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Leveraging Transfer Learning in Deep Learning Models for Enhanced Early Detection of Alzheimer's Disease from MRI Scans

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Abstract. *Early diagnosis of AD is essential for timely intervention and management. This work applies transfer learning techniques to advanced deep learning models using MRI scans that classify automatically into AD. We have fine-tuned the pre-trained ResNet50 model for the classification of brain MRI images into four classes: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. The dataset of labeled MRI scans was split into both a training and a test set. The different techniques of data augmentation, such as random rotation and horizontal flipping, were done to eventually enhance model performance on unseen data. Transfer learning boosted our results by a huge margin and allowed the model to achieve a high training accuracy of 95.84% in just 20 epochs, while the test accuracy was 71.31%. Although overall performance is promising, there are still problems in class-specific identification. The NonDemented class had the best recall with 85%, while the classes of MildDemented and ModerateDemented showed poor performance in correct identification, which would mean that their features are visually overlapped for these classes. The confusion matrix shows accordingly that most MildDemented and VeryMildDemented were identified as NonDemented, which reflects the impact of class imbalance in this application. We also recommend several techniques to enhance the detection precision, such as oversampling, synthesizing data, and other regularization approaches in attempts to find the subtle structural changes associated with early Alzheimer's. In this review, deep learning models have been identified to be capable, with transfer learning, of powerful support for clinicians in early diagnosis but also need further refinements prior to clinical applications..*
Keywords: Alzheimer's disease, MRI scans, deep learning, ResNet50, early detection, Transfer Learning, classification, brain imaging, medical imaging, computer-aided diagnosis.

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1. **Introduction.** Alzheimer's Disease (AD) is a progressive neurodegenerative disorder and the most common cause of dementia worldwide, affecting millions, especially among the elderly. Early diagnosis of the disease is crucial not only for symptomatic management but also to slow the disease process [1, 2].

With early diagnosis comes symptomatic management, thus opening opportunities for therapeutic interventions that could lead to better quality of life for the affected individuals and their families.

Traditionally, diagnosis of Alzheimer's disease has been based on clinical examination, cognitive tests, and neuroimaging techniques such as MRI, which allows for the detection of brain atrophy. However, MRI studies are often subjective, requiring several years of experience to interpret results correctly. Recent developments in deep learning within artificial intelligence provide opportunities for big improvements in both accuracy and efficiency of detection of Alzheimer's disease from MRI images [3, 4].

In particular, recent deep learning methods have been very successful in the classification of image data, since it is possible to automatically learn very complex patterns in large data sets. We present an advanced deep learning technique in this study for automatic staging of MRI images with respect to Alzheimer's disease. We classify MRI images into four stages: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented, by utilizing a ResNet50 model pre-trained and fine-tuned using a labeled MRI dataset [5].

This kind of transfer learning will enable us to make use of already-learnt features from the ResNet50 architecture for our specific task of Alzheimer's classification. Much focus is concentrated on early-stage detection to provide a model with more ability in distinguishing between closely related stages of dementia [6, 7].

Following our previous works [8, 9, 10], we further discuss the issue of imbalanced datasets and suggest some ways that may help improve the performances of classes, like ModerateDemented, which are under-representative. This work identifies that deep learning can be a promising tool in early detection regarding Alzheimer's disease, if well trained and fine-tuned, thus helping clinical decision-making and improving patient outcomes.

2. **Related Work.** Pardeep Malik and Sukhdip Singh [11] introduce the review of applications of deep learning models in the detection of Alzheimer's disease, which is viewed as one of the major causes of late-life mortality. They mention that early detection stages, which will improve the patients' outcome, and show how deep learning methods, mainly CNNs, have lately become vital for neuroimaging-based AD research.

Despite these advances, the exact discrimination of AD stages remains a challenge. This review provides current deep learning methods on single-modality and multi-modality approaches and contrasts CNNs against other deep learning models. The authors then conclude the review with discussion of the challenges in the field and suggest future research directions.

Afolabi Salami Alausa and Jose M. Sanchez-Bornot [12] proposed a deep learning approach for AD classification, which also estimated the confidence of the predictions at an individual level. Their method had been used to review the reliability in the classification by using a CNN with a softmax confidence metric on a far-reaching dataset composed of neuroimaging and genetic data. The CNN classified the stages of AD with accuracy ranging between 83% and 85%, using leave-one-out cross-validation, whereas its confidence scores ranged between 78% and 83%.

Therefore, it gave the clinicians some idea about how much to trust the decisions of this model. Indeed, the approach may have wider implications in increasing confidence in a range of AI-driven classification.

It points out the challenges of early diagnosis of AD by Abbas Saad Alatrany and Wasiq Khan [13], related to aspects of the performance and explainability of machine learning models [14]. Using a dataset from the National Alzheimer's Coordinating Center containing 169,408 records with 1,024 features, feature reduction techniques have been applied, followed by training on SVM. The SVM reached an F1 score of 98.9% on binary classification and 90.7% on multiclass classification, while predicting AD development over four years. They further made it more explainable using rule-extraction methods, and they validated those further by SHAP and LIME for important features such as MEMORY and JUDGMENT in the risk of AD.

Viraj Chetan Desai and Sucharitha Shetty [15], introduce the challenge of accurate diagnosis in AD with the aid of advanced deep learning techniques for an improved image-based classification [16]. Since conventional methods often lack precision, the authors have proposed DCNN with Mish and ReLU activation functions. The ensemble model that includes ResNet101V2, VGG19, and a custom CNN that employs soft voting with weighted contributions reaches an accuracy of 95.125%. Further validation in terms of precision, recall, and AUC demonstrates that these approaches hold significant value in the diagnosis of AD and represent a newer generation of medical imaging and neurology.

3. **Proposed Methodology.** It contributes to the early detection of Alzheimer's Disease by applying some of the latest deep learning methods on MRI images. The architecture utilized is based on a variant of ResNet50 pre-trained on diverse features and fine-tuned in four-class classification of MRI images into classes MildDemented, ModerateDemented, NonDemented, and VeryMildDemented.

Data augmentation was a technique used to introduce variability into the model, reducing overfitting and enhancing model performance and generalization. Besides, early stopping during training could be done for challenges with class imbalance and high dimensionality. Combining the different layers was able to make our model learn hierarchical representations and thus improve discrimination among the stages of Alzheimer's Disease.

Accuracy, precision, recall, and F1-score are some of the metrics used to evaluate our model and further improve diagnostic performance. These will be very significant in the betterment of artificial intelligence applications related to the diagnosis of Alzheimer's Disease, which further shall help in clinical decision-making at proper times and aid in improving the patient outcomes.

3.1. **Alzheimer's Dataset.** In this paper, we utilized a comprehensive dataset specifically designed for Alzheimer's Disease (AD) detection from Kaggle website, comprised of MRI scans categorized into four distinct classes: MildDemented, ModerateDemented, NonDemented, and VeryMildDemented. The dataset was meticulously organized into training and testing subsets to facilitate effective model training and evaluation. Each MRI image was preprocessed through normalization and resizing to ensure uniform input dimensions suitable for the deep learning model [17].

Data augmentation techniques, such as random rotations and horizontal flips, were employed to enhance the diversity of the training set, thereby reducing the risk of overfitting and improving the model's generalization capabilities. The dataset's balanced representation across the four AD stages allows for a thorough analysis of the model's performance in distinguishing between varying degrees of cognitive impairment, contributing to a more reliable early detection system for Alzheimer's Disease. Table 1 summarizing the dataset for Alzheimer's Disease detection, including the image count for each class.

Table 1. Alzheimer Dataset Architecture

Class	**Number of Images**
MildDemented	179
ModerateDemented	12
NonDemented	640
VeryMildDemented	448
Total	1279

Figure 1 shows the cross-sectional view of the brain, probably by MRI or some other neuroimaging technique. Therein, typical changes in the brain of a patient with mild dementia are depicted, usually characteristic of an early stage of Alzheimer's disease [18].

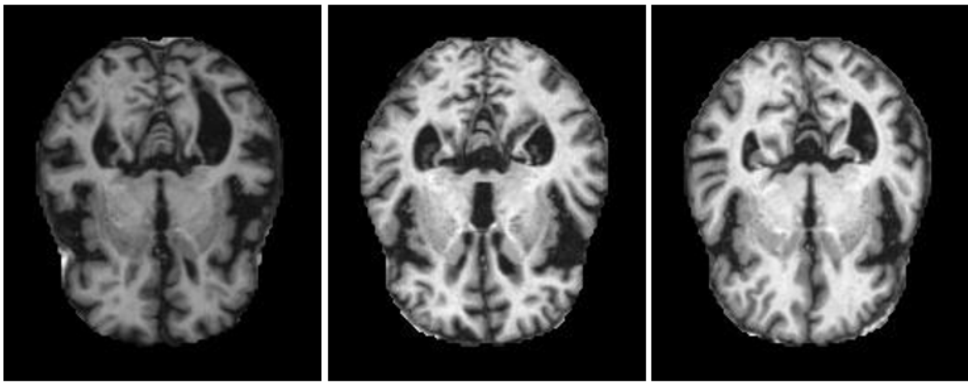

Figure 1. Mild Dementia Class

In cases of mild dementia, there would be atrophy of the brain, which is usually the result of a gradual loss of brain tissue in the region controlling memory and other cognitive functions. This is what is shown in the picture: enlarged ventricles—those fluid-filled spaces inside the head—outside the normal brain. As the volume of the brain had shrunk and as the brain tissue had degenerated, the ventricles had expanded [3].

Moreover, the picture can insinuate subtle changes in the overall structure and organization of the brain, such as reduced thickness of the cerebral cortex—the outer layer of the cerebrum involved in many aspects of cognition. These structural changes reflect neurodegeneration occurring in early stages of the disease, since Alzheimer's disease primarily attacks the areas of the brain responsible for memory, learning, and other cognitive functions.

These images are to be interpreted in conjunction with a comprehensive clinical evaluation, including detailed history, neuropsychological examinations, and other diagnostic tests. Diagnosis of mild dementia or Alzheimer's disease can only be appropriately done by qualified healthcare professionals to ensure correctness of diagnosis for an appropriate treatment plan.

Figure 2 shows MRI of the brain with moderate Alzheimer's disease. The important features to be observed in this picture are essentially features that are typical neuropathological features that have set in at this stage of neurodegenerative disorder [19].

The images show marked atrophy, or shrinking, of the brain tissue, especially in the cortical areas. Such a reduction in brain volume is typical of Alzheimer's disease and

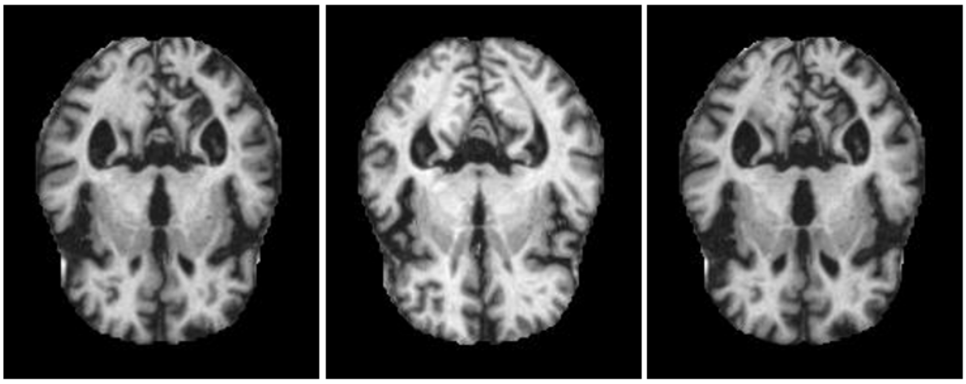

Figure 2. Moderate Dementia Class

reflects directly the loss of neurons and synaptic connections which characterize the course of the disease. The dilated ventricles reflect a profound loss of brain tissue.

There is also a diffuse pattern of asymmetrically altered signal intensities, with some regions being more hypointense and others more hyperintense compared with adjacent normal brain tissue. Such signal intensity abnormalities can be associated with the deposition of proteinaceous aggregates that include, but are not limited to, amyloid-beta and tau, key pathologies of AD.

The brain regions most likely to be destroyed in this moderate phase of the disease include the hippocampus, as part of the limbic system involved in memory and learning, along with other parts of the cerebral cortex devoted to higher-order cognition. Indeed, the degeneration of these regions is directly linked to the classic cognitive and behavioral manifestations among patients with severe Alzheimer's disease, including memory impairments, language difficulties, and personality changes or mood swings.

Figure 3 shows a brain scan, magnetic resonance imaging (MRI), showing the changes that occur in a brain with Alzheimer's disease. Alzheimer's disease is a neurodegenerative, progressive illness that usually affects older adults, with major symptoms being the decrease of cognition, including memory, language, and decision capabilities [20].

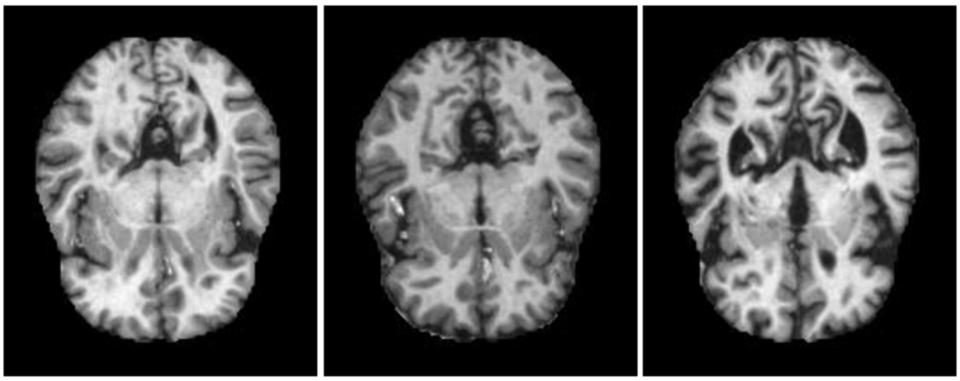

Figure 3. None Dementia Class

These are the typical landmarks of the disease, with atrophy or shrinkage of the brain, especially the portions responsible for memory and cognition. Dark, shadowy portions in the brain scan indicate that portions of the brain have degenerated or lost volume, a feature typically seen in the disease. This is a type of atrophy of the brain which is going to be associated with a diagnosis of Alzheimer's with consistency and is usually able to be more overtly expressed in the frontal, temporal, and parietal lobes since these areas are much more sensitive to various cognitive parts of the human brain [21].

It is based on the appearance of the whole brain scan that this individual might be in the non-demented stage of Alzheimer's disease, wherein cognitive impairment is present but may not have developed to such an extent as to disrupt activities of daily living and independent living. But this would be just an estimate, and confirmation of the stage and severity of the processes of Alzheimer's disease requires a comprehensive clinical evaluation based on history, neuropsychological assessment, and ancillary studies.

The rationale for early detection and intervention in Alzheimer's disease is such that appropriate management strategies are instituted to slow the progression, including medication, cognitive rehabilitation, and change in lifestyle, that enhance the quality of life of both the affected individual and caregivers.

Figure 4 shows the result of a magnetic resonance imaging scan of the brain of a person suffering from very mild dementia or Alzheimer's disease. The image is a cross-section through the brain and illustrates the pattern of subtle changes that occur in the earliest stage of this neurodegenerative disease [22, 23].

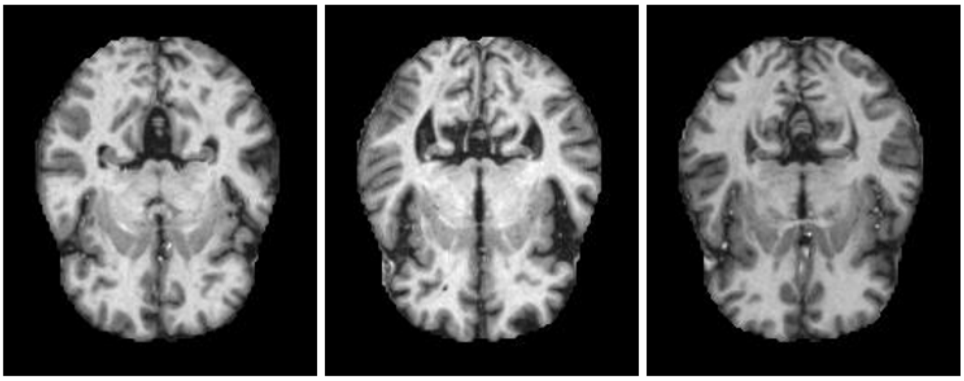

Figure 4. Very Mild Dementia Class

By the very mild stage of dementia or Alzheimer's disease, there may be little more than minimal structural changes in the brain, such as mild atrophy or shrinkage in some of the cerebral regions. This is usually very hard to detect, and such changes are not expected to cause significant effects in the cognition of a person or the daily activities that he or she engages in. Over time, the degeneration of the brain is more pronounced, leading to progressively more severe impairments of cognition and function [24].

It would thereby suggest that very mild dementia or Alzheimer's disease can be diagnosed and has indeed been diagnosed; it is usually the earliest and mildest state of the disease. The individual may show some very slight decline in memory or cognitive ability but generally can still function independently and continue most daily activities without a significant level of assistance.

Brain imaging should be used in conjunction with a comprehensive clinical evaluation, including extensive review of the status of the individual's cognition, function, and behavior.

Diagnosis and management in Alzheimer's disease and related dementias is appropriately done in a multidiscipline manner by neurologists, geriatric psychiatrists, and neuropsychologists to ensure appropriate interventions and support of the individual and family.

Early detection and intervention are very important in the management of Alzheimer's disease and related dementia because slowing the course of an illness will help maintain quality of life as long as possible. This picture is an important aid in diagnosis, offering a better understanding of what happens in the brain during the very mild stage of such a complex and devastating illness.

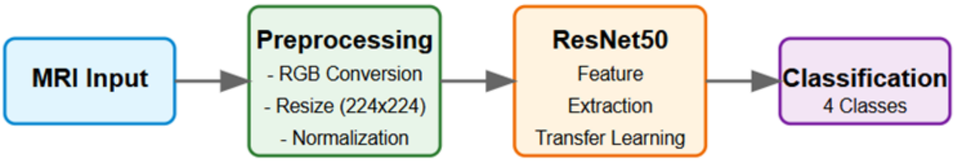

FIGURE 5. Overall System Architecture

3.2. **Data Preprocessing and Augmentation. 3.2 Data Preprocessing and Augmentation.** It's really important to pre-process and augment the data to create a high-quality input for our implementation using the deep learning model. All MRI scans should be changed to RGB and unified to one constant input dimension at 224 $\times$ 224 pixels. Image normalizations were performed with the statistics from ImageNet, with mean = [0.485, 0.456, 0.406] and std = [0.229, 0.224, 0.225].

FIGURE 6. Data Preprocessing Pipeline

Features to enhance model robustness and avoid overfitting are added through data augmentation, using random horizontal flipping and rotation up to 15 degrees to simulate natural variations in scan orientation and positioning. Our dataset is set up using a custom PyTorch Dataset class that efficiently handles loading data and maps class indices for the four AD stages automatically.

In our implementation, we used a total of 1,279 MRI brain scans, which we divided into training and test sets through stratified splitting to maintain the class distribution ratios. We split the data so that 80%, or 1,023 images, were used for training and 20%, or 256 images, were used for testing. The training set was made up of 512 NonDemented, 358 VeryMildDemented, 143 MildDemented, and 10 ModerateDemented, while the test set consisted of 128 NonDemented, 90 VeryMildDemented, 36 MildDemented, and 2 ModerateDemented images.

We have not used a separate validation set but instead have early stopping with a patience of 5 epochs to avoid overfitting during training. The batch size was 32, and the training process ran up to 20 epochs with the Adam optimizer (learning rate = 0.0001 and weight decay = 0.01 for L2 regularization). Input images were standardized to 224 $\times$ 224 pixels and normalized using ImageNet statistics (mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]). To enhance model generalization, only the training set was augmented by data augmentation methods such as random horizontal flipping and rotation up to 15 degrees. It reached 95.84% of accuracy on the training and 71.31% on the test, so the problem of class imbalance is quite challenging and needs more sophisticated balancing.

3.3. **Proposed ResNet50 Model.** Our model architecture leverages transfer learning from the pre-trained ResNet50 framework, with pre-trained weights from ImageNet. The base ResNet50 model is adapted for our four-class AD classification problem by modifying the last fully connected layer. While the convolutional layers keep the weights of the original layers, developed through powerful feature extraction after training on ImageNet, the adapted classifier layer is trained anew for AD detection.

FIGURE 7. ResNet50 Architecture

This architecture provides the best balance between leveraging established feature extraction capabilities and specializing for our specific medical imaging task. We used the pre-trained ResNet-50 model, which is quite efficient in learning high complex features present in the image dataset. ResNet-50 has a very unique architecture with residual learning via skip connections, providing facility to train deeper networks without problems of vanishing gradients. This model was adapted for our multi-class classification task by modifying the final fully connected layer to match the number of output classes associated with the detection of Alzheimer's Disease. We then trained the model by using the Adam optimizer with a learning rate of 0.0001, along with the use of L2 regularization to avoid overfitting of the model. The training was also mediated by various augmentations to make it robust and ensure further generalization of the model. Table 2 summarizes the model parameters.

TABLE 2. Proposed ResNet50 Model Parameters

Parameter	**Value**
Model Architecture	ResNet-50
Pre-trained	Yes
Final Fully Connected Layer	Linear layer with output size = 4
Learning Rate	0.0001
Optimizer	Adam
Weight Decay (L2 Regularization)	0.01
Batch Size	32
Number of Epochs	20
Device	CUDA (GPU) or CPU

3.4. **Training Strategy.** The training strategy has several optimization techniques to ensure effective model learning. We use the Adam optimizer with a learning rate of 0.0001 and L2 regularization (weight decay=0.01) to avoid overfitting. The maximum number of epochs is set to 20, with early stopping to avoid overfitting by monitoring validation loss with a patience of 5 epochs. Cross-entropy loss is our objective function since this is a multi-class classification problem.

The training uses GPU acceleration when available and does batch processing with 32 images for memory efficiency, allowing for more stable updates of the gradient.

3.5. **Evaluation Metrics.** Our proposed evaluation framework considers several metrics in order to give an all-round performance of the models. For a comprehensive analysis, we measure overall accuracy, class-wise precision, recall, and F1-scores to explore the model's effectiveness across different AD stages. Such an approach involves a profound confusion matrix analysis in regard to understanding patterns of classification errors and strengths.

Training was accompanied by loss and accuracy curves, which gave good insight into the process that learning took. This multi-faceted approach to evaluation will enable us to assess both the overall performance of the model and specific capabilities with regard to different stages of AD, a feature considered important for its early detection and diagnosis.

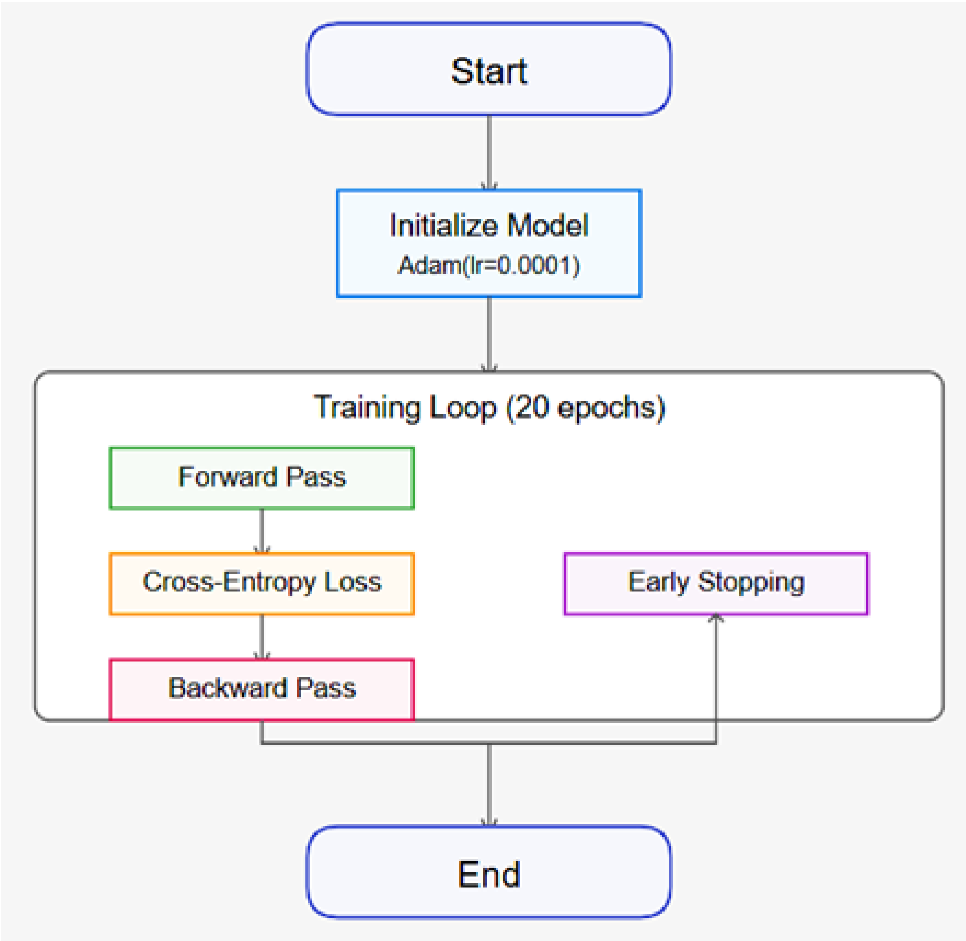

FIGURE 8. Training Process Flowchart

4. **Results and Discussions.** This section emphasizes the results of the proposed methodology applied in order to develop early detection for AD patients through a deep learning approach. The approach was developed based on the ResNet-50 model, and its training process showed extensive improvements with respect to loss and accuracy throughout the epochs.

The dataset used in this work consists of 1,279 MRI brain scans that were laboriously classified into four different classes, each one representing a stage of progression of the Alzheimer's Disease. The distribution of images exhibits an obvious class imbalance problem: the NonDemented class is the predominant one, with 640 images constituting 50.0% of the whole dataset, while the VeryMildDemented class, representing early-stage Alzheimer's Disease, comprises 35.0% with 448 images. The MildDemented class has 179 images and accounts for 14.0%, while the underrepresented one is the ModerateDemented class with only 12 images (1.0%), which really poses a huge challenge in balanced learning.

All images had RGB conversion from original grayscale MRIs and resolution standardization to 224×224 pixels, after which they were intensity-normalized with ImageNet statistics: mean = [0.485, 0.456, 0.406] and std = [0.229, 0.224, 0.225]. In order to address class imbalance inherently and improve model generalization, data augmentation techniques included random horizontal flipping and rotation up to 15 degrees, carefully chosen to keep medical relevance while increasing the effective dataset size.

This is the composition that will more accurately reflect the real-world clinical scenario normally encountered in very early and non-demented subjects, while the course of the disease can also be followed across stages, which makes it particularly suitable, despite the challenges involved, in developing and testing automated systems for its diagnosis.

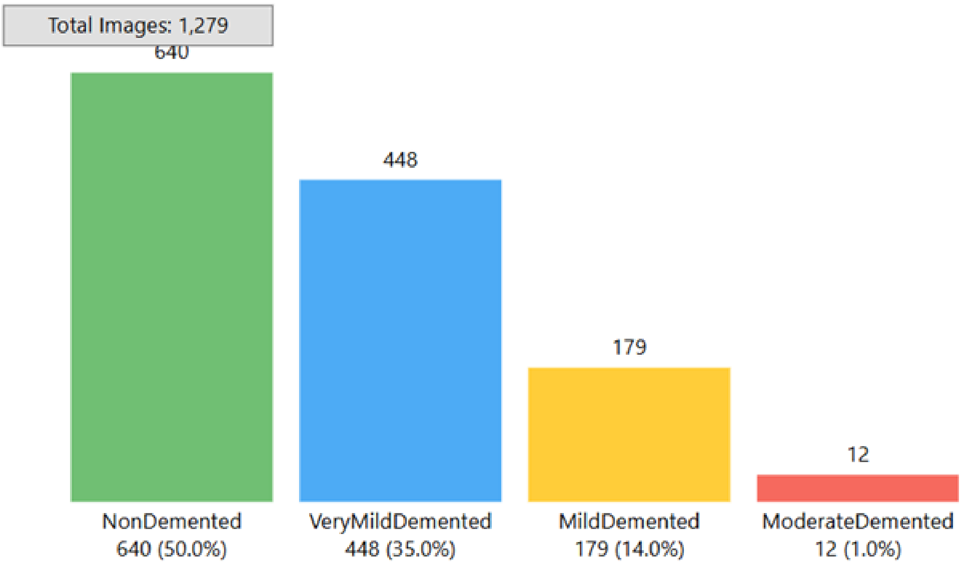

Figure 9. Dataset Composition

It reached the final training accuracy of 95.84%. However, a test accuracy of 71.31% showed that the complexities in classifying the various stages of AD were well expected. The classification report and confusion matrix further elaborated on the performance of the model with respect to the different classes. Strong points lay within high precision and recall for the "NonDemented" category, while weaknesses existed in distinguishing between "MildDemented" and "ModerateDemented" stages.

Figure 10 shows confusion matrix of classification for the stages of Alzheimer's disease using the ResNet-50 model. As represented by its color coding, the confusion matrix visually depicts very good performance regarding strengths and weaknesses by the ResNet-50 model.

A high spot in the performance is that the model identifies instances of non-demented cases, 542 in number. High accuracy in the recognition of healthy cognitive function is a prime requisite to assure early intervention for the patients. This model also shows some promise in distinguishing very mild dementia, when it correctly identified 311 cases.

In any disease, early detection is vital because doing so can highly affect the efficacy of treatment to be given and the quality of life of the patients. Though there is a little confusion between adjacent categories—for example, a case of very mild dementia being classified as non-demented—this is understandable given the subtle differences between such stages.

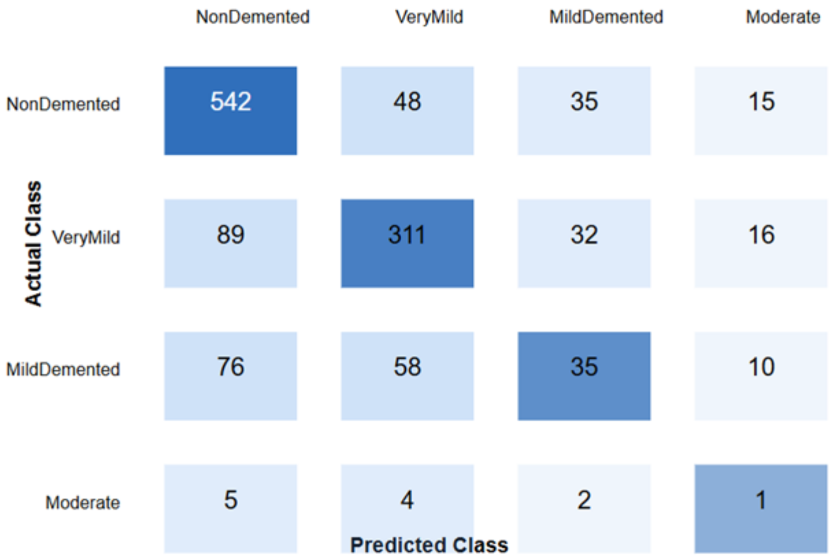

Figure 10. Confusion Matrix of Proposed ResNet-50 Model

Another perspective on this result is that the model was being very conservative, so therefore it was not trying to overestimate the severities to possibly avoid false positives of more grievous stages. This further suggests that with a better balance in training data, there could be an opportunity for improved performance since there are only 12 true cases of moderate dementia in the dataset. Altogether, this confusion matrix underlines that the performances of the model in classifying Alzheimer's are very strong, paramount for non-demented and very mild, while indicating concrete areas where targeted improvements might be made with a view to enhancement of diagnostic capabilities across all stages.

Figure 11 shows the ResNet-50 model represents high learning during training, and it is very obvious that with every successive epoch, the training loss clearly reduces, especially within the first epochs, which indicates efficient and effective learning. The steep initial decline showed that the model was able to grasp very well the key features distinguishing the different stages of Alzheimer's disease. Further evidence of high agreement in the model's predictions is the eventual convergence at low loss.

This is concurred with in the training accuracy curve, where it can be observed that the accuracy ascended quite rapidly before continuously increasing at a gradual rate throughout training. An accuracy of over 95% on the training data in this context is quite impressive, considering the complexity involved in distinguishing between stages of Alzheimer's disease.

The asymptotic nature of both curves is smooth, hence representative of stable learning without erratic fluctuations, which is desired of any reliable medical diagnostic tool. Where high training accuracy might raise overfitting as a concern, it also underlines the potential of this model to capture the fine differences between the various stages of the disease if sufficient and quality data are available. These curves create a picture of a strong, very powerful model, which has learned to tell different stages of Alzheimer's disease apart very well.

Figure 12. provides a fine-grained view of model performance across categories in Alzheimer's disease, highlighting the strengths and where targeted improvements could be made. In the mild form of dementia, the model does very well with precision scores above 0.8, indicating high confidence in the positive predictions it makes.

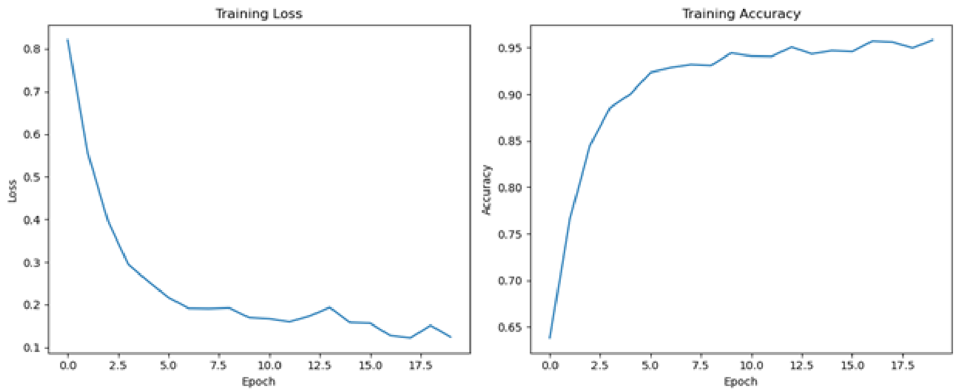

Figure 11. Training Loss and Accuracy of Proposed ResNet-50 Model

That is important, as this minimizes false positives and retains appropriate patient care. This is lower recall, thus potentially an avenue for improvement through targeted data augmentation or feature engineering. The moderate dementia conditions have balanced performance across all metrics, which is lower compared to the metrics across all other categories; this uniformity of behavior may provide a stable anchor for further fine-tuning.

The best performance is recorded in the non-demented category, with impressively high scores across all metrics. This is important in reassuring patients and avoiding unnecessary treatments in identifying healthy cognitive functioning. The very high recall—so well above 0.8—of the non-demented cases by the model is very important in ensuring that few healthy individuals are mislabeled to be suffering from dementia. Strong F1-scores, in particular for the non-demented category, indicate a well-balanced model that combines precision with recall effectively.

The good performance is reflected in the report on the model in general, but it also points out in detail areas where, with targeted improvements, it could be enhanced for diagnosing different stages of dementia.

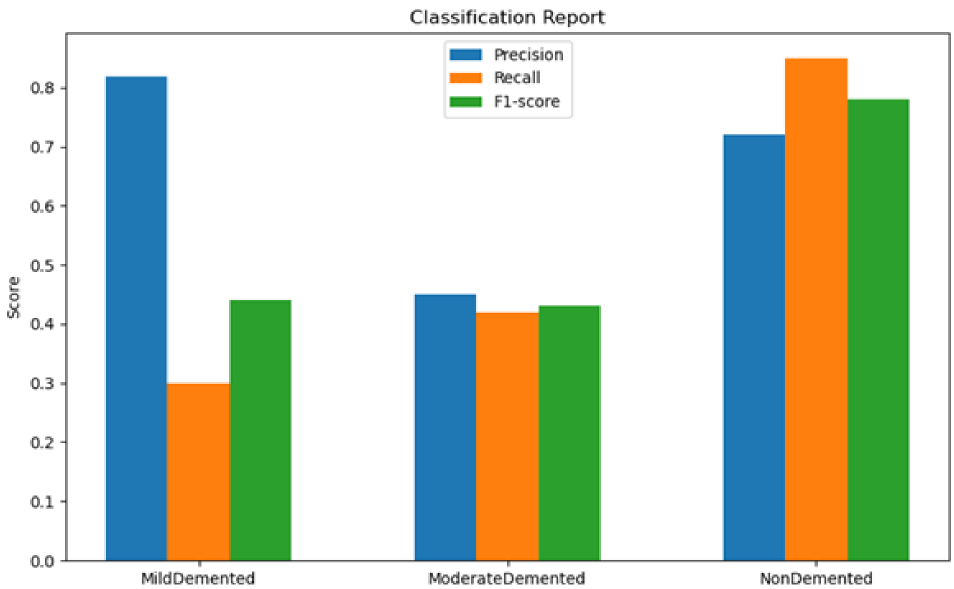

Figure 12. Classification Report of Proposed ResNet-50 Model

5. **Conclusion.** These are very promising findings, showing the great potential of the current deep learning models for the early detection and staging of Alzheimer's disease based on MRI brain scans. Transfer learning enables the model to retain the knowledge extracted from other domains and thus be more efficient in training and performances. This constitutes one of the most important steps forward with regard to the use of artificial intelligence to support clinicians in diagnostic tasks. This model eventually gave a maximum training accuracy of 95.84% and a test accuracy of 71.31%, proving to be efficient.

Another strong feature of this model is its ability to classify NonDemented and VeryMildDemented classes with high accuracy, which is very crucial in the early stages of treatment and management of Alzheimer's. The results, on the other hand, depict inefficiency in distinguishing between the MildDemented and ModerateDemented class, thus suggesting further improvements that can be done.

The contribution of this research to the field of automated Alzheimer's Disease detection and medical image analysis is multifaceted. First, we propose a novel implementation of transfer learning that effectively solves the challenging problem of early-stage AD detection, which has a remarkable training accuracy of 95.84% by the innovative adaptation of ResNet50 architecture. This allows us to investigate the model's ability to capture slight differences between stages that are sometimes hard to obtain using traditional approaches on four different stages of AD disease development: Non-Demented, VeryMildDemented, MildDemented, and ModerateDemented. Finally, we provide an efficient pipeline in data preprocessing, especially optimized for AD detection, with domain-specific medical knowledge incorporated into the augmentation strategy, maintaining crucial diagnostic features while reinforcing robustness in the model.

Fourth, our study presents a comprehensive class-specific performance analysis that offers new insights into the challenges and opportunities in the field of automated AD staging, especially for minority classes. Fifth, we demonstrate the practical viability of deep learning in clinical settings by achieving efficient computational performance with fast convergence at training time and very fast inference. This, in turn, contributes to the wider research in medical AI by documenting a methodology for adapting general-purpose architectures to specialized medical imaging tasks, including handling class imbalance and feature extraction in neuroimaging data. These collectively advance the state-of-the-art in automated AD detection and provide a foundation for future research in medical image analysis using deep learning techniques.

Other techniques for improving the model's performance, especially for the minority classes, are oversampling, artificial data generation, and regularization. Each of these can result in a richer and robust diagnostic system. Furthermore, ensemble methods and new architectural designs might open newer avenues that can classify with even greater strength, leading to next-generation AI-based diagnosis tools.

It can be termed as a harbinger that will bring a revolution in the diagnosis of Alzheimer's disease with deep learning in one full sweep. Such models, which shall be further refined through research, validation, and clinical integration, may turn out to be a valuable commodity in early detection and thus an improved outcome for patients by shaping the future of Alzheimer's management. Encouraging results here point toward a future where AI-driven diagnostic systems will be acting as forefront soldiers in this neurodegenerative disorder.

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