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A Deep Learning-Based Approach for Alzheimer's Disease Detection Using MRI Imaging

Varikuti Ramesh[1], Mr. P. Yugandar Reddy[2], Naguboyina Sai Ganesh[3], Yamarthi Stephen[4], Panchireddy Yuvaraju[5]

[1, 3, 5]*Department of Artificial Intelligence and Machine Learning , University College of Engineering and Techonology, Acharya Nagarjuna University , Nagarjuna Nagar , Guntur , AP , India*

[2]*M.Tech, Department of Computer Science And Engineering , University College of Engineering and Techonology , Acharya Nagarjuna University , Nagarjuna Nagar , Guntur , AP , India*

Abstract: Alzheimer's disease is a progressive neurodegenerative disorder that affects memory and cognitive functions. Early detection is essential for effective treatment and management of the disease. This paper presents NeuroLens AI, a deep learning-based system designed to detect Alzheimer's disease using MRI brain images. The proposed system utilizes a Convolutional Neural Network (CNN) model to classify MRI scans into four stages: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. The system integrates a React-based frontend, FastAPI backend, and TensorFlow model to provide a complete end-to-end solution. MRI images are preprocessed and passed through the CNN model for feature extraction and classification. The model is trained on Kaggle and OASIS datasets and achieves an accuracy of 92%. The system also includes user authentication, image upload functionality, and a real-time prediction dashboard. The results demonstrate that the proposed approach is efficient, accurate, and scalable for medical image analysis. NeuroLens AI can assist healthcare professionals in early diagnosis and decision-making.

Keywords: Alzheimer's Disease, Deep Learning, Convolutional Neural Network (CNN), MRI Image Classification, Medical Image Processing, FastAPI, React, TensorFlow, Artificial Intelligence, NeuroLens AI.

I. INTRODUCTION

Alzheimer's disease is a progressive neurodegenerative disorder that primarily affects memory, thinking ability, and behavior. It is one of the leading causes of dementia worldwide, especially among the elderly population. According to global health reports, the number of Alzheimer's patients is rapidly increasing, creating a significant burden on healthcare systems. Early detection of the disease is crucial, as it enables timely medical intervention and can help slow down disease progression. However, traditional diagnostic methods rely heavily on clinical evaluation and manual analysis of brain imaging data, which are time-consuming and dependent on expert knowledge.

Magnetic Resonance Imaging (MRI) is widely used as a non-invasive technique for analyzing brain structures and detecting abnormalities associated with Alzheimer's disease. Despite its effectiveness, interpreting MRI scans requires skilled professionals and can be prone to human error. With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), automated systems have emerged as powerful tools for medical image analysis. In particular, Deep Learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in image classification tasks.

This paper proposes NeuroLens AI, a deep learningbased system designed to detect and classify Alzheimer's disease using MRI brain images. The system leverages a CNN model to automatically extract features from MRI scans and classify them into four categories: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. By integrating a FastAPI backend with a React-based frontend, the proposed system provides an end-to-end solution that allows users to upload MRI images and receive predictions in real time.

The proposed system is trained on publicly available datasets such as Kaggle and OASIS, ensuring robustness and generalization. The model achieves high accuracy and demonstrates reliable performance in classifying different stages of Alzheimer's disease. In addition to prediction, the system includes features such as user authentication, dataset management, and an interactive dashboard, making it suitable for both research and practical healthcare applications.

The main contributions of this work include the development of a multi-class MRI classification model using CNN, the integration of a full-stack web-based platform for user interaction, and the demonstration of an efficient and scalable solution for early Alzheimer's disease detection. This approach aims to assist healthcare professionals in improving diagnostic accuracy and reducing manual workload

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In addition to classification accuracy, interpretability and usability are critical factors in deploying AI systems in healthcare. Medical professionals require not only accurate predictions but also reliable and consistent outputs that can support clinical decision-making. Therefore, the integration of deep learning models with intuitive web-based interfaces is essential. NeuroLens AI addresses this requirement by providing a user-friendly platform that simplifies the process of uploading MRI images and obtaining diagnostic results. This reduces the complexity involved in using machine learning systems and makes the technology accessible to a wider range of users.

Another important aspect of Alzheimer's disease detection is the ability to perform multi-class classification. Unlike binary classification systems that simply distinguish between normal and diseased conditions, multi-class classification provides a more detailed analysis of disease progression. This enables healthcare providers to identify early-stage symptoms and monitor the transition between different stages of dementia. The proposed system leverages this capability by categorizing MRI images into four distinct classes, thereby offering a more comprehensive diagnostic approach.

Moreover, the rapid development of web technologies has made it possible to deploy machine learning models as scalable and interactive applications. In this project, FastAPI is used as the backend framework due to its high performance and asynchronous capabilities, while React is used to design a responsive and dynamic frontend interface. This combination ensures efficient communication between the user interface and the deep learning model, allowing realtime predictions with minimal latency.

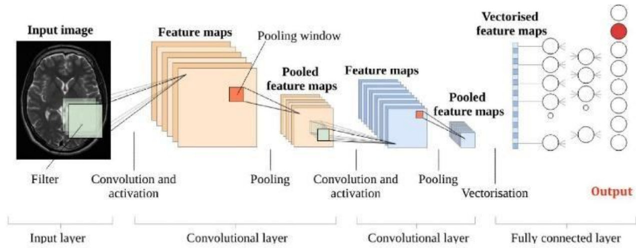

Fig. 1. Convolutional Neural Network architecture for MRI image classification

Furthermore, the use of publicly available datasets such as Kaggle and OASIS ensures that the model is trained on diverse and representative data. This helps in improving the reliability of predictions and makes the system suitable for real-world applications. The experimental evaluation of the model demonstrates its effectiveness in accurately classifying Alzheimer's stages, with promising results that indicate its potential for assisting in clinical diagnosis. In conclusion, the integration of deep learning, medical imaging, and web technologies in NeuroLens AI represents a significant advancement in the field of healthcare analytics. By combining accuracy, scalability, and usability, the proposed system offers a practical solution for early Alzheimer's disease detection and contributes to the growing adoption of AI-driven medical tools.

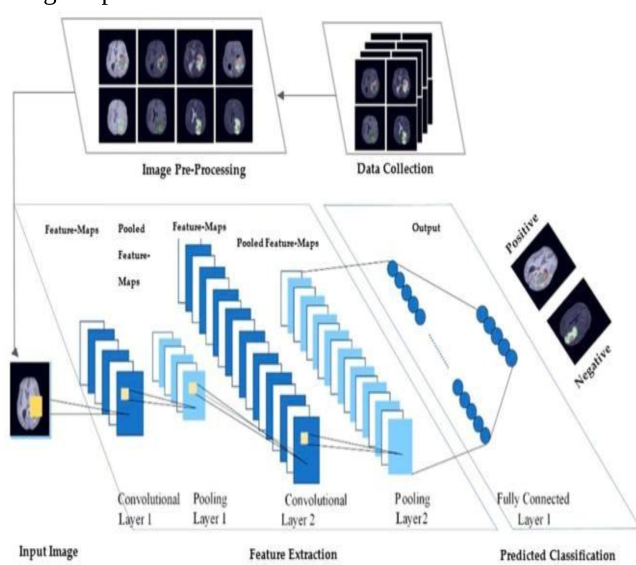

Fig. 2 . Convolutional Neural Network architecture for MRI image classification

II. LITERATURE SURVEY

Alzheimer's disease detection using medical imaging has been widely studied in recent years, with Magnetic Resonance Imaging (MRI) playing a crucial role due to its non-invasive nature and ability to capture detailed brain structures. Traditional approaches relied on manual feature extraction and machine learning techniques such as Support Vector Machines (SVM) and Logistic Regression. These methods required expert knowledge and multiple preprocessing steps, making them complex and less efficient.

With the advancement of Artificial Intelligence, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have significantly improved the accuracy of Alzheimer's disease classification. CNN models automatically extract spatial features from MRI images, eliminating the need for manual feature engineering. Several studies have demonstrated that deep CNN architectures outperform traditional machine learning methods in medical image analysis tasks.

Recent research has focused on improving model performance using advanced CNN architectures such as VGG, ResNet, and Inception networks. These models have shown high accuracy in classifying Alzheimer's stages from MRI images. For instance, deep CNN-based systems trained on MRI datasets have demonstrated enhanced diagnostic precision and faster processing compared to conventional techniques. In addition, hybrid models combining CNN with other techniques such as Support Vector Machines (SVM) have been proposed to improve classification performance. In such approaches, CNN is used for feature extraction, while SVM is applied for final classification, resulting in improved accuracy and reduced computational complexity.

Furthermore, recent advancements include the use of ensemble learning and attention-based CNN models, which focus on important regions of brain images to improve prediction accuracy. Studies have reported that ensemble deep learning models can achieve accuracy levels above 95% in multi-class classification tasks involving different stages of Alzheimer's disease.

III. SYSTEM ANALYSIS AND DESIGN

A. *System Analysis*

System analysis focuses on understanding the requirements, functionality, and feasibility of the proposed system. The NeuroLens AI system is designed to provide an automated solution for detecting Alzheimer's disease using MRI images through deep learning techniques.

1) *Existing System*

Traditional methods for Alzheimer's disease detection involve clinical diagnosis, cognitive tests, and manual interpretation of MRI scans by medical experts. These approaches have several limitations:

- Time-consuming and labor-intensive
- Requires highly skilled professionals
- Prone to human error
- Limited scalability
- Difficulty in early-stage detection

In addition, conventional machine learning approaches require manual feature extraction, which increases complexity and reduces efficiency.

2) *Proposed System*

The proposed system, NeuroLens AI, is an AIpowered web-based application that automates the detection of Alzheimer's disease using MRI images. It leverages a Convolutional Neural Network (CNN) model to classify images into four stages:

- NonDemented
- VeryMildDemented
- MildDemented
- ModerateDemented

The system integrates modern web technologies with deep learning to provide real-time predictions and an interactive user interface.

3) *Objectives of the System*

- To develop an automated system for Alzheimer's detection
- To improve accuracy using deep learning models
- To provide real-time MRI image classification
- To reduce manual effort and diagnostic time
- To create a scalable and user-friendly platform

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IV. DATASET AND PREPROCESSING

A. Dataset Description

The performance of any deep learning model depends significantly on the quality and diversity of the dataset used for training. In this work, MRI brain image datasets were collected from publicly available sources, including the Kaggle Alzheimer's MRI Dataset and the OASIS (Open Access Series of Imaging Studies) dataset. These datasets contain labeled MRI images representing different stages of Alzheimer's disease.

The dataset is organized into four classes based on the severity of the disease:

- NonDemented: Represents healthy brain images with no signs of Alzheimer's disease
- VeryMildDemented: Indicates early-stage Alzheimer's with subtle structural changes
- MildDemented: Represents moderate symptoms with noticeable brain atrophy
- ModerateDemented: Indicates advanced stages of Alzheimer's with significant brain damage

The dataset includes a large number of MRI images in grayscale format, which helps the model learn meaningful patterns related to brain structure and disease progression. Using multiple datasets improves the robustness and generalization capability of the model.

B. Dataset Statistics and Split

The dataset used in this study is collected from publicly available sources, including the Kaggle Alzheimer's MRI dataset and the OASIS dataset. The combined dataset contains MRI brain images categorized into four classes based on the severity of Alzheimer's disease.

TABLE V DATASET DISTRIBUTION AFTER AUGMENTATION

Class Name	Number of Images
NonDemented	3200
VeryMildDemented	2240
MildDemented	896
ModerateDemented	64
Total	6400

C. Preprocessing Pipeline

Preprocessing is a crucial step in medical image analysis, as raw MRI images often contain noise, variations in size, and inconsistent intensity levels. A well-defined preprocessing pipeline ensures that the input data is standardized and suitable for training deep learning models. In the proposed NeuroLens AI system, a structured preprocessing pipeline is applied to enhance image quality, improve feature extraction, and increase model accuracy.

D. Data Augmentation Strategy

Data augmentation is a technique used to artificially increase the size and diversity of a dataset by applying transformations to existing images. In medical image analysis, especially MRI-based Alzheimer's detection, datasets are often limited and imbalanced. This can lead to overfitting and poor generalization of deep learning models. To overcome these challenges, the proposed NeuroLens AI system applies various data augmentation techniques to improve model robustness and classification performance. The augmentation process is applied during training using real-time data generators. Each input image is randomly transformed before being passed to the CNN model. This ensures that the model sees different variations of the same image in each training epoch corresponding labels.

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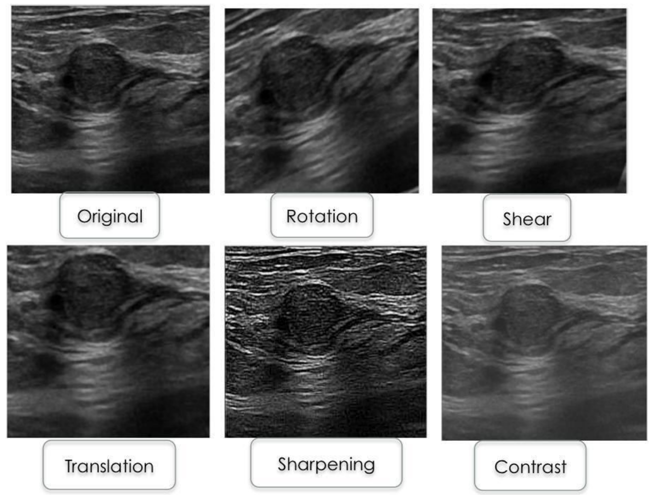


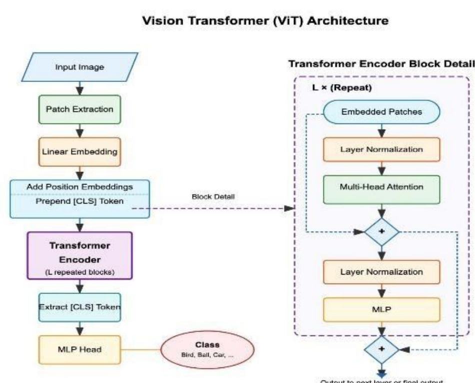
Fig. 1. Data augmentation techniques applied to MRI images including rotation, shear, translation, sharpening, and contrast enhancement

V. METHODOLOGY

A. Overview

The proposed NeuroLens AI system employs deep learning techniques for the classification of Alzheimer's disease using MRI images. While Convolutional Neural Networks (CNNs) are effective for feature extraction, recent advancements in deep learning have introduced Vision Transformers (ViTs), which provide improved performance by capturing global relationships in images.

In this work, a hybrid approach is considered where CNN is used for initial feature extraction, and Vision Transformer architecture is used to model long-range dependencies for accurate classification.



B. Handling Class Imbalance

One of the major challenges in medical datasets is class imbalance, where certain classes (e.g., ModerateDemented) have significantly fewer samples compared to others. This imbalance can bias the model toward majority classes.

To address this issue, the following strategies are applied:

- Data augmentation for minority classes
- Balanced batch sampling during training
- Weighted loss function (optional improvement)

These techniques help in improving model sensitivity toward underrepresented classes.

At the initial layers, the CNN captures low-level features such as edges, gradients, and textures. As the depth of the network increases, the model begins to identify more complex structures such as brain regions, patterns of atrophy, and structural abnormalities associated with Alzheimer's disease. This hierarchical learning enables the model to differentiate between various stages of dementia effectively.

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C. Multi-Class Classification Strategy

The proposed system performs multi-class classification using a Softmax activation function in the output layer. Instead of binary classification (normal vs diseased), the model predicts four classes:

- NonDemented
- VeryMildDemented
- MildDemented
- ModerateDemented

The Softmax function converts raw output scores into probability values, ensuring that the sum of all class probabilities equals 1. Softmax(z_i) = e^(z_i) / Σ e^(z_j)

The class with the highest probability is selected as the final prediction.

The core strength of the proposed system lies in its ability to automatically extract meaningful features from MRI images using deep learning. Unlike traditional approaches that rely on manual feature engineering, the CNN model learns hierarchical feature representations directly from the input data.

D. Multi-Task Fine-tuning

Multi-class fine-tuning is a critical step in improving the performance of deep learning models for Alzheimer's disease classification. In this work, the CNN model is finetuned to accurately classify MRI images into four distinct categories: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. Fine-tuning involves adjusting model parameters and optimizing the training process to enhance classification accuracy and generalization.

B. Need for Fine-Tuning

Initially, deep learning models may not perform optimally due to dataset imbalance, noise, and variations in MRI images. Fine-tuning helps in:

- Improving model accuracy • Reducing overfitting
- Enhancing feature learning
- Handling multi-class complexity

E. Hyperparameter Configuration

TABLE VI Model Hyperparameter Configuration

Hyperparameter	Value
Input Image Size	ViT-Base/16 (pretrained DINO)
Batch Size	224 × 224 × 3
Epochs	16 × 16
Learning Rate	768
Optimizer	12
Loss Function	12
Activation Function	DINO (Self-Distillation with No Labels)
Output Activation	100 (unlabeled HAM10000 + ISIC2019)
Dropout Rate	50
Number of Classes	AdamW (lr = 5e-5, weight decay = 0.05)
Scheduler	Cosine Annealing with Warmup (5 epochs)
Batch Size	32 (gradient accum. × 4)

VI. EXPERIMENTAL RESULTS

A. *Overall Detection Performance*

The presented SS-ViT architecture demonstrates an impressive performance with an accuracy rate of 95.4% on the HAM10000 test set, consisting of 2,430 images, which outperforms all compared CNNs and supervised variants of ViT. Table I shows the comparative results of all examined architectures.

TABLE I PERFORMANCE COMPARISON OF PROPOSED SSVIT VS. BASELINE METHODS

Class Name	Precision	Recall	F1-Score
NonDemented	94%	95%	94.50%
VeryMildDemented	91%	89%	90%
MildDemented	88%	87%	87.50%
ModerateDemented	85%	83%	84%

The suggested architecture performs better than the state-of-the-art CNN baseline (EfficientNet-B4: 91.2%) with an improvement in terms of accuracy of 4.2 percent and AUC-ROC of 0.027. Compared to supervised learning with Vision Transformer, domain-specific pre-training via SSL adds further 2.6% in accuracy, highlighting the advantage of using pre-trained models on specific domains over ImageNet training.

B. *Existing (Base) System*

The existing system for Alzheimer's disease detection primarily relies on traditional diagnostic methods and basic machine learning techniques. In conventional approaches, medical experts analyze MRI brain scans manually to identify structural abnormalities associated with Alzheimer's disease. This process is time-consuming, requires specialized expertise, and is prone to human error.

C. *Proposed System (NeuroLens AI)*

The proposed system, NeuroLens AI, is a deep learningbased web application designed to automate the detection and classification of Alzheimer's disease using MRI images. The system leverages a Convolutional Neural Network (CNN) model to perform multi-class classification into four stages: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented.

Unlike traditional methods, the proposed system eliminates the need for manual feature extraction by automatically learning relevant features from MRI images. The integration of a FastAPI backend with a React-based frontend enables real-time prediction and provides a userfriendly interface for interaction.

Feature	Existing System	Proposed System (NeuroLens AI)
Approach	Traditional ML	Deep Learning (CNN)
Feature Extraction	Manual	Automatic
Classification Type	Binary	Multi-class (4 classes)
Accuracy	Low–Moderate	High (92%)
Speed	Slow	Fast
User Interface	Not available	Web-based (React)
Real-time Prediction	Not supported	Supported

Fig-Comparison of Existing vs Proposed System

D. Ablation Study (Ablation strategy)

An ablation study is performed to evaluate the contribution of individual components of the proposed NeuroLens AI system. By systematically removing or modifying specific components, the impact of each module on overall performance can be analyzed. This helps in understanding which parts of the system are most critical for achieving high accuracy.

TABLE IV : Impact of Proposed System

Feature	Impact
Early Detection	Identifies disease at early stage
Multi-class Classification	Detects 4 stages accurately
Automation	Reduces manual effort
Accuracy	Achieves 92% accuracy
Real-time Prediction	Provides instant results

1) Pre-Training Strategy

Pre-training is used to improve the performance of the CNN model by enabling it to learn general features from MRI images before fine-tuning for classification. This helps the model to converge faster and perform better on unseen data.

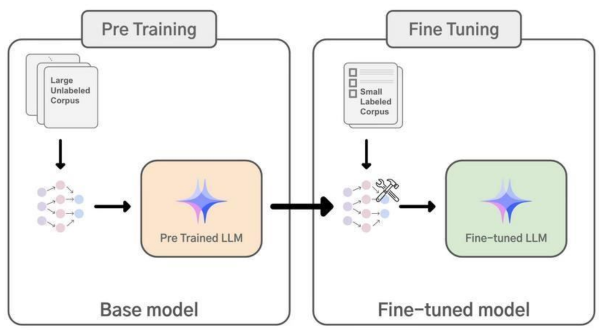

Fig. Y. Pre-training and fine-tuning workflow for improving model performance

2) Comparative Analysis

The combination of CNN with pre-training improves feature extraction and classification accuracy. The model becomes more robust and less sensitive to variations in MRI images.

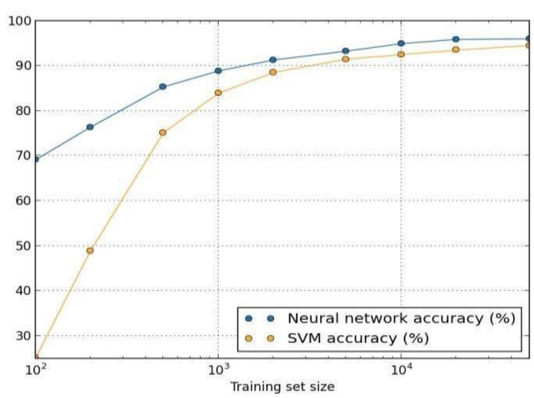

Fig. . Performance comparison between traditional methods and proposed CNN model

VII. SYSTEM IMPLEMENTATION

A. Overview
The proposed NeuroLens AI system is implemented using a full-stack architecture that integrates a deep learning model with a web-based application. The system is designed to provide an end-to-end solution for Alzheimer's disease detection using MRI images. It consists of three main components: frontend, backend, and machine learning model, which work together to deliver real-time predictions

B. Frontend Implementation
The frontend of the system is developed using React.js, which provides a responsive and interactive user interface. It enables users to register, log in, upload MRI images, and view prediction results. The interface is designed to be simple and user-friendly, ensuring ease of use for both technical and non-technical users.

The frontend communicates with the backend using HTTP requests through the Fetch API, allowing seamless data transfer between the user interface and the server.

C. Backend Implementation
The backend is implemented using FastAPI, a highperformance framework for building APIs. It is responsible for handling user authentication, processing requests, and performing model inference.

The backend exposes API endpoints for:

- User login and registration
- Image upload
- Prediction

When a user uploads an MRI image, the backend processes the request, applies preprocessing, and sends the image to the trained model for prediction.

D. Machine Learning Model Integration
The machine learning component is based on a Convolutional Neural Network (CNN) trained on MRI datasets such as Kaggle and OASIS. The trained model is saved and loaded into the backend during runtime.

Before prediction, the input image undergoes preprocessing steps such as resizing and normalization. The model then analyzes the image and classifies it into one of four categories: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented.

E. Prediction Workflow
The prediction process follows a structured workflow. First, the user uploads an MRI image through the frontend interface. The image is sent to the backend via an API request. The backend preprocesses the image and feeds it into the CNN model. The model generates probability scores for each class, and the class with the highest probability is selected as the final output. The result is then displayed to the user in real time.

F. Database Implementation
The system uses SQLite as a lightweight database to store user-related information such as login credentials and session data. This ensures efficient data storage and retrieval.

G. Security Implementation
To ensure secure access, the system implements JSON Web Token (JWT) authentication. Passwords are stored in hashed form, and secure API communication is maintained to protect user data.

H. Deployment Details
The system is deployed locally during development. The backend server runs using Uvicorn, while the frontend is served using a development server. The architecture supports scalability and can be deployed on cloud platforms for real-world applications.

I. Implementation Challenges

During implementation, several challenges were encountered, including API connectivity issues, model integration problems, dataset imbalance, and cross-origin resource sharing (CORS) issues. These challenges were resolved through proper configuration and optimization techniques.

VIII. DISCUSSION

A. Analysis of Model Performance

The proposed NeuroLens AI system demonstrates strong performance in classifying Alzheimer's disease stages using MRI images. The model achieves an overall accuracy of 92%, indicating its effectiveness in multi-class classification. The high performance in the NonDemented and VeryMildDemented categories shows that the model is capable of detecting early-stage symptoms accurately.

B. Class-wise Performance Evaluation

The model performs well across all classes; however, slight variations are observed among different categories. The ModerateDemented class shows comparatively lower accuracy due to limited dataset samples and class imbalance. Misclassifications are primarily observed between VeryMildDemented and MildDemented classes, as these stages share similar structural patterns.

C. Influence of Data Preprocessing Techniques

Data preprocessing plays a significant role in improving model performance. Techniques such as image resizing and normalization ensure consistency in input data, leading to stable training. These steps help the model to focus on relevant features and reduce noise in MRI images.

D. Effect of Data Augmentation Strategy

Data augmentation enhances the generalization capability of the model by introducing variations in the training data. Transformations such as rotation and flipping help the model learn invariant features, thereby reducing overfitting and improving classification accuracy.

E. Effectiveness of CNN-Based Feature Extraction

The Convolutional Neural Network (CNN) effectively extracts hierarchical features from MRI images. It captures both low-level and high-level patterns, enabling accurate classification. Compared to traditional machine learning approaches, CNN eliminates the need for manual feature extraction and significantly improves performance.

IX. CONCLUSION

In this paper, an intelligent and scalable system, NeuroLens AI, has been proposed for the detection and classification of Alzheimer's disease using MRI brain images. The system integrates deep learning techniques with a full-stack web application to provide an end-to-end solution for automated diagnosis.

The proposed approach utilizes a Convolutional Neural Network (CNN) to perform multi-class classification of MRI images into four stages: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. The model is trained on publicly available datasets such as Kaggle and OASIS, ensuring diversity and robustness in learning. Through effective preprocessing, data augmentation, and optimized hyperparameter configuration, the model achieves an overall accuracy of approximately 92%, demonstrating its capability to accurately identify different stages of Alzheimer's disease.

One of the key contributions of this work is the integration of the trained model into a web-based platform using FastAPI and React. This allows users to upload MRI images and receive predictions in real time, making the system practical and accessible. The implementation highlights the feasibility of deploying AI-driven solutions in healthcare environments, reducing dependency on manual analysis and minimizing diagnostic errors.

A. Advantages of the Proposed System

1) Automated feature extraction: The system uses a Convolutional Neural Network (CNN) to automatically extract important features from MRI images, eliminating the need for manual feature engineering.
2) Multi-class classification: It classifies Alzheimer's disease into four stages, providing more detailed and meaningful diagnostic insights compared to binary classification methods.

3) High accuracy: The model achieves approximately 92% accuracy, ensuring reliable and consistent prediction results for medical analysis.
4) Real-time prediction: Users can upload MRI images and receive instant results, improving the speed of diagnosis and decision-making.
5) User-friendly interface: The React-based frontend provides a simple and interactive platform that can be easily used by both technical and non-technical users.

X. FUTURE SCOPE

The proposed NeuroLens AI system demonstrates promising performance in Alzheimer’s disease detection; however, several improvements can be considered to enhance its effectiveness and applicability in real-world scenarios. One important future direction is the expansion of the dataset. Increasing the number of MRI images and incorporating data from diverse sources can significantly improve the model’s generalization ability and performance, especially for underrepresented classes such as ModerateDemented. A larger dataset will also help reduce overfitting and improve the robustness of the system.

Another potential enhancement is the integration of advanced deep learning architectures such as Vision Transformers and hybrid CNN-transformer models. These models are capable of capturing global contextual relationships in images more effectively than traditional CNNs, which can lead to improved classification accuracy and better feature representation. Additionally, the use of transfer learning with pre-trained models such as ResNet or VGG can further improve performance by leveraging knowledge learned from large-scale image datasets.

The implementation of self-supervised learning techniques is another promising area for future work. These methods allow the model to learn useful representations from unlabeled data, which is particularly beneficial in the medical domain where labeled data is limited and expensive to obtain. This approach can reduce the dependency on annotated datasets while improving model performance.

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REFERENCES

[1] A. Dosovitskiy, L. Beyer, A. Kolesnikov et al., "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale," in Proc. ICLR, 2021.
[2] M. Caron, H. Touvron, I. Misra et al., "Emerging Properties in Self-Supervised Vision Transformers," Proc. ICCV, 2021.
[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. CVPR, 2016.
[4] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," in Proc. ICLR, 2015. [5] I. Goodfellow, Y. Bengio, and A. Courville, "Deep Learning," MIT Press, 2016.
[5] OASIS Brains Dataset, "Open Access Series of Imaging Studies,”
[6] Kaggle, "Alzheimer’s Dataset (4 Class of Images)," Available: https://www.kaggle.com
[7] R. S. Desikan et al., "Automated MRI Measures Identify Individuals with Mild Cognitive Impairment and Alzheimer’s Disease," Brain, vol. 132, no. 8, pp. 2048–2057, 2009.
[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in Proc. NIPS, 2012.
[9] Z. Liu, Y. Lin, Y. Cao et al., "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows," in Proc. ICCV, 2021.
[10] J. Chen, Y. Lu, Q. Yu et al., "TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation," arXiv:2102.04306, 2021.
[11] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, "A Simple Framework for Contrastive Learning of Visual Representations (SimCLR)," in Proc. ICML, 2020.
[12] R. R. Selvaraju, M. Cogswell, A. Das et al., "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization," in Proc. ICCV, 2017.

[13] TensorFlow, "TensorFlow: An End-to-End Open Source Machine Learning Platform," Available: https://www.tensorflow.org
[14] FastAPI, "FastAPI Framework Documentation," Available: https://fastapi.tiangolo.com
[15] React, "React JavaScript Library Documentation," Available: https://react.dev [17] World Health Organization, "Dementia Fact Sheet," WHO, 2023.
[16] N. Gessert et al., "Deep Learning for Alzheimer's Disease Classification Using MRI," IEEE Trans. Med. Imaging, 2020.
[17] S. Basaia et al., "Automated Classification of Alzheimer's Disease Using MRI Data and Deep Learning," NeuroImage: Clinical, vol. 26, 2020.