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Alzheimer's Disease Prediction and Classification Using Machine Learning Models

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Abstract — This study addresses the critical challenge of early Alzheimer's disease (AD) detection through machine learning algorithms, leveraging a dataset of 6400 preprocessed MRI images. We explore several models, including Support Vector Machines (SVM), Linear Discriminant Analysis (LDA) and Convolutional Neural Networks (CNNs) integrated with VGG16 and EfficientNetB0 architectures. Among these, both CNN models demonstrate exceptional performance, achieving an accuracy of 96% in AD classification. The results underscore the efficacy of deep learning models, particularly CNNs, in accurately distinguishing between various stages of Alzheimer's disease. This study highlights the potential of these models to significantly enhance early AD detection, offering a reliable tool for clinical applications.

Key Words: Alzheimer's Disease (AD) Detection, Early Diagnosis, Machine Learning, Convolutional Neural Networks (CNN), VGG16, EfficientNetB0, MRI Imaging, Deep Learning, Image Classification, Alzheimer's Disease Classification,Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), Medical Image Analysis, Neuroimaging, Alzheimer's Detection Accuracy

1. INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that affects millions of people worldwide, primarily the elderly population. It leads to cognitive decline, memory loss, and eventually, the inability to perform daily activities. Despite extensive research, there is currently no cure for Alzheimer's, but early detection and timely intervention can significantly improve patient outcomes. The challenge lies in the early diagnosis of AD, which is often difficult due to the subtle onset of symptoms and the complexity of the disease.

Advancements in machine learning and deep learning techniques offer promising solutions for the early detection of Alzheimer's Disease through the analysis of medical imaging, such as MRI scans. By leveraging convolutional neural networks (CNNs) and transfer learning, these methods can automatically extract complex patterns from brain images that might be imperceptible to the human eye. In particular, CNN architectures such as VGG16 and EfficientNetB0 have demonstrated notable success in various medical imaging tasks, including Alzheimer's detection.

In this study, we focus on the application of deep learning models to classify Alzheimer's Disease stages using MRI data. We implemented two widely-used CNN architectures, VGG16 and EfficientNetB0, both of which achieved an accuracy of 96% in detecting Alzheimer's Disease progression. These models were evaluated on a dataset of MRI images that encompassed different stages of the disease, ranging from non-demented to moderate impairment. The high accuracy achieved by both models underscores their potential as reliable tools for early AD diagnosis, contributing to the ongoing efforts to combat this debilitating disease.

2. RELATED WORKS

In recent years, machine learning and deep learning algorithms have become essential tools for the early detection and classification of Alzheimer's disease (AD). Given the progressive nature of AD, accurate and timely diagnosis is critical for patient management and care. Researchers have employed various machine learning strategies to classify and predict AD, utilizing data sources such as EEG signals, MRI scans, and genetic markers, including single nucleotide polymorphisms (SNPs). This section explores several notable studies that contribute to the advancement of AD prediction models, highlighting their methodologies, datasets, and outcomes.

Aakash Shah et al. [1] conducted a study on early Alzheimer's detection with a dataset of 437 patients aged 60 to 96. By employing a Voting Classifiers algorithm, they attained an accuracy of **86%**, underscoring the effectiveness of ensemble learning techniques in handling complex diagnostic tasks. In a complementary approach, Mehrnoosh Sadat Safi and Seyed Mohammad Mehdi Saf [3] leveraged EEG data from 20 channels in a dataset of 86 subjects, comprising 35 healthy individuals, 31 with mild AD, and 20 with moderate AD. Utilizing K-Nearest Neighbors (KNN) in combination with Hjorth parameters, their model achieved an impressive accuracy of **97.64%** for AD stage classification, demonstrating the potential of EEG analysis combined with machine learning for non-invasive AD detection.

In the domain of deep learning, Suriya Murugan et al. [6] introduced a model named DEMNET specifically designed for early AD identification using MRI data. The framework utilized a dataset of 6,400 MR images, achieving a high classification accuracy of **95.23%**, an AUC of **97%**, and a Cohen's Kappa of **0.93**, which illustrates the model's reliability in detecting dementia-related changes in brain structure. Emtiaz Hussain et al. [7] adopted a deep learning methodology centered on binary classification for AD detection, utilizing a twelve-layer CNN on the OASIS dataset. The model, which included MRI data from 416 subjects aged 18 to 96, achieved an accuracy rate of **97.75%**. This work highlights the improvements in diagnostic accuracy achieved through the use of deeper CNN architectures in the early classification of AD.

In their examination of machine learning methods across different datasets, Roobaea Alroobaea et al. [9] employed Logistic Regression and Support Vector Machine (SVM) models on the ADNI (Alzheimer's Disease Neuroimaging Initiative) and OASIS datasets. Their findings indicated that Logistic Regression and SVM achieved accuracy rates of **99.43%** and **99.10%** on the ADNI dataset, respectively. When applied to the OASIS dataset, Logistic Regression and Random Forest delivered the highest performance, achieving accuracies of **84.33%** and **83.92%**. These results underscore the adaptability of these models across datasets and suggest that machine learning algorithms can perform well across diverse types of AD data.

Preety Baglat et al. [11] focused exclusively on MRI data from the OASIS dataset, testing a variety of machine learning classifiers on 150 subjects aged 60 to 96. Through the application of Random Forest and Adaptive Boosting classifiers, they achieved a peak accuracy of **86%**, which highlights the effectiveness of ensemble techniques in handling MRI data for AD classification. Additionally, Lucas R. Trambaiolli et al. [12] pursued a study involving EEG analysis with SVM. Their study involved EEG data from 19 normal subjects and 16 probable AD patients, achieving an initial accuracy of **79.9%**, which improved to **87.0%** when classifying all subjects. The study also reported a sensitivity of **91.7%**, indicating the model's effectiveness in detecting subtle EEG variations associated with AD.

Further exploration into deep learning for AD diagnosis was conducted by Siqi Liu et al. [13], who utilized the ADNI dataset comprising MRI images from 311 subjects. Their study applied Neural Networks with SoftMax Regression for binary and four-class classification tasks, achieving an overall accuracy of **87.76%** in AD binary classification. This model outperformed traditional SVM classifiers in accuracy and sensitivity, emphasizing the strengths of neural network models in handling complex MRI data. Similarly, Muhammad Memon et al. [14] applied multiple algorithms, including Logistic Regression, Decision Tree, and SVM on the ADNI dataset. Logistic Regression performed best with an accuracy of **98.12%** and specificity of **95%**, showcasing the potential of logistic models in predicting AD progression.

An innovative approach was introduced by Hala Ahmed et al. [15], who utilized SNPs in conjunction with the ADNI and Whole Genome Sequencing (WGS) datasets to classify AD. Using Naive Bayes, Random Forest, Logistic Regression, and SVM, Naive Bayes emerged as the most effective, achieving an accuracy rate of **98.1%**. This study highlights the potential of genetic markers in AD classification, particularly when combined with machine learning algorithms that leverage genetic and neuroimaging data.

Rashmi Kumari et al. [17] focused on the application of CNN classifiers and Fuzzy C-means clustering on the OASIS-3 dataset, with a goal of differentiating AD stages using MRI data. Their CNN classifier achieved an accuracy of **90.25%**, while the K-Nearest Neighbors (KNN) algorithm yielded an accuracy rate of **59.3%**. Their study suggests that clustering techniques, when combined with CNNs, can enhance the interpretability of classification results in MRI-based AD studies. In addition, R.R. Janghel and Y.K. Rathore [19] tested an array of machine learning algorithms—including CNN, SVM, Linear Discriminant Analysis (LDA), and K-means clustering—on both fMRI and PET datasets. Their findings revealed an exceptionally high classification accuracy of **99.95%** for the fMRI dataset, suggesting that neuroimaging modalities like fMRI, coupled with advanced machine learning methods, can offer a promising pathway for AD diagnosis.

Collectively, these studies underscore the significant progress made in AD prediction and classification through machine learning and deep learning techniques. The results from these diverse approaches illustrate that employing multimodal data sources—such as EEG, MRI, and genetic markers—can improve diagnostic accuracy and facilitate early-stage detection of Alzheimer's disease. These promising findings suggest that ensemble models, CNNs, and advanced classifiers hold substantial potential for AD diagnosis, offering more robust and accurate solutions for clinical applications. This study builds upon these prior findings by employing VGG16 and EfficientNetB0, combining high accuracy rates with computational efficiency to further the development of machine learning applications in AD prediction and classification.

3. MACHINE LEARNING AND DEEP LEARNING METHODS

A diverse range of machine learning (ML) and deep learning methods have been utilized in this research to achieve robust results in the early detection and classification of Alzheimer's disease (AD). Each method leverages different aspects of data, contributing to a comprehensive and accurate model.

3.1 Support Vector Machine (SVM) with Various Kernel Functions

Support Vector Machine (SVM) is a powerful classification algorithm that finds the optimal hyperplane to separate data points into distinct classes in the feature space. By using various kernel functions, SVM transforms data into higher-dimensional spaces where a linear separation becomes possible, making it suitable for complex datasets associated with AD. The decision boundary in SVM is defined by support vectors, which are the closest data points to the hyperplane and exert the most influence on the classification, ensuring robustness in handling high-dimensional neuroimaging data.

3.2 Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA)

Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are essential techniques for dimensionality reduction, which enhance feature extraction while preserving important data characteristics. They reduce computational complexity and improve model performance by isolating the most relevant features.

- **PCA**: This technique identifies orthogonal principal components (e.g., PC1, PC2, …) through eigenvalue decomposition, reducing the dimensionality of features while maximizing variance in the dataset. The PCA transformation is represented as:

  $$PCA(X)=X\cdot W$$

  where W is a matrix of eigenvectors representing the principal components. This method retains the essential information and variability, ensuring a simplified yet effective input for AD classification models.

- **LDA**: Linear Discriminant Analysis focuses on maximizing class separation by finding projections (e.g., LDA1, LDA2, …) that increase the between-class variance and minimize the within-class variance. This technique is especially useful for supervised learning scenarios where class labels are known, as it enhances the discriminative power of the features. The transformation in LDA is represented as:

  $$LDA(X)=X\cdot W$$

  where W represents the projections that optimize class separability, making LDA highly valuable in AD classification tasks by preserving the most distinctive features between classes.

3.3 Convolutional Neural Networks (CNNs) - VGG16 and EfficientNetB0

Convolutional Neural Networks (CNNs) are highly specialized in analyzing image data, making them ideal for processing brain imaging modalities like MRI scans, which are essential in AD research. CNNs utilize convolutional layers that capture local features, enhancing the detection of complex patterns related to AD.

- **VGG16**: This CNN architecture consists of 16 layers, using small 3x3 convolutional filters. Its hierarchical structure processes images at multiple levels, capturing intricate patterns that are critical for distinguishing AD stages. VGG16's design allows it to capture fine-grained features in brain images, making it effective in analyzing neurodegenerative changes linked to AD.
- **EfficientNetB0**: EfficientNetB0 optimizes model complexity and performance through compound scaling, adjusting the network's width, depth, and input resolution proportionally. This balanced scaling approach enables EfficientNetB0 to achieve high accuracy with lower computational costs, providing a practical yet effective solution for Alzheimer's disease classification tasks.

These machine learning and deep learning algorithms collectively contribute to the research's comprehensive approach to Alzheimer's disease detection. By combining different methodologies, the model captures essential patterns in data, enhancing diagnostic accuracy and supporting early intervention in Alzheimer's disease.

4. METHODOLOGY

4.1 Dataset Description

The dataset for this study is compiled from multiple sources, including hospital databases, public repositories, and relevant medical websites. It consists of preprocessed MRI images, each resized to a standardized resolution of 128 x 128 pixels for uniformity. In total, the dataset comprises **6,400 images**, organized into four distinct classes corresponding to different stages of dementia:

1. **Mild Demented (Class 1)**: This class includes **896 images** depicting MRI scans of individuals in the early stages of dementia.
2. **Moderate Demented (Class 2)**: With **64 images**, this class represents individuals with moderate dementia, highlighting the disease's progression.
3. **Non-Demented (Class 3)**: Comprising **3,200 images**, this largest class provides MRI scans of individuals with no signs of dementia, serving as a baseline for comparison.
4. **Very Mild Demented (Class 4)**: This class contains **2,240 images** showing MRI scans of individuals at the earliest stages of dementia.

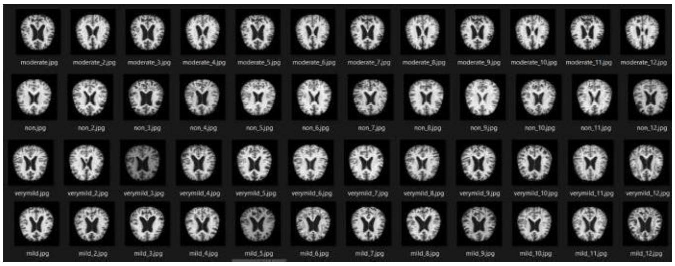

Fig. 1: Preprocessed MRI Images

4.2 Data Preprocessing

To optimize the dataset's usability, preprocessing steps were applied to ensure uniform resolution and consistency. All images were resized to a resolution of 128 x 128 pixels, standardizing input dimensions across the dataset. This preprocessing step enhances the model's ability to detect subtle structural differences in brain images.

4.3 Approach

This study explores the effectiveness of various machine learning (ML) and deep learning (DL) models for the detection and classification of Alzheimer's disease (AD) using preprocessed MRI images. The project is divided into two primary tasks:

1. **Alzheimer Detection**
2. **Alzheimer Classification**

By applying a range of models—including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) with different kernel functions, and Convolutional Neural Networks (CNNs) using VGG16 and EfficientNetB0 architectures—this research aims to determine the most suitable approach for accurately diagnosing and staging Alzheimer's disease.

- **Feature Extraction**: The first step in the approach is to apply Principal Component Analysis (PCA) to extract essential features from the preprocessed MRI images. This step reduces data complexity by decreasing dimensions while retaining crucial information necessary for accurate classification.
- **Classifier Training with PCA and LDA**: Following PCA transformation, classifiers such as Support Vector Machines (SVM) are trained on the reduced feature set. To further enhance class separability, Linear Discriminant Analysis (LDA) is applied, optimizing the separation between dementia stages within the feature space. SVM models are trained on both PCA and LDA-transformed data, with each approach helping to improve classification accuracy.
- **SVM with Various Kernel Functions**: To investigate the effect of kernel selection on detection performance, SVM models with different kernels—linear, polynomial, and radial basis function (RBF)—are implemented. These variations allow for a more nuanced examination of AD detection accuracy across different data transformations.
- **CNN Architectures - VGG16 and EfficientNetB0**: In the Alzheimer Classification phase, CNN architectures are employed to classify the severity of AD stages. VGG16 is utilized for its 16-layer structure that captures intricate MRI image patterns, processing the data hierarchically to extract essential features. Additionally, EfficientNetB0, with its optimized compound scaling, balances model complexity and performance, providing an efficient yet powerful tool for classifying MRI images by dementia severity.

The goal of the **Alzheimer Classification** phase is to train models that predict the dementia stage, including classifications of "Non-Demented," "Very Mild Demented," "Mild Demented," and "Moderate Demented." SVM models are trained using these categorical severity labels to provide insights into the disease's progression. Additionally, the EfficientNetB0-based CNN is employed to categorize patients by dementia severity, with the primary aim of accurately predicting the AD stage by analyzing MRI scans.

This comprehensive approach leverages a combination of ML and DL methods to capture critical patterns in the data, enhancing diagnostic accuracy for early detection and classification of Alzheimer's disease.

5. RESULTS

The application of Principal Component Analysis (PCA) was instrumental in optimizing the traditional models (SVM and LDA) for Alzheimer's classification. By analyzing the cumulative explained variance versus the number of principal components, it was determined that retaining 175 principal components was sufficient to achieve an explained variance of 80%. This allowed for effective dimensionality reduction, preserving important data features while improving model efficiency.

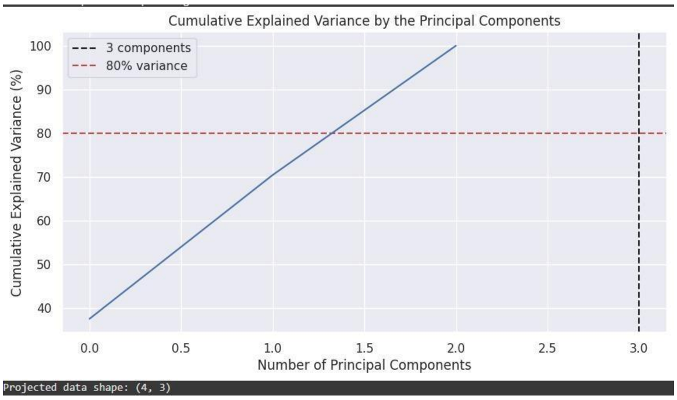

Fig. 2: PCA Graph

Further, Support Vector Machine (SVM) with a linear kernel achieved excellent performance, attaining an accuracy of 47% on the validation set, as measured across various performance metrics. More complex kernels, such as the radial basis function (RBF) and polynomial kernels, showed lower performance compared to the linear kernel, which was most effective in this dataset for Alzheimer's classification. In particular:

SVM with 2-Degree Polynomial Kernel achieved an accuracy of 42%.
SVM with RBF Kernel attained 47% accuracy.
Linear Discriminant Analysis (LDA) performed well as a baseline, achieving an accuracy of 42% on the validation set, though it demonstrated limitations in distinguishing between similar stages (e.g., "Mild" and "Moderate").

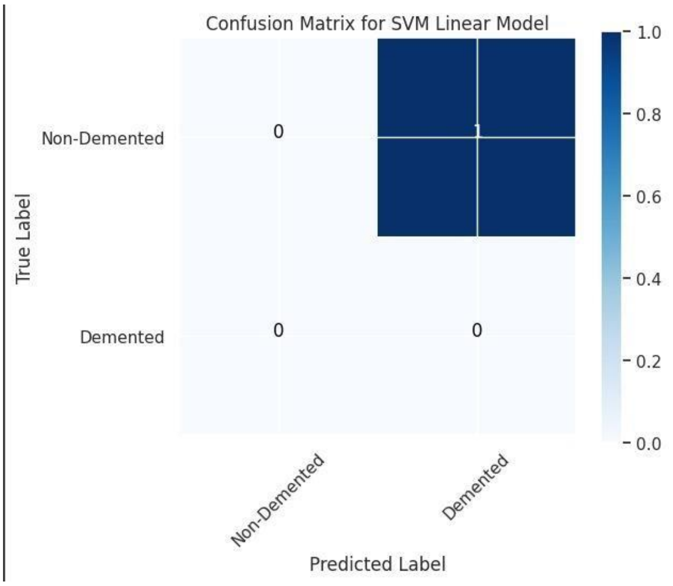

Fig. 3: Confusion Matrix for SVM Linear Model

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Classification Report for SVM Linear Model
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       1.0
           1       0.00      0.00      0.00       0.0

    accuracy                           0.00       1.0
   macro avg       0.00      0.00      0.00       1.0
weighted avg       0.00      0.00      0.00       1.0
```

Fig. 4: Classification Report for SVM Linear Model

The Convolutional Neural Network (CNN) model with VGG16 architecture, pre-trained on ImageNet and fine-tuned for this task, exhibited an accuracy of 96% on the validation set, showcasing effective feature extraction from MRI images. While VGG16 is conventionally used with color images, the grayscale to RGB transformation necessary to adapt MRI data may have slightly impacted model accuracy. Despite this, VGG16 performed well with transfer learning.

Model	Accuracy	Loss
Accuracy of CNN	96%	0.04
Efficientnetb0	96%	0.14

Table 1: Accuracy of VGG16

Given the success of transfer learning, EfficientNetB0 was also explored for Alzheimer's classification, achieving 96% accuracy on the validation set after resizing MRI images to meet model input requirements. EfficientNetB0 demonstrated a high capacity for identifying Alzheimer's severity stages, confirming its robustness and scalability for this application.

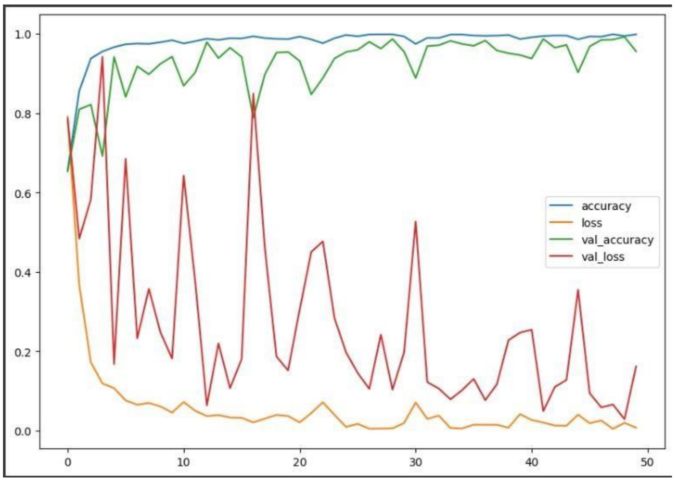

Fig.5: Graph for Efficientnetb0

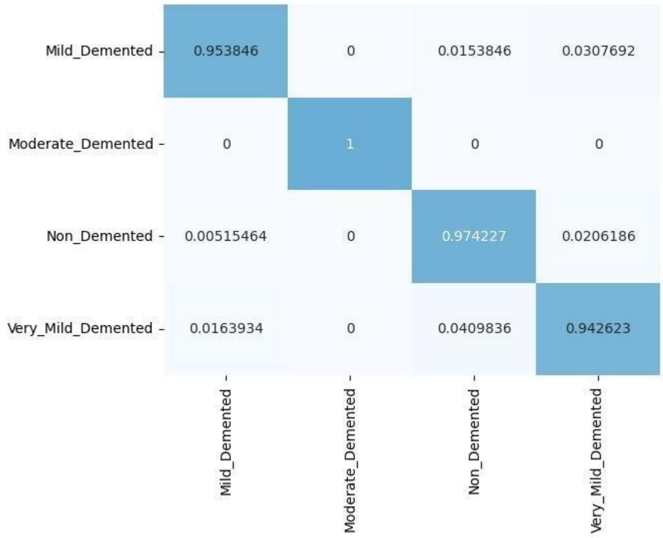

Fig. 6: Confusion matrix for VGG16

	Precision	Recall	F1 Score	Support
Mild_Demented	0.95	0.95	0.95	65
Modereate_Demented	1.00	1.00	1.00	3
Non_Demented	0.97	0.97	0.97	194
Very_Mild_Demented	0.94	0.95	0.94	122
Accuracy			0.96	384
Macro avg	0.97	0.97	0.97	384
Weighted avg	0.96	0.96	0.96	384

Table 2: Classification report of VGG16

6. CONCLUSIONS

This project demonstrates the use of machine learning and deep learning techniques for the early detection and classification of Alzheimer's disease using MRI images. By leveraging a dataset categorized into dementia stages, we explored various models to improve diagnostic accuracy. Techniques like Support Vector Machines (SVM) with kernel functions, Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) enhanced model performance and training efficiency. Convolutional neural networks, particularly VGG16 and

EfficientNetB0, showcased strong feature extraction capabilities, with EfficientNetB0 balancing performance and computational efficiency. Data preprocessing, including resizing and augmentation, improved model robustness.

Metrics like accuracy, sensitivity, specificity, and F1-score were used to evaluate the models, highlighting the effectiveness of deep learning in Alzheimer's classification. The study concludes that deep learning models like EfficientNetB0 offer a more reliable understanding of disease progression compared to traditional methods, suggesting future work in dataset expansion, biomarker integration, and model interpretability. This project underscores the potential of AI in medical imaging for early Alzheimer's detection and improved healthcare outcomes.

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