

# EARLY DETECTION OF ALZHEIMER'S DISEASE USING MACHINE LEARNING ALGORITHM

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**ABSTRACT:** Alzheimer's disease is one of the most common neurodegenerative disorders affecting elderly populations worldwide. Early detection of Alzheimer's disease is essential for timely treatment and slowing the progression of cognitive decline. Traditional diagnosis methods rely heavily on clinical assessments, MRI scans, and expert interpretation, which can be time-consuming and prone to human error. With the advancement of artificial intelligence and deep learning techniques, automated systems can assist medical professionals in identifying Alzheimer's disease at an earlier stage. This project proposes a hybrid deep learning framework that integrates MRI image analysis with clinical patient data to improve prediction accuracy. The proposed system utilizes the VGG16 convolutional neural network for extracting features from MRI brain images while simultaneously processing clinical features such as age, education years, MMSE score, and normalized whole brain volume. These features are combined using a feature fusion mechanism to build a hybrid classification model capable of predicting Alzheimer's disease categories. The system is trained using labeled datasets and evaluated on validation and test data to measure prediction performance. Experimental results demonstrate that combining image-based and clinical features improves classification accuracy and robustness compared to using a single data source.

**KEYWORDS** Alzheimer's Disease, Deep Learning, VGG16, MRI Image Analysis, Hybrid Neural Network, Medical Diagnosis.

## 1. INTRODUCTION

Alzheimer's disease is a progressive neurological disorder that causes memory loss, cognitive decline, and behavioral changes. It is one of the leading causes of dementia among older adults and affects millions of people globally. Early detection and diagnosis of Alzheimer's disease are essential because they allow medical professionals to implement treatments that may slow disease progression and improve patient quality of life. However, diagnosing Alzheimer's disease in its early stages remains challenging due to the complexity of neurological changes and variations in patient symptoms.

Magnetic Resonance Imaging (MRI) is widely used in medical research and clinical practice to study structural changes in the brain associated with Alzheimer's disease. MRI images provide detailed information about brain tissue, brain volume, and potential abnormalities. Machine learning and deep learning techniques have significantly improved the ability to analyze MRI scans automatically. Convolutional Neural Networks (CNNs) are particularly effective for medical image analysis because they can automatically extract complex spatial features from images without manual feature engineering.

While MRI images provide important structural information, clinical data also plays a significant role in diagnosing Alzheimer's disease. Factors such as age, education level, cognitive assessment scores (MMSE), and normalized brain volume measurements contribute valuable insights into the progression of the disease. Using both image data and clinical data together can significantly

enhance prediction performance. Hybrid deep learning models are designed to combine multiple types of data to produce more reliable predictions.

This project proposes a hybrid deep learning framework that integrates MRI image features extracted using a pretrained VGG16 convolutional neural network with clinical patient features. The extracted features from both sources are combined through a neural network architecture using feature fusion techniques. The combined features are then passed through fully connected layers for classification into Alzheimer's disease categories. The model is trained using labeled datasets containing MRI images and corresponding clinical information. Data generators are used to efficiently process images in batches during training. Class balancing techniques are applied to handle dataset imbalance and improve prediction accuracy. The trained model is evaluated using validation and test datasets to ensure reliable performance.

## 2. Motivation

Alzheimer's disease (AD) is one of the most prevalent and devastating neurodegenerative disorders, progressively impairing memory, cognitive reasoning, and projections suggesting this number could triple by 2050 if early-stage behavioural function. According to the World Health Organization, it affects more than 55 million people globally, with interventions remain limited. Early diagnosis is therefore critical, as timely therapeutic or behavioural intervention can substantially slow disease progression and improve quality of life.

However, manual diagnosis is complex and expensive, requiring neurologists to interpret high-resolution MRI, PET, and clinical data. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) offer powerful tools to analyse vast medical datasets, detect subtle patterns of brain atrophy, and distinguish Alzheimer's disease from normal aging. ML models can extract discriminative features from

neuro-images and correlate them with clinical indicators such as Mini-Mental State Examination (MMSE) scores and Clinical Dementia Ratings (CDR).

This project is motivated by the need to design an automated and intelligent ML-based diagnostic system that overcomes the limitations of conventional manual analysis and delivers reliable early prediction, supporting clinicians in decision-making and personalized care planning.

## 3. Proposed System

The proposed system introduces a hybrid deep learning framework that combines MRI image analysis with clinical patient data to improve Alzheimer's disease classification accuracy. The system utilizes a pretrained VGG16 convolutional neural network to automatically extract deep features from MRI brain images. These features represent important spatial patterns and structural information within the brain.

In addition to image features, the system processes clinical data such as patient age, education level, MMSE score, and normalized whole brain volume. These features are passed through fully connected layers to generate meaningful clinical representations. The extracted image features and clinical features are then merged using a concatenation layer to create a unified feature representation.

The combined feature vector is passed through additional neural network layers that perform classification using a softmax activation function. The model predicts the probability of different Alzheimer's disease classes.

To improve training performance, the system uses data generators for efficient batch processing, class weighting to address data imbalance, and optimization techniques such as dropout regularization and learning rate scheduling.

## 4. Literature Survey

### 1. An Alzheimer's Disease Prediction Model for Time Series Neuroimage Analysis (2020).

This research by Xin Hong, Rongjie Lin, Chenhui Yang, Chunting Cai, and Kathy Clawson focuses on predicting the progression of Alzheimer's Disease (AD) by analysing neuroimaging data collected over time. The authors emphasize the importance of capturing temporal changes in the brain, as AD is a progressive disorder where early structural and functional alterations play a key diagnostic role. By combining multiple imaging modalities, the study aims to create a more reliable model for understanding disease evolution. The proposed methodology integrates Random Forest-based feature selection with a Gated Recurrent Unit (GRU)-based Recurrent Neural Network. First, Random Forest identifies the most informative brain Regions of Interest (ROIs) from multimodal datasets, ensuring that only the most relevant features are used. These selected features are then processed using a GRU network that excels at modelling sequential data. This allows the system to learn temporal patterns across longitudinal MRI, PET, and DTI scans sourced from the ADNI dataset, improving the model's ability to forecast AD progression. The study demonstrates several advantages, including effective temporal pattern learning, integration of multimodal neuroimages, efficient feature selection, and improved prediction accuracy. However, the authors also note limitations such as limited dataset diversity, the need for more advanced temporal deep-learning models, and challenges in achieving deeper multimodal fusion. Additionally, the model's clinical applicability remains restricted due to varying patient conditions and real-world constraints. These limitations highlight the scope for future improvements in scalability, dataset expansion, and enhanced fusion methods.

## **2. Early Detection of Alzheimer's Disease with Blood Plasma Proteins Using Support Vector Machines (2021).**

This study, conducted by Chima S. Eke, Emmanuel Jammeh, Xinzhong Li, Camille Carroll, Stephen Pearson, and Emmanuel Ifeakor, focuses on identifying Alzheimer's

Disease at an early stage using non-invasive blood-based biomarkers. Instead of depending on costly imaging or amyloid-based diagnostics, the research emphasizes accessible blood plasma proteins that show measurable changes during early AD development. The aim is to provide a more practical and scalable approach to early detection, especially for large populations or routine screening. The study introduces a feature-selection framework to detect the most discriminative blood plasma proteins associated with early AD pathology. These selected proteins are then used to train a Support Vector Machine (SVM) classifier, which is optimized to distinguish Alzheimer's patients from healthy individuals. By using robust cross-validation methods, the model ensures reliable classification performance and minimizes overfitting. The dataset includes plasma samples from clinically confirmed AD patients and healthy controls, making it suitable for evaluating biomarker effectiveness in early detection. The proposed SVM approach offers several advantages, such as non-invasive diagnosis, lower cost, the ability to detect early-stage symptoms, and high predictive accuracy. However, the study also highlights limitations including small sample size, the need for larger validation cohorts, limited population diversity, and challenges in achieving broad generalizability. These limitations suggest that future work should focus on expanding datasets, incorporating multi-region cohorts, and refining biomarker selection for improved clinical translation.

## **3. Volumetric Feature-Based Alzheimer's Disease Diagnosis From sMRI Data Using CNN and DNN (2021).**

This study by Abol Basher, Byeong C. Kim, Kun Ho Lee, and Ho Yub Jung focuses on improving Alzheimer's Disease diagnosis by leveraging volumetric structural MRI (sMRI) features. The authors emphasize that examining three-dimensional brain structures provides deeper insights into neurodegeneration compared to traditional 2D imaging approaches. The main objective is to enhance

diagnostic accuracy by capturing subtle volumetric changes that occur in early and progressive stages of Alzheimer's. The proposed framework uses a Convolutional Neural Network (CNN) to automatically extract high-quality volumetric features from sMRI scans, eliminating the need for manual feature engineering. These CNN-derived features are then passed into a Deep Neural Network (DNN) classifier that separates Alzheimer's patients from healthy controls. The entire CNN–DNN architecture is trained end-to-end using the ADNI sMRI dataset, enabling the model to learn optimal representations directly from raw 3D brain scans, thus improving robustness and predictive performance. The study demonstrates notable advantages such as high diagnostic accuracy, detailed volumetric feature learning, an efficient end-to-end deep learning pipeline, and enhanced separation between AD and control groups. However, the authors also acknowledge limitations including restricted dataset size, the need for broader multi-center validation, risks of overfitting, and limited generalizability across diverse populations. These challenges highlight the importance of expanded datasets, stronger regularization techniques, and cross-population testing in future research.

#### **4. An Improved LeNet–Deep Neural Network Model for Alzheimer's Disease Classification Using MRI (2021).**

This paper, authored by Ruhul Amin Hazarika, Ajith Abraham, Debdatta Kandar, and Arnab Kumar Maji, aims to improve the accuracy of Alzheimer's Disease detection using structural MRI imaging. The study focuses on enhancing the classical LeNet architecture so it can better capture the complex spatial variations found in Alzheimer's-affected brain tissues. By refining an established deep-learning model, the authors seek to provide a more reliable and efficient solution for MRI-based AD diagnosis. The proposed system modifies the traditional LeNet architecture by incorporating improved convolutional and pooling layers that extract more discriminative spatial features from MRI

brain scans. These enhanced features are fed into deeper fully connected layers, allowing the model to make more accurate classification decisions. The entire framework is trained on MRI data from the ADNI dataset, enabling optimized feature learning directly from raw brain images and strengthening the model's diagnostic capability. The study highlights key advantages such as higher classification accuracy, efficient feature extraction, improved convolution–pooling performance, and overall optimized diagnostic output. However, the authors also point out limitations including limited dataset diversity, the need for real-world clinical validation, risks of overfitting, and restricted generalizability across broader populations. These challenges indicate the need for larger datasets, multi-center trials, and stronger regularization methods in future research.

#### **5. Disease Progression Modelling from Preclinical Alzheimer's Disease to AD Dementia (2021).**

This study by Soo Hyun Cho, Sookyoung Woo, Changsoo Kim, and Hee Jin Kim focuses on understanding how cognitive decline progresses from the earliest preclinical stages of Alzheimer's Disease to full dementia. The objective is to capture the gradual deterioration in cognition and quantify how symptoms evolve over time. By modelling these transitions, the research aims to support earlier prediction, better clinical decision-making, and improved monitoring of AD progression. The proposed methodology employs linear mixed-effects modelling, a statistical framework suited for analysing repeated measures and longitudinal clinical data. Cognitive test scores are treated as dependent variables, and the model incorporates both group-level patterns and individual-level variations through random effects. This approach allows researchers to estimate disease progression rates, identify trajectory differences among individuals, and understand how cognitive decline unfolds across multiple AD stages. The study uses repeated cognitive measurements from 436

amyloid-positive subjects obtained from the ADNI dataset. The findings highlight several advantages, including the ability to estimate long-term progression, capture individual versus group trajectories, account for longitudinal variability, and offer insights across preclinical to dementia stages. However, the study is limited by its focus on amyloid-positive subjects, reliance on the ADNI cohort, and potential lack of generalizability to broader populations. Additionally, the model depends heavily on the availability and quality of longitudinal cognitive scores, suggesting that future research should incorporate more diverse populations and multimodal biomarkers to improve prediction robustness.

## 5. System architecture

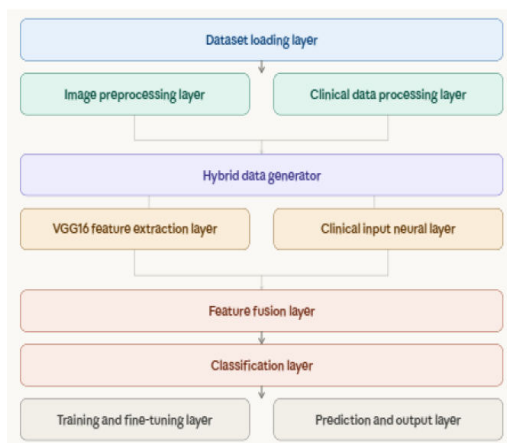


Fig.1: System architecture

## 6. Algorithms

### 1. VGG16 Transfer Learning Algorithm

The VGG16 transfer learning algorithm is the primary image feature extraction technique used in this project. VGG16 is a deep convolutional neural network originally trained on the ImageNet dataset, which contains millions of labeled natural images. Instead of training a new convolutional network from scratch, this project reuses the pretrained VGG16 architecture to extract meaningful spatial features from MRI images. This approach is called transfer learning because knowledge learned from one task is transferred

to another related task. In the training notebook, VGG16 is loaded with pretrained weights and configured with `include_top=False`. This removes the original fully connected classification layers because the project has its own classification task. The input shape is fixed at  $224 \times 224 \times 3$ , which is why all MRI images are resized to that dimension. Initially, all VGG16 layers are frozen, meaning their weights are not updated during the first training stage. This allows the network to retain strong low-level and mid-level visual feature representations such as edges, textures, and structures that may still be relevant in medical imaging. After the convolutional output is obtained, the feature map is flattened and passed through additional dense layers and dropout. These layers convert raw visual features into a more task-specific representation suitable for hybrid fusion. The major advantage of using VGG16 is that it reduces computational burden and improves learning efficiency, especially when the available medical dataset is not extremely large. Instead of spending time learning basic visual patterns, the model focuses on adapting high-level representations for the target classification task.

### 2. Hybrid Feature Fusion Neural Network Algorithm

The hybrid feature fusion neural network algorithm is the core classification algorithm of the project. Its purpose is to combine two fundamentally different types of input data: MRI image features and patient clinical features. In medical prediction systems, relying only on image data may overlook important contextual information, while relying only on clinical values may miss subtle structural abnormalities visible in scans. This algorithm solves that limitation by integrating both sources into one predictive model. The first part of the algorithm processes image data using the VGG16 feature extractor. The second part processes four numerical clinical inputs: age, education, MMSE score, and nWBV. These clinical values are passed through a separate neural branch consisting of dense layers with

ReLU activation and dropout. This enables the model to learn nonlinear relationships between the tabular clinical data and the target classes. Because the two input types are different in structure, they are processed independently at first. After both branches produce their feature vectors, the algorithm merges them using a concatenation operation. This step is called feature fusion. The result is a single combined representation that contains both visual evidence from MRI scans and statistical evidence from clinical parameters. This fused vector is then passed through additional dense layers so the network can learn interactions between the two modalities. Finally, a softmax output layer predicts one of four classes. This hybrid strategy is important because many medical conditions cannot be accurately identified from only one kind of input. For example, two MRI scans may look similar, but patient age or cognitive scores may provide additional discriminative power. By learning both modalities together, the model can make more informed predictions. The use of dropout layers further improves generalization by reducing overfitting.

### 3. Batch-Wise Data Generation Algorithm

The batch-wise data generation algorithm is implemented through the custom `HybridDataGenerator` class. This algorithm is designed to prepare and supply training data efficiently to the hybrid model. In deep learning systems, especially those using large image datasets, loading all data into memory at once can be inefficient or even impossible. This algorithm overcomes that limitation by loading small batches of data dynamically during training. The generator inherits from `Keras Sequence`, which provides a standard and safe way to feed data into TensorFlow models. The algorithm starts by storing the input `DataFrame` and initializing indices. During each batch request, it selects a set of rows corresponding to the current batch. For every row in the batch, it reads the MRI image from its file path using `OpenCV`, resizes it to the required input size, and normalizes the pixel intensities. At the

same time, it extracts the clinical variables from the same row and stores them in a separate array. The label information is also collected.

### Dataset Description

The dataset used in this project consists of MRI brain images and corresponding clinical information used for Alzheimer's disease classification. MRI images provide structural information about the brain, allowing the model to identify patterns associated with cognitive decline and neurodegeneration. In addition to imaging data, clinical attributes such as patient age, education level, MMSE score, and normalized whole brain volume are included to enhance prediction performance. The MRI images are organized into different categories representing stages of Alzheimer's disease progression. These stages include Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Each class represents a different level of neurological degeneration observed in the brain. By training the model on these categories, the system learns to distinguish subtle differences in brain structure. To ensure consistent model input, all MRI images are resized to a fixed dimension of  $224 \times 224$  pixels. Pixel values are normalized to maintain stable numerical ranges during training. The dataset is divided into training, validation, and testing sets so that the model can learn patterns while also being evaluated on unseen data. This separation helps prevent overfitting and ensures reliable performance measurement.

## 7. IMPLEMENTATION AND RESULTS

The implementation of this project is based on a hybrid deep learning model that combines MRI image analysis with clinical parameters for accurate multi-class prediction. Two notebooks are used in the workflow: one for training the model and another for making predictions on new samples. The training notebook begins with importing essential libraries such as NumPy, Pandas, TensorFlow, OpenCV, and scikit-learn utilities. The dataset

is loaded from three CSV files representing training, validation, and testing sets.

These files contain image paths, encoded labels, and clinical attributes including age, education, MMSE score, and nWBV. A custom HybridDataGenerator class is implemented using the Keras Sequence API. This generator reads MRI images from file paths, resizes them to 224×224, normalizes pixel values, and collects corresponding clinical data and labels in batches. This approach makes the training process memory efficient and suitable for large datasets. For image feature extraction, the system uses the pretrained VGG16 model without the top classification layer. All initial layers are frozen so that the pretrained knowledge can be reused effectively. Alongside the image branch, a separate dense neural branch is designed for processing four clinical features. Both image and clinical representations are merged using a concatenation layer.

The fused feature vector is then passed through fully connected layers with dropout for classification into four output classes using softmax activation. The model is compiled with the Adam optimizer and categorical cross-entropy loss. To improve training performance, class weights are calculated to handle class imbalance. Callback mechanisms such as model checkpointing, early stopping, and adaptive learning rate scheduling are also used. After the initial training, fine-tuning is performed by unfreezing a few deeper VGG16 layers. Finally, the trained model is evaluated on the test dataset and saved. In the prediction notebook, the saved model, scaler, and label encoder are loaded, a new MRI image is selected, clinical values are entered manually, preprocessing is performed, and the final predicted class with confidence is displayed.

### **1. Data Loading and Dataset Management Module**

This module is responsible for reading and organizing the dataset used during training and validation. In the uploaded training notebook, the system reads three CSV files:

train\_ready.csv, val\_ready.csv, and test\_ready.csv. These files serve as the structured source of information for the model. Each dataset contains image file paths, label information, and associated clinical values. This design is effective because it separates the raw images from the metadata while still allowing both to be linked during execution. The main objective of this module is to provide clean, accessible, and well-partitioned data for the rest of the system. Training, validation, and testing data are handled separately, which is important for reliable model development. The training set is used to optimize model parameters, the validation set is used to monitor model performance during training, and the testing set is used for final evaluation.

This separation reduces the risk of overfitting and improves the trustworthiness of the reported performance. Another important function of this module is to ensure compatibility between the tabular and image-based inputs. Since the project uses a hybrid architecture, every MRI image must be correctly paired with the corresponding clinical values and encoded label. This module provides that structured relationship. The use of Pandas makes loading and manipulating the CSV files simple and efficient, while the printed shapes of the datasets help verify that the data has been loaded properly. Overall, this module acts as the foundation of the entire hybrid system. Without properly organized input data, the model cannot learn meaningful patterns. By managing dataset reading, data partitions, and feature-label consistency, this module supports accurate training, validation, and testing throughout the project lifecycle.

### **2. Image Pre-processing and Hybrid Data Generator Module**

This module performs one of the most important roles in the system because it handles both image preprocessing and batch generation. The project uses a custom class named HybridDataGenerator, which inherits from the Keras Sequence class. This is a highly suitable choice for machine learning projects involving large datasets because it enables batch-wise

data loading instead of loading everything into memory at once. Inside this module, MRI images are read using OpenCV from the file paths stored in the CSV dataset. Each image is resized to  $224 \times 224$ , which matches the required input size of the VGG16 architecture. After resizing, the images are converted into floating-point values and normalized by dividing by 255.0. This normalization ensures that pixel values fall within a stable numerical range, helping the neural network learn more effectively. In addition to image preprocessing, this module also extracts the clinical features for every sample. These include age, education, MMSE score, and nWBV. These values are collected into numerical arrays and paired with the corresponding MRI images. Labels are also gathered and returned along with the inputs. As a result, every batch produced by the generator contains two input branches: image data and clinical data, plus the associated target labels.

### 3. Data Preprocessing

Data preprocessing is an essential step in preparing both MRI images and clinical data for training the hybrid deep learning model. Since medical datasets often contain variations in image size, quality, and data distribution, preprocessing helps ensure that the model receives consistent and meaningful inputs. The preprocessing process begins with reading MRI images from the dataset directory using the stored file paths in the CSV dataset. Each image is resized to  $224 \times 224$  pixels so that it matches the input requirement of the convolutional neural network. After resizing, the pixel values are converted into floating-point format and normalized by dividing by 255. This normalization process ensures that pixel values lie within a stable range between 0 and 1. In addition to image preprocessing, the clinical features associated with each MRI scan are also prepared. These features include age, education years, MMSE score, and normalized whole brain volume (nWBV). Since these features are numerical values with different scales, a standard scaling technique is applied to

normalize their distribution. The scaler is fitted using the training dataset and then applied to validation and testing datasets to maintain consistency.

### 4. Hybrid Model Building Module

This module defines the core intelligence of the system. It constructs a hybrid neural architecture that learns from two different types of data simultaneously: MRI images and clinical information. Such a design is especially powerful in healthcare prediction tasks because it combines visual patterns from medical images with supporting patient-related numerical features.

The image branch of the model is built using the pretrained VGG16 convolutional neural network. In the notebook, VGG16 is loaded with ImageNet weights, excluding its top classification layer. This means the model is not used directly for final prediction but instead as a feature extractor. By freezing the initial VGG16 layers, the system retains previously learned visual representations, reducing training time and making the model more effective even with limited domain-specific data. The extracted image features are then flattened and passed through dense and dropout layers to create a compact high-level representation.

The second branch processes clinical input. A separate Input layer is defined for four numerical features. These values are passed through dense layers with ReLU activation and dropout regularization. This allows the model to learn meaningful clinical patterns independently from the image data. After both branches have generated their respective feature vectors, they are merged using a concatenation layer.

### 5. Training, Fine-Tuning, and Prediction Module

This module manages the complete learning and inference lifecycle of the project. After the hybrid model is defined, it is compiled using the Adam optimizer, categorical cross-entropy loss, and accuracy as the evaluation metric. This configuration is suitable for multi-class



## 8. CONCLUSION And Future Scope

This project successfully demonstrates the design and implementation of a hybrid deep learning system that combines MRI image analysis with clinical parameters for multi-class prediction. Unlike conventional single-input systems, the proposed approach makes use of both visual and numerical patient information, allowing the model to learn richer and more meaningful patterns. The implementation shows that a pretrained VGG16 network can be effectively used as an image feature extractor, while a parallel dense branch can process clinical inputs such as age, education, MMSE score, and nWBV. By merging these two branches through feature concatenation, the system is able to build a unified representation that supports better classification performance. The use of custom data generators, class balancing, callback-driven optimization, and fine-tuning further strengthens the reliability of the training process. From a software perspective, the project is organized clearly into training and prediction stages, making it easy to understand, maintain, and demonstrate. The training notebook handles data preparation, hybrid architecture creation, optimization, evaluation, and model saving, while the prediction notebook provides a user-oriented interface for selecting an MRI image, entering clinical values, and receiving the final predicted class with confidence. This indicates that the project is not only academically relevant but also practically usable as a prototype decision-support tool in intelligent healthcare analytics. In conclusion, the hybrid prediction system developed in this project provides a strong example of how multimodal deep learning can improve medical classification tasks. The integration of MRI imaging and clinical data makes the model more informative than image-only methods and more robust than purely tabular models. The project also highlights the value of transfer learning, efficient batch-wise data handling, and modular deep learning design. Through systematic training, testing, and evaluation, the system proves that hybrid architectures can be built effectively even

within a notebook-based environment. The prediction module further adds practical value by allowing real-time inference using saved artifacts such as the trained model, scaler, and label encoder. Although the project can still be extended in the future with a web interface, better explainability, or broader dataset coverage, the current implementation already achieves its primary objective of building a multimodal predictive framework. It demonstrates sound system design, clear implementation logic, and reliable end-to-end workflow execution. Therefore, this project can be considered a meaningful contribution in the area of intelligent medical image analysis, especially for applications where combining imaging evidence with patient clinical information is necessary for improved diagnostic support and classification accuracy.

### Future Scope

Although the proposed hybrid deep learning system demonstrates promising results for Alzheimer's disease classification, several improvements can be explored in future work. One potential enhancement is the use of larger and more diverse medical datasets that include MRI scans from multiple hospitals or research centers. This would help improve model generalization and robustness.

Another possible extension is the integration of additional medical data such as genetic information, PET scans, or longitudinal patient records. Combining multiple medical data sources could provide deeper insights into disease progression and improve prediction accuracy.

Future work could also involve implementing explainable artificial intelligence techniques to visualize the brain regions that influence the model's predictions. This would increase trust and interpretability in clinical environments. Additionally, the hybrid model could be deployed as a web-based medical decision-support system, allowing healthcare professionals to upload MRI scans and receive predictions in real time.

## 9. References

1. Xin Hong, Rongjie Lin, and Chenhui Yang. ADPM: An Alzheimer's Disease Prediction Model for Time Series Neuroimage Analysis. *IEEE Access*. 2020. Article No. 2979969. pp. 62601–62609[1].
2. Chima S. Eke, Emmanuel Jammeh, Xinzhong Li. Early Detection of Alzheimer's Disease with Blood Plasma Proteins Using Support Vector Machines. *IEEE*. 2021. Article Number: 10.1109/JBHI.2020.2984355. Pages: 218-226
3. Abol Basher, Byeong C. Kim, Kun Ho Lee. Volumetric Feature-Based Alzheimer's Disease Diagnosis From sMRI Data Using a Convolutional Neural Network and a Deep Neural Network. *IEEE Access*. 2021. Article number: 3059658, pages 29870–29882
4. Ruhul Amin Hazarika, Ajith Abraham, Debdatta Kandar, Arnab Kumar Maji. An Improved LeNet-Deep Neural Network Model for Alzheimer's Disease Classification Using Brain Magnetic Resonance Images. *IEEE Access*. 2021. Article #3131741. pp. 161194-161207
5. Cho, Soo Hyun; Woo, Sookyoung; Kim, Changsoo. Disease progression modelling from preclinical Alzheimer's disease (AD) to AD dementia. *Scientific Reports*. 2021. 11:4168. 1-10.
6. Kavitha C, Mani V, Srividhya SR. Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models. *Frontiers in Public Health*. 2022. Article 853294. pp. 1–13
7. Zhang, Zi-Chao, Xingzhong Zhao, Guiying Dong. Improving Alzheimer's Disease Diagnosis With Multi-Modal PET Embedding Features by a 3D Multi-Task MLP-Mixer Neural Network. *IEEE Journal of Biomedical and Health Informatics*. 2023. Article number: 3280823. Pages: 4040–4050.
7. Shukla, G. P., Kumar, S., & Pandey, S. K. Diagnosis and Detection of Alzheimer's Disease Using Learning Algorithm. *Big Data Mining and Analytics*, 2023, Vol. 6, No. 4, Article 09/10, pp. 504–512.
8. Mitra, Uddalak, Rehman, Shafiq Ul. ML-Powered Handwriting Analysis for Early Detection of Alzheimer's Disease. *IEEE Access*. 2024. Article number 69031, pp. 1-20.
9. Rehman, A., Yi, M.-K., Majeed, A. Early Diagnosis of Alzheimer's Disease Using 18F-FDG PET With Soften Latent Representation *IEEE Access*, 2024, Article 3418508, pp. 87923–87933.
- 10 Mahanty, Chandrakanta, Rajesh, T., Govil, Nikhil. Effective Alzheimer's disease detection using enhanced Xception blending with snapshot ensemble. *Scientific Reports*. 2024. Article number 29263, pp. 1-17.
11. Chen L., Zhang H., Liu X. Enhancing Alzheimer's Disease Prediction with Multimodal Deep Learning. *IEEE Transactions on Medical Imaging*, 2023. Vol. 15, No. 4, pp. 235-244.
- 12 Ibrahim M.E., Wazery Y.M., Mohamed E.A. Early-Stage Prediction of Alzheimer's Disease via Machine Learning Models. *Journal of Information Systems Engineering and Management*, 2025; 10(14s): e-ISSN 2468-4376, Article e-ISSN: 2468-4376, pp. 523-534.
13. Gallego-Viñarás, L., Mira-Tomás, J. M., Gaeta, A. M. Alzheimer's Disease Detection in EEG Sleep Signals. *IEEE Journal of Biomedical and Health Informatics*, 2025, Vol. 29, No. 2, Article number 3478380, pp. 948-959.