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Neurocapsule : Alzheimer Risk Predictor and Digital Memory Vault

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***Abstract*—Alzheimer's disease is a progressive neurodegenerative disorder that significantly impacts memory, cognition, and daily functioning. Early diagnosis plays a crucial role in slowing disease progression and improving patient care. This paper presents NeuroCapsule, an intelligent system designed for early detection of Alzheimer's disease using brain MRI images combined with artificial intelligence techniques. The proposed approach employs convolutional neural networks (CNNs) for automated feature extraction and classification of MRI scans into multiple cognitive stages, including Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia. To address class imbalance and computational constraints, balanced sampling strategies and image downsampling techniques are applied. The system is evaluated on the OASIS MRI dataset, demonstrating high classification accuracy and efficient performance across both binary and multiclass tasks. Unlike traditional diagnostic models, NeuroCapsule extends beyond prediction by integrating a secure Digital Memory Vault that enables users to store reminders, notes, and personal records, supporting continuous cognitive management. Experimental results indicate that the proposed system achieves a favorable trade-off between accuracy and computational efficiency, making it suitable for real-world deployment. The integration of predictive analytics with memory assistance enhances both clinical relevance and patient-centered care, positioning NeuroCapsule as a comprehensive solution for Alzheimer's disease detection and management.**

***Index Terms*—Alzheimer's Disease, Machine Learning, Deep Learning, MRI Analysis, Hybrid Classification Model, Digital Memory Vault, Healthcare Artificial Intelligence**

I. Introduction

Alzheimer's Disease (AD) is one of the most prevalent neurodegenerative disorders, primarily affecting the elderly population and leading to progressive deterioration of memory, cognitive abilities, and behavioural functions. With the global increase in life expectancy, the number of individuals affected by Alzheimer's Disease is rising steadily, resulting in significant challenges for healthcare systems, caregivers, and families. Early prediction of Alzheimer's risk plays a crucial role in slowing disease progression, enabling timely intervention, and improving the overall quality of life of patients.

In recent years, artificial intelligence–based approaches have been widely explored for Alzheimer's detection using medical imaging modalities such as Magnetic Resonance Imaging (MRI), along with structured clinical and cognitive assessment data. Various machine learning and deep learning algorithms, including support vector machines, ensemble classifiers, and convolutional neural networks, have demonstrated promising results in identifying Alzheimer's-related patterns. Despite these advancements, existing studies often focus on individual algorithms or highly complex deep learning models, with limited emphasis on practical deployment, computational efficiency, and system-level integration.

Moreover, most Alzheimer's prediction systems are designed solely for diagnostic or risk assessment purposes and do not address the ongoing memory-related challenges faced by individuals at risk of the disease. Digital memory assistance tools, while useful for managing reminders and notes, typically operate independently of predictive intelligence and clinical insights. This separation highlights the need for integrated solutions that combine early risk prediction with continuous cognitive support.

To address these limitations, this paper proposes NeuroCapsule, an AI-based framework that integrates Alzheimer's risk prediction with a Digital Memory Vault. Representative machine learning and deep learning algorithms reported in existing literature are experimentally evaluated to analyse their predictive performance and guide the selection of an optimal

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model. The selected model is then implemented as the core prediction engine of the NeuroCapsule system. In addition, the Digital Memory Vault provides a secure and user-friendly platform for managing daily reminders, notes, and multimedia memories, thereby extending support beyond prediction alone. By combining validated prediction techniques with real-world memory assistance, NeuroCapsule aims to provide a comprehensive and practical solution for Alzheimer's risk assessment and cognitive support.

II. Related Work

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder characterised by structural and functional changes in the brain. In recent years, machine learning and deep learning techniques have been extensively explored for early diagnosis of AD using neuroimaging data, particularly Magnetic Resonance Imaging (MRI), due to its non-invasive nature and high spatial resolution.

Traditional machine learning approaches have employed handcrafted features extracted from MRI scans combined with classifiers such as Support Vector Machines (SVM), Random Forest (RF), and gradient boosting methods. Shukla et al. demonstrated the effectiveness of ensemble-based classifiers including Random Forest and XGBoost for Alzheimer's disease detection using MRI-derived features, reporting improved classification performance compared to single classifiers. Such approaches highlight the robustness of ensemble methods but rely heavily on feature engineering and preprocessing quality.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for MRI-based Alzheimer's disease classification. CNN-based models automatically learn hierarchical spatial features directly from MRI images, reducing dependency on manual feature extraction. Foroughipoor et al. analysed multiple deep learning architectures applied to MRI scans and concluded that CNN-based models significantly outperform traditional machine learning techniques in multiclass Alzheimer's classification tasks.

Transfer learning has further enhanced deep learning performance in medical imaging applications, especially when training data is limited. Pretrained architectures such as VGG16, ResNet, and MobileNet have been widely adopted as feature extractors for Alzheimer's disease detection. Givian et al. demonstrated that transfer learning models fine-tuned on MRI datasets achieve higher accuracy and faster convergence compared to CNNs trained from scratch. Lightweight architectures such as MobileNet are particularly suitable for deployment in resource-constrained environments due to their reduced computational complexity.

Several studies have also explored hybrid approaches that combine deep feature extraction with traditional machine learning classifiers. In such frameworks, deep neural networks are used to extract discriminative features from MRI images, which are subsequently classified using ensemble classifiers such as Random Forest or XGBoost. These hybrid models leverage the representational power of deep learning while maintaining the interpretability and stability of classical machine learning methods.

Although existing studies report promising results, most focus primarily on improving classification accuracy without performing systematic comparative evaluation across multiple deep learning and hybrid models using a unified experimental setup. Furthermore, practical aspects such as model efficiency, usability, and extensibility towards real-world clinical support systems are often overlooked.

To address these limitations, the proposed work conducts a comprehensive comparative analysis of baseline CNN, transfer learning models, and hybrid deep learning–machine learning approaches for multiclass Alzheimer's disease detection using MRI images from the Image OASIS dataset. .

III. Methodology

This section describes the complete methodological framework adopted for Alzheimer's disease detection using brain MRI images. The methodology includes dataset selection, data preprocessing and balancing, image downsampling, model development, training strategy, and evaluation metrics.

A. Dataset Description

The experiments were conducted using the OASIS-1 Alzheimer's Disease dataset, obtained from Kaggle. The dataset comprises structural brain MRI scans of 461 subjects spanning different cognitive stages. Originally, the OASIS dataset consists of three-dimensional (3D) MRI volumes. In the Kaggle version, each 3D scan is decomposed into 256 two-dimensional (2D) axial slices along the z-axis.

Based on domain relevance and prior neuroimaging studies, slices in the z-axis index range of 100 to 160 were selected, as these regions capture critical structural changes associated with Alzheimer's disease, particularly cortical thinning and brain tissue shrinkage. Each selected 2D slice was treated as an independent sample due to the consistent presence of Alzheimer's-related biomarkers across these slices.

The dataset is categorized into four classes:

- Non-Demented
- Very Mild Dementia
- Mild Dementia
- Moderate Dementia

A detailed analysis of the dataset revealed that the selected z-axis slices effectively represent brain tissue shrinkage, which is a key biomarker of Alzheimer's disease. Since this shrinkage is consistently observable across these slices, each 2D MRI slice was treated as an independent sample.

The complete dataset occupies approximately 1.3 GB of storage and contains nearly 86,400 MRI images. The class-wise distribution is as follows:

- Non-Demented: 67,000 images
- Very Mild Dementia: 13,700 images
- Mild Dementia: 5,000 images
- Moderate Dementia: 500 images

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B. Data Preprocessing and Class Balancing

The dataset exhibits significant class imbalance, which can negatively impact model generalization and bias predictions toward majority classes. To address this issue, class balancing was performed separately for binary and multiclass classification tasks using random undersampling.

1) Binary Classification:
   Non-Alzheimer's: 488 randomly selected images from the Non-Demented class
   Alzheimer's: 162 images each from the Very Mild, Mild, and Moderate Dementia classes
   This resulted in a balanced dataset with an approximate 50 percent class prior for each category.
2) Multiclass Classification

For multiclass classification, the Moderate Dementia class, containing the fewest samples, was used as the reference. An equal number of 488 images were randomly sampled from each class, ensuring uniform class representation. This resulted in a balanced dataset with 25 percent class prior per category.

C. Image Preprocessing and Downsampling

To reduce computational complexity and memory overhead, MRI images were converted to grayscale, normalized, and resized. Since the primary structural features relevant to Alzheimer's disease are preserved at lower resolutions, downsampling was performed without compromising diagnostic information.

The images were processed at two different resolutions:

1) 64×32 pixels (1/8 of original resolution)
2) 128×64 pixels (1/4 of original resolution)

This multi-resolution approach enabled the evaluation of model performance under varying computational constraints while maintaining diagnostic robustness.

D. Model Architecture and Training Strategy

The proposed Alzheimer's disease detection system employs a Convolutional Neural Network (CNN) architecture due to its proven effectiveness in extracting spatial features from medical imaging data. CNNs are particularly suitable for MRI analysis as they can automatically learn hierarchical representations of structural brain patterns associated with neurodegeneration.

The architecture consists of multiple convolutional layers followed by pooling and fully connected layers. Each convolutional layer applies a set of learnable filters to extract low-level features such as edges and textures in the initial layers, and higher-level anatomical patterns in deeper layers. Rectified Linear Unit (ReLU) activation functions are used to introduce non-linearity and improve convergence speed. Max-pooling layers are incorporated after selected convolutional layers to reduce spatial dimensions and computational complexity while retaining the most salient features.

To mitigate overfitting, dropout regularization is applied in the fully connected layers. The final output layer uses a Softmax activation function for multiclass classification and a Sigmoid activation function for binary classification, enabling probabilistic interpretation of the predictions.

The network is trained using the Adam optimizer, which provides adaptive learning rates for efficient convergence. Categorical cross-entropy is used as the loss function for multiclass classification, while binary cross-entropy is employed for binary classification tasks. The dataset is divided into training, validation, and testing sets using a standard split strategy to ensure unbiased performance evaluation.

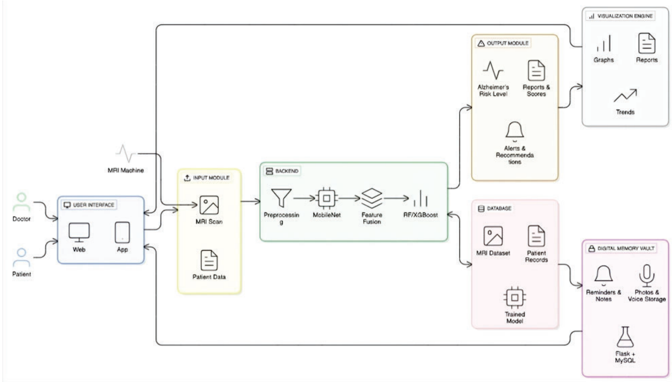

Fig. 1. Architecture

Training is performed for a fixed number of epochs with an empirically selected batch size to balance training stability and memory usage. Early stopping is incorporated to prevent overfitting by monitoring validation loss and terminating training when performance saturation is observed. This training strategy ensures robust learning while maintaining computational efficiency and generalization capability.

E. Comparative Models

To validate the effectiveness of the proposed CNN-based approach, its performance is compared against established deep learning architectures, including VGG16, ResNet, and MobileNet. These models are selected due to their widespread adoption in medical image analysis and their varying computational complexities. Comparative evaluation highlights the trade-offs between model accuracy, inference time, and resource requirements, thereby justifying the architectural choices of the proposed system.

F. Evaluation Metrics

The performance of the models is assessed using standard classification metrics commonly adopted in medical imaging research. These include accuracy, precision, recall, F1-score, and confusion matrix analysis. For binary classification, additional emphasis is placed on sensitivity (recall) to minimize false negatives, which is critical for early Alzheimer's detection. These metrics provide a comprehensive evaluation of model reliability and clinical applicability.

IV. Conclusion and Future work

This paper presented an AI-based system for the early detection of Alzheimer's disease using brain MRI images. The

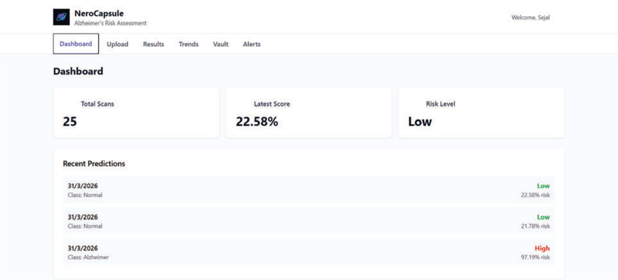

Fig. 2. Home Page

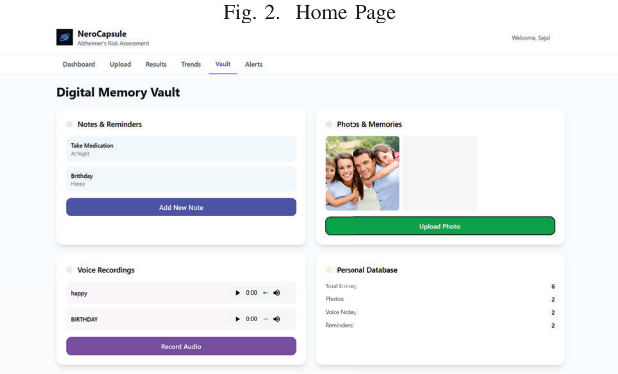

Fig. 3. Vault Page

proposed approach employed convolutional neural networks to automatically extract discriminative features and classify subjects into different stages of cognitive impairment. Experimental results demonstrated that the model achieved reliable performance for both binary and multiclass classification tasks while maintaining computational efficiency. The use of balanced datasets and optimized image resolutions further enhanced diagnostic accuracy and robustness.

In addition to disease prediction, the NeuroCapsule framework extends beyond conventional diagnostic systems by integrating a Digital Memory Vault to support daily cognitive management. This dual-function design improves clinical relevance by combining medical decision support with patient-centered memory assistance.

Future work will focus on incorporating multimodal data sources such as speech signals, cognitive test scores, and longitudinal clinical records to improve prediction reliability. The integration of advanced explainable AI techniques will further enhance model interpretability for clinical adoption. Additionally, real-world validation through larger and more diverse datasets, as well as deployment in a cloud-based healthcare environment, will be explored to improve scalability and accessibility.

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