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Research Paper

A CNN Framework for Alzheimer's Diagnosis Using Landmark-Based Hippocampal Region Extraction from MRI

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***Abstract*— Alzheimer's disease (AD) is a serious neurological disorder that affects memory and cognitive function, making early diagnosis very important. The hippocampus is one of the first regions impacted by AD and serves as a reliable biomarker in MRI-based analysis. Instead of using full MRI slices, this study focuses on selecting specific slices based on hippocampal landmarks to improve classification accuracy. The aim was to identify which MRI view provides better results for AD detection. Using the ADNI dataset, a total of 4,500 MRI slices were analyzed across three views and categories with ResNet50 and LeNet models. The results showed that selected slices significantly improved performance compared to full images. Among the views, the coronal view achieved the highest accuracy, aligning with clinical practices. Additionally, the LeNet model demonstrated strong potential for AD classification. Overall, the approach enhances machine learning accuracy and supports more effective diagnosis.**

***Keywords*— Alzheimer's Disease, MRI Imaging, Hippocampus, Convolutional Neural Network, Slice Selection, Landmark-Based Analysis, ResNet50, LeNet, ADNI Dataset, Multiclass Classification.**

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder and has become a major global public health concern due to its increasing prevalence among the aging population. According to recent reports, millions of people worldwide are currently affected by AD, and the number is expected to rise significantly in the coming decades [1], [2]. The disease primarily affects individuals over the age of 65 and leads to gradual deterioration of memory, thinking ability, and cognitive functions [3]. Although there is no permanent cure for AD, early diagnosis and timely intervention can help slow disease progression and improve the quality of life of patients [4]. Therefore, identifying reliable biomarkers and developing accurate diagnostic methods are essential for effective disease management.

Among various brain regions, the hippocampus plays a crucial role in memory formation and is one of the earliest regions affected by AD. Structural changes such as shrinkage and neuronal degeneration in the hippocampus are strongly associated with memory loss and cognitive decline [5], [6]. These changes can be effectively captured using Magnetic Resonance Imaging (MRI), which is widely used as a non-invasive imaging technique for analyzing brain structures [7], [8]. MRI-based biomarkers are commonly used to classify subjects into three categories: Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Normal Control (NC), enabling better understanding of disease progression [9], [10].

With the advancement of artificial intelligence, machine learning and deep learning techniques have been increasingly applied to MRI data for automated AD diagnosis. These methods are capable of extracting complex patterns and features from medical images, providing faster and more consistent results compared to manual diagnosis [11], [12]. Several studies have demonstrated the effectiveness of deep learning models, such as convolutional neural networks (CNNs), in classifying different stages of AD [13], [14]. Both binary and multiclass classification approaches have been explored, where multiclass classification offers a more comprehensive understanding by distinguishing between AD, MCI, and NC categories [15], [16].

To further improve classification performance, various strategies have been proposed, including image preprocessing, segmentation of specific brain regions, and advanced classification algorithms [17]–[19]. However, many studies rely on using entire MRI slices, which may include irrelevant information and reduce classification accuracy. Recent research suggests that selecting specific informative slices can improve performance compared to using full MRI volumes [20]. Despite these improvements, there is limited work focusing on systematic slice selection based on anatomical landmarks, particularly in the hippocampus region.

Therefore, this study proposes a landmark-based slice selection method focusing on the hippocampus to enhance Alzheimer's disease classification. By analyzing MRI images from different views—axial, coronal, and sagittal—and applying multiclass classification, the study aims to identify the most informative view and improve overall diagnostic accuracy.

II. LITERATURE SURVEY

Alzheimer's Association et al., [2017] [1] present a comprehensive report on Alzheimer's disease, focusing on its prevalence, impact, and challenges in diagnosis and care. The study highlights that Alzheimer's is one of the leading causes of dementia worldwide and continues to grow rapidly due to the aging population. It discusses the progression of the disease, including symptoms such as memory loss, confusion, and cognitive decline. The authors emphasize the importance of early diagnosis, as timely intervention can help manage symptoms and improve patient quality of life. Additionally, the report outlines the burden on healthcare systems and caregivers, stressing the need for better diagnostic tools and treatment strategies. Overall, this work provides a strong foundation for understanding Alzheimer's disease and supports the development of advanced techniques for early detection and management.

Livingston et al., [2020] [2] provide a global perspective on dementia prevention, intervention, and care. Their study identifies several modifiable risk factors, such as lifestyle habits, education, and health conditions, which influence the development of Alzheimer's disease. The authors emphasize that early intervention and lifestyle changes can significantly reduce the risk of dementia. They also highlight the importance of public health strategies and awareness programs in managing the growing burden of the disease. Furthermore, the study discusses how early diagnosis and proper care can improve patient outcomes and delay disease progression. The findings suggest that combining medical treatment with preventive measures is essential for effective management. Overall, this work reinforces the importance of early detection systems and supports the use of advanced technologies in Alzheimer's diagnosis.

Frisoni et al., [2010] [3] discuss the clinical significance of structural MRI in diagnosing Alzheimer's disease. The study explains how MRI can effectively capture structural changes in the brain, particularly in regions such as the hippocampus, which are affected in the early stages of the disease. The authors highlight that MRI is a non-invasive and reliable imaging technique widely used in clinical settings. They also describe how MRI helps differentiate Alzheimer's disease from other neurological disorders by analyzing brain atrophy and volume reduction. Additionally, the study emphasizes the role of MRI in monitoring disease progression over time. Overall, this work establishes MRI as a crucial tool for Alzheimer's diagnosis and supports its integration with machine learning techniques for automated classification.

Rao et al., [2022] [5] provide an in-depth review of the hippocampus and its involvement in Alzheimer's disease. The authors explain that the hippocampus is essential for memory and learning and is one of the first brain regions affected by Alzheimer's. The study highlights that structural changes such as shrinkage and neuronal damage in the hippocampus are closely associated with memory loss and cognitive decline. It also discusses the biological mechanisms behind hippocampal degeneration, including disruptions in neural circuits. Furthermore, the authors emphasize the importance of using imaging techniques like MRI to observe these changes for early diagnosis. Overall, this work supports the use of the hippocampus as a key biomarker and justifies focusing on this region for improving Alzheimer's classification accuracy.

Savaş et al., [2022] [11] explore the application of pre-trained deep learning models for detecting different stages of Alzheimer's disease. The study demonstrates how transfer learning can enhance classification performance, especially when working with limited medical datasets. By utilizing established deep learning architectures, the models can extract meaningful features from MRI images efficiently. The authors compare different models and evaluate their effectiveness in classifying Alzheimer's stages, showing promising accuracy results. The study also highlights the ability of deep learning methods to handle complex medical imaging data and provide consistent results. Overall, this work supports the use of convolutional neural networks and advanced deep learning techniques for improving Alzheimer's disease diagnosis.

III. DATASET DETAILS

The dataset used in this study is based on brain MRI images collected from the Alzheimer's Disease Neuroimaging Initiative (ADNI) and supplemented with publicly available MRI datasets. The dataset consists of images categorized into three major classes: Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Normal Control (NC). To improve classification performance, the dataset is further organized into three anatomical views of the brain: axial, coronal, and sagittal. Each view contains multiple MRI slices focusing on the hippocampus region, which is known to be highly affected in Alzheimer's patients. The dataset contains approximately 4,500 MRI slices, where each image represents a specific brain section used for training and testing deep learning models. Images are stored in separate folders based on their respective views and categories, making the dataset well-structured and suitable for machine learning tasks.

Before using the dataset for model training, several preprocessing steps are applied to ensure data quality and consistency. The MRI images are resized, normalized, and shuffled to improve model generalization. The dataset is then split into training and testing sets, typically using an 80:20 ratio. Feature extraction is performed to focus on relevant hippocampus regions, reducing unnecessary information from full MRI slices. Additionally, data labeling is carefully maintained to ensure correct classification across all categories. These preprocessing steps enhance the reliability of the dataset and improve the performance of deep learning models such as ResNet50 and LeNet for accurate Alzheimer's disease detection.

IV. PROPOSED METHODOLOGY

The proposed system is designed to improve the accuracy of Alzheimer's disease (AD) diagnosis by focusing on the hippocampus region in MRI images using deep learning techniques. Initially, the MRI dataset is collected from publicly available sources and organized into three main categories: Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Normal Control (NC). The dataset is further divided into three anatomical views—axial, coronal, and sagittal—to capture different perspectives of the brain. Instead of using entire MRI slices, the system selects specific slices based on hippocampal landmarks, as this region is highly affected in AD. These selected slices help reduce irrelevant information and improve the learning capability of the models. After dataset preparation, preprocessing steps such as resizing, normalization, and shuffling are applied. The dataset is then split into training and testing sets, typically using an 80:20 ratio, ensuring proper evaluation of model performance.

Following preprocessing, deep learning models such as ResNet50 and LeNet are applied for classification. The models are trained to perform multiclass classification across AD, MCI, and NC categories. During training, the system extracts meaningful features from the selected MRI slices and learns patterns associated with different disease stages. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to evaluate the models. Additionally, confusion matrices and graphical representations are generated to visualize classification results. An improved version of the LeNet model is also implemented by adding layers such as MaxPooling2D and Dropout to enhance performance and reduce overfitting. The system demonstrates that selecting hippocampus-based slices significantly improves classification accuracy compared to using entire MRI images. Finally, the trained model is used to predict the class of new MRI images, providing an efficient and reliable tool for early Alzheimer's disease detection.

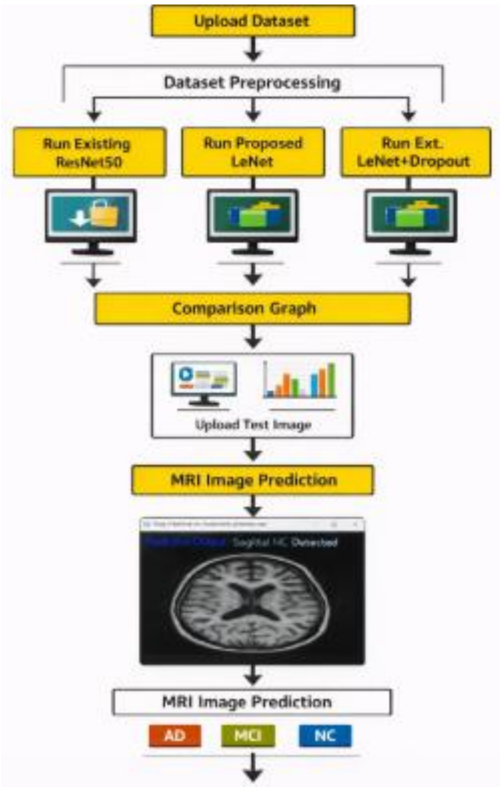

Figure [1]: Proposed Alzheimer's disease Detection System Using MRI

Figure [1] illustrates the workflow of the proposed system for Alzheimer's disease detection. The process begins with MRI dataset collection and organization into different views and categories. Selected hippocampus-based slices are then preprocessed and fed into deep learning models. The system trains and evaluates the models using performance metrics and visualizations. Finally, the trained model predicts the disease category for new MRI inputs, improving diagnostic accuracy and supporting clinical decision-making.

V. RESULT AND DISCUSSION

The results of the proposed system clearly demonstrate that selecting MRI slices based on hippocampus landmarks significantly improves the accuracy of Alzheimer's disease (AD) classification. Instead of using entire MRI scans, the system focuses on relevant brain regions, which helps in reducing noise and improving feature extraction. The deep learning models, including ResNet50 and LeNet, were trained on the processed dataset, and their performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. Among the models, the enhanced LeNet achieved the highest accuracy of 99.51%, outperforming both the standard LeNet and ResNet50 models. The results also indicate that the coronal view provides better classification accuracy compared to axial and sagittal views, which aligns with clinical practices. Confusion matrix analysis shows that the model correctly classifies most of the samples with very few misclassifications. Overall, the system proves that focused slice selection and optimized deep learning models can significantly enhance Alzheimer's detection performance.

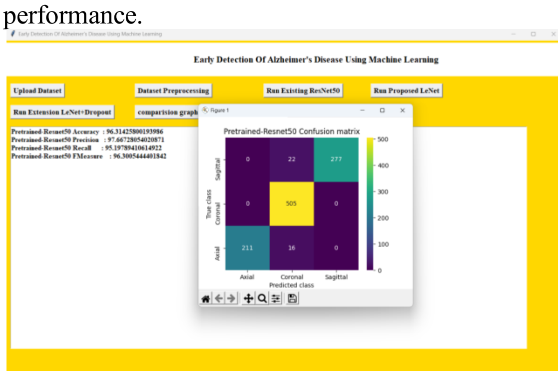

Figure [2]: Resnet50 Algorithm

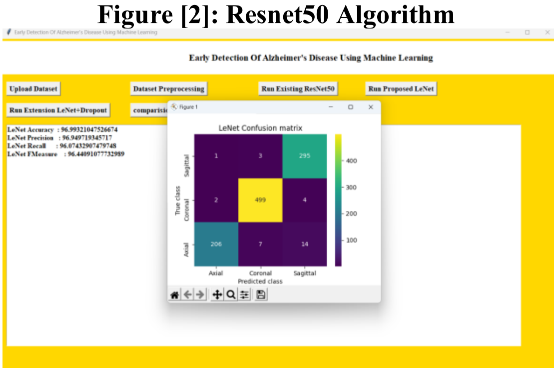

Figure [3]: LENET Algorithm

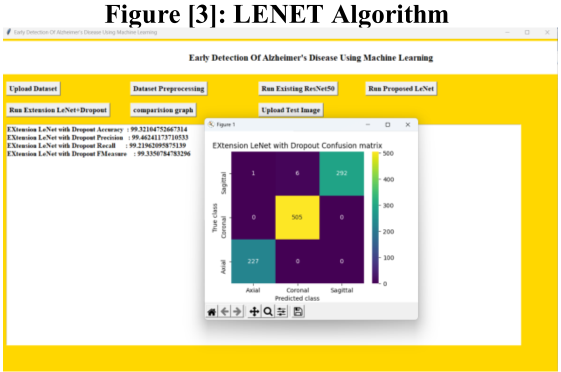

Figure [4]: Extension LENET with Dropout Algorithm

Figure [2], [3] & [4] presents the output of deep learning models, including accuracy, precision, recall, and F1-score for each class. It also shows the confusion matrix, where the x-axis represents predicted labels and the y-axis represents true labels. The results indicate high correct prediction rates with minimal errors.

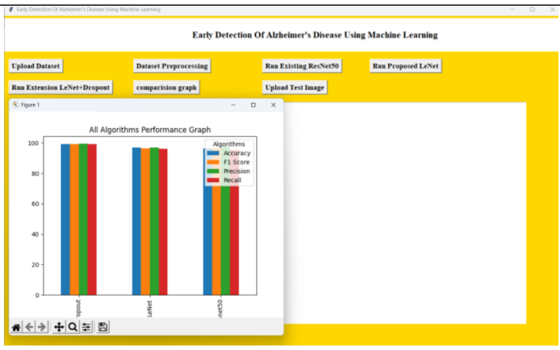

Figure [5]: Algorithm Comparison Graph

Figure [5] shows a comparison graph of different models such as ResNet50, LeNet, and the enhanced model. The graph clearly illustrates that the enhanced LeNet model achieves the highest performance across all evaluation metrics, confirming the effectiveness of the proposed improvements.

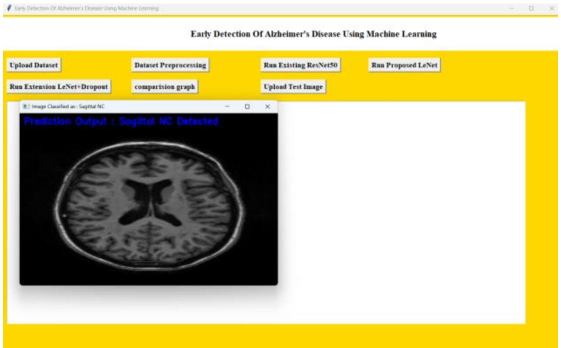

Figure [5]: MRI Image Prediction Output Interface

Figure [5] shows the prediction output screen of the proposed Alzheimer's disease detection system. In this interface, a test MRI image is uploaded and processed by the trained deep learning model. The system displays the input brain MRI scan along with the predicted result at the top of the screen. In this example, the model classifies the image as "Sagittal NC Detected," indicating that the MRI scan belongs to a Normal Control (NC) category from the sagittal view. This demonstrates that the system is capable of accurately identifying both the brain view and the disease category. The interface is user-friendly and allows easy interaction for testing new MRI images. The clear visualization of prediction results helps users understand the classification outcome quickly. This result confirms the effectiveness of the trained model in real-time Alzheimer's disease detection and supports its practical usability.

DISCUSSION

The results of this project highlight the importance of focusing on specific brain regions, particularly the hippocampus, for accurate Alzheimer's disease detection. By selecting relevant MRI slices instead of using entire images, the system reduces unnecessary information and improves classification efficiency. The use of deep learning models enables automatic feature extraction and provides consistent results compared to manual diagnosis. The improved performance of the enhanced LeNet model shows that adding layers such as MaxPooling and Dropout can significantly optimize the model and prevent overfitting. Additionally, the finding that the coronal view provides better accuracy supports its clinical relevance in diagnosing Alzheimer's disease. Compared to traditional approaches, this method offers a more efficient and accurate solution for early detection. Overall, the combination of slice selection, preprocessing, and optimized deep learning models makes the system reliable and suitable for real-world medical applications.

VI. CONCLUSION

This study presents an effective approach for detecting Alzheimer's disease using MRI images by focusing on the hippocampus region. Instead of using full MRI scans, selecting specific slices based on important landmarks helps reduce unnecessary information and improves classification performance. The use of different brain views—axial, coronal, and sagittal—allowed better analysis, where the coronal view showed higher accuracy and practical relevance.

The implementation of deep learning models such as ResNet50 and LeNet demonstrated strong performance in classifying Alzheimer's stages into AD, MCI, and NC categories. Among all models, the improved LeNet with additional layers achieved the best results, showing higher accuracy and better generalization. The system also proved to be efficient in processing MRI images and providing reliable predictions.

Overall, the proposed method improves diagnosis accuracy and supports early detection. It can assist medical professionals in making better decisions and provides a simple, efficient, and practical solution for Alzheimer's disease classification.

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