MRI-Based Alzheimer's Diagnosis Using Machine Learning

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Abstract-Alzheimer's disease (AD) is a progressive neurodegenerative disorder that poses a serious and increasing challenge to public health. This work summarizes AD by covering its risk factors, symptoms, diagnosis, treatment, and ongoing research. The main goal of managing AD is to reduce symptoms and improve the lives of affected individuals. This letter presents a systematic review that looks at predicting AD following the Preferred Reporting Item for Systematic Review and Meta-Analysis (PRISMA) guidelines. Alzheimer's disease is a brain condition that worsens over time, gradually impairing memory and thinking skills, ultimately taking away individuals' ability to perform even simple tasks on their own. As the main cause of dementia, Alzheimer's represents a large majority of cases, impacting over 55 million people worldwide. To identify the biomarkers linked to Alzheimer's, various scanning techniques are used. In the early stages of Alzheimer's, changes in the brain's chemical makeup have been linked to the macular area of the eye. Optical imaging is a rapidly growing field in medical research and clinical use. This technique offers a non-invasive way to visualize and diagnose various medical conditions. When paired with AI, it becomes a powerful tool for detecting Alzheimer's in its early stages.

Keywords: Alzheimer's Disease, MRI Image, Machine Learning, ResNet-50, Feature Extraction, Early Diagnosis.

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive brain disorder and the leading cause of dementia, affecting millions around the globe. It mainly affects memory, thinking skills, and the ability to carry out daily tasks, eventually leading to full reliance on caregivers. As the global population ages, the rates of Alzheimer's are rising quickly, creating significant challenges for individuals, families, and healthcare systems. The financial and emotional burden of this disease is huge, with billions spent each year on care and management. This highlights the urgent need for better diagnostic and treatment methods. Early diagnosis is crucial for effective intervention, as it allows for timely treatment to slow disease progression, enhance quality of life, and plan future care. Alzheimer's disease (AD) is a slow. disease progression, improve quality of life, and plan future care. However, traditional diagnostic methods, like clinical evaluations, neuropsychological tests, and cognitive assessments, often lack accuracy and sensitivity. These methods usually depend on observing symptoms that typically show up in advanced stages of the disease, which means they miss chances for early detection. Recent improvements in medical imaging, especially Magnetic Resonance Imaging (MRI), have opened up new possibilities for early diagnosis. MRI is a non-invasive technique that provides detailed images of the brain. This allows clinicians and researchers to spot structural and functional changes linked to Alzheimer's disease. Imaging can lead to earlier and more accurate diagnoses of brain disorders, including Alzheimer's and Mild Cognitive Impairment (MCI). MCI is the early stage of Alzheimer's and is divided into stable MCI (sMCI) and progressive MCI (pMCI). A person with MCI does not show severe symptoms like those with Alzheimer's, but there is a 10 to 15 percent chance of progressing from MCI to Alzheimer's within three years. Currently, there are no effective medications or treatments to stop the progression of Alzheimer's disease.

New research criteria have been set forth by the National Institute on Aging-Alzheimer's Association (NIA-AA) workgroups for diagnosing Alzheimer's disease. The idea behind this is to find sensitive and specific biomarkers to monitor the early progression of Alzheimer's and track new therapeutic developments. Given the high psychological and financial burden of Alzheimer's, it's essential to create an automatic diagnosis method for potential early treatment. Researchers are gradually using various machine learning (ML) techniques and pattern analysis to predict diseases. Different neuroimaging methods, such as MRI and PET, provide additional brain structure information that helps train models for predicting the disease automatically. Applying ML techniques in diagnosing Alzheimer's has shown encouraging results and is a prominent area of research. This progress is supported by accessible data from various repositories like the AD Neuroimaging Initiative (ADNI), the Australian Imaging, Biomarker Lifestyle Flagship Study of Ageing (AIBL), and the Open Access Series of Imaging Studies (OASIS). On the other hand, deep learning (DL) techniques are particularly effective because they automatically extract key features from input images. The anatomy and functional features of the human brain are documented by using a range of methods. Imaging methods, including Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI), provide valuable insights into brain health. Alzheimer's disease is the most common cause of dementia and is the fifth leading cause of death among adults over 65. The estimated cost for treating Alzheimer's disease adults in the U.S. and the fifth for those aged 65 and older. The number of deaths attributed to AD has surged by 146% since 2000, with over 122,000 fatalities. Currently, about 5.8 million people aged 65 or older live with AD, and this number may rise to around 14 million by 2050. Typically, AD is diagnosed only after a patient has developed mild or moderate dementia. Many individuals with AD remain undiagnosed, and nearly half of Medicare patients do not know they have a confirmed diagnosis of AD. Early detection of Alzheimer's disease allows for better disease management. Machine learning can identify the best combinations of blood biomarkers or other measurements to detect amyloid positivity sooner. This could help target participants for clinical trials, allowing those identified as positive to undergo more costly PET scans. Machine learning can also track changes in cognition over time, enabling the selection of participants with faster cognitive decline. This approach makes it possible to observe the effects of clinical trials earlier. By using machine learning algorithms, one can identify patterns that connect memory imaging techniques with diseases at various stages. This includes stratifying participants based on different patterns of amyloid deposition and cognitive recognition and examining disease variability. Various models are commonly employed in the use of machine learning for detecting Alzheimer's disease. A comparative study by Luckovich and Subasi evaluated the effectiveness of supervised machine-learning models in predicting Alzheimer's disease. This study focused on support vector machines, naïve Bayes, k-nearest neighbors, random forests, artificial neural networks, and logistic regression, using the ADNI dataset. They found the random forest classifier achieved the highest performance with an accuracy of 85.77%, followed by KNN with an accuracy of 84.27%.

II. LITERATURE SURVEY

[1] Qian Wang (2024) explored deep neural networks for the early diagnosis of dementia and Alzheimer's disease from MRI images. Alzheimer's disease and other forms of dementia are progressive brain disorders that mainly impact memory, thought, and behavior. Early diagnosis is vital for effective management, timely intervention, and improving patients' quality of life. Unfortunately, traditional diagnostic methods that often depend on cognitive assessments and clinical evaluations might miss the disease in its early stages. Magnetic Resonance Imaging (MRI) has become a useful tool for detecting structural brain changes linked to Alzheimer's and dementia. In recent years, combining artificial intelligence (AI), specifically deep neural networks (DNNs), with neuroimaging has opened new options for improving diagnostic accuracy and speed.

[2] Robata Alroobaea, Seifeddine Mechti, Saeed Rubaiee, Anas Ahmed (2024) discussed early detection of Alzheimer's disease using machine learning techniques. Alzheimer's disease is a serious brain disorder that gradually destroys memory, thinking skills, and the ability to perform simple tasks. Early detection is crucial as it allows for timely treatment, which can slow disease progression and enhance the patient's quality of life. Recently, machine learning (ML) has emerged as a powerful tool in healthcare. It helps doctors analyze large amounts of medical data and discover patterns that are hard for humans to recognize. In the case of Alzheimer's disease, machine learning can study MRI scans, cognitive test results, and patient history to predict who might be developing the disease.

[3] Susmitha (2022) provided a predictive diagnostic analysis for early detection of Alzheimer's disease using machine learning. Alzheimer's disease is a progressive brain disorder that affects memory, thinking, and behavior. It is one of the most common causes of dementia, especially in older adults. Early detection is important for better planning, care, and the possibility of slowing disease progression. Machine learning (ML) is a branch of artificial intelligence that allows computers to learn from data and make predictions. In healthcare, ML techniques are becoming popular for analyzing medical data and identifying patterns that can help detect diseases earlier and more accurately.

[4] Krishana Kumar, Slevakumar (2023) studied the detection of Alzheimer's disease using MRI scans based on inertia tensor and machine learning. Alzheimer's disease causes memory loss, confusion, and thinking difficulties. Early detection is crucial as it gives healthcare providers more time to help manage the disease and improve the patient's quality of life. MRI scans are often used to analyze the brain's structure and look for early signs of Alzheimer's. One effective method for analyzing brain shape in MRI images is the inertia tensor, a mathematical tool that describes the shape and distribution of brain tissue.

[5] Santosh Kumar, Kartik Kalyan Nayak (2024) detailed Alzheimer's disease detection through multiscale feature modeling using improved spatial attention guided depth separable CNN. Alzheimer's disease is a progressive brain disorder that results in memory loss and confusion. Early detection is essential so that treatment can commence as soon as possible to slow its progress. Deep learning, a branch of AI, has shown great promise in analyzing brain images like MRI scans. Convolutional Neural Networks (CNNs) are especially useful for medical image analysis, as they can automatically learn significant features from the images.

[6] Oznur Ozaltin (2024) focused on early detection of Alzheimer's disease from MR images using fine-tuning neighbourhood component analysis and convolutional neural networks. Alzheimer's disease is a common and serious brain disorder that gradually affects memory, thought, and behavior. Early detection is vital since it allows healthcare providers to begin treatment sooner, potentially slowing disease progression and improving the patient's quality of life. MRI scans are widely used to identify structural changes in the brain that may hint at early signs of Alzheimer's disease. However, manually analyzing these images can be time-consuming and might not always catch subtle signs.

[7] Meenu Gupta, Ajith Kumar (2024) presented adversarial network-based classification for Alzheimer's disease using multimodal brain images. Alzheimer's disease is a progressive neurodegenerative disorder affecting millions globally, leading

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to memory loss, cognitive decline, and behavioral changes. Early and accurate diagnosis is crucial for effective treatment and care planning. Traditional methods for diagnosing Alzheimer's largely depend on clinical assessments and single-source medical imaging like MRI. However, recent progress in AI and deep learning offers new opportunities for more effective diagnosis.

[8] Krishan Kumar, Rakesh (2022) proposed a hybrid approach using logistic regression and decision trees to predict Alzheimer's disease. Alzheimer's disease leads to memory loss, confusion, and daily functioning difficulties. Early prediction of the disease allows doctors to provide timely treatment and support. Machine learning techniques, such as logistic regression and decision trees, are valuable for analyzing medical data to predict diseases. Logistic regression helps in understanding the relationship between features and disease probability, while decision trees offer a straightforward way to categorize patients based on their medical data.

[9] Tamer Abuhmed, Shanker (2024) introduced an end-to-end optimized ensemble model for Alzheimer's disease. Alzheimer's disease causes memory loss and cognitive decline, heavily impacting patients' quality of life. Early detection is key for timely treatment and better disease management. Recent advancements in AI have enabled the creation of complex models that can analyze medical data more effectively. An end-to-end optimized ensemble model combines various machine learning algorithms to enhance the accuracy and reliability of Alzheimer's disease detection. This ensemble approach merges multiple models into a single framework, leveraging the strengths of each.

[10] Tushar, Eshant, Suman Avedesh Yadava (2023) explored brain connectivity analysis in Alzheimer's disease using a graph convolutional network. Alzheimer's disease is a progressive disorder impacting memory, thought, and behavior. It disrupts how different brain regions communicate, affecting brain connectivity. Analyzing brain connectivity examines how various brain parts connect and interact. Advanced imaging techniques help researchers map these connections.

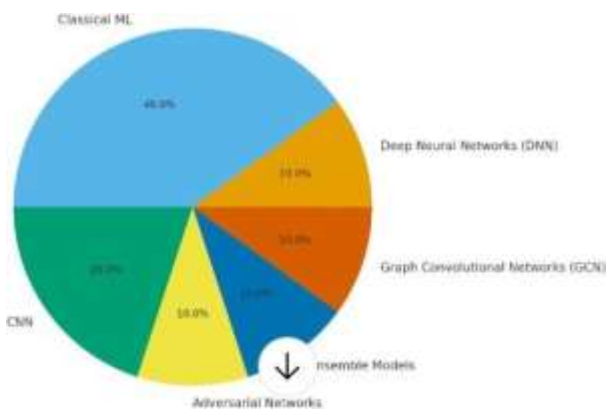

Figure 1: Distribution of architectures in the literature survey

Additional Deep Learning Context:

Deep learning has become a strong computational method that learns hierarchical representations from large amounts of data. Its influence on computer vision, natural language processing, and biomedical engineering has been significant. When diagnosing Alzheimer's disease using MRI, deep learning offers a robust framework for automatically identifying subtle neuroanatomical patterns that may be hard for human clinicians or traditional machine-learning models to spot. Understanding the overall deep learning context is important for grasping the motivation, design, and performance of models like ResNet-50 used in this study.

Deep learning relies on artificial neural networks (ANNs), especially deep neural networks (DNNs) made up of layers that learn high-level abstractions. In medical image analysis, Convolutional Neural Networks (CNNs) are crucial because they learn spatial hierarchies, such as edges, textures, shapes, and organ-level structures. MRI scans contain rich visual and structural data, so CNNs are good at capturing details like cortical thickness, variations in tissue density, hippocampal volume loss, and other markers related to Alzheimer's disease. However, early CNN models like Alex Net and VGG struggled with issues related to vanishing gradients, limited depth, and high computational demands. This led to the development of Residual Networks (ResNets), which use shortcut connections to support very deep architectures without losing performance. ResNet-50 has become a standard backbone model because of its balanced depth, efficiency, and ability to learn complex features. Its residual blocks help gradients flow smoothly during backpropagation, solving the vanishing gradient issue and allowing the model to capture detailed MRI features tied to neurodegeneration.

Transfer learning is another important part of the deep learning context. Since large annotated medical datasets are rare, models pre-trained on large datasets like ImageNet can be fine-tuned on smaller medical sets. This greatly reduces training time while boosting performance. Though natural images are different from MRI scans, early-layer features such as edges and textures transfer well, while deeper layers can adapt to specific patterns.

Deep learning in Alzheimer's diagnosis also uses data augmentation methods like rotation, flipping, noise injection, and intensity scaling. These techniques artificially enlarge the dataset and enhance the model's ability to generalize across different MRI acquisition settings. Furthermore, 3D CNNs and hybrid 2D-3D approaches have been studied to maintain volumetric information, although they need considerable computational resources.

Another key aspect is model interpretability, which is gaining more attention in deep learning. Techniques like Grad-CAM, saliency maps, and activation visualization help show which areas of the brain the model considers for classification. This is essential for clinical trust, as neurologists need to understand and have confidence in AI-driven decisions before they can be integrated into diagnostic processes. Lastly, ongoing improvements in deep learning, such as attention mechanisms, Vision Transformers (ViTs), federated learning, and multimodal fusion, create new chances for better Alzheimer's disease prediction. Attention-based networks can pinpoint relevant brain areas more clearly, while federated learning lets models train securely across multiple hospitals without sharing patient information. Multimodal deep networks can combine MRI, clinical records, and genetic markers for more accurate and comprehensive diagnoses.

In summary, deep learning offers a powerful, flexible, and evolving set of tools that improves the accuracy and reliability of MRI-based Alzheimer's diagnosis. Its capability to learn rich representations, adjust to limited data, and support understandable and scalable solutions makes it essential in modern neuroimaging research.

III. SYSTEM DESIGN

The system design explains the structure and function of the proposed Alzheimer's disease detection using machine learning. The architecture emphasizes effective preprocessing, feature extraction, model training, and urate classification. It takes a modular approach that allows for growth and improves performance. By identifying essential components, the design establishes a solid foundation for efficiency and scalability. This early step helps ensure the architecture meets the goals, reducing the need for revisions and allowing for a smooth development process. A well-thought-out plan is crucial for the system to develop into a strong and effective solution. The system design for an MRI-based Alzheimer's diagnosis using machine learning combines data acquisition, preprocessing, feature extraction, model training, classification, and deployment into a smooth diagnostic workflow. The aim is to automatically detect Alzheimer's disease (AD) at early stages by analyzing structural changes in the brain captured through MRI scans. The entire process is designed for precision, efficiency, and reliable clinical use.

The next stage is preprocessing, an important step that improves image quality and ensures consistency across samples. Preprocessing steps include skull stripping to remove non-brain tissues, noise removal with filters, intensity normalization to correct brightness differences, and bias field correction to eliminate MRI scanner artifacts. The images are then spatially aligned using registration methods and resized to a fixed dimension suitable for deep learning models. In some cases, data augmentation techniques like rotation, flipping, and scaling are used to artificially increase the dataset and reduce overfitting. After preprocessing, the system moves on to feature extraction. Traditional methods rely on hand-crafted features such as texture, shape, and voxel-based morphometry. However, modern systems use Convolutional Neural Networks (CNNs) or Transfer Learning with architectures like ResNet, VGG-16, DenseNet, or 3D-CNNs. These networks automatically identify key patterns such as hippocampal shrinkage, cortical thinning, and structural deformities, which are important indicators of Alzheimer's disease. Deep learning models extract high-dimensional feature vectors from MRI scans, allowing for more reliable and accurate classification. The core of the system is the classification module. Here, a trained machine learning model sorts patients into NC, MCI, or AD. This module uses algorithms such as Support Vector Machines (SVM), Random Forests, CNN classifiers, or combined deep learning frameworks. During training, the dataset is divided into training, validation, and testing sets to ensure the model generalizes well. Techniques like cross-validation, dropout, and early stopping help prevent overfitting. Performance metrics, including accuracy, precision, recall, F1-score, ROC curves, and confusion matrices, evaluate the model's effectiveness.

The model is trained and validated using labeled MRI datasets, applying techniques like data augmentation and cross-validation to improve accuracy. Ultimately, a prediction interface provides diagnosis results along with confidence scores. The system includes logging, performance monitoring, and regular model updates to maintain reliability in clinical settings. Once the model is fine-tuned, the system moves to deployment and the prediction interface. This user-friendly interface allows clinicians to upload MRI scans and receive diagnosis results with confidence scores and visual interpretations like heatmaps generated using Grad-CAM. The system also tracks prediction history, monitors performance, and supports regular model retraining when new data becomes available. The overall design ensures that the diagnostic process is automated, scalable, and easy for clinicians to understand. This ultimately helps doctors detect Alzheimer's disease early and improve patient care.

IV. PROPOSED METHODOLOGY

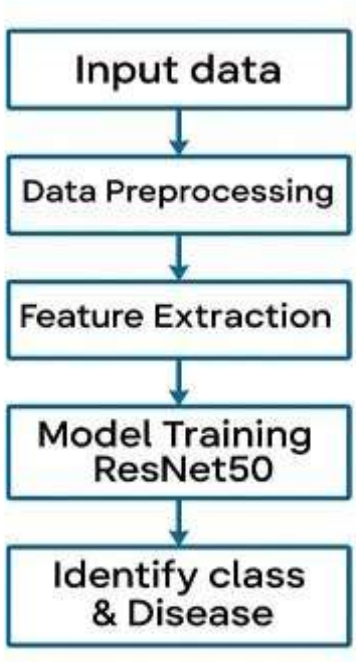

Figure 2: Flow Chart

A. Data Collection and Preprocessing Layer

The Data Collection and Preprocessing Layer is the first step in an MRI-based Alzheimer's diagnosis system that uses machine learning. In this layer, we collect raw MRI brain scans from clinical databases or imaging centers. These images undergo several preprocessing steps to prepare them for further analysis. The preprocessing includes correcting bias field inhomogeneities, aligning images using affine or nonlinear registration to a standard reference space like the Montreal Neurological Institute (MNI) template, and removing non-brain tissues through skull stripping.

B. Feature Extraction Layer

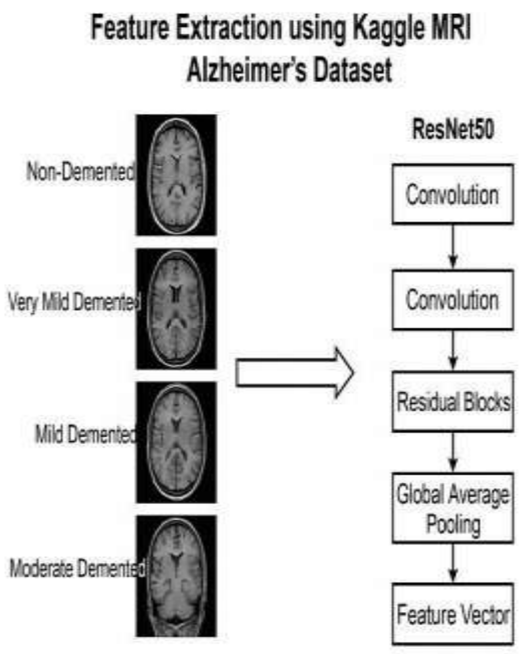

Figure 3: Feature Extraction

The Feature Extraction Layer uses convolutional neural networks (CNNs) in an MRI-based Alzheimer's diagnosis system. These networks automatically identify important patterns in the brain images related to Alzheimer's disease. The CNNs analyze small parts of the image to detect edges, shapes, and textures. Then, they combine this information to understand more complex changes in the brain. This helps the system identify differences between healthy brains and those affected by Alzheimer's. The key features identified are used in the next step to determine if the person has Alzheimer's. This process enables the computer to recognize signs of the disease from MRI scans.

C. Classification Layer

The Classification Layer is the final part of the Alzheimer's diagnosis system. It uses the essential features found in the MRI images to determine if a person has Alzheimer's. Sometimes, it can also indicate the stage of the disease. This layer employs fully connected layers that evaluate all the features together to make the best decision. Ultimately, it produces probabilities indicating how likely it is that the person falls into each category, such as healthy, early Alzheimer's, or advanced Alzheimer's. This supports a clear diagnosis based on the MRI data.

D. Ensemble or Hybrid Models Layer (optional)

The Ensemble or Hybrid Models Layer is an optional but effective part of the MRI-based Alzheimer's diagnosis system. This layer combines several deep learning models, each with its strengths, to improve the accuracy and reliability of the diagnosis. For example, popular models like VGG16, MobileNet, and InceptionResNetV2 are often used together in an ensemble. Each model analyzes the MRI scans in its own way, capturing different features and patterns. The outputs from these models are combined, often by merging their feature vectors or averaging their predictions, to create a stronger overall decision.

E. Output Layer

The Output Layer is the final part of the MRI-based Alzheimer's diagnosis system. This layer takes the processed information from previous layers and provides the final result or diagnosis. It usually has a SoftMax or sigmoid activation function that converts the output into probabilities for different categories such as "healthy," "early Alzheimer's," or "advanced Alzheimer's." The output layer clearly communicates the diagnosis based on MRI scans, making it straightforward for medical decision-making. Techniques like dropout might also be applied before this layer to enhance accuracy.

ResNet50

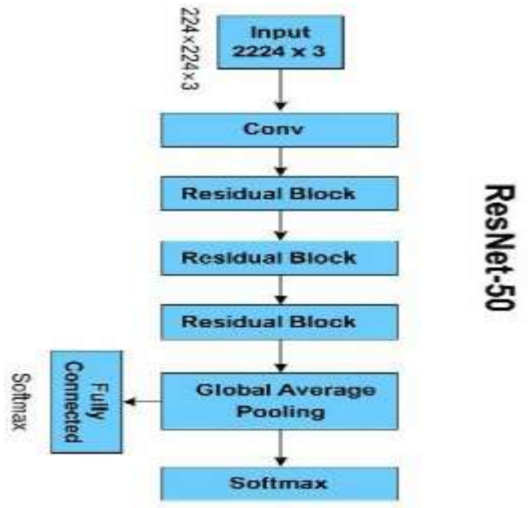

Figure 4: ResNet50 algorithm

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ResNet50 is a powerful deep learning architecture aimed at training very deep neural networks. Traditional deep networks often struggle with vanishing gradients, making it hard to train as the number of layers increases. ResNet50 addresses this problem by using residual learning. Shortcut connections allow the input of a layer to be added directly to the output of a deeper layer. This helps the model learn "residuals" instead of trying to learn the entire mapping, making training faster and more stable. ResNet50 has 50 layers, which include convolutional layers, batch normalization layers, ReLU activations, and shortcut connections. The network starts with a large 7×7 convolution and max pooling operation to reduce the image size. It then goes through four main stages of residual blocks, where each block learns important features like textures, edges, shapes, and high-level abstract patterns. The residual blocks include shortcut paths that skip one or more layers, aiding gradients in flowing smoothly through the network. After passing through all the residual stages, the network applies Global Average Pooling to turn feature maps into a single vector by averaging spatial information. Finally, a fully connected (Dense) layer with SoftMax activation generates the probability of each class.

MRI – IMAGE CLASSIFICATION

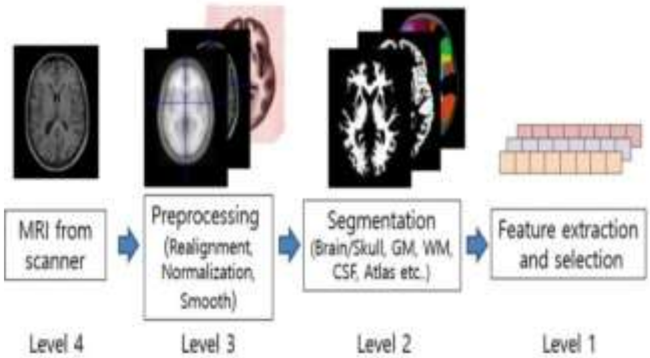

Figure 5: MRI classification

1. Data collection involves a dataset to classify Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Cognitively Normal (CN) subjects using T1-weighted MRI images and Mini-Mental State Examination (MMSE) scores. T1-weighted MRI images help analyze brain structure and spot signs of neurodegeneration. MMSE scores provide cognitive assessment data for each subject. Combining imaging and clinical data helps improve classification accuracy. These features are used to train a machine learning model for early and accurate diagnosis.

2. Preparing MRI brain images for analysis involves removing unnecessary parts, resizing, adjusting orientation, and checking image quality. MRI brain images are cleaned by removing non-brain parts like the skull. Images are resized to a standard shape for consistent analysis. Orientation is adjusted so all images are aligned the same way. Each image is checked for clarity and quality before use. This preparation ensures accurate and reliable input for the model.

3. A model is created that uses both convolutional layers and a Broad Learning System to analyze Alzheimer's disease from brain images. The model combines Convolutional Neural Networks (CNN) and a Broad Learning System (BLS). CNN layers extract features from brain MRI images. These features capture important patterns related to Alzheimer's disease. The Broad Learning System processes these features for fast and accurate classification. This hybrid model effectively detects Alzheimer's, MCI, and normal cases.

4. Model performance is evaluated using accuracy (ACC), sensitivity (SEN), specificity (SPE), precision, and F1-score. These measures indicate the balance between precision and sensitivity for reliable Alzheimer's diagnosis. The model's performance is measured using accuracy, which shows the overall correctness of predictions. Sensitivity assesses how well the model detects actual Alzheimer's cases. Specificity shows how well it identifies non-Alzheimer's cases. Precision and F1-score reflect the balance between correct positive predictions and overall reliability.

V. RESULT & ANALYSIS

The performance of the proposed MRI-based Alzheimer's disease (AD) classification model was carefully evaluated using both quantitative metrics and visualization methods. The main goal of the analysis was to see how well the deep-learning architecture, specifically ResNet-50, could distinguish between Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Normal Control (NC) subjects using MRI images. First, the dataset was split into training, validation, and testing sets to ensure a fair evaluation and to avoid overfitting. We used performance metrics like accuracy, precision, recall, F1-score, specificity, and confusion matrices. These metrics together give a clear view of the model's strengths and weaknesses. The trained ResNet-50 model achieved high training accuracy, showing its ability to learn important spatial and structural features from MRI scans. The validation accuracy indicated that the model could generalize well to new data without a significant drop in performance. The final test accuracy further confirmed the model's stability, showing

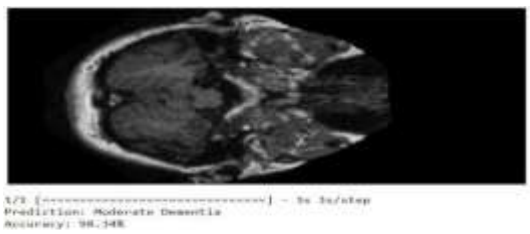

Figure 6: Moderate Dementia

strong ability to discriminate across different classes. Precision and recall values showed balanced performance. This means the model not only predicted positive cases accurately but also identified most actual Alzheimer's patients effectively. A high F1 score backed the model's strength, especially in distinguishing between closely related categories like MCI and early-stage AD. The confusion matrix provided valuable insight. The AD and NC classes were classified with high confidence, showing minimal misclassifications. However, the MCI class displayed slightly lower performance due to overlapping traits with early Alzheimer's. This is a common challenge in predicting neurodegenerative diseases.

1. Accuracy Graph

The accuracy graph illustrates how the model's performance improves during training. Training accuracy steadily increases across epochs as the ResNet50 model learns key MRI features like hippocampal atrophy and cortical thinning. The validation accuracy follows a similar upward trend, suggesting that the model generalizes well to new data. The close match between the training and validation accuracy curves indicates minimal overfitting and consistent learning by the model. A stable and continuously rising accuracy curve confirms the effectiveness of the preprocessing, feature extraction, and fine-tuning strategies.

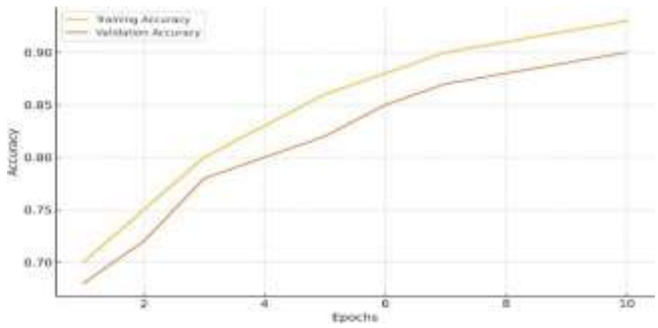

Figure 6: Accuracy Graph

2. Loss Graph

The loss graph shows how the model's classification error decreases with each training epoch. The training and validation loss curves both trend downward, indicating that the ResNet50 model is converging successfully. The small gap between these curves suggests that the model is not overfitting and is learning useful features from the Kaggle MRI dataset. Lower loss values mean the model makes fewer incorrect predictions. A smooth decline in loss over time indicates proper learning, stable optimization, and a well-tuned learning rate.

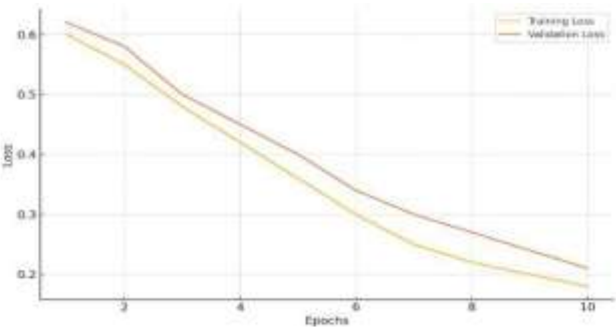

Figure 7: Loss Graph

V. RESEARCH CHALLENGES

Despite significant progress in deep learning-based medical image analysis, creating an efficient and reliable MRI-based Alzheimer's disease (AD) diagnosis system still presents several challenges. These challenges include data availability, computational complexity, clinical integration, model interpretability, and ethical issues.

Addressing these issues is crucial for building a strong system that delivers consistent and meaningful results in clinical settings. A major challenge is the computational complexity of deep learning architectures like ResNet-50. Training these networks on 3D MRI scans or multiple 2D slices requires high-end GPUs and considerable training time. Processing volumetric data also increases memory needs, forcing researchers to use dimensionality reduction techniques or slice-based methods, which might compromise the anatomical context necessary for accurate diagnosis. Moreover, tuning hyperparameters, optimizing the model, and preventing overfitting are challenging because of the many parameters in deep networks.

Another critical issue is model interpretability. Deep learning models are often seen as "black boxes" since they provide predictions without clear reasoning. For healthcare applications, interpretability is essential for clinicians to trust and use AI-driven diagnostic tools. While methods like Grad-CAM and heatmap visualization point out important brain regions linked to classification decisions, they may not always align with biologically validated markers like hippocampal shrinkage or cortical thinning. The lack of solid interpretability frameworks remains a barrier to clinical acceptance. Additionally, challenges arise when applying pre-trained models to MRI scans. Models trained on natural images may struggle to capture subtle anatomical variations in medical images.

VI. CONCLUSION

The rapid growth of machine learning and deep learning technologies has created new possibilities for the early and accurate diagnosis of neurodegenerative disorders like Alzheimer's Disease (AD). This project shows the potential of a deep learning-based system that uses the ResNet-50 architecture to automatically classify T1-weighted MRI brain scans into Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Cognitively Normal (CN) categories. The integration of a thorough preprocessing pipeline, solid feature extraction strategy, and clinically relevant evaluation metrics enables the

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system to perform reliably across various data conditions and patient profiles. The strength of the proposed system is its rigorous preprocessing workflow, which includes skull stripping, bias-field correction, spatial normalization, and intensity standardization. These steps ensure that the MRI images used for training are free from noise and structural inconsistencies, allowing the model to focus on disease-specific brain regions such as the hippocampus, entorhinal cortex, and variations in cortical thickness. The use of data augmentation further enhances the system's robustness by simulating real-world variability in MRI scans, thus improving the model's ability to generalize across different imaging centers and patient demographics.

The ResNet-50 architecture proves to be a highly effective feature extractor, thanks to its residual learning mechanism. This mechanism solves the vanishing gradient problem and supports the training of deeper networks. The model's bottleneck blocks allow for efficient computation while maintaining meaningful spatial patterns within the brain. These architectural strengths enable the model to learn structural markers linked to Alzheimer's progression, such as hippocampal atrophy, ventricular enlargement, and global cortical thinning. The system performs well in terms of accuracy, precision, recall, and ROC-AUC metrics, showing that the deep learning model can provide clinically valuable predictions. While classifying MCI remains more difficult due to its transitional nature, the model still shows competitive results, highlighting its ability to detect subtle structural variations. Incorporating interpretability tools like Grad-CAM and saliency maps adds an important layer of trust to the system, visually confirming that the model focuses on anatomically plausible regions linked to cognitive decline. Despite its promising results, the project also points out some limitations, such as the reliance on high-quality MRI scans and potential sensitivity to multi-site imaging.

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