RESEARCH DAY

EARLY DETECTION OF ALZHEIMER'S USING DEEP LEARNING AND MEDICAL IMAGING

SUDHARSHINI R
PROJECT MENTOR: DR.A.SATHYA

E0322019
3rd Year AIDA

CONTENT

INTRODUCTION

- Alzheimer’s disease is a progressive disorder affecting memory and daily functioning.
- Early detection is crucial for timely intervention, potentially slowing progression.
- Traditional diagnostics rely on clinical assessments and tests, which can be subjective and time-consuming.
- Deep learning models provide a promising method for early detection by analyzing medical data and making accurate predictions.
- This project utilizes DL techniques to detect early signs of Alzheimer’s through neuroimaging data.

PROBLEM STATEMENT

Alzheimer’s disease is often diagnosed in its later stages when significant neuronal damage has occurred, limiting treatment effectiveness. Challenges in early detection include:

- Lack of objective, automated diagnostic tools for early-stage detection.
- Variability in disease progression and symptom manifestation across patients.
- Large, complex datasets from medical imaging that require advanced analysis techniques.

The objective of this project is to develop a deep learning model capable of detecting Alzheimer’s disease at an early stage by analyzing MRI images, identifying key patterns, and providing interpretable predictions.

METHODOLOGY

Data Collection

- Collected MRI image datasets from multiple sources in the internet.

Data Preprocessing

- Ensured that the dataset contained balanced class distribution to prevent model bias.

Feature Extraction & Model Architecture

- The CNN model includes three convolutional layers with 16, 32, and 64 filters, each followed by a MaxPooling layer.

Model Training

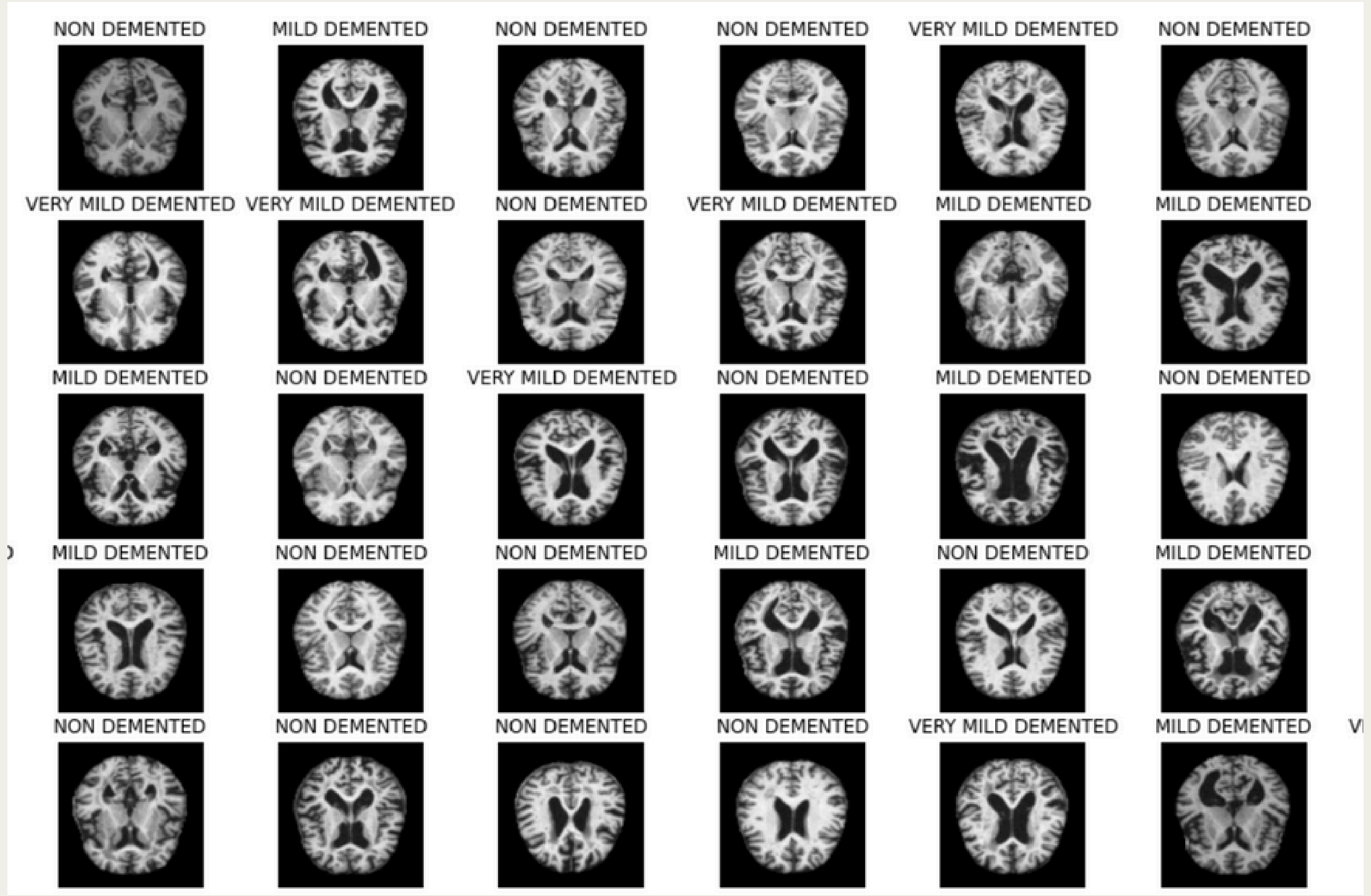
- Split data into training (80%), validation (10%), and test (10%) sets.

Model Evaluation

- Final performance was assessed using model.evaluate(test_ds) on the test dataset.

DATA COLLECTION AND PREPROCESSING

- Collected MRI image datasets from multiple sources in the internet.
- Ensured that the dataset contained balanced class distribution to prevent model bias.
- Resized images to a standard dimension for consistency.
- Normalized pixel values to scale them between 0 and 1 for better model performance.
- Applied data augmentation (rotation, flipping, contrast adjustment) to improve generalization.



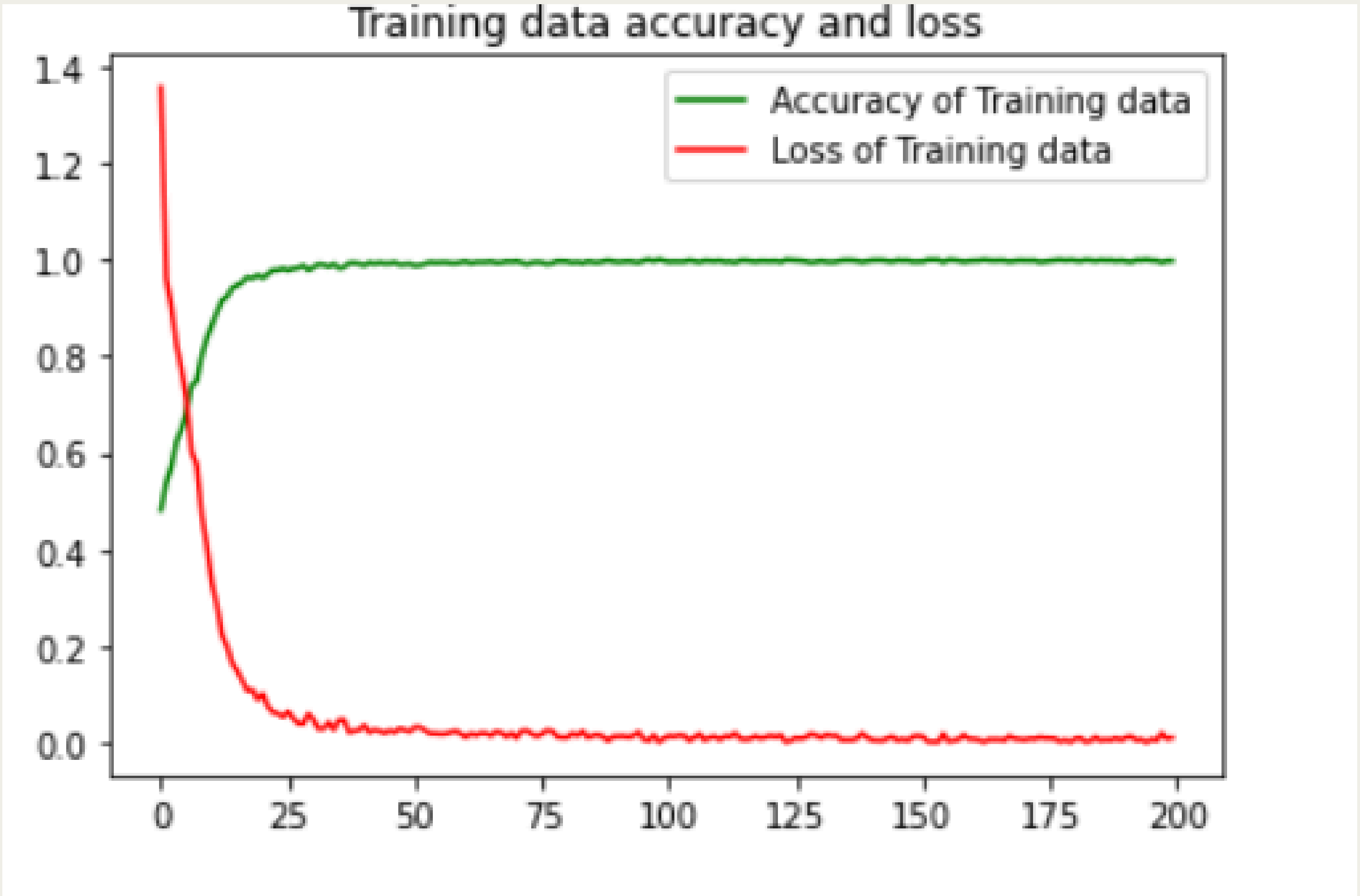
FEATURE EXTRACTION AND MODEL ARCHITECTURE

- The CNN model includes three convolutional layers with 16, 32, and 64 filters, each followed by a MaxPooling layer.
- Dropout layers (0.2 and 0.25) were added to prevent overfitting.
- Fully connected layers include 128 neurons (ReLU), 64 neurons (ReLU), and 4 output neurons (Softmax activation) for multi-class classification.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 128, 128, 3)       0

 conv2d (Conv2D)             (None, 128, 128, 16)      448

 max_pooling2d (MaxPooling2D  (None, 64, 64, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 64, 64, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 32, 32, 32)       0
 2D)

 dropout (Dropout)           (None, 32, 32, 32)        0

 conv2d_2 (Conv2D)           (None, 32, 32, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 16, 16, 64)       0
 2D)

 dropout_1 (Dropout)         (None, 16, 16, 64)        0

...
Total params: 2,129,380
Trainable params: 2,129,380
Non-trainable params: 0
```

MODEL TRAINING AND MODEL EVALUATION

- Split data into training (80%), validation (10%), and test (10%) sets.
- Compiled the model using the Adam optimizer and sparse categorical cross-entropy loss function.
- Trained the model for 200 epochs using mini-batches of 64 images per iteration.
- Evaluated the model using training and validation accuracy and loss.
- Plotted accuracy and loss curves to analyze model performance over epochs.
- Final performance was assessed using model.evaluate(test_ds) on the test dataset.



APPLICATION

Early Diagnosis:

- **Improved Patient Outcomes:** Early detection allows for personalized treatment plans that can significantly improve the quality of life for patients by managing symptoms more effectively.

Risk Assessment:

- **Targeted Prevention Programs:** Identifying individuals at high risk enables the creation of tailored prevention and lifestyle modification programs to reduce the likelihood of disease development.

Clinical Decision Support:

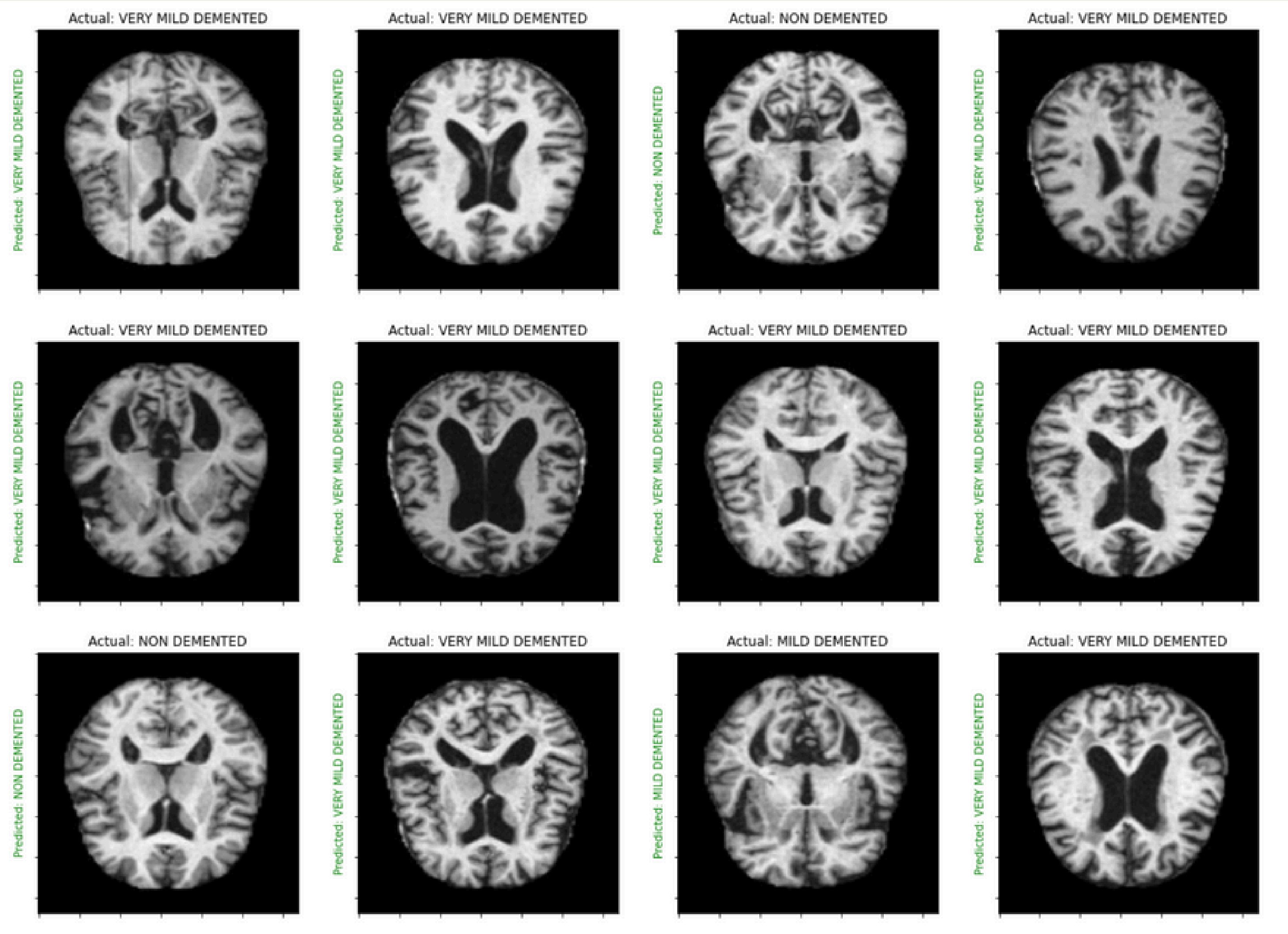
- **Enhanced Accuracy:** By integrating patient history and genetic information, decision support systems can provide more accurate diagnoses and recommendations, reducing human error.

Healthcare Optimization:

- **Scalable Solutions:** Automating diagnosis with deep learning models can handle large patient datasets, making healthcare systems more scalable and efficient in diagnosing Alzheimer’s on a population level.

RESULTS AND DISCUSSION

- **Best Performing Model:** The CNN model demonstrated high accuracy in MRI-based diagnosis.
- **Performance Metrics:** Model accuracy and loss were evaluated across training and validation sets, and the results were visualized through plotted curves.
- **Feature Importance:** Brain atrophy and hippocampal volume reduction were the most significant indicators of Alzheimer’s.
- **Insights:** The model successfully identified early-stage Alzheimer’s patients with high accuracy, showcasing the potential for clinical implementation.
- **Challenges:** Model interpretability and dataset limitations remain concerns for real-world deployment.



CONCLUSION

Deep learning offers a powerful tool for the early detection of Alzheimer's disease, aiding in timely diagnosis and treatment planning. Future work will focus on improving model interpretability, expanding datasets, and integrating multi-modal data sources for enhanced accuracy.