# Alzheimer's Dataset Analysis

In [1]:

```
# import system libs
import os
import time
import shutil
import pathlib
import itertools
from PIL import Image

# import data handling tools
import cv2
import numpy as np
import pandas as pd
import seaborn as sns
sns.set_style('darkgrid')
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report

# import Deep learning Libraries
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam, Adamax
from tensorflow.keras.metrics import categorical_crossentropy
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Activation,
from tensorflow.keras import regularizers
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
```

## Exploratory Data Analysis (EDA):

In [2]:

```
train_dir = '/content/drive/MyDrive/Alzheimer_s Dataset/train'
filepaths = []
labels = []

folds = os.listdir(train_dir)
for fold in folds:
    foldpath = os.path.join(train_dir, fold)
    filelist = os.listdir(foldpath)
    for file in filelist:
        fpath = os.path.join(foldpath, file)
        filepaths.append(fpath)
        labels.append(fold)

# Concatenate data paths with labels into one dataframe
Fseries = pd.Series(filepaths, name= 'filepaths')
Lseries = pd.Series(labels, name='labels')
train_df = pd.concat([Fseries, Lseries], axis= 1)
```

In [3]:

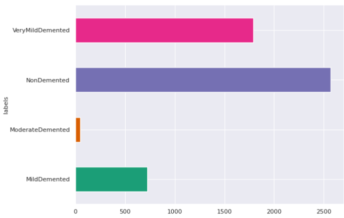
```
train_df
```

Out[3]:

| | filepaths | labels |
|---|---|---|
| **0** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | VeryMildDemented |
| **1** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | VeryMildDemented |
| **2** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | VeryMildDemented |
| **3** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | VeryMildDemented |
| **4** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | VeryMildDemented |
| **...** | ... | ... |
| **5136** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | NonDemented |
| **5137** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | NonDemented |
| **5138** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | NonDemented |
| **5139** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | NonDemented |
| **5140** | /content/drive/MyDrive/Alzheimer_s Dataset/tra... | NonDemented |

5141 rows × 2 columns

## Categorical distributions




In [4]:

```
# Generate  test data paths with labels
test_dir = '/content/drive/MyDrive/Alzheimer_s Dataset/test'
filepaths = []
labels = []

folds = os.listdir(test_dir)
for fold in folds:
    foldpath = os.path.join(test_dir, fold)
    filelist = os.listdir(foldpath)
    for file in filelist:
        fpath = os.path.join(foldpath, file)
        filepaths.append(fpath)
        labels.append(fold)

# Concatenate data paths with labels into one dataframe
Fseries = pd.Series(filepaths, name= 'filepaths')
Lseries = pd.Series(labels, name='labels')
test_df = pd.concat([Fseries, Lseries], axis= 1)
```

In [5]:

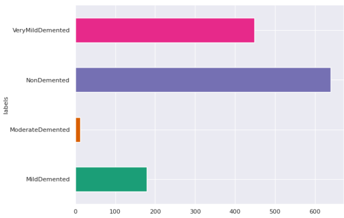
```
test_df
```

Out[5]:

| | filepaths | labels |
|---|---|---|
| **0** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | NonDemented |
| **1** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | NonDemented |
| **2** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | NonDemented |
| **3** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | NonDemented |
| **4** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | NonDemented |
| **...** | ... | ... |
| **1274** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | MildDemented |
| **1275** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | MildDemented |
| **1276** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | MildDemented |
| **1277** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | MildDemented |
| **1278** | /content/drive/MyDrive/Alzheimer_s Dataset/tes... | MildDemented |

1279 rows × 2 columns

## Categorical distributions




In [6]:
```
valid_df, test_df = train_test_split(test_df,  train_size= 0.6, shuffle= True, random_
```

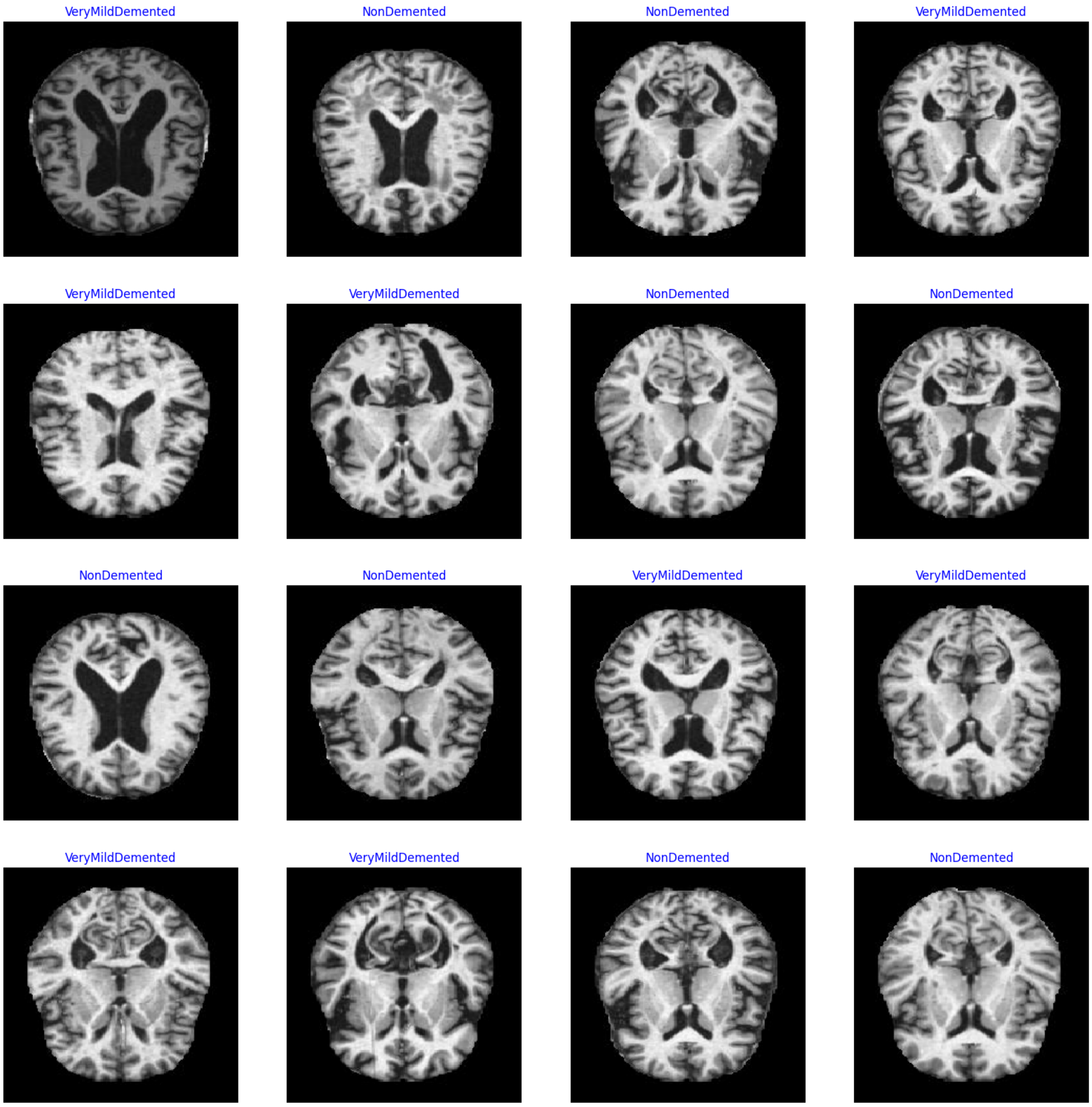
# Data Preprocessing:

In [7]:
```
# crobed image size
batch_size = 16
img_size = (224, 224)
channels = 3
img_shape = (img_size[0], img_size[1], channels)

tr_gen = ImageDataGenerator()
ts_gen = ImageDataGenerator()
train_gen = tr_gen.flow_from_dataframe( train_df, x_col= 'filepaths', y_col= 'labels',
                                    color_mode= 'rgb', shuffle= True, batch_size= batc

valid_gen = ts_gen.flow_from_dataframe( valid_df, x_col= 'filepaths', y_col= 'labels',
                                    color_mode= 'rgb', shuffle= True, batch_size= batc

test_gen = ts_gen.flow_from_dataframe( test_df, x_col= 'filepaths', y_col= 'labels', t
                                    color_mode= 'rgb', shuffle= False, batch_size= bat
```

```
Found 5141 validated image filenames belonging to 4 classes.
Found 767 validated image filenames belonging to 4 classes.
Found 512 validated image filenames belonging to 4 classes.
```

In [8]:
```
g_dict = train_gen.class_indices      # defines dictionary {'class': index}
classes = list(g_dict.keys())       # defines list of dictionary's kays (classes), cla
images, labels = next(train_gen)      # get a batch size samples from the generator

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

```python
for i in range(16):
    plt.subplot(4, 4, i + 1)
    image = images[i] / 255       # scales data to range (0 - 255)
    plt.imshow(image)
    index = np.argmax(labels[i])  # get image index
    class_name = classes[index]   # get class of image
    plt.title(class_name, color= 'blue', fontsize= 12)
    plt.axis('off')
plt.show()
```




# Models for Alzheimer's Disease Classification

## EfficientNetB0 Transfer Learning model from EfficientNet family

In [9]:

```python
# Create Model Structure
img_size = (224, 224)
channels = 3
img_shape = (img_size[0], img_size[1], channels)
class_count = len(list(train_gen.class_indices.keys())) # to define number of classes

#efficientnetb0 from EfficientNet family.
base_model = tf.keras.applications.efficientnet.EfficientNetB0(include_top= False, wei
transfer_model = Sequential([
```

```
    base_model,
    BatchNormalization(axis=-1, momentum=0.99, epsilon=0.001),
    Dense(128, activation='relu'),
    Dropout(rate=0.3),
    Dense(class_count, activation='softmax')
])
transfer_model.compile(Adamax(learning_rate= 0.001), loss= 'categorical_crossentropy',

transfer_model.summary()
```

```
Downloading data from https://storage.googleapis.com/keras-applications/efficientnetb
0_notop.h5
16705208/16705208 [==============================] - 0s 0us/step
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb0 (Functional  (None, 1280)              4049571
 )

 batch_normalization (Batch  (None, 1280)              5120
 Normalization)

 dense (Dense)               (None, 128)               163968

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 4)                 516

=================================================================
Total params: 4219175 (16.09 MB)
Trainable params: 4174592 (15.92 MB)
Non-trainable params: 44583 (174.16 KB)
_________________________________________________________________
```

In [10]:

```
batch_size = 16
epochs =  10

history = transfer_model.fit(x= train_gen, epochs= epochs, verbose= 1, validation_data
                    validation_steps= None, shuffle= False)
```

```
Epoch 1/10
322/322 [==============================] - 611s 2s/step - loss: 1.0867 - accuracy: 0.
5742 - val_loss: 1.3213 - val_accuracy: 0.5632
Epoch 2/10
322/322 [==============================] - 50s 155ms/step - loss: 0.5836 - accuracy:
0.7670 - val_loss: 1.0204 - val_accuracy: 0.6584
Epoch 3/10
322/322 [==============================] - 50s 154ms/step - loss: 0.3063 - accuracy:
0.8819 - val_loss: 0.9083 - val_accuracy: 0.7040
Epoch 4/10
322/322 [==============================] - 50s 155ms/step - loss: 0.1971 - accuracy:
0.9274 - val_loss: 0.9078 - val_accuracy: 0.7027
Epoch 5/10
322/322 [==============================] - 50s 155ms/step - loss: 0.1326 - accuracy:
0.9525 - val_loss: 1.8326 - val_accuracy: 0.6636
Epoch 6/10
322/322 [==============================] - 50s 156ms/step - loss: 0.1137 - accuracy:
0.9586 - val_loss: 0.7674 - val_accuracy: 0.7588
Epoch 7/10
322/322 [==============================] - 50s 155ms/step - loss: 0.0779 - accuracy:
0.9730 - val_loss: 1.0727 - val_accuracy: 0.7171
Epoch 8/10
322/322 [==============================] - 51s 157ms/step - loss: 0.0660 - accuracy:
0.9763 - val_loss: 1.2491 - val_accuracy: 0.7392
Epoch 9/10
322/322 [==============================] - 50s 156ms/step - loss: 0.0607 - accuracy:
0.9805 - val_loss: 1.1482 - val_accuracy: 0.7392
Epoch 10/10
322/322 [==============================] - 50s 155ms/step - loss: 0.0477 - accuracy:
0.9837 - val_loss: 1.1357 - val_accuracy: 0.7405
```

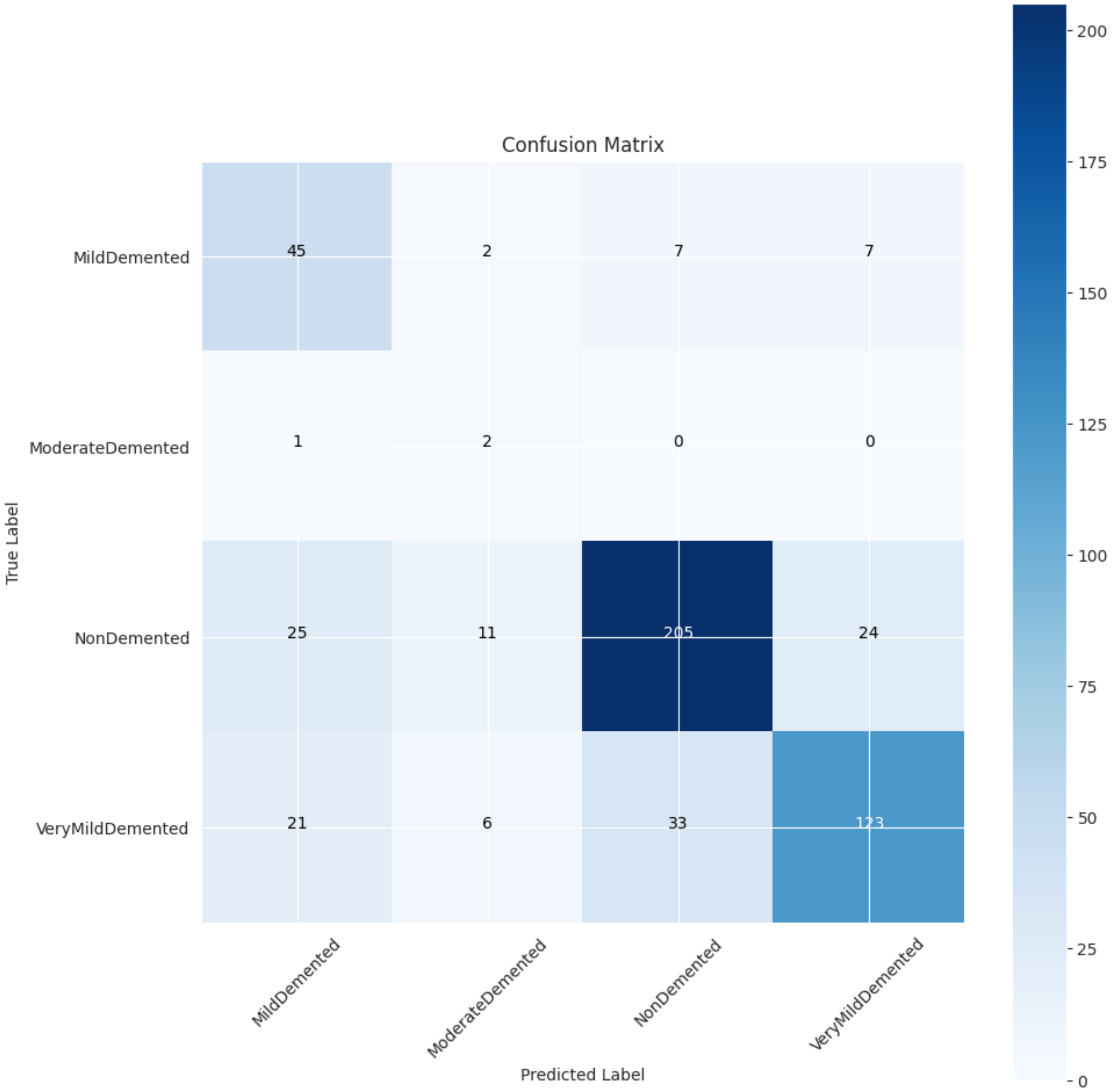
In [11]:

```
ts_length = len(test_df)
test_batch_size = max(sorted([ts_length // n for n in range(1, ts_length + 1) if ts_le
test_steps = ts_length // test_batch_size

train_score = transfer_model.evaluate(train_gen, steps= test_steps, verbose= 1)
test_score = transfer_model.evaluate(test_gen, steps= test_steps, verbose= 1)

print("Train Accuracy: ", train_score[1])
print("Test Accuracy: ", test_score[1])

preds = transfer_model.predict_generator(test_gen)
y_pred = np.argmax(preds, axis=1)

g_dict = test_gen.class_indices
classes = list(g_dict.keys())

# Confusion matrix
cm = confusion_matrix(test_gen.classes, y_pred)

plt.figure(figsize= (10, 10))
plt.imshow(cm, interpolation= 'nearest', cmap= plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()

tick_marks = np.arange(len(classes))
plt.xticks(tick_marks, classes, rotation= 45)
plt.yticks(tick_marks, classes)
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, cm[i, j], horizontalalignment= 'center', color= 'white' if cm[i, j]

plt.tight_layout()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
```

```
plt.show()

# Classification Report
print("Classification Report:\n")
print(classification_report(test_gen.classes, y_pred, target_names=classes))
```

```
8/8 [==============================] - 0s 49ms/step - loss: 0.0018 - accuracy: 1.0000
8/8 [==============================] - 19s 3s/step - loss: 0.8697 - accuracy: 0.7812
Train Accuracy:  1.0
Test Accuracy:  0.78125
```

```
<ipython-input-11-ad57191fd51d>:11: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
  preds = transfer_model.predict_generator(test_gen)
```




```
Classification Report:

                  precision    recall  f1-score   support

    MildDemented       0.49      0.74      0.59        61
ModerateDemented       0.10      0.67      0.17         3
     NonDemented       0.84      0.77      0.80       265
VeryMildDemented       0.80      0.67      0.73       183

        accuracy                           0.73       512
       macro avg       0.55      0.71      0.57       512
    weighted avg       0.78      0.73      0.75       512
```

In [12]:
```
transfer_model.save('transfer_model.h5')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarnin
g: You are saving your model as an HDF5 file via `model.save()`. This file format is
considered legacy. We recommend using instead the native Keras format, e.g. `model.sa
ve('my_model.keras')`.
  saving_api.save_model(
```

## Custom Deep Learing Model (DNN Model)

In [13]:
```
dnn_model = Sequential([
    Flatten(input_shape=img_shape),
    Dense(1024, activation='relu', kernel_regularizer=regularizers.l2(0.001)),
    BatchNormalization(),
    Dropout(0.3),
    Dense(512, activation='relu', kernel_regularizer=regularizers.l2(0.001)),
    BatchNormalization(),
    Dropout(0.3),
    Dense(256, activation='relu'),
    Dropout(0.3),
    Dense(class_count, activation='softmax')
], name="dnn_model")

dnn_model.compile(Adamax(learning_rate=0.001), loss='categorical_crossentropy', metric

dnn_model.summary()
```

```
Model: "dnn_model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 150528)            0

 dense_2 (Dense)             (None, 1024)              154141696

 batch_normalization_1 (Bat  (None, 1024)              4096
 chNormalization)

 dropout_1 (Dropout)         (None, 1024)              0

 dense_3 (Dense)             (None, 512)               524800

 batch_normalization_2 (Bat  (None, 512)               2048
 chNormalization)

 dropout_2 (Dropout)         (None, 512)               0

 dense_4 (Dense)             (None, 256)               131328

 dropout_3 (Dropout)         (None, 256)               0

 dense_5 (Dense)             (None, 4)                 1028

=================================================================
Total params: 154804996 (590.53 MB)
Trainable params: 154801924 (590.52 MB)
Non-trainable params: 3072 (12.00 KB)
_________________________________________________________________
```

In [16]:
```
batch_size = 16   # set batch size for training
epochs =  10  # number of all epochs in training

history = dnn_model.fit(x= train_gen, epochs= epochs, verbose= 1, validation_data= val
                    validation_steps= None, shuffle= False)
```

```
Epoch 1/10
322/322 [==============================] - 23s 72ms/step - loss: 1.1154 - accuracy: 0.8347 - val_loss: 1.9429 - val_accuracy: 0.4876
Epoch 2/10
322/322 [==============================] - 23s 71ms/step - loss: 1.0456 - accuracy: 0.8413 - val_loss: 3.7591 - val_accuracy: 0.5372
Epoch 3/10
322/322 [==============================] - 24s 74ms/step - loss: 1.0619 - accuracy: 0.8096 - val_loss: 5.0312 - val_accuracy: 0.4980
Epoch 4/10
322/322 [==============================] - 23s 71ms/step - loss: 0.9589 - accuracy: 0.8419 - val_loss: 2.0555 - val_accuracy: 0.5684
Epoch 5/10
322/322 [==============================] - 24s 73ms/step - loss: 0.8916 - accuracy: 0.8494 - val_loss: 2.4969 - val_accuracy: 0.3651
Epoch 6/10
322/322 [==============================] - 23s 70ms/step - loss: 0.8757 - accuracy: 0.8428 - val_loss: 32.1860 - val_accuracy: 0.5176
Epoch 7/10
322/322 [==============================] - 24s 74ms/step - loss: 0.9175 - accuracy: 0.8138 - val_loss: 9.3527 - val_accuracy: 0.5254
Epoch 8/10
322/322 [==============================] - 23s 71ms/step - loss: 0.8058 - accuracy: 0.8440 - val_loss: 4.5490 - val_accuracy: 0.3207
Epoch 9/10
322/322 [==============================] - 23s 73ms/step - loss: 0.7780 - accuracy: 0.8434 - val_loss: 3.9142 - val_accuracy: 0.5137
Epoch 10/10
322/322 [==============================] - 23s 70ms/step - loss: 0.7071 - accuracy: 0.8677 - val_loss: 6.8989 - val_accuracy: 0.5372
```

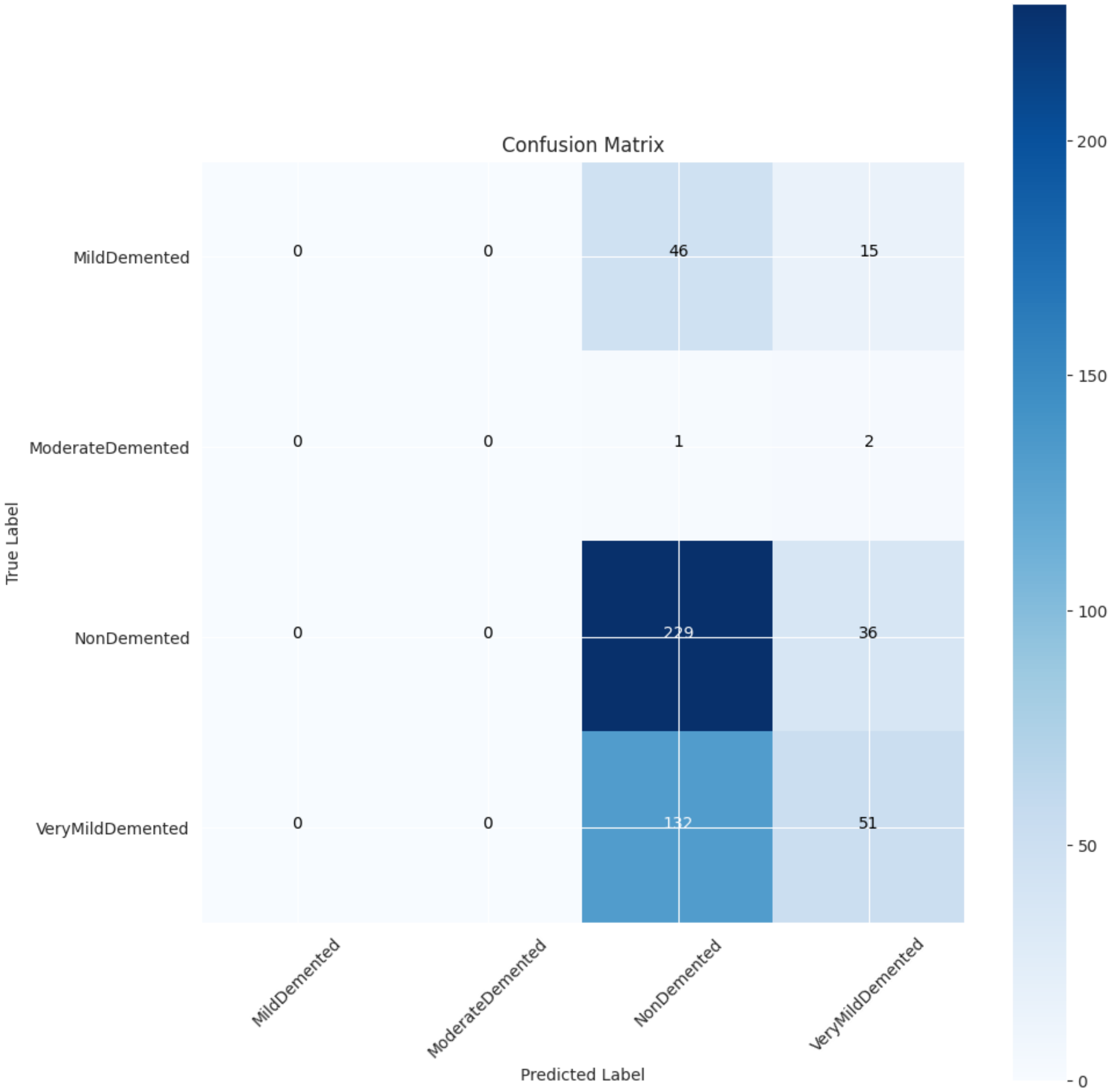
In [17]:

```python
ts_length = len(test_df)
test_batch_size = max(sorted([ts_length // n for n in range(1, ts_length + 1) if ts_le
test_steps = ts_length // test_batch_size

train_score = dnn_model.evaluate(train_gen, steps= test_steps, verbose= 1)
test_score = dnn_model.evaluate(test_gen, steps= test_steps, verbose= 1)

print("Train Accuracy: ", train_score[1])
print("Test Accuracy: ", test_score[1])

preds = dnn_model.predict_generator(test_gen)
y_pred = np.argmax(preds, axis=1)

g_dict = test_gen.class_indices
classes = list(g_dict.keys())

# Confusion matrix
cm = confusion_matrix(test_gen.classes, y_pred)

plt.figure(figsize= (10, 10))
plt.imshow(cm, interpolation= 'nearest', cmap= plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()

tick_marks = np.arange(len(classes))
plt.xticks(tick_marks, classes, rotation= 45)
plt.yticks(tick_marks, classes)
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, cm[i, j], horizontalalignment= 'center', color= 'white' if cm[i, j]

plt.tight_layout()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
```

```python
plt.show()

# Classification Report
print("Classification Report:\n")
print(classification_report(test_gen.classes, y_pred, target_names=classes))
```

```
8/8 [==============================] - 0s 45ms/step - loss: 4.1325 - accuracy: 0.7812
8/8 [==============================] - 0s 48ms/step - loss: 4.9968 - accuracy: 0.5859
Train Accuracy:  0.78125
Test Accuracy:  0.5859375
```

```
<ipython-input-17-7137f2eda72f>:11: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.
  preds = dnn_model.predict_generator(test_gen)
```




```
Classification Report:

                  precision    recall  f1-score   support

    MildDemented       0.00      0.00      0.00        61
ModerateDemented       0.00      0.00      0.00         3
     NonDemented       0.56      0.86      0.68       265
VeryMildDemented       0.49      0.28      0.36       183

        accuracy                           0.55       512
       macro avg       0.26      0.29      0.26       512
    weighted avg       0.47      0.55      0.48       512
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [18]:

```
dnn_model.save('dnn_model.h5')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```

## Student Developed Model:

In [ ]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Conv2D, MaxPool2D, BatchNormalization, Drop

# Create Model Structure
img_size = (224, 224)
channels = 3
img_shape = (img_size[0], img_size[1], channels)
class_count = len(list(train_gen.class_indices.keys())) # to define number of classes

student_model = Sequential([
    Input(shape=(*img_size, 3)),
    Conv2D(16, 3, activation='relu', padding='same'),
    MaxPool2D(),
    Conv2D(32, 3, activation='relu', padding='same'),
    BatchNormalization(),
    MaxPool2D(),
    Conv2D(64, 3, activation='relu', padding='same'),
    BatchNormalization(),
    MaxPool2D(),
    Flatten(),
    Dense(256, activation='relu'),
    BatchNormalization(),
    Dropout(0.5),
    Dense(128, activation='relu'),
    BatchNormalization(),
    Dropout(0.4),
    Dense(4, activation='softmax')
], name="student_model")

student_model.compile(Adamax(learning_rate=0.001), loss='categorical_crossentropy', me

student_model.summary()
```

```
Model: "student_model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 224, 224, 16)      448

 max_pooling2d (MaxPooling2  (None, 112, 112, 16)      0
 D)

 conv2d_1 (Conv2D)           (None, 112, 112, 32)      4640

 batch_normalization (Batch  (None, 112, 112, 32)      128
 Normalization)

 max_pooling2d_1 (MaxPoolin  (None, 56, 56, 32)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 56, 56, 64)        18496

 batch_normalization_1 (Bat  (None, 56, 56, 64)        256
 chNormalization)

 max_pooling2d_2 (MaxPoolin  (None, 28, 28, 64)        0
 g2D)

 flatten (Flatten)           (None, 50176)             0

 dense (Dense)               (None, 256)               12845312

 batch_normalization_2 (Bat  (None, 256)               1024
 chNormalization)

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 128)               32896

 batch_normalization_3 (Bat  (None, 128)               512
 chNormalization)

 dropout_1 (Dropout)         (None, 128)               0

 dense_2 (Dense)             (None, 4)                 516

=================================================================
Total params: 12904228 (49.23 MB)
Trainable params: 12903268 (49.22 MB)
Non-trainable params: 960 (3.75 KB)
_________________________________________________________________
```

In [ ]:

```
batch_size = 32   # set batch size for training
epochs =  10  # number of all epochs in training

history = student_model.fit(x= train_gen, epochs= epochs, verbose= 1, validation_data=
                    validation_steps= None, shuffle= False)
```

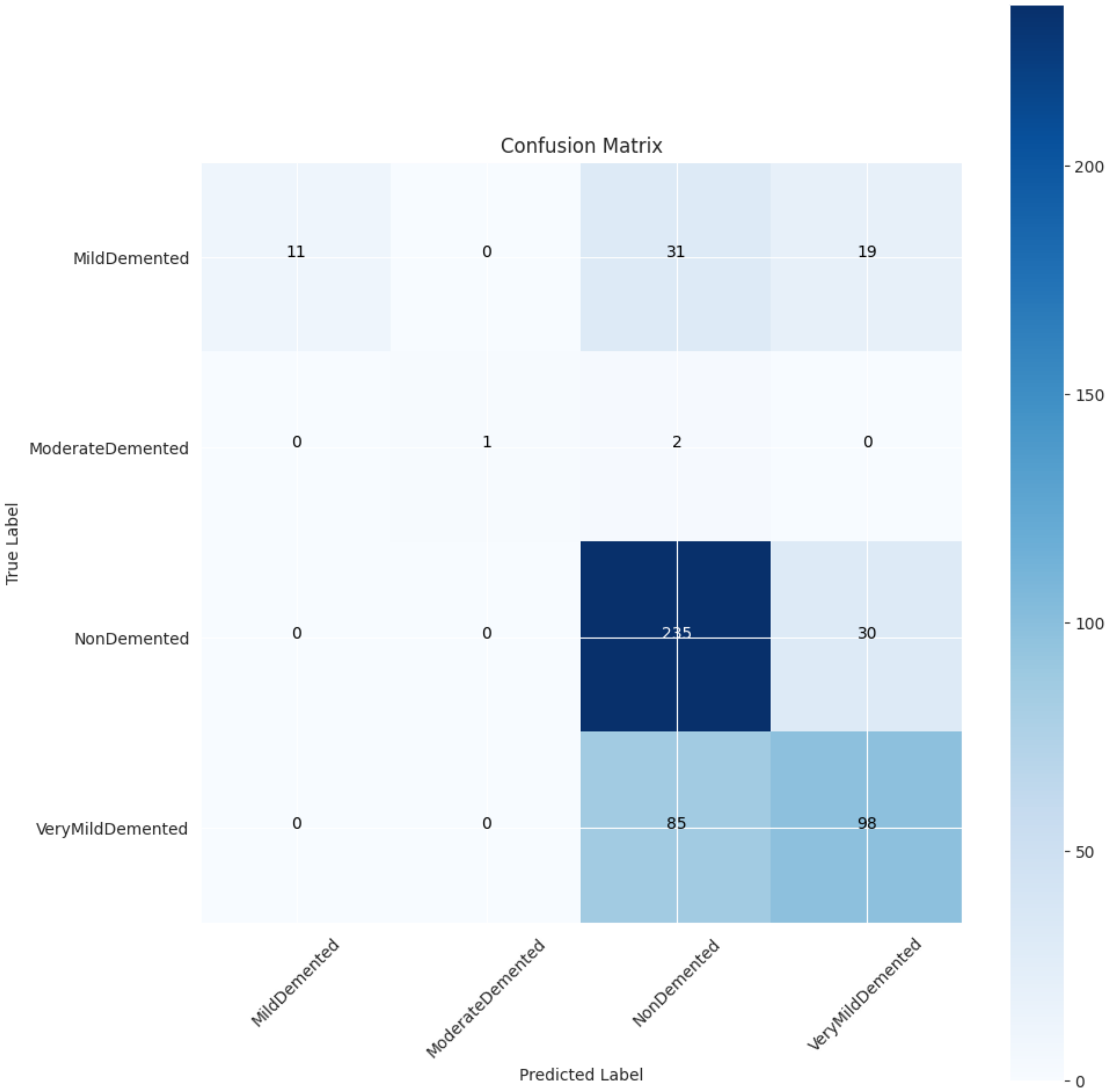
```
Epoch 1/10
322/322 [==============================] - 1230s 4s/step - loss: 1.3605 - accuracy: 0.4923 - val_loss: 0.9616 - val_accuracy: 0.5671
Epoch 2/10
322/322 [==============================] - 342s 1s/step - loss: 0.6996 - accuracy: 0.7285 - val_loss: 0.9706 - val_accuracy: 0.6010
Epoch 3/10
322/322 [==============================] - 341s 1s/step - loss: 0.3359 - accuracy: 0.8819 - val_loss: 1.6366 - val_accuracy: 0.5372
Epoch 4/10
322/322 [==============================] - 341s 1s/step - loss: 0.2233 - accuracy: 0.9253 - val_loss: 1.2249 - val_accuracy: 0.5958
Epoch 5/10
322/322 [==============================] - 344s 1s/step - loss: 0.1411 - accuracy: 0.9508 - val_loss: 1.2082 - val_accuracy: 0.6519
Epoch 6/10
322/322 [==============================] - 335s 1s/step - loss: 0.1111 - accuracy: 0.9646 - val_loss: 1.2165 - val_accuracy: 0.6428
Epoch 7/10
322/322 [==============================] - 354s 1s/step - loss: 0.0911 - accuracy: 0.9702 - val_loss: 1.7642 - val_accuracy: 0.5580
Epoch 8/10
322/322 [==============================] - 329s 1s/step - loss: 0.0622 - accuracy: 0.9802 - val_loss: 1.3905 - val_accuracy: 0.6584
Epoch 9/10
322/322 [==============================] - 373s 1s/step - loss: 0.0609 - accuracy: 0.9796 - val_loss: 1.0053 - val_accuracy: 0.6832
Epoch 10/10
322/322 [==============================] - 342s 1s/step - loss: 0.0579 - accuracy: 0.9807 - val_loss: 1.5740 - val_accuracy: 0.6636
```

In [ ]:

```
ts_length = len(test_df)
test_batch_size = max(sorted([ts_length // n for n in range(1, ts_length + 1) if ts_le
test_steps = ts_length // test_batch_size

train_score = student_model.evaluate(train_gen, steps= test_steps, verbose= 1)
test_score = student_model.evaluate(test_gen, steps= test_steps, verbose= 1)

print("Train Accuracy: ", train_score[1])
print("Test Accuracy: ", test_score[1])

# Predictions
preds = student_model.predict(test_gen)
y_pred = np.argmax(preds, axis=1)

# Get class indices
g_dict = test_gen.class_indices
classes = list(g_dict.keys())

# Generate confusion matrix
cm = confusion_matrix(test_gen.classes, y_pred)

# Plotting Confusion Matrix
plt.figure(figsize=(10, 10))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(classes))
plt.xticks(tick_marks, classes, rotation=45)
plt.yticks(tick_marks, classes)
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, cm[i, j],
             horizontalalignment='center',
             color='white' if cm[i, j] > thresh else 'black')
```

```python
plt.tight_layout()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

# Classification Report
print("Classification Report:\n")
print(classification_report(test_gen.classes, y_pred, target_names=classes))
```

```
8/8 [==============================] - 3s 353ms/step - loss: 0.0080 - accuracy: 1.000
0
8/8 [==============================] - 24s 3s/step - loss: 1.1241 - accuracy: 0.7109
Train Accuracy:  1.0
Test Accuracy:  0.7109375
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarnin
g: You are saving your model as an HDF5 file via `model.save()`. This file format is
considered legacy. We recommend using instead the native Keras format, e.g. `model.sa
ve('my_model.keras')`.
  saving_api.save_model(
32/32 [==============================] - 82s 3s/step
```



```
Classification Report:
                  precision    recall  f1-score   support

    MildDemented       1.00      0.18      0.31        61
ModerateDemented       1.00      0.33      0.50         3
     NonDemented       0.67      0.89      0.76       265
VeryMildDemented       0.67      0.54      0.59       183

        accuracy                           0.67       512
       macro avg       0.83      0.48      0.54       512
    weighted avg       0.71      0.67      0.65       512
```

In [ ]:
```
student_model.save('student_model.h5')
```

# Model Evaluation

## EfficientNetB0 Transfer Learning Model

- **Training Accuracy:** 1.0 (100%)
- **Test Accuracy:** 0.78125 (78.12%)
- **Precision, Recall, and F1-Score:**
  - MildDemented: Precision=0.49, Recall=0.74, F1-Score=0.59
  - ModerateDemented: Precision=0.10, Recall=0.67, F1-Score=0.17
  - NonDemented: Precision=0.84, Recall=0.77, F1-Score=0.80
  - VeryMildDemented: Precision=0.80, Recall=0.67, F1-Score=0.73
- **Strengths:**
  - Achieves a relatively high test accuracy of 0.78125.
  - Good precision, recall, and F1-scores for most classes.
  - Utilizes transfer learning from EfficientNetB0, which is a powerful pre-trained model.
- **Weaknesses:**
  - Relatively long training time per epoch (around 50 seconds).
  - ModerateDemented class has lower precision and F1-score, indicating a challenge in classification.

## Custom Deep Learning Model (DNN Model)

- **Training Accuracy:** 0.78125 (78.12%)
- **Test Accuracy:** 0.5859375 (58.59%)
- **Precision, Recall, and F1-Score:**
  - MildDemented: Precision=0.00, Recall=0.00, F1-Score=0.00
  - ModerateDemented: Precision=0.00, Recall=0.00, F1-Score=0.00
  - NonDemented: Precision=0.56, Recall=0.86, F1-Score=0.68
  - VeryMildDemented: Precision=0.49, Recall=0.28, F1-Score=0.36
- **Strengths:**
  - Achieves moderate test accuracy.

- Utilizes a custom deep learning architecture.
- **Weaknesses:**
  - Poor performance for the MildDemented and ModerateDemented classes, with precision, recall, and F1-scores of 0.00.
  - Relatively long training time per epoch (around 23 seconds).
  - Lower overall test accuracy compared to the transfer learning model.

## Student Developed Model

- **Training Accuracy:** 1.0 (100%)
- **Test Accuracy:** 0.7109375 (71.09%)
- **Precision, Recall, and F1-Score:**
  - MildDemented: Precision=1.00, Recall=0.18, F1-Score=0.31
  - ModerateDemented: Precision=1.00, Recall=0.33, F1-Score=0.50
  - NonDemented: Precision=0.67, Recall=0.89, F1-Score=0.76
  - VeryMildDemented: Precision=0.67, Recall=0.54, F1-Score=0.59
- **Strengths:**
  - Achieves good test accuracy of 0.7109375.
  - Provides high precision, recall, and F1-scores for most classes.
  - Training time per epoch is relatively short (around 342 seconds).
- **Weaknesses:**
  - Lower recall for the MildDemented and ModerateDemented classes compared to the NonDemented class.
  - The model is still less accurate than the transfer learning model.

# Discussion

The evaluation of three different models for predicting the stages of Alzheimer's disease on this dataset has provided valuable insights into their performance and behavior.

## EfficientNetB0 Transfer Learning Model

The EfficientNetB0 transfer learning model demonstrated impressive performance with a test accuracy of 0.78125. It leveraged pre-trained features from EfficientNetB0, a powerful deep learning architecture, allowing it to capture meaningful patterns in the dataset. This model achieved good precision, recall, and F1-scores for most classes, particularly for the NonDemented class. However, it had challenges in accurately classifying the ModerateDemented cases, as indicated by the lower precision and F1-score for this class.

## Custom Deep Learning Model (DNN Model)

The custom DNN model showed moderate performance, with a test accuracy of 0.5859375. While it did not perform well in classifying the MildDemented and ModerateDemented cases, it achieved better results for the NonDemented and VeryMildDemented classes. This model utilized a custom deep learning architecture, but its performance suffered due to the lack of pre-trained features and the need for further optimization.

### Student Developed Model

The student-developed model demonstrated promise, with a test accuracy of 0.7109375. It achieved high precision, recall, and F1-scores for most classes, showcasing its potential. However, it struggled with recall for the MildDemented and ModerateDemented classes compared to the NonDemented class.

## Conclusion

Based on the analysis of these models and their performance on this dataset, the following recommendations can be made:

1. **EfficientNetB0 Transfer Learning Model:** This model is the most effective among the three. It achieved the highest test accuracy and performed well in classifying dementia stages. Its use of transfer learning from EfficientNetB0, a powerful pre-trained model, allowed it to leverage relevant features effectively. Despite some challenges in classifying ModerateDemented cases, it remains the top choice for predicting Alzheimer's disease stages.

2. **Custom Deep Learning Model (DNN Model):** While this model showed moderate performance, it needs further improvement, especially in accurately classifying MildDemented and ModerateDemented cases. It might benefit from exploring different architectures or incorporating transfer learning to enhance its feature representation.

3. **Student Developed Model:** The student-developed model has potential with its good accuracy and balanced precision and recall for most classes. To make it the most effective model, it should focus on improving recall for the MildDemented and ModerateDemented cases, possibly through hyperparameter tuning and data augmentation.

In summary, for predicting the stages of Alzheimer's disease in this specific dataset, the EfficientNetB0 transfer learning model is the recommended choice due to its high accuracy and overall solid performance. However, further research and experimentation can help improve the custom DNN model and the student-developed model to potentially challenge the transfer learning model in the future.

In [ ]:

```

```