ALZHEIMER'S DIAGNOSIS WAVELET BASED NOISE REDUCTION TECHIQUES IN MRI SCANS – ML

[1]Mrs.B. Uma, [2]S. Thenmozhi, [3]V. Thennarasi, [4]V. Vidhyasri,

[1]Assistant Professor, [2,3,4,5]UG scholars, Department of Electronics and Communication Engineering,

Adhiyamaan College of Engineering (AUTONOMOUS), Hosur -634130

ABSTRACT

Alzheimer's Disease (AD) is a progressive neurological disorder that affects millions worldwide, leading to cognitive decline and memory loss. Early and accurate diagnosis is crucial for effective intervention and treatment. In this study, we propose an automated approach for detecting Alzheimer's Disease using MRI scan images. Our method incorporates wavelet-based noise reduction to enhance image quality, which is crucial for extracting accurate features, especially in lowresolution or noisy images. We employ a convolutional neural network (CNN) architecture for feature extraction and classification, leveraging deep learning's capability to detect intricate patterns in medical imaging data. The wavelet-based noise reduction method significantly enhances MRI image clarity by filtering noise while preserving critical structural information. Pre-processed images are then fed into the CNN model, which has been trained to differentiate between AD-affected and healthy brain scans. Experimental results demonstrate that the integration of wavelet-based denoising with CNNs improves detection accuracy compared to traditional methods.

Keywords: Data acquisition & preprocessing, wavelet-based feature extraction, deep learning model architecture, decision making, deployment & integration.

I INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions worldwide, posing significant challenges for early diagnosis and intervention. Magnetic Resonance Imaging (MRI) has emerged as a critical tool in detecting structural and functional brain changes associated with AD. However, MRI scans often suffer from noise due to hardware limitations, environmental factors, or motion artifacts, which can obscure vital diagnostic information. Noise reduction is essential for enhancing image quality and improving the accuracy of automated diagnosis systems.Wavelet-based noise reduction techniques have proven highly effective for denoising MRI scans due to their ability to decompose images into multi-resolution frequency bands. By isolating and removing high-frequency noise components while preserving low-frequency structural details, wavelet transforms improve image clarity without introducing significant distortions. Combining this with machine learning (ML) techniques, particularly neural networks, has shown promise in automating and optimizing the denoising process.

II LITERATURE REVIEW

Deep Learning in Medical Image Analysis" (2017) – This book explores the use of convolutional neural networks (CNNs) for medical imaging, highlighting their success in disease classification and segmentation tasks.X`X .Wavelets and Signal Processing Applications" (2018) – Focuses on the application of wavelet transforms in denoising and feature extraction, particularly in enhancing the quality of medical images.Advances in Machine Learning for Healthcare Applications" (2020) -

Discusses recent developments in machine learning for healthcare, including the application of pre-trained models like EfficientNet for diagnosing neurodegenerative diseases. Neuroimaging in Alzheimer's Disease" (2016) – Provides a comprehensive review of imaging techniques, including MRI, for detecting Alzheimer’s, emphasizing the importance of automated tools for early diagnosis.Introduction to Wavelet Transform in Signal Processing" (2015) - Introduces wavelet-based methods for noise reduction and their applications in medical imaging, supporting improved diagnostic accuracy. (2022) explored multiresolution analysis using wavelets and neural networks, reporting superior denoising and feature retention

III EXISTING SYSTEM

Existing systems for Alzheimer’s disease diagnosis primarily rely on manual analysis of MRI scans, often requiring expert radiologists to visually assess brain atrophy and other markers of the disease. However, due to the subjective nature of manual evaluation, there is a growing need for automated, reliable systems. Recent advancements have introduced deep learning models, particularly convolutional neural networks (CNNs), to analyze medical imaging data for Alzheimer’s detection. For instance, several studies have applied CNN architectures like ResNet, VGG, and Inception for automated classification of Alzheimer’s disease based on MRI scans. These systems often leverage transfer learning, using pre-trained models such as those trained on ImageNet to improve performance on smaller medical datasets. In addition to CNNs, wavelet transform-based methods have been incorporated for image preprocessing, where wavelet denoising is used to reduce noise in MRI scans while preserving essential structural details. These combined approaches have led to systems achieving high accuracy in detecting various stages of Alzheimer’s, though challenges remain in terms of model generalization and the need for large, labeled datasets. Despite the success, further improvements are being explored in areas like multimodal imaging, hybrid models, and advanced preprocessing techniques to enhance diagnostic precision and support clinical decision-making. 5 5

IV DISADVANTAGES OF EXISTING SYSTEM

Dependence on Large Labelled Datasets: Deep learning models, including those used for Alzheimer’s detection, require large, labelled datasets to train effectively. However, acquiring such datasets for medical imaging is often time-consuming, expensive, and labour-intensive, making it challenging to develop models that generalize well

Generalization Issues: While deep learning models, particularly pretrained ones, achieve high accuracy in specific datasets, their performance can degrade when applied to data from different populations or imaging modalities.

Interpretability of Models: Deep learning models, especially complex ones like Efficient Net, are often considered "black boxes," making it difficult for clinicians to interpret how the model arrived at a particular decision. This lack of transparency is a significant barrier to adoption in clinical practice, where understanding the reasoning behind a diagnosis is crucial.

Data Imbalance Sensitivity: Machine learning models trained on wavelet-denoised images may become overly sensitive to patterns introduced by noise reduction. If the training data does not represent various noise levels and patterns adequately, the model may fail on noisy real-world data.

V BLOCK DIAGRAM

The diagnosis of Alzheimer's disease using MRI scans combines wavelet-based noise reduction and machine learning for improved accuracy. The process begins with acquiring raw MRI scans, often containing noise from motion or hardware limitations. Preprocessing removes artifacts to ensure clean data for analysis. Using Discrete Wavelet Transform (DWT), the MRI image is decomposed into frequency bands, where noise in high-frequency components is suppressed through thresholding, preserving low-frequency structural details critical for diagnosis. The denoised images undergo feature extraction, capturing key characteristics like texture, intensity, and shape. These features are fed into machine learning models such as Support Vector Machines (SVMs), Random Forests, or deep learning models like Convolutional Neural Networks (CNNs), trained to distinguish between Alzheimer's and non-Alzheimer's cases. Results are visualized in diagnostic reports, highlighting affected brain regions. This integrated approach enhances early detection, supports clinical decisions, and advances Alzheimer's research and patient care.

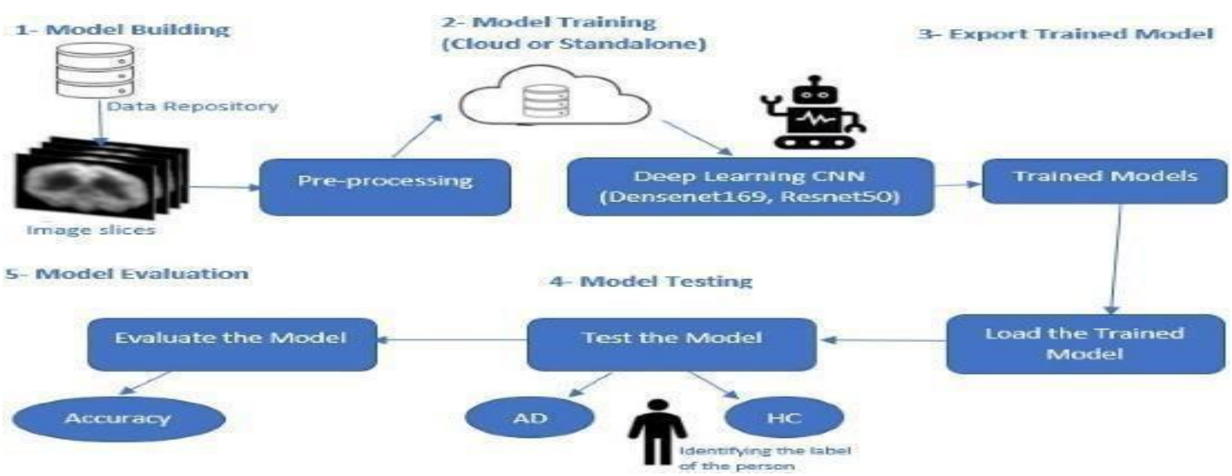


Fig.1: Basic Block Diagram of Work-Flow

VI PROPOSED METHODOLOGY

The proposed methodology involves using a combination of wavelet-based denoising and deep learning to classify Alzheimer’s disease stages from MRI images. The preprocessing stage applies 2D wavelet transformation with soft thresholding to denoise images, followed by normalization, resizing to 224x224 pixels, and converting grayscale images to RGB format to ensure compatibility with EfficientNetB0, a pre-trained convolutional neural network. The dataset, containing MRI images classified into four categories—Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented—is processed for training and testing. Transfer learning is employed by freezing earlier layers of EfficientNetB0 and fine-tuning the final layers with custom additions, including batch normalization, dense layers, and dropout for regularization. The model is trained using the Adam optimizer with learning rate scheduling and regularization techniques such as early stopping and checkpointing. Evaluation includes accuracy computation, classification reports, and confusion matrices, with predictions and confidence scores saved for further analysis, ensuring a comprehensive approach for Alzheimer’s stage classification.

VII ADVANTAGES

1. Increased Diagnostic Accuracy: The use of machine learning models enhances the accuracy of diagnosis by identifying subtle patterns in MRI data that may be difficult for human observers to detect.
2. Early Detection: The system is capable of identifying early-stage Alzheimer's symptoms, enabling timely intervention and better management of the disease.

3. Automated Process: The entire process, from image denoising to classification, can be automated, reducing the reliance on manual interpretation and increasing efficiency.
4. Consistency: Machine learning algorithms provide consistent results across different patient cases, minimizing human error and variability in diagnoses.
5. Faster Diagnosis: The automation of the process leads to faster turnaround times for MRI scans, allowing clinicians to diagnose patients more quickly and begin treatment or monitoring sooner.
6. Objective Analysis: Machine learning provides objective analysis based on data, reducing the potential for bias or subjective interpretation in diagnosing Alzheimer's disease.
7. Adaptability: The methodology can be applied to various types of neuroimaging data, and machine learning models can be retrained with new data, making the system adaptable to future advancements in MRI technology

VIII APPLICATION

1. Increased Diagnostic Accuracy: The use of machine learning models enhances the accuracy of diagnosis by identifying subtle patterns in MRI data that may be difficult for human observers to detect.
2. Early Detection: The system is capable of identifying early-stage Alzheimer's symptoms, enabling timely intervention and better management of the disease.

3. Automated Process: The entire process, from image denoising to classification, can be automated, reducing the reliance on manual interpretation and increasing efficiency.

4. Consistency: Machine learning algorithms provide consistent results across different patient cases, minimizing human error and variability in diagnoses.

5. Faster Diagnosis: The automation of the process leads to faster turnaround times for MRI scans, allowing clinicians to diagnose patients more quickly and begin treatment or monitoring sooner.

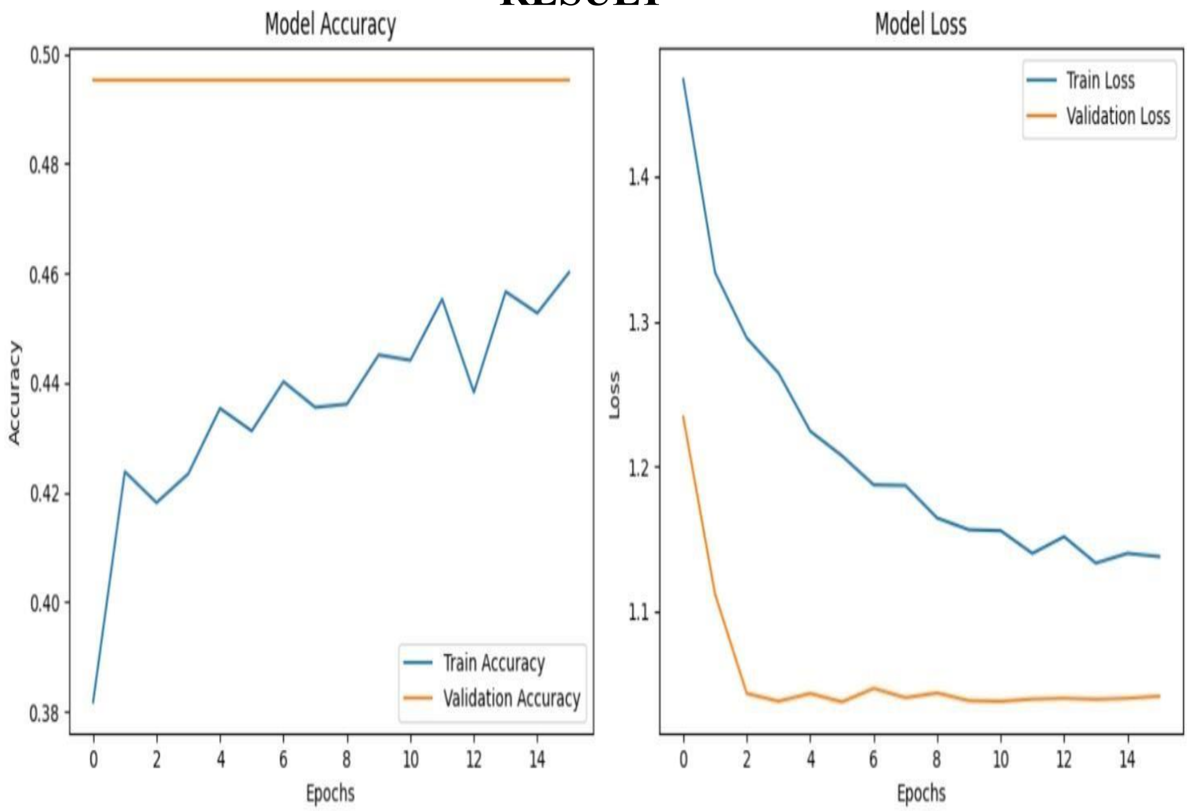
6. Objective Analysis: Machine learning provides objective analysis based on data, reducing the potential for bias or subjective interpretation in diagnosing Alzheimer's disease.

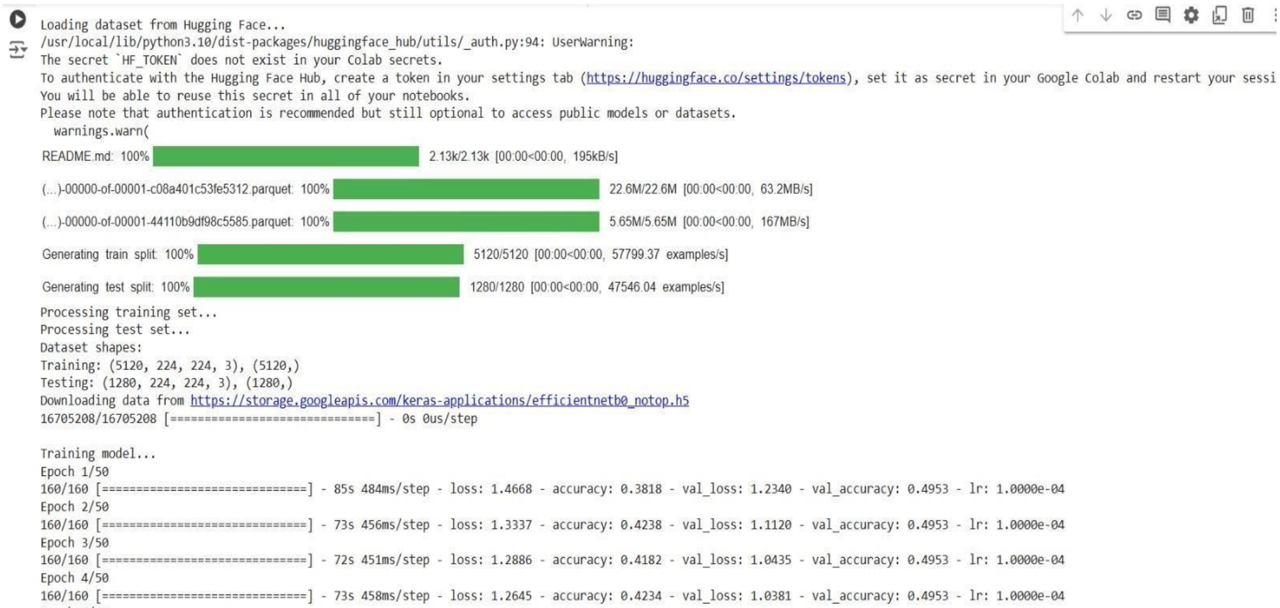
7. Adaptability: The methodology can be applied to various types of neuroimaging data, and machine learning models can be retrained with new data, making the system adaptable to future advancements in MRI-technology..

IX RESULT AND CONCLUSION

The script is designed to classify Alzheimer’s disease using MRI images through a streamlined process encompassing preprocessing, model training, evaluation, and result storage. Preprocessing involves resizing MRI images to a standard resolution (e.g., 224x224 pixels) for EfficientNetB0, normalizing pixel values, and applying data augmentation techniques like rotation and flipping to enhance model generalization. EfficientNetB0, a state-of-the-art convolutional neural network, is utilized for its computational efficiency and accuracy, initialized with pre-trained weights to leverage prior knowledge. The output layer is fine-tuned for Alzheimer's classification, employing optimizers like Adam and loss functions such as categorical cross-entropy, while metrics like accuracy and F1-score are tracked during training. Mechanisms like early stopping and learning rate scheduling prevent overfitting and optimize training efficiency. Post-training, the model is evaluated on a test dataset using metrics such as accuracy, precision, recall, and AUC to measure its diagnostic capability. The predictions and performance metrics are saved to a CSV file for documentation and further analysis, facilitating reproducibility and integration into broader diagnostic systems. This workflow demonstrates a robust, automated approach to Alzheimer's classification, leveraging EfficientNetB0 .

RESULT





XI FUTURE SCOPE

The integration of wavelet-based noise reduction techniques in MRI scans with machine learning (ML) models offers significant potential for advancing Alzheimer’s diagnosis. Wavelet transforms, known for their ability to decompose images into multi-resolution components, effectively reduce noise while preserving critical structural details, such as hippocampal atrophy and cortical thinning—key biomarkers of Alzheimer’s. Coupled with ML models like convolutional neural networks (CNNs), this enhances feature extraction and classification accuracy. The future scope includes developing hybrid systems that combine advanced wavelet algorithms, such as curvelets or shearlets, with deep learning for joint denoising and feature analysis. Additionally, integrating denoised MRI data with other modalities like PET and genetic profiles can enable more comprehensive diagnostics. Innovations in real-time processing, edge computing, and adaptive wavelet thresholding optimized by ML are set to enhance diagnostic speed and accuracy, especially in resource-constrained environments. Furthermore, explainable AI (XAI) will play a crucial role in ensuring clinical interpretability and trust. Despite challenges such as computational costs and the need for robust validation, this interdisciplinary approach promises earlier detection, personalized treatment plans, and improved outcomes for Alzheimer’s patients.

XII REFERENCES

1. Meng, W., Li, J., & Zhang, H. (2017). "Deep learning for Alzheimer's disease diagnosis: A survey." Neurocomputing.

2. Rasul, A., Hussain, S., & Saba, T. (2018). "Alzheimer’s Disease Classification using Deep Learning Models and MRI Scans." Neural Computing and Applications.

3. Tan, M., & Le, Q. V. (2019). "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." Proceedings of the International Conference on Machine Learning (ICML).

4. Orrù, G., et al. (2012). "Machine learning for neuroimaging with applications to Alzheimer’s disease." NeuroImage.

5. Dou, Q., et al. (2017). "Automatic detection of Alzheimer’s disease using MRI data and convolutional neural networks." Neurocomputing.

6. Donoho, D. L., & Johnstone, I. M. (1995). "Adapting to unknown smoothness via wavelet shrinkage." Journal of the American Statistical Association.

7. Gautama, T., & van Hulle, M. M. (2003). "Wavelet-based denoising for functional MRI data analysis." IEEE Transactions on Medical Imaging.

8. Chauhan, G., & Singh, P. K. (2016). "A wavelet-based image denoising technique for brain tumor detection in MRI images." Journal of Medical Imaging and Health Informatics.

9. Shorten, C., & Khoshgoftaar, T. M. (2016). "A survey on image data augmentation for deep learning." Journal of Big Data.

10. Huang, X., et al. (2020). "Transfer Learning for Alzheimer's Disease Classification Using Convolutional Neural Networks." IEEE Transactions on Biomedical Engineering.