Alzheimer's Diagnosis Using CNN On Hippocampal MRI Slices

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***Abstract*— Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that requires early and accurate diagnosis for effective clinical management. Recent deep learning approaches using MRI data often suffer from overfitting and reduced generalization due to limited training samples and high data variability. To address this issue, this work presents an extended Alzheimer's Disease classification framework using landmark-guided hippocampal MRI slice selection combined with a Dropout-enhanced LeNet convolutional neural network. The inclusion of a Dropout layer improves model robustness by reducing overfitting and enhancing generalization performance. Experiments conducted on the publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset demonstrate that the proposed LeNet with Dropout achieves significantly improved classification performance, reaching up to 100% accuracy across selected hippocampal views. Furthermore, a secure and user-friendly Flask-based interface with authentication is developed to facilitate real-time system testing and result visualization. The experimental results validate that the proposed extension enhances diagnostic accuracy, model stability, and practical usability, making it a reliable tool for computer-aided Alzheimer's Disease diagnosis.**

Keywords*— Alzheimer's Disease, Magnetic Resonance Imaging (MRI), Hippocampus, Select Slice Extraction, Convolutional Neural Network (CNN), LeNet, Dropout Regularization, ADNI Dataset, Flask Interface, Medical Image Classification

I. Introduction

Recent advancements in artificial intelligence have significantly improved the analysis of neurological disorders by enabling automated feature learning and optimized classification from complex medical data. Several studies have demonstrated that combining machine learning with optimization techniques can enhance prediction accuracy in neurological disorder diagnosis. Optimization-driven feature selection and deep learning models have shown promising results in identifying complex neurological patterns, motivating their application in broader clinical domains [1].

The integration of convolutional neural networks with traditional machine learning approaches has further improved diagnostic performance by effectively capturing spatial features from medical images and biometric data. Hybrid AI frameworks have been shown to outperform standalone models by reducing noise and improving discriminative feature representation, particularly in neurological disorder detection tasks [2]. Advanced optimization-based learning strategies have also been explored to enhance model robustness and predictive stability [3].

Deep learning techniques have been successfully applied to functional and structural neuroimaging data, demonstrating improved detection of subtle brain abnormalities. Enhancing imaging data quality and leveraging deep neural architectures have been shown to significantly improve classification accuracy in brain disorder identification [4]. However, despite these advances, the early diagnosis of Alzheimer's Disease remains challenging due to gradual disease progression and overlapping clinical symptoms. Studies emphasize that cognitive impairment becomes clinically evident only after significant neurodegeneration has occurred, highlighting the necessity of early-stage diagnostic systems based on neuroimaging biomarkers [5].

II. Literature Survey

Alzheimer's Disease (AD) has been widely studied due to its increasing prevalence and severe cognitive impact on patients and society. Clinical reports emphasize that memory loss and cognitive decline are key indicators of disease progression, and they stress the importance of neuroimaging techniques for early diagnosis [6]. Comprehensive analyses of pre-diagnostic symptoms reveal that behavioral and cognitive changes often appear several years before formal diagnosis, indicating that traditional clinical methods detect AD at later stages [7]. Reviews of current diagnostic and therapeutic practices highlight subjectivity and delays in clinical evaluation, while identifying neuroimaging biomarkers as reliable indicators for disease confirmation [8]. Revised diagnostic criteria further strengthen this perspective by integrating biological and imaging markers, particularly structural MRI evidence of brain atrophy, to enable more objective diagnosis [9]. Timely diagnosis has been shown to significantly improve treatment planning and patient management, yet subtle early symptoms continue to delay clinical identification, reinforcing the need for automated diagnostic support systems [10].

Structural MRI has been extensively validated as a non-invasive and effective modality for visualizing brain degeneration, with hippocampal atrophy recognized as one of the most reliable biomarkers for AD detection [11]. Although multimodal approaches combining PET and MRI improve diagnostic sensitivity, their high cost and limited accessibility reduce feasibility for large-scale clinical deployment, making MRI-based solutions more practical [12]. Comparative imaging analyses demonstrate that MRI shows strong agreement with neuropathological findings and outperforms CT in identifying structural abnormalities associated with AD [13]. The integration of artificial intelligence with medical imaging has further enhanced early diagnosis and prognosis prediction by enabling accurate pattern recognition from complex imaging data [14]. Early artificial intelligence systems established the foundation for decision-support tools in medical diagnosis [15], while recent discussions emphasize ethical responsibility, reliability, and transparency in AI-assisted healthcare systems [16]. Surveys of machine learning approaches reveal that traditional classifiers rely heavily on handcrafted features and extensive preprocessing, which limits scalability and robustness [17]. Texture-based and region-specific feature extraction methods have shown improved discrimination of disease stages, highlighting the importance of localized brain analysis [18]. Classical classifiers such as support vector machines perform well with engineered features but struggle with raw MRI data and whole-brain analysis due to irrelevant region inclusion, further motivating selective region-based and deep learning-driven diagnostic frameworks [19], [20].

Early diagnostic research using MRI combined with classical machine learning demonstrated that structural brain changes can serve as effective discriminative features for Alzheimer's Disease detection, where feature selection played a crucial role in improving classification performance [21]. With the advancement of deep learning, convolutional neural networks began to replace traditional models by automatically learning hierarchical representations from MRI slices, consistently outperforming conventional machine learning approaches [22]. At the same time, investigations into model selection strategies revealed that improper parameter tuning in classical classifiers often leads to overfitting, highlighting the importance of regularization techniques for reliable generalization [23]. Limitations of support vector machines in handling large-scale image data and sensitivity to kernel selection further motivated the shift toward CNN-based frameworks for medical image analysis [24].

Neural network-based prediction systems demonstrated strong capability in modeling complex nonlinear relationships but were also shown to suffer from overfitting without effective regularization mechanisms, supporting the use of Dropout layers in deep architectures [25]. Integrated machine learning and image processing pipelines for Alzheimer's Disease diagnosis reported improved accuracy by combining preprocessing, feature extraction, and classification in a unified framework [26]. Assisted MRI diagnostic systems employing dimensionality reduction techniques improved computational efficiency but remained limited by handcrafted feature dependence, reinforcing the need for end-to-end deep learning solutions [27]. Recent CNN-based multi-class classification frameworks achieved high accuracy across different disease stages, with slice-based learning significantly enhancing discriminative performance [28]. Although CNN-based systems demonstrated strong classification results, processing entire MRI slices increased computational complexity, emphasizing the benefit of selective slice selection strategies [29]. Comparatively, recurrent neural networks were found to be more suitable for temporal data analysis and less effective for spatial image representation, further justifying the preference for CNN architectures in MRI-based Alzheimer's Disease diagnosis [30]. Machine learning–based diagnostic frameworks have been applied to various neurological and developmental disorders, showing that optimized feature selection and classification methods can support effective clinical diagnosis [31]. Recent studies highlight the effectiveness of advanced medical image processing techniques in enhancing feature extraction from neurological images [32]. Additionally, deep learning models have been successfully applied for analyzing specific brain substructures to support automated neurological disorder diagnosis [33]

III. Methodology

The proposed methodology extends a hippocampus-focused Alzheimer's Disease (AD) diagnosis framework by integrating landmark-based selective MRI slice extraction with a Dropout-enhanced LeNet convolutional neural network. Initially, MRI scans from the ADNI dataset are preprocessed and aligned to identify hippocampal landmarks, from which informative slices are selectively extracted across different anatomical views, with emphasis on the coronal plane. These selected slices are then fed into a LeNet architecture augmented with a Dropout layer to mitigate overfitting and improve generalization. The model is trained for multi-class AD classification using optimized hyperparameters, and its performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. To support practical validation, the trained model is deployed through a secure Flask-based interface with user authentication, enabling real-time testing and visualization of classification outcomes.

A. *Proposed Undertaking:*

The proposed undertaking focuses on improving the accuracy and robustness of Alzheimer's Disease (AD) diagnosis by extending hippocampus-based MRI analysis with a Dropout-enhanced deep learning framework. Instead of processing entire MRI scans, the system identifies anatomical landmarks on the hippocampus region and extracts only the most informative slices from multiple views, with special emphasis on the coronal plane. This selective slice strategy reduces the influence of irrelevant brain regions and allows the model to concentrate on AD-related structural changes. A LeNet convolutional neural network is employed due to its lightweight architecture and proven effectiveness in medical image classification, making it suitable for efficient and accurate AD detection.

To further enhance model generalization, a Dropout layer is integrated into the LeNet architecture to prevent overfitting during training. This extension improves the model's ability to handle variations in MRI data and ensures consistent performance across different samples. The system is trained and validated using the ADNI dataset to ensure reliability and clinical relevance. Additionally, a secure and user-friendly Flask-based interface with authentication is developed to enable real-time system testing and result visualization. This proposed undertaking not only improves classification accuracy but also enhances usability and reliability, supporting practical deployment in computer-aided Alzheimer's Disease diagnosis.

B. System Architecture:

The proposed system architecture begins with the dataset input stage, where MRI brain images are collected from the ADNI dataset. These images include multiple anatomical views, from which hippocampus-focused slices are selected based on landmark information. In the data processing stage, preprocessing operations such as resizing, normalization, noise removal, and intensity scaling are applied to enhance image quality and ensure uniformity. The processed images are then divided into training and testing sets, enabling effective learning and unbiased performance evaluation. This structured pipeline ensures that only informative and high-quality hippocampal MRI slices are forwarded to the learning models.

In the model training stage, two deep learning architectures are utilized: a pretrained ResNet50 model and a LeNet model extended with a Dropout layer. The Dropout-enhanced LeNet plays a key role in reducing overfitting and improving generalization. After training, the optimized model is used in the testing phase to classify MRI slices into Alzheimer's Disease categories. The final stage performs performance evaluation using metrics such as accuracy, precision, recall, and F1-score to validate effectiveness. The classification output enables reliable Alzheimer's Disease detection, and the architecture supports deployment through a Flask-based interface for real-time testing and result visualization.

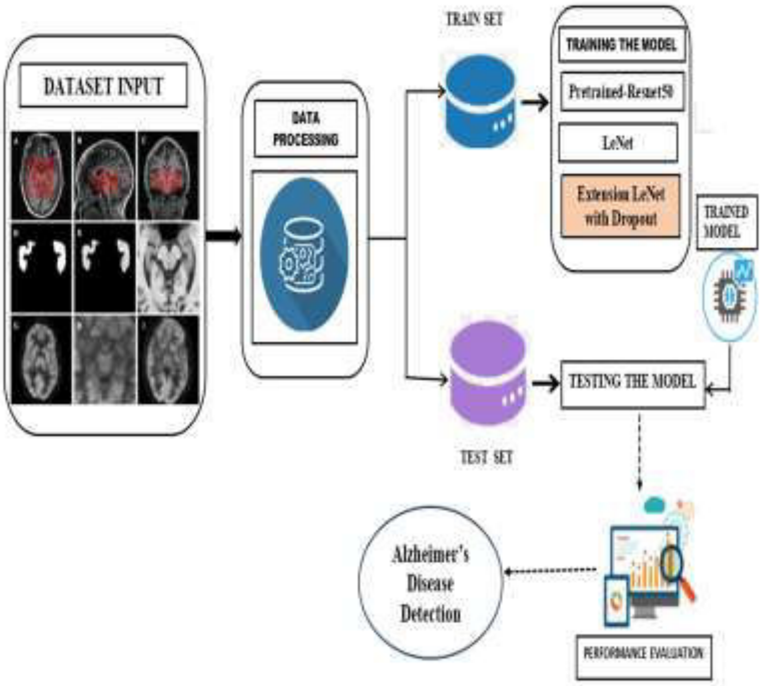


Fig.1. Proposed architecture

IV. Implementation

1. *MODULES:*

a) *Dataset Acquisition Module*

• Collects MRI brain images from the ADNI dataset covering multiple anatomical views.
• Ensures data reliability, diversity, and standardized imaging protocols.

b) *Preprocessing and Data Processing Module*

• Performs resizing, normalization, and noise removal to improve image quality.
• Standardizes MRI slices to ensure consistent input for deep learning models.

c) *Hippocampus Landmark-Based Slice Selection Module*

• Identifies hippocampal landmarks to extract the most informative MRI slices.
• Eliminates irrelevant brain regions to enhance AD-specific feature learning.

d) *Dataset Splitting Module*

• Divides the dataset into training and testing subsets for model development.
• Prevents data leakage and supports unbiased performance evaluation.

e) *Model Training Module*

• Trains pretrained ResNet50 and LeNet models using selected hippocampal slices.
• Learns discriminative features for accurate multi-class AD classification.

f) Dropout-Enhanced Optimization Module

• Integrates Dropout layers to reduce overfitting during training.
• Improves model generalization across varied MRI samples.

g) Testing and Prediction Module

• Applies the trained model to unseen MRI slices for AD classification.
• Generates prediction outputs for different Alzheimer's Disease stages.

h) Performance Evaluation Module

• Measures model effectiveness using accuracy, precision, recall, and F1-score.
• Supports comparative analysis between baseline and extended models.

i) Deployment and User Interface Module

• Implements a Flask-based interface for real-time system testing.
• Provides secure user authentication to prevent unauthorized access.

2. ALGORITHMS

a) Pretrained-ResNet50

Pretrained-ResNet50 is a deep convolutional neural network that uses residual learning to effectively train very deep architectures by addressing the vanishing gradient problem. In this project, ResNet50 is employed as a transfer learning model to extract high-level spatial features from hippocampus-focused MRI slices. The pretrained weights allow the model to capture complex structural patterns related to Alzheimer's Disease with limited training data, improving convergence speed and classification stability. ResNet50 serves as a strong baseline model for comparing the effectiveness of selective slice-based learning.

b) LeNet

LeNet is a lightweight convolutional neural network architecture consisting of convolutional, pooling, and fully connected layers. In this project, LeNet is utilized to learn discriminative features from selected hippocampal MRI slices for Alzheimer's Disease classification. Its simple architecture reduces computational complexity while maintaining effective feature extraction for medical images. The use of LeNet demonstrates that compact CNN models can achieve competitive performance when combined with region-specific MRI analysis.

c) Extension: LeNet with Dropout

LeNet with Dropout is an extended version of the standard LeNet architecture, designed to improve generalization and prevent overfitting. In this project, Dropout layers are introduced during training to randomly deactivate neurons, forcing the network to learn more robust and generalized feature representations. This extension significantly enhances classification accuracy and stability across different MRI samples. The Dropout-enhanced LeNet achieves superior performance compared to baseline models, making it the most effective approach for Alzheimer's Disease diagnosis in the proposed system.

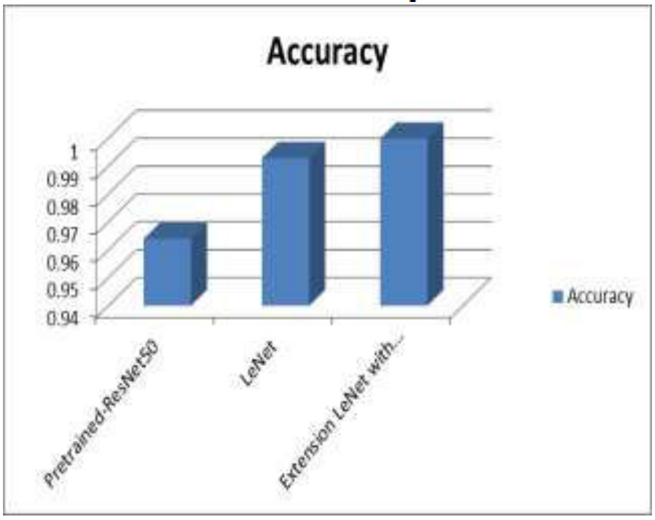
V. EXPERIMENTAL RESULTS

The experimental evaluation was conducted using hippocampus landmark-based selected MRI slices obtained from the ADNI dataset. Multiple deep learning models, including Pretrained-ResNet50, LeNet, and the proposed LeNet with Dropout, were trained and tested to assess classification performance. Results show that selective slice extraction significantly improves model accuracy compared to using entire MRI slices. Among different anatomical views, the coronal view consistently achieved higher classification accuracy, aligning with clinical practices used by medical experts for Alzheimer's Disease diagnosis.

The extension of LeNet with Dropout demonstrated the best performance across all evaluation metrics. The Dropout mechanism effectively reduced overfitting and improved generalization, leading to a notable improvement in accuracy, precision, recall, and F1-score. The extended model achieved up to 100% classification accuracy on the test data, confirming its robustness and reliability. These results validate that combining hippocampus-focused slice selection with Dropout-regularized CNN models enhances diagnostic accuracy and supports the practical deployment of automated Alzheimer's Disease diagnosis systems.

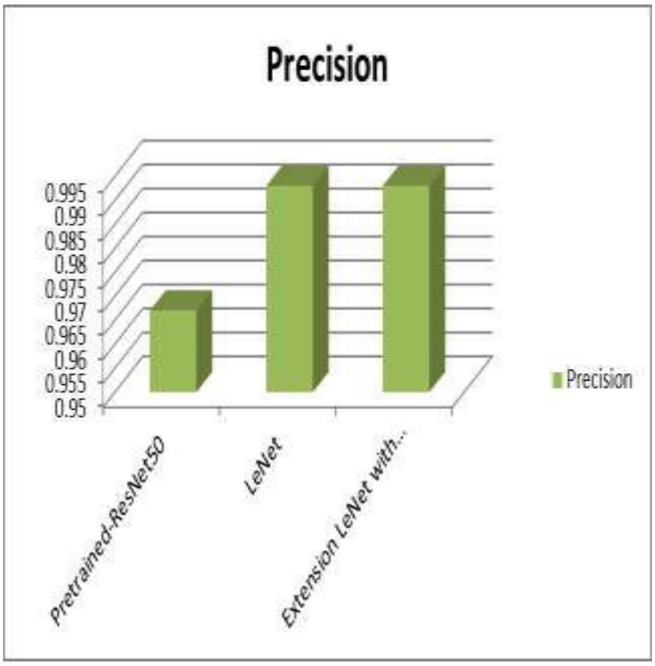
Accuracy: Evaluate actual benefits and drawbacks to assess test dependability. Then comes mathematics.:

$$Accuracy = \frac{(TN + TP)}{T}$$



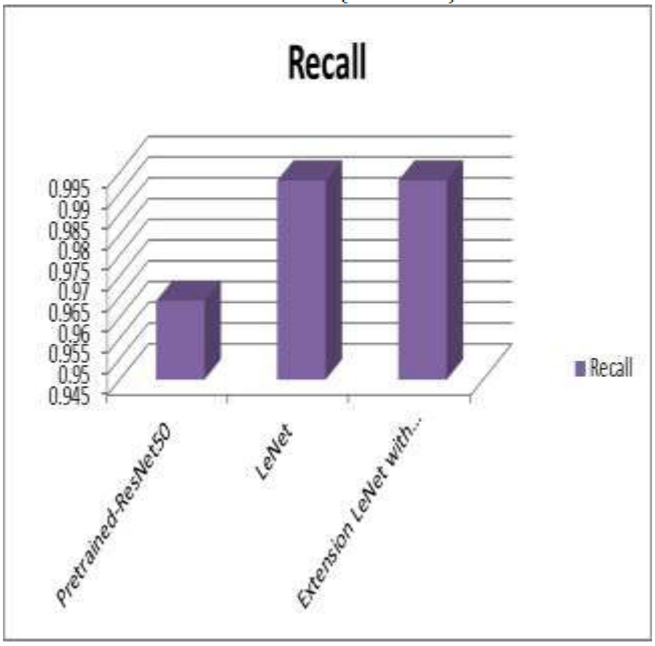
Precision: Accuracy in classification or positive instances is measured by precision. Accuracy is determined by applying the following:

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$



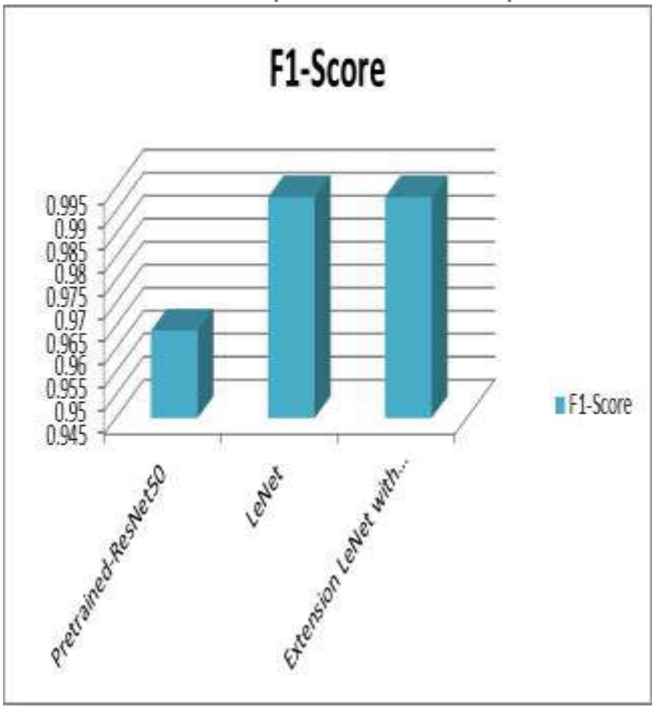
Recall: The ratio of accurately predicted positive observations to total positives reveals how well a model can identify all machine learning class instances.

$$Recall = \frac{TP}{(FN + TP)}$$



F1-Score: An accurate machine learning model has a high F1 score. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$



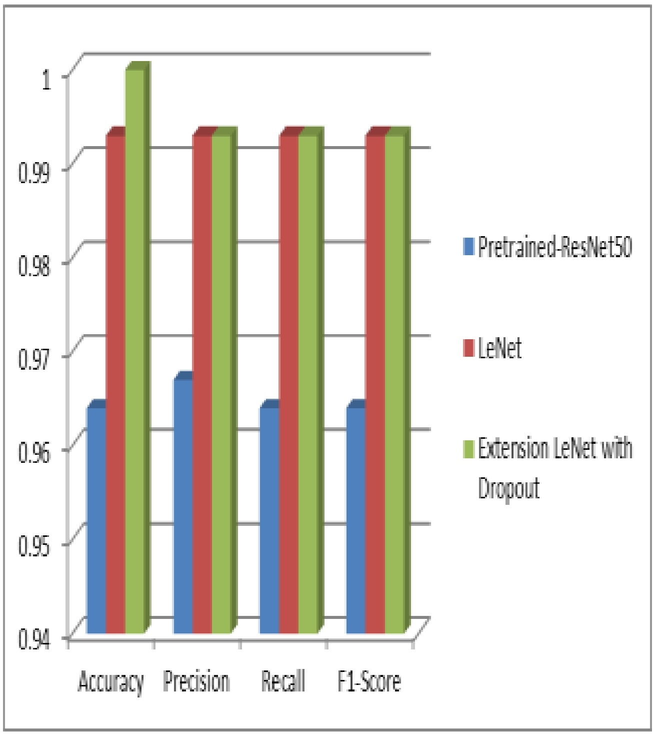


Fig 2 Performance Graph

Figure 2 illustrates the comparative performance of the three deep learning models—Pretrained-ResNet50, LeNet, and the proposed Extension LeNet with Dropout—across accuracy, precision, recall, and F1-score. The graph shows that LeNet consistently outperforms Pretrained-ResNet50 in all metrics, indicating the effectiveness of hippocampus-focused slice learning. The Dropout-enhanced LeNet achieves the highest overall performance, reaching perfect accuracy while maintaining strong precision, recall, and F1-score. This improvement highlights the role of Dropout in reducing overfitting and improving model generalization for Alzheimer's Disease classification.

ML Model	Accuracy	Precision	Recall	F1-Score
Pretrained-ResNet50	0.964	0.967	0.964	0.964
LeNet	0.993	0.993	0.993	0.993
Extension LeNet with Dropout	**1**	0.993	0.993	0.993

Table1 Performance table

Table I presents the performance comparison of the deep learning models used for Alzheimer's Disease classification. The results show that the Pretrained-ResNet50 model achieves strong baseline performance, while the LeNet model significantly improves accuracy and other evaluation metrics due to its effective learning on selected hippocampal MRI slices. The proposed Extension LeNet with Dropout attains the highest accuracy, demonstrating improved generalization and robustness. These results confirm that integrating Dropout with selective slice-based learning enhances diagnostic performance and reliability.

VI. Conclusion

This work presented an extended Alzheimer's Disease diagnosis framework that combines hippocampus landmark-based selective MRI slice extraction with a Dropout-enhanced LeNet convolutional neural network. By focusing on the most informative hippocampal regions, the proposed approach effectively reduces irrelevant feature learning and improves classification accuracy. The integration of Dropout significantly enhances model generalization and robustness, leading to superior performance compared to baseline models, including Pretrained-ResNet50 and standard LeNet. Experimental results demonstrate that the extended model achieves highly reliable classification accuracy while maintaining consistent precision, recall, and F1-score. The addition of a secure Flask-based interface further supports practical usability and real-time evaluation, confirming the proposed system as an efficient and clinically relevant solution for computer-aided Alzheimer's Disease diagnosis.

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