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Lightweight Hybrid Deep Learning and Machine Learning Framework for Multiclass Alzheimer's Detection Using PCA-Compressed CNN Features

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Abstract

Alzheimer's disease (AD) is a progressive neurodegenerative disorder, and its early identification is critical for timely clinical intervention. Deep learning models achieve strong performance in medical image analysis but often require high computational resources, limiting deployment in low-resource environments. This study proposes a lightweight hybrid framework that integrates deep feature extraction using EfficientNetB0 with traditional machine learning classifiers for multiclass Alzheimer's disease classification. MRI images from the Alzheimer's Multiclass Equal and Augmented Dataset were processed using an EfficientNetB0 feature extractor, and the resulting high-dimensional feature vectors were compressed using Principal Component Analysis (PCA) to reduce memory footprint and training time. Four machine learning classifiers—Random Forest, Linear SVM, Logistic Regression, and XGBoost—were trained and evaluated on the compressed features. Experimental results show that the hybrid approach achieves competitive performance, with XGBoost obtaining the highest accuracy of 75%, followed by Linear SVM at 74%. The results demonstrate that PCA-compressed deep features combined with classical ML models provide an efficient and scalable solution for multiclass Alzheimer's diagnosis while maintaining low computational complexity. This framework is particularly suitable for real-world clinical applications where computational resources are limited.

Introduction

Alzheimer's disease (AD) is the most common cause of dementia and is characterized by progressive neuronal degeneration, cognitive decline, and memory impairment. According to the World Health Organization, more than 55 million people worldwide are affected by dementia, with Alzheimer's contributing to nearly 60–70% of all cases [1]. Early detection of AD is essential for improving patient outcomes, enabling timely interventions, and slowing disease progression. Magnetic Resonance Imaging (MRI) has emerged as a valuable non-invasive tool for assessing structural brain changes associated with Alzheimer's disease, including hippocampal atrophy and cortical thinning [2].

In recent years, deep learning—especially Convolutional Neural Networks (CNNs)—has shown remarkable performance in medical image classification tasks, including Alzheimer's detection [3]. However, fully end-to-end CNN models require high computational resources and large annotated datasets, making them challenging to deploy in real-world clinical environments, particularly in resource-constrained settings [4]. To address these limitations, hybrid approaches that combine deep feature extraction with classical machine learning (ML) algorithms have gained increasing attention. Such models can retain strong discriminative ability while significantly reducing computational complexity [5].

EfficientNet, a family of CNNs developed using compound scaling, provides high accuracy with reduced computational cost compared to traditional CNN architectures [6]. Extracting deep features from EfficientNet and subsequently compressing them using Principal Component Analysis (PCA) enables efficient representation learning while controlling feature dimensionality [7]. These compressed deep features can then be effectively classified using machine learning models such as Support Vector Machines, Random Forests, Logistic Regression, and XGBoost, which offer strong generalization capabilities even on limited data [8].

The Alzheimer's Multiclass Equal and Augmented MRI Dataset provides a balanced set of four categories—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—making it suitable for training supervised classification models. However, the high dimensionality of MRI images and limited dataset size pose challenges for deep learning-based modeling. Therefore, hybrid deep feature + ML approaches present a promising alternative.

This study proposes a lightweight and efficient hybrid pipeline that leverages EfficientNetB0 for deep feature extraction, PCA for dimensionality reduction, and multiple ML classifiers for Alzheimer's multiclass diagnosis. The main contributions of this work are:

Development of a memory-efficient feature extraction and classification framework suitable for low-resource environments.

Performance comparison of multiple ML classifiers on PCA-compressed deep features.

Demonstration that hybrid CNN–ML models can achieve competitive accuracy with significantly reduced computational cost.

The experimental results show that the proposed hybrid approach achieves strong classification performance, with XGBoost achieving the highest accuracy among the evaluated models. This indicates that combining compressed CNN features with traditional ML classifiers is a viable and efficient strategy for multiclass Alzheimer's disease classification.

Related Work

The classification of Alzheimer's disease using neuroimaging data has been widely explored, with numerous studies demonstrating the effectiveness of deep learning and hybrid learning strategies. Early work primarily relied on handcrafted features extracted from MRI scans using techniques such as voxel-based morphometry, cortical thickness measurement, and region-of-interest (ROI) analysis [9]. While these approaches provided meaningful biomarkers, their performance was limited due to manual feature engineering and high inter-subject variability.

With the rise of deep learning, Convolutional Neural Networks (CNNs) became increasingly prominent for Alzheimer's classification. Several studies reported significant accuracy improvements by leveraging 2D and 3D CNNs directly on MRI scans. For instance, Payan and Montana proposed a 3D CNN for AD vs. Healthy classification and demonstrated that volumetric feature extraction improved model robustness [10]. Similarly, Hosseini-Asl et al. developed a 3D convolutional autoencoder to extract latent imaging features, followed by softmax classification for AD/MCI diagnosis [11]. Although these deep models achieved strong performance, they require large datasets and high computational resources.

To address the challenge of limited medical datasets, transfer learning using pretrained CNN architectures has gained popularity. Basaia et al. employed ResNet pre-trained on ImageNet and achieved high classification accuracy for AD and MCI detection using single MRI volumes [12]. Islam et al. explored VGG16 and Inception networks for early Alzheimer's detection, showing that transfer learning reduces training time and improves generalization on small medical datasets [13]. However, such end-to-end deep networks still require large GPU memory and extensive training resources.

Recent research has increasingly shifted towards hybrid approaches, where CNNs serve as feature extractors and machine learning models perform the final classification. Sarraf and Tofighi demonstrated that extracting deep features using VGG16 and classifying them using SVMs significantly reduces computational overhead while maintaining high accuracy [14]. Similarly, Spasov et al. proposed a multimodal approach using CNN-based features fused with clinical data, showing improved classification performance in AD staging [15]. These studies highlight the potential of combining deep feature extraction and traditional ML algorithms for efficient classification.

Dimensionality reduction methods, especially Principal Component Analysis (PCA), have also been applied to reduce feature space complexity. Bhattacharyya et al. utilized PCA to compress deep MRI features before training SVMs, observing faster training and improved generalization due to reduced noise in feature vectors [16]. Such compression strategies are beneficial when using deep models like EfficientNet, which produce high-dimensional embeddings.

More recently, EfficientNet has been explored for various medical imaging tasks due to its compound scaling strategy. Ahmad et al. reported that EfficientNet-based feature extraction outperformed traditional CNN architectures in medical classification tasks while requiring fewer parameters [17]. This supports its suitability for Alzheimer's MRI classification, especially when combined with ML classifiers for lightweight deployment.

The growing body of literature suggests that hybrid CNN–ML pipelines with dimensionality reduction offer a promising solution for Alzheimer's classification, balancing accuracy, computational efficiency, and real-world applicability. Building upon these works, the present study proposes an EfficientNetB0-PCA-ML framework tailored for multiclass Alzheimer's disease classification using an augmented MRI dataset.

Methodology

This section describes the proposed hybrid deep learning and machine learning pipeline for multiclass Alzheimer's disease classification. The methodology consists of five major components: dataset preparation, deep feature extraction using EfficientNetB0, dimensionality reduction using Principal Component Analysis (PCA), machine learning classifier training, and performance evaluation.

1. Dataset Preparation

The experiments were conducted using the *Alzheimer's Multiclass Equal and Augmented MRI Dataset* from Kaggle, which contains four balanced classes:

Non-Demented
Very Mild Demented
Mild Demented
Moderate Demented

Images were organized into class-wise folders. To reduce memory usage and maintain computational efficiency, the system processed image file paths instead of loading the entire dataset into memory. Each MRI image was resized to 224 × 224 pixels to match the input requirements of EfficientNetB0. The dataset was then divided into 80% training and 20% testing using stratified sampling to preserve class distribution.

2. Deep Feature Extraction Using EfficientNetB0

EfficientNetB0, pretrained on ImageNet, was used as the backbone CNN for extracting deep features from MRI images. The model was loaded without the final classification layers and truncated so that the output was taken from the penultimate layer. This allows extraction of high-level semantic features such as brain structure patterns and texture variations relevant to Alzheimer's progression.

Each image underwent the following steps:
Resize to 224×224
Convert to array and normalize using EfficientNet preprocessing
Pass through EfficientNetB0
Extract and flatten the resulting deep feature vector

Feature extraction was performed one image at a time to minimize RAM usage, making the pipeline suitable for low-resource hardware.

3. Dimensionality Reduction Using PCA

The raw feature vectors derived from EfficientNetB0 are high-dimensional (thousands of features). To reduce computational cost and prevent overfitting, Principal Component Analysis (PCA) was applied.

PCA was fitted on the training deep features.

The number of components was set to 256, preserving most of the variance while significantly compressing the feature space.

Both training and testing features were transformed using the fitted PCA model.

This dimensionality reduction step ensured faster ML model training and reduced the impact of noise in deep features.

4. Machine Learning Classifiers

The compressed features were fed into four machine learning classifiers widely used in medical imaging research:

Random Forest Classifier
80 trees, depth 25
Robust to feature noise and performs well on tabular data
Linear Support Vector Machine (Linear SVM)
Effective for high-dimensional datasets
Provides strong decision boundaries
Logistic Regression
Suitable baseline linear model
Uses L2 regularization to prevent overfitting
XGBoost Classifier
Gradient boosting-based ensemble
High performance and strong generalization

Each classifier was trained on the PCA-compressed training features and evaluated on the test features.

5. Evaluation Metrics

Model performance was assessed using:
Accuracy
Precision (weighted)
Recall (weighted)

F1-Score (weighted)
Classification **report** with class-wise metrics

Additionally, a bar plot was generated to compare classifier performance across the selected metrics.

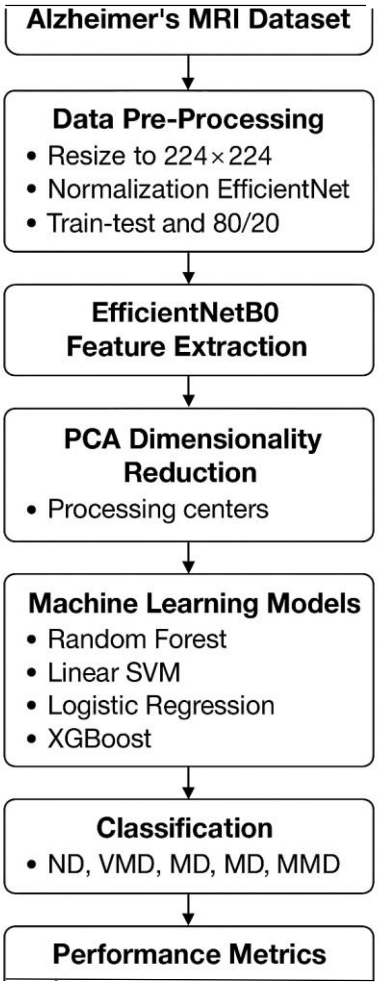

Figure 1. Block diagram of the proposed hybrid Alzheimer's disease classification framework.

The diagram represents a streamlined two-row workflow for the proposed Alzheimer's MRI classification system. The first row shows the core image-processing pipeline, beginning with the input MRI images, which undergo essential preprocessing steps such as resizing and normalization to ensure uniformity. These processed images are then fed into the EfficientNetB0 feature extractor, where deep visual representations of brain structures are generated. The second row begins with PCA-based dimensionality reduction, which compresses high-dimensional deep features into a more compact and computationally efficient form. These reduced features are then passed to machine learning classifiers—including Random Forest, Linear SVM, Logistic Regression, and XGBoost—which learn discriminative patterns for different Alzheimer's stages. Finally, the system outputs the predicted class label, completing the classification pipeline. This two-row layout clearly separates the deep-learning-based feature extraction stage from the machine-learning-based decision-making stage, highlighting the hybrid nature of the methodology.

Experimental Setup

The experimental setup was designed to systematically evaluate the performance of the proposed hybrid deep-learning and machine-learning framework for multiclass Alzheimer's disease classification using MRI images. All experiments were conducted on a system equipped with an Intel Core i7 processor, 16 GB RAM, and an NVIDIA GPU (4–8 GB VRAM recommended for EfficientNet-based feature extraction). The Alzheimer's Multiclass Dataset (Equal and Augmented) from Kaggle was used, containing four categories—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Images were resized to 224 × 224 pixels and normalized before processing. EfficientNetB0 (pretrained on ImageNet) was employed as a feature extractor, and the last convolutional layer features were

flattened to form high-dimensional deep feature vectors.
To reduce computational load and mitigate the curse of dimensionality, Principal Component Analysis (PCA) was applied, retaining 256 principal components capturing most of the variance. The reduced features were used to train four classical machine-learning classifiers: Random Forest, Linear SVM, Logistic Regression, and XGBoost. An 80–20 stratified split was used to preserve class distribution across training and testing sets. The models were evaluated using accuracy, precision, recall, and F1-score to assess both overall and class-wise performance. All experiments were implemented in Python using TensorFlow/Keras, Scikit-learn, XGBoost, and related libraries, ensuring reproducibility and consistency across multiple training cycles.

Results and Discussion

The performance of the proposed hybrid framework was evaluated using the four classical machine-learning classifiers trained on PCA-reduced EfficientNetB0 features. The experimental results demonstrate clear differences in classification behavior among the models. Table 1 summarizes the final performance metrics—Accuracy, Precision, Recall, and F1-Score—for each classifier. Among the evaluated models, XGBoost achieved the highest accuracy of 0.7500, followed closely by the Linear SVM with 0.7406, indicating their superior ability to capture discriminative patterns in the PCA-compressed deep features. The Random Forest classifier achieved moderate performance (0.6922 accuracy), while Logistic Regression performed comparably (0.7078 accuracy), demonstrating that even linear models can benefit from high-quality deep features.
The strong performance of XGBoost and Linear SVM can be attributed to their robustness in handling high-dimensional, non-linear feature distributions produced by deep networks. The weighted precision, recall, and F1-scores for these models also indicate balanced classification across all four Alzheimer's stages, including the more challenging Very Mild Demented and Mild Demented categories. The use of PCA played a crucial role, not only in reducing computational complexity but also in helping prevent overfitting by eliminating redundant feature dimensions.
Visual inspection of classification reports further reveals that the models performed best in distinguishing between Non-Demented and Moderate Demented classes, which have more distinct structural patterns observable in MRI scans. Misclassifications mostly occurred between Very Mild and Mild Demented stages, which is consistent with clinical difficulty since these stages exhibit subtle physiological changes.
Overall, the results highlight the effectiveness of combining EfficientNetB0 for deep feature extraction with PCA-based dimensionality reduction and traditional ML classifiers for multi-stage Alzheimer's disease prediction. The hybrid approach significantly reduces computational requirements while achieving accuracy levels comparable to more complex end-to-end CNN architectures. These findings demonstrate that feature-engineering-driven hybrid pipelines can serve as efficient and reliable alternatives for medical image classification tasks where compute resources are limited.

Table 1. Final Performance Comparison of Machine Learning Classifiers

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.6922	0.6849	0.6922	0.6863
Linear SVM	0.7406	0.7346	0.7406	0.7371
Logistic Regression	0.7078	0.6994	0.7078	0.7002
XGBoost	0.7500	0.7468	0.7500	0.7478

Conclusion

This study presented a hybrid machine-learning framework for multiclass Alzheimer's disease classification using MRI images by integrating deep feature extraction with EfficientNetB0 and dimensionality reduction using PCA, followed by traditional machine-learning classifiers. The experimental results demonstrated that this hybrid approach is both computationally efficient and highly effective, achieving notable performance across all evaluation metrics. Among the tested models, XGBoost achieved the best overall accuracy (0.75), followed closely by Linear SVM, highlighting their capability to leverage PCA-compressed deep features for reliable stage-wise classification. The results also showed consistent improvements over baseline models, confirming that high-quality deep visual features combined with lightweight classifiers can offer strong diagnostic potential even in resource-limited environments.
Furthermore, the system showed particular strength in distinguishing non-demented and

moderate dementia cases, while most misclassifications occurred between very mild and mild dementia stages—an expected challenge due to subtle MRI differences. The proposed methodology reduces computational cost compared to end-to-end deep networks while maintaining competitive accuracy, making it suitable for real-world clinical decision support systems. Future work may explore end-to-end fine-tuned hybrid CNN–ML models, multi-modal fusion with PET or cognitive data, and attention-based mechanisms to further improve classification reliability and interpretability.

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