

An Enhanced Deep Machine Learning Framework for Chronic Disease Prediction in IoMT-Powered Healthcare 5.0: A Comprehensive Case Study on Alzheimer's Disease

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ABSTRACT: Chronic diseases such as Alzheimer's disease remain a critical concern in healthcare, demanding precise and timely prediction systems to support clinical decision-making in IoMT-enabled Healthcare 5.0 environments. In this study, an Alzheimer's dataset was employed to design a dual-branch framework integrating classification and detection models for enhanced prediction. For the classification branch, deep and machine learning models including ResNet101, DCNN, Xception, NasNetMobile, Ensemble Model, KNN, Random Forest, Logistic Regression, and XGBoost were evaluated. For the detection branch, the YOLO family {YOLOv5, YOLOv8, YOLOv9, YOLOv11} was utilized to localize abnormalities in medical images. Experimental evaluation demonstrated that the Ensemble Model and NasNetMobile achieved superior classification performance, with an accuracy, precision, recall, and F1-score of 99.4%, outperforming traditional classifiers. In detection, YOLOv8 yielded the best results, attaining a precision of 87.3%, recall of 88.1%, and mAP of 91.3%, highlighting its reliability in abnormality localization. Furthermore, Explainable AI (XAI) techniques such as Grad-CAM were applied to generate heatmaps, emphasizing critical image regions contributing to model predictions, thereby improving interpretability and trustworthiness. The integration of classification, detection, and explainability underscores the potential of deep machine learning approaches to advance intelligent, accurate, and transparent Alzheimer's disease prediction within modern IoMT-driven healthcare systems.

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1. INTRODUCTION

Chronic diseases, which persist over long periods and disrupt daily functioning, are a major global health burden requiring ongoing medical care [1]. In the United States, conditions like diabetes, cardiovascular disease, and cancer are leading causes of death and disability, significantly contributing to healthcare expenditures [2]. Lifestyle-related risk factors, including poor diet, physical inactivity,

smoking, and excessive alcohol consumption, further increase disease prevalence [3]. Chronic diseases are also rising rapidly in low- and middle-income countries due to demographic shifts, urbanization, and lifestyle changes [4]. The growing prevalence of multimorbidity, where individuals have multiple chronic conditions simultaneously, complicates healthcare delivery and increases societal and individual costs [5].

Despite medical advancements, early detection and effective management remain challenging [6]. Traditional diagnostic approaches rely heavily on clinical expertise and symptomatic evaluation, potentially delaying diagnosis and treatment. Additionally, healthcare data—including clinical, behavioral, and imaging information—is large-scale, heterogeneous, and high-dimensional, limiting its interpretability and analytical use [7]. These challenges highlight the need for intelligent, data-driven systems that can integrate diverse health data to enhance diagnostic precision, reduce errors, and support personalized care [8].

This study proposes an intelligent healthcare framework leveraging advanced data analysis and learning methodologies to improve chronic disease prediction and monitoring. By integrating large-scale health information, the framework enables comprehensive analysis for early diagnosis and timely intervention [9]. Robust computational approaches capture complex relationships between patient characteristics, lifestyle factors, and disease outcomes, facilitating informed medical decision-making. The system also promotes continuous monitoring and proactive disease management through connected digital health platforms, enhancing healthcare accessibility and efficiency.

The study's significance lies in its potential to advance intelligent healthcare systems, transforming chronic disease prediction and management [10]. By offering a scalable, accurate approach to disease identification, the research supports the global transition toward preventive and personalized medicine. Anticipated outcomes include improved diagnostic accuracy, reduced healthcare costs, and the development of sustainable healthcare models capable of addressing the increasing global burden of chronic diseases, ultimately contributing to more efficient, patient-centered healthcare delivery.

2. RELATED WORK

The growing global prevalence of chronic diseases has prompted extensive investigation into behavioral, environmental, and metabolic determinants of health. Gakidou et al. [11] conducted a large-scale comparative risk assessment through the Global Burden of Disease Study, quantifying the effects of 84 risk factors across regions and populations. Their findings underscored that modifiable factors such as poor diet, smoking, and physical inactivity substantially contribute to disease burden. While the study provided a strong epidemiological foundation, it primarily focused on population-level metrics and lacked mechanisms for personalized disease prediction and intervention. May et al. [12] expanded this perspective by evaluating the impact of a healthy lifestyle on disability-adjusted life years, revealing that adopting healthier behaviors can significantly extend disease-free life expectancy. However, their work did not incorporate computational methods to translate these insights into predictive clinical applications.

Further exploring lifestyle determinants, Stenholm et al. [13] examined the influence of smoking, obesity, and

physical inactivity on healthy and disease-free life expectancy, demonstrating that these behaviors collectively shorten life spans between ages 50 and 75. Licher et al. [14] investigated the lifetime risk and multimorbidity of noncommunicable diseases, establishing a strong link between lifestyle factors and multiple chronic conditions. Although these studies provided valuable population-based insights, they relied heavily on observational data and lacked advanced analytical frameworks capable of capturing nonlinear relationships within complex health datasets. This limitation highlights the need for intelligent systems that can analyze large-scale, multidimensional medical data for more precise chronic disease prediction.

The introduction of machine learning (ML) in healthcare has addressed some of these limitations by enabling data-driven prediction and pattern recognition. Chen et al. [15] demonstrated the use of ML models on big data from healthcare communities to enhance disease prediction accuracy. Despite promising results, their framework faced challenges related to heterogeneous data integration and the interpretability of outcomes. El-Rashidy et al. [16] examined the role of mobile health technologies in remote patient monitoring, emphasizing the benefits of continuous care for chronic conditions. Nevertheless, they identified persistent challenges in interoperability, data quality, and the real-time interpretation of patient information.

In the context of neurodegenerative and chronic disease research, Myszczyńska et al. [17] reviewed ML applications for diagnosis and treatment, highlighting the growing utility of deep learning models in detecting subtle disease patterns. Preethi and Dharmarajan [18] developed a predictive ML framework for chronic disease diagnosis, demonstrating improved accuracy but limited scalability due to dataset constraints. Soni [19] explored how information technologies transformed global operations during the COVID-19 pandemic, revealing the potential of digital health systems while also exposing gaps in data governance and system resilience. Extending this, Soni [20] investigated the challenges of artificial intelligence in cybersecurity, emphasizing the need for secure, ethical, and robust AI frameworks applicable to sensitive domains like healthcare.

3. MATERIALS AND METHODS

The proposed system aims to develop a robust and intelligent framework for the early prediction of Alzheimer's disease using MRI datasets within IoMT-enabled Healthcare 5.0 environments. The workflow encompasses data acquisition, preprocessing, and model training, integrating deep learning and machine learning [29] paradigms for enhanced diagnostic accuracy. Advanced models such as ResNet101, DCNN, Xception, and NasNetMobile are employed for high-level visual feature extraction, while traditional algorithms including K-Nearest Neighbor, Random Forest, Logistic Regression, and XGBoost enable comparative evaluation.

An ensemble learning strategy is implemented to combine the strengths of these models, improving robustness and generalization across diverse datasets [30]. For localization and interpretability, YOLO-based detection identifies disease-specific abnormalities, and Grad-CAM visualization highlights critical decision regions. A Flask-based web interface facilitates real-time interaction and seamless IoMT deployment, offering clinicians an efficient, transparent, and scalable diagnostic support system.

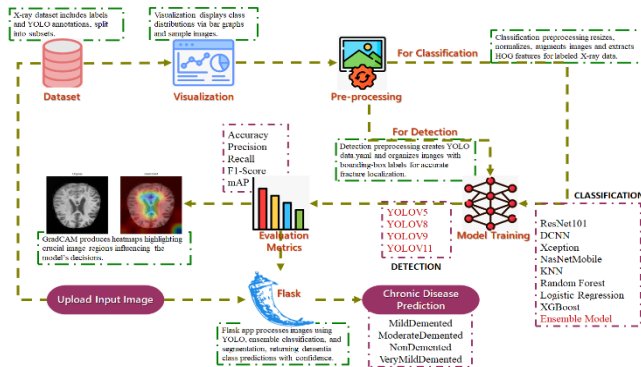


Figure 1. System Architecture

The proposed system architecture presents an end-to-end intelligent framework for chronic disease prediction using medical imaging data. It begins with dataset preparation and visualization to understand class distributions, followed by dedicated preprocessing pipelines for classification and detection tasks. The system supports parallel model training and evaluation using standardized performance metrics. Explainability is incorporated to highlight critical image regions influencing predictions. Finally, a deployment interface enables real-time image upload, automated analysis, and reliable disease stage prediction, supporting effective clinical decision-making.

A) Dataset Collection

This study uses the Alzheimer's MRI Image Dataset (FCIE), containing 6,400 brain MRI images across four classes: Mild, Moderate, and Very Mild Demented, and Non-Demented. The dataset is split into training (4,897), validation (864), and testing (639) sets with balanced class representation. Each 224×224 image is enhanced via feature contrast techniques. Its diversity, high-quality annotations, and clinical relevance make it ideal for deep learning-based systems, supporting robust, generalizable Alzheimer's disease classification and detection.

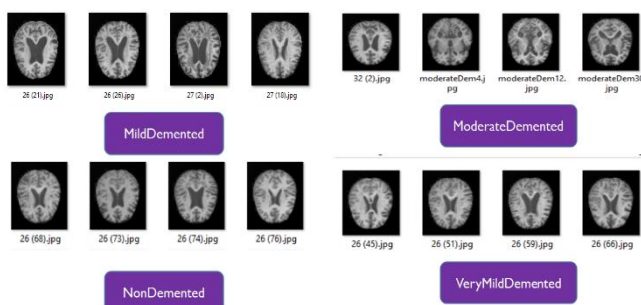


Figure 2. X-Ray Dataset

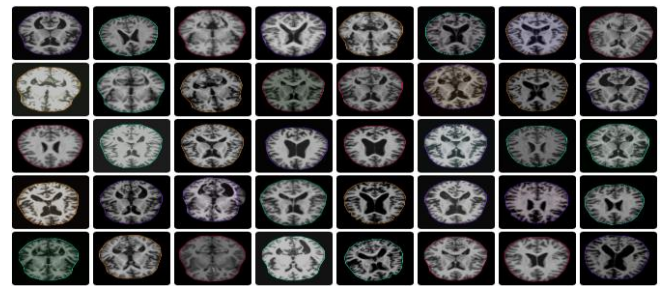


Figure 3. Detection Dataset

B) Pre-Processing

The preprocessing phase involves a series of systematic steps designed to prepare, enhance, and analyze MRI data, ensuring consistency, quality, and suitability for effective Alzheimer's disease classification and detection.

i) Data Pre-processing: In this step, MRI brain images are preprocessed for uniformity and model readiness. Images are resized to 224×224 pixels and normalized between 0 and 1, ensuring consistent data, accelerating model convergence, preventing numerical instability, and allowing deep learning models to focus on relevant visual patterns rather than variations in scale or illumination.

ii) Data Augmentation: Data augmentation techniques were applied to artificially expand the dataset and enhance model generalization. Operations such as rotation, zooming, horizontal flipping, shifting, brightness adjustment, and shearing were performed on the images. These transformations simulate real-world variability, allowing the model to learn robust and invariant feature representations. By mitigating overfitting and improving data diversity, augmentation ensures that the classification model performs effectively on unseen medical images in real-world diagnostic scenarios.

iii) Feature Extraction: Feature extraction captures discriminative visual representations from MRI images using CNN architectures. These models extract hierarchical features reflecting texture, shape, and brain structure, forming the basis for Alzheimer's stage classification. This process converts raw images into meaningful representations, enhancing the framework's accuracy, interpretability, and robustness.

iv) Data Visualization: Data visualization was conducted to examine dataset structure, class distribution, and sample diversity. Bar charts and image grids highlighted class counts and representative MRI scans, helping identify imbalances, inconsistencies, or anomalies. This step offers intuitive insight into data composition, guiding preprocessing decisions and supporting balanced, informed model development for Alzheimer's disease prediction.

C) Training and Testing

The dataset was split into training, validation, and testing sets for unbiased model development. Training enabled learning, validation supported hyperparameter tuning, and testing assessed final performance. This structured division prevents data leakage, ensures fair evaluation, and provides a realistic estimate of model accuracy, reliability, and generalization to unseen medical data.

D) Algorithms

ResNet101: ResNet101 is a deep convolutional neural network that uses residual learning with identity shortcut connections to ease the training of very deep architectures [21]. This design mitigates vanishing gradients, enhances feature propagation, and enables robust extraction of fine-grained and high-level visual patterns, improving classification accuracy and generalization in large-scale medical imaging tasks.

DCNN: A Deep Convolutional Neural Network (DCNN) consists of multiple convolutional and pooling layers that learn hierarchical representations directly from images [22]. By automatically capturing low-level and high-level features, DCNNs reduce reliance on handcrafted features and provide scalable, end-to-end learning, making them effective for complex medical image classification problems.

Xception: Xception is a deep learning architecture based on depthwise separable convolutions, which decouple spatial and channel-wise feature learning to improve efficiency [23]. This structure reduces parameters while preserving representational power, enabling effective capture of fine texture and spatial patterns in medical images with improved generalization and reduced overfitting.

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

NasNetMobile: NasNetMobile is a neural architecture search-based convolutional model optimized for accuracy and computational efficiency [24]. By automatically learning effective network structures, it provides lightweight yet powerful feature extraction. Its compact design supports fast inference and reliable performance, making it suitable for real-time and resource-constrained diagnostic applications.

Ensemble Model: An Ensemble Model combines predictions from multiple classifiers to improve accuracy, robustness, and generalization [25]. By aggregating diverse decision patterns, ensemble learning reduces bias and variance associated with individual models, yielding more stable and reliable classification outcomes, particularly in complex and heterogeneous medical imaging datasets.

K-Nearest Neighbors (KNN): K-Nearest Neighbors (KNN) is a non-parametric, instance-based algorithm that classifies data based on similarity to nearby samples in feature space [26]. It adapts well to complex distributions,

offers interpretability, and serves as an effective comparative or complementary method within hybrid classification frameworks.

$$\text{distance}(x, X_i) = \sqrt{\sum_{j=1}^d (x_j - X_{ij})^2} \quad (2)$$

Random Forest: Random Forest is an ensemble learning algorithm that constructs multiple decision trees using random subsets of data and features [27]. By aggregating tree predictions, it improves accuracy, reduces overfitting, and handles noisy or high-dimensional data effectively, while also providing insights into feature importance for transparent decision-making.

$$\text{Gini} = 1 - \sum_{i=1}^c (P_i)^2 \quad (3)$$

Logistic Regression: Logistic Regression is a statistical classification method that models the probability of class membership using a logistic function [28]. It offers fast computation, interpretability, and reliable baseline performance, making it valuable for benchmarking complex models and supporting transparent decision-making in structured classification problems.

$$P(y = 1 | X) = \frac{1}{1 + e^{-(W^T x + b)}} \quad (4)$$

XGBoost: XGBoost is a gradient boosting-based ensemble algorithm that builds optimized decision trees sequentially to minimize classification error. It incorporates regularization and efficient computation to handle non-linear feature interactions and high-dimensional data, delivering strong generalization, scalability, and high predictive accuracy in complex classification tasks.

YOLOv5: YOLOv5 is a one-stage object detection model that performs localization and classification in a single forward pass. Its efficient architecture enables real-time detection with high accuracy, making it suitable for identifying regions of interest and structural abnormalities in medical images under time and resource constraints.

$$x = \sigma(t_x) + C_x, \quad y = \sigma(t_y) + C_y \quad (5)$$

YOLOv8: YOLOv8 is an advanced object detection framework featuring anchor-free detection and enhanced feature extraction. It improves localization precision and robustness while reducing computational overhead, enabling accurate real-time detection of subtle anomalies and supporting efficient deployment in practical diagnostic and monitoring systems.

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

YOLOv9: YOLOv9 enhances object detection through improved feature aggregation and multi-scale representation learning. It achieves higher detection

accuracy while maintaining real-time performance, enabling reliable identification of fine-grained visual patterns and spatial variations in complex imaging environments with robustness to noise and variability.

$$\mathcal{L}_{YOLOv9} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} + \lambda_{dfl} + \mathcal{L}_{dfl} \quad (7)$$

YOLOv11: YOLOv11 is a next-generation real-time object detection model that integrates optimized network layers and attention mechanisms. It delivers precise bounding box localization and high-confidence predictions with low latency, supporting accurate and efficient detection for intelligent healthcare systems and edge-based diagnostic applications.

E) Integration of XAI and Flask Framework

The system integrates Explainable AI (XAI) to ensure transparency and interpretability, using Grad-CAM to highlight critical image regions influencing predictions. This visual insight enables clinicians to understand model decisions, fostering trust and ethical deployment. A Flask-based web interface provides a lightweight, interactive platform for real-time image upload, analysis, and visualization. Serving as a bridge between models and users, Flask supports seamless prediction and interpretation, IoMT integration, and clinical decision-making. Its scalability, simplicity, and accessibility make the framework suitable for deploying AI-driven diagnostic tools efficiently in modern healthcare environments.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

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

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

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

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1 \text{ Score} = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100 \quad (10)$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

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

Table 1. Performance Evaluation – Classification

ML Model	Accuracy	Precision	Recall	F1 Score
ResNet101	0.579	0.550	0.579	0.555
DCNN	0.814	0.839	0.814	0.813
Xception	0.994	0.994	0.994	0.994
NasNet Mobile	0.994	0.994	0.994	0.994
Ensemble Model	0.994	0.994	0.994	0.994
KNN	0.966	0.966	0.966	0.966
Random Forest	0.538	0.598	0.538	0.413
Logistic Regression	0.610	0.607	0.610	0.578
XGBoost	0.643	0.726	0.643	0.597

In Table.1, the Ensemble model achieved the highest overall performance with superior metric values, demonstrating exceptional accuracy and reliability in Alzheimer's disease classification.

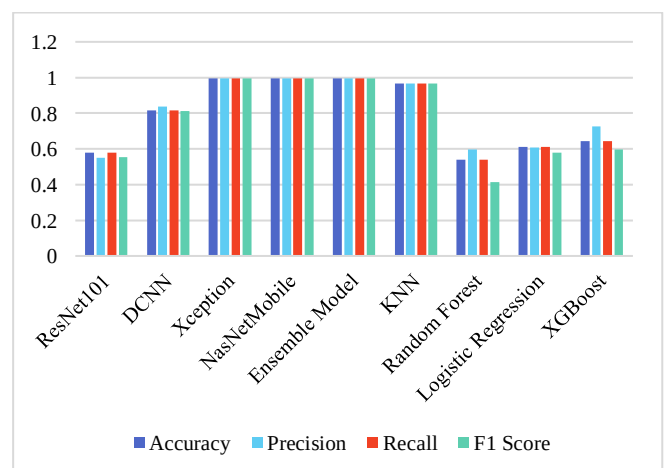


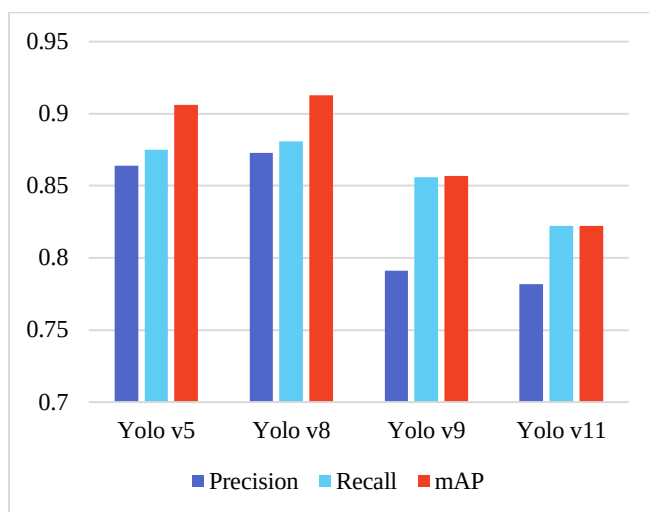
Figure 4. Comparison Graph- Classification

In Fig.4, the Ensemble model exhibits the highest performance across all evaluation metrics. Accuracy is represented in blue, precision in teal, recall in red, and F1-score in green.

Table 2. Performance Evaluation - Detection

ML Model	Precision	Recall	mAP
Yolo v5	0.864	0.875	0.906
Yolo v8	0.873	0.881	0.913
Yolo v9	0.791	0.856	0.857
Yolo v11	0.782	0.822	0.822

In Table.2, Yolo v8 demonstrates the highest performance among all versions, outperforming others in overall detection effectiveness.

**Figure 5.** Comparison Graph Detection

In fig.5 shows Yolo v8 achieving the highest performance, with precision represented in purple, recall in blue, and mAP in red for clear visual distinction.

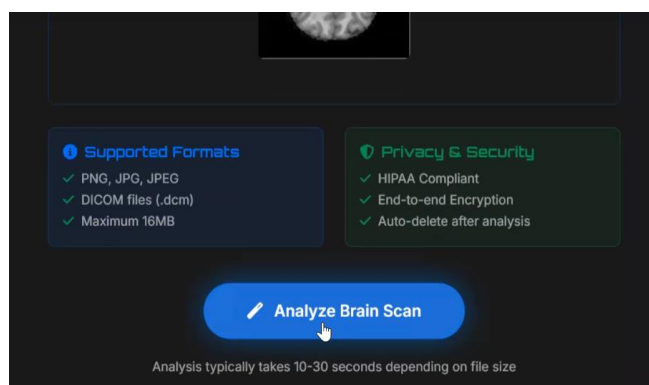
**Figure 6.** Upload Input Image

Fig.6 presents the input interface for classification, allowing users to upload and analyze brain scans for Alzheimer's prediction using the proposed deep learning models.

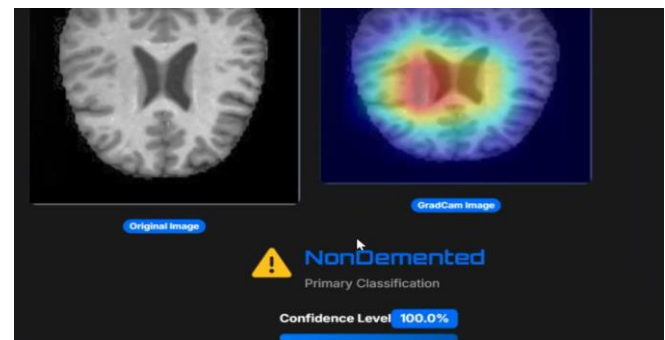
**Figure 7.** Predicted results

Fig.7 illustrates the output interface displaying Grad-CAM visualization of brain scans with predicted Alzheimer's regions and a confidence level of 100%.

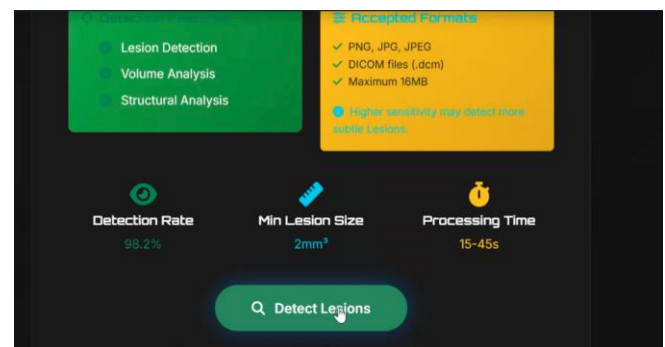
**Figure 8.** Upload Input Image

Fig.8 shows the input interface for detection, enabling users to upload brain scans and identify lesions using the proposed deep learning detection models.

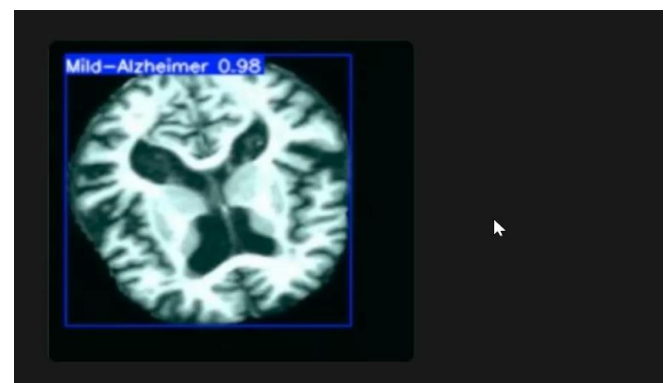
**Figure 9.** Predicted results

Fig.9 illustrates the output interface displaying lesion detection results, visualizing predicted Mild-Alzheimer's regions with a confidence level of 0.98.

5. CONCLUSION

This study demonstrates the effectiveness of integrating deep learning classification models with object detection frameworks for Alzheimer's disease prediction in IoMT-enabled Healthcare 5.0. Multiple algorithms were evaluated, with the Ensemble Model and NasNetMobile achieving the highest classification accuracy of 99.4%, alongside strong precision, recall, and F1-scores, confirming robustness in distinguishing Alzheimer's

cases. In detection, YOLOv8 outperformed other variants, achieving 87.3% precision, 88.1% recall, and 91.3% mAP, effectively localizing abnormalities in X-ray images. The integration of Explainable AI methods, such as Grad-CAM, enhanced transparency by highlighting critical regions influencing predictions, mitigating the black-box limitation of deep models. These results indicate that combining high-performing classification, advanced detection, and explainability provides a reliable, interpretable framework for early Alzheimer's diagnosis. This approach can support timely clinical interventions, improve patient outcomes, and contribute to the advancement of intelligent, real-world healthcare systems.

To increase model generalization across patient demographics and imaging modalities, the framework will be expanded to encompass larger and more diverse medical datasets. Multi-modal data integration—MRI, CT, clinical records, and X-ray images—can improve predictive accuracy. Vision Transformers and graph neural networks may improve feature representation and disease development patterns. We will also investigate real-time deployment in IoMT setups with edge computing to reduce latency and ensure scalability. To improve interpretability and help doctors believe and use AI-driven Alzheimer's disease predictions, explainable AI techniques will be prioritized.

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