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Early Alzheimer's Diagnosis Using Neural Networks

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ABSTRACT
Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions worldwide, with early diagnosis being crucial for effective intervention. Traditional diagnostic methods are often time-consuming and prone to subjectivity, necessitating automated approaches for improved accuracy and efficiency. This project proposes a deep learning-based framework for early Alzheimer's detection using a ResNet (Residual Network) model trained on MRI and PET brain scan images. The ResNet architecture is chosen for its ability to learn deep hierarchical features while mitigating vanishing gradient issues, enabling robust classification of Alzheimer's stages. The dataset is preprocessed to enhance image quality, and the model is trained and evaluated using standard metrics such as accuracy, sensitivity, and specificity. Experimental results demonstrate the potential of deep learning in achieving high diagnostic accuracy, aiding clinicians in early detection and intervention. This work contributes to advancing AI-driven medical diagnostics, offering a scalable and reliable solution for Alzheimer's screening.

1. INTRODUCTION

1.1GENERAL

Alzheimer's Disease is a progressive brain disorder that causes memory loss and cognitive decline, mainly affecting people over 65. Early diagnosis is crucial as it allows for timely intervention and better care planning. However, traditional diagnostic methods are often slow, subjective, and depend heavily on specialists. These limitations are more pronounced in areas lacking medical resources. To address this, AI and deep learning are increasingly being used to automate and improve the accuracy of Alzheimer's detection through medical imaging.

1.2 PROJECT OVERVIEW

Project aims to detect Alzheimer's Disease early using deep learning techniques on medical imaging. Traditional diagnosis methods are slow, subjective, and rely on specialists, making early detection challenging. Early diagnosis is vital for better treatment planning and slowing disease progression. AI offers a faster, more accurate, and consistent alternative for identifying early signs. The system reduces human error and helps in areas with limited medical resources. It supports healthcare professionals by easing their workload and improving diagnostic reach. The project also has potential for future expansion to other neurological disorders

1.3 OBJECTIVE

- Design and implement ResNet model to classify Alzheimer's severity levels from MRI and PET brain scan
- Preprocess and augment neuroimaging data to enhance model training and reduce noise.
- Evaluate the model using accuracy, sensitivity, specificity, and confusion matrix analysis.

 Demonstrate the effectiveness of deep learning in Alzheimer’s medical image diagnosis.

2. LITERATURE SURVEY:

1. Transfer Learning For Alzheimere’s Disease Through Neuroimaging Biomarkers: A Systematic Review (2021)

Authors: Agarwal, D.; Marques, G.; De La Torre-Díez, I.

Uses Transfer Learning And Addresses Data Scarcity In Medical Imaging.

2. Single-Slice Alzheimer’s Disease Classification And Diseae Regional Analysis With Supervised Switching Autoencoders (2020)

Authors: Mendoza-Léon, R.; Puentes, J.; Uriza

Presents A Supervised Autoencoder For Alzheimer’s Classification And Region Detection From Brain Mris.

3. Stacked Autoencoders As New Models For An Accurate Alzheimer’s Disease Classification Support Using Resting State Eeg And Mri Measurements (2021)

Authors: Ferri, R.; Babiloni, C.; Karami, V.

Uses Stacked Autoencoders To Accurately Classify Alzheimer’s Disease By Integrating Resting-State Eeg And Mri Data.

4. A How-To Guide For A Precision Medicine Approach To The Diagnosis And Treatment Of Alzheimer’s Disease (2023)

Authors: Devi, G.

Presents A Precision Medicine Framework For Alzheimer’s Diagnosis And Treatment.

5. China Alzheimer’s Disease: Facts And Figures (2023)

Authors: Xiao, J.; Li, J.; Wang, J.; Zhang

Provides Updated Statistics, Trends, And Insights Into The Prevalence, Impact, And Challenges Of Alzheimer’s Disease In China.

6. The Alzheimer’s Disease Neuroimaging Initiative In The Era Of Alzheimer’s Disease Treatment (2024)

Authors: Veitch, D.P.; Weiner, M.W.; Miller, M.

Highlights The Evolving Role Of The Alzheimer’s Disease Neuroimaging Initiative (Adni) In Supporting Treatment Development And Monitoring In The Context Of Emerging Alzheimer’s Therapies.

7. The Contribution Of Small Vessel Disease To Neurodegeneration: Focus On Alzheimer’s Disease (2021)

Authors: Tönges, L.; Buhmann, C.; Klebe, S.

Examines How Small Vessel Disease Contributes To Neurodegeneration, With A Specific Focus On Its Role In The Development And Progression Of Alzheimer’s Disease.

8. Imaging Techniques In Alzheimer’s Disease: A Review Of Applications In Early Diagnosis And Longitudinal Monitoring (2021)

Authors: Van Oostveen, W.M.; De Lange.

Reviews Various Imaging Techniques Used For Long-Term Monitoring Of Alzheimer’s Disease Progression.

9. Transfer Learning Assisted Classification And Detection Of Alzheimer’s Disease Stages Using 3d Mri Scans (2019)

Authors: Maqsood, M.; Nazir, F.; Khan, U

Uses Transfer Learning To Improve Classification Of Alzheimer's Stages From 3d Mri Scans.

10. Fsnet: Dual Interpretable Graph Convolutional Network For Alzheimer’s Disease Analysis (2022)

Authors: Li, H.; Shi, X.; Zhu

Proposes FSNet, a dual interpretable graph convolutional network, for analyzing Alzheimer’s disease by capturing both structural and functional brain networks.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Clinical Evaluations: Review of medical history, physical and neurological exams, and cognitive tests.

Neuroimaging Techniques: Use of MRI and PET scans to detect brain atrophy and structural changes.

Manual Image Interpretation: Brain scans analyzed manually by experts, making it subjective.

Traditional Machine Learning Methods: Algorithms like SVM and Decision Trees using handcrafted features from imaging data.

Limitations of Existing Systems:

- Clinical diagnosis is subjective, relying on physician expertise.
- The process is time-consuming, delaying treatment.
- Manual feature engineering in traditional ML limits pattern detection and adds bias.
- Lack of automation prevents large-scale screenings in resource-limited areas.
- Early detection is limited, and MRI/PET data integration is underused.

3.2 PROPOSED SYSTEM

The proposed system leverages deep learning, specifically a ResNet-based model, to detect and classify Alzheimer's disease stages using MRI and PET scan images with high accuracy and efficiency.

Key Features:

- ResNet-based deep learning model for Alzheimer's diagnosis
- Hierarchical feature extraction using residual learning
- Data preprocessing (resizing, normalization, augmentation) for consistent inputs
- Model training and evaluation using performance metrics like accuracy, sensitivity, and specificity
- Realistic medical dataset with labeled stages

Workflow:

1. Collect and preprocess labeled MRI and PET scan images.
2. Train a ResNet model for feature extraction and classification.
3. Evaluate model performance using key metrics
4. Optimize and deploy the final model for clinical use.

3.2.1 ADVANTAGES

- High Accuracy in detecting various stages of Alzheimer’s disease using neuroimaging data
- Improved Generalization with ResNet’s residual learning and transfer learning
- Adaptability to new datasets and evolving diagnostic techniques with model retraining
- Scalability with cloud-based platforms like Google Colab for training with large datasets
- Real-world use with standard imaging data and easy clinical tool integration

4. REQUIREMENT SPECIFICATIONS

4.1 SOFTWARE REQUIREMENTS

- Language: Python – for machine learning and data science support
- Platform: Google Colab or local Jupyter Notebook – cloud-based GPU/CPU access
- Libraries:
- Data Handling: NumPy, Pandas
- Image Processing: OpenCV, PIL (Python Imaging Library), scikit-image
- ML: TensorFlow (or PyTorch), scikit-learn
- Visualization: Matplotlib, Seaborn
- Purpose: To enable efficient development, training, and evaluation of the deep learning model for Alzheimer's diagnosis

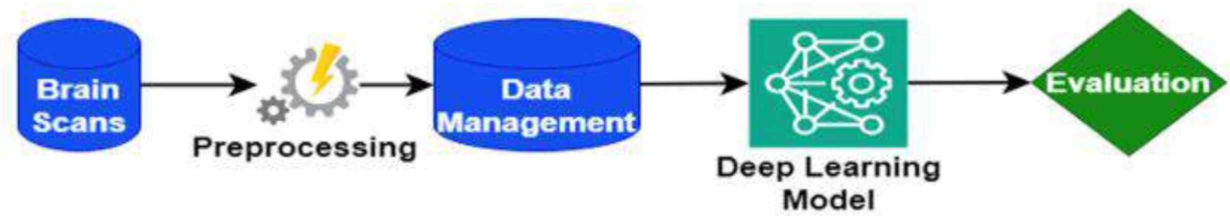
4.2 HARDWARE REQUIREMENTS

- Development Machine: PC with 8 GB RAM, Intel i5 / Ryzen 5 (minimum) for local development.
- GPU Requirement: NVIDIA GTX 1050+ locally; Tesla T4/P100 on Google Colab for better performance.
- Cloud Resource: Google Colab (Intel Xeon, 2 vCPUs, 13 GB RAM) for scalable training.
- Storage: At least 100 GB SSD; 256 GB SSD recommended for faster data handling.
- Setup: Hybrid environment (local machine + Google Colab) for efficient training and evaluation
- Purpose: Hybrid setup (local + Colab) for efficient, scalable ResNet training on neuroimaging data.

5. SYSTEM DESIGN

5.1 SYSTEM ARCHITECTUR E

The proposed system for early Alzheimer's diagnosis uses a ResNet-based deep learning model trained on MRI and PET scan images. The process starts with the collection of labeled neuroimaging data, which is then preprocessed (resizing, normalization, and augmentation) to ensure consistency across the dataset. The preprocessed images are fed into the ResNet model, which extracts hierarchical features through residual learning. This allows the model to overcome vanishing gradient issues and effectively classify images into stages of Alzheimer's: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The dataset is split into training, validation, and test sets. The model is trained and evaluated using performance metrics like accuracy, sensitivity, and specificity. Hyperparameter tuning is performed to optimize the model's performance. The best-performing model is then selected for deployment, offering an automated solution for early Alzheimer's detection in clinical settings.



5.2 UML DIAGRAMS

1. Use Case Diagram – Workflow

Shows how external users (e.g., medical professionals) interact with system functionalities like loading MRI/PET images, preprocessing data, training the model, and classifying Alzheimer's stages.

2. Class Diagram – Workflow

Represents system structure with classes like ImageLoader, DataPreprocessor, ModelTrainer, ModelEvaluator, etc., including their attributes, methods, and relationships.

3. Object Diagram – Workflow

Displays runtime instances of classes (e.g., imageLoader1, preprocessorA) and how data flows between them during system execution.

4. Sequence Diagram – Workflow

Depicts the order of operations: image loading → preprocessing → model training → Alzheimer's stage classification → output diagnosis, showing interactions over time.

5. Activity Diagram – Workflow

Illustrates the process flow from loading MRI/PET images to Alzheimer's stage classification, including decision points like "Is data ready?" or "Is model performance satisfactory?"

6. State Diagram – Workflow

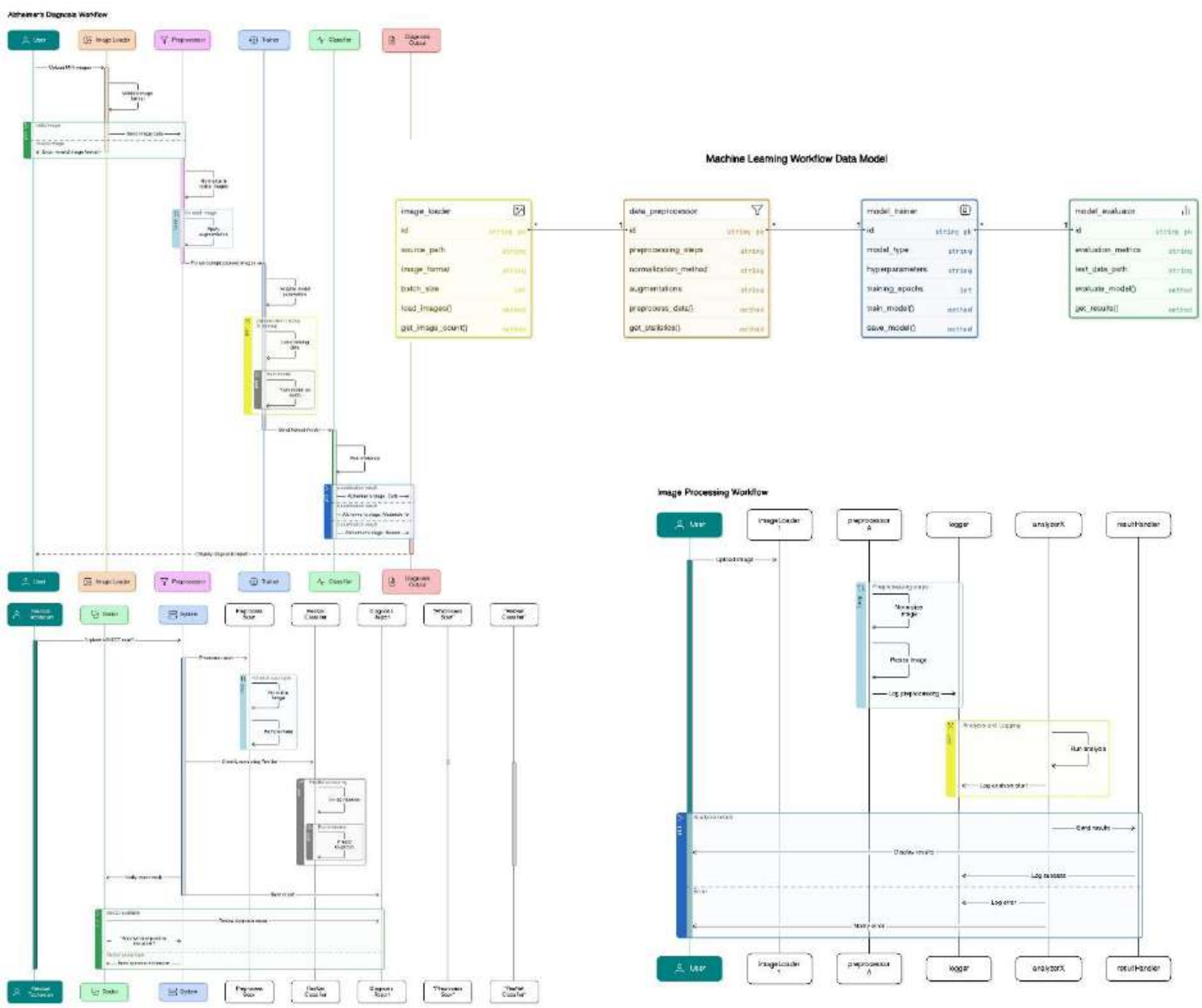
Shows system states like Idle, Loading Images, Preprocessing, Training, Classifying, and transitions based on events like data availability or model evaluation completion.

7. Component Diagram – Workflow

Breaks the system into components: UI, Image Preprocessing, Model Trainer, Classifier, and Output, showing their interconnections.

8. Deployment Diagram – Workflow

Maps software modules onto hardware (local machine, cloud-based resources like Google Colab), showing network communication between image loading, training, classification, and user systems.



5.3 MODULE

1. Image Loading Module

Loads MRI/PET images from the dataset directories, categorizes them based on Alzheimer's stages, and prepares the data for further processing.

2. Data Preprocessing Module

Prepares the dataset for training by applying image augmentation, resizing, and normalizing the images using the ImageDataGenerator for better model performance.

3. Feature Extraction & Augmentation Module

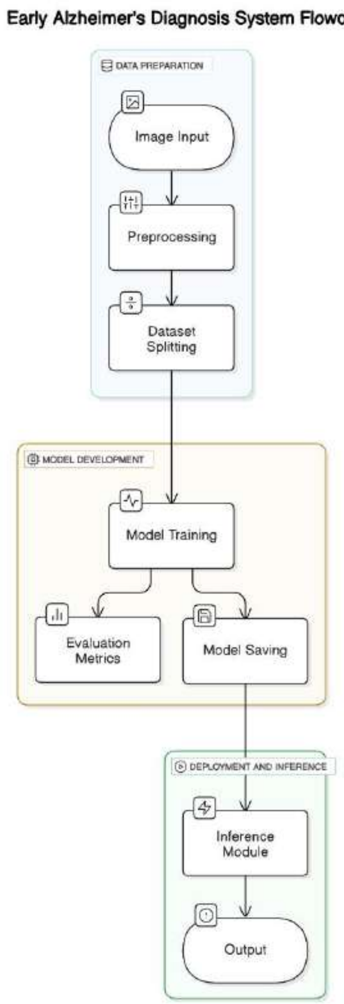
Augments the image data using random transformations (rotation, flipping) and prepares it for feeding into the ResNet50 model to extract deep features.

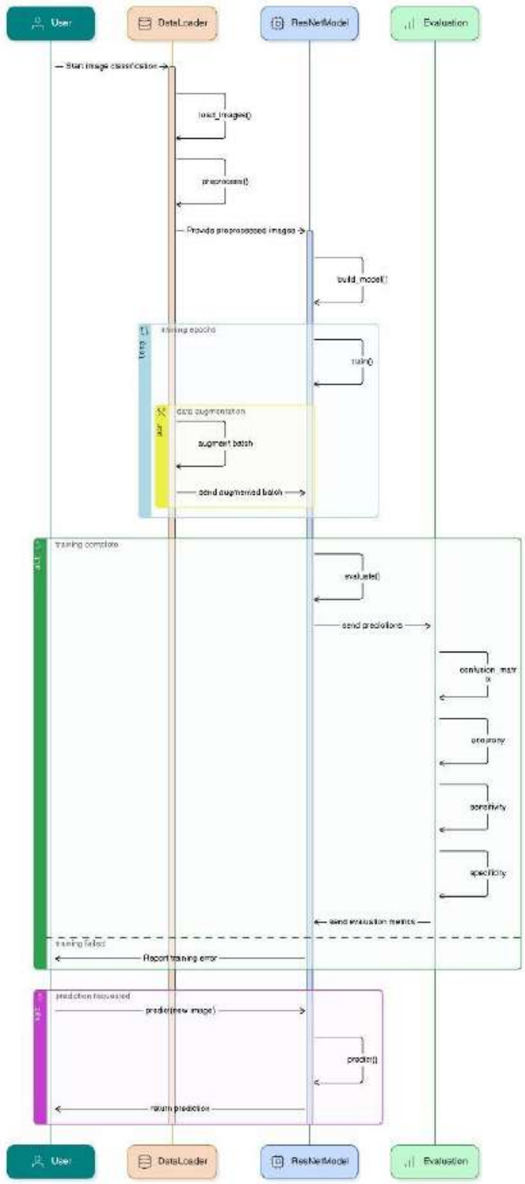
4. Model Architecture Module

Defines the ResNet50-based model, with additional layers (Dense, Flatten) for classification, and compiles the model using the Adam optimizer and categorical cross-entropy loss function.

5. Model Training & Evaluation Module

Trains the model on the training data, validates it using the validation set, saves the model at checkpoints, and evaluates performance on test data with accuracy, precision, recall, and F1-score.





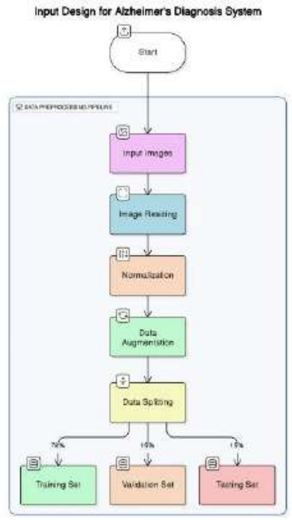
6. IMPLEMENTATION

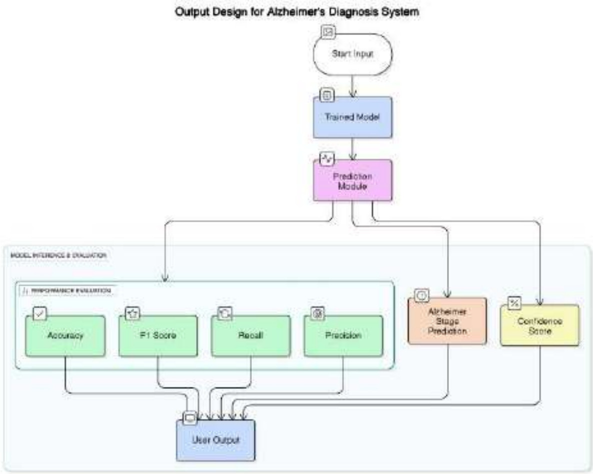
6.1 INPUT DESIGN

The input consists of MRI/PET scan images representing different Alzheimer's stages (Non-Demented, Very Mild, Mild, and Moderate Demented). These images are resized, normalized, and augmented before being split into training, validation, and test sets for model training.

6.2 OUTPUT ESIGN

The system outputs the predicted Alzheimer's stage for each image, along with the corresponding confidence score. It also provides performance metrics like accuracy and F1-score, helping medical professionals in early diagnosis.





6.

3 SAMPLE CODE

The Alzheimer’s diagnosis system uses Python libraries like pandas, numpy, TensorFlow, and Keras for model training and prediction.

Data Preprocessing: MRI/PET scan images are resized, normalized, and augmented to enhance generalization and prevent overfitting.

Data Splitting: The dataset is divided into training, validation, and test sets with balanced classes.

Model Definition: A pre-trained ResNet50 model is used with additional dense layers for classification; base layers are frozen to reduce overfitting.

Model Compilation & Training: The model is compiled with Adam optimizer and categorical cross-entropy loss, trained with early stopping and learning rate reduction for optimal performance.

Evaluation & Prediction: Performance is evaluated using metrics like accuracy, precision, recall, and F1-score. The trained model predicts Alzheimer’s stages from new scans with confidence scores.

6.4 IMPLEMENTATION

The implementation phase begins with loading and preprocessing MRI/PET scan images, resizing them to a consistent shape (244x244 pixels) and normalizing the pixel values. The dataset is split into training (70%), validation (15%), and testing (15%) sets. The ResNet50-based deep learning model is trained to classify Alzheimer's stages, with performance evaluated using accuracy, precision, recall, and F1-score.

The trained model is saved for future use, and an inference function processes new images to predict Alzheimer's stages in real-time or batch mode. This implementation validates the model's capability to accurately detect different Alzheimer's stages from brain scan images.

7. SOFTWARE TESTING

Software testing ensures the reliability and accuracy of the Alzheimer’s detection system, validating the complete pipeline—from image loading to final prediction.

Unit Testing was applied to individual components like image preprocessors, dataset loaders, and label encoders to verify proper functionality and robustness against unexpected inputs.

Integration Testing confirmed smooth operation between preprocessing, model training, and prediction stages, ensuring consistent image dimensions, data formats, and class mappings.

Model Evaluation involved testing the ResNet-based classifier using key metrics such as accuracy, precision, recall, F1-score, and confusion matrix to assess classification performance across all classes.

Performance Testing assessed training speed and prediction latency on GPU-backed environments verifying feasibility for clinical or real-time scenarios. The system demonstrated strong generalization and stability. Fine-tuning further improved performance, validating the model's readiness for deployment.

Key Metrics Explained:

Confusion Matrix: Visualizes actual vs. predicted classes, highlighting correct and misclassified cases.

Accuracy: Overall correctness of predictions across all classes.

Precision: Proportion of correctly identified class instances among all predicted as that class.

Recall: Ability to identify all actual instances of a given class.

F1-Score: Balanced metric combining precision and recall, ideal for imbalanced datasets.

8. RESULT ANALYSIS

The model was evaluated using a ResNet50-based architecture for classifying Alzheimer's stages. Metrics such as Accuracy, Precision, Recall, F1-score, training time, and prediction latency were considered.

Training Time:

- **ResNet50 (Transfer Learning):**

Took moderate training time (~2m 45s/epoch (~27m total for 10 epochs on GPU)).

Efficient due to frozen base layers; suitable for medical diagnostics with limited data.

Prediction Time:

- **ResNet50 Model**:

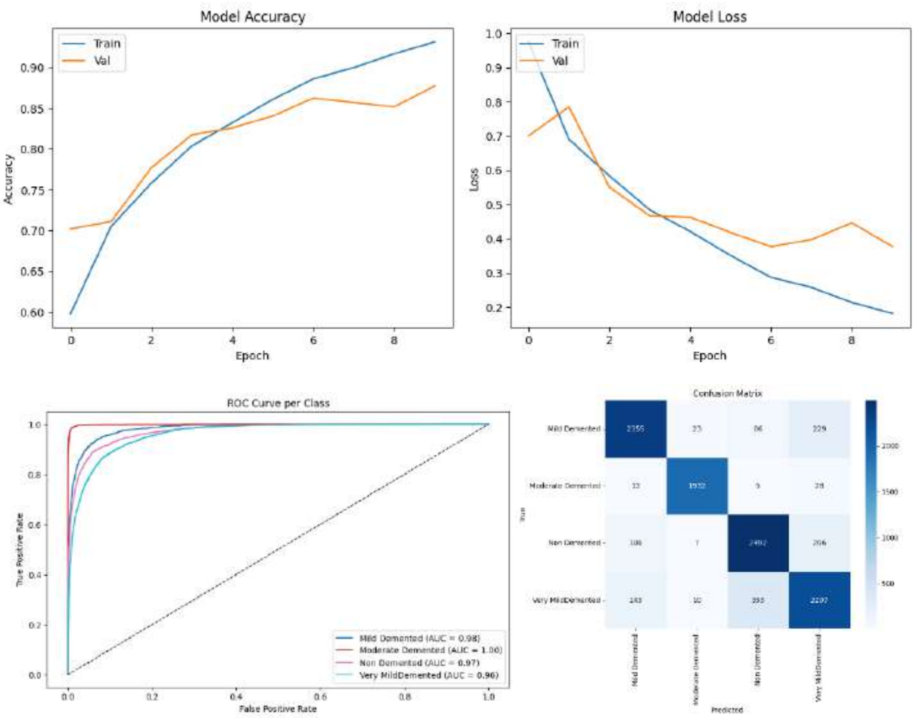
Delivered fast inference (~<1 sec per image batch). Appropriate for both batch and near real-time clinical predictions.

Performance Metrics:

- **Accuracy:** ~88% on validation and test sets.
- **Precision & Recall:** Ranged between 0.83–0.98 across classes.
- **F1-Score:** Maintained strong class-wise balance (0.82–0.98).
- **Confusion Matrix:** Minor misclassifications, mainly between Mild and Very Mild Demented.

Overall comparison:

The ResNet50 model offers a strong balance between high classification performance and efficient deployment time, making it suitable for real-world Alzheimer's screening systems.



9. FUTURE SCOPE & CONCLUSION

9.1 FUTURE SCOPE

The future scope of this work offers multiple promising directions for both research and clinical applications. One of the key areas is the incorporation of additional imaging modalities such as EEG (Electroencephalogram) and CT (Computed Tomography) scans. By fusing data from multiple sources, the diagnostic model can achieve greater accuracy and a more comprehensive understanding of brain health. Another major direction is real-time clinical implementation by optimizing the model's architecture and deployment pipeline, it can be integrated into hospital systems for live diagnostic support, enabling faster decision-making and treatment planning.

9.2 CONCLUSION

The ResNet-based deep learning model proves to be a powerful tool for the early detection of Alzheimer's Disease, offering higher accuracy than traditional diagnostic approaches by effectively analyzing MRI and PET scans. Its residual learning design enables deeper, more meaningful feature extraction, capturing subtle brain changes across different disease stages. The model also shows strong advantages in training speed, scalability, and generalization, making it both efficient and reliable. These strengths position the system as a practical and impactful solution for assisting clinicians in early diagnosis, ultimately contributing to more intelligent, automated, and accessible healthcare.

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