**SASTRA DEEMED TO BE UNIVERSITY**
**DEPARTMENT OF CSE, B-TECH MINI PROJECT,2024-2025**
**SECOND REVIEW**

# FINE-TUNING ALZHEIMER'S DISEASE DIAGNOSIS USING IMPROVED WAVELET CONVOLUTION NEURAL NETWORK [IWCNN]


**TEAM MEMBERS:**

Bhuvana B - 226003022
Harini J - 226003170
Chitte Renuka Reddy - 226003034

**GUIDED BY**

Dr. R Thanuja,
Assistant Professor – II,
Department of CSE, SRC .

## CONTENTS:


- Base paper Title and Info
- Abstract
- Problem Statement
- Literature Survey
- Architecture Diagram
- Work Plan
- Feature Extraction Algorithms
- Dataset Description
- Implementation
- Result
- List of References

# BASE PAPER:

- **Title:** Advancing early diagnosis of Alzheimer's disease with next-generation deep learning methods
- **Authors:** Cuneyt Ozdemir, Yahya Dogan, **Journal:** Biomedical Signal Processing and Control
- **Volume:** Volume 96
- **Publication Date:** July2024
- **Indexing:** SCI-E Q1
- **Publisher Name:** Elsevier

Biomedical Signal Processing and Control 96 (2024) 106614

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Advancing early diagnosis of Alzheimer's disease with next-generation deep learning methods

Cuneyt Ozdemir *, Yahya Dogan

*Computer Engineering, Engineering Faculty, Siirt University, 56100, Siirt, Turkey*

ARTICLE INFO

Dataset link: https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images

*Keywords:*
Alzheimer's disease
Deep learning
SMOTE
Squeeze and excitation block
Avg-TopK

ABSTRACT

Alzheimer's disease, characterized by cognitive decline and memory impairment, poses a significant healthcare challenge. This study presents a specially designed CNN model, utilizing contemporary approaches, to distinguish between various types of Alzheimer's disease. This model can serve as an early diagnostic tool to prevent the disease from progressing towards more pronounced and severe dementia symptoms. In this context, the performance of various transfer learning models has been examined, leading to the development of a specialized model integrating compression and excitation blocks, an innovative Avg-TopK pooling layer, and the SMOTE technique to handle data imbalance. The ablation study results demonstrate the critical role of these components, highlighting the model's effectiveness and innovative design. This study is novel in that it combines modern methodologies for detecting Alzheimer's disease, resulting in a model with state-of-the-art accuracy of 99.84% and improved computing efficiency. Grad-CAM analysis further demonstrates that the model focuses on cortical areas during classification, underscoring its potential as a robust diagnostic tool. These innovations represent a significant advancement over existing models, positioning this study as a pioneering effort in the early diagnosis of Alzheimer's disease. This study aims to contribute significantly to both academic research and medical applications by focusing on integrating artificial intelligence methodologies into medical diagnosis.

**1. Introduction**

Alzheimer's disease (AD) is a neurodegenerative disease primarily observed in the elderly population, characterized by cognitive decline, memory impairment, and behavioral changes [1,2]. As the disease progresses, cognitive abilities, including thinking skills and the ability to recall information, begin to deteriorate. AD is a leading cause of death worldwide, affecting individuals, families, and healthcare systems [3,4]. AD was initially identified by Dr. Alois Alzheimer in 1907. The disease was diagnosed in a 51-year-old female patient who was undergoing treatment at the psychiatric hospital in Frankfurt am Main. As the disease progressed, the patient exhibited various complex symptoms and experienced significant memory loss. It was observed that she could correctly name a series of objects when shown to her, but shortly after, she would forget everything. Additionally, difficulties in comprehension, hallucinations, and reading problems were detected. The disease process lasted for approximately four and a half years, and the patient passed away at the end of this period [5]. The World Health Organization (WHO) has indicated that approximately 10 million new cases are reported each year, and globally, more than 55 million people live with dementia, with over 60% of these residing in low and middle-income countries. Dementia is currently the seventh leading cause of death and leads to disability and dependency among the elderly population worldwide [6].

AD is one of the most common diseases in elderly individuals, characterized by a gradual slowing and deterioration of cognitive abilities. Early symptoms of the disease include difficulties in recent memory recall, word-finding difficulties, repetition, multitasking impairments, and mood or behavioral changes. As the disease progresses, individuals may experience more pronounced memory loss, lose simple functions such as dressing or bathing, encounter difficulties in language and comprehension, exhibit aggression, engage in wandering behavior, and even experience hallucinations. The severity of symptoms corresponds to the extent of nerve cell damage in the brain [7–9].

The rapid and accurate diagnosis of AD is crucial for effective disease management and treatment. Recently, CNN models have achieved notable success in various fields, including healthcare services [10–16]. Despite their success, current methodologies often face constraints such as high computational requirements and inefficiencies when dealing with imbalanced datasets. These challenges highlight the need for innovative approaches that are both effective and resource-efficient.

* Corresponding author.
*E-mail addresses:* cozdemir@siirt.edu.tr (C. Ozdemir), yahyadogan@siirt.edu.tr (Y. Dogan).

https://doi.org/10.1016/j.bspc.2024.106614
Received 23 August 2023; Received in revised form 29 May 2024; Accepted 25 June 2024
Available online 6 July 2024

## ABSTRACT

Alzheimer's disease(AD) is a progressive neurodegenerative disorder marked by memory loss and cognitive decline. Traditional diagnostics are often subjective, prompting the need for automated solutions. This project applies **Discrete Wavelet Transform (DWT)** to MRI scans, enhancing structural features. These are used to train an **Improved Wavelet CNN** for multi-class classification (AD, NC, EMCI, LMCI). **Synthetic Minority Oversampling Technique** (SMOTE) handles class imbalance by generating synthetic samples, while **Gradient-weighted Class Activation Mapping** (Grad-CAM) improves model interpretability by highlighting key brain regions. The proposed WCNN achieves **95.62% test accuracy**, outperforming baseline and deeper CNN models. This approach offers a reliable and interpretable tool for early Alzheimer's detection.

## PROBLEM STATEMENT:

- Alzheimer's disease remains challenging to detect in its early stages, limiting timely intervention and effective treatment. Existing diagnostic methods, including traditional assessments and AI-based models, often struggle with accuracy and reliability.
- One major challenge is the imbalance in MRI datasets, where fewer cases of severe Alzheimer's leads to biased models that underperform on underrepresented categories. Additionally, conventional CNNs primarily extract spatial features but struggle to capture crucial frequency-based patterns, reducing classification accuracy. Moreover, deep learning models often function as black boxes, offering little transparency in their decision-making process, which makes clinical adoption difficult.

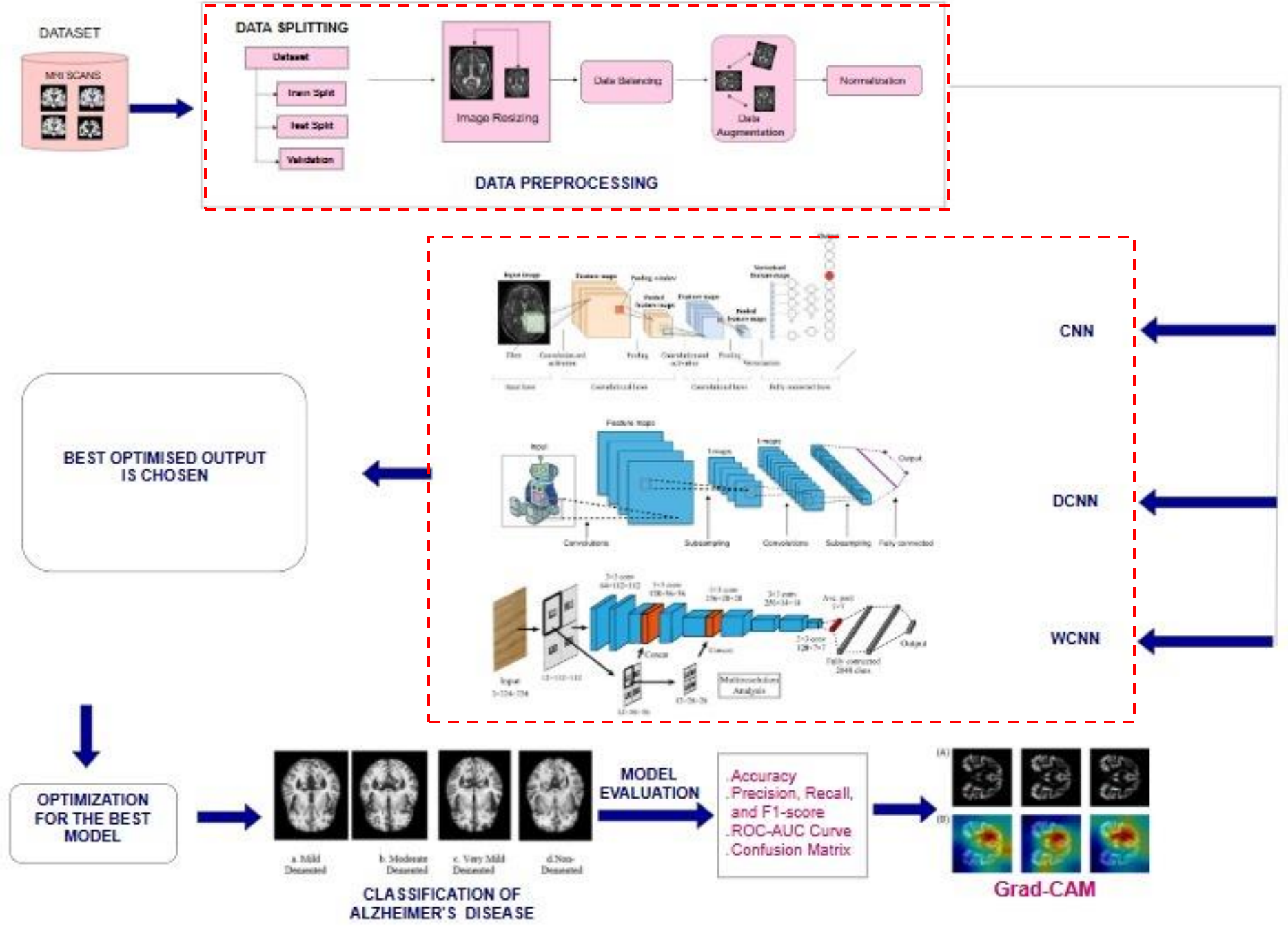
# LITERATURE SURVEY

| S.NO | TITLE | JOURNAL | YEAR | AUTHOR(S) | TECHNIQUES USED | MERITS | DEMERITS |
|---|---|---|---|---|---|---|---|
| 1. | **Pipelined Deep Learning Architecture for the Detection of Alzheimer's Disease** | Biomedical Signal Processing and Control (Science Direct) | 2024 | T. Prasath, V. Sumathi | Pipelined LeNet (PLN) architecture, Image Fusion, MRI preprocessing | High classification accuracy (99.5%), faster execution time (0.65 ms) | Limited evaluation on real-world diverse datasets |
| 2. | **Machine and Deep Learning Approaches for Alzheimer's Disease Detection Using Magnetic Resonance Images: An Updated Review** | Measurement (Science Direct) | 2024 | M. Menagadevi, Somasundaram Devaraj, et al. | CNN, SVM, Transfer Learning, Preprocessing (Histogram Equalization, Contrast Stretching) | Comprehensive review covering 2013-2023 studies, highlights key ML and DL techniques | Lacks experimental validation of reviewed techniques |
| 3. | **Bio-Inspired Deep Learning-Personalized Ensemble Alzheimer's Diagnosis Model for Mental Well-Being** | SLAS Technology (Science Direct) | 2024 | Ajmeera Kiran, Mahmood Alsaadi, et al. | Personalized dynamically ensemble CNN (PDECNN), Attention Mechanism | Improves classification accuracy by 4%-11%, adapts to variations in brain degeneration | High computational complexity |

| s.no | TITLE | JOURNAL | YEAR | AUTHOR(S) | TECHNIQUES USED | MERITS | DEMERITS |
|---|---|---|---|---|---|---|---|
| 4. | **Fine-Grained and Multiple Classification for Alzheimer's Disease With Wavelet Convolution Unit Network** | IEEE Transactions on Biomedical Engineering | 2023 | Jinyu Wen, Yang Li, Meie Fang, et al. | Wavelet Convolution Unit (WCU), Multi-scale Wavelet Decomposition, Diffusion Tensor Imaging (DTI) | Achieves state-of-the-art fine-grained classification accuracy (97.89%) | Requires extensive computational resources |
| 5. | **Detection of Alzheimer's Disease Using Deep Learning Models: A Systematic Literature Review** | Informatics in Medicine Unlocked | 2024 | Eqtidar M. Mohammed, Ahmed M. Fakhrudeen, et al. | Various CNN architectures (ResNet, AlexNet, GoogleNet, EfficientNetB7), RNN, Deep Belief Networks | Summarizes 45 research papers on AD detection using deep learning | Lacks focus on non-imaging biomarkers |

| s.no | TITLE | JOURNAL | YEAR | AUTHOR(S) | TECHNIQUES USED | MERITS | DEMERITS |
|---|---|---|---|---|---|---|---|
| 6. | **Deep Learning-based Alzheimer's disease classification using MRI and PET images** | Neuro computing | 2024 | R.S.Karthik, M.Sharma, etal. | CNN, Transfer learning, Multi-modal fusion(MRI + PET) | Achieves high classification Accuracy(98.2%). Effective multi-modal feature extraction. | Requires large-scale labelled datasets for training. |
| 7. | **Alzheimer's Disease Diagnosis using 3D Convolution Neural Networks and MRI scans** | Medical Image Analysis | 2024 | L Chen, H.Wang, et al. | 3D-CNN, Data Argumentation, Pretrained ResNet-50 | Effectively processes 3D brain scans, achieves robust feature extraction | Requires high computational power for 3D processing |
| 8. | **Hybrid Deep Learning Model for Early Detection of Alzheimer's Disease** | IEEE Access | 2023 | N. Verma, A. Gupta, et al. | Hybrid CNN-RNN architecture, Attention Mechanism | Improves early detection accuracy, extracts spatial and temporal features. | High training time and memory usage |

# ARCHITECTURE DIAGRAM


DATASET
MRI SCANS
DATA SPLITTING
Dataset
Train Split
Test Split
Validation
Image Resizing
Data Balancing
Data Augmentation
Normalization
DATA PREPROCESSING
CNN
DCNN
WCNN
BEST OPTIMISED OUTPUT IS CHOSEN
OPTIMIZATION FOR THE BEST MODEL
a. Mild Demented
b. Moderate Demented
c. Very Mild Demented
d.Non-Demented
CLASSIFICATION OF ALZHEIMER'S DISEASE
MODEL EVALUATION
.Accuracy
.Precision, Recall, and F1-score
.ROC-AUC Curve
.Confusion Matrix
Grad-CAM

# WORK PLAN :

## Module 1 : (23/01/2025 -16/02/2025)

**Dataset Understanding & Preprocessing**

- **Base Paper Analysis:** Studied algorithms and methodologies.
- **Dataset Collection:** Sourced MRI dataset from Kaggle.

## Module 2 : (19/02/2025 - 14/03/2025)

**Preprocessing, Feature Extraction & Model Training**

- **Preprocessing:** Grayscale conversion, resizing (128x128), normalization.
- **Class Balancing:** Applied SMOTE/oversampling to handle data imbalance.
- **Feature Extraction:** Squeeze-Excitation Networks, Avg-TopK Pooling.
- **Model Training:**
  1. **CNN (Baseline Model)** – Standard convolutional model.
  2. **DCNN (Deep CNN)** – Enhanced architecture with deeper layers.
  3. **WCNN(Wavelet-Based)** - Optimised Model

# WORK PLAN :

## Module 3 : (21/03/2025 -10/04/2025)

**Model Evaluation & Prediction**

- **Enhancements:** Train Improved Wavelet Convolution Neural Network.
- **Metrics:** Accuracy, Precision, Recall, F1-score, confusion matrix.
- **Comparison:** Evaluate CNN vs. DCNN vs. Wavelet-CNN.
- **Explainability:** Use Grad-CAM to visualize model focus areas.
- **Deployment:** Final model for Alzheimer's stage classification.

# FEATURE EXTRACTION ALGORITHMS

# AVERAGE-TOPK

- The **Average-topk** function computes the mean of the top k highest values in a given set, reducing sensitivity to outliers and improving stability in optimization tasks.
- Formula:

Let $X = \{x_1, x_2, \ldots, x_n\}$ be a set of $n$ numerical values.

1. **Sort** the values in descending order:

$$x_{(1)} \geq x_{(2)} \geq \cdots \geq x_{(n)}$$

where $x_{(i)}$ represents the $i$-th largest value in the set.

2. **Select the top-k values**:

$$S_k = \{x_{(1)}, x_{(2)}, \ldots, x_{(k)}\}$$

3. **Compute the AVERAGEtopk**:

$$\text{AVERAGEtopk}(X, k) = \frac{1}{k} \sum_{i=1}^{k} x_{(i)}$$

where $x_{(i)}$ are the top $k$ largest values from $X$.

# SQUEEZE-AND-EXCITATION BLOCK

- The **SE block** is like a smart filter for images in deep learning. It helps a neural network focus on the most important parts of an image while ignoring less useful details.

- It works in three simple steps:

1. **Squeeze** – Looks at the whole image and figures out what features are most important.
2. **Excitation** – Decides how much attention each feature should get.
3. **Recalibration** – Adjusts the image data to highlight the important parts and reduce the noise.

## 1. Squeeze (Global Average Pooling - GAP)

Each channel's global feature is computed as:

$$s_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_c(i,j)$$

where:

- $X_c(i,j)$ is the feature map value at position $(i,j)$ for channel $c$.
- $H, W$ are the height and width of the feature map.
- $s_c$ is the **global descriptor** for each channel.

## 2. Excitation (Fully Connected Layers & Activations)

The channel-wise attention scores are obtained using two fully connected layers:

$$z = \sigma(W_2 \delta(W_1 s))$$

where:

- $W_1$ and $W_2$ are learnable weight matrices.
- $\delta$ is the **ReLU activation** function.
- $\sigma$ is the **Sigmoid activation** to scale values between 0 and 1.
- $z$ is the attention weight for each channel.

## 3. Recalibration (Channel-wise Scaling)

The recalibrated feature map is obtained by scaling each channel with its corresponding attention weight:

$$X'_c = z_c \cdot X_c$$

where $z_c$ is the learned attention weight for channel $c$, and $X'_c$ is the enhanced feature map.

This process **amplifies important features** and **suppresses less useful ones**, improving CNN performance with minimal extra computation! 🚀

# CNN PSEUDOCODE:

**Input:**

d: dataset, l: dataset true labels, t: target size

**Output:**

Classified stage of Alzheimer's Disease on MRI scan

```
Let i be the MRI scan to be classified
for i in dataset do ImageDataGenerator
        ftrain, ftest, ltrain, ltest ← split feature set and labels
         into train subset and test subset
         S ← build_model(ftrain, ltrain)
         Let Conv2D be the convolutional layer and AvgTopKPooling be the pooling layer
         for j in layers do
            tf.keras.layers.Conv2D(filters, (3,3)padding="same", activation='relu')
            tf.keras.layers.BatchNormalization()
            tf.keras.layers.ReLU()
            se_block()

Let DIR be the path joining version for other paths

        for k in categories do
            DIR = main_path + 'category'
            dataset_length.append(category_length)
            Result ← evaluate(DIR, ltest, S)
Return result;
```

# DCNN PSEUDOCODE:

**Input:**

d: dataset, l: dataset true labels, t: target size

**Output:**

Classified stage of Alzheimer's Disease on MRI scan

```
Let i be the MRI scan to be classified
For i in dataset, do ImageDataGenerator
    ftrain, ftest, ltrain, ltest ← split feature set and labels into train subset and test subset
    S ← DCNN(ftrain, ltrain)
            Let Conv2D be the convolutional layer and AvgTopKPooling be the pooling layer
            for j in layers do
                tf.keras.layers.Conv2D(filters, (3,3), padding="same", activation='relu')
                AvgTopKPooling(k=3)
            Let DIR be the path joining version for other paths
            for k in categories do
                DIR = main_path + 'category'
                dataset_length.append(category_length)
                Result ← evaluate(DIR, ltest, S)
Return result;
```

# WCNN PSEUDOCODE:

**Input:**
d: dataset, l: dataset true labels, t: target size
**Output:**
Classified stage of Alzheimer's Disease on MRI scan

For i in dataset, do

Apply wavelet transform to i using Haar DWT

Retain only approximation coefficients (LL)

Reshape input to (64, 64, 1)

S ← WCNN (X_train, y_train)

For j in layers do

Conv2D (filters, (3,3), padding="same", activation='relu')

BatchNormalization()

MaxPooling2D ((2,2))

```
Flatten → Dense (256, 'relu') → Dropout (0.5) → Dense (4, 'softmax')
```
Evaluate (DIR, X_test, S)

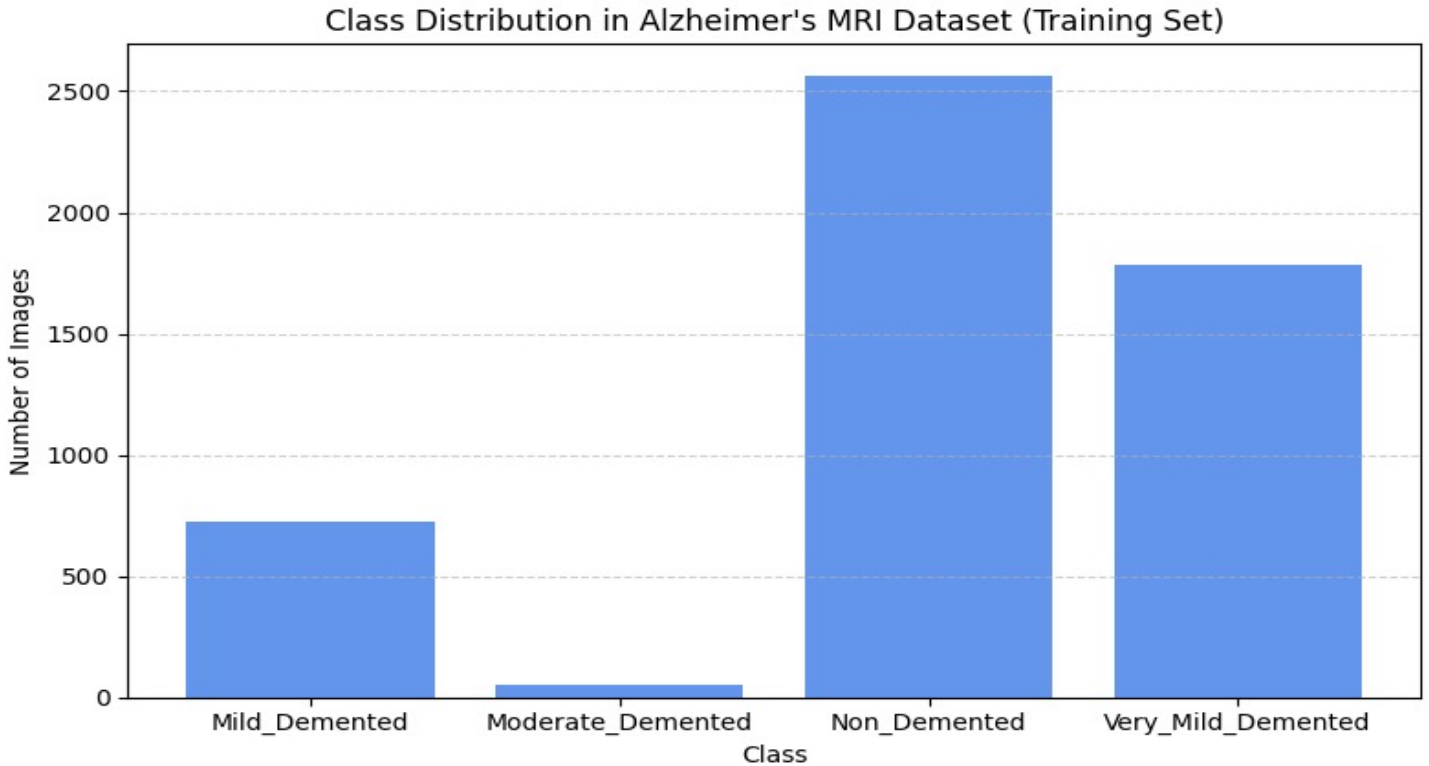
Return result

## DATASET DESCRIPTION :

The research uses an Alzheimer's disease brain MRI dataset from Kaggle, which contains 6,400 images classified into four different classes:

- Non-Demented
- Very Mild Demented
- Mild Demented
- Moderate Demented

**Dataset Link:**
https://www.kaggle.com/datasets/borhanitrash/alzheimer-mri-disease-classification-dataset




| Class | Training Set | Validation Set | Test Set |
|---|---|---|---|
| Mild Demented (0) | 579 images | 145 images | 172 images |
| Moderate Demented (1) | 39 images | 10 images | 15 images |
| Non-Demented (2) | 2053 images | 513 images | 634 images |
| Very Mild Demented (3) | 1425 images | 356 images | 459 images |

# IMPLEMENTATION

```python
import pandas as pd

# Correct file paths
train_path = "/kaggle/input/alzheimer-mri-disease-classification-dataset/Alzheimer MRI Disease Classification Dataset/Data/train-00000-of-00001-c08a401c53fe5312.parquet"
test_path = "/kaggle/input/alzheimer-mri-disease-classification-dataset/Alzheimer MRI Disease Classification Dataset/Data/test-00000-of-00001-44110b9df98c5585.parquet"

# Load the datasets
train_df = pd.read_parquet(train_path)
test_df = pd.read_parquet(test_path)

# Display first few rows
print("Train Data:")
display(train_df.head())

print("\nTest Data:")
display(test_df.head())
```

```
Train Data:
```

| | image | label |
|---|---|---|
| 0 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 2 |
| 1 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 0 |
| 2 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 3 |
| 3 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 3 |
| 4 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 2 |

```
Test Data:
```

| | image | label |
|---|---|---|
| 0 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 3 |
| 1 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 0 |
| 2 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 2 |
| 3 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 3 |
| 4 | {'bytes': b'\xff\xd8\xff\xe0\x00\x10JFIF\x00\x... | 0 |

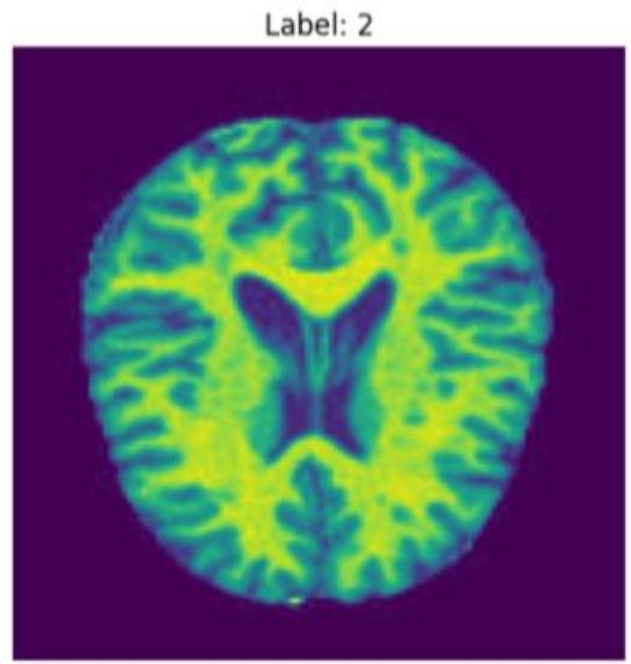
```python
# Check unique class labels
print("Unique Labels in Train Dataset:")
print(train_df["label"].unique())

# Count instances per class
print("\nClass Distribution:")
print(train_df["label"].value_counts())
```

```
Unique Labels in Train Dataset:
[2 0 3 1]

Class Distribution:
label
2    2566
3    1781
0     724
1      49
Name: count, dtype: int64
```

```python
#convert all images to NumPy arrays for model training
import tensorflow as tf

# Function to process images
def preprocess_image(image_data):
    img = decode_image(image_data)  # Decode
    img = img.resize((128, 128))  # Resize
    img = np.array(img) / 255.0  # Normalize
    return img

# Apply transformation
X_train = np.array([preprocess_image(i['bytes']) for i in train_df["image"]])
y_train = np.array(train_df["label"])

X_test = np.array([preprocess_image(i['bytes']) for i in test_df["image"]])
y_test = np.array(test_df["label"])

print(f"Processed Train Data: {X_train.shape}, Labels: {y_train.shape}")
print(f"Processed Test Data: {X_test.shape}, Labels: {y_test.shape}")
```

```
Processed Train Data: (5120, 128, 128), Labels: (5120,)
Processed Test Data: (1280, 128, 128), Labels: (1280,)
```

```python
#Decode Image Data
import io
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image

# Function to decode image
def decode_image(image_data):
    return Image.open(io.BytesIO(image_data))

# Extract the first image
first_image_data = train_df["image"].iloc[0]['bytes']
first_image = decode_image(first_image_data)

# Display image
plt.imshow(first_image)
plt.axis("off")
plt.title(f"Label: {train_df['label'].iloc[0]}")
plt.show()
```

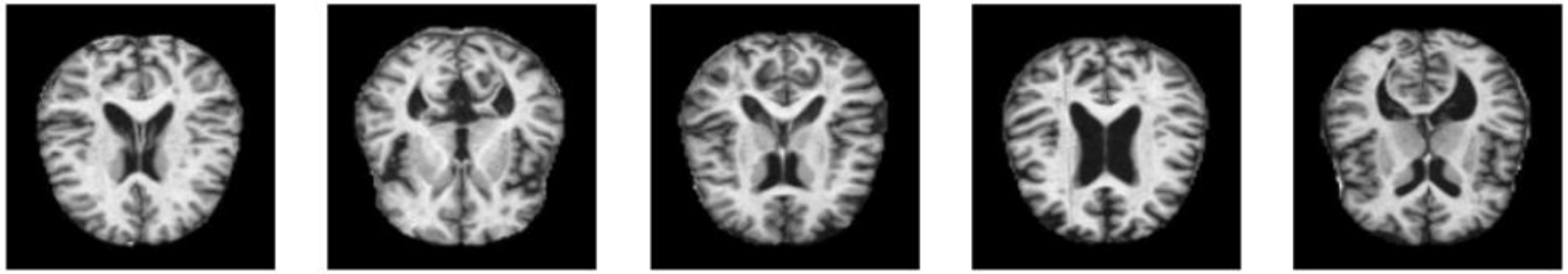


# PREPROCESSED IMAGES:

```
print(X_train.shape)  #gray-scale image
```

```
(5120, 128, 128)
```

```
import matplotlib.pyplot as plt

# Show some grayscale images
plt.figure(figsize=(10, 5))
for i in range(5):  # Show first 5 images
    plt.subplot(1, 5, i + 1)
    plt.imshow(X_train[i], cmap="gray")  # Use cmap="gray" for grayscale images
    plt.axis("off")

plt.show()
```



```python
# 1️⃣ Split training data into training & validation sets
# 2️⃣ Apply SMOTE to balance classes in the training set
from sklearn.model_selection import train_test_split

# Split into train and validation (80-20 split)
X_train_res, X_val, y_train_res, y_val = train_test_split(
    X_train, y_train, test_size=0.2, stratify=y_train, random_state=42
)

print(f"Train Set: {X_train_res.shape}, Labels: {y_train_res.shape}")
print(f"Validation Set: {X_val.shape}, Labels: {y_val.shape}")
```

```
Train Set: (4096, 128, 128), Labels: (4096,)
Validation Set: (1024, 128, 128), Labels: (1024,)
```

```python
from imblearn.over_sampling import SMOTE

# Reshape for SMOTE (flatten images)
X_train_flat = X_train_res.reshape(X_train_res.shape[0], -1)

# Apply SMOTE
smote = SMOTE(random_state=42)
X_train_balanced, y_train_balanced = smote.fit_resample(X_train_flat, y_train_res)

# Reshape back to image format
X_train_balanced = X_train_balanced.reshape(-1, 128, 128)

print(f"Balanced Train Set: {X_train_balanced.shape}, Labels: {y_train_balanced.shape}")
```

```
Balanced Train Set: (8212, 128, 128), Labels: (8212,)
```

```python
#Build CNN Model with SE Blocks & Avg-TopK Pooling
import tensorflow as tf
from tensorflow.keras.layers import Conv2D, Dense, Dropout, GlobalAveragePooling2D, Multiply, Reshape

# Squeeze & Excitation Block
def se_block(input_tensor, ratio=16):
    """Squeeze & Excitation Block"""
    filters = input_tensor.shape[-1]

    # Squeeze: Global Average Pooling
    se = GlobalAveragePooling2D()(input_tensor)
    se = Dense(filters // ratio, activation="relu")(se)
    se = Dense(filters, activation="sigmoid")(se)

    # Excite: Scale feature maps
    se = Reshape((1, 1, filters))(se)
    return Multiply()([input_tensor, se])
```

```python
import tensorflow.keras.backend as K
from tensorflow.keras.layers import Layer

class AvgTopKPooling(Layer):
    """Avg-TopK Pooling Layer"""
    def __init__(self, k=3, **kwargs):
        super(AvgTopKPooling, self).__init__(**kwargs)
        self.k = k

    def call(self, inputs):
        top_k, _ = tf.math.top_k(inputs, k=self.k, sorted=False)
        return K.mean(top_k, axis=-1)

    def compute_output_shape(self, input_shape):
        return input_shape[:-1]
```

# MODEL 1: CNN

```python
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, BatchNormalization, ReLU, Flatten, Dense, Dropout

# Define CNN Model
def build_model(input_shape=(128, 128, 1), num_classes=4):
    inputs = Input(shape=input_shape)

    # Block 1
    x = Conv2D(32, (3, 3), padding="same")(inputs)
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Block 2
    x = Conv2D(64, (3, 3), padding="same")(x)
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Block 3
    x = Conv2D(128, (3, 3), padding="same")(x)
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Block 4
    x = Conv2D(256, (3, 3), padding="same")(x)
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Avg-TopK Pooling
    x = AvgTopKPooling(k=3)(x)

    # Flatten & Fully Connected Layers
    x = Flatten()(x)
    x = Dense(128, activation="relu")(x)
    x = Dropout(0.3)(x)
    x = Dense(64, activation="relu")(x)
    x = Dropout(0.3)(x)

    # Output Layer
    outputs = Dense(num_classes, activation="softmax")(x)

    model = Model(inputs, outputs)
    return model
```

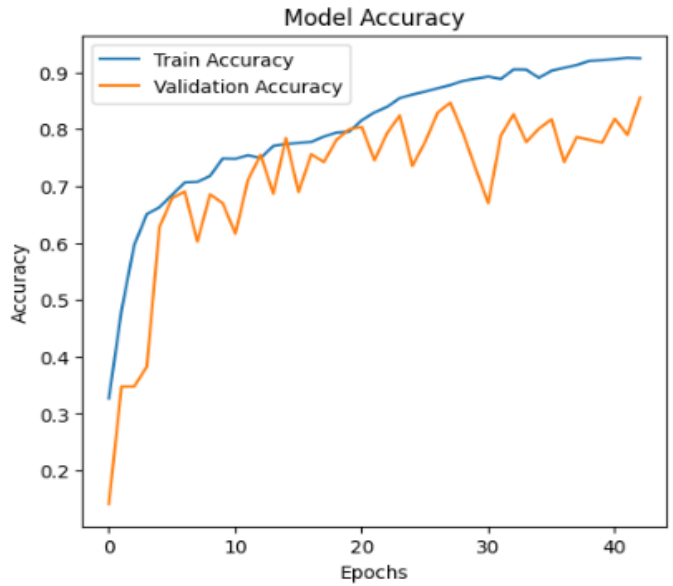
# MODEL 2: DCNN

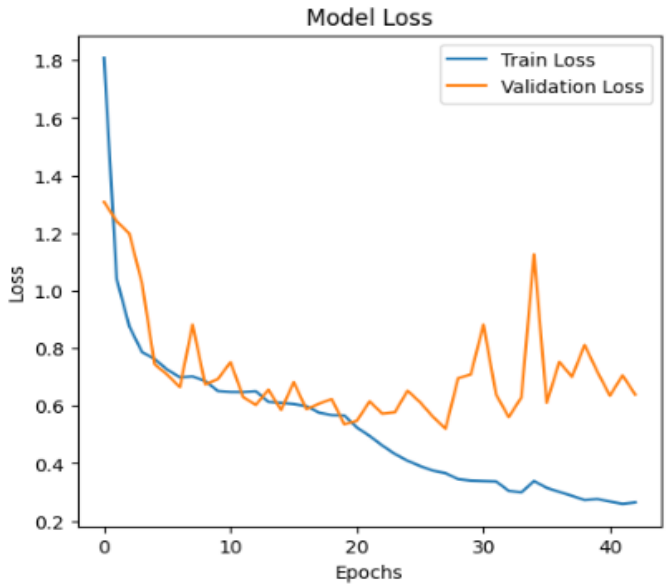
```python
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, BatchNormalization, ReLU, Flatten, Dense, Dropout

# Define Deep CNN Model
def build_model(input_shape=(128, 128, 1), num_classes=4):
    inputs = Input(shape=input_shape)

    # Block 1
    x = Conv2D(32, (3, 3), padding="same")(inputs)
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Block 2
    x = Conv2D(64, (3, 3), padding="same", strides=2)(x)  # Downsampling with stride
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Block 3
    x = Conv2D(128, (3, 3), padding="same")(x)
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Block 4
    x = Conv2D(256, (3, 3), padding="same", strides=2)(x)  # Another downsampling
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Block 5
    x = Conv2D(512, (3, 3), padding="same")(x)
    x = BatchNormalization()(x)
    x = ReLU()(x)
    x = se_block(x)

    # Avg-TopK Pooling
    x = AvgTopKPooling(k=3)(x)

    # Flatten & Fully Connected Layers
    x = Flatten()(x)
    x = Dense(256, activation="relu")(x)
    x = Dropout(0.4)(x)
    x = Dense(128, activation="relu")(x)
    x = Dropout(0.3)(x)
    x = Dense(64, activation="relu")(x)
    x = Dropout(0.3)(x)

    # Output Layer
    outputs = Dense(num_classes, activation="softmax")(x)

    model = Model(inputs, outputs)
    return model
```

# MODEL 1: CNN

```python
# Evaluate on test data
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=1)

print(f"\nTest Accuracy: {test_acc*100:.2f}%")
print(f"Test Loss: {test_loss:.4f}")
```

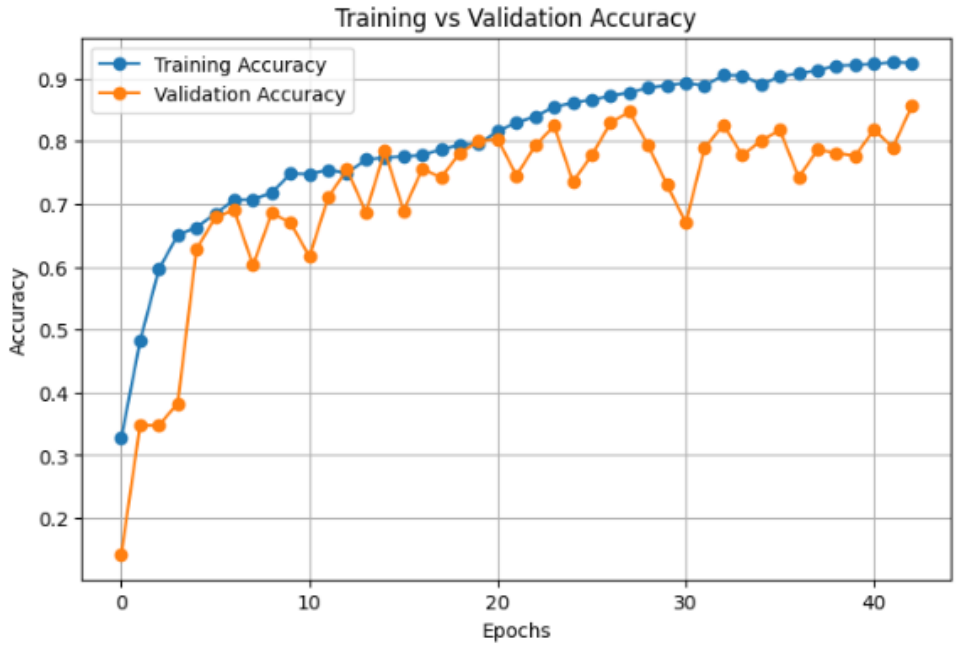
```
40/40 ━━━━━━━━━━━━━━━━━━━━ 12s 135ms/step - accuracy: 0.8413 - loss: 0.5900

Test Accuracy: 84.53%
Test Loss: 0.5134
```

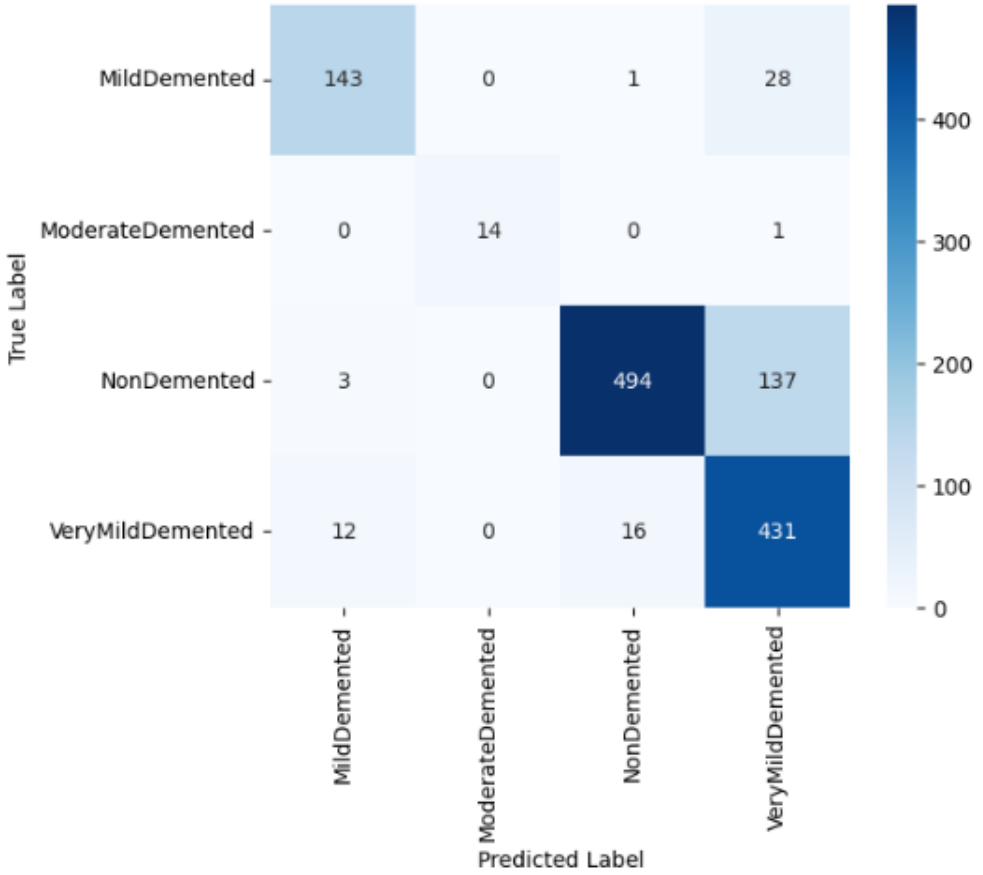


# MODEL 1: CNN

```
Final Training Accuracy: 92.46%
Final Validation Accuracy: 85.55%
```



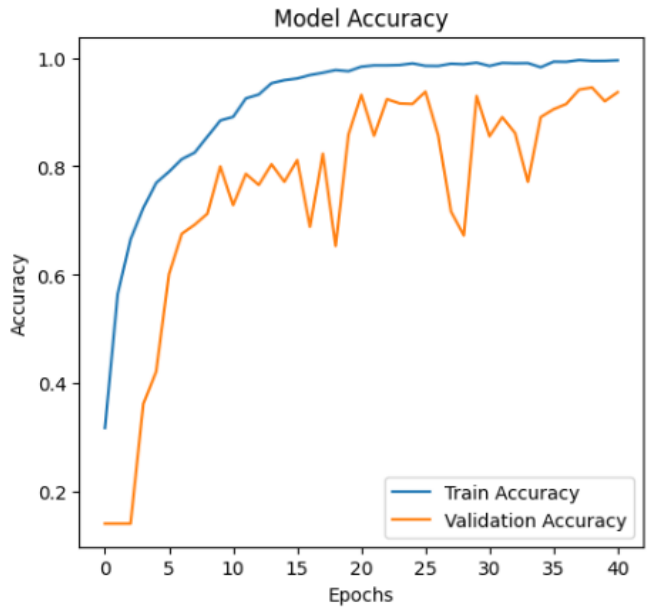

Classification Report:

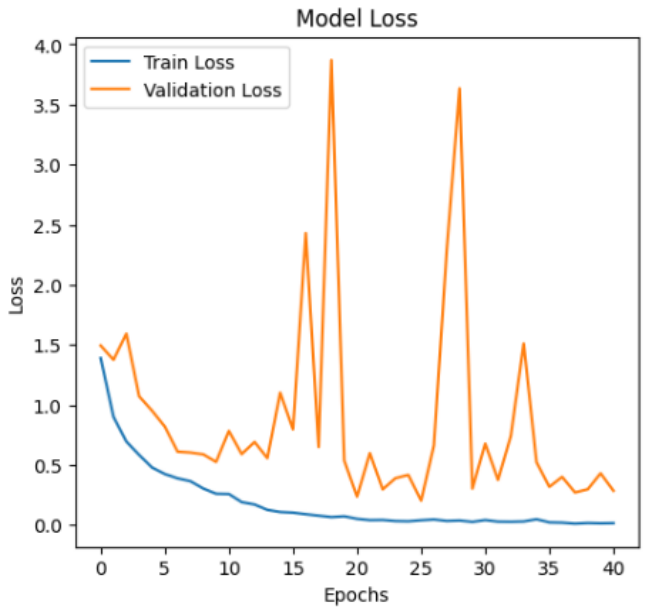
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| MildDemented | 0.91 | 0.83 | 0.87 | 172 |
| ModerateDemented | 1.00 | 0.93 | 0.97 | 15 |
| NonDemented | 0.97 | 0.78 | 0.86 | 634 |
| VeryMildDemented | 0.72 | 0.94 | 0.82 | 459 |
| accuracy | | | 0.85 | 1280 |
| macro avg | 0.90 | 0.87 | 0.88 | 1280 |
| weighted avg | 0.87 | 0.85 | 0.85 | 1280 |

# MODEL 2: DCNN

```python
# Evaluate on test data
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=1)

print(f"\nTest Accuracy: {test_acc*100:.2f}%")
print(f"Test Loss: {test_loss:.4f}")
```

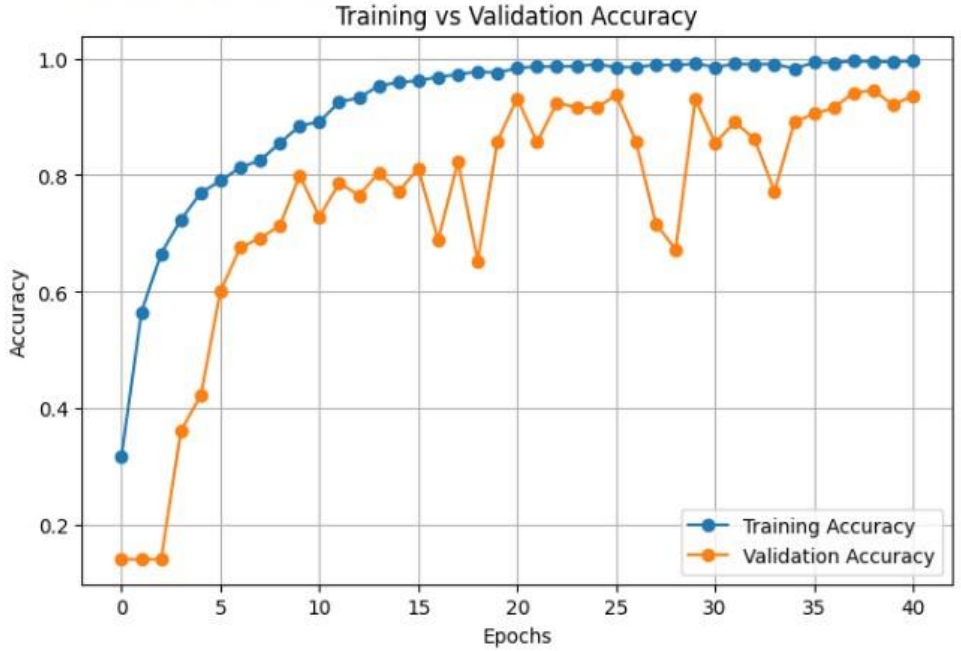
```
40/40 ━━━━━━━━━━━━━━━━━━━━ 6s 35ms/step - accuracy: 0.9311 - loss: 0.3274

Test Accuracy: 93.44%
Test Loss: 0.2707
```

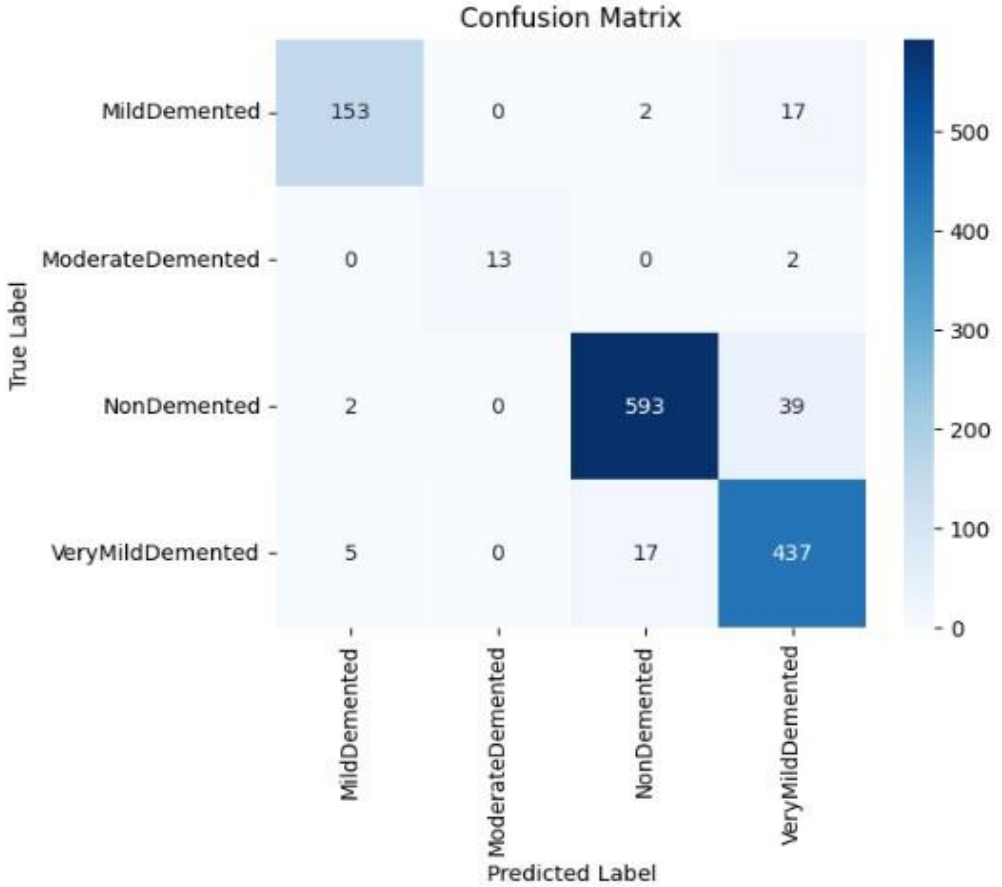


# MODEL 2: DCNN

```
Final Training Accuracy: 99.54%
Final Validation Accuracy: 93.65%
```




Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| MildDemented | 0.96 | 0.89 | 0.92 | 172 |
| ModerateDemented | 1.00 | 0.87 | 0.93 | 15 |
| NonDemented | 0.97 | 0.94 | 0.95 | 634 |
| VeryMildDemented | 0.88 | 0.95 | 0.92 | 459 |
| accuracy | | | 0.93 | 1280 |
| macro avg | 0.95 | 0.91 | 0.93 | 1280 |
| weighted avg | 0.94 | 0.93 | 0.93 | 1280 |

# MODEL 3: WCNN

```python
def wavelet_transform(image):
    """
    Apply Discrete Wavelet Transform (DWT) to the image.
    Returns the Approximation Coefficients (LL) as the wavelet-transformed image.
    """
    coeffs2 = pywt.dwt2(image, 'haar')  # Apply 2D Haar wavelet transform
    LL, (LH, HL, HH) = coeffs2  # Extract coefficients
    return LL  # Keep only approximation coefficients

# Apply Wavelet Transform to dataset
X_train_wcnn = np.array([wavelet_transform(img.squeeze()) for img in X_train_balanced])
X_val_wcnn = np.array([wavelet_transform(img.squeeze()) for img in X_val])
X_test_wcnn = np.array([wavelet_transform(img.squeeze()) for img in X_test])

# Reshape to match input shape (adding channel dimension back)
X_train_wcnn = X_train_wcnn.reshape(-1, 64, 64, 1)  # Wavelet reduces size by half
X_val_wcnn = X_val_wcnn.reshape(-1, 64, 64, 1)
X_test_wcnn = X_test_wcnn.reshape(-1, 64, 64, 1)
```

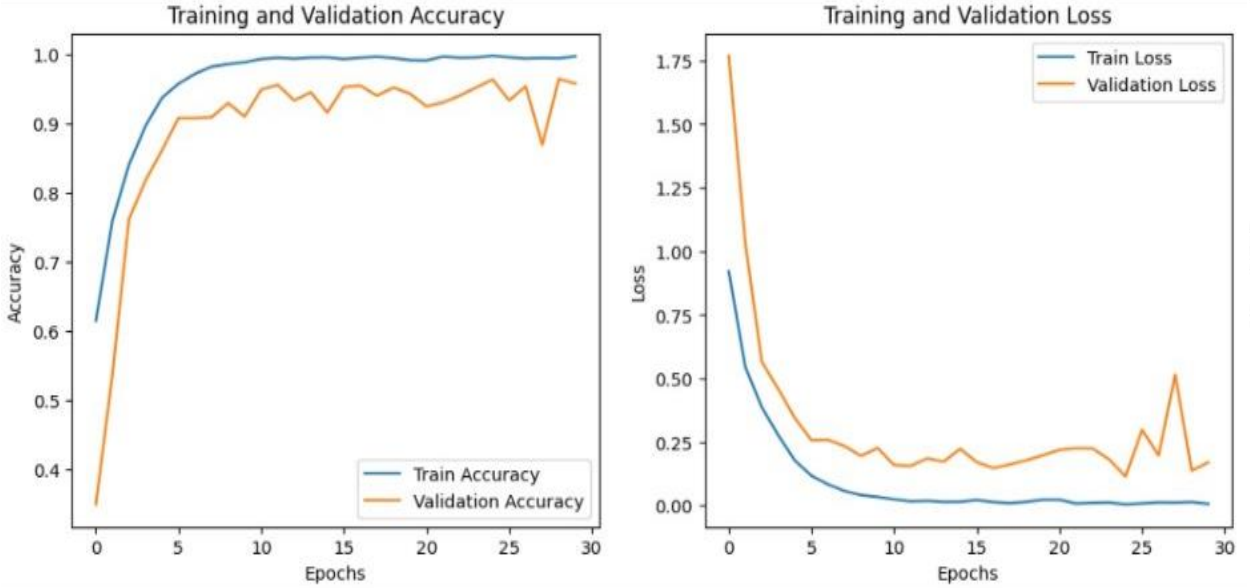
# MODEL 3: WCNN

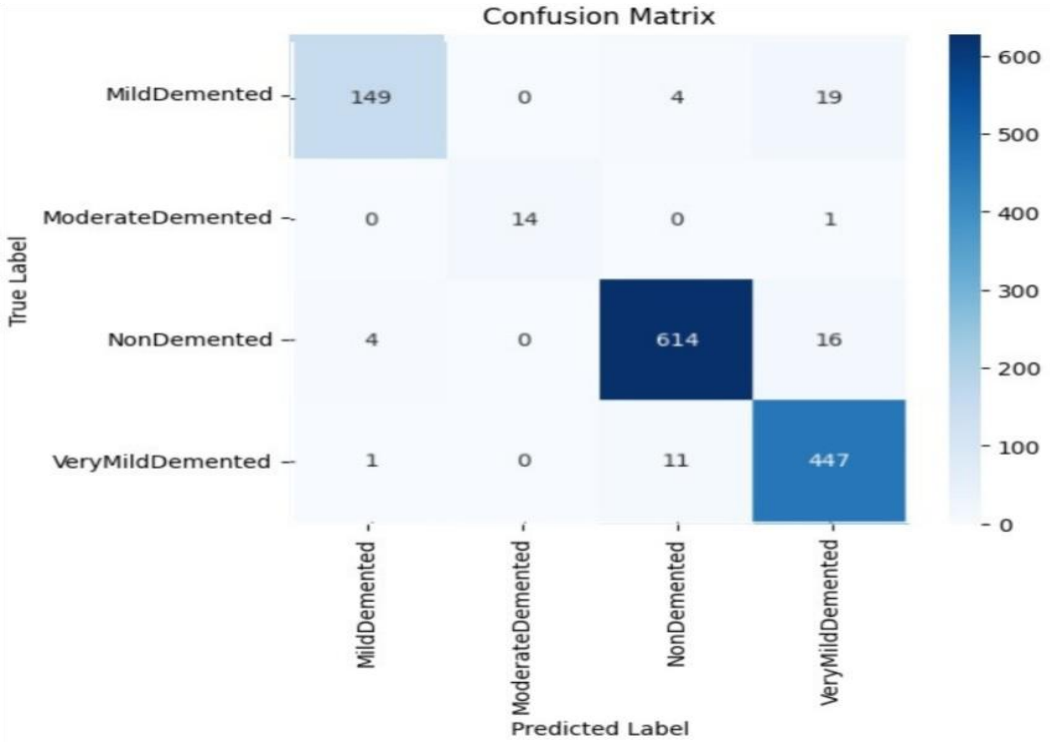
```
# Define WCNN Model
wcnn_model = Sequential([
    Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(64, 64, 1)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    Conv2D(64, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    Conv2D(128, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    Flatten(),
    Dense(256, activation='relu'),
    Dropout(0.5),
    Dense(4, activation='softmax')  # 4 output classes
])

# Compile the model
wcnn_model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model
wcnn_history = wcnn_model.fit(
    X_train_wcnn, y_train_balanced,
    validation_data=(X_val_wcnn, y_val),
    epochs=30,
    batch_size=32
)
```

```
train_acc = wcnn_history.history['accuracy'][-1]  # Last epoch training accuracy
val_acc = wcnn_history.history['val_accuracy'][-1]  # Last epoch validation accuracy

print(f"Final Training Accuracy: {train_acc:.4f}")
print(f"Final Validation Accuracy: {val_acc:.4f}")
```

```
Final Training Accuracy: 0.9988
Final Validation Accuracy: 0.9209
```

# MODEL 3: WCNN




Test Accuracy: 95.62 %

Classification Report:

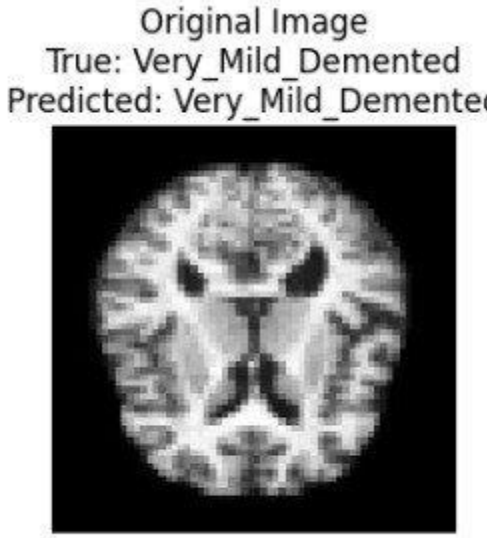
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Mild_Demented | 0.97 | 0.87 | 0.91 | 172 |
| Moderate_Demented | 1.00 | 0.93 | 0.97 | 15 |
| Non_Demented | 0.98 | 0.97 | 0.97 | 634 |
| Very_Mild_Demented | 0.93 | 0.97 | 0.95 | 459 |
| accuracy | | | 0.96 | 1280 |
| macro avg | 0.97 | 0.94 | 0.95 | 1280 |
| weighted avg | 0.96 | 0.96 | 0.96 | 1280 |

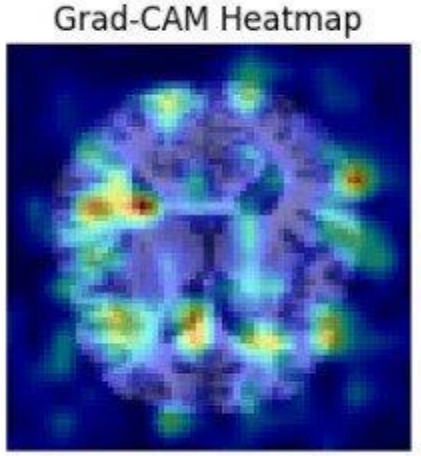
# Comparison of CNN, DCNN and WCNN

In this study, the effectiveness of frequency-aware feature extraction through wavelet-based downsampling is clearly demonstrated by the superior performance of the WCNN model. The CNN model, integrated with SE blocks and Avg-TopK pooling, achieved a test accuracy of 84.53%, indicating moderate performance. The deeper DCNN model, which incorporated strided convolutions and SE blocks, significantly enhanced generalization capability and reached a test accuracy of 93.44%. The proposed WCNN model, utilizing discrete wavelet transform (Haar) for downsampling instead of traditional pooling operations, outperformed the others with a test accuracy of 95.63%. Despite having fewer layers and no SE blocks, WCNN effectively preserved essential frequency and spatial features from the MRI scans, enabling more accurate classification. These results demonstrate the robustness of WCNN and establish it as the most suitable and efficient model for Alzheimer's disease classification in this research. The WCNN model outperformed the CNN and DCNN models across all datasets, achieving the highest train, validation, and test accuracies.

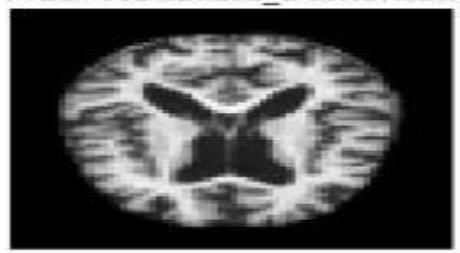
# Grad-CAM:

**Gradient-weighted Class Activation Mapping (Grad-CAM)** is a technique developed to help interpret and visualize the decision-making process of convolutional neural networks (CNNs), particularly in image classification tasks. The core idea behind Grad-CAM is to generate a heatmap that highlights the regions of an input image that are most important for the model's prediction. This is achieved by leveraging the gradients of the target class (the class the model is predicting) with respect to the feature maps of the final convolutional layer.

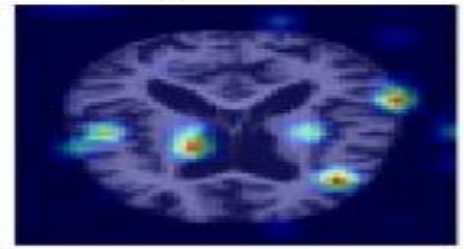



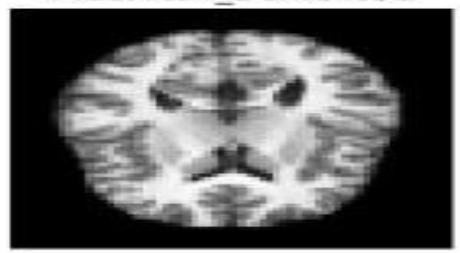
Original
True: Moderate_Demented
Pred: Moderate_Demented



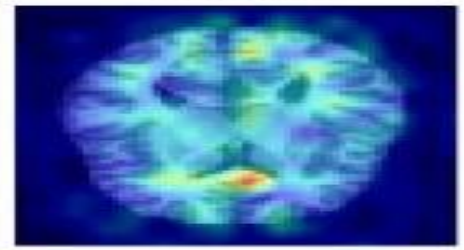
Grad-CAM



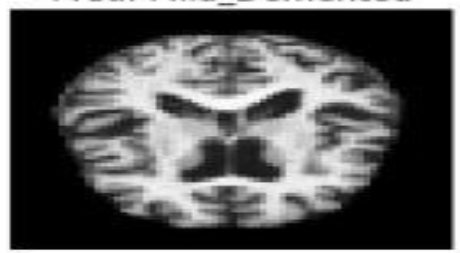
Original
True: Non_Demented
Pred: Non_Demented



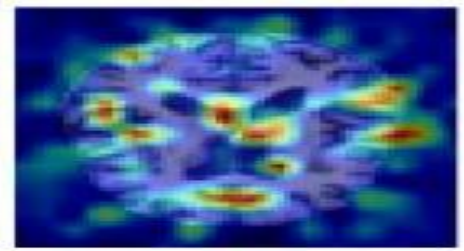
Grad-CAM



Original
True: Mild_Demented
Pred: Mild_Demented

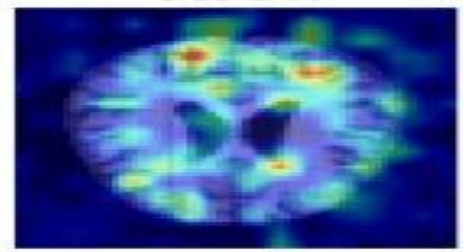


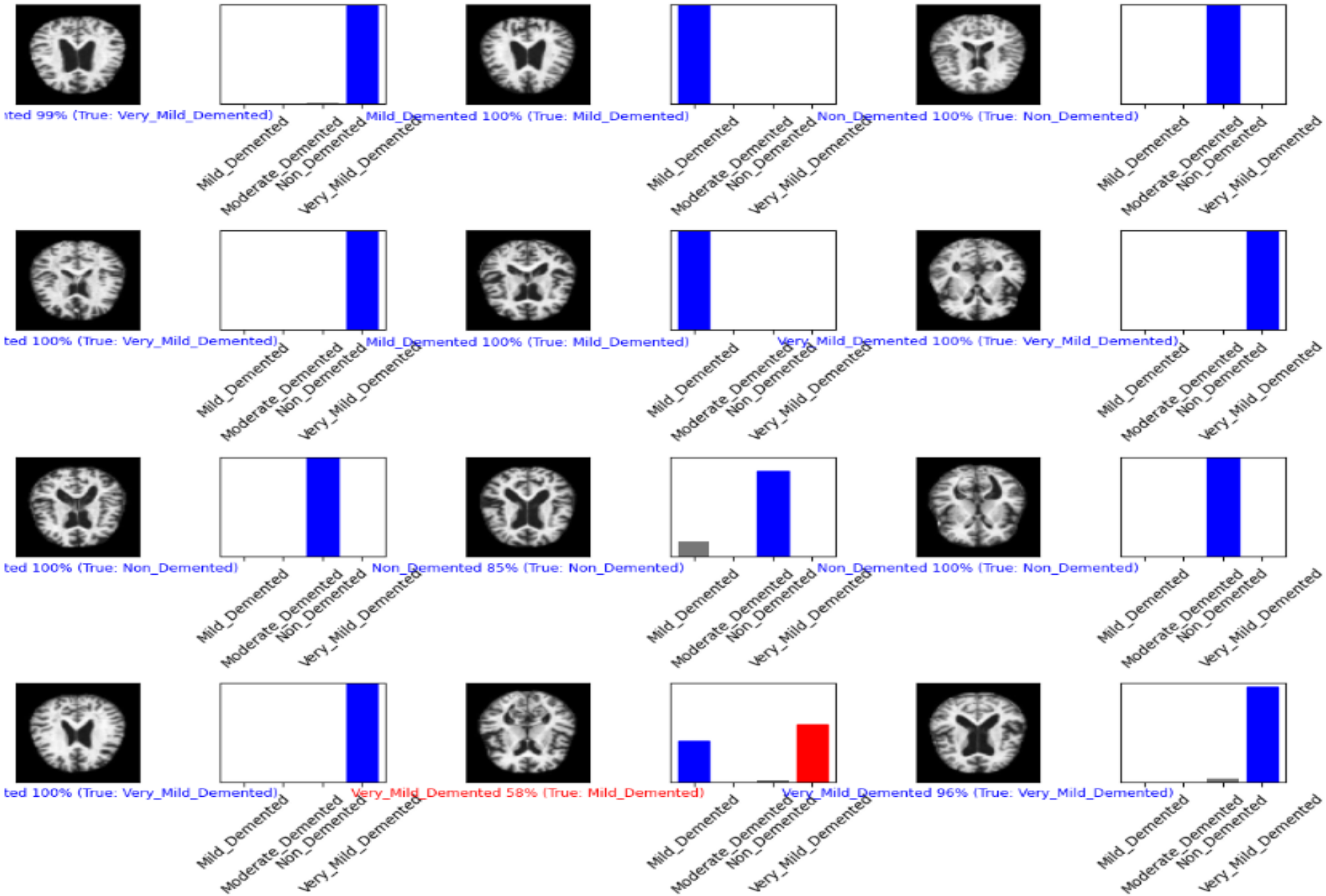
Grad-CAM



Original
True: Very_Mild_Demented
Pred: Very_Mild_Demented

Grad-CAM




ıted 99% (True: Very_Mild_Demented)
Mild_Demented 100% (True: Mild_Demented)
Non_Demented 100% (True: Non_Demented)
ted 100% (True: Very_Mild_Demented)
Mild_Demented 100% (True: Mild_Demented)
Very_Mild_Demented 100% (True: Very_Mild_Demented)
ted 100% (True: Non_Demented)
Non_Demented 85% (True: Non_Demented)
Non_Demented 100% (True: Non_Demented)
ted 100% (True: Very_Mild_Demented)
Very_Mild_Demented 58% (True: Mild_Demented)
Very_Mild_Demented 96% (True: Very_Mild_Demented)
Mild_Demented
Moderate_Demented
Non_Demented
Very_Mild_Demented

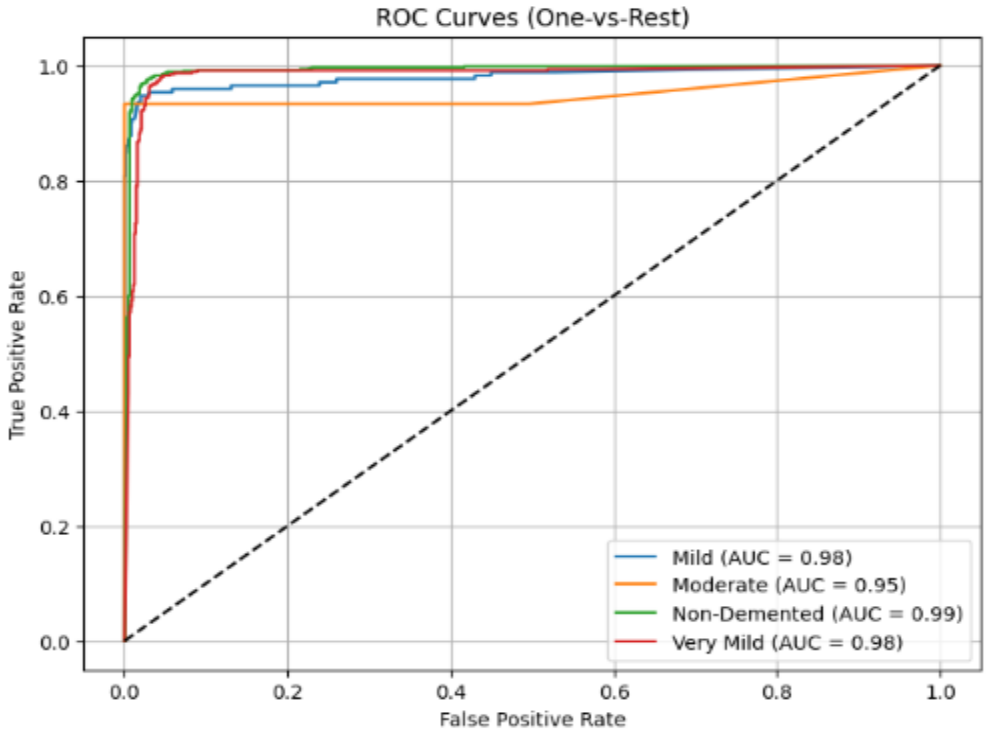
# RESULT:

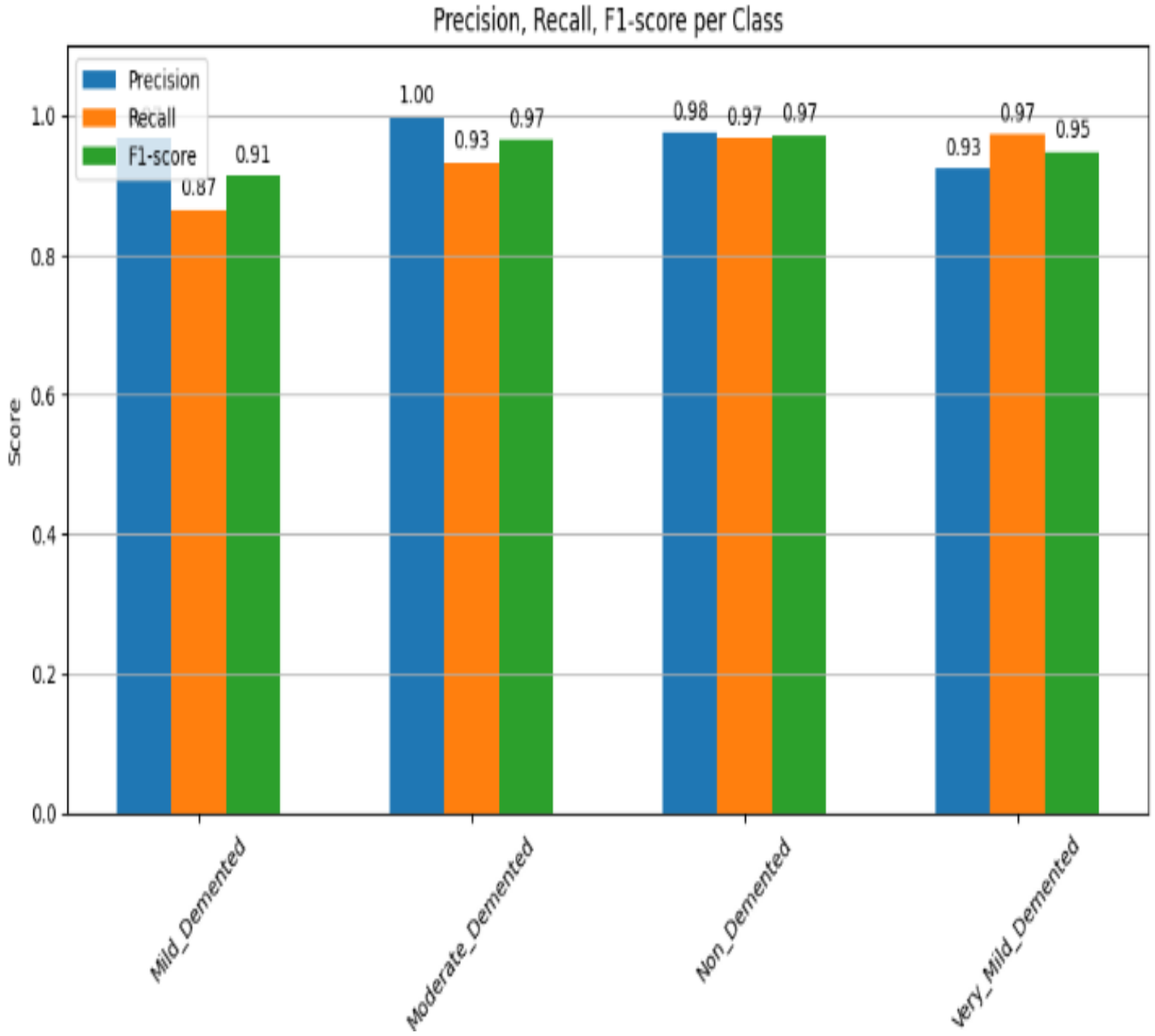
The results and outcomes of the models that were put into practice are displayed in this part. Among the three models evaluated (CNN, DCNN, and WCNN) - WCNN demonstrated the most effective performance in classifying Alzheimer's disease into four categories. As shown in the graphs ,WCNN demonstrates a smoother and more consistent learning curve compared to CNN and DCNN, indicating better generalization and stability during training. While CNN and DCNN show fluctuations in validation loss, WCNN maintains low and stable values, confirming its robustness in learning complex patterns from MRI images. These graphical results further validate the effectiveness of the WCNN model in comparison to traditional CNN architectures for Alzheimer's disease classification.

# RESULT:

| Models | Train Accuracy | Validation Accuracy | Test Accuracy |
|---|---|---|---|
| CNN | 92.46% | 85.55% | 84.53% |
| DCNN | 99.54% | 93.65% | 93.44% |
| WCNN | 99.74% | 95.80% | 95.63% |

ROC curve of WCNN:






The bar chart illustrates the model's Precision, Recall, and F1-score across all four classes of Alzheimer's classification. The model demonstrates excellent performance overall, with scores above 0.87 in all metrics for every class

# LIST OF REFERENCES:


- Jinyu Wen, Yang Li, Meie Fang, Lei Zhu and Ping Li, David Dagan Feng, Life Fellow, Member, IEEE.(2023).Fine-Grained and Multiple Classification for Alzheimer's Disease With Wavelet Convolution Unit Network

- Shamrat, F.J.M., Akter, S., Azam, S., Karim, A., Ghosh, P., Tasnim, Z., Hasib, K.M., De Boer, F., & Ahmed, K. (2023). AlzheimerNet: An effective deep learning-based proposition for Alzheimer's disease stages classification from functional brain changes in magnetic resonance images. IEEE Access, 11, 16376–16395.

- World Health Organization. (2020). The top 10 causes of death. Retrieved from https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death.

- Illakiya, T., & Ramamurthy, K. (2023). AHANet: Adaptive Hybrid Attention Network for Alzheimer's Disease Classification Using Brain Magnetic Resonance Imaging. Bioengineering, 10(6), 714.

- Finder, S. E., Amoyal, R., Treister, E., & Freifeld, O. (2024). Wavelet Convolutions for Large Receptive Fields. In Proceedings of the European Conference on Computer Vision (ECCV). Available at https://arxiv.org/abs/2407.05848

# THANK YOU!