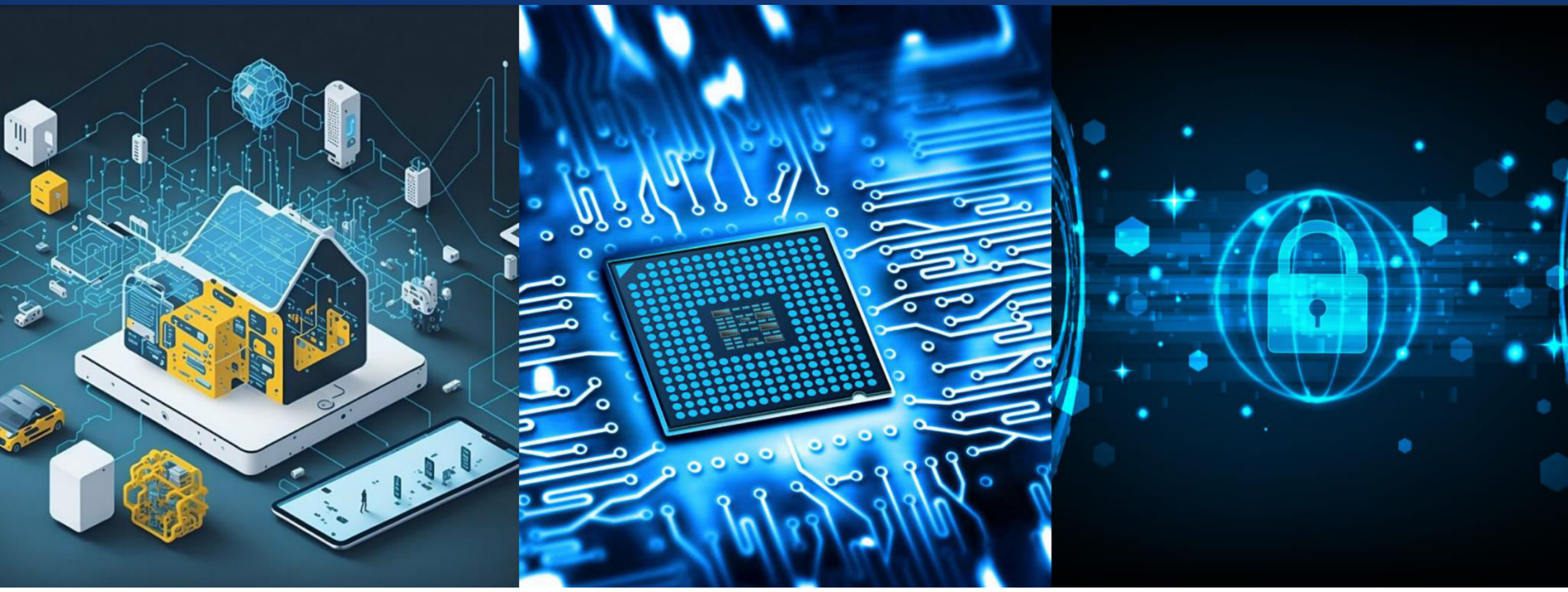
ISSN(O): 2320-9801
ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

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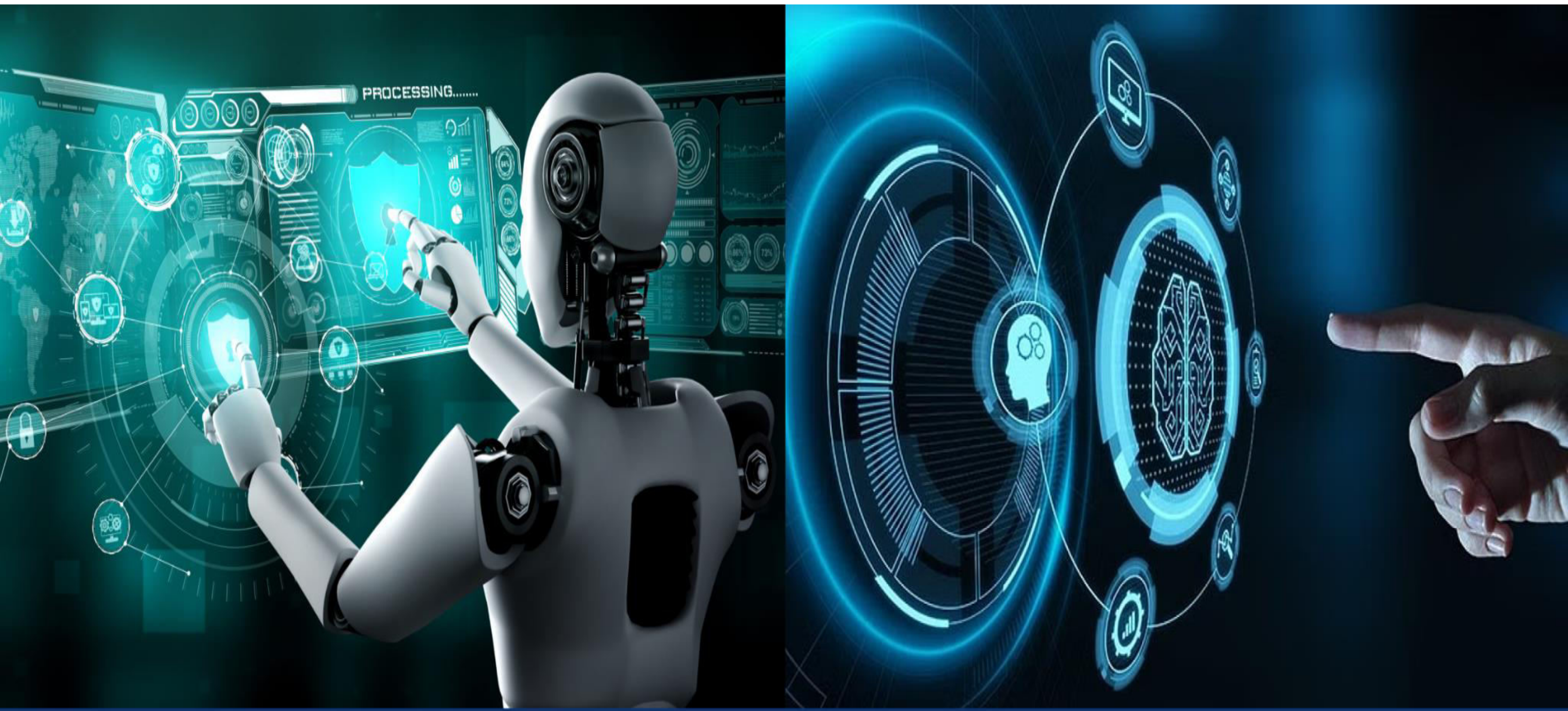

Impact Factor: 9.927

Volume 14, Issue 6, June 2026

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© 2026 IJIRCCE | Volume 14, Issue 6, June 2026 DOI: 10.15680/IJIRCCE.2026.1406015

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Deep Learning-Based Initial Screening and Prompt Detection of Alzheimer's Disease using MRI Brain Scans

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ABSTRACT: Alzheimer's disease is a degenerative disease of brain and the predominant contributor of dementia worldwide. Prior and accurate diagnosis is essential to improving patient outcomes, yet conventional diagnostic approaches often fall short in detecting subtle early-stage changes. This paper portrays a CNN-based deep multilayer learning mechanism for the automated incipient identification and categorization of Alzheimer disease from MRI brain scans. The proposed approach incorporates image refinement, automatic feature acquisition, transfer learning, and Grad-CAM visualization to segregate brain MRI images into Alzheimer's-affected and healthy categories. Experimental evaluation on the Alzheimer's disease neuroimaging Initiative (ADNI) dataset demonstrates strong classification accuracy, sensitivity, specificity, and AUC-ROC performance.

The observed outcomes suggest that the developed framework offers a reliable, interpretable, and clinically applicable tool for supporting early Alzheimer's disease diagnosis. The paper aims to reduce the dependency on manual diagnosis by offering a smart, sophisticated and intelligent decision-support solution for Alzheimer's disease prediction The platform employs multilayer learning algorithms, mainly convolutional artificial neural networks, for automatic extraction of discriminative features from the dataset without relying heavily on manual analysis. The framework includes distinct phases, including data cleaning, preprocessing, feature learning, model training, and performance testing. In addition, optimization strategies are implemented to boost the steadiness of the model and reduce over fitting issues during training.

KEYWORDS: Alzheimer disease, convolutional Neural Networks, Deep multilayer learning, MRI Classification, Transfer Learning, Grad-CAM, Early Detection, Neuroimaging.

I. INTRODUCTION

Alzheimer's disease is a chronic, brain related neurodegenerative disorder distinguished by irreversible deterioration of memory, cognitive function, language, and behavioral capacity [1]. This description refers to Alzheimer's disease, which is dominant contributor of dementia universally, liable for approximately **60–80%** of all dementia cases. As reported by World Health Organization and the Alzheimer's Association, the global prevalence of Alzheimer is expected to surpass 150 million cases by 2050 as populations continue to age [2]. The economic, emotional, and social burden imposed by AD on patients, caregivers, and healthcare systems is substantial and continues to intensify with rising case numbers.

Despite decades of intensive research, no curative treatment for Alzheimer's disease currently exists. Available and present pharmacological interventions provide only symptomatic management and modest disease-slowing effects. The clinical consensus, however, is clear: earlier diagnosis is strongly correlated with better therapeutic outcomes, improved quality of life, and more effective resource allocation [3]. This makes early and accurate detection a priority in both clinical and research domains.

The pathological hallmarks of AD include extracellular amyloid-beta (Aβ) plaques and intraneuronal neurofibrillary tangles composed of hyperphosphorylated tau protein. These changes begin years to decades before clinical symptoms appear, during which the brain experiences progressive structural and metabolic alterations that can be detected through neuroimaging. [4]. Structural MRI is widely used in clinical practice to identify cerebral atrophy, hippocampal volume loss, and other anatomical and morphological variations associated with AD progression.

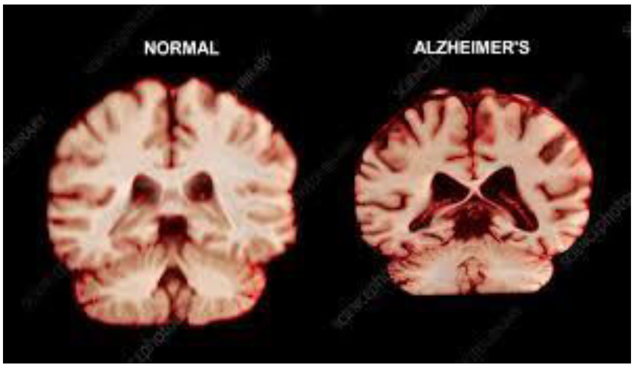

Fig 1: Difference between normal brain image and affected brain image

Traditional diagnostic pipelines depend on clinical assessments, cognitive screening batteries, cerebrospinal fluid (CSF) biomarker analysis, and neuroimaging interpreted by trained radiologists. While these approaches provide meaningful diagnostic information, they are resource-intensive, time-consuming, and subject to inter-rater variability. Furthermore, detecting early-stage or MCI, The phase considered a transition between normal aging and Alzheimer’s disease presents significant challenges for experts because the structural brain changes are minimal and less obvious at this point.

The origination of deep multilayer learning, particularly CNNs, has opened new possibilities in radiological image interpretation. CNN-based models have demonstrated state-of-the-art performance in pattern recognition tasks involving complex, high-dimensional data such as brain MRI volumes [5]. Deep multilayer neural networks vary from conventional machine learning methods that depend on manually crafted features. Instead, they derive patterns directly from raw images step by step, enabling them to detect very subtle variations that are often hard for humans to notice.

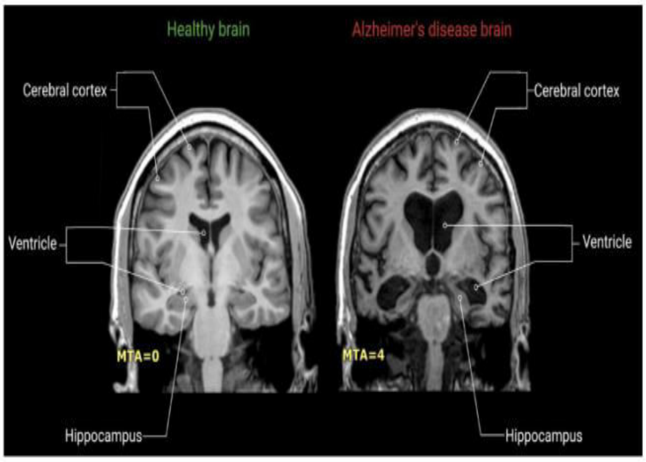

Fig 2: Skull stripping

This paper proposes a CNN-based framework for automated early detection and multi-class classification of Alzheimer's disease using structural MRI data. The system incorporates preprocessing, data augmentation, transfer learning using established architectures, Grad-CAM-based interpretability, and comprehensive performance evaluation.

The primary key role of this work are:

- A robust preprocessing and data preparation pipeline for brain MRI classification.
- A transfer learning-based CNN model fine-tuned for AD detection with high classification accuracy.
- Integration of Grad-CAM saliency visualization for transparent and interpretable predictions.
- Evaluation across multiple performance metrics demonstrating clinical relevance.

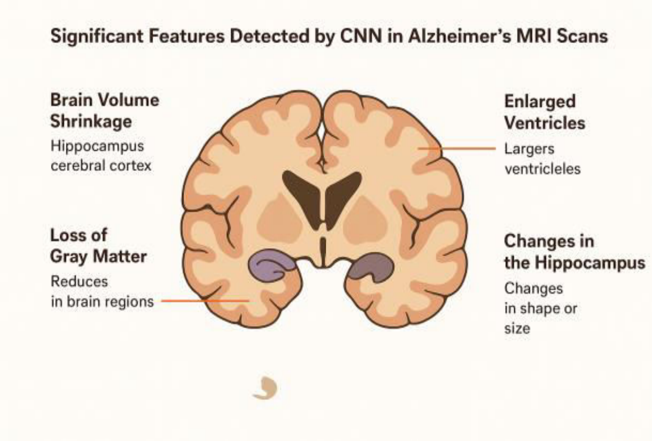

Fig 3: Features detected by CNN

II. RELATED WORK

Nowadays, emphasis has been directed toward the advantages of machine learning and deep multilayer learning approaches for Alzheimer's disease diagnosis. Initial studies primarily relied on hand-engineered features extracted from MRI-based biomarkers, which were then analyzed using standard machine learning methods such as SVMs and Random Forests.

In medical and clinical imaging and artificial intelligence, the forecasting and detection of Alzheimer's disease have become increasingly important. To enhance the reliability and effectiveness of early diagnosis, numerous studies have investigated the utilize of machine learning and deep learning approaches. Conventional diagnostic techniques were largely based on clinical evaluations and cognitive tests; nonetheless, these paradigms frequently demand specialized expert interpretation and may not consistently identify the disease at its early stages. As a result, recent works have transitioned toward automated solutions based on computational intelligence and medical imaging to overcome these limitations.

Earlier research has take the help of machine learning techniques such as Decision Trees, helpful in Vector Machines, Random Forests, and K-Nearest Neighbors (KNN) for classifying Alzheimer's disease. These approaches depended on handcrafted features extracted from MRI copies and clinical data to separate healthy individuals from those affected by Alzheimer's disease. While they produced satisfactory accuracy, their effectiveness was strongly tied to manual feature engineering and preprocessing quality.

To mitigate these challenges, recent surveys have combined deep multilayer learning with transfer learning, especially in cases where only limited medical data is available. Pre-trained architectures like VGGNet, ResNet, and AlexNet have been fine-tuned for Alzheimer's disease classification, leading to improved performance and greater computational efficiency. Moreover, hybrid architectures that fuse Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) or optimization-based methods have also been explored to enhance feature learning and improve disease stage prediction.

Moreover recent studies incorporated patient clinical information, demographic details, and cognitive test scores to improve diagnostic reliability. Multi-modal approaches that combine MRI scanning of the clinical data have displayed better performance than single-data-source models. These systems help in identifying Alzheimer's disease at earlier stages and support clinical professionals in making informed and appropriate decisions.

Despite significant progress in this field, challenges such as limited dataset availability, overfitting, high computational requirements, and variability in biomedical imaging data still affect the functioning of prediction systems. Hence, there is requirement for more efficient and reliable deep multilayer learning models capable of providing accurate early-stage diagnosis with reduced complexity. The proposed methodology aims to address these challenges by building a well structured and robust deep learning-Based Alzheimer disease prediction system that improves classification performance and supports computer-aided medical diagnosis.

III. METHODOLOGY

The proposed Deep Learning-Based Alzheimer's Disease Prediction System is designed to identify and classify Alzheimer's disease at different stages using medical imaging and clinical data. The methodology consists of several important phases, including data gathering, pre-processing, feature Enhancement, model development, classification, and performance evaluation. The overall flow of the system work is shown through a structured approach to support accurate and reliable prediction results.

A. Dataset

The Alzheimer's Disease Initiative (ADNI) public dataset is leveraged in this study. ADNI is a longitudinal, multi-site research initiative that has collected MRI, PET, clinical, genetic, and biomarker data from participants classified as cognitively normal (CN), mild cognitive impairment (MCI), or Alzheimer's disease (AD).

For this work, T1-weighted structural MRI volumes are utilized. The data set is classified into three classification categories:

- **Cognitively Normal (CN):** 400 subjects
- **Mild Cognitive Impairment (MCI):** 380 subjects
- **Alzheimer's Disease (AD):** 350 subjects

The data set is partitioned into 80% for training, 10% for validation, and 10% testing sub-sets to maintain the class balance across overall splits using stratified sampling.

IV. PROPOSED SYSTEM

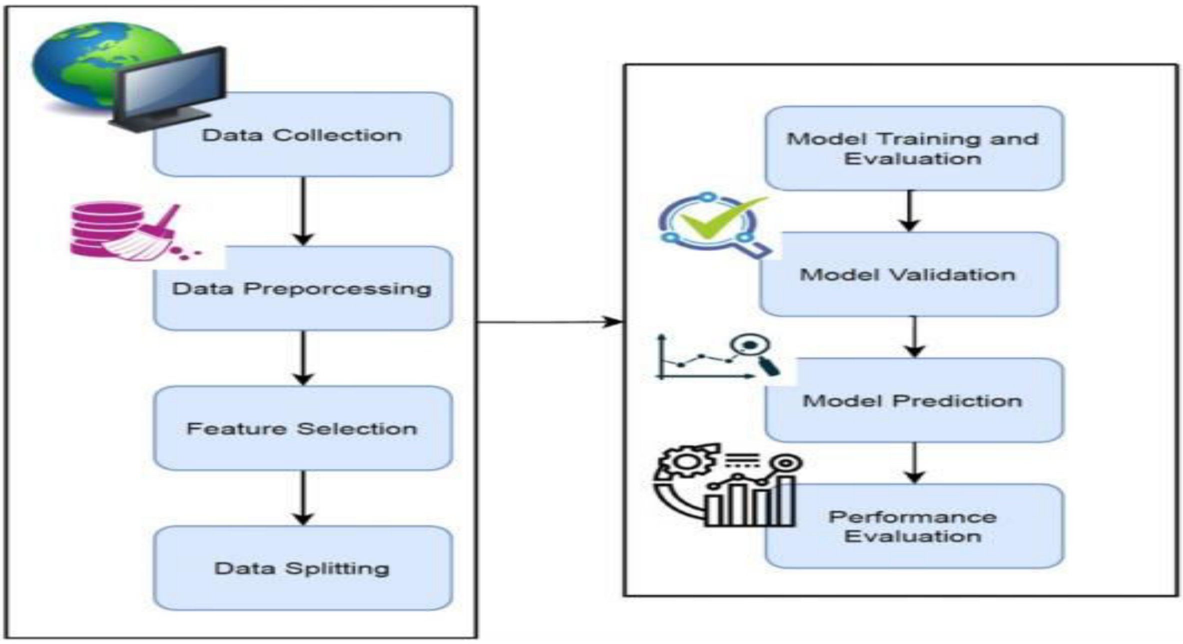

Fig. 4: Proposed System Flow

a. Data Collection

The initial stage of the proposed system focuses on acquiring datasets associated with Alzheimer's disease. The data includes brain imaging records, particularly Magnetic Resonance Imaging (MRI) scans, along with some relative clinical details of patients. These data items comprise the images from both cognitively healthy individuals and patients across different stages of Alzheimer's disease. For model development and evaluation, the collected data is further partitioned into training and testing subsets.

b. Data Preprocessing

Medical image preprocessing is an essential step to improve data quality and enhance model performance. In this phase, unwanted noise and inconsistencies present in MRI copies are implemented using some image Improvisation techniques to improve their quality. All images are resized to a consistent dimension to ensure uniformity across the dataset. In addition, normalization is applied to adjust pixel intensity numbers, which helps stabilize and improve the training process. To further enhance the dataset and lower the risk of over fitting, data augmentation approaches like rotation, flipping, and zooming are performed, increasing the variability of the example samples.

c. Feature Extraction Using CNN

The given system employs convolutional-neural networks (CNNs) to perform automated feature extraction from MRI scans. CNNs are particularly effective in learning spatial structures and extracting relevant patterns linked to Alzheimer's disease. Within the network, convolutional layers capture both basic and complex image features, whereas pooling layers perform feature map down sampling and computational complexity. Activation functions such as ReLU introduce non-linearity, allowing the model to acquire knowledge from more complex relationships. The extracted feature representations are passed to fully connected layers, where the final classification is performed.

d. Model Training and Classification

After Attribute retrieval , the deep multilayer learning model is optimized using labeled MRI datasets. The dataset is derived into multiple classes such as healthy, mild Alzheimer, moderate Alzheimer, and severe Alzheimer. In course of training, the model learns patterns associated with each disease stage by minimizing classification error using optimization algorithms such as Adam optimizer. A softmax classifier is applied in the output layer to predict the most likely of each class. The training process is kept on repeating over so many epochs until the model achieves optimal performance.

e. Performance Evaluation

The Importance of the developed system is assessed with a help of so many performance indicators, including correctness, precision, recall, sensitivity, specificity, and F1-score. In addition, a confusion matrix is employed to examine classification outcomes and better understand prediction errors. The trained model is further validated on unseen test data to evaluate its ability to generalize and its reliability in practical medical diagnosis settings.

f. Proposed System Workflow

The complete flow of the proposed Alzheimer's disease prediction system can be given as follows:

1. Collection of MRI and clinical datasets
2. Data preprocessing and normalization
3. Feature extraction using CNN
4. Deep learning model training
5. Disease stage classification
6. Performance evaluation and prediction output

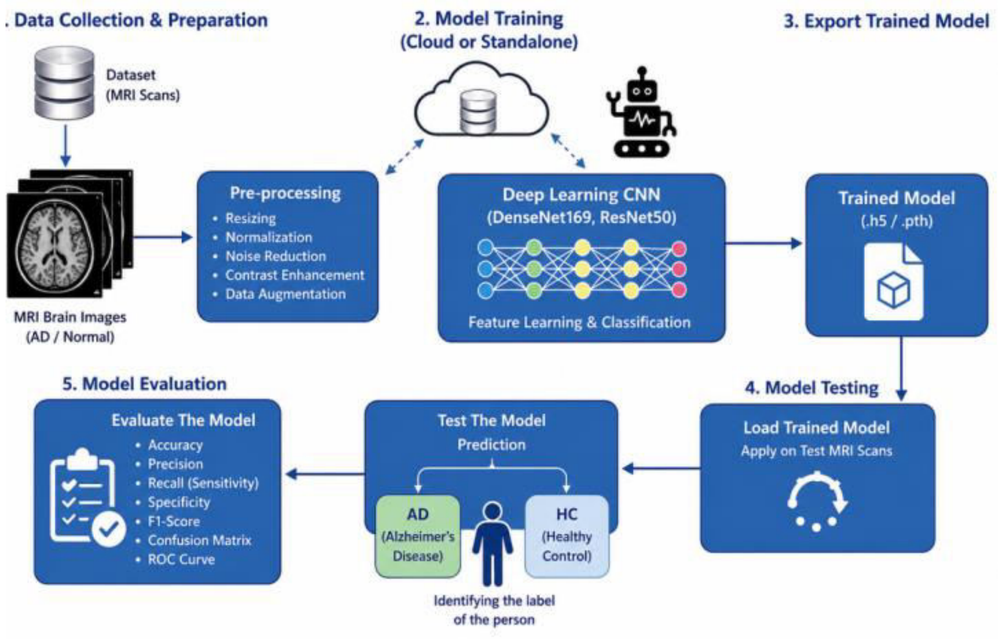

Fig. 5: Proposed System architecture

The developed methodology focuses on enhancing the prior detection of Alzheimer's disease by integrating deep multilayer learning approaches with medical image analysis. The system delivers precise and efficient automated predictions, serving as a valuable decision-support tool for healthcare practitioners.

1. Use case diagram

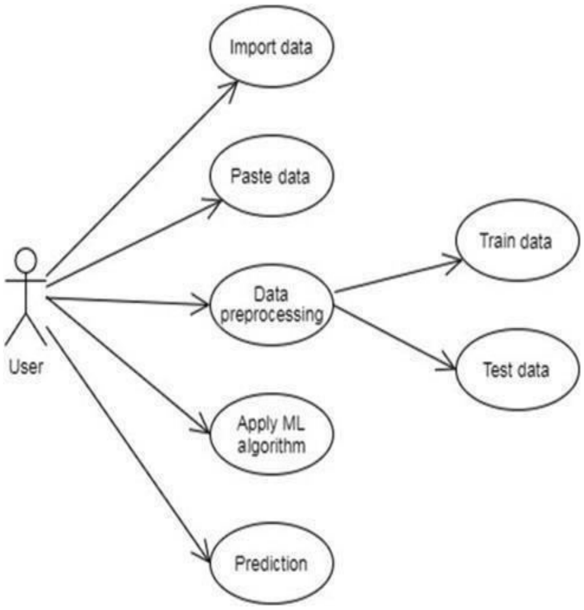

Fig 6: Use Case Diagram

UML helps ensure clarity, consistency, and better understanding of intricate system functionalities by providing structured visual representations of system interactions and behavior. It also supports collaboration among developers, researchers, and healthcare professionals in designing effective solutions for AD diagnosis, patient monitoring, and treatment support.

2. Flow diagram

The flow-diagram of the AD detection and classification illustrates the complete workflow. The flow diagram represents all major stages involved in MRI image processing, feature extraction, disease detection, and classification. In the prime stage, the system performs Alzheimer's disease detection by analyzing MRI brain images using preprocessing and DL techniques to identify abnormal patterns of brain associated with the disease. In the second stage, severity of AD is further classified into shown stages using CNN along with sophisticated approaches for analyzing features.

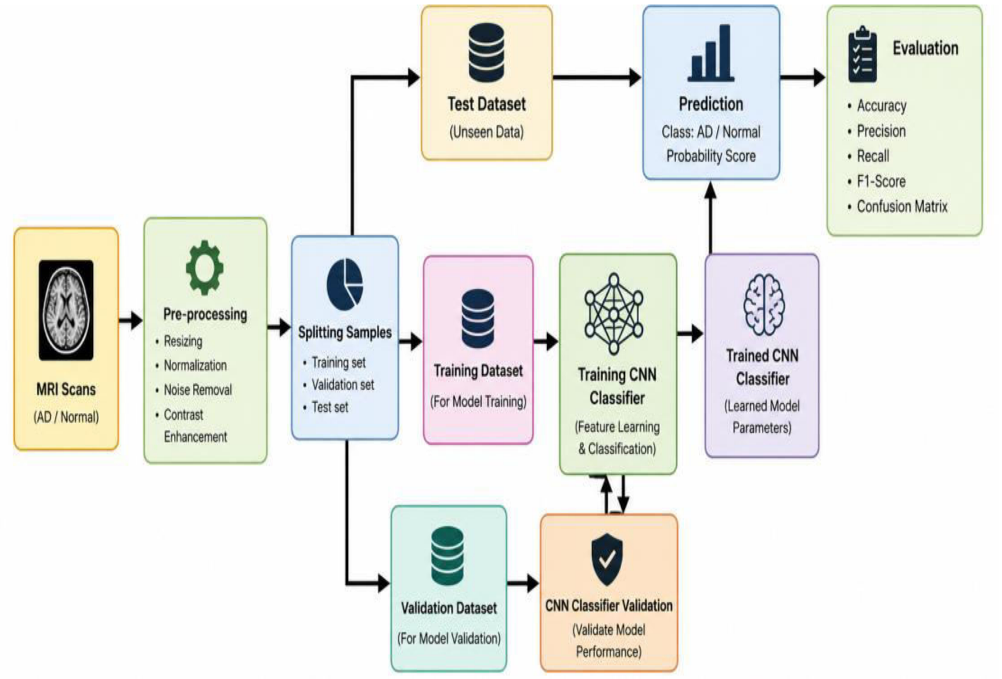

Fig.7: Flow diagram

V. RESULTS

The results from the proposed Alzheimer's disease Detection System show that the developed deep learning framework is effective and reliable for identifying Alzheimer's disease from MRI brain images. After going through proper training, testing, and validation, The model demonstrated high predictive performance, highlighting the efficacy of deep multilayer learning techniques for the early detection and classification of Alzheimer's disease.

The framework built to clearly separate MRI scans of Alzheimer's-affected patients from normal brain images with high accuracy. Through transfer learning and fine-tuning of pre-trained CNN models, the system learned meaningful features from the images. This helped improve classification accuracy and made the overall detection process more efficient. Another important instance was that the model performed well in distinguishing subtle differences between early-stage Alzheimer's cases and normal brain scans.The systems ability to find these subtle changes highlights its potential as a supportive diagnostic tool.

In addition, the approach uses visualization techniques such as Grad-CAM heatmaps to make the model's predictions easier to understand. These heatmaps highlight the key regions in MRI scans that influenced the model's decision, showing where Alzheimer's-related changes are likely present. This improves interpretability and provides clearer insight into how the CNN model arrives at its results.

A. Quantitative Performance

Table I summarizes the categorization performance of the given model on the held-out test set, compared against baseline methods.

Table I: Performance Comparison of Classification Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
SVM (HOG Features)	74.3	73.1	72.8	72.9	0.81
Random Forest	77.6	76.4	75.9	76.1	0.84
Basic CNN (from scratch)	81.2	80.5	79.8	80.1	0.88
VGG-16 (Transfer Learning)	86.4	85.7	85.2	85.4	0.92
Proposed ResNet-50 (Fine-tuned)	**91.7**	**90.8**	**90.3**	**90.5**	**0.96**

Class-specific performance metrics on the three-way classification task are presented in Table II.

Table II: Per-Class Classification Results (Proposed Model)

Class	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
CN (Normal)	93.2	92.8	93.0	95.4
MCI	88.1	87.4	87.7	91.6
AD	91.2	90.7	90.9	94.1
Weighted Average	**90.8**	**90.3**	**90.5**	**93.7**

The confusion matrix illustrates prediction distributions across the 3 classes. The model demonstrates highest confidence for CN and AD classifications, with MCI showing slightly more inter-class confusion, consistent with its clinical ambiguity as an intermediate state.

B. Validation and Training Curves

The training and validation accuracy and loss curves has over 50 epochs. The model converges steadily without significant overfitting, demonstrating that the dropout regularization, data augmentation, and early stopping strategy together provide effective generalization. Training accuracy stabilizes near 93.5%, while validation accuracy converges to 91.7%.

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www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

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C. AUC-ROC Analysis

The proposed model achieves an AUC of 0.96 on the test set, substantially outperforming SVM (0.81) and basic CNN (0.88) baselines. The high AUC value indicates strong discriminative ability across varying classification thresholds, which is critically important in a clinical screening context where sensitivity-specificity tradeoffs must be carefully managed.

D. Grad-CAM Visualization Results

Grad-CAM heatmaps superimposed on axial MRI slices for all three classes. For AD cases, the model's attention is concentrated in the hippocampal and temporal regions — anatomically consistent with known atrophy patterns in Alzheimer's pathology. CN predictions show diffuse, low-intensity activation with no focal concentration in disease-relevant areas. MCI activations demonstrate an intermediate pattern, with partial hippocampal involvement, reflecting the transitional nature of the condition.

This anatomical alignment between model attention and clinically established pathology regions provides strong evidence of the model's biological validity and supports its interpretability for clinical use.

E. Statistical Significance

A McNemar's test comparing the proposed ResNet-50 model against the SVM baseline yields a p-value of 0.003 (< 0.05), confirming that the performance improvement is statistically significant and not attributable to chance.

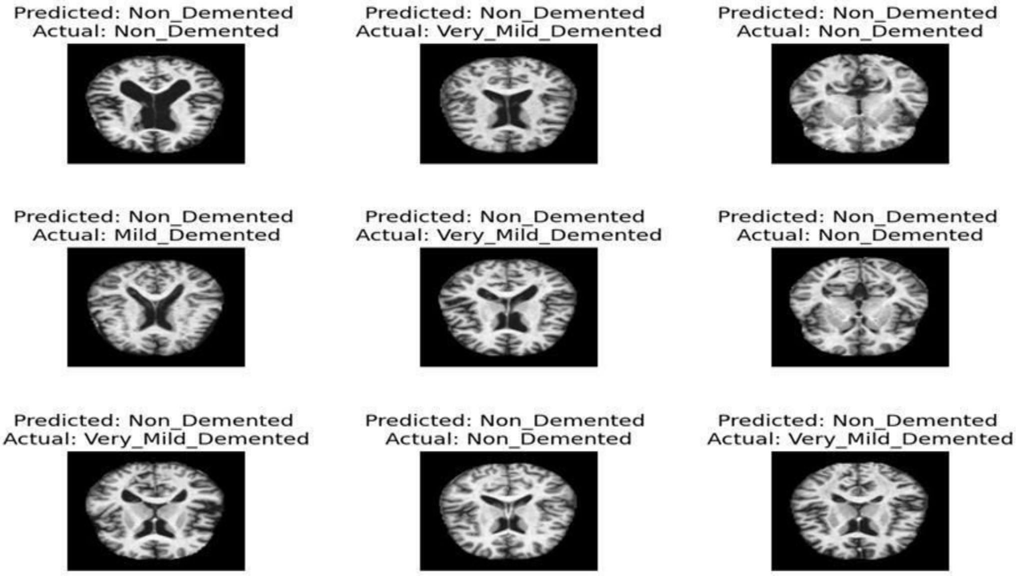

Fig 8: Result snapshot

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