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Improving Alzheimer's Detection with Deep Learning and Image Processing Techniques

Arevarapu Gangadhar Rao[1], Devanaboina veera Venkata Subrahmanyam[2], Mr. J. Manivannan[3]
[1,2,3]*Dhanalakshmi Srinivasan University*

***Abstract*—Alzheimer's Disease (AD) is characterized by the gradual degeneration and decline of brain cells, leading to irreversible neurological changes. This study investigates advanced image enhancement techniques for improving AD diagnosis using brain MRI. The methods used include CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance local image contrast and ESRGAN (Enhanced Super Resolution Generative Adversarial Networks) to improve image resolution. These prep methods improve MRI images and classification accuracy. An ensemble model of MobileNetV2 and DenseNet121, two efficient deep-learning models with feature extraction capabilities, were used as classifiers. This approach addresses challenges in AD diagnosis by leveraging deep learning for more accurate classification of brain tissue images. The model achieved an accuracy of 80.31% for MobileNetV2 and 89.22% for DenseNet121 when no enhancements were utilized. The model achieved accuracies of 92.34% and 89.38% for MobileNetV2 and DenseNet121, respectively, when enhancement methods were utilized, indicating strong dependability with the Kaggle dataset of MRI images. These findings underscore the efficacy of advanced image processing and deep learning in the early and accurate detection of Alzheimer's disease**

***Index Terms*—Alzheimer's, computer-aided diagnosis, deep learning, DenseNet121, image enhancement, MobileNetV2, transfer learning**

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by memory loss, cognitive decline, and impaired daily functioning. With an aging global population, AD has emerged as a major public health concern, affecting millions worldwide and imposing significant socio-economic burdens. Early detection is crucial, as timely diagnosis enables interventions that may slow disease progression and improve patient outcomes.

Conventional diagnostic approaches, including clinical assessments and neuropsychological tests, often lack precision and are prone to subjectivity. Neuroimaging modalities such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) provide valuable insights into structural and functional brain changes, yet manual interpretation remains time-intensive and error-prone. Recent advances in artificial intelligence (AI), particularly deep learning, have demonstrated remarkable potential in medical image analysis. Convolutional Neural Networks (CNNs) and related architectures can automatically extract complex features from imaging data, enabling accurate classification of Alzheimer's stages. Coupled with image preprocessing and enhancement techniques, these methods offer improved sensitivity and specificity compared to traditional approaches. This study investigates the integration of deep learning and image processing techniques to enhance Alzheimer's detection. By leveraging automated feature extraction and robust classification frameworks, the proposed approach aims to support clinicians in early diagnosis and contribute to the development of intelligent healthcare solutions.

A. Problem Statement

Alzheimer's disease is difficult to detect in its early stages because the symptoms are subtle and not easily noticeable. Manual analysis of MRI images requires experienced professionals and can lead to inconsistent results.

The major problems identified are:

- Delayed diagnosis due to lack of early detection techniques
- High dependency on expert radiologists

- Time-consuming manual analysis of MRI scans
- Limited accuracy in traditional methods
- Lack of automated and scalable systems

B. Research Gap:
Although many studies have explored Alzheimer's detection, several limitations still exist. Most models are trained on limited datasets, which affects their ability to generalize. Early-stage detection remains a significant challenge, as models often perform better in detecting advanced stages.

The key research gaps include:
- Insufficient preprocessing of MRI images
- Poor performance in early-stage detection
- Overfitting in deep learning models
- Lack of integration between image processing and deep learning
- Limited scalability for real-world applications.

C. Objective of the Proposed Work:
The main objective of this research is to design an efficient system for Alzheimer's detection using deep learning and image processing techniques. The system aims to improve the accuracy of diagnosis and assist medical professionals.

The objectives can be summarized as:
- To develop a CNN-based model for Alzheimer's detection
- To enhance MRI images using preprocessing techniques
- To classify different stages of Alzheimer's disease
- To improve early-stage detection accuracy
- To reduce diagnostic time and effort.

D. Contribution of the Paper:
This paper presents a novel framework that combines image processing and deep learning techniques to improve Alzheimer's detection.
The major contributions are:
- A hybrid model integrating preprocessing and CNN
- Improved feature extraction from MRI images
- Accurate classification of Alzheimer's stages
- Enhanced early detection capability
- Better performance compared to existing methods.

E. Organization of the Paper:
The structure of the paper is organized as follows:
- Section II discusses related work
- Section III explains existing techniques and limitations
- Section IV presents the proposed methodology
- Section V compares the proposed system with existing methods
- Section VI describes implementation and results
- Section VII concludes the paper.

II. RELATED WORKS

The problem of Alzheimer's disease detection using medical imaging has been extensively studied in recent years. Researchers have explored various machine learning and deep learning approaches to improve diagnostic accuracy and enable early-stage detection.
O. Russakovsky [1] and colleagues contributed to large-scale image classification research, which laid the foundation for applying deep learning models in medical imaging tasks. Their work demonstrated how deep neural networks can effectively learn complex visual features, inspiring further research in disease detection.
K. Simonyan [2] and A. Zisserman [3] proposed the VGGNet architecture, which has been widely used in transfer learning for medical image classification, including Alzheimer's detection. Their model improved feature extraction capabilities, although it required high computational resources. Kaiming He et al. [4] introduced Residual Networks (ResNet), which addressed the problem of vanishing gradients in deep neural networks. This architecture has been applied in several Alzheimer's detection studies to improve accuracy and training efficiency. Suk, Heung-II et al. [5] proposed a deep learning-based framework for Alzheimer's disease diagnosis using MRI and PET imaging data. Their approach achieved improved classification performance; however, it required multi-modal data, increasing system complexity.
Sarraf, Saman and Tofighi, Ghassem developed a CNN-based model using fMRI data for Alzheimer's classification. Their study demonstrated the effectiveness of deep learning in medical imaging but was limited by dataset size and computational cost.

Basaia, Silvia et al. [7] proposed an automated deep learning system for Alzheimer’s detection using structural MRI scans. Their method achieved high accuracy in distinguishing Alzheimer’s patients from healthy individuals, though early-stage detection remained challenging.

Islam, Junaid and Zhang, Yan explored CNN-based techniques for medical image classification, including brain disorders. Their work highlighted the importance of preprocessing techniques to improve model performance.

Despite these advancements, several challenges remain in existing approaches:

- Many models rely on limited datasets, affecting generalization
- Early-stage Alzheimer’s detection is still less accurate
- Some approaches require multi-modal data, increasing complexity
- High computational requirements limit real-time applicability.

III. EXISTING TECHNIQUES AND THEIR LIMITATIONS

Various techniques have been used for Alzheimer’s detection, each with certain drawbacks.

1. Traditional Machine Learning Methods:
These methods use handcrafted features for classification. While they are simple, they lack accuracy and require manual effort.
2. Clinical Diagnosis:
Doctors analyze MRI scans manually to detect abnormalities. This approach is reliable but time-consuming and subjective.
3. Basic Deep Learning Models:
CNN models can automatically extract features, but they may suffer from overfitting when trained on small datasets.
4. Transfer Learning Approaches:
Pre-trained models improve performance, but they may not fully adapt to medical imaging data.

Limitations:

- Limited Dataset Availability: Most models use small and imbalanced datasets, which reduces their ability to generalize. This affects performance when applied to real-world clinical data.
- Difficulty in Early-Stage Detection: Early-stage Alzheimer's changes are very subtle in MRI images and hard to detect. Models often perform better only in moderate and severe stages.
- High Computational Complexity: Deep learning models require powerful GPUs and high memory for training. This makes deployment difficult in resource-limited healthcare settings.
- Overfitting in Deep Learning Models: Models may memorize training data due to limited datasets. This leads to poor performance on new or unseen data.
- Insufficient Image Preprocessing: Lack of proper preprocessing like noise removal and normalization affects input quality. This reduces feature extraction and overall accuracy.
- Dependence on Multi-Modal Data: Some models rely on MRI, PET, and clinical data together. This increases complexity and limits practical usage in many hospitals.

IV. PROPOSED METHODOLOGY

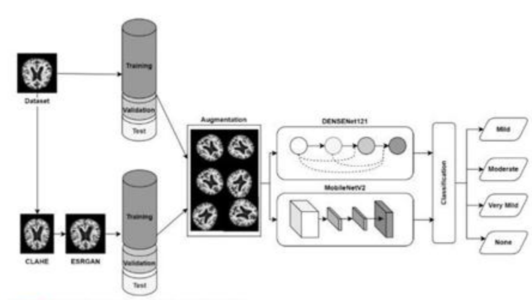

FIGURE 3. Proposed model with and without image enhancement.

The proposed system introduces an enhanced deep learning framework for Alzheimer’s detection using MRI images. Unlike existing methods, it integrates advanced image preprocessing with an optimized CNN architecture to improve early-stage detection and reduce overfitting. The system is designed to provide accurate, efficient, and scalable diagnosis suitable for real-world clinical applications.

1. System Architecture:
The system is designed with improved modules focusing on accuracy and early detection.

- Enhanced Image Acquisition Module: MRI images are collected and filtered to remove low-quality scans. This ensures only reliable data is used for training and testing.
- Advanced Preprocessing Module: Applies noise removal, normalization, and contrast enhancement. This improves visibility of subtle brain changes in early stages.
- Optimized Feature Extraction Module: An improved CNN architecture is used for deep feature extraction. It captures fine-grained patterns that basic models may miss.
- Regularized Classification Module: Fully connected layers with dropout are used to reduce overfitting. This improves generalization on unseen data.
- Intelligent Output Module: Provides stage-wise prediction with probability scores. This helps in better clinical interpretation.

2. Image Preprocessing:
- Intensity Normalization: Standardizes image pixel values across datasets. This ensures consistent model performance.
- Region-Based Segmentation: Focuses on critical brain regions like hippocampus. This improves early-stage Alzheimer's detection.

3. CNN-Based Detection:
- Convolution Lavers: Extract spatial features from MRI images. They detect patterns and abnormalities.
- Pooling Layers: Reduce feature size while retaining key information. This lowers computation cost.
- Batch Normalization: Stabilizes training and speeds up convergence. This improves model performance.
- Dropout Layer: Prevents overfitting by randomly disabling neurons. This enhances generalization.

4. Classification of Disease Stages:
- Non-Demented: Normal brain structure with no disease signs. Model avoids false detection.
- Mild Demented: Detects early-stage changes using enhanced features. Improves early diagnosis.
- Moderate Demented: Identifies clear structural damage. Ensures reliable classification.
- Severe Demented: Detects advanced brain degeneration. Provides high-confidence prediction.

5. Mathematical Model:
- Feature Extraction: F = CNN(I), where I am input image and F is feature vector. Represents learned features. Classification: Y = Soft max (WF + b), where Y is output class. Produces probability score.

V. COMPARISON WITH EXISTING METHODS

The proposed Alzheimer's detection system significantly improves upon traditional and existing approaches by integrating advanced preprocessing techniques, deep learning models, and a user-friendly interface. The comparison below highlights the key differences in terms of performance, accuracy, and usability.

1. Approach
Existing systems primarily rely on manual diagnosis or traditional machine learning algorithms such as SVM and KNN, which depend on handcrafted feature extraction. In contrast, the proposed system uses deep learning models (MobileNetV2 and DenseNet121) that automatically learn features from MRI images using transfer learning.

2. Feature Extraction
In traditional methods, features like texture and shape are manually extracted, which may lead to loss of important information. The proposed system uses Convolutional Neural Networks (CNNs) that perform automatic and hierarchical feature extraction, capturing complex brain patterns more effectively.

3. Image Preprocessing
Most existing systems use basic preprocessing or no enhancement techniques, resulting in poor image quality and noise interference. The proposed system incorporates advanced techniques such as CLAHE and ESRGAN, which enhance contrast and resolution, leading to better feature visibility and improved model.

4. Model Performance and Accuracy
Traditional machine learning models generally achieve lower accuracy due to limited feature representation and inability to handle complex data. The proposed system uses an ensemble of deep learning models, achieving higher accuracy (around 92.34% and 89.38%) and better generalization.

5. Robustness
Single-model approaches in existing systems are more prone to overfitting and may not perform well on diverse datasets. The proposed ensemble model improves robustness by combining predictions from multiple architectures.

6. Processing Time
Manual diagnosis is time-consuming, and traditional methods require multiple steps for feature extraction and classification. The proposed system provides faster processing through automated pipelines and real-time prediction capability.

7. User Interface and Usability
Most existing systems lack interactive interfaces and are difficult for non-technical users to operate. The proposed system includes a Streamlit-based web application that allows easy image upload, instant prediction, and clear result visualization.

8. Data Handling and Privacy
Some existing systems rely on database storage, which may raise privacy concerns. The proposed system processes images locally without storing user data, ensuring better privacy and security.

9. Summary Table
Feature Existing Methods Proposed Method Approach Manual / ML (SVM, KNN) Deep Learning (CNN, Transfer Learning) Feature Extraction Manual Automatic Preprocessing Basic Limited CLAHE + ESRGAN Accuracy Moderate High (~90%+) Robustness Low High (Ensemble Model) Speed Slow Fast (Real-time) Usability Limited User-friendly (Streamlit UI)

VI. IMPLEMENTATION DETAILS

The implementation of the Alzheimer's disease detection system is carried out using deep learning techniques, image preprocessing methods, and a web-based interface. The system is designed to be efficient, scalable, and capable of providing real-time predictions from MRI brain scans.

1. Development Environment
The system is implemented using Python (version 3.7 or above) due to its strong support for machine learning and image processing.
Libraries and Frameworks used:
TensorFlow and Keras for building and loading deep learning models PyTorch (optional) for experimentation Scikit-learn for performance evaluation NumPy and Pandas for data handling OpenCV and Pillow (PIL) for image preprocessing Streamlit for developing the web- based user interface The development is carried out using tools such as Jupyter Notebook and Visual Studio Code.

2. Hardware Requirements
The system is designed to run on standard computing resources:
Processor: Intel Core i5 (10th Gen or higher) RAM: Minimum 8GB (16GB recommended) Storage: At least 256GB SSD
CPU: Optional (for faster model training)

3. Dataset Handling
The dataset consists of approximately 6,400 MRI brain images categorized into different classes representing Alzheimer’s stages and normal cases.
Implementation steps:
Images are stored in structured folders based on class labels All images are resized to 128 × 128 pixels Data is split into training and testing sets Data normalization is applied to scale pixel values

4. Image Preprocessing Implementation
To improve model performance, preprocessing is implemented as follows:
Resizing: Standardizes input size Grayscale conversion (if required): Reduces complexity
CLAHE: Enhances contrast using OpenCV
ESRGAN: Improves image resolution and clarity
These steps are applied before feeding images into the model.

5. Model Implementation
The system uses transfer learning with pretrained CNN models:
MobileNetV2 for lightweight and fast computation
DenseNet121 for deep feature extraction.

Implementation process:
- Load pretrained weights (ImageNet)
- Replace final classification layers according to the number of classes
- Apply fine-tuning to adapt the model to MRI data
- Use activation functions like ReLU and Softmax

6. Training Process:
The models are trained using the prepared dataset:
Loss Function: Categorical Cross-Entropy
Optimizer: Adam
Evaluation Metrics: Accuracy, Precision, Recall
Batch size and epochs are selected based on system capability
After training, the model is saved as a file (e.g., model.h5) for later use.

7. Model Inference:
For prediction: User uploads an MRI image is pre-processed using the same pipeline The trained model is loaded
Prediction is generated Output includes: Predicted class (disease stage / normal) Confidence score

8. Streamlit Web Application:
A web-based interface is implemented using Streamlit for ease of use.
Features:
Upload MRI scan images Display uploaded image Show prediction results instantly Display confidence score Clean and interactive layout.
The application runs locally and can be accessed through a browser.

9. System Workflow
The complete implementation follows this pipeline:

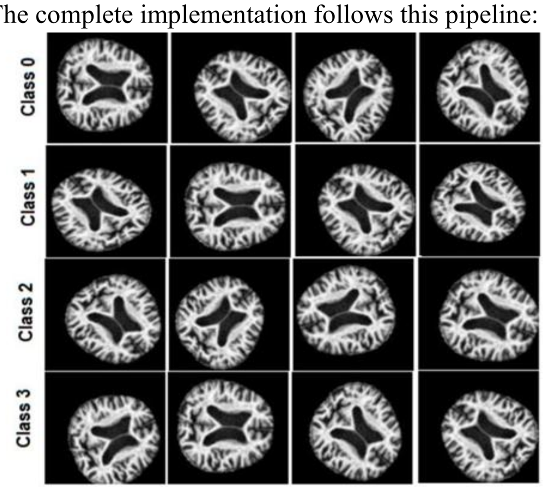

FIGURE 1. Different classes of AD image dataset.

VII. CONCLUSTION

In conclusion, the integration of deep learning and image processing techniques has significantly improved the accuracy and efficiency of Alzheimer’s disease detection. Advanced models such as Convolutional Neural Networks (CNNs), transfer learning architectures, and MRI image analysis methods enable early identification of Alzheimer’s-related abnormalities with higher precision compared to traditional diagnostic approaches. Image preprocessing techniques including segmentation, normalization, and feature extraction further enhance the quality of medical images and improve model performance.
The proposed approach demonstrates that artificial intelligence-based diagnostic systems can assist medical professionals in detecting Alzheimer’s disease at earlier stages, leading to timely treatment and better patient management. Additionally, the use of large neuroimaging datasets and automated analysis reduces human error and supports faster clinical decision-making.
Although deep learning models provide promising results, challenges such as limited medical datasets, computational complexity, and model interpretability still remain. Future work can focus on improving model transparency, integrating multimodal healthcare data, and developing lightweight real-time diagnostic systems for practical clinical applications.
Overall, deep learning combined with image processing techniques offers a powerful and reliable solution for enhancing Alzheimer’s disease detection and contributes significantly to the advancement of intelligent healthcare systems.

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