AlzAware: An AI-Based System for Early Detection of Alzheimer's Disease Using Multimodal Data and Machine Learning

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Abstract—**Alzheimer's Disease (AD) is a progressive neurodegenerative disorder marked by gradual cognitive decline and memory loss. Early-stage identification of AD is a global medical challenge, as symptoms often overlap with natural aging or mild cognitive impairment. This paper presents *AlzAware*, an intelligent multimodal system that facilitates early detection of Alzheimer's Disease using both MRI imaging and cognitive behavioral tests. The proposed framework integrates a fine-tuned ResNet50 deep learning model for MRI analysis with a cognitive assessment module powered by machine learning algorithms. The system provides two interactive dashboards — one for patients and another for doctors — enabling complete diagnostic support, from cognitive testing and MRI-based screening to doctor consultation and report generation. The model achieves high classification accuracy across four dementia stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, with overall ROC-AUC values exceeding 0.99. The integration of explainable AI tools such as Grad-CAM and SHAP ensures transparency and interpretability. The *AlzAware* platform contributes toward affordable, accessible, and explainable Alzheimer's detection suitable for clinical and telemedicine applications.**

Index Terms—**Alzheimer's Disease, Deep Learning, MRI Classification, Cognitive Assessment, Explainable AI, ResNet50, Multimodal Diagnosis.**

I. INTRODUCTION

Alzheimer's Disease (AD) affects millions of individuals worldwide, leading to irreversible neuronal loss and functional impairment. Current diagnostic practices rely heavily on clinical interviews, MRI or PET imaging, and neuropsychological testing, which are often costly, time-consuming, and inaccessible to many. Early diagnosis can significantly slow disease progression and improve patient outcomes. However, differentiating early-stage AD from normal aging remains complex.

The *AlzAware* framework bridges this gap by integrating Artificial Intelligence (AI) with clinical and behavioral analytics. The system uses a deep learning approach on MRI scans combined with cognitive assessments to predict Alzheimer's risk at its earliest possible stage. A distinctive feature of the system is the inclusion of two dashboards—one for patients and one for doctors—to enable interaction, result monitoring, and clinical decision support.

II. LITERATURE SURVEY

Recent advancements in AI and neuroimaging have revolutionized Alzheimer's detection. Studies using Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and multimodal frameworks have shown high accuracy in differentiating between healthy and impaired brains. However, most prior systems rely on single modalities such as MRI or EEG and lack interactive clinical integration.

To address these gaps, *AlzAware* employs a hybrid approach combining MRI-based deep learning with cognitive tests. The system ensures interpretability using explainable AI tools, making it suitable for real-world healthcare environments.

Sl. No.	Author(s) & Year	Objective / Methodology	Key Findings	Limitations
1	Glymour et al., 2024	RF on EHR and genetic data to predict AD onset.	AUC 0.72–0.81; APOE and sex-specific predictors.	Data imbalance; UCSF-specific; labeling noise.
2	Park et al., 2023	3D CNN + LSTM on tau-PET images + clinical data.	AUC ≈0.95–0.98 (AD vs CN); improved with fusion.	Small dataset; partial slices; clinical not pathological labels.
3	El-Assy et al., 2024	Novel 3D CNN on ADNI MRI for 5-way classification.	99% accuracy; strong features from MRI scans.	Only on ADNI; risk of overfitting.
4	Raj & Mirzaei, 2023	Reinforcement Learning (RL) + CNN on MRI ROIs.	≈70% accuracy; best recall among tested methods.	Used only 2D slices; modest accuracy.
5	Alatrany et al., 2024	Explainable SVM on NACC dataset.	F1 ~99% (binary), ~88% (progression); rule-based logic.	Discretization losses; NACC-only data.
6	Clark et al., 2022	Deep learning with imaging + neuropsych data.	Interpretability aligned with pathology; high accuracy.	Over-representation of AD; generalization issues.
7	Vichianin et al., 2021	SVM on hippocampal volume + cognitive scores.	Scores alone yielded ~90% accuracy.	No added value from imaging; small sample.
8	Saoud & AlMarzouqi, 2024	3D Vision Transformers on segmented MRI.	≈99% accuracy; interpretable attention maps.	Only on ADNI; compute-heavy; possible overfitting.
9	Yuda et al., 2024	WGAN-GP for MRI data augmentation.	Improved 4-class accuracy to 56.8%.	Synthetic data realism concerns; moderate accuracy.
10	Senan et al., 2024	SVM on genes, SNPs, and cognitive scores.	AUC ≈0.94; SHAP showed key gene contributions.	Preselected features; only ADNI data.
11	Saeed et al., 2024	Random Survival Forest on MCI to AD conversion.	C-index up to 0.90; improved by adding CSF.	Longitudinal data requirements; ADNI-specific.
12	Zhang et al., 2024	STGC-GCAM on fMRI for biomarkers.	AUC >0.95; conversion prediction with HR≈3.89.	Limited diversity; resting-state only.
13	Lee et al., 2024	cKNN on EEG from cognitive tasks.	93% accuracy (4-class); task-state better than rest.	Small sample; no external validation.
14	Li et al., 2021	Transfer learning CNN for MRI phenotyping.	Linked image features to AD pathology markers.	Associative only; research-quality scans.
15	Fathi et al., 2024	Ensemble CNNs on ADNI MRIs.	98.6% accuracy; robust to external testing.	High compute; ADNI-focused.
16	Gao et al., 2023	XGBoost on UK Biobank	AUC ~0.88; novel EHR	Limited ancestry; retrospective.

		+ polygenic risk scores.	predictors identified.	
17	Sá et al., 2022	Ensemble ML on T1-MRI from ADNI+OASIS.	Accuracy ~91% (HC vs AD); generalized well.	No cognitive features; no longitudinal updates.
18	Mun et al., 2023	Transformer NLP on interview transcripts.	78.5% accuracy for predicting AD progression.	Text only; small homogeneous sample.
19	Alp et al., 2024	3D ViT + BiLSTM on MRI for AD/MCI/CN.	≈99% accuracy; outperformed CNN baselines.	Complex; overfitting concerns; ADNI-only.
20	Jo et al., 2019	Review of deep learning models (2013–2018).	Autoencoders and multimodal inputs showed promise.	Small early datasets; limited explainability.

III. PROPOSED METHODOLOGY

The proposed AlzAware framework integrates two independent yet complementary modules: an MRI Image Classification Module and a Cognitive Assessment Module. The outputs from these modules are fused through a weighted decision model for holistic Alzheimer's risk prediction.

A. System Overview

The AlzAware system consists of two primary modules:

1. MRI Image Classification Module – Performs automated brain MRI analysis using a deep convolutional neural network to classify patients into four categories: *Non-Demented, Very Mild Demented, Mild Demented,* and *Moderate Demented*.

2. Cognitive Assessment Module – Evaluates neurocognitive patterns through structured memory tests, puzzles, reasoning assessments, and language-based question responses to measure mental agility, memory retention, and logical reasoning.

Both modules operate independently and contribute probabilistic predictions to a **fusion layer**, which integrates results to produce a unified risk score for the patient.

B. Dataset Description

The MRI dataset utilized is sourced from the publicly available Alzheimer's MRI Dataset on Kaggle, comprising approximately 6,400 MRI images. The dataset is balanced across the four dementia categories. Each image is a T1-weighted MRI slice representing the axial view of the human brain.

The cognitive dataset is generated internally through custom-designed web-based tests that assess:

- Short-term and working memory (pattern recall, number series, image retention)
- Linguistic understanding (synonym–antonym recognition)
- Reasoning ability (puzzle-based and logic-based questions)
- Reaction time and response accuracy

The combination of both image and behavioral data provides a richer understanding of early Alzheimer's patterns compared to using imaging alone.

C. Preprocessing and Feature Engineering

1. MRI Preprocessing

o *Resizing:* All MRI images are resized to 224×224×3 pixels for compatibility with ResNet50 input dimensions.

o *Normalization:* Pixel intensity normalization ensures consistent contrast across samples.

o *Augmentation:* Random flips, rotations (±10°), zoom, and contrast variation are applied to improve generalization.

o *Noise Reduction:* Gaussian filtering is applied to remove imaging artifacts.

o *Splitting:* Data is divided as 80% for training, 10% for validation, and 10% for testing.

2. Cognitive Data Preprocessing

o Test results are normalized on a scale of 0–1.

o Missing responses are handled through median imputation.

o Cognitive parameters (e.g., memory score, response time, accuracy) are vectorized into a numerical feature array.

D. Deep Learning Model (ResNet50)

The ResNet50 architecture serves as the backbone for MRI classification. It leverages residual connections that help mitigate the vanishing gradient problem, enabling deeper network training. The pre-trained weights from ImageNet are fine-tuned on the Alzheimer's dataset with a modified output layer comprising four neurons, each representing one dementia stage.

The final fully connected (FC) layer is followed by a Softmax activation to yield class probabilities. The model is trained using the Adam optimizer with:

- Learning rate = 0.0001
- Batch size = 32
- Loss function = categorical cross-entropy
- Dropout = 0.4 for regularization

The ResNet50 model extracts spatial features from MRI scans, effectively capturing atrophy patterns in brain regions such as the hippocampus and cortex.

E. Cognitive Analysis Model

The cognitive analysis module uses Support Vector Machines (SVM) and Random Forest (RF) classifiers trained on collected test data. These algorithms predict cognitive decline severity based on:

- Score deviation from healthy baseline
- Reaction time anomalies
- Logical reasoning and linguistic understanding accuracy

Each model outputs a probability P_{Cog} representing the likelihood of Alzheimer's risk derived from cognitive metrics.

F. Multimodal Fusion Layer

To combine MRI and cognitive predictions, a weighted decision-level fusion is implemented:

$$R = \alpha \times P_{MRI} + (1 - \alpha) \times P_{Cog}$$

where

R = final Alzheimer's risk score,
P_{MRI} = probability from MRI classifier,
P_{Cog} = probability from cognitive

model,
and $\alpha = 0.7$ denotes the weight given to MRI inference due to its higher diagnostic precision.

The fusion approach provides a balanced diagnosis, leveraging imaging accuracy with cognitive behavior sensitivity.

G. Explainability and Visualization

Interpretability is ensured through Grad-CAM (Gradient-weighted Class Activation Mapping), which visualizes salient regions in MRI scans contributing to classification. This allows clinicians to verify whether model attention aligns with medically significant brain regions, such as the hippocampus and amygdala.

For cognitive results, SHAP (SHapley Additive exPlanations) values are generated to explain feature importance, identifying which specific test results influenced the final prediction.

H. System Implementation

The system is implemented using:

- Frontend: React.js (patient and doctor dashboards)
- Backend: Python (FastAPI)
- Database: MongoDB (secure record storage)
- Frameworks: PyTorch, Torchvision, scikit-learn
- Execution Environment: Google Colab (NVIDIA T4 GPU)

The system provides a user-friendly web portal where clinicians or caregivers can upload MRI images, conduct cognitive tests, and receive real-time AI-based reports.

I. MRI Image Classification Module

A pre-trained ResNet50 model is fine-tuned on the Alzheimer MRI Dataset (Kaggle). The dataset contains over 10,000 MRI brain scans divided into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The preprocessing steps include image resizing (224×224 pixels), normalization, augmentation (rotation, flip, zoom, brightness), and denoising. The final layer of ResNet50 is replaced with a four-class Softmax layer. The model is trained using Adam optimizer (learning rate = 0.0001) and categorical cross-entropy loss.

J. Cognitive Assessment Module

The cognitive module assesses mental agility through tests such as memory games, image identification, simple arithmetic problems, and logical puzzles. It uses Support Vector Machine (SVM) and Random Forest (RF) models to predict cognitive decline based on memory recall, response time, and reasoning accuracy. The normalized test results are stored in a secure database for fusion with MRI results.

K. Explainability and Visualization

Grad-CAM heatmaps visualize brain regions influencing MRI-based predictions, while SHAP values explain which cognitive features (reaction time, memory accuracy) impacted the final decision. This ensures interpretability and clinician trust.

L. Workflow Summary

1. Data Input (MRI + Cognitive Test Results)
2. Preprocessing and Feature Extraction
3. MRI Classification via ResNet50
4. Cognitive Assessment via ML Models
5. Decision Fusion and Risk Calculation
6. Visualization (Grad-CAM, SHAP)
7. Report Generation and Recommendation

The overall architecture ensures that AlzAware functions as an end-to-end diagnostic support platform capable of screening, monitoring, and analyzing Alzheimer's risk in a reliable and interpretable manner.

IV. SYSTEM DESIGN AND FUNCTIONALITY

A. User Roles and Dashboards

1. Patient Dashboard:

- Take cognitive tests (memory, arithmetic, reasoning, image recognition).
- Upload MRI brain scans (only MRI file types accepted).
- View AI-based diagnosis results showing dementia probability (No, Mild, Moderate, or Severe).
- Access a list of certified doctors and send consultation requests.

2. Doctor Dashboard:

- Maintain professional profile (qualification, specialization, experience).
- Access list of patient requests with AI-generated reports.
- Upload MRI scans for offline patients and conduct in-clinic cognitive tests.
- View predicted impairment percentage and localized brain regions affected.
- Generate and download detailed clinical reports.

B. Data Management

Separate collections are maintained for patients and doctors. Each test record (MRI or cognitive) is timestamped, ensuring traceability. The database supports report generation and historical tracking for progressive analysis.

C. Workflow Summary

1. Patient logs in and performs cognitive test.
2. MRI image uploaded for AI-based screening.
3. System fuses cognitive and imaging scores to generate Alzheimer's risk.
4. Doctor reviews report, interprets results, and shares observations with the patient.
5. Clinical diagnosis or follow-up scheduled based on results.

V. RESULTS AND DISCUSSION

The proposed AlzAware system was evaluated on the Alzheimer's MRI dataset and cognitive assessment data to analyze its performance in classifying dementia stages and estimating overall risk. The results demonstrate that the multimodal approach significantly enhances diagnostic accuracy and interpretability compared to single-modality systems.

A. Quantitative Evaluation

The ResNet50 model fine-tuned on MRI scans achieved high accuracy across all four dementia categories: 99.1% for *Non-Demented*, 94.9% for *Very Mild Demented*, 96.6% for *Mild Demented*, and 100% for *Moderate Demented* cases. The macro-average accuracy was 97.6%, with precision, recall, and F1-scores exceeding 96% for most classes. The ROC-AUC values were consistently above 0.99, indicating strong discriminatory capability and model robustness.

A comparative analysis was also performed between the MRI-only model and the multimodal fusion approach. The inclusion of cognitive data improved early-stage (very mild) detection accuracy by 4.2%, particularly in differentiating between healthy and

borderline cases where MRI features alone can appear visually similar.

B. Visualization and Explainability

Grad-CAM visualizations were generated for each prediction to highlight the most influential brain regions contributing to the classification. The heatmaps consistently focused on hippocampal, entorhinal, and temporal lobe regions—areas clinically associated with memory and cognitive processing. This alignment between the model's visual attention and known neuropathological markers strengthens clinical trust and interpretability.

Similarly, SHAP plots were used to interpret cognitive assessment results. They revealed that features such as *response time*, *memory recall score*, and *logic puzzle accuracy* had the highest impact on cognitive-based predictions. This helps clinicians understand the behavioral basis behind the AI inference.

C. Performance Comparison and Discussion

When compared to existing CNN-based Alzheimer's classifiers such as VGG16, DenseNet, and EfficientNet, the proposed ResNet50 architecture demonstrated comparable or superior accuracy while maintaining lower overfitting tendencies due to regularization and data augmentation. Furthermore, the fusion of cognitive and imaging data proved advantageous in borderline or mild cases, which are typically the most difficult to diagnose in early Alzheimer's progression.

The results confirm that the AlzAware system not only achieves high quantitative accuracy but also provides qualitative interpretability through explainable visualizations. These characteristics make it suitable for potential clinical adoption and future integration into telemedicine or hospital diagnostic workflows.

VI. CONCLUSION AND FUTURE WORK

This paper presented AlzAware, an innovative AI-based multimodal framework designed for the early detection of Alzheimer's Disease (AD) through the integration of *MRI image analysis* and *cognitive assessment data*. The system leverages the power of deep learning, specifically a fine-tuned ResNet50 architecture, to analyze structural brain changes while simultaneously incorporating cognitive performance metrics to enhance prediction reliability. The multimodal approach effectively bridges the gap between image-based and behavioral diagnostics, providing a more comprehensive and interpretable solution compared to traditional single-source systems.

Experimental evaluations demonstrated that AlzAware achieved exceptionally high classification accuracy across multiple dementia stages, with ROC-AUC values exceeding 0.99, confirming the robustness of the model. The integration of cognitive assessment improved early-stage detection by over 4%, which is crucial for timely medical intervention. Moreover, the inclusion of explainability tools such as Grad-CAM and SHAP ensures that clinicians can visualize the reasoning behind each prediction, making the system both transparent and trustworthy in real-world applications.

From a broader perspective, AlzAware contributes to the growing field of AI-driven healthcare diagnostics, emphasizing affordability, accessibility, and interpretability. By providing a platform that can be deployed on cloud-based or hospital infrastructures, it offers scalable potential for mass screening and early intervention in resource-limited settings.

Looking ahead, several directions for future enhancement are identified:

1. Integration of Additional Modalities: Incorporating PET (Positron Emission Tomography) and EEG (Electroencephalogram) data to enable deeper neurological analysis and multimodal correlation.

2. Dataset Expansion: Collecting larger and more diverse datasets covering multiple demographics and imaging conditions to improve generalization.

3. Lightweight Model Deployment: Developing compressed or quantized CNN models for mobile and edge device deployment, enabling real-time screening in rural and telehealth environments.

4. Longitudinal Monitoring: Extending AlzAware to support continuous monitoring, tracking cognitive decline over time to assess disease progression and treatment effectiveness.

5. Clinical Validation: Collaborating with neurologists and healthcare institutions to conduct clinical trials for evaluating system

accuracy and usability in practical healthcare workflows.

By advancing in these directions, AlzAware can evolve into a clinically dependable, globally deployable AI assistant for early Alzheimer's detection, ultimately

contributing to improved patient outcomes, reduced diagnostic delays, and a better quality of life for millions at risk of neurodegenerative decline.

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