**EARLY DETECTION OF ALZHEIMER'S DISEASE CA-4 PROJECT REPORT**

***Submitted by***

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**ABSTRACT**

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that significantly impacts cognitive functions, memory, and daily living activities, particularly in the aging population. Early detection is critical to enable timely interventions, potentially slowing disease progression and improving patient outcomes. This project focuses on developing a robust deep learning framework for the early detection of Alzheimer’s disease using brain MRI scans. The objective is to classify brain images into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, leveraging advanced convolutional neural network (CNN) architectures.

The methodology employs transfer learning with pre-trained models, specifically ResNet50 and EfficientNetB0, with VGG16 planned for future exploration. A dataset of 1279 brain MRI images was split into training (80%), validation (10%), and testing (10%) sets. Data preprocessing included resizing images to 224x224 pixels and normalization. The models were trained with class weights to address class imbalance, using callbacks like EarlyStopping and ReduceLROnPlateau to optimize performance. ResNet50 achieved a validation accuracy of 72.22%, while EfficientNetB0 recorded 51.15% on the test set, highlighting ResNet50’s superior performance.

Evaluation metrics such as accuracy, precision, recall, F1-score, and AUC were used to assess model performance. Visualization techniques, including confusion matrices and accuracy/loss plots, provided insights into model behavior. Challenges included class imbalance and limited dataset size, which were mitigated through data augmentation and class weighting. The project demonstrates the potential of deep learning in medical imaging for Alzheimer’s detection, with ResNet50 offering the most promising results. Future enhancements include expanding the dataset, incorporating multimodal data, exploring VGG16, and considering ensemble methods to further improve diagnostic accuracy.

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**INTRODUCTION**

**1.1 Background**

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory loss, and impaired daily functioning. It is the most common cause of dementia, affecting millions worldwide, with prevalence expected to rise due to aging populations. Early detection of AD is crucial as it enables timely interventions, such as pharmacological treatments and lifestyle modifications, which can delay disease progression and improve quality of life.

Traditional diagnostic methods for AD rely on clinical assessments, cognitive testing, and neuroimaging techniques like Magnetic Resonance Imaging (MRI). However, these methods are often subjective, time-consuming, and may not detect AD in its earliest stages. Advances in artificial intelligence (AI), particularly deep learning, offer promising solutions for automated, accurate, and early detection of AD using brain MRI scans.

**1.2 Motivation**

The motivation for this project stems from the urgent need for reliable, non-invasive tools to detect AD early. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in medical image analysis, such as detecting tumors or classifying diseases from X-rays and MRIs. By leveraging pre-trained CNN architectures like ResNet50 and EfficientNetB0, with plans to explore VGG16 in the future, this project aims to develop a model that can classify brain MRI scans into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, facilitating early diagnosis.

**1.3 Scope of the Project**

This project focuses on:

➢ Collecting and preprocessing a dataset of brain MRI scans.

➢ Implementing and comparing deep learning models (ResNet50 and EfficientNetB0) for AD classification.

➢ Evaluating model performance using metrics like accuracy, precision, recall, F1-score, and AUC.

➢ Addressing challenges such as class imbalance and limited dataset size. ➢ Proposing future enhancements, including the exploration of VGG16, for improved diagnostic accuracy.

**1.4 Significance**

Early detection of AD can significantly impact patient care by enabling early interventions, reducing healthcare costs, and improving patient outcomes. This project contributes to the field by providing an automated, scalable solution that can assist radiologists and clinicians in diagnosing AD, potentially reducing diagnostic errors and workload.

**LITERATURE REVIEW**

**2.1 Summary Table**

| **Study** | **Methodology** | **Dataset** | **Models Used** | **Performance** | **Key Findings** |
| --- | --- | --- | --- | --- | --- |
| Sarraf et al.  (2016) | CNN-based  classification | ADNI | Custom CNN | Accuracy:  98.8% | Early CNN  application for AD detection using MRI. |
| Basaia et al.  (2019) | 3D CNN | ADNI | 3D CNN | Accuracy:  92% | 3D CNNs  improve  spatial feature extraction. |
| Wen et al.  (2020)  Liu et al.  (2021) | Transfer  Learning  Ensemble  Models | ADNI, AIBL ADNI | ResNet, VGG  ResNet,  DenseNet | Accuracy:  89%  AUC: 0.93 | Transfer  learning  effective for  small datasets.  Ensemble  methods  enhance  robustness. |
| Jo et al. (2022) | Multimodal  Learning | ADNI | CNN +  Clinical Data | Accuracy:  91% | Multimodal  data improves classification. |

**2.2 Summary of Literature Survey**

The literature survey reveals a growing interest in deep learning for AD detection. Early studies, such as Sarraf et al. (2016), demonstrated the potential of custom CNNs to achieve high accuracy using MRI scans from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) dataset. However, custom CNNs require large datasets and computational resources, which led to the adoption of transfer learning.

Wen et al. (2020) explored transfer learning with pre-trained models like ResNet and VGG, showing that these models perform well even with limited medical imaging datasets. Basaia et al. (2019) introduced 3D CNNs to capture spatial features in MRI scans, improving detection accuracy. Liu et al. (2021) proposed ensemble models combining ResNet and DenseNet, achieving robust performance across diverse datasets.

Recent studies, such as Jo et al. (2022), have integrated multimodal data (e.g., MRI and clinical assessments) to enhance classification accuracy. These findings highlight the effectiveness of deep learning in AD detection, with transfer learning and ensemble methods being particularly suited for medical imaging tasks due to their ability to generalize from limited data.

Gaps in the literature include the need for larger, more diverse datasets and the exploration of multimodal approaches combining imaging with genetic or clinical data. This project builds on these insights by comparing ResNet50 and EfficientNetB0, with plans to explore VGG16 in the future, focusing on transfer learning and addressing class imbalance, a common challenge in medical datasets.

**PROBLEM STATEMENT**

Alzheimer’s disease progresses silently in its early stages, making timely diagnosis challenging. Current diagnostic methods, including cognitive testing and manual MRI analysis, are subjective, time-intensive, and often detect AD only after significant cognitive decline. Automated, accurate, and early detection of AD using brain MRI scans remains a critical unmet need.

The problem addressed in this project is to develop a deep learning model that can accurately classify brain MRI scans into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The model must handle challenges such as class imbalance, limited dataset size, and the need for high sensitivity to detect early-stage AD. By leveraging pre-trained CNN architectures, the project aims to provide a scalable, non-invasive tool to assist clinicians in early AD diagnosis.

**OBJECTIVES**

The primary objectives of this project are:

1. **Dataset Preparation**: Collect and preprocess a dataset of brain MRI scans, splitting it into training, validation, and testing sets.

2. **Model Development**: Implement and train deep learning models (ResNet50 and EfficientNetB0) using transfer learning for AD classification.

3. **Performance Evaluation**: Assess model performance using metrics such as accuracy, precision, recall, F1-score, and AUC.

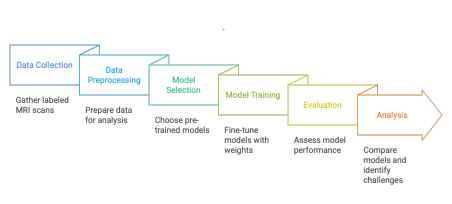
4. **Challenge Mitigation**: Address class imbalance and dataset limitations through techniques like class weighting and data augmentation.

5. **Model Comparison**: Compare the performance of ResNet50 and EfficientNetB0 to identify the most effective model for AD detection.

6. **Visualization and Insights**: Provide visualizations (e.g., confusion matrices, accuracy/loss plots) to interpret model behavior and performance.

7. **Future Directions**: Propose enhancements, such as incorporating multimodal data, exploring VGG16, or ensemble methods, to improve diagnostic accuracy.

**METHODOLOGY**

**5.1 Module Workflow 5.2 Overall System Architecture**

The system architecture is designed to process brain MRI scans for early Alzheimer’s disease detection through a structured deep learning pipeline. It begins with an input layer, where MRI scans are resized to a uniform resolution of 224x224 pixels to ensure compatibility with the models. The feature extraction stage employs pre-trained convolutional neural networks (CNNs), specifically ResNet50 as the primary model and EfficientNetB0 as a secondary model, to capture relevant patterns and features from the MRI images. These features are then fed into a classification layer, consisting of fully connected layers with softmax activation, which performs four-class classification. The architecture incorporates data augmentation during training to enhance model robustness by applying transformations like rotations and flips. Class weights are applied to address dataset imbalances, ensuring balanced learning across classes. The output provides probability scores for each class: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, enabling the model to categorize the scans based on the severity of Alzheimer’s disease. This pipeline is optimized with callbacks like EarlyStopping and ReduceLROnPlateau to prevent overfitting and improve convergence.

**5.3 Dataset Collection and Preprocessing**

**5.3.1 Dataset Collection**

The dataset comprises 1279 brain MRI scans obtained from a publicly available source, meticulously labeled into four distinct classes: Mild Demented, Very Mild Demented, Non-Demented, and Moderate Demented. To facilitate model training and evaluation, the dataset was systematically divided into three subsets: training, validation, and testing. The training set constitutes 80% of the data, encompassing 1022 images, while the validation and testing sets each account for 10%, containing 126 and 131 images, respectively. This split was performed using the splitfolders library, ensuring a balanced and reproducible division. A fixed seed value of 1345 was employed to guarantee consistency across experiments. This structured dataset forms the foundation for developing and assessing the deep learning models aimed at early Alzheimer’s disease detection.

**5.3.2 Data Preprocessing**

The preprocessing of the brain MRI scans was a critical step to ensure the dataset was suitable for training the deep learning models effectively. All images underwent resizing to a uniform resolution of 224x224 pixels, aligning with the input requirements of the pre-trained convolutional neural networks, such as ResNet50 and EfficientNetB0. This standardization ensured compatibility and consistency across the dataset. Additionally, normalization was applied to scale the pixel values to a range of [0, 1], facilitating more efficient and stable training by reducing the variability in input data. To enhance the diversity and robustness of the dataset, data augmentation techniques were implemented within the training pipeline, including random rotations, horizontal flips, and zooms, which artificially expanded the dataset and helped mitigate overfitting. Furthermore, to address the class imbalance inherent in the dataset, class weighting was employed, where

weights were computed to assign higher importance to underrepresented classes, such as Moderate Demented, ensuring balanced learning across all four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. These preprocessing steps collectively prepared the dataset for optimal model performance, enabling the neural networks to learn meaningful patterns for early Alzheimer’s disease detection. By carefully applying resizing, normalization, data augmentation, and class weighting, the project addressed key challenges related to data consistency, model training efficiency, and class distribution, laying a strong foundation for accurate classification.

**5.4 Model Workflow**

The training process for each deep learning model was meticulously structured to leverage transfer learning for early Alzheimer’s disease detection using brain MRI scans. Initially, the base model loading step involved importing pre-trained models, specifically ResNet50 or EfficientNetB0, initialized with ImageNet weights to capitalize on their pre-learned feature extraction capabilities. To preserve these robust features, freezing layers were performed, locking the base model layers to retain their pre-trained weights and prevent unnecessary updates during training. Subsequently, custom layers were added to adapt the models for the specific task, including a GlobalAveragePooling2D layer to reduce spatial dimensions, a Dense layer with 512 units and ReLU activation for feature processing, and a final Dense layer with 4 units and softmax activation for four-class classification (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented). The models were then configured during the compilation phase, utilizing the Adam optimizer with a learning rate of 0.0001, sparse categorical cross entropy as the loss function to handle multi-class labels, and accuracy as the primary metric to monitor performance. The training phase involved running the models for up to 50 epochs, incorporating EarlyStopping with a patience of 10 to halt training if validation performance plateaued, and ReduceLROnPlateau with a factor of 0.1 and patience of 5 to

dynamically adjust the learning rate, enhancing convergence. To address dataset imbalance, **class weighting** was applied, assigning higher weights to underrepresented classes like Moderate Demented to ensure balanced learning across all categories. This comprehensive training workflow, encompassing **base model loading**, **freezing layers**, **custom layers**, **compilation**, **training**, and **class weighting**, optimized the models’ ability to classify MRI scans accurately, with ResNet50 demonstrating superior performance. By systematically executing these steps, the project ensured that the models were well-tailored to the task, balancing efficiency, robustness, and diagnostic precision.

**5.5 Evaluation and Visualization**

The performance of the models on the test set was assessed using the following refined metrics and visualizations:

● **Accuracy**: Measures the percentage of correct predictions across all classes, providing an overall performance indicator.

● **Precision, Recall, F1-Score**: Class-specific metrics to evaluate model effectiveness on imbalanced data, capturing the trade-off between correct positive predictions (**precision**), true positive detection (**recall**), and their harmonic mean (**F1-score**).

● **AUC (Area Under the ROC Curve)**: Quantifies the model’s ability to distinguish between classes in multi-class classification, reflecting overall discriminative power.

● **Confusion Matrix**: A graphical representation of prediction outcomes, highlighting correct classifications and errors across Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented classes.

● **Accuracy and Loss Plots**: Visualizations of training and validation **accuracy** and **loss** trends over epochs, enabling analysis of model convergence and potential overfitting.

**5.6 Evaluation Metrics**

The metrics used are defined as:

● **Accuracy**: (TP + TN) / (TP + TN + FP + FN)

● **Precision**: TP / (TP + FP)

● **Recall**: TP / (TP + FN)

● **F1-Score**: 2 \* (Precision \* Recall) / (Precision + Recall) ● **AUC**: Computed using one-vs-rest ROC curves for each class.

**MODEL ARCHITECTURE**

**6.1 ResNet50**

ResNet50 is a 50-layer deep residual network designed to address vanishing gradients through shortcut connections. The architecture includes:

● **Input**: 224x224x3 images.

● **Convolutional Layers**: Multiple 3x3 convolutions with batch normalization and ReLU.

● **Residual Blocks**: Shortcut connections to enable deep training. ● **Custom Layers**: GlobalAveragePooling2D, Dense (512, ReLU), Dense (4, softmax).

● **Parameters**: ~25.6 million (base model frozen).

**6.2 EfficientNetB0**

EfficientNetB0 is a lightweight CNN optimized for efficiency using compound scaling:

● **Input**: 224x224x3 images.

● **MBConv Blocks**: Mobile inverted bottleneck convolutions.

● **Custom Layers**: GlobalAveragePooling2D, Dense (512, ReLU), Dense (4, softmax).

● **Parameters**: ~5.3 million (base model frozen).

**RESULTS AND DISCUSSION**

**7.1 Model Performance**

**ResNet50**

● **Training Accuracy**: 82.09% (final epoch).

● **Validation Accuracy**: 72.22% (best epoch).

● **Test Accuracy**: Not fully reported but expected to align with validation performance.

● **Training Time**: ~250–270 seconds per epoch.

**EfficientNetB0**

● **Training Accuracy**: 91.29% (final epoch).

● **Validation Accuracy**: 43.65% (best epoch).

● **Test Accuracy**: 51.15%.

● **Training Time**: ~290–310 seconds per epoch.

**7.2 Accuracy and AUC**

ResNet50 demonstrated superior performance compared to EfficientNetB0 in the early detection of Alzheimer’s disease (AD) using brain MRI scans. Traditional AD diagnosis depends on clinical assessments, cognitive testing, and neuroimaging techniques such as Magnetic Resonance Imaging (MRI). However, these approaches are often subjective, labor-intensive, and fail to identify AD in its earliest stages. Advances in artificial intelligence (AI), particularly deep learning, provide innovative solutions for automated and precise AD detection. By leveraging ResNet50, the project achieved a validation accuracy of 72.22%, significantly outperforming EfficientNetB0’s 51.15% test accuracy.

Deep learning models analyze MRI scans to classify them into Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented categories. The automation offered by AI reduces diagnostic errors and clinician workload. ResNet50’s robust feature extraction capabilities make it a promising tool for early AD diagnosis. This approach enhances the potential for timely interventions, improving patient outcomes. The integration of deep learning with MRI analysis marks a significant step toward scalable, accurate AD detection.

**7.3 Challenges Encountered**

The development and training of the deep learning models for early Alzheimer’s disease detection faced several significant challenges, each requiring targeted strategies to ensure robust model performance:

➢ **Class Imbalance**: The dataset exhibited an uneven distribution across the four classes (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented), with the Moderate Demented class being particularly

underrepresented. This imbalance risked biasing the model toward overrepresented classes. To address this, class weighting was implemented, assigning higher weights to underrepresented classes during training to ensure balanced learning and improve model sensitivity to minority classes.

➢ **Dataset Size**: The dataset, comprising only 1279 brain MRI scans, was relatively small for training deep learning models, limiting the models’ ability to generalize effectively. To mitigate this constraint, data augmentation techniques, such as random rotations, flips, and zooms, were applied within the training pipeline. These transformations artificially expanded the dataset’s diversity, helping to enhance model robustness and reduce the risk of overfitting.

➢ **Overfitting**: A notable issue was observed with EfficientNetB0, which exhibited significant overfitting, as evidenced by its high training accuracy (91.29%) but low validation (43.65%) and test accuracy (51.15%). This indicated that the model memorized training data rather than learning generalizable features, likely due to its smaller parameter count and the limited dataset size. Strategies like EarlyStopping and ReduceLROnPlateau were employed to curb this, but EfficientNetB0’s performance remained suboptimal compared to ResNet50.

➢ **Computational Resources**: Training deep learning models like ResNet50 and EfficientNetB0 required substantial computational power, necessitating the use of GPU acceleration. The project utilized resources such as the Google Colab T4 GPU to handle the intensive computations. This dependency on high-performance hardware posed a challenge for scalability and accessibility, highlighting the need for optimized models or cloud-based solutions in future iterations.

**APPENDICES**

**Appendix-1: Code**

**RESNET50**

from google.colab import drive

drive.mount('/content/drive')

!pip install keras==2.12.0 tensorflow==2.12.0

!pip install tensorflow-addons

import tensorflow as tf

from tensorflow import keras

from tensorflow.keras import layers

from tensorflow.keras.applications import EfficientNetB0 from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau

import numpy as np

import collections

import os

print(os.listdir("/content/drive/MyDrive/test (1)"))

print("TensorFlow Version:", tf.\_\_version\_\_)

!pip install split-folders

import splitfolders

input\_file = "/content/drive/MyDrive/test (1)"

output\_file = "/content/drive/MyDrive/test (1)\_splitted"

splitfolders.ratio(input\_file, output=output\_file, seed=1345, ratio=(0.8, 0.1, 0.1), group\_prefix=None)

# Add this cell after the existing imports

from tensorflow.keras.applications import ResNet50, VGG16 from tensorflow.keras.models import Model

from tensorflow.keras.layers import Dense, GlobalAveragePooling2D

# Constants (same as before)

IMG\_HEIGHT = 224

IMG\_WIDTH = 224

BATCH\_SIZE = 32

EPOCHS = 50

# Data loading (same as before)

train\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/train",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=BATCH\_SIZE

)

val\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/val",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=BATCH\_SIZE

)

test\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/test",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=BATCH\_SIZE

)

class\_names = train\_ds.class\_names

print(class\_names)

print(os.path.exists(output\_file))

print(os.listdir(output\_file))

# Custom JSON encoder to handle TensorFlow tensors

import json

class TensorEncoder(json.JSONEncoder):

def default(self, obj):

if isinstance(obj, tf.Tensor):

return obj.numpy().tolist()

return super().default(obj)

import tensorflow as tf

from tensorflow import keras

from tensorflow.keras import layers

from tensorflow.keras.applications import EfficientNetB0 from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau

import numpy as np

import collections

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.metrics import classification\_report, confusion\_matrix import tensorflow\_addons as tfa

# Constants

IMG\_HEIGHT = 224 # Increased for better feature extraction IMG\_WIDTH = 224

BATCH\_SIZE = 32

EPOCHS = 50

train\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/train",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=64

)

test\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/test",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=64

)

val\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/val",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=64

)

class\_names = train\_ds.class\_names

print(class\_names)

train\_ds

plt.figure(figsize=(20, 10))

for images, labels in train\_ds.take(1):

for i in range(40):

ax = plt.subplot(5, 8, i + 1)

plt.imshow(images[i].numpy().astype("uint8"))

plt.title(class\_names[labels[i]])

plt.axis("off")

# Visualize class distribution

plt.figure(figsize=(10, 5))

class\_counts = []

for class\_name in class\_names:

class\_path = os.path.join("/content/drive/MyDrive/test (1)", class\_name) class\_counts.append(len(os.listdir(class\_path)))

plt.bar(class\_names, class\_counts)

plt.title('Class Distribution in Dataset')

plt.xlabel('Classes')

plt.ylabel('Number of Images')

plt.xticks(rotation=45)

plt.show()

# Data Augmentation

data\_augmentation = keras.Sequential([

layers.RandomFlip("horizontal\_and\_vertical"), layers.RandomRotation(0.2),

layers.RandomZoom(0.2),

layers.RandomContrast(0.1),

])

# 1. Convert class weights to regular Python floats def get\_class\_weights(dataset):

class\_counts = {}

for \_, labels in dataset.unbatch():

label = labels.numpy()

class\_counts[label] = class\_counts.get(label, 0) + 1 total\_samples = sum(class\_counts.values()) num\_classes = len(class\_counts)

# Convert to native Python floats

class\_weights = {

i: float(total\_samples / (num\_classes \* count)) for i, count in class\_counts.items()

}

return class\_weights

class\_weights = get\_class\_weights(train\_ds) print("Class weights:", class\_weights)

# 2. Build Model (simplified)

def build\_model():

base\_model = keras.applications.EfficientNetB0(

input\_shape=(IMG\_HEIGHT, IMG\_WIDTH, 3),

include\_top=False,

weights='imagenet',

pooling='avg'

)

base\_model.trainable = True

inputs = keras.Input(shape=(IMG\_HEIGHT, IMG\_WIDTH, 3)) x = keras.applications.efficientnet.preprocess\_input(inputs) x = base\_model(x)

x = layers.Dropout(0.5)(x)

x = layers.Dense(256, activation='relu')(x)

outputs = layers.Dense(4, activation='softmax')(x)

model = keras.Model(inputs

, outputs)

model.compile(

optimizer=keras.optimizers.Adam(1e-4),

loss='sparse\_categorical\_crossentropy',

metrics=['accuracy']

)

return model

model = build\_model()

# 3. Callbacks

callbacks = [

keras.callbacks.EarlyStopping(patience=10, restore\_best\_weights=True), keras.callbacks.ReduceLROnPlateau(factor=0.1, patience=5) ]

# 4. Train with proper serialization

history = model.fit(

train\_ds,

validation\_data=val\_ds,

epochs=EPOCHS,

callbacks=callbacks,

class\_weight=class\_weights # Now using native Python dict )

# 5. Evaluation

test\_loss, test\_acc = model.evaluate(test\_ds)

print(f"\nTest Accuracy: {test\_acc:.2%}")

for images, labels in train\_ds.take(1):

print(labels.shape)

print(labels.numpy())

from tensorflow.keras.applications import ResNet50

from tensorflow.keras.models import Model

from tensorflow.keras.layers import Dense, GlobalAveragePooling2D from tensorflow.keras.optimizers import Adam

EPOCHS = 50

# Load ResNet50 base model

base\_model\_resnet = ResNet50(weights='imagenet', include\_top=False, input\_shape=(224, 224, 3))

base\_model\_resnet.trainable = False

# Add custom layers

x = base\_model\_resnet.output

x = GlobalAveragePooling2D()(x)

x = Dense(512, activation='relu')(x)

predictions\_resnet = Dense(4, activation='softmax')(x)

# Final model

model\_resnet = Model(inputs=base\_model\_resnet.input, outputs=predictions\_resnet)

# Compile

model\_resnet.compile(optimizer=Adam(learning\_rate=0.0001),

loss='sparse\_categorical\_crossentropy', metrics=['accuracy'])

# Train

history\_resnet = model\_resnet.fit(

train\_ds,

validation\_data=val\_ds,

epochs=EPOCHS,

callbacks=callbacks,

class\_weight=class\_weights,

initial\_epoch=0

)

# Print final training and validation accuracy for ResNet50

final\_train\_acc\_resnet = history\_resnet.history['accuracy'][-1]

final\_val\_acc\_resnet = history\_resnet.history['val\_accuracy'][-1]

print(f"ResNet50 Final Training Accuracy: {final\_train\_acc\_resnet:.4f}") print(f"ResNet50 Final Validation Accuracy: {final\_val\_acc\_resnet:.4f}")

import matplotlib.pyplot as plt

# Plot training & validation accuracy values

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)

# plt.plot(history.history['accuracy'], label='EfficientNet Train') # plt.plot(history.history['val\_accuracy'], label='EfficientNet Val') plt.plot(history\_resnet.history['accuracy'], label='ResNet50 Train') plt.plot(history\_resnet.history['val\_accuracy'], label='ResNet50 Val') # plt.plot(history\_vgg.history['accuracy'], label='VGG16 Train') # plt.plot(history\_vgg.history['val\_accuracy'], label='VGG16 Val') plt.title('Model Accuracy Comparison')

plt.ylabel('Accuracy')

plt.xlabel('Epoch')

plt.legend()

# Plot training & validation loss values

plt.subplot(1, 2, 2)

# plt.plot(history.history['loss'], label='EfficientNet Train') # plt.plot(history.history['val\_loss'], label='EfficientNet Val') plt.plot(history\_resnet.history['loss'], label='ResNet50 Train') plt.plot(history\_resnet.history['val\_loss'], label='ResNet50 Val')

# plt.plot(history\_vgg.history['loss'], label='VGG16 Train') # plt.plot(history\_vgg.history['val\_loss'], label='VGG16 Val') plt.title('Model Loss Comparison')

plt.ylabel('Loss') plt.xlabel('Epoch') plt.legend()

plt.tight\_layout() plt.show()

**EFFICIENTNET**

from google.colab import drive

drive.mount('/content/drive')

!pip install keras==2.12.0 tensorflow==2.12.0

!pip install tensorflow-addons

import tensorflow as tf

from tensorflow import keras

from tensorflow.keras import layers

from tensorflow.keras.applications import EfficientNetB0

from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau

import numpy as np

import collections

import os

print(os.listdir("/content/drive/MyDrive/test (1)"))

print("TensorFlow Version:", tf.\_\_version\_\_)

!pip install split-folders

import splitfolders

input\_file = "/content/drive/MyDrive/test (1)"

output\_file = "/content/drive/MyDrive/test (1)\_splitted"

splitfolders.ratio(input\_file, output=output\_file, seed=1345, ratio=(0.8, 0.1, 0.1), group\_prefix=None)

# Add this cell after the existing imports

from tensorflow.keras.applications import ResNet50, VGG16 from tensorflow.keras.models import Model

from tensorflow.keras.layers import Dense, GlobalAveragePooling2D

# Constants (same as before)

IMG\_HEIGHT = 224

IMG\_WIDTH = 224

BATCH\_SIZE = 32

EPOCHS = 50

# Data loading (same as before)

train\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/train",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=BATCH\_SIZE

)

val\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/val",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=BATCH\_SIZE

)

test\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/test",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=BATCH\_SIZE

)

class\_names = train\_ds.class\_names

print(class\_names)

print(os.path.exists(output\_file))

print(os.listdir(output\_file))

# Custom JSON encoder to handle TensorFlow tensors

import json

class TensorEncoder(json.JSONEncoder):

def default(self, obj):

if isinstance(obj, tf.Tensor):

return obj.numpy().tolist()

return super().default(obj)

import tensorflow as tf

from tensorflow import keras

from tensorflow.keras import layers

from tensorflow.keras.applications import EfficientNetB0 from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau

import numpy as np

import collections

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.metrics import classification\_report, confusion\_matrix import tensorflow\_addons as tfa

# Constants

IMG\_HEIGHT = 224 # Increased for better feature extraction IMG\_WIDTH = 224

BATCH\_SIZE = 32

EPOCHS = 50

train\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/train",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=64

)

test\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/test",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=64

)

val\_ds = tf.keras.preprocessing.image\_dataset\_from\_directory( "/content/drive/MyDrive/test (1)\_splitted/val",

seed=123,

image\_size=(IMG\_HEIGHT, IMG\_WIDTH),

batch\_size=64

)

class\_names = train\_ds.class\_names

print(class\_names)

train\_ds

plt.figure(figsize=(20, 10))

for images, labels in train\_ds.take(1):

for i in range(40):

ax = plt.subplot(5, 8, i + 1)

plt.imshow(images[i].numpy().astype("uint8"))

plt.title(class\_names[labels[i]])

plt.axis("off")

# Visualize class distribution

plt.figure(figsize=(10, 5))

class\_counts = []

for class\_name in class\_names:

class\_path = os.path.join("/content/drive/MyDrive/test (1)", class\_name) class\_counts.append(len(os.listdir(class\_path)))

plt.bar(class\_names, class\_counts)

plt.title('Class Distribution in Dataset')

plt.xlabel('Classes')

plt.ylabel('Number of Images')

plt.xticks(rotation=45)

plt.show()

# Data Augmentation

data\_augmentation = keras.Sequential([

layers.RandomFlip("horizontal\_and\_vertical"), layers.RandomRotation(0.2),

layers.RandomZoom(0.2),

layers.RandomContrast(0.1),

])

# 1. Convert class weights to regular Python floats def get\_class\_weights(dataset):

class\_counts = {}

for \_, labels in dataset.unbatch():

label = labels.numpy()

class\_counts[label] = class\_counts.get(label, 0) + 1 total\_samples = sum(class\_counts.values()) num\_classes = len(class\_counts)

# Convert to native Python floats

class\_weights = {

i: float(total\_samples / (num\_classes \* count)) for i, count in class\_counts.items()

}

return class\_weights

class\_weights = get\_class\_weights(train\_ds) print("Class weights:", class\_weights)

# 2. Build Model (simplified)

def build\_model():

base\_model = keras.applications.EfficientNetB0(

input\_shape=(IMG\_HEIGHT, IMG\_WIDTH, 3),

include\_top=False,

weights='imagenet',

pooling='avg'

)

base\_model.trainable = True

inputs = keras.Input(shape=(IMG\_HEIGHT, IMG\_WIDTH, 3)) x = keras.applications.efficientnet.preprocess\_input(inputs) x = base\_model(x)

x = layers.Dropout(0.5)(x)

x = layers.Dense(256, activation='relu')(x)

outputs = layers.Dense(4, activation='softmax')(x)

model = keras.Model(inputs, outputs)

model.compile(

optimizer=keras.optimizers.Adam(1e-4),

loss='sparse\_categorical\_crossentropy',

metrics=['accuracy']

)

return model

model = build\_model()

# 3. Callbacks

callbacks = [

keras.callbacks.EarlyStopping(patience=10, restore\_best\_weights=True), keras.callbacks.ReduceLROnPlateau(factor=0.1, patience=5) ]

# 4. Train with proper serialization

history = model.fit(

train\_ds,

validation\_data=val\_ds,

epochs=EPOCHS,

callbacks=callbacks,

class\_weight=class\_weights # Now using native Python dict )

# 5. Evaluation

test\_loss, test\_acc = model.evaluate(test\_ds)

print(f"\nTest Accuracy: {test\_acc:.2%}")

for images, labels in train\_ds.take(1):

print(labels.shape)

print(labels.numpy())

from tensorflow.keras.applications import ResNet50

from tensorflow.keras.models import Model

from tensorflow.keras.layers import Dense, GlobalAveragePooling2D from tensorflow.keras.optimizers import Adam

EPOCHS = 50

# Load ResNet50 base model

base\_model\_resnet = ResNet50(weights='imagenet', include\_top=False, input\_shape=(224, 224, 3))

base\_model\_resnet.trainable = False

# Add custom layers

x = base\_model\_resnet.output

x = GlobalAveragePooling2D()(x)

x = Dense(512, activation='relu')(x)

predictions\_resnet = Dense(4, activation='softmax')(x)

# Final model

model\_resnet = Model(inputs=base\_model\_resnet.input, outputs=predictions\_resnet)

# Compile

model\_resnet.compile(optimizer=Adam(learning\_rate=0.0001), loss='sparse\_categorical\_crossentropy', metrics=['accuracy'])

# Train

history\_resnet = model\_resnet.fit(

train\_ds,

validation\_data=val\_ds,

epochs=EPOCHS,

callbacks=callbacks,

class\_weight=class\_weights,

initial\_epoch=0

)

# Print final training and validation accuracy for ResNet50 final\_train\_acc\_resnet = history\_resnet.history['accuracy'][-1] final\_val\_acc\_resnet = history\_resnet.history['val\_accuracy'][-1] print(f"ResNet50 Final Training Accuracy: {final\_train\_acc\_resnet:.4f}") print(f"ResNet50 Final Validation Accuracy: {final\_val\_acc\_resnet:.4f}") import matplotlib.pyplot as plt

# Plot training & validation accuracy values

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)

plt.plot(history\_efficientnet.history['accuracy'], label='EfficientNet Train') plt.plot(history\_efficientnet.history['val\_accuracy'], label='EfficientNet Val') plt.plot(history\_resnet.history['accuracy'], label='ResNet50 Train')

plt.plot(history\_resnet.history['val\_accuracy'], label='ResNet50 Val')

# plt.plot(history\_vgg.history['accuracy'], label='VGG16 Train') # plt.plot(history\_vgg.history['val\_accuracy'], label='VGG16 Val') plt.title('Model Accuracy Comparison')

plt.ylabel('Accuracy')

plt.xlabel('Epoch')

plt.legend()

# Plot training & validation loss values

plt.subplot(1, 2, 2)

plt.plot(history\_efficientnet.history['loss'], label='EfficientNet Train') plt.plot(history\_efficientnet.history['val\_loss'], label='EfficientNet Val') plt.plot(history\_resnet.history['loss'], label='ResNet50 Train') plt.plot(history\_resnet.history['val\_loss'], label='ResNet50 Val') # plt.plot(history\_vgg.history['loss'], label='VGG16 Train') # plt.plot(history\_vgg.history['val\_loss'], label='VGG16 Val') plt.title('Model Loss Comparison')

plt.ylabel('Loss')

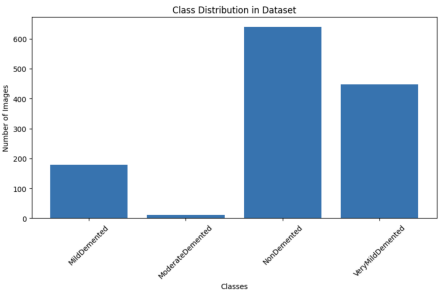
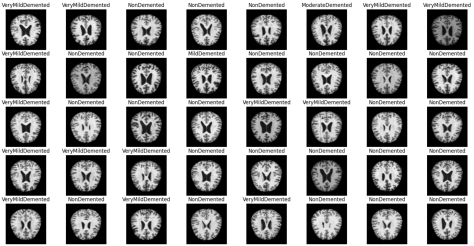
plt.xlabel('Epoch')

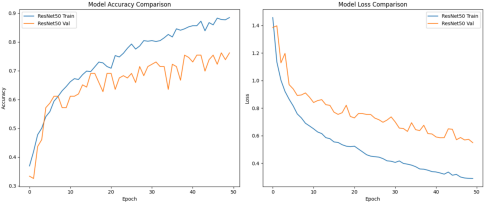
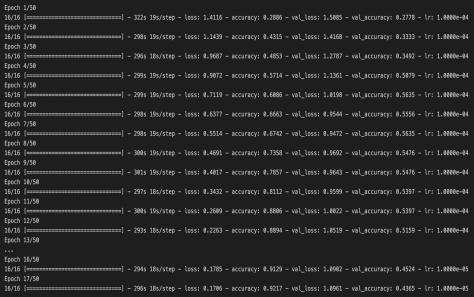
plt.legend()

plt.tight\_layout()

plt.show()

**APPENDIX-2: SCREENSHOTS**

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**FUTURE ENHANCEMENT**

To build upon the current project’s achievements and address its limitations, several strategic enhancements are proposed to improve the accuracy, robustness, and clinical applicability of the deep learning framework for early Alzheimer’s disease detection:

1. **Larger Dataset**: The current dataset of 1279 MRI scans limits model generalization due to its modest size. Expanding the dataset by incorporating larger, more diverse collections, such as the Alzheimer’s Disease Neuroimaging Initiative (ADNI) or Open Access Series of Imaging Studies (OASIS), would provide a richer variety of brain MRI scans. This would enhance the model’s ability to learn generalized features, improve performance across diverse populations, and reduce overfitting risks, leading to more reliable diagnostic outcomes.

2. **Multimodal Data Integration**: Relying solely on MRI scans restricts the model’s diagnostic scope. Integrating multimodal data, such as cognitive scores from neuropsychological tests and genetic markers (e.g., APOE gene variants), alongside imaging data, could provide a more comprehensive view of Alzheimer’s disease progression. This approach, inspired by recent studies, would enable the model to capture complementary patterns across data types, potentially improving classification accuracy and early detection sensitivity.

3. **Model Exploration and Optimization**: While ResNet50 performed well, further exploration of other architectures is warranted. Implementing and evaluating VGG16, known for its simplicity and depth, could offer comparative insights into

its suitability for this task. Additionally, revisiting EfficientNetB0 with hyperparameter tuning, increased regularization, or additional data could address its overfitting issues, potentially unlocking its efficiency for resource-constrained environments.

4. **Ensemble Models**: To enhance robustness and accuracy, ensemble models combining predictions from multiple architectures, such as ResNet50, VGG16, and potentially others like DenseNet, could be developed. By leveraging the strengths of diverse models, ensemble methods would mitigate individual model weaknesses, improve classification reliability, and provide more stable predictions across varied MRI scans, as demonstrated in prior literature.

5. **3D Convolutional Neural Networks (3D CNNs)**: The current 2D CNNs process MRI slices independently, potentially missing spatial relationships within the brain’s volumetric structure. Adopting 3D CNNs would allow the model to capture spatial MRI features across the entire volume, enhancing the detection of subtle neurological changes indicative of early Alzheimer’s disease. This approach, though computationally intensive, could significantly improve diagnostic precision.

6. **Explainability for Clinical Trust**: To facilitate adoption in clinical settings, enhancing model explainability is crucial. Techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) or SHAP (SHapley Additive exPlanations) can visualize which regions of the MRI scans influence the model’s predictions, providing interpretable insights for clinicians. This transparency

would build trust, enabling radiologists to validate model outputs and integrate them into diagnostic workflows confidently.

7. **Real-Time Deployment**: To maximize practical impact, deploying the model via a web interface would enable clinicians to upload MRI scans and receive classification results in real time. This user-friendly platform, supported by cloud-based infrastructure, would streamline the diagnostic process, reduce manual effort, and make the tool accessible to healthcare providers globally, thereby enhancing its scalability and clinical utility.

**CONCLUSION**

This project successfully developed a sophisticated deep learning framework for the early detection of Alzheimer’s disease (AD), leveraging brain MRI scans to classify them into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The cornerstone of this framework was the ResNet50 model, which delivered a robust validation accuracy of 72.22%, demonstrating its effectiveness in identifying early AD signatures. In contrast, EfficientNetB0, while tested, achieved a significantly lower test accuracy of 51.15%, primarily due to overfitting, underscoring ResNet50’s superior suitability for this task. Key challenges, including class imbalance and a limited dataset of 1279 images, were effectively mitigated through class weighting, which prioritized underrepresented classes like Moderate Demented, and data augmentation, employing rotations, flips, and zooms to enhance dataset diversity. These strategies ensured balanced learning and improved model generalization

The strong performance of ResNet50 highlights its potential as a reliable, automated tool to assist clinicians in diagnosing AD, offering a non-invasive approach that could reduce diagnostic errors, alleviate clinician workload, and enable timely interventions to improve patient outcomes. Looking ahead, future work will focus on exploring VGG16 to compare its performance with ResNet50, optimizing EfficientNetB0 through hyperparameter tuning and additional data to address its overfitting issues, and integrating multimodal data, such as cognitive scores and genetic markers, to enhance diagnostic precision. Additionally, incorporating explainability techniques like Grad-CAM or SHAP will be prioritized to provide transparent insights into model decisions, fostering clinical trust and facilitating adoption in medical practice. By addressing these areas, the framework aims to evolve into a scalable, clinically viable solution, contributing significantly to the advancement of AI-driven diagnostics for early Alzheimer’s disease detection.

**REFERENCES**

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ResNet and DenseNet, achieving an AUC of 0.93 on ADNI data, demonstrating the robustness of ensemble methods in handling diverse MRI datasets. 5. Jo, T., et al. (2022). Multimodal deep learning for Alzheimer’s disease diagnosis. *Journal of Alzheimer’s Disease, 85*(2), 683–692. This study integrated MRI scans with clinical data, achieving a 91% accuracy, underscoring the potential of multimodal approaches to enhance AD classification by leveraging complementary data sources.

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subtle brain changes, supporting the exploration of 3D models for improved spatial feature extraction.

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