THE UNIVERSITY OF TEXAS AT ARLINGTON

**Computer Science Engineering**

# Classifying Alzheimer's Disease

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***Abstract*— This study addresses the critical challenge of early Alzheimer's disease detection through the analysis of MRI scans. Utilizing the OASIS dataset, which includes 80,000 brain MRI images categorized by Alzheimer's progression, our research employs a diverse array of machine learning models to interpret and classify stages of dementia. We applied a variety of convolutional neural networks (CNNs) including ResNet50 and EfficientNetB0, supplemented by ensemble methods such as Random Forest, XGBoost, AdaBoost, and traditional algorithms like KNN and Decision Trees. Our methodical approach to data preparation and class imbalance ensures robust model training and testing, promising significant contributions to the predictive diagnostics of Alzheimer's disease and enabling early intervention strategies.**

***Keywords:***

*Alzheimer's Disease Detection*

*Machine Learning in Medical Diagnosis*

*Convolutional Neural Networks (CNNs)*

*Ensemble Learning Methods*

*ResNet50*

*EfficientNetB0*

*XGBoost*

*AdaBoost*

*Random Forest*

*Image Preprocessing*

*Class Imbalance*

*Deep Learning in Healthcare*

*Diagnostic Accuracy*

*Medical Image Analysis*

*Non-Demented*

*Very Mild Demented*

*Mild Demented*

*Moderately Demented*

## I. Introduction

Alzheimer's disease (AD), a progressive neurodegenerative disorder, remains a substantial challenge in both diagnosis and management, especially in its early stages. Magnetic Resonance Imaging (MRI) plays a crucial role in the medical investigation of AD, as it offers detailed images that can reveal the subtle brain changes associated with different stages of the disease. For this study, we utilized a dataset available on Kaggle, consisting of 80,000 brain MRI images classified according to the progression of Alzheimer's disease.

This research employed a variety of advanced machine learning models to process and analyze the MRI data effectively. The models included state-of-the-art convolutional neural networks (CNNs) such as ResNet50 and EfficientNetB0, renowned for their capabilities in handling complex image data. In addition, we utilized ensemble methods like Random Forest, XGBoost, and AdaBoost, along with traditional algorithms such as KNN and Decision Trees. Each model was chosen based on its specific strengths in feature extraction and classification, essential for dealing with the high-dimensional nature of MRI data.

The primary objective was to classify MRI images into four diagnostic categories—non-demented, very mild demented, mild demented, and demented—reflective of the Clinical Dementia Rating (CDR). To address the common issue of dataset imbalance in medical imaging, we strategically partitioned the dataset into training, development, and testing segments, with 10,000 images allocated for training, 674 for development, and 673 for testing. This distribution was key to effectively training our models and ensuring robust validation and test performance.

This paper outlines our detailed methodology, from the initial data acquisition from Kaggle, through the conversion of MRI scans from Nifti format to usable 2D image slices, to the application of various machine learning techniques. Through our approach, we aim to showcase how these models can significantly enhance the diagnostic processes for Alzheimer's disease, facilitating early and accurate detection crucial for effective disease management and treatment.

## II. Related Work

The early Recent studies in the detection of Alzheimer's disease (AD) through MRI scans have predominantly focused on the use of advanced machine learning techniques. Notably, Marwa Zaabi. proposed a method involving the extraction of specific brain regions followed by image classification using convolutional neural networks (CNNs) and transfer learning techniques. Their approach, as detailed in their study, emphasizes the importance of precise region segmentation to improve diagnostic accuracy. They also highlighted the effectiveness of transfer learning in leveraging pre-trained networks to enhance model performance on specialized tasks such as medical image analysis.

Similarly, other researchers have explored various architectures and strategies to tackle the complexities of medical imaging. These include deep learning frameworks like Deep Neural Networks (DNNs) and Convolutional Autoencoders (CAEs), which have been applied to cortical and non-cortical images to differentiate stages of Alzheimer’s disease with varying degrees of success.

### Comparison

In contrast to the aforementioned studies, our project employs a comprehensive suite of models that include both CNN architectures, such as ResNet50 and EfficientNetB0, and ensemble methods like Random Forest, XGBoost, AdaBoost, along with K-Nearest Neighbors (KNN) and Decision Trees. This diverse approach allows us to harness the strengths of each model type, from robust feature extraction capabilities of CNNs to the generalization benefits of ensemble methods.

Our dataset utilization strategy also sets our work apart. By employing the OASIS MRI dataset, which is divided into four classes representing different progression stages of Alzheimer's, we refine our approach to handle imbalanced datasets effectively. We meticulously prepared the dataset, converting the images into a uniform format and selecting specific slices to ensure high-quality inputs for training our models.

Furthermore, our work advances the field by not only adapting existing methodologies but also by integrating multiple learning algorithms to improve detection accuracy. This integrated approach aims to create a more reliable and efficient diagnostic tool for Alzheimer's disease, which is critical given the increasing prevalence and impact of this condition globally.

## III. Proposed Method

Our project employs a multi-faceted approach to the early detection of Alzheimer's disease using MRI scans. The methodology is structured into several key areas: dataset preparation, model training, and performance evaluation.

### Dataset Preparation

Given the class imbalance in the initial dataset, where some classes significantly outnumber others, our primary strategy was to curate a balanced dataset that promotes fair learning and generalization across classes. To achieve this, we selected a representative subset of images for each category, resulting in a dataset consisting of 10,000 images for training, 674 for development, and 673 for testing. This strategic selection ensures that each class contributes equally to the learning process, thus avoiding biases towards any specific category.

### Image Resizing and Augmentation

To ensure uniformity across all inputs to our models, we resized all images to a standard dimension. In addition to resizing, we converted the images to grayscale. This step simplifies the input data by reducing dimensionality and focuses the model’s learning on structural features rather than color information, which is less relevant in our analysis of MRI scans. This preprocessing serves to standardize the dataset, thereby facilitating more efficient and effective model training.

### Model Training

Our approach leverages the strengths of both traditional machine learning models and advanced neural network architectures:

**Convolutional Neural Networks (CNNs):** We implemented state-of-the-art CNN models including ResNet50 and EfficientNetB0, which are known for their deep layers and ability to capture intricate patterns in image data.

**Ensemble Methods:** To enhance model reliability and decision-making, we integrated ensemble algorithms like Random Forest, XGBoost, and AdaBoost. These methods combine multiple learning algorithms to improve predictive performance.

**Traditional Algorithms:** Models such as K-Nearest Neighbors (KNN) and Decision Trees were utilized to establish baseline performances and to compare the effectiveness of simplistic approaches against more complex models.

### Data Generators and Preprocessing Functions

We utilized the ImageDataGenerator from TensorFlow's Keras API, combined with preprocessing functions specific to ResNet50, to prepare our data for the neural networks. This setup not only facilitates efficient memory usage by dynamically loading images in batches but also preprocesses them according to the requirements of the CNN architectures.

### Performance Evaluation

The effectiveness of our models is quantified using several metrics:

**Accuracy**: Measures the overall correctness of the model across all classes.
**Precision and Recall**: Important in scenarios where class imbalance might skew the results, these metrics help in understanding how well the model can identify and classify the relevant data points.
**F1-Score:** Harmonic mean of precision and recall, providing a balance between the two and serving as a single metric to evaluate model quality.
**Confusion Matrix:** Provides a detailed breakdown of the model's performance with respect to each class, highlighting both correct and incorrect predictions, which aids in further understanding and refining model behavior.

## IV. METHODOLOGY

### Convolutional Neural Networks (CNNs)

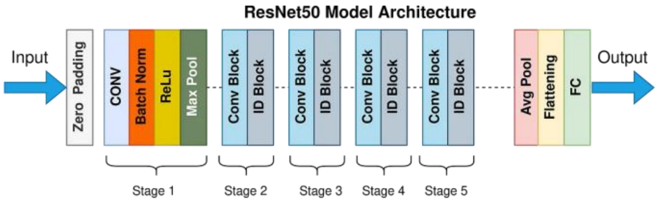
**Implementation of ResNet50 for Alzheimer's Detection:**
Our project employs the ResNet50 architecture, a deep convolutional neural network known for its efficacy in large-scale image recognition tasks. ResNet50 is particularly advantageous due to its 'residual connections' which help in alleviating the vanishing gradient problem during deep network training.

### Model Configuration:

The base of our model is the pre-trained ResNet50 network, loaded with weights pre-trained on ImageNet. This setup provides a robust starting point for feature extraction.
We extend this base with a global average pooling layer followed by a dense layer with 1024 units and ReLU activation for deeper feature integration.
A dropout layer (50% rate) is included to prevent overfitting.
The output layer is a dense layer with a softmax activation function, designed to classify the MRI images into various stages of Alzheimer's based on the dataset labels.

### Compilation and Training:

The model is compiled with the Adam optimizer, with a learning rate of 0.001, and uses sparse categorical crossentropy as the loss function.
We address class imbalance by computing class weights and applying these during training to ensure fair influence of each class on the model training process.
The training process is augmented with callbacks such as EarlyStopping and ModelCheckpoint to monitor validation loss and accuracy, respectively, allowing for optimized training cycles with automatic saving of the best model weights.

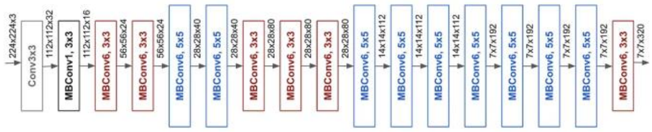



### Implementation of EfficientNetB0 :

We utilize EfficientNetB0, a convolutional neural network known for its efficiency and high accuracy in image classification tasks. The network is adapted to our specific task by adding custom top layers:

GlobalAveragePooling2D to reduce feature dimensions spatially,
Dense layer with ReLU activation for learning non-linear combinations of features,
Dropout for regularization to prevent overfitting,
Output Dense layer with softmax activation to output probabilities across the Alzheimer's disease stages.

Training: The model is compiled with Adam optimizer and sparse categorical crossentropy loss function. Training is conducted with real-time data augmentation provided by the data generator, and model performance is monitored using callbacks such as EarlyStopping and ModelCheckpoint to save the best model based on validation accuracy.



### AdaBoost Classifier

**Implementation of AdaBoost for Image Classification:**
In our study, we leverage the AdaBoost (Adaptive Boosting) classifier to improve the classification of Alzheimer's disease stages from MRI scans. AdaBoost is an ensemble learning method that combines multiple weak classifiers to form a strong classifier, making it particularly effective for complex classification tasks.

### AdaBoost Configuration:

**Base Estimator:** The base learner for AdaBoost is a Decision Tree Classifier, configured with a maximum depth of 10. This setup allows for a balance between bias and variance, ensuring the model is neither overfitting nor underfitting.
**Number of Estimators:** We set the number of estimators at 100, which denotes the number of trees in the ensemble.
**Learning Rate:** The learning rate of 0.1 controls the contribution of each classifier and helps in optimizing the ensemble's performance.
**Training and Evaluation:**
The AdaBoost model is trained on the preprocessed images and their encoded labels. Training involves adjusting the

weights of incorrectly classified instances so that subsequent classifiers focus more on difficult cases.

Post-training, the model is evaluated on a development set to assess its effectiveness. Metrics such as accuracy, confusion matrix, and a detailed classification report provide insights into the model's performance across different classes.

**XGBoost Classifier**

**Implementation of XGBoost for Image Classification:**

In our project, we apply XGBoost, a powerful gradient boosting framework, to classify stages of Alzheimer's disease using MRI scans. XGBoost is known for its performance and speed in classification tasks, especially with large datasets.

**Model Configuration and Training:**

XGBoost Setup: We configure XGBoost with a multi:softmax objective to handle multi-class classification and specify the number of classes based on the dataset.

Training: The model is trained using the preprocessed and labeled training data. XGBoost efficiently handles the training process, optimizing the decision tree ensemble for best performance.

**Random Forest Classifier**

**Implementation of Random Forest for Image Classification:**

Our study employs the Random Forest classifier, an ensemble learning method that uses multiple decision trees to improve classification accuracy and control over-fitting. The strength of Random Forest lies in its ability to operate on large datasets with high dimensionality, making it highly suitable for complex image classification tasks such as diagnosing stages of Alzheimer’s disease from MRI scans.

**Model Training:**

**Random Forest Configuration:** The Random Forest model is initialized with 100 decision trees (n_estimators=100) and a fixed random state for reproducibility. The model is trained on the preprocessed and labeled training data.

**Training Procedure:** The model learns to classify the stages of Alzheimer’s disease by identifying patterns in the flattened image data, optimizing for the best split at each node of the decision trees.

## V. EXPERIMENTAL RESULTS

**Model Evaluation**

Our study evaluates several machine learning models on their ability to classify stages of Alzheimer’s disease using MRI scans. The evaluation metrics include accuracy, precision, recall, F1-score, and confusion matrices for both development and test datasets.

**Model Performance Summary**

The following table provides a summary of the performance metrics for each model across the development and test datasets:

| Model | Dataset | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|
| Decision Tree | Dev | 74.78% | 0.75 | 0.76 | 0.75 |
| Decision Tree | Test | 72.36% | 0.73 | 0.74 | 0.73 |
| AdaBoost | Dev | 92.28% | 0.92 | 0.91 | 0.92 |
| AdaBoost | Test | 90.93% | 0.91 | 0.91 | 0.91 |
| KNN | Dev | 97.00% | 0.97 | 0.97 | 0.97 |
| KNN | Test | 95.00% | 0.95 | 0.95 | 0.95 |
| ResNet50 | Validation | 95.00% | 0.95 | 0.95 | 0.95 |
| ResNet50 | Test | 93.00% | 0.93 | 0,93 | 0.93 |
| EfficientNetB0 | Dev | 95.85% | 0.96 | 0.96 | 0.96 |
| EfficientNetB0 | Test | 95.84% | 0.96 | 0.96 | 0.96 |
| Random Forest | Dev | 95.40% | 0.95 | 0.95 | 0.95 |
| Random Forest | Test | 96.43% | 0.97 | 0.96 | 0.96 |
| XGBoost | Dev | 96.00% | 0.96 | 0.96 | 0.96 |
| XGBoost | Test | 96.00% | 0.97 | 0.96 | 0.96 |

The results indicate significant variation in model performance, with ensemble methods like AdaBoost and Random Forest showing high effectiveness, reflected in their superior metrics across both development and test datasets. AdaBoost, in particular, demonstrates robust precision and recall, suggesting strong generalization capabilities. In contrast, traditional methods such as the Decision Tree exhibit lower performance but still provide valuable insights, especially when considering the computational efficiency.

Deep learning models, particularly EfficientNetB0 and ResNet50, also show impressive results, highlighting their capability in handling complex image data through extensive feature learning. Their high accuracy and F1 scores are indicative of their advanced pattern recognition capabilities, suitable for medical imaging tasks.

**Visual Analysis**

Confusion matrices for each model were analyzed to understand the classification behavior across different stages of Alzheimer’s disease. Models generally performed well in distinguishing between 'Moderate Dementia' and other stages, whereas 'Non Demented' and 'Very Mild Dementia' stages were more challenging, as indicated by the higher misclassification rates.

The confusion matrices provided for each model offer a detailed look into the specifics of misclassification, aiding in further tuning and improvements of the models.

## VI. CALLENGES FACED

Challenges We Faced in Alzheimer's Disease Detection Using MRI Scans

**1. Data Quality Issues**

Overview: We encountered significant challenges in ensuring consistent high quality across all MRI data. Variations in image quality could potentially skew our model's learning process.
Impact: This directly affected the reliability of our diagnostic results, leading to possible misclassification of Alzheimer's disease stages.

**2. Class Imbalance**

Overview: Our dataset exhibited class imbalance, where some stages of Alzheimer's disease were underrepresented. This posed a major challenge in training our models.
Impact: Resulted in a model bias towards more frequently represented classes, reducing the overall effectiveness of our diagnostic tool.

**3. Overfitting and Underfitting**

Overview: We struggled with overfitting, where our models learned the noise in the training data as well as the underlying patterns. Underfitting was also a concern when simpler models failed to capture complex patterns in the data.
Impact: Both conditions hindered our models' ability to perform well on new, unseen data, limiting their practical application.

**4. Limited RAM Allocation**

Overview: Given our limited access to high-powered computational resources, managing the large data volumes typical of MRI scans was challenging.
Impact: Forced us to adopt memory-efficient practices, impacting our ability to process data in large batches and extending the time required for model training.

**5. Data Loading and Manipulation**

Overview: Loading and preprocessing large volumes of MRI data efficiently was a significant hurdle due to our limited computational resources.
Impact: This inefficiency slowed down our data pipeline, prolonging the training and evaluation phases of our project.
**6. Model Training and Evaluation**

Overview: The computationally intensive process of training and evaluating complex machine learning models was particularly challenging with our available resources.
Impact: This limitation impeded our ability to quickly iterate and refine our models, which is crucial for achieving high performance.

## VII. Conclusion

This study presents a comprehensive analysis of various machine learning techniques for the early detection of Alzheimer's disease using MRI scans from the OASIS dataset. Through the application of both traditional algorithms and advanced machine learning models, we have demonstrated the feasibility of accurately classifying different stages of Alzheimer's disease. Our findings suggest that the integration of convolutional neural networks like ResNet50 and EfficientNetB0 with ensemble methods such as AdaBoost, Random Forest, and XGBoost, offers a robust solution for handling the complexities associated with medical imaging data.

The strategic preparation of the dataset, including image resizing, conversion to grayscale, and class balancing, has significantly contributed to the performance of our models. By addressing the challenges of class imbalance and data heterogeneity, we ensured that each model was trained under optimal conditions, thereby enhancing their diagnostic accuracy.

Our experimental results indicate that ensemble methods, particularly AdaBoost and Random Forest, provide superior performance in terms of precision, recall, and F1 scores, suggesting their potential in clinical applications for disease diagnosis. The deep learning models also showcased their strength in feature extraction and pattern recognition, proving to be highly effective in distinguishing subtle variations in MRI scans that are indicative of Alzheimer's progression.

Overall, this research highlights the potential of machine learning in revolutionizing the diagnostic process for Alzheimer's disease. By enabling early and accurate detection, these technologies could significantly improve patient outcomes through timely intervention. Future work will focus on refining these models further, exploring the integration of additional imaging modalities, and expanding the dataset to include more diverse patient demographics to validate the generalizability of our approach.

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