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Research Paper

A LIGHTWEIGHT AND RESOURCE-ADAPTIVE DEEP LEARNING FRAMEWORK FOR ALZHEIMER'S DISEASE CLASSIFICATION ON LIMITED MRI DATASETS

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ABSTRACT

Alzheimer's disease is a progressive neurological disorder that affects memory, cognitive abilities, and daily functioning. Early and accurate classification of the disease is important for supporting clinical assessment and timely medical intervention. However, developing reliable deep learning models for Alzheimer's disease classification remains challenging because of the limited availability of labeled Magnetic Resonance Imaging (MRI) datasets and the high computational requirements of complex neural networks. This paper proposes "A Lightweight and Resource-Adaptive Deep Learning Framework for Alzheimer's Disease Classification on Limited MRI Datasets" to address these challenges through an efficient and computationally economical classification approach. The proposed framework involves MRI image preprocessing, data augmentation, feature extraction, and lightweight deep learning-based classification to identify relevant patterns associated with different stages of Alzheimer's disease. Resource-adaptive mechanisms are incorporated to optimize model complexity and computational requirements according to the available dataset and hardware resources. Transfer learning and regularization techniques can be employed to improve feature learning and reduce overfitting when training data are limited. The framework aims to classify MRI images into clinically relevant categories, such as cognitively normal, mild cognitive impairment, and Alzheimer's disease, depending on the selected dataset and its available labels. Its performance can be evaluated using accuracy, precision, recall, F1-score, model size, inference time, and computational resource utilization. By balancing classification performance with computational efficiency, the proposed approach seeks to provide a practical solution for Alzheimer's disease classification in resource-constrained environments. The framework may support research in computer-aided neurological assessment, although its predictions require clinical validation before use in real-world medical decision-making.

Keywords: Alzheimer's disease, deep learning, magnetic resonance imaging, lightweight neural networks, limited datasets, resource adaptation, medical image classification, transfer learning.

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects memory, thinking ability, and cognitive functioning, particularly among older adults. Early identification of the disease is important for supporting clinical evaluation, monitoring disease progression, and improving patient management. Magnetic Resonance Imaging (MRI) is widely used in neurological research because it provides detailed structural information about the brain and helps identify changes associated with Alzheimer's disease. However, manually analyzing MRI images can be time-consuming and may require considerable expertise. Consequently, automated medical image classification using deep learning has gained attention as a potential approach for assisting Alzheimer's disease assessment.

Deep learning techniques have demonstrated promising results in identifying disease-related patterns from brain MRI images. Islam and Zhang [1] investigated an ensemble of deep

convolutional neural networks for Alzheimer's disease diagnosis, demonstrating the potential of combining multiple deep learning models for brain image analysis. Similarly, Basaia et al. [2] proposed an automated classification approach using a single MRI scan and deep neural networks to distinguish Alzheimer's disease and mild cognitive impairment. Tufail et al. [3] explored structural MRI-based classification using deep learning, highlighting the usefulness of automatically learned image features for disease identification. Furthermore, Wen et al. [4] reviewed and evaluated convolutional neural network approaches for Alzheimer's disease classification, emphasizing the importance of reproducible evaluation procedures and consistent experimental settings.

Despite these developments, training reliable deep learning models remains challenging when only a limited number of labeled MRI images are available. Complex neural networks generally require sufficient training samples to learn representative features and generalize effectively to unseen images. When the dataset is small, models may overfit the training samples and produce inconsistent classification results. Nanni et al. [5] compared transfer learning and conventional machine learning techniques for structural brain MRI analysis, providing a basis for investigating methods that can improve learning efficiency when developing diagnostic models. Tanveer et al. [6] explored an ensemble of deep neural networks trained through transfer learning, while Ghaffari et al. [7] investigated a deep transfer learning approach for automated Alzheimer's disease detection and classification. These studies motivate the use of pretrained representations and computationally efficient architectures to reduce dependence on large labeled datasets. Another important consideration is the computational cost associated with deep learning-based medical image analysis. Models with numerous parameters may require substantial memory, processing power, and inference time, limiting their deployment on resource-constrained systems. Yang et al. [8] investigated brain imaging-based deep learning using a large collection of samples, illustrating the potential of data-driven classification at scale. Khan et al. [9] explored transfer learning for multiclass Alzheimer's disease classification, while Pallawi et al. [10] reviewed deep neural network models used for MRI-based disease classification. Coelho et al. [11] further examined deep learning methods for Alzheimer's disease detection through a systematic review. These studies provide useful insights into classification strategies, although the combined challenges of limited data, model complexity, and resource availability remain important considerations when designing practical systems.

Recent research has continued to investigate improved classification methods and transfer learning strategies. An integrated deep transfer learning approach for Alzheimer's disease category prediction was presented in [12]. Jia et al. [13] examined a transfer learning-based deep Q-network method for Alzheimer's disease classification, while Zia-ur-Rehman et al. [14] investigated DenseNet-201-based transfer learning for disease identification. Turrisi et al. [15] explored transfer learning for Alzheimer's disease prediction under evolving MRI data conditions. Collectively, these studies indicate that deep learning and transfer learning offer promising directions for MRI-based classification. Nevertheless, selecting an appropriate model for small datasets requires careful consideration of classification performance, generalization, computational requirements, and the risk of overfitting.

To address these challenges, this paper proposes a Lightweight and Resource-Adaptive Deep Learning Framework for Alzheimer's Disease Classification on Limited MRI Datasets. The proposed framework focuses on MRI image preprocessing, suitable data augmentation, efficient feature extraction, and lightweight classification. Transfer learning and regularization techniques can be incorporated to improve feature learning and reduce overfitting when the number of labeled images is limited. The resource-adaptive component aims to align model complexity and computational requirements with the available hardware and dataset characteristics. Depending on the selected dataset, the framework can classify MRI

images into categories such as cognitively normal, mild cognitive impairment, and Alzheimer's disease. Its effectiveness can be assessed using accuracy, precision, recall, F1-score, model size, inference time, and resource utilization.

The primary objective of this research is to investigate whether a lightweight, resource-adaptive deep learning approach can achieve a practical balance between classification performance and computational efficiency under limited-data conditions. By combining efficient model design with appropriate training strategies, the proposed framework aims to support the development of accessible computer-aided Alzheimer's disease classification systems. However, its outputs should be considered research predictions rather than definitive diagnoses, and clinical validation on independent datasets is necessary before practical medical use.

II. LITERATURE SURVEY

Islam and Zhang (2018) investigated an ensemble system of deep convolutional neural networks for Alzheimer's disease diagnosis using brain MRI images. Their approach combined multiple neural networks to extract relevant features and improve classification performance. The study demonstrated the potential of deep learning for automated medical image analysis. However, ensemble models may require substantial computational resources and memory, making them less suitable for resource-constrained environments.

Basaia et al. (2019) developed an automated classification approach using a single MRI scan and deep neural networks to distinguish Alzheimer's disease, mild cognitive impairment, and cognitively normal individuals. Their research highlighted the importance of structural brain imaging for identifying disease-related patterns. The approach demonstrated the potential of automated classification for neurological assessment. However, reliable performance across different patient populations and imaging conditions remains a challenge.

Wen et al. (2020) examined convolutional neural network approaches for Alzheimer's disease classification and emphasized the importance of reproducible model evaluation. Their research highlighted how differences in experimental design, data preprocessing, and evaluation procedures can influence reported performance. The study provides useful guidance for comparing deep learning models. Nevertheless, improving computational efficiency while maintaining consistent classification performance remains an important research objective.

Nanni et al. (2020) compared transfer learning and conventional machine learning techniques for structural brain MRI analysis in Alzheimer's disease diagnosis and prognosis. Their research explored alternative methods for extracting meaningful features from medical images. Transfer learning can reduce training requirements by reusing pretrained representations, making it useful when labeled MRI datasets are limited. However, its effectiveness depends on the suitability of the pretrained model and the characteristics of the available data.

Tanveer et al. (2022) investigated an ensemble of deep neural networks trained through transfer learning for Alzheimer's disease classification. Their approach utilized pretrained feature representations and combined multiple networks to support disease classification. This strategy offers potential benefits when training data are limited. However, ensemble-based approaches may increase model size, inference time, and memory requirements, motivating the development of lightweight classification architectures.

Zia-ur-Rehman et al. (2024) investigated DenseNet-201-based transfer learning for Alzheimer's disease classification. Their approach utilized a deep neural network architecture that promotes feature reuse through connections between layers. Transfer learning can help extract meaningful image representations without training the entire network from scratch. However, deep architectures may require considerable computational resources, highlighting the need for resource-adaptive frameworks that provide an effective balance between classification performance and computational efficiency.

III. EXISTING SYSTEM

The existing system for Alzheimer's disease classification primarily uses conventional machine learning algorithms and deep

learning models to analyze brain Magnetic Resonance Imaging (MRI) images. Traditional approaches rely on manually extracted features, such as brain structure measurements, tissue characteristics, and region-specific abnormalities, to identify patterns associated with the disease. More recent methods employ convolutional neural networks (CNNs), transfer learning, and ensemble learning to automatically extract relevant features and classify MRI images into diagnostic categories. Although these techniques have demonstrated potential for automated disease classification, their performance can depend on dataset size, image quality, preprocessing methods, and model architecture.

Existing deep learning approaches often require considerable computational resources, including processing power, memory, and training time. Complex architectures and ensemble models may be difficult to deploy on systems with limited hardware capabilities. Furthermore, training deep neural networks on small MRI datasets can lead to overfitting, poor generalization, and inconsistent classification results. Differences in MRI acquisition settings and imbalanced class distributions can introduce additional challenges. Therefore, conventional and existing deep learning methods may not provide an ideal balance between classification performance, computational efficiency, and adaptability when only limited MRI data and hardware resources are available.

IV. PROPOSED SYSTEM

The proposed system introduces a Lightweight and Resource-Adaptive Deep Learning Framework for Alzheimer's Disease Classification on Limited MRI Datasets. The framework aims to classify brain MRI images efficiently while addressing the challenges of limited training samples, overfitting, and high computational requirements. It incorporates MRI image preprocessing, data augmentation, lightweight feature extraction, and deep learning-based classification. Transfer learning can be used to reuse pretrained image representations, reducing the need to train a complex network entirely from scratch. These strategies are relevant because limited annotated medical imaging data can affect model generalization, while transfer learning offers a practical way to improve learning efficiency.

The framework also incorporates a resource-adaptive strategy to align model complexity and computational requirements with the available dataset and hardware resources. Depending on the selected dataset, the system can classify MRI images into categories such as cognitively normal, mild cognitive impairment, and Alzheimer's disease. Model performance can be evaluated using accuracy, precision, recall, F1-score, model size, inference time, and memory utilization. The objective is to achieve a practical balance between classification performance and computational efficiency, enabling the framework to be investigated in resource-constrained research environments. The resulting predictions are intended to support research and computer-aided assessment rather than replace professional medical diagnosis.

V. SYSTEM ARCHITECTURE

The system architecture of the proposed Lightweight and Resource-Adaptive Deep Learning Framework for Alzheimer's Disease Classification on Limited MRI Datasets consists of several interconnected modules designed to classify brain MRI images efficiently while minimizing computational requirements.

The first module is the Input MRI Dataset, which contains brain MRI images representing different categories, such as Alzheimer's disease (AD), mild cognitive impairment (MCI), and cognitively normal (CN). These images serve as the primary input to the framework. The quality and diversity of the available MRI images influence the model's ability to learn meaningful patterns and distinguish between the different categories.

The second module is Preprocessing, which prepares the MRI images for model training and classification. This stage may include skull stripping to remove non-brain regions, image resizing to maintain a consistent input dimension, intensity normalization to standardize pixel values, and noise removal to reduce unwanted image variations. These operations help improve image consistency and prepare the data for subsequent processing.

The third module is Data Augmentation, which increases the diversity of the training dataset through transformations such as rotation, flipping, and scaling. These transformations can help the model learn more robust features from limited MRI samples and reduce overfitting. Augmentation must be applied carefully to avoid introducing unrealistic images or altering clinically meaningful information.

The fourth module is Feature Extraction Using a Lightweight Deep Learning Model. A pretrained lightweight convolutional neural network, such as MobileNet or EfficientNet, can be used to extract relevant features from the processed MRI images. These features may represent structural patterns and image characteristics associated with different disease categories. Lightweight architectures are selected to reduce model size, memory consumption, and computational requirements compared with larger deep learning networks.

The fifth module is the Resource-Adaptive Module, which considers the available hardware resources, dataset size, and model configuration. Depending on the implementation, this module can adjust parameters such as input image size, network depth, or the number of filters to accommodate available computational resources. Its purpose is to balance classification performance with processing efficiency, particularly when the framework operates on systems with limited memory or processing power.

The sixth module is the Classification Module, where the extracted features are passed through fully connected layers and a softmax classifier. The classifier estimates the probability that an MRI image belongs to each supported category. The category with the highest predicted probability is selected as the model's output. This stage converts the learned image representations into a final classification result.

The seventh module is the Output Classes, which presents the predicted category as cognitively normal, mild cognitive impairment, or Alzheimer's disease. The available output categories depend on the labels present in the selected dataset and the classes used during model training. These predictions can support research and computer-aided assessment but should not be considered a substitute for clinical diagnosis.

Finally, the Evaluation and Feedback Module assesses the framework using accuracy, precision, recall, F1-score, inference time, model size, and memory usage. Classification metrics measure predictive performance, while computational metrics indicate how efficiently the model operates. The evaluation results can guide adjustments to the model configuration and resource-adaptive strategy. Through this feedback process, the framework aims to achieve an appropriate balance between classification reliability and computational efficiency when working with limited MRI datasets.

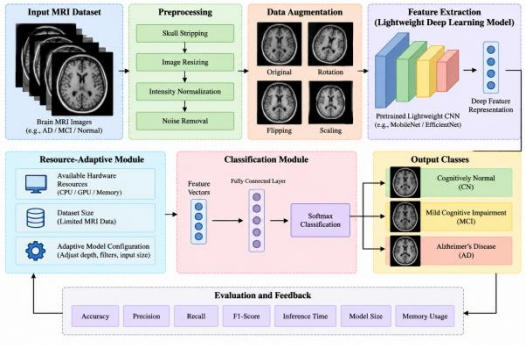


Fig 5.1 System Architecture

VI. ALGORITHM

Algorithm: Lightweight and Resource-Adaptive Deep Learning Framework for Alzheimer's Disease Classification (LRADL-ADC)

Input:

\(D\) ← Brain MRI dataset containing labeled images of Alzheimer's disease (AD), mild cognitive impairment (MCI), and cognitively normal (CN) subjects.

\(R\) ← Available computational resources (CPU, GPU, and memory).

\(M_L\) ← Lightweight pretrained CNN model (e.g., MobileNet or EfficientNet).

\(E_{\max}\) ← Maximum number of training epochs.

\(B\) ← Batch size.

\(\theta\) ← Model training parameters.

\(\tau\) ← Classification decision criterion.

Output:

\(M^*\) ← Optimized trained classification model.

\(\hat{y}\) ← Predicted MRI class (CN, MCI, or AD).

\(P\) ← Classification performance and computational efficiency metrics.

Steps:
1. Start.
2. Load the labeled brain MRI dataset \(D\) from the specified dataset directory.
3. Verify the image files and associated class labels; remove corrupted images and invalid records.
4. Divide the dataset into training, validation, and testing subsets using a stratified split to preserve class proportions and avoid data leakage.
5. Apply MRI preprocessing to each image:
Perform skull stripping when suitable brain masks are available.
Resize the image to the selected input dimensions.
Normalize image intensity values.
Apply appropriate noise reduction when necessary.
6. Apply data augmentation only to the training subset using suitable transformations, such as small rotations, flipping where anatomically appropriate, and scaling.
7. Analyze the available computational resources \(R\), including memory capacity, processing capability, and GPU availability.
8. Select the lightweight pretrained CNN model \(M_L\) according to the resource constraints and input image requirements.
9. Initialize the feature extraction network using pretrained weights and replace its original classification head with a task-specific classification layer for the available MRI categories.
10. Freeze selected early network layers when appropriate to reduce training complexity and limit overfitting on the small dataset.
11. Extract feature representations from the training MRI images using the lightweight CNN.
12. Pass the extracted features through the classification head to obtain class probabilities:
\[P(y=c\mid x)= \frac{e^{z_c}}{\sum_{j=1}^{C}e^{z_j}} \]
where \(z_c\) represents the output logit for class \(c\), and \(C\) denotes the number of classes.
13. Calculate the classification loss using the ground-truth labels and predicted probabilities. For multiclass classification, use categorical cross-entropy or its equivalent for integer-encoded labels.
14. Update the trainable model parameters using a suitable optimizer, such as Adam, and apply regularization when necessary.
15. Evaluate the model on the validation subset after each training epoch.
16. Monitor validation loss and classification performance to identify overfitting. Apply early stopping if the validation performance fails to improve for the specified patience period.
17. Adapt the model configuration according to available resources and validation results. If memory usage exceeds the permitted limit, reduce the batch size or input resolution, or select a smaller compatible architecture, and retrain or fine-tune the modified model.
18. Save the model configuration and weights that achieve the best validation performance while satisfying the resource constraints.
19. Load the selected model \(M^*\) and evaluate it on the independent test subset without further parameter tuning.
20. Calculate classification metrics, including accuracy, precision, recall, and F1-score.
21. Measure computational efficiency using model size, inference time, and memory usage.
22. For a new MRI image \(x_{\text{new}}\), apply the same preprocessing operations used during training.
23. Pass \(x_{\text{new}}\) through the trained model to obtain its predicted class probabilities.
24. Determine the predicted category:
\[\hat{y}=\arg\max_{c\in\{1,\ldots,C\}}P(y=c\mid x_{\text{new}}) \]
25. Return the predicted category (CN, MCI, or AD, according to the trained dataset labels) together with the associated class probabilities and model evaluation results.
26. Stop.

Computational Complexity

Let \(N\) denote the number of training images, \(E\) the number of training epochs, and \(F\) the computational cost of one forward-and-backward training pass for an image. The approximate training complexity is
\[O(NEF) \]

For a fixed trained model, inference over \(N_t\) test images has approximate complexity

\[O(N_tF_{\mathrm{inf}}) \]

where \(F_{\mathrm{inf}}\) represents the forward-pass cost per image. Using a lightweight CNN is intended to reduce \(F\) and \(F_{\mathrm{inf}}\), although the actual savings depend on the selected architecture, input resolution, and hardware.

VII. CONCLUSION

The proposed Lightweight and Resource-Adaptive Deep Learning Framework for Alzheimer's Disease Classification on Limited MRI Datasets aims to address the challenges of limited training data, computational complexity, and overfitting in automated brain MRI analysis. The framework integrates MRI preprocessing, data augmentation, lightweight convolutional neural networks, transfer learning, and resource-aware model configuration to extract relevant features and classify images into cognitively normal, mild cognitive impairment, and Alzheimer's disease categories, depending on the dataset labels. By considering both classification performance and computational requirements, the approach aims to reduce model size, inference time, and memory consumption while maintaining reliable predictive capability. Its effectiveness can be assessed using accuracy, precision, recall, F1-score, and computational efficiency metrics against suitable baseline models. Future improvements may include evaluation on larger and independent MRI datasets, patient-level validation, explainable artificial intelligence, and adaptation to different imaging conditions. Overall, the framework provides a practical research direction for developing efficient, data-conscious Alzheimer's disease classification systems, although its clinical reliability must be established through rigorous experimental testing and independent clinical validation.

VIII. FUTURE SCOPE

The future scope of the proposed Lightweight and Resource-Adaptive Deep Learning Framework for Alzheimer's Disease Classification on Limited MRI Datasets includes improving classification accuracy, computational efficiency, and generalization across diverse patient populations. Future research can investigate advanced lightweight architectures, optimized transfer learning techniques, and knowledge distillation to reduce model size and memory requirements without substantially compromising predictive performance. The framework can also be extended using larger, multicenter MRI datasets to improve robustness across different scanners, imaging protocols, and demographic groups. Explainable artificial intelligence techniques may be integrated to highlight relevant brain regions and provide greater transparency in model predictions. Furthermore, adaptive learning and federated learning could be explored to support model improvement across institutions while reducing the need to centralize sensitive medical images. Future implementations may also incorporate longitudinal MRI data and complementary clinical information to investigate disease progression and improve classification. Finally, rigorous external validation, patient-level testing, bias assessment, and clinical evaluation will be essential before practical deployment. These developments could help establish a more efficient, scalable, and trustworthy computer-aided framework for Alzheimer's disease research and clinical assessment.

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