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# Integrative Framework for Alzheimer Detection Using Bio-Marker Analysis and CT-Scan Image Segmentation

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**Abstract:** A progressive loss of brain function is the hallmark of Alzheimer's disease (AD), which is frequently linked to a serious deterioration in cognitive abilities. Early detection is therefore essential for successful treatments. Introducing two specialised models for medical imaging and CSF values analysis, this work addresses the critical demand for precise diagnostic instruments in radiology and neurology. The first model, Biomarker, is carefully designed for biomarker analysis and achieves 100% accuracy in AD identification on a dataset of 810 patients. The deployment of a Random Forest Classifier enables this noteworthy result, demonstrating Biomarker's effectiveness in differentiating AD cases from non-AD cases. The second model, YOLOv8, is exceptional at identifying brain anomalies in MRI scans. Using advanced post-processing algorithms, batch normalisation, and convolutional layers, YOLOv8 achieves an impressive mean Average Precision (mAP) of 99.8%. YOLOv8 accurately distinguished among the various phases of cognitive impairment, including extremely mild, mild, moderate, and non-demented cases. Both approaches show great promise for early diagnosis and clinical decision-making when combined with the Biomarker (Random Forest) model for detecting Alzheimer's disease, thereby improving patient outcomes.

**Keywords:** Random Forest Classifier; Performance Metrics; Convolutional Neural Network; CT-Scan and MRI; Brain Function; Alzheimer's Disease; Radiology and Neurology; Mean Average Precision.

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## 1. Introduction

A progressive neurological disease, Alzheimer's disease presents a serious threat to public health systems around the world, particularly in India, where its incidence is rising. Alzheimer's disease, which is marked by memory loss and cognitive decline, impacts people directly, as well as putting a significant strain on families and healthcare systems. Alzheimer's disease is on the rise in India due to the country's sizable and ageing population. It's estimated that a significant portion of India's elderly population is affected by Alzheimer's or related dementias. The impact of this disease extends beyond the personal realm, affecting the nation's socio-economic fabric. The main concerns related to Alzheimer's disease in India are the burden it places on caregivers and families. Caring for individuals with Alzheimer's often requires substantial time, effort, and financial resources. The cost of caregiving, combined with the expenses of medical treatment and support services, can strain families financially and emotionally. Additionally, those who have Alzheimer's disease lose their freedom and productivity. As the illness worsens, people might need help with everyday tasks, reducing their productivity and involvement in the workforce.

This loss of productivity not only affects the individuals involved but also the economy. Adequate care and assistance for people with Alzheimer's disease is a challenge for India's healthcare system. A lack of skilled healthcare providers with dementia care training hampers early identification and management of dementia. Furthermore, the stigma associated with dementia often results in delayed diagnosis and limited access to support services. In addressing the challenges posed by Alzheimer's disease in India, early detection and intervention are crucial. Early diagnosis and tracking of illness progression can be facilitated by integrated techniques that leverage cutting-edge technologies such as biomarkers and neuroimaging. Artificial intelligence and machine learning algorithms can help medical practitioners analyse complex medical data and identify trends indicative of Alzheimer's disease [1]. In this regard, our combined Bio-Markers and MRI scan model is essential for early diagnosis and treatment of Alzheimer's disease. Our model helps medical practitioners spot early signs of Alzheimer's disease in brain imaging by leveraging cutting-edge machine learning and computer vision. This enables timely intervention and personalised treatment plans, ultimately contributing to the mitigation of the adverse effects of Alzheimer's disease [13].

## 2. Related Works

Alzheimer's disease (AD) is a progressive and irreversible brain disorder that progressively deteriorates memory and cognitive functions. AD is the main cause of dementia among those over 65 worldwide. Many Artificial Intelligence (AI)-based Computer-aided Diagnostic (CAD) techniques have been developed using brain imaging data, as accurate detection of AD is essential. The current developments in AI-based CAD systems for identifying AD and its several stages are the main topic of this literature review, which highlights the use of structural MRI because it is affordable and doesn't emit ionising radiation [2]. Huang et al. [3] proposed a convolutional neural network (CNN) to integrate multimodal information from T1-MR and FDG-PET images, focusing on the hippocampus, to aid in diagnosing Alzheimer’s disease. In contrast to conventional machine learning methods, this strategy does not rely on manually extracted features [4]. Rather, it utilises 3D image-processing CNNs to learn features for diagnosing or prognosing AD automatically. The research involved training the classifier using paired T1-MR and FDG-PET images sourced from the ADNI datasets, which comprised 731 cognitively unimpaired (CN) individuals, 647 AD patients, 441 subjects with stable mild cognitive impairment (sMCI), and 326 subjects with progressive mild cognitive impairment (PMCI). The findings demonstrated accuracy rates of 90.10% for distinguishing CN from AD, 87.46% for distinguishing CN from PMCI, and 76.90% for distinguishing SMCI from PMCI. Additionally, it was concluded that segmentation is unnecessary when using a CNN for classification and that integrating data from two imaging modalities improves outcomes. Subasi et al. [5] propose a simple, quick method for the automatic detection of Alzheimer's disease using AI techniques. The focus is on using AI methods to detect AD via brain imaging.

The results show that the Convolutional Neural Network (CNN) achieved test accuracy of 95.70% and validation accuracy of 99.71% in diagnosing AD from brain MRI scans. He et al. [6] proposed a model that incorporates Rectified Linear Units (ReLUs), which are crucial for cutting-edge neural networks. This study enhances the rectifier neural networks for image classification from two perspectives. Firstly, it introduces a Parametric Rectified Linear Unit (PReLU) that extends the traditional rectified unit, leading to improved model fitting with almost no additional computational cost and minimal risk of overfitting. Secondly, it presents a robust initialisation technique that specifically accounts for rectifier non-linearity, allowing the training of very deep rectified models from scratch and enabling the exploration of deeper or wider network architectures. Leveraging a learnable activation function and advanced initialisation, researchers achieved a top-5 test error of 4.94% on the ImageNet 2012 classification dataset. This represents a 26% relative improvement over the ILSVRC 2014 champion (GoogleNet, 6.66%). To our knowledge, this result is the first to exceed the reported human-level performance (5.1%) on this dataset. Cheng et al. [7] proposed that traditional methods focus on extracting manually crafted features, such as grey matter volumes and cortical thickness, and then train a classifier to differentiate Alzheimer's disease from other groups. They introduced multiple deep 3D convolutional neural networks (3D-CNNs) designed to learn different features from localised brain images, which collectively contribute to the final classification for AD diagnosis [8]. Initially, several local image patches

are extracted from the full brain image, and a 3D-CNN is trained on each patch to convert the local image into more concise, high-level features.

The upper convolutional and fully connected layers are fine-tuned to integrate multiple 3D-CNNs for image classification. The suggested method can automatically learn general features from imaging data for classification. Researchers assessed our method using T1-weighted structural MR brain images from 428 participants, including 199 AD patients and 229 normal controls, sourced from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The experimental findings indicate that the proposed approach achieves 87.15% accuracy and an AUC (area under the ROC curve) of 92.26% for AD classification, highlighting its promising performance. Liu et al. [9] propose a cascaded CNN to extract multi-level, multimodal features from MRI and PET brain images for the classification of Alzheimer's disease. Initially, several deep 3D-CNNs are developed based on different local image patches to convert local brain images into more concise high-level features. Subsequently, a higher-level 2D-CNN, followed by a SoftMax layer, is integrated to combine high-level features learned across multiple modalities, thereby generating latent multimodal correlation features for the image patches used in the classification task. Ultimately, these derived features are merged using a fully connected layer and a SoftMax layer for AD classification. The evaluation is performed on baseline MRI and PET images from 397 individuals, which include 93 AD patients, 204 individuals with mild cognitive impairment (MCI, comprising 76 with progressive mild cognitive impairment and 128 with stable mild cognitive impairment), and 100 normal controls sourced from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) database.

The existing literature indicates that this approach can achieve 93.26% accuracy in distinguishing AD from NC and 82.95% in differentiating pMCI from NC, highlighting its effective classification capabilities. Wildah et al. [10] proposed a method to improve patient care, reduce costs, and enable fast, reliable analysis in large studies. The model will be implemented in Python, a language very useful for doctors in classifying Alzheimer's disease. The model uses 70% of the image for training and 30% for validation, and our trained model achieved 100% accuracy on a held-out test set. Recent breakthroughs in Magnetic Resonance Imaging (MRI) technology have spurred research into AI-enhanced diagnostics for Alzheimer's disease, creating optimism for earlier detection and timely intervention [11]. This progress has enabled the development of advanced algorithms and models capable of analysing intricate brain imaging data, thereby enhancing both diagnostic accuracy and efficiency. These advancements bolster hope for the transformative potential of AI-driven diagnostics to revolutionise the management of Alzheimer's disease, potentially supporting more effective treatment strategies and improving patient outcomes [12]. Rehman et al. [14] present a comprehensive approach that utilises the hippocampus and the VGG16 model through transfer learning for the early detection of Alzheimer's disease. Using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset and enhancing training with sophisticated image preprocessing methods, the study achieved remarkable accuracy (98.17% in testing, 97.52% in validation, and 99.62% in training).

The study also focuses on practical implementation, offering an intuitive website that enables radiologists to forecast class probabilities, monitor disease progression, and view patient images in both 2D and 3D formats, making a significant contribution to the progress of early Alzheimer's detection. Sharma et al. [15] introduced a hybrid AI model that integrates transfer learning (TL) and a permutation-based voting classifier in two main phases. The initial phase involves two TL models, specifically DenseNet-121 and DenseNet-201, which are used for feature extraction. In contrast, the subsequent phase employs three different machine learning classifiers: SVM, Naïve Bayes, and XGBoost, for classification purposes. The classifiers' results are assessed using a permutation-based voting mechanism. The proposed model achieved an accuracy of 91.75%, a specificity of 96.5%, and an F1-score of 90.25. The training dataset was sourced from Kaggle and consists of 6200 images, including 896 classified as mildly demented, 64 as moderately demented, 3200 as non-demented, and 1966 as extremely mildly demented. Using regional volumes from 2250 brain MRIs, Song et al. [16] present a variety of machine learning models: 687 normal controls (NC), 1094 moderate cognitive impairment (MCI), and 469 AD that were provided by the Alzheimer's disease Neuroimaging Initiative database (ADNI). Classification accuracies were calculated using RF, Support Vector Machine (SVM), Multi-layer Perceptron (MLP), and Convolutional Neural Network (CNN) on three different feature sets (63, 29, and 22 features). MLP and CNN showed decreases in accuracy of −6.8% and −4.5%, respectively, with changes in standard deviation from 3.3% to 4.0% for MLP and from 2.1% to 7.0% for CNN.

It is interesting to note that when 22 features were used, RF showed the smallest decrease in accuracy, −3.8%, and the standard deviation did not change significantly. This suggests that RF performs more reliably at predicting AD with fewer features. According to XU et al. [17], the current standard for diagnosing Alzheimer's disease (AD) is frequently intrusive or costly, like brain scans, and imprecise, like memory tests. Several models have been developed for diagnostic use based on notable variations in miRNA expression between blood profiles (serum and plasma), and pathways and target gene networks are used to verify miRNA biomarkers for AD diagnosis. When trained on filtered disease-specific miRNA datasets, the top-performing serum-based machine learning model identified miRNA biomarkers with 92.0% accuracy. In comparison, the top-performing plasma-based machine learning model identified miRNA biomarkers with 90.9% accuracy. Umeda-Kameyama et al. [18] examined whether artificial intelligence (AI) could differentiate between the faces of individuals with cognitive impairment and those without dementia. The study included 117 cognitively healthy volunteers and 121 patients with cognitive impairment.

Two optimisers and five deep learning models were examined. A "Face AI score" was used to indicate whether a face image was dementia- or non-dementia-related. The best-performing model was Xception with the Adam optimiser. According to the ROC AUC, the Xception AI system's overall sensitivity, specificity, and accuracy were 87.31%, 94.57%, and 92.56%, respectively, with an AUC of 0.9717.

**Table 1:** Summary of the existing works surveyed on hand gesture recognition

| Authors and Year | Model | Approach | Dataset | Accuracy / Precision (%) |
|---|---|---|---|---|
| Huang et al. [3] | Image model 3D-CNN | Deep learning | ADNI | 90.10% |
| Subasi et al. [5] | CNN | Deep learning | ADNI | 95.70% |
| Cheng et al. [7] | Image model 3D-CNN | Deep learning | ADNI | 87.15% |
| Liu et al. [9] | Image model 2D-CNN and 3D-CNN | Deep learning | ADNI | 93.26% |
| Rehman et al. [14] | Image model VGG-16 | Deep learning | ADNI | 98.17% |
| Sharma et al. [15] | Image model XG-BOOST | Machine learning | Kaggle | 91.75% |
| Song et al. [16] | Image model: Random Forest, SVM, MLP, CNN | Machine learning and Deep learning | ADNI | 90.2%<br>89.6%<br>90.5% |
| XU et al. [17] | miRNA Biomarker | Machine learning | Not mentioned | 92.0% |
| Umeda-Kameyama et al. [18] | FACE AI Xception with ADAM | Deep learning | Not mentioned | 94.57% |

A performance comparison of the different models is shown in Table 1. Antibody-based clearance of cerebral amyloid β (Aβ) plaques may remove tau tangles and somewhat reduce cognitive loss in symptomatic Alzheimer's disease (AD), according to clinical study data reported in 2019. In addition to discussing prospective screening methods for people with cognitive symptoms, the update examines current advancements in fluid and imaging biomarkers for AD-related diseases [19]. It highlights the need for more research into common co-pathologies, discusses recent data on biomarkers for inflammation, neurodegeneration, Aβ and tau pathology, and synaptic dysfunction, and suggests that combining various biomarkers could help develop and implement novel AD drug candidates. Additionally, around 60 studies that have used a popular theme or architecture for AD are examined [20]. Graph-based deep architectures, self-supervised learning, normalising flows, explainable models, and attention methods are considered. This corpus of literature's primary issues have been divided into three categories and explained: data-related, methodology-related, and clinical adoption-related. Our work aims to introduce two models that address the critical need for precise diagnostic instruments in radiology and neurology. By combining Bio-Marker's biomarker-based AD identification with YOLOv8's effective detection of brain abnormalities in MRI scans, our work addresses the drawbacks of existing approaches highlighted in the literature.

## 3. Methodology

The proposed methodology addresses the challenges of Alzheimer's disease in India by combining advanced medical imaging analysis and Bio-Marker assessment, facilitated by YOLOv8 for image analysis and a Random Forest algorithm for Bio-Marker assessment. The primary goal is early detection, efficient diagnosis, and precise characterisation of Alzheimer's pathology. To achieve this, researchers employ a synergistic model composed of two key components: the Bio-Marker and Image models. Utilising a Random Forest classifier, the Bio-Marker model analyses particular biomarkers associated with brain health in cerebrospinal fluid (CSF) testing. A key component of our approach is Bio-Marker, which serves as the initial screening tool to identify potential issues with AD biomarkers. The Image model is a real-time object detection system built on top of the YOLOv8 (You Only Look Once) architecture, as shown in Figure 1. Researchers have modified it to identify and categorise brain lesions or anomalies. YOLOv8 is quite good at accurately locating and recognising objects in images. In this case, it focuses on identifying brain anomalies and giving specific details about their dimensions, orientation, and position in the picture. A large dataset of various brain scans supports our methodology. The dataset includes Bio-Markers and MRI scans, both of which are necessary for a thorough knowledge of brain health. The dataset includes more than 5000 medical images, many of which come from hospitals around the world. This ensures that our models are trained on information relevant to a wide range of demographics.

### 3.1. Image Scan Module

The YOLOv8-based image model serves as a real-time classification system for identifying Alzheimer's disease. It is specifically designed to categorise brain alterations linked to Alzheimer's disease in our situation, offering comprehensive details regarding the kind and degree of changes seen in neuroimaging. YOLOv8 is highly proficient at correctly recognising

and categorising various stages of cognitive impairment, helping distinguish between non-demented, extremely mild, mild, and moderate cases.

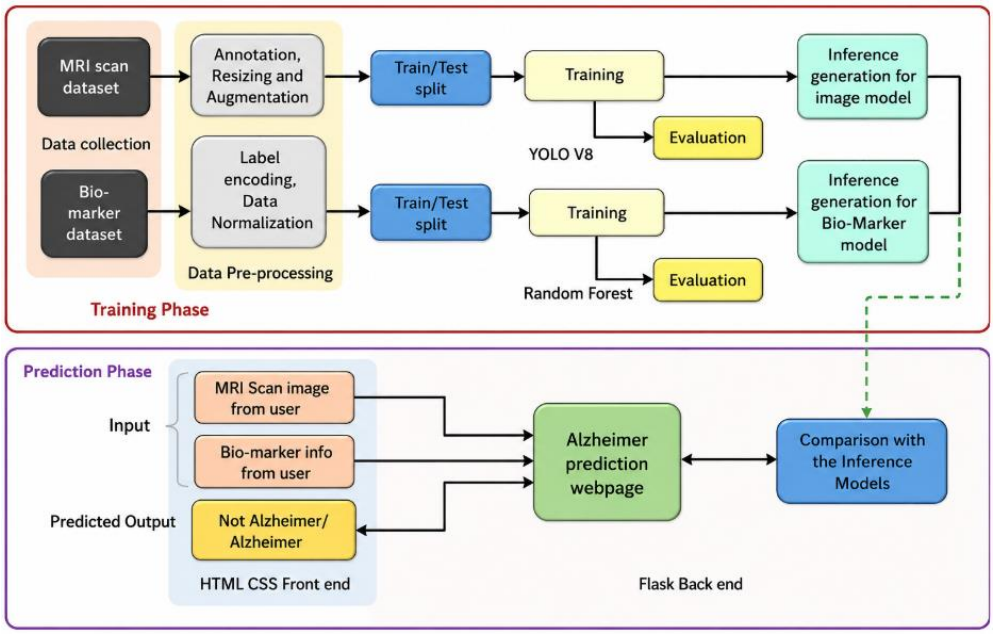


**Figure 1:** Functional block diagram

### 3.1.1. YOLOv8 Architecture

YOLOv8, as shown in Figure 2, uses the following components:

- **Backbone:** The backbone is the base structure of the YOLOv8 model and is a modified version of CSPDarknet53. This provides a strong framework for feature extraction and enhances the ability of the model to detect and classify objects in images.
- **Neck:** The neck of YOLOv8 is PANet [Path Aggregation Network], which is a new neck design for object detection models. It is designed to improve object detection model performance by aggregating information across different model layers.
- **Head:** It takes feature maps from the backbone and neck and processes them to generate predictions for bounding boxes, objectness scores, and class probabilities for objects in the input image.

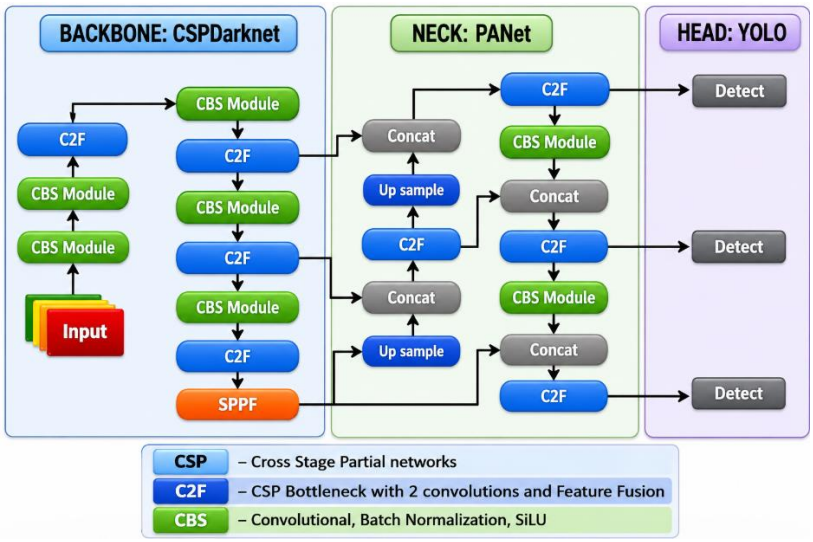


**Figure 2:** YOLO v8 architecture

The C2f (CSP Bottleneck with 2 convolutions and Feature Fusion) module is crucial for improving the gradient flow through the network. It introduces two parallel flows, which allows better transfer of information between layers, essential for maintaining the performance and accuracy of the model. The Spatial Pyramid Pooling Fusion (SPPF) module first splits the input data into multiple regions spatially and then pools the features in each region independently. This enables the model to recognise objects of different sizes and scales within images. Transfer learning, a valuable technique for quickly retraining a model on new data without retraining the entire network, was used to train this model. This provides for quicker training times and uses fewer resources than standard training. During the iteration, the ratio between the predicted and true values is calculated using the loss function. The Loss Function for YOLOv8 consists of three components.

The localisation loss (***Lbox***): Quantifies the prediction error for the bounding box coordinates.

Confidence loss (***L***cnf): Assesses how confident the model is in its ability to foretell.

Class loss (***Lcls***): Determines how inaccurately each class's probabilities were predicted:

$$\boldsymbol{L_T = L_{clss} + L_{cnf} + L_{box}} \quad (1)$$

where L_T is the total loss, L_clss is represented as a classification loss and expressed in equation 2. L_cnf is denoted as confidence loss and expressed in equation 3, and L_box is the bounding box loss:

$$\boldsymbol{L_{clss} = \sum_{i=0}^{x^2} l_i^{obj} \sum_{j=0}^{R} \left[ \left( Pi(c) - \widehat{Pi}\,(c) \right)^2 \right]} \quad (2)$$

$$\boldsymbol{L_{cnf} = \sum_{i=0}^{x^2} \sum_{j=0}^{R} l_i^{obj} \left[ \left( Ci - \widehat{Ci} \right)^2 \right] + \beta_{noobj} \sum_{i=0}^{x^2} \sum_{j=0}^{R} l_i^{noobj} \left[ \left( Ci - \widehat{Ci} \right)^2 \right]} \quad (3)$$

where, $\boldsymbol{l_i^{obj}}$ is denoted as a probability of being an object. $liobj$ and $linoobj$are represented as the indicator function. $Ci$ is denoted as the objectness.

The performance of the YOLOv8 model is evaluated using various metrics, including Precision, Recall, F1-score, and Prediction time. The various parameters are expressed in equations 4, 5, and 6:

$$\boldsymbol{Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}} \quad (4)$$

$$\boldsymbol{Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}} \quad (5)$$

$$\boldsymbol{F1 - Score = 2.\frac{Precision\ .Recall}{Precision + Recall}} \quad (6)$$

### 3.2. Bio Marker Model

The Bio-Marker model is a Random Forest classifier designed to analyse specific biomarkers of the amyloid protein. Total tau protein and phosphorylated tau protein health in the Cerebrospinal fluid (CSF) test. Bio-Marker is an integral part of our methodology, serving as the initial screening tool for identifying potential Alzheimer's disease issues.

#### 3.2.1. Random Forest Architecture – Bio-Marker Model

The Random Forest, as shown in Figure 3, is an ensemble machine learning algorithm that combines the predictions of multiple decision trees to produce more accurate predictions. Random Forest includes several hyperparameters that can be tuned to optimise model performance. These hyperparameters include the number of trees in the ensemble, the maximum depth of individual trees, the number of features considered for splitting at each node, and the minimum number of samples required for splitting at a node. Fine-tuning these hyperparameters is critical to achieving the model's perfect balance of bias and variance. An inherent advantage of Random Forests is their interpretability. Decision trees are easy to interpret, allowing users to understand how the model makes predictions. Additionally, Random Forest provides feature importance metrics that elucidate each feature's contribution to the model's predictive performance. This transparency is valuable for understanding the inherent patterns within the data and gaining insights into the predictive process. Random Forest uses an approach known as bootstrapping to generate several training data subsets for every decision tree. A technique called bootstrapping involves randomly selecting data points from the original dataset so that each sample can be replaced. This results in a situation where

every decision tree in the ensemble is trained on a distinct subset of the data, thus adding diversity. In addition to bootstrapping, Random Forest introduces randomness into the feature selection process at every decision tree split.

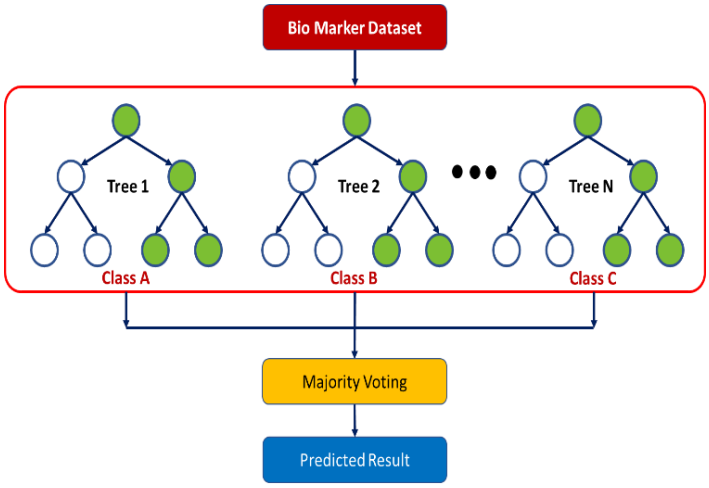


**Figure 3:** Random forest architecture

A random subset of features is chosen for consideration, rather than considering every feature at every node. This technique facilitates decorrelation among trees in the ensemble, thereby mitigating the risk of overfitting and enhancing generalisation. The Random Forest algorithm uses ensemble learning, combining predictions from multiple models to produce a final prediction. The final forecast is generated by combining the predictions made by each decision tree after they have all been trained. This method is very useful for classification problems. The most frequently predicted class among the trees determines the final prediction in classification tasks. On the other hand, in regression tasks, the average of the projected values over all trees is used to get the final prediction. Random Forest has several hyperparameters that are used to fine-tune and maximise the model's performance. The number of trees in the ensemble, the maximum depth of a single tree, the number of features split at each node, and the minimum number of samples required for node splitting are examples of these hyperparameters. To achieve the ideal balance of bias and variance in the model, it is imperative to fine-tune these hyperparameters.

## 4. Experimental Setup

### 4.1. Data Collection and Pre-Processing

**Yolov8-based Image Model:** The image model begins by aggregating a comprehensive dataset of 5000 brain MRI scans, classified as very mild, mild, moderate, and non-demted. Through augmentation, the dataset expands to 13932 images. Subsequently, a 7:2:1 split is used to allocate the training and test sets. Figure 4 illustrates the sample data used for training the Yolov8t-based image model.

**Biomarker Model:** The Bio-Marker model is designed to detect Alzheimer's disease early by evaluating the threshold values of key Bio-Markers, including amyloid protein, total tau protein, and phosphorylated tau protein. These Bio-Marker values are obtained from cerebrospinal fluid tests performed via lumbar puncture. For further confirmation, the model calculates the ratio of phosphorylated tau to total tau and checks whether it exceeds a predefined threshold value of 0.2. To achieve this functionality, the Bio-Marker model utilises a random forest model for analysis and computation. This approach enables efficient processing and interpretation of Bio-Marker data, facilitating early detection and intervention in Alzheimer's disease. To ensure the quality and reliability of the dataset, a total of more than 810 patient samples were collected, including 402 patients with Alzheimer’s disease and 408 controls (without Alzheimer’s disease).

The dataset has been thoroughly pre-processed for data cleaning including handling of null values using appropriate statistical techniques such as mean and mode imputation. In addition, normalisation was carried out to improve consistency and comparability of the numerical features. Thus the final dataset consisted of the Bio-Marker data carefully preprocessed and balanced between Alzheimer’s disease and Control cases. The dataset provided the study with a solid basis for developing and testing machine learning models that would be able to accurately diagnose Alzheimer’s disease using these diverse and informative BioMarkers. The balanced data set, preprocessing efforts and normalisation procedures together enabled high accuracy and reliability of the model for distinguishing Alzheimer’s disease from the control cases.

### 4.2. Model Training

**Image Model:** The YOLOv8 model is trained on pre-trained weights from the COCO dataset. The training and testing phases employ the customised dataset. The AdamW optimisation approach is used to improve the training model. With a batch size of 16, the model has been trained for 10, 50, 100, and 200 epochs using the Adam optimiser with a learning rate of 0.01 and momentum of 0.937. Using Python tools from the Deep Learning Toolbox and the Jupyter Notebook framework, Google Colab is used to train the model. Python modules such as Pandas, Matplotlib, NumPy, and OpenCV are used in the experimental analysis. Using CUDA enhances training speed by leveraging the T4 GPU's capabilities for image training.

**Bio-Marker Model:** Train the selected model on the training dataset. During training, the model will learn the relationship between the input Bio-Markers and the CSF labels. The model was trained on Machine Learning Algorithms, Random Forest, KNN classifiers, Logistic regression, and Decision tree to analyse the performance and found that Random Forest performs well.

### 4.3. Model Evaluation

**Image model:** The trained model's performance was evaluated on the validation set using a suite of key performance metrics, including Average Precision, Average Recall, F1-Score, and Prediction Time, to assess the YOLOv8 model's effectiveness. With an IoU threshold of 0.65, the performance of the models is assessed at various epochs (10, 50, 100, and 200). At each epoch, it demonstrated impressive performance in Alzheimer detection.

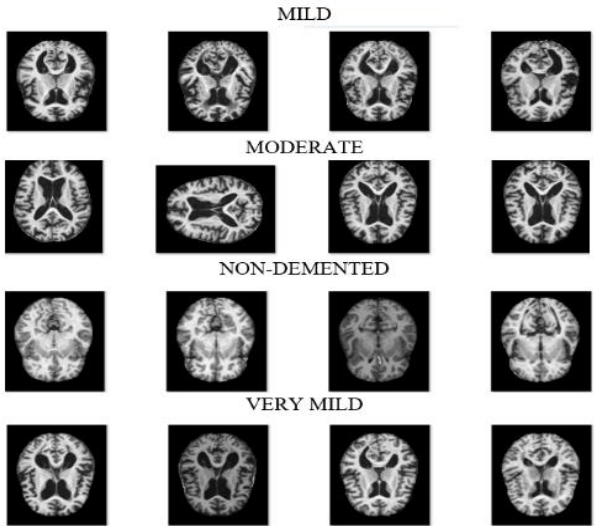


**Figure 4:** Sample MRI data from the dataset

**Bio-marker model:** The evaluation of the bio-marker model's effectiveness involves using metrics such as Average Precision, Average Recall, F1-Score, and Prediction Time. The performance is assessed for Logistic Regression, KNN classifier, and Random Forest. The Random Forest Classifier performs comparatively better and demonstrates an overall accuracy of 100% in diagnosing Alzheimer's disease (AD).

### 4.4. Model Implementation

There are two HTML templates: index.html serves as the main page for entering biomarker data, while result.html displays prediction results. CSS styling defined in style.css enhances the user interface. A multi-step form for biomarker data entry is implemented using HTML and JavaScript. Users progress through different input steps to provide biomarker data. JavaScript manages form navigation, allowing users to move forward and backwards through the form steps. On the Flask-based backend, a Flask web application is created with routes to render the initial biomarker input page (index.html) and handle form submission (predict). The predictive route enables users to upload medical images for processing. User-entered biomarker data is stored in user_biomarkers.csv for reference and preprocessing. Biomarker prediction involves capturing user-entered data, preprocessing it to match the model's input requirements, and applying a pre-trained Biomarker model to enter cerebrospinal fluid (CSF) data. Model output is translated into human-readable labels. In the context of image analysis, the Yolo model is employed to detect Alzheimer's disease (AD) in medical images, specifically MRI scans, to assist in diagnosis. When users

upload a medical image in the prediction App, the Yolo v8 model is used to detect AD stage, including very mild, mild, moderate, and non-demented. Trained on medical image datasets, the model identifies and localises these predictions and classification probabilities. The detected images are then visually overlaid on the original image, providing users with a clear representation of potential AD biomarkers. Additionally, the identified objects are seamlessly integrated into the prediction results, offering valuable insights for diagnosis and assessment. This integration enhances the web application's functionality by automating image analysis and facilitating the identification of AD-related features, thereby improving patient care. Frontend Interface (HTML, CSS, JavaScript).

## 5. Results and Discussion

### 5.1. Alzheimer's Disease Detection Using MRI Scan Image Processing

YOLOv8 offers a comprehensive suite of classification models [nano, small, medium, large, extra-large] that cater to a wide range of performance requirements. The pre-trained weights from the COCO dataset are used to train the YOLOv8 models. The training and testing phases employ the customised dataset. The AdamW optimisation approach is used to improve the training model. With a batch size of 16, the model has been trained for 10 epochs on different YOLOv8 models, and the prediction speed results are shown in Table 2.

**Table 2:** Prediction speed across the YOLOV8 model

| YOLO Model | Pre-process (ms) | Inference (ms) | Post-process (ms) | Total (ms) |
|---|---|---|---|---|
| Nano | 1.8 | 2.5 | 2.7 | 8.0 |
| Small | 0.5 | 6.9 | 4.6 | 12.0 |
| Medium | 0.4 | 13.4 | 6.0 | 19.8 |
| Large | 0.5 | 20.6 | 3.3 | 24.4 |
| Extra Large | 0.3 | 33.2 | 3.4 | 36.9 |

When comparing the five versions of the YOLO architecture, researchers observe notable variations in performance metrics and speed. The metrics, including precision and recall, provide insights into the model's object detection accuracy, while the speed indicates its computational efficiency. Among the configurations, the "Nano" model demonstrates a strong balance between speed and accuracy, making it a compelling choice. It achieves high precision and recall, indicating strong object detection. Furthermore, the "Nano" model offers a remarkable speed advantage, striking a balance between computational efficiency and accuracy. This model is well-suited for real-time or resource-constrained applications, where both speed and accuracy are crucial factors. As a result, the "Nano" model is the preferred choice, offering a favourable trade-off between speed and accuracy and making it an excellent candidate for a wide range of practical applications. The MRI scan dataset is used to train and test the YOLOv8 model. Using the AdamW optimiser, a 16-batch deep learning model is trained for Very Mild, Mild, Moderate, and Non-demented detection. AdamW has a learning rate of 0.001429, momentum of 0.9, and parameter groups: 66 weights (decay=0.0), 77 weights (decay=0.0005), 76 biases (decay=0.0). The YOLOv8 model is trained using transfer learning from the COCO128 dataset, with pre-trained weights. The proposed YOLOv8 model is a lightweight, time-efficient, high-precision detection model.

**Table 3:** Performance metrics of image classification

| Epochs | Precision | Recall | F1-Score |
|---|---|---|---|
| 10 | 0.935 | 0.886 | 0.923 |
| 50 | 0.981 | 0.958 | 0.964 |
| 100 | 0.981 | 0.969 | 0.964 |
| 200 | 0.986 | 0.962 | 0.975 |

In this study, the performance of an object detection model was evaluated on a dataset of 13000 images. The model was trained with 10, 50, 100 and 200 epochs, and the best results were obtained with 200 epochs. It showed promising results with high precision and recall at Epoch 10 as depicted in Table 3. The model had a much better performance by Epoch 50, which shows that the model could detect and localise objects accurately. It sustained high precision and recall at Epoch 100, showing consistent performance across IOU thresholds. Epoch 200 performed well with consistent precision and recall, indicating the model’s ability to accurately detect and localise objects. The promising results with high accuracy at Epoch 10 are shown in Table 4. The performance of the model shows a significant improvement at Epoch 50, indicating accurate prediction. It was very accurate at Epoch 100 and its performance was consistent. By epoch 200 we achieved 99.8% accuracy. This demonstrates the potential of the model to detect Alzheimer’s.

**Table 4:** Performance metrics for each epoch

| Epochs | Top-1 Accuracy (%) | Top-5 Accuracy (%) |
|---|---|---|
| 10 | 94.3 | 100 |
| 50 | 99.3 | 100 |
| 100 | 99.6 | 100 |
| 200 | 99.8 | 100 |

Figure 5 represents the performance curves for the Image model. It indicates that the model can detect with high accuracy. The model's performance is also relatively consistent across all classes, with no major differences in accuracy.

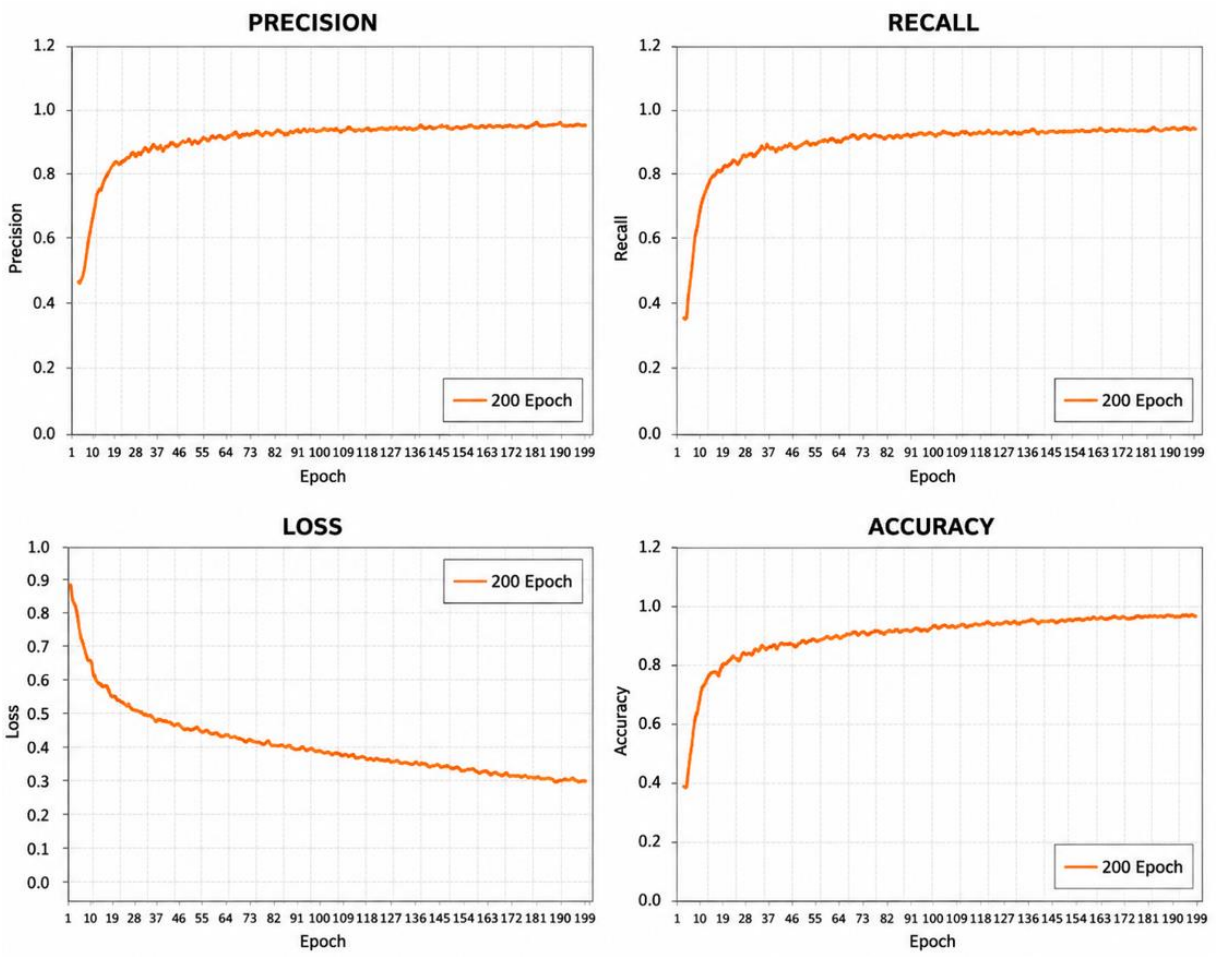


**Figure 5:** Performance curve of image model

Figure 6 shows that the model performs very accurately while detecting the cases. This may be because the model can learn more discriminative features for prediction. The results suggest that early stopping can be an effective way to prevent overfitting in object detection models. In this study, the model achieved its best performance at 200 epochs. Training the model for longer did not improve its performance and, in fact, led to a decrease in performance on the validation dataset. This suggests that the model started to overfit the training data after 100 epochs. These results indicate that the model can accurately classify four Alzheimer's disease subtypes. The model's performance is also relatively consistent across all classes, with no major differences in accuracy. From Figure 7, the overall findings of this study indicate that the model is a proficient and reliable tool for detecting Alzheimer 's-related brain changes with high accuracy. The model demonstrates proficiency in identifying both structural anomalies and functional changes, suggesting its potential for comprehensive diagnosis of Alzheimer's disease. Moreover, the model exhibits strong generalisation capabilities, which bodes well for its performance with new data. This study highlights the potential of deep learning as a potent tool in Alzheimer's disease diagnosis, offering superior accuracy and adaptability compared to conventional diagnostic approaches.

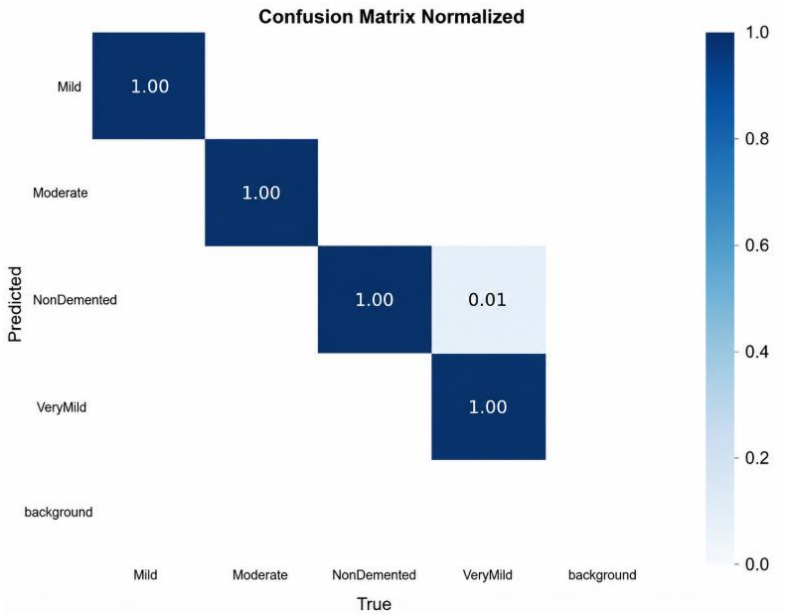


**Figure 6:** Normalised confusion matrix for image model

This advancement holds promise for enhancing early detection and management of Alzheimer's disease, ultimately leading to improved patient outcomes and alleviating the healthcare burden associated with this debilitating condition.

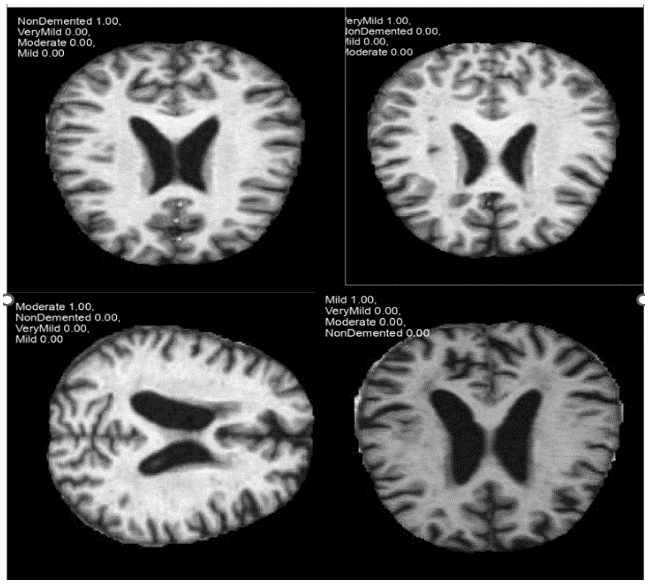


**Figure 7:** Image model prediction results

### 5.2. Alzheimer's Disease Detection Using Bio-Marker Model

The Bio-Marker model, trained on a dataset comprising 5 biomarkers, aims to classify whether a patient has Alzheimer's disease (AD) using binary classification. The performance of four distinct machine learning models: Logistic Regression, K-Nearest Neighbours (KNN), Decision Tree Classifier, and Random Forest Classifier, for a binary classification task. The goal is to assess how well these models perform on both the training and test datasets, focusing on metrics such as accuracy, ROC AUC, precision, recall, and F1-score. By comparing and contrasting the strengths and weaknesses of these models, researchers aim to make an informed decision on which is most suitable for the specific task at hand, considering factors such as model simplicity, interpretability, and the ability to handle complex data distributions. This analysis will help guide our selection of the most appropriate machine learning model for effectively addressing the binary classification problem. Table 5 presents the performance metrics of various classification models for identifying Alzheimer's disease (AD). The Random Forest Classifier

demonstrates exceptional technical performance across all metrics. With 100% precision for AD, the model accurately identifies all positive instances without any false positives, achieving 100% recall, indicating its ability to capture all AD cases in the dataset.

**Table 5:** Performance metrics of various biomarker models

| Model | Class | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| Random Forest | AD | 100 | 100 | 100 |
| Random Forest | Control | 100 | 100 | 100 |
| Decision Tree | AD | 100 | 99.54 | 99.75 |
| Decision Tree | Control | 99.50 | 100 | 98.86 |
| Logistic Regression | AD | 100 | 97.67 | 98.82 |
| Logistic Regression | Control | 97.43 | 100 | 98.70 |
| KNN | AD | 100 | 95.34 | 97.61 |
| KNN | Control | 95 | 100 | 97.43 |

The resulting F1-score of 100% indicates balanced accuracy in AD classification. Similarly, for Control, the model achieves 100% precision and 100% recall, demonstrating its ability to accurately classify negative instances without false negatives. The corresponding F1-score of 100% underscores the model's outstanding accuracy and reliability in identifying Control cases. The Random Forest Classifier demonstrates remarkable precision, recall, and F1-scores for both AD and Control classes, highlighting its robustness and effectiveness in classification tasks. The Decision Tree Classifier demonstrates robust performance, achieving 100% precision and 98.54% recall for AD, resulting in an F1 Score of 99.75% and balanced accuracy. Similarly, for Control, the precision, recall, and F1-score all exceed 98%, indicating consistent performance in identifying Not-CKD instances. The Logistic Regression model achieves 100% precision, indicating that all positively classified AD instances are accurate, while achieving 97.67% recall, indicating the successful identification of 97.67% of all AD cases. The F1-score of 98.82% highlights a well-balanced performance in terms of both precision and recall. Regarding instances classified as Control, the model achieves 97.43% precision, indicating that 97.43% were correctly classified, with flawless recall of 100%. The F1-score of 98.7% underscores a commendable balance between precision and recall for Control cases.

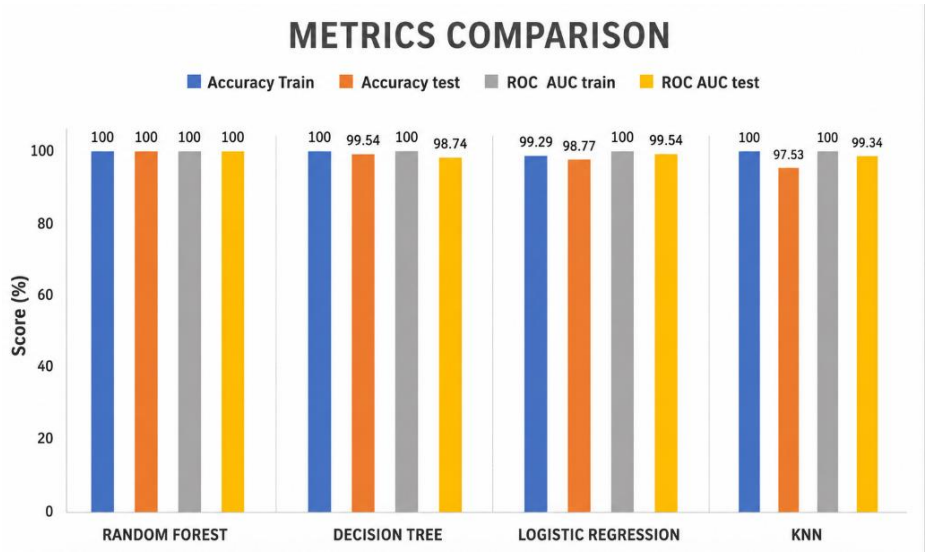


**Figure 8:** Comparison of performance metrics in different bio-marker classifier models

The K-Nearest Neighbours (KNN) achieves 100% precision for AD and 95% for the Control class, reflecting precise classification. Nonetheless, its AD recall 95.34% implies that 95.34% of actual AD cases were correctly identified. With an F1-score of 97.61% for AD, it maintains a good equilibrium between precision and recall. As for Control, the model achieves 100% recall, ensuring accurate identification, with an F1-score of 97.43%. Precision, recall, and F1-score are significant indicators of classification accuracy and reliability in the thorough analysis of models for AD and Control categorisation. The Random Forest Classifier is the most effective model among those examined; it consistently performs better on these criteria for the AD and Control categories. The Random Forest Classifier is quite good at differentiating between AD and Control cases; recall values are almost flawless, and it produces strong F1-scores of 100% for AD and 100% for Control. Furthermore, the model skillfully strikes a careful balance between recall and precision, highlighting its reliability and robustness in correctly

classifying examples from both groups. With its outstanding performance and dependability in medical diagnostic applications, the Random Forest Classifier is the most appropriate model for precisely classifying AD or Control cases. The performance accuracy comparison across various Bio-Marker classifier models is shown in Figure 8.

The Random Forest Classifier chose to do AD prediction for a variety of persuasive reasons. For starters, it consistently performed well, with high accuracy and ROC AUC scores on both the training and test datasets. This impressive result demonstrates its ability to categorise examples and generalise to previously encountered data effectively. The Random Forest is an ensemble approach that aggregates forecasts from multiple decision trees. It reduces overfitting and improves model robustness by capturing complicated data patterns. Furthermore, the Random Forest produces useful feature importance scores that reveal the most relevant characteristics for classification, thereby improving model interpretability and guiding feature selection. Its ability to handle numerical and categorical features makes it appropriate for a wide range of datasets. At the same time, its tolerance for data pre-processing and scaling changes streamlines the data preparation workflow. Individual decision trees are less resilient to overfitting than the Random Forest method. This makes it a reliable solution for real-world datasets with noise and complex relationships. In summary, the Random Forest Classifier is chosen for its outstanding predictive performance, robustness, and agility in handling complex datasets, making it a reliable solution for binary classification tasks in technical applications. Random Forest possesses various advantages for predicting Alzheimer's disease (AD) and control cases.

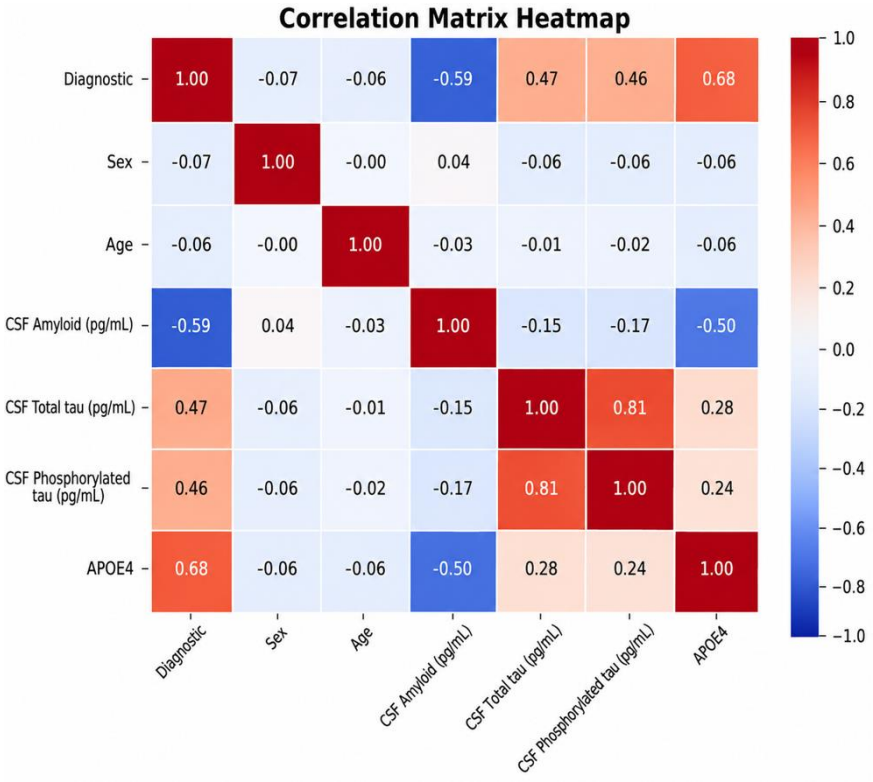


**Figure 9:** Heatmap of feature extraction in random forest bio-marker model

For instance, its capacity to handle convoluted, high-dimensional datasets makes it ideal for medical applications that require precise diagnosis based on multiple patient attributes. Second, the Random Forest uses the aggregation of predictions from several decision trees to improve predictive accuracy while minimising overfitting. It also performs well on unseen data. Third, its ability to detect nonlinear correlations between patient characteristics and disease outcomes allows it to identify subtle patterns that contribute to AD risk, enhancing diagnostic accuracy. Furthermore, Random Forest's feature importance analysis makes it easier to identify critical variables that contribute to AD diagnosis, helping doctors better understand disease mechanisms and inform targeted therapies and treatment options. Overall, Random Forest's accuracy, robustness, interpretability, and ability to handle complex data structures make it a highly reliable and clinically useful technique for predicting AD and control cases. Figure 9 illustrates the heatmap of feature extraction in the random forest bio-marker model. Heat map for feature extraction in random forest" is a visual tool utilised to discern the significance of features within a dataset, particularly in predicting Alzheimer's disease (AD) or Control status. This dataset includes biomarker data such as Age, diagnosis, Sex, CSF Amyloid protein, CSF Total tau, and CSF Phosphorylated tau protein. After training a Random Forest

classifier on this dataset, feature importance is calculated based on how effectively each feature distinguishes between AD and Control cases. The resulting heatmap visually showcases the relative importance of each feature, aiding in feature extraction and facilitating informed decision-making in healthcare settings for the diagnosis and management of Alzheimer's disease.

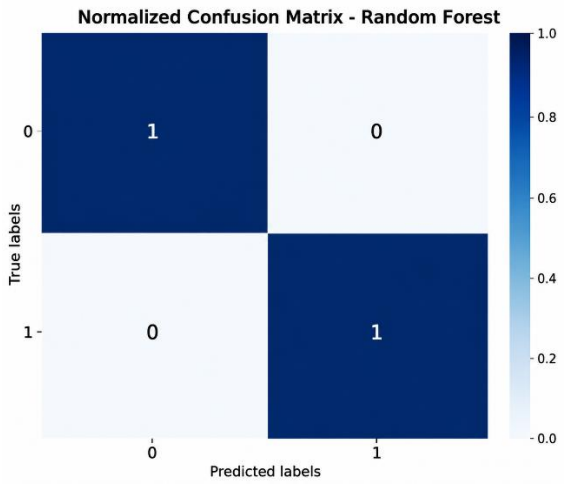


**Figure 10:** Confusion matrix of random forest

Figure 10 displays the confusion matrix for the Random Forest Bio-Marker model. The developed confusion matrix for detecting AD vs Control shows promising results, correctly classifying both AD and Control cases. Further research and optimisation of the model can improve its diagnostic accuracy, making it more reliable for detecting AD cases in clinical settings.

### 5.3. Implementation of the Model

Implementing the AD model on a handheld device is crucial for Alzheimer's detection, given its potential for point-of-care testing and remote healthcare applications. Handheld devices offer portability, allowing medical professionals to perform brain scans conveniently at the patient's bedside or in remote locations where access to advanced medical equipment may be limited. This feature enables early detection of brain abnormalities, enabling timely diagnosis and intervention, which is crucial for improving patient outcomes, particularly in resource-constrained settings. Furthermore, real-time data processing on handheld devices enables rapid decision-making and enables healthcare providers to initiate appropriate treatment protocols quickly. Figure 11 demonstrates the real-time implementation of our AD model on a handheld device, with a live data feed during operation. Users manually enter required biomarker information collected from the biomarker procedure and MRI scan images into the handheld device. After receiving real-time data, the hybrid model processes it and displays the expected outcomes on the screen immediately. This arrangement enables quick assessment and diagnosis of kidney problems, providing healthcare providers with real-time insights.

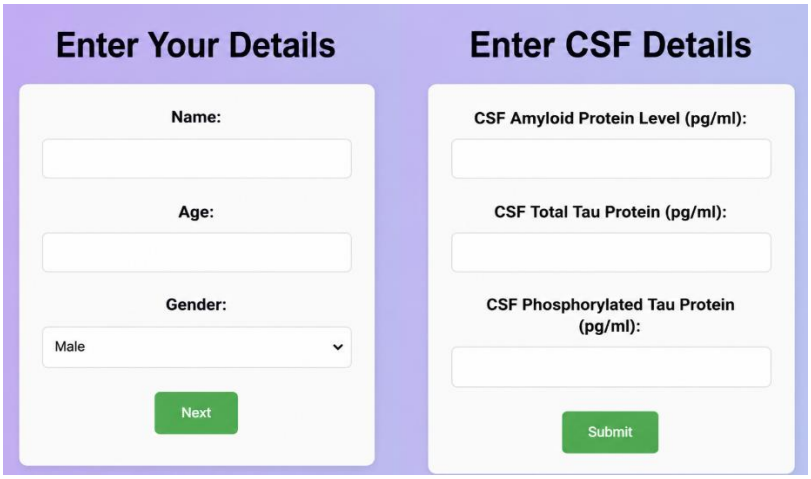


**Figure 11:** Real-time implementation of our model – data feed

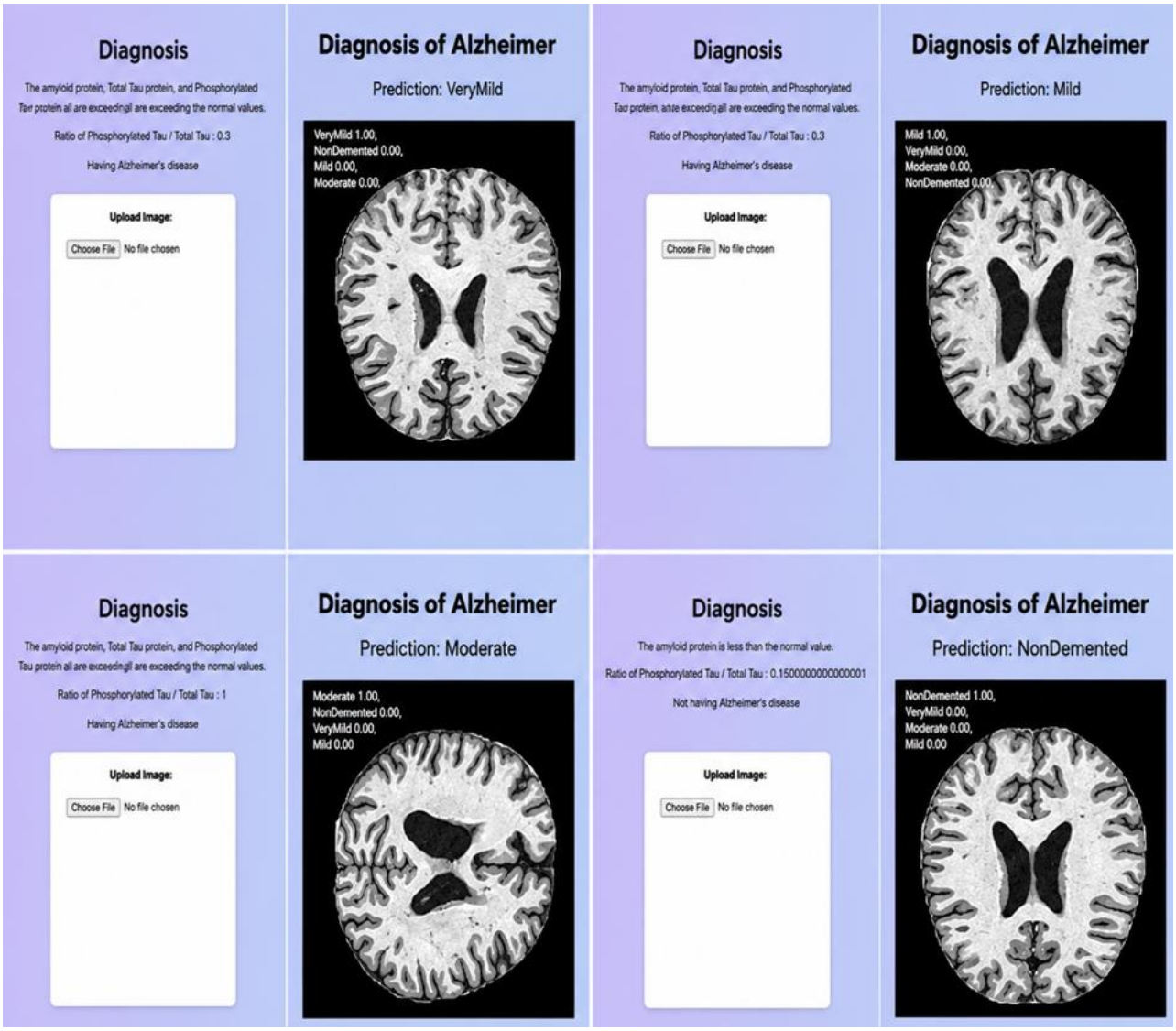


**Figure 12:** Output prediction on handheld device as Very mild, Mild, Moderate, Non demented

Figure 12 shows the predicted, segmented, and classed outputs for Very mild, Mild, Moderate, and Non-Demented circumstances, respectively, generated by our AD model using a mobile device. The model's output predictions displayed on a handheld device indicate its ability to reliably identify various Alzheimer stages, including very mild, mild, moderate, and non-demented. These forecasts are critical for enabling point-of-care diagnostics and expanding healthcare services into remote places where advanced medical facilities are scarce. Using the AD model's real-time functionality on portable devices, healthcare providers can quickly monitor renal health status, enabling timely intervention.

## 6. Conclusion

Promise of the integrative framework for addressing Alzheimer's disease issues in India. The Bio-Marker and YOLOv8 models use powerful machine learning and deep learning to detect, diagnose and treat Alzheimer's disease early. The Bio-Marker model predicts Alzheimer's disease with 100% accuracy using Bio-Marker data. This would help in the early detection of anomalies in the Alzheimer's Bio-Marker and hence improving patient care. Deep learning has many advantages over conventional approaches for Alzheimer disease diagnosis. First, machine learning models can detect complex patterns in large patient datasets that humans may miss. Second, these models can be updated continuously with new data to enhance their accuracy and effectiveness over time. Third, machine learning models in computer software make it possible to efficiently diagnose Alzheimer's disease in clinical settings. YOLOv8 Image model detects and localises brain alterations related to Alzheimer's disease in neuroimaging data in real time with 99.8% mean Average Precision. It gives detailed information which helps physicians diagnose and treat cortical thinning and hippocampal atrophy. Both models are based on large datasets, ensuring local relevance. Transfer learning accelerates training, building models that are lightweight and efficient. Fast,

informed decision-making is crucial in healthcare. With these models and a user friendly interface for Bio-Marker data entry and picture analysis, a complete solution for early detection and management of Alzheimer's disease in India is provided. The findings and approach of this study suggest that better patient care can mitigate the extensive health and economic burden of Alzheimer's disease.

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**Ethics and Consent Statement:** All authors confirm that the study was conducted in accordance with established ethical standards, with informed consent obtained and participant confidentiality maintained.

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