negative (TN) – This occurs when the model rightly identifies a negative case. Specifically, the actual class is negative, and the model predicts it as negative.
3. False Positive (FP) – Type I Error This occurs when the model inaptly identifies a negative case as positive. Specifically, the actual class is negative, but the model predicts it as positive.
4. False Negative (FN) – This occurs when the model inaptly identifies a positive case as negative. Specifically, the actual class is positive, but the model predicts it as negative.

From these values:

$$\text{Precision(P)}= \frac{TP}{TP+FP} \qquad (1)$$

$$\text{Recall (R)} = \frac{TP}{TP+FN} \qquad (2)$$

4. Results and Discussion

In this section, the results are explained after training, testing, and evaluating the models.

A. YOLO Object Detection and Classification

YOLO versions 8, 9, and 5 were used for object detection and classification of Alzheimer's disease on a dataset of 500 MRI images.

1. **YOLOv8** as shown in Table 2 achieved an accuracy of 64%, 78%, 82%, and 84% over epochs 5, 20, 50, and 100 respectively. The results show moderate to high performance of the model. Additionally, Figures 1-3 present the confusion matrix, train batch example, and results of epoch 5. Next, Figures 4-6 present the confusion matrix, train batch example, and results of epoch 2. Figures 7-9 present the confusion matrix, train batch example, and results of epoch 50. Finally, Figures 10-12 present the confusion matrix, train batch example, and results of epoch 100.

Table 2: YOLOv8 accuracy over epochs

Model	Epoch	Accuracy
YOLOv8	5	64%
	20	78%
	50	82%
	100	84%

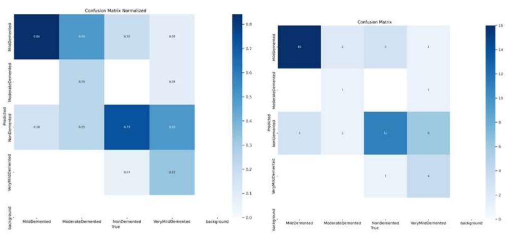

Fig.1 Confusion matrix for YOLO v8 epoch 5

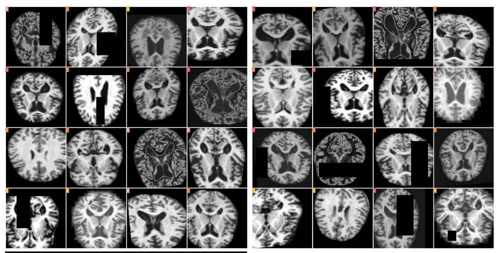

Fig. 2 Train batch for YOLO v8 epoch 5

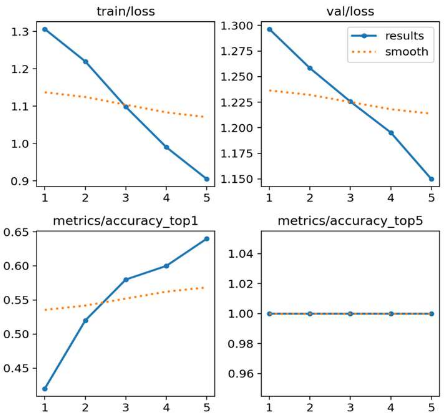

Fig. 3 Results for YOLO v8 epoch 5

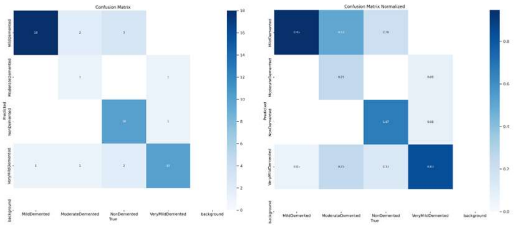

Fig.4 Confusion matrix for YOLO v8 epoch 20

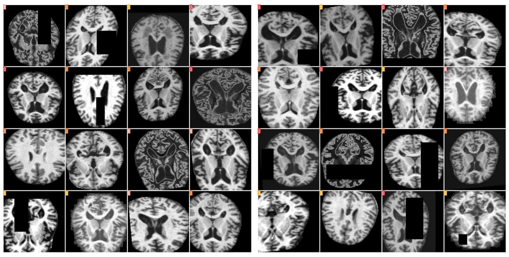

Fig. 5 Train batch for YOLO v8 epoch 20

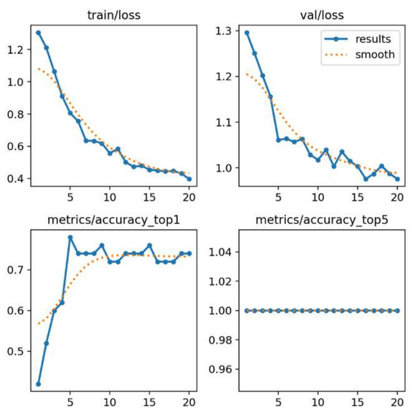

Fig. 6 Results for YOLO v8 epoch 20

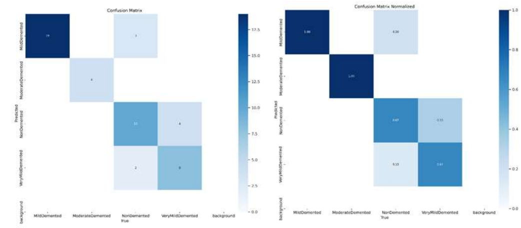

Fig.7 Confusion matrix for YOLO v8 epoch 50

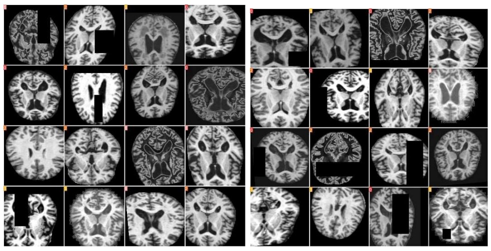

Fig. 8 Train batch for YOLO v8 epoch 50

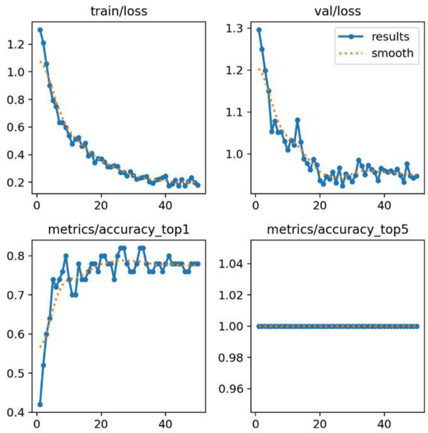

Fig. 9 Results for YOLO v8 epoch 50

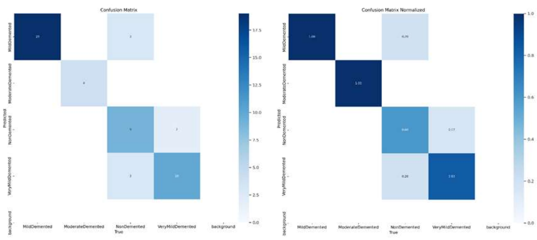

Fig.10 Confusion matrix for YOLO v8 epoch 100

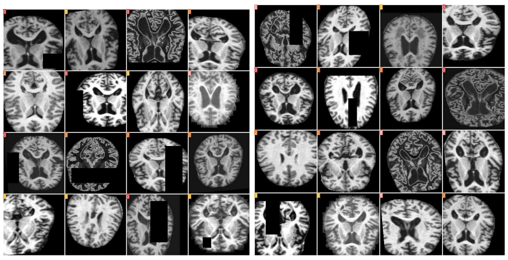

Fig. 11 Train batch for YOLO v8 epoch 100

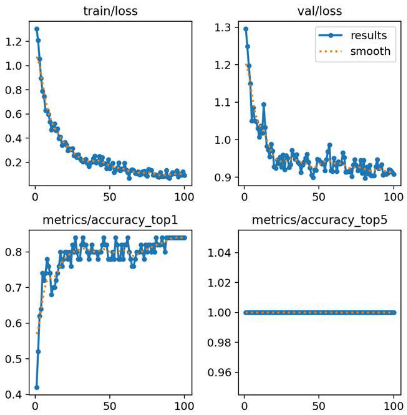

Fig. 12 Results for YOLO v8 epoch 100

The results presented in Table 2 show the results for YOLOv8 for classification, whose accuracy is calculated using TOP -N, and Figures 1-12 show the confusion matrix, accuracy, and loss for both training and validation at each Epoch from 5 to 100.

2. **YOLOv9** for object detection as shown in Table 3 achieved a higher accuracy of 86.1% after 100 epochs, 84.6% after 50 epochs, and 69.7% after 10 epochs. Figures 13 to 18 present the confusion matrix and results of each epoch from 10 to 100.

Table 3 YOLO v9 accuracy over epochs

Model	Epoch	Accuracy
YOLO v9	10	69.7%
	50	84.6%
	100	**86.1%**

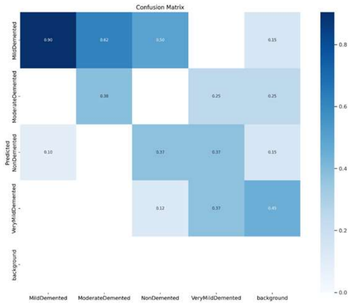

Fig.13 Confusion matrix for YOLO v9 epoch 10

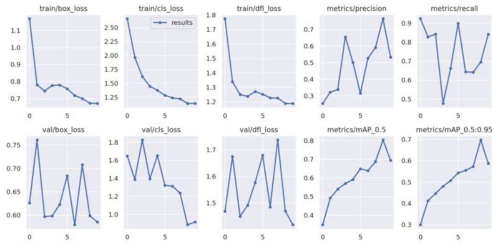

Fig. 14 Results for YOLO v9 epoch 10

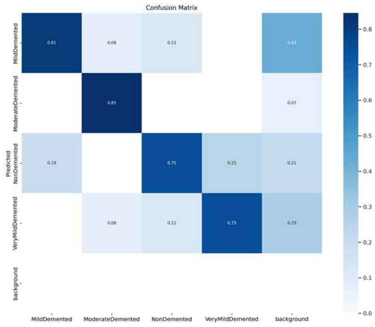

Fig.15 Confusion matrix for YOLO v9 epoch 50

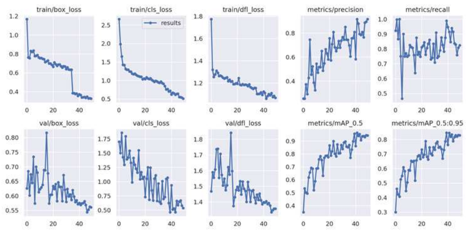

Fig. 16 Results for YOLO v9 epoch 50

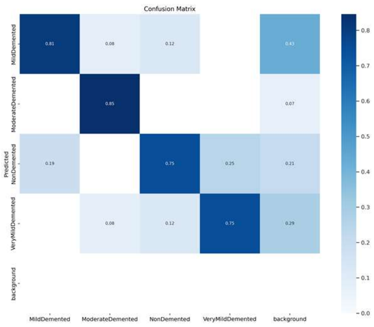

Fig.17 Confusion matrix for YOLO v9 epoch 100

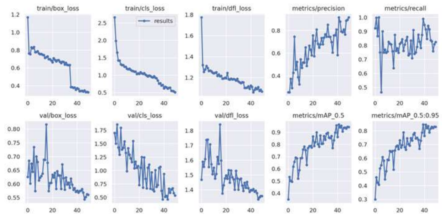

Fig.18 results for YOLO v9 epoch 100

The results show that the accuracy of YOLO v9 at Epoch 100 is the highest. Table 4 shows the details of the results of YOLO v9 at Epoch 50, and Table 5 shows the details of the results of YOLO v9 at Epoch 100.

Table 4: Details of the results of YOLO v9 at Epoch 50

Class	**P (%)**	**R (%)**	**mAp 50%**	**mAp 50-95%**
All	80.9	99	95.6	84.6
MildDemented	83.9	100	98.4	91.5
ModerateDemented	100	96	99.5	85.8
NonDemented	75.2	100	89.2	79.5
VeryMildDemented	64.6	100	95.4	81.4

Table 5: Details of the results of YOLO v9 at Epoch 100

Class	**P (%)**	**R (%)**	**mAp 50%**	**mAp 50-95%**
All	97.2	91.5	97.5	**86.1**
MildDemented	94.5	100	99.1	91.1
ModerateDemented	100	94.8	99.5	86.1
NonDemented	94.3	75	92	81.1
VeryMildDemented	100	96.2	99.5	85.9

Based on key metrics such as Precision (P), mean Average Precision at 50% (mAP50), and mean Average Precision at different thresholds (mAP50-95), it is evident that Table 5 demonstrates better overall performance. This is indicated by higher precision across all categories, higher mean average precision at 50%, and higher mean average precision at different thresholds. Therefore, it can be concluded that the results in Table 5 are superior.

3. **YOLOv5** as shown in Table 6 and 7 achieved low accuracies of 56.4% and 61.5% after 50 and 100 epochs, respectively. Table 6 shows details of the key metrics for yolov5 at epoch 50 and at epoch 100 in Table 7. Figures 19-22 present the confusion matrix and results for epochs 50 and 100.

Table 6: Details of the results of YOLO v5 at Epoch 50

Class	**P (%)**	**R (%)**	**mAp 50%**	**mAp 50-95%**
All	24.7	100	65.2	56.4
MildDemented	41.4	100	78.4	70.7
ModerateDemented	26	100	68.6	58.1
NonDemented	15.7	100	47.3	41.1
VeryMildDemented	15.8	100	66.3	55.7

Table 7: Details of the results of YOLO v5 at Epoch 100

Class	**P (%)**	**R (%)**	**mAp 50%**	**mAp 50-95%**
All	43	78.4	70.5	**61.5**
MildDemented	60.9	100	74.6	68.4
ModerateDemented	27.4	38.5	45.8	39.7
NonDemented	33.1	75	67.2	57.4
VeryMildDemented	50.6	100	94.5	80.4

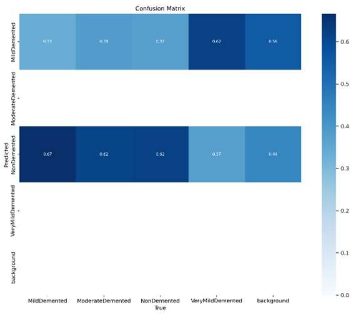

Fig.19 Confusion matrix for YOLO v5 epoch 50

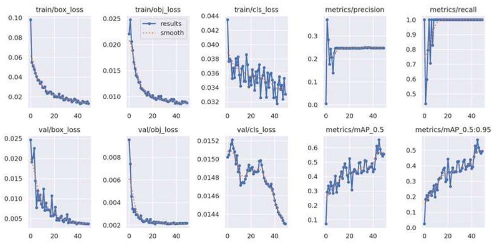

Fig.20 results for YOLO v5 epoch 50.

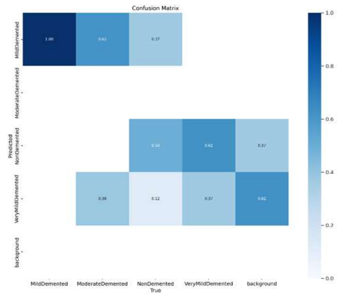

Fig.21 Confusion matrix for YOLO v5 epoch 100

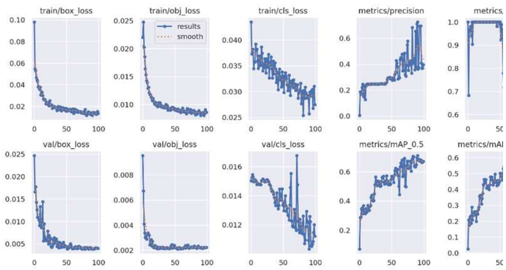

Fig.22 results for YOLO v5 epoch 100

Moreover, the comparison of YOLO versions for object detection and classification in Table 8 highlights the effectiveness of YOLOv8 and YOLOv9 in achieving high accuracies, especially when compared to YOLOv5. YOLOv9, in particular, shows high accuracy with lower epoch and efficient object detection of Alzheimer's disease diagnosis.

Table 8: Comparison of YOLO v5, 8, and 9

Type	Version	Epoch	Accuracy
Object Detection	Yolov5	50	56.4%
		100	61.5%
Classification	Yolov8	50	82%
		100	84%
Object Detection	Yolov9	50	84.6%
		100	**86.1%**

B. VGG16 Neural Network Model

A modified VGG16 architecture was used for neural network modeling. It was used for Alzheimer's disease classification, where the model achieved an average training accuracy of approximately 99% over 25 epochs as shown in Figure 20 and the confusion matrix is presented in Figure 19. However, the accuracy on the test dataset was approximately 78%. In addition, the VGG16 model's performance was strong in training. On the other hand, it decreased on the test dataset and the categorical cross-entropy loss on the test dataset was observed to be approximately 0.7762 as shown in Figure 23.

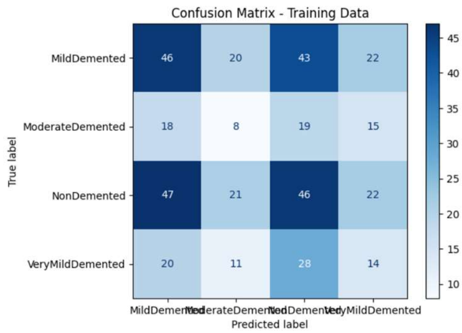

Fig. 23 Confusion Matrix of VGG 16 train

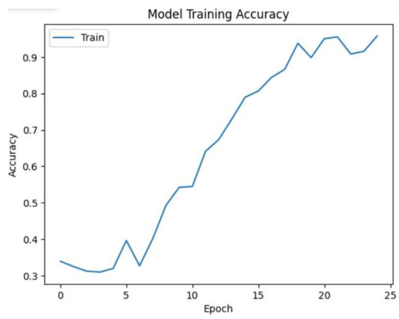

Fig. 24 Training accuracy of VGG 16 train

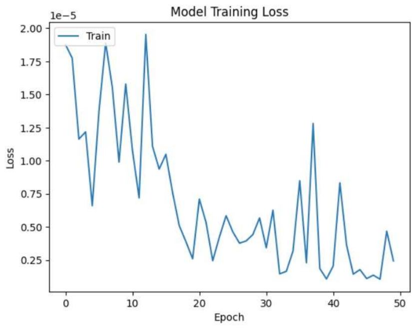

Fig. 25 Training Loss of VGG 16 train

C. Sample of The Testing

After training all models and discussing their accuracy rates, below in Figures 26-28 are some samples that show the results of the testing process for each YOLO model with the highest accuracy.

1. YOLO v5

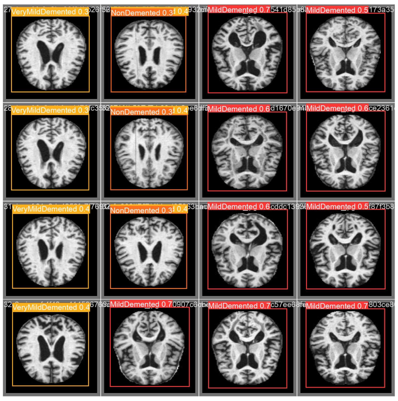

Fig.26 Testing sample of YOLO v5

2. YOLO v8

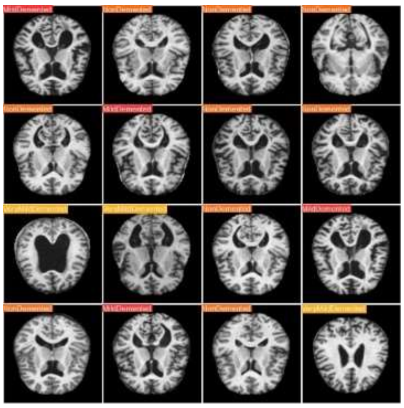

Fig.27 Testing sample of YOLO v8

3. YOLO v9

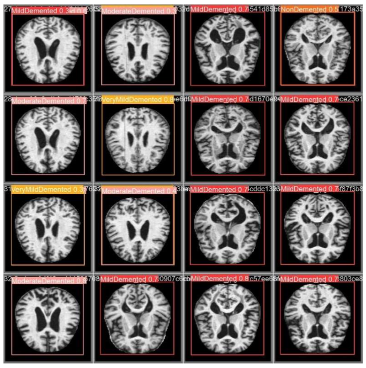

Fig.28 Testing sample of YOLO v9

D. Overall Comparison and Insights

Overall, the results demonstrate the effectiveness of deep learning models, such as YOLO and VGG16, in classifying Alzheimer's disease. The YOLO models, especially YOLOv8 and YOLOv9, demonstrated superior performance in classifying Alzheimer's disease compared to the VGG16 model. YOLOv8 and YOLOv9 achieved high accuracies, with YOLOv9 showing promise for efficient object detection. In contrast, although VGG16 performed well during training, it displayed signs of overfitting, which shows its need for optimization.

As it is clear in Table 8, YOLO v9 reached the best results for Alzheimer's disease object detection with 86.1% accuracy. Meanwhile, YOLO v5 showed very low results, and YOLO v8 showed moderate results. While the VGG 16 showed promising results in training but decreased in testing.

5. Conclusion

Many studies on Alzheimer's disease focus on using convolutional neural networks to achieve high accuracy. However, this study distinguishes itself by addressing a significant gap in research regarding the lack of modern techniques that use convolutional neural networks, such as You Only Look Once (YOLO). YOLO has several versions, with the latest being the ninth version, which can detect objects using images or classification. The study used the VGG-16 technique, which focuses on image classification. This research will open up a crucial area for further exploration and deserves attention in comparing the use of YOLO versions to detect Alzheimer's disease with the results of previous research. To summarize, the models' performances varied depending on the number of iterations and the tasks they were trained for. YOLO v5 had an accuracy of 61.5% after 100 iterations. YOLO v8 (cls) showed increasing accuracy with more iterations, reaching 84% after 100 iterations. YOLO v9 (object detection) had an overall accuracy of 86.1%, with different accuracies for different classes. The VGG 16 model had a high accuracy in training, reaching 99%, but its accuracy dropped to 78% in testing due to various reasons, including the size and complexity of the test dataset. Overall, these results emphasize the importance of selecting the right model and iterating on it to achieve higher accuracies in classification and object detection tasks.

6. Acknowledgment

We would like to express our sincere gratitude to Umm Al-Qura University for providing the necessary resources and environment for us to conduct this research.

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