# Satellite Images Classification using Pretrained Models using Attention Mechanism


```
import numpy as np
import pandas as pd

image_dir = '/kaggle/input/remote-sensing-satellite-images/Remote
Sensing Data.v2i.yolov8/train/images'
label_dir = '/kaggle/input/remote-sensing-satellite-images/Remote
Sensing Data.v2i.yolov8/train/labels'

image_files = sorted([f for f in os.listdir(image_dir) if
f.endswith('.jpg') or f.endswith('.png')])
label_files = sorted([f for f in os.listdir(label_dir) if
f.endswith('.txt')])

image_paths = []
class_labels = []
center_x = []
center_y = []
width = []
height = []

for img, lbl in zip(image_files, label_files):

    img_path = os.path.join(image_dir, img)
```

```
    label_path = os.path.join(label_dir, lbl)

    with open(label_path, 'r') as file:
        for line in file:

            parts = line.strip().split()
            if len(parts) == 5:

                image_paths.append(img_path)
                class_labels.append(int(parts[0]))
                center_x.append(float(parts[1]))
                center_y.append(float(parts[2]))
                width.append(float(parts[3]))
                height.append(float(parts[4]))

df = pd.DataFrame({
    'image_path': image_paths,
    'class_label': class_labels,
    'center_x': center_x,
    'center_y': center_y,
    'width': width,
    'height': height
})

df.head()
```

```
                                          image_path  class_label
center_x  \
0  /kaggle/input/remote-sensing-satellite-images/...            2
0.498437
1  /kaggle/input/remote-sensing-satellite-images/...           10
0.510938
2  /kaggle/input/remote-sensing-satellite-images/...            9
0.498437
3  /kaggle/input/remote-sensing-satellite-images/...            4
0.498437
4  /kaggle/input/remote-sensing-satellite-images/...            5
0.498437

   center_y     width    height
0  0.498437  0.996094  0.996094
1  0.618750  0.970313  0.754687
2  0.498437  0.996094  0.996094
3  0.498437  0.996094  0.996094
4  0.498437  0.996094  0.996094
```

```
df.tail()
```

```
                                          image_path  class_label
center_x  \
```

```
743  /kaggle/input/remote-sensing-satellite-images/...            7
0.498437
744  /kaggle/input/remote-sensing-satellite-images/...            3
0.498437
745  /kaggle/input/remote-sensing-satellite-images/...            2
0.498437
746  /kaggle/input/remote-sensing-satellite-images/...            3
0.182031
747  /kaggle/input/remote-sensing-satellite-images/...           11
0.662500

     center_y     width    height
743  0.498437  0.996094  0.996094
744  0.498437  0.996094  0.996094
745  0.498437  0.996094  0.996094
746  0.498437  0.364063  0.996094
747  0.498437  0.667969  0.996094
```

```
df.shape
```

```
(748, 6)
```

```
df.columns
```

```
Index(['image_path', 'class_label', 'center_x', 'center_y', 'width',
'height'], dtype='object')
```

```
df.duplicated().sum()
```

```
0
```

```
df.isnull().sum()
```

```
image_path     0
class_label    0
center_x       0
center_y       0
width          0
height         0
dtype: int64
```

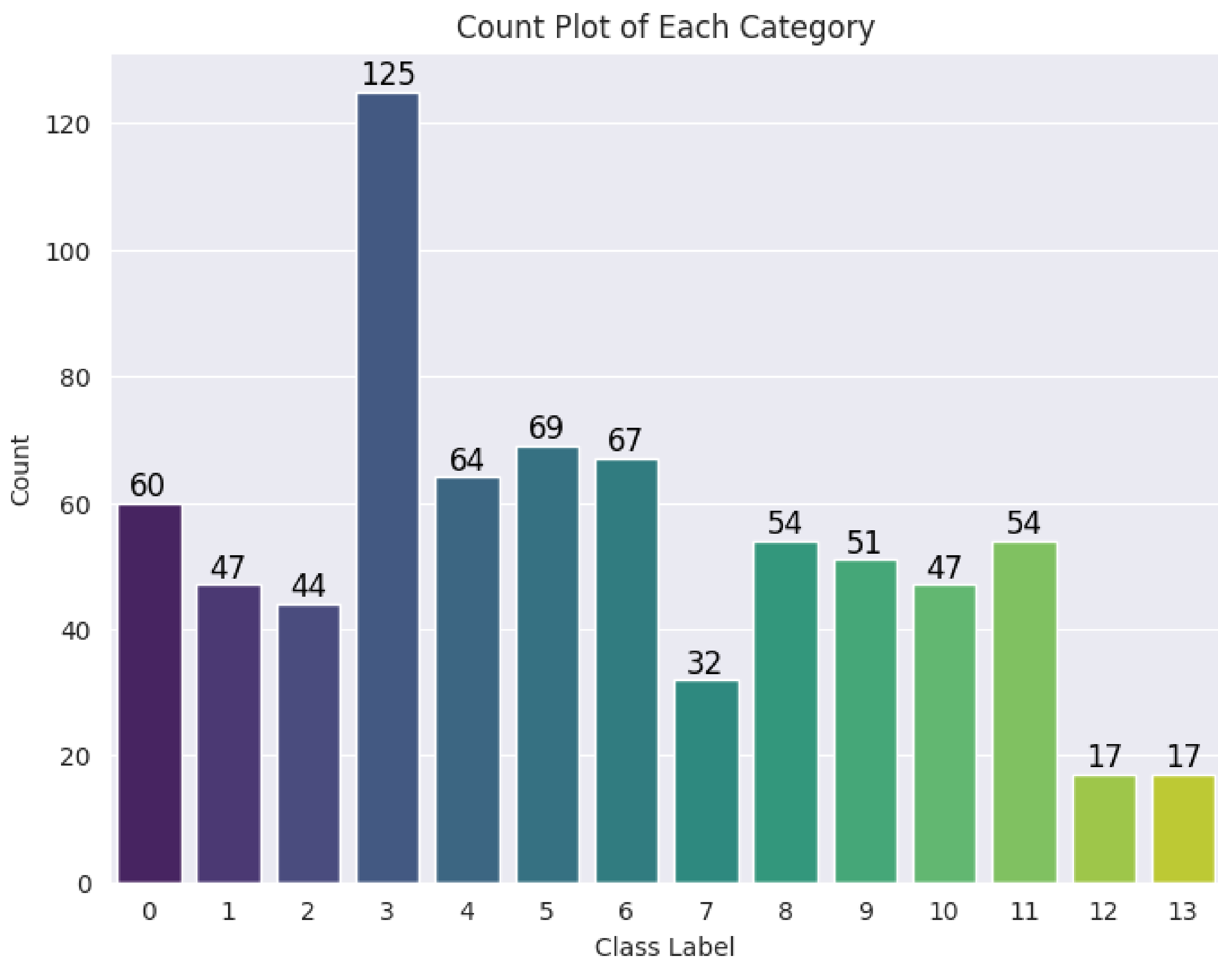
```
df = df[['image_path', 'class_label']]
```

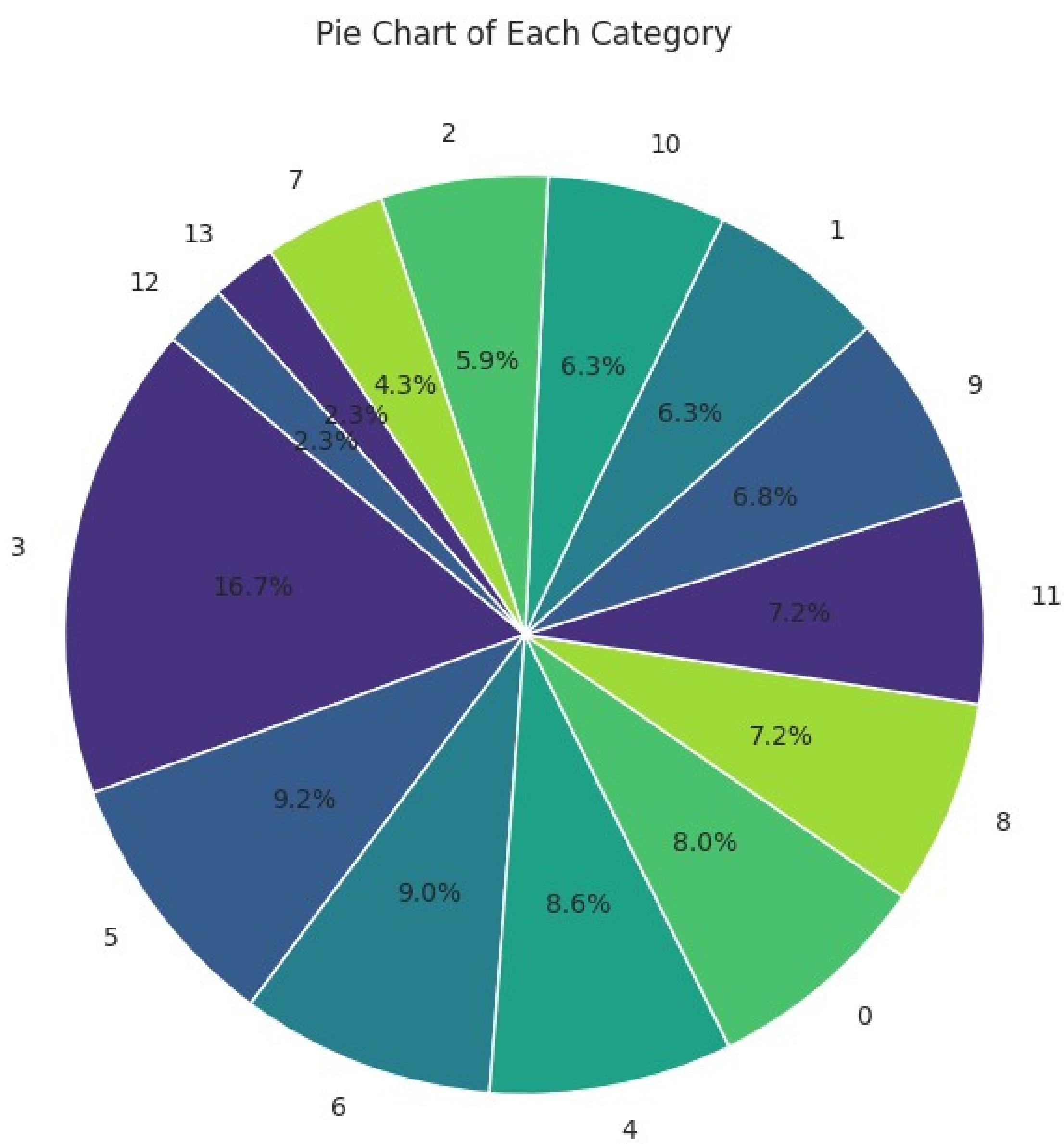
```
df
```

```
                                            image_path  class_label
0    /kaggle/input/remote-sensing-satellite-images/...            2
1    /kaggle/input/remote-sensing-satellite-images/...           10
2    /kaggle/input/remote-sensing-satellite-images/...            9
3    /kaggle/input/remote-sensing-satellite-images/...            4
4    /kaggle/input/remote-sensing-satellite-images/...            5
..                                                 ...          ...
```

```
743  /kaggle/input/remote-sensing-satellite-images/...           7
744  /kaggle/input/remote-sensing-satellite-images/...           3
745  /kaggle/input/remote-sensing-satellite-images/...           2
746  /kaggle/input/remote-sensing-satellite-images/...           3
747  /kaggle/input/remote-sensing-satellite-images/...          11

[748 rows x 2 columns]
```

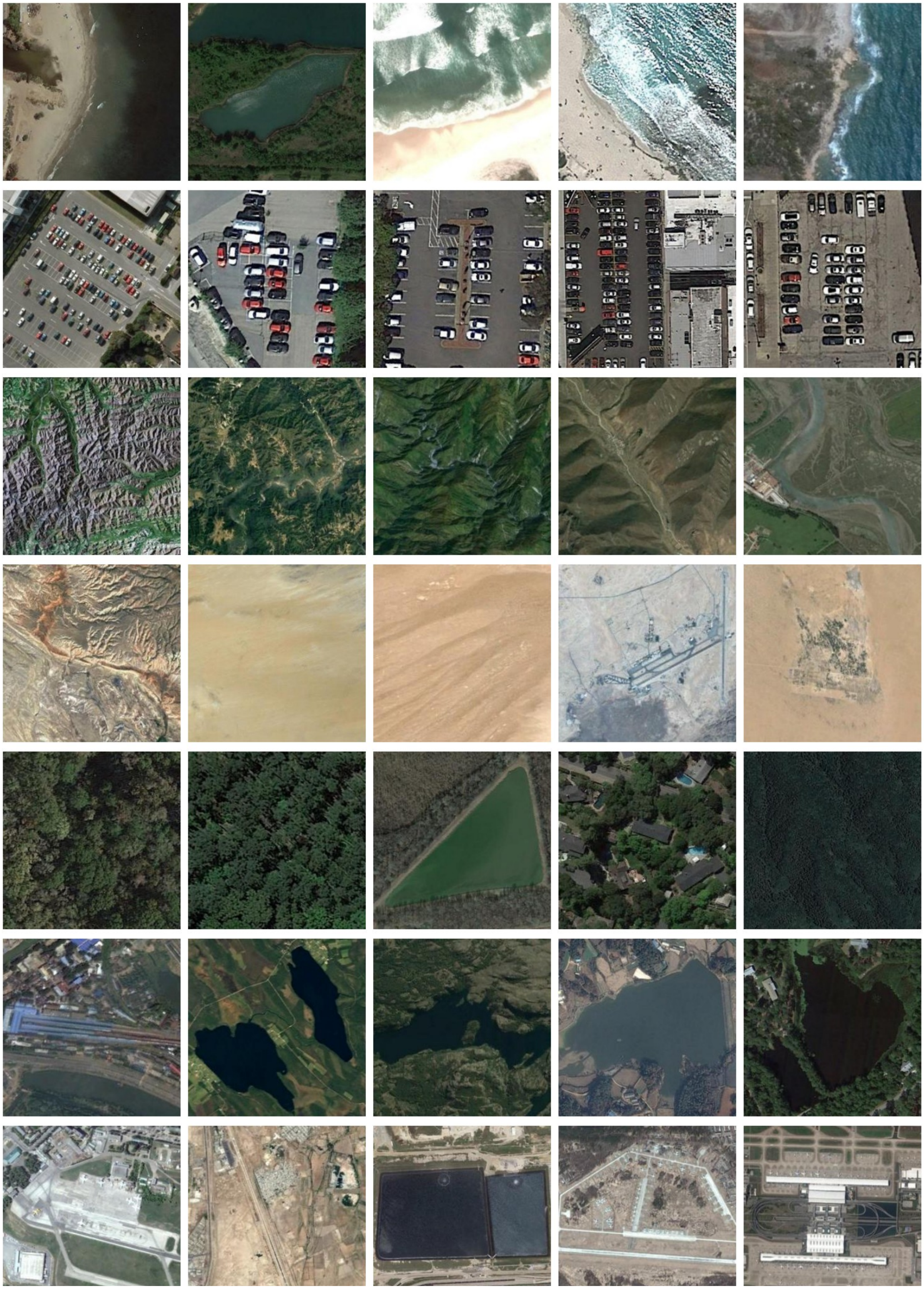
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
ax = sns.countplot(data=df, x='class_label', palette="viridis")
plt.title('Count Plot of Each Category')
plt.xlabel('Class Label')
plt.ylabel('Count')


for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2, p.get_height()),
                ha='center', va='bottom', fontsize=12, color='black')

plt.show()

plt.figure(figsize=(8, 8))
class_counts = df['class_label'].value_counts()
plt.pie(class_counts, labels=class_counts.index, autopct='%1.1f%%',
colors=sns.color_palette("viridis"), startangle=140)

plt.title('Pie Chart of Each Category')
plt.show()
```


Count Plot of Each Category
Count
Class Label
0
20
40
60
80
100
120
125
60
47
44
64
69
67
32
54
51
47
54
17
17
0
1
2
3
4
5
6
7
8
9
10
11
12
13




```
import random
from PIL import Image

images_per_category = 5

class_labels = df['class_label'].unique()

fig, axes = plt.subplots(len(class_labels), images_per_category,
figsize=(15, 3 * len(class_labels)))

for i, class_label in enumerate(class_labels):
```

```
    class_images = df[df['class_label'] == class_label]
['image_path'].tolist()

    sampled_images = random.sample(class_images,
min(images_per_category, len(class_images)))

    for j, image_path in enumerate(sampled_images):
        img = Image.open(image_path)

        axes[i, j].imshow(img)
        axes[i, j].axis('off')

        if j == 0:
            axes[i, j].set_ylabel(f"Class {class_label}", rotation=0,
labelpad=50, fontsize=12, ha='right', va='center')

plt.tight_layout()
plt.show()
```



```python
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler(random_state=42)
X_resampled, y_resampled = ros.fit_resample(df[['image_path']],
df['class_label'])

df_resampled = pd.DataFrame(X_resampled, columns=['image_path'])
df_resampled['class_label'] = y_resampled

print("\nClass distribution after oversampling:")
print(df_resampled['class_label'].value_counts())
```

```
Class distribution after oversampling:
class_label
2     125
10    125
9     125
4     125
5     125
8     125
1     125
13    125
0     125
3     125
11    125
6     125
7     125
12    125
Name: count, dtype: int64
```

```python
df_resampled
```

```
                                             image_path  class_label
0     /kaggle/input/remote-sensing-satellite-images/...            2
1     /kaggle/input/remote-sensing-satellite-images/...           10
2     /kaggle/input/remote-sensing-satellite-images/...            9
3     /kaggle/input/remote-sensing-satellite-images/...            4
4     /kaggle/input/remote-sensing-satellite-images/...            5
...                                                 ...          ...
1745  /kaggle/input/remote-sensing-satellite-images/...           13
1746  /kaggle/input/remote-sensing-satellite-images/...           13
1747  /kaggle/input/remote-sensing-satellite-images/...           13
1748  /kaggle/input/remote-sensing-satellite-images/...           13
1749  /kaggle/input/remote-sensing-satellite-images/...           13

[1750 rows x 2 columns]
```

```python
import time
import shutil
import pathlib
```

```python
import itertools
from PIL import Image

import cv2
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 tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam, Adamax
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Activation, Dropout, BatchNormalization
from tensorflow.keras import regularizers

import warnings
warnings.filterwarnings("ignore")

print ('check')
```

```
check
```

```python
df_resampled['class_label'] = df_resampled['class_label'].astype(str)

train_df_new, temp_df_new = train_test_split(
    df_resampled,
    train_size=0.8,
    shuffle=True,
    random_state=42,
    stratify=df_resampled['class_label']
)

valid_df_new, test_df_new = train_test_split(
    temp_df_new,
    test_size=0.5,
    shuffle=True,
    random_state=42,
    stratify=temp_df_new['class_label']
)

from tensorflow.keras.preprocessing.image import ImageDataGenerator

batch_size = 16
img_size = (224, 224)
channels = 3
img_shape = (img_size[0], img_size[1], channels)
```

```python
tr_gen = ImageDataGenerator(rescale=1./255)
ts_gen = ImageDataGenerator(rescale=1./255)

train_gen_new = tr_gen.flow_from_dataframe(
    train_df_new,
    x_col='image_path',
    y_col='class_label',
    target_size=img_size,
    class_mode='sparse',
    color_mode='rgb',
    shuffle=True,
    batch_size=batch_size
)

valid_gen_new = ts_gen.flow_from_dataframe(
    valid_df_new,
    x_col='image_path',
    y_col='class_label',
    target_size=img_size,
    class_mode='sparse',
    color_mode='rgb',
    shuffle=True,
    batch_size=batch_size
)

test_gen_new = ts_gen.flow_from_dataframe(
    test_df_new,
    x_col='image_path',
    y_col='class_label',
    target_size=img_size,
    class_mode='sparse',
    color_mode='rgb',
    shuffle=False,
    batch_size=batch_size
)
```

```
Found 1400 validated image filenames belonging to 14 classes.
Found 175 validated image filenames belonging to 14 classes.
Found 175 validated image filenames belonging to 14 classes.
```

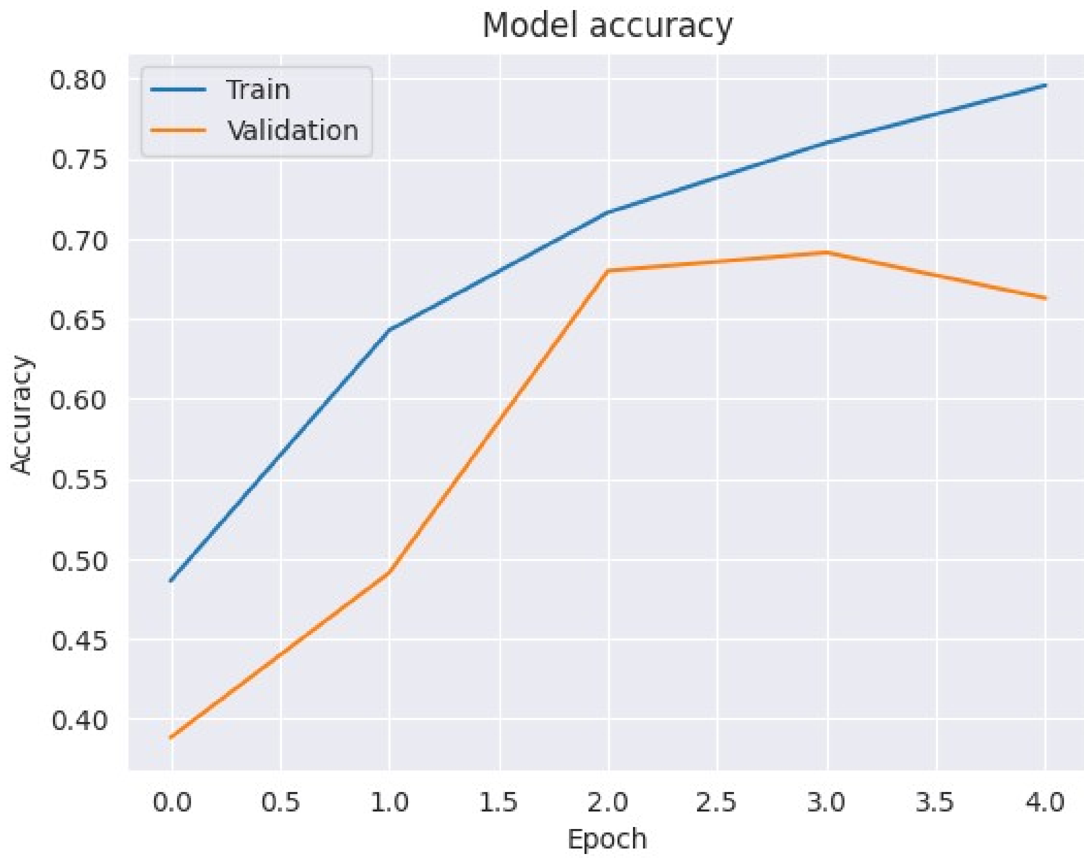
```python
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

physical_devices = tf.config.list_physical_devices('GPU')
if physical_devices:
    print("Using GPU")
else:
    print("Using CPU")
```

```
Using GPU

early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense,
Dropout, BatchNormalization, GaussianNoise, Input, MultiHeadAttention,
Reshape
from tensorflow.keras.optimizers import Adam
import tensorflow as tf

def create_vgg16_model(input_shape):

    inputs = Input(shape=input_shape)

    base_model = VGG16(weights='imagenet', input_tensor=inputs,
include_top=False)

    for layer in base_model.layers:
        layer.trainable = False

    x = base_model.output

    height, width, channels = 7, 7, 512
    x = Reshape((height * width, channels))(x)

    attention_output = MultiHeadAttention(num_heads=8,
key_dim=channels)(x, x)

    attention_output = Reshape((height, width, channels))
(attention_output)

    x = GaussianNoise(0.25)(attention_output)
    x = GlobalAveragePooling2D()(x)

    x = Dense(512, activation='relu')(x)
    x = BatchNormalization()(x)
    x = GaussianNoise(0.25)(x)
    x = Dropout(0.25)(x)

    outputs = Dense(14, activation='softmax')(x)

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

    return model

input_shape = (224, 224, 3)
cnn_model = create_vgg16_model(input_shape)
```

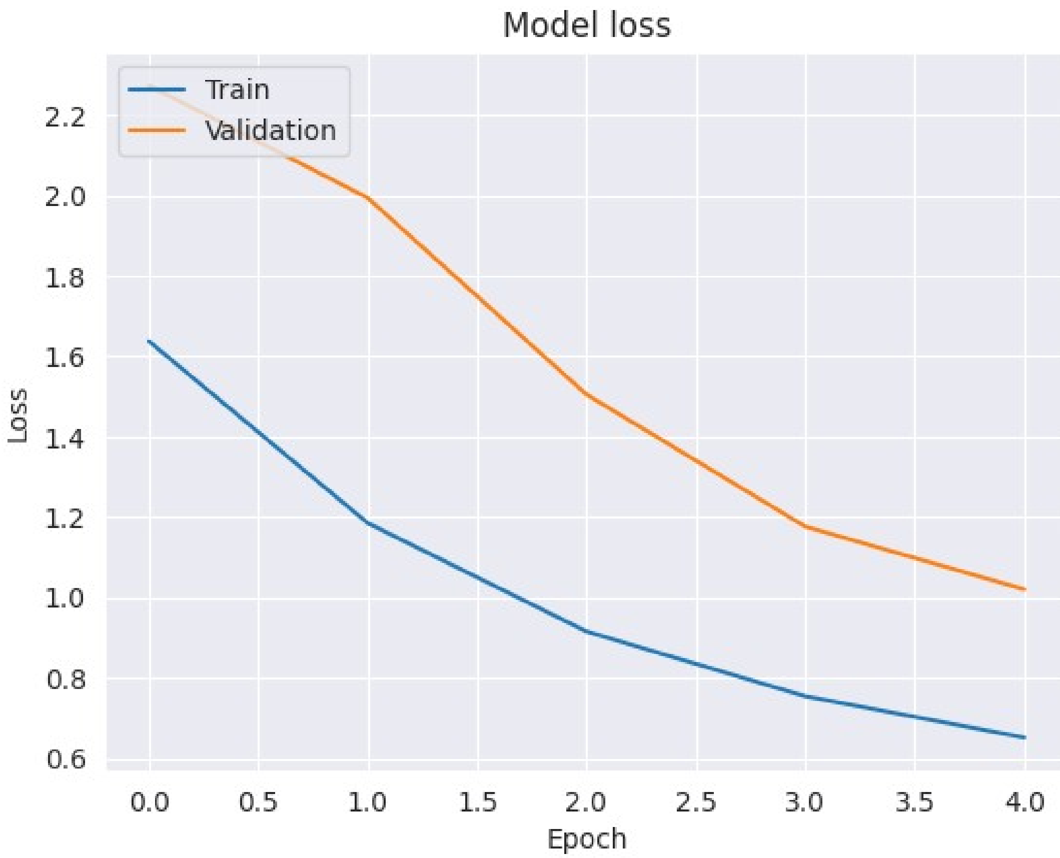
```
cnn_model.compile(optimizer=Adam(learning_rate=0.0001),
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])

history = cnn_model.fit(
    train_gen_new,
    validation_data=valid_gen_new,
    epochs=5,
    callbacks=[early_stopping],
    verbose=1
)
```

```
Epoch 1/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 23s 167ms/step - accuracy: 0.3485 - loss:
2.0396 - val_accuracy: 0.3886 - val_loss: 2.2730
Epoch 2/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 8s 90ms/step - accuracy: 0.6384 - loss:
1.2135 - val_accuracy: 0.4914 - val_loss: 1.9934
Epoch 3/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 8s 91ms/step - accuracy: 0.6936 - loss:
0.9943 - val_accuracy: 0.6800 - val_loss: 1.5046
Epoch 4/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 8s 91ms/step - accuracy: 0.7599 - loss:
0.7450 - val_accuracy: 0.6914 - val_loss: 1.1762
Epoch 5/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 8s 90ms/step - accuracy: 0.8017 - loss:
0.6267 - val_accuracy: 0.6629 - val_loss: 1.0204
```

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```



Model accuracy
Train
Validation
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
Accuracy
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epoch




```
test_labels = test_gen_new.classes
predictions = cnn_model.predict(test_gen_new)
predicted_classes = np.argmax(predictions, axis=1)
```

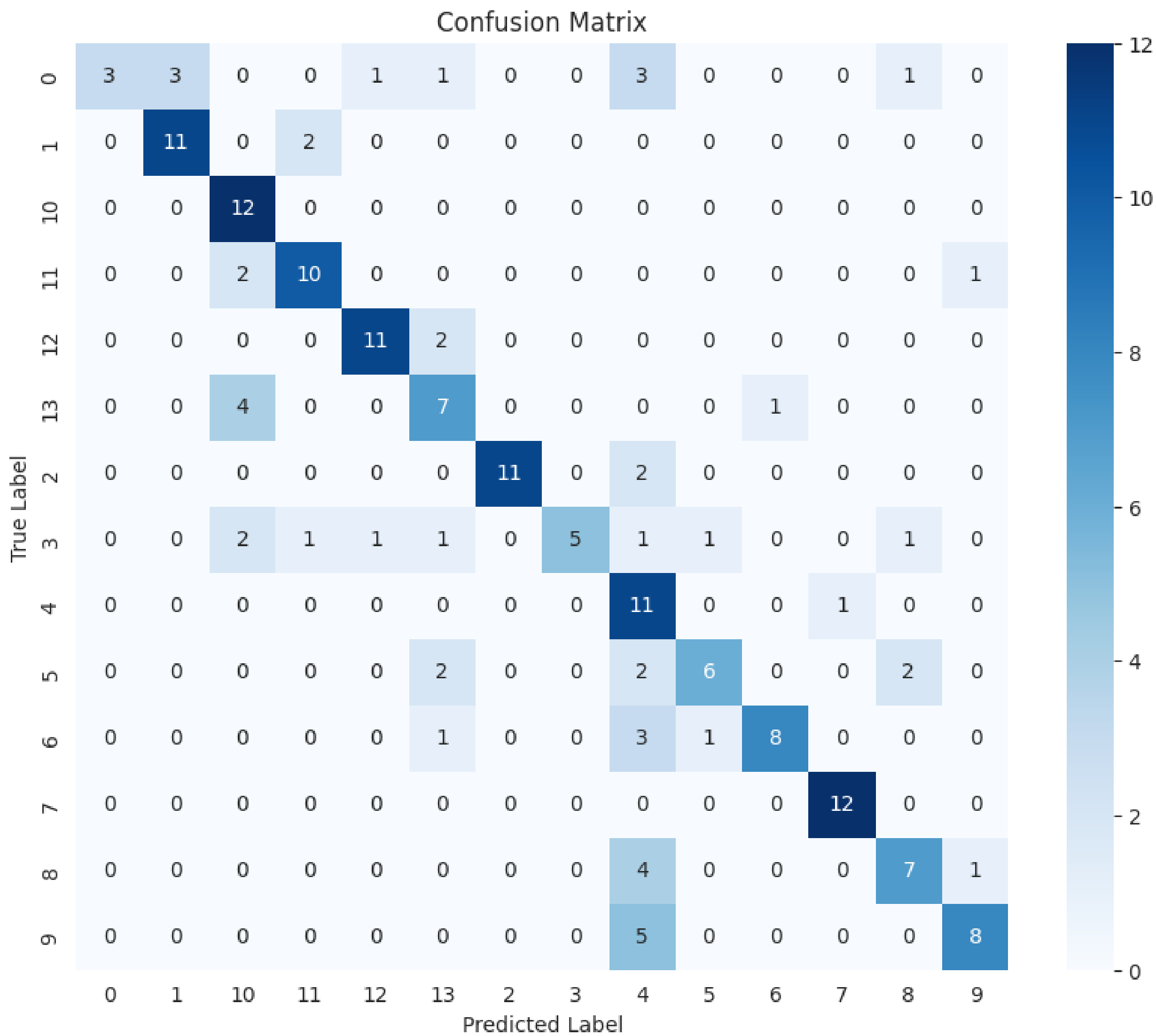
```
11/11 ━━━━━━━━━━━━━━━━━━━━ 2s 125ms/step
```

```
report = classification_report(test_labels, predicted_classes,
target_names=list(test_gen_new.class_indices.keys()))
print(report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.25      0.40        12
           1       0.79      0.85      0.81        13
          10       0.60      1.00      0.75        12
          11       0.77      0.77      0.77        13
          12       0.85      0.85      0.85        13
          13       0.50      0.58      0.54        12
           2       1.00      0.85      0.92        13
           3       1.00      0.38      0.56        13
           4       0.35      0.92      0.51        12
           5       0.75      0.50      0.60        12
           6       0.89      0.62      0.73        13
```

```
              7       0.92      1.00      0.96        12
              8       0.64      0.58      0.61        12
              9       0.80      0.62      0.70        13

    accuracy                            0.70       175
   macro avg       0.78      0.70      0.69       175
weighted avg       0.78      0.70      0.70       175
```

```python
conf_matrix = confusion_matrix(test_labels, predicted_classes)

plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=list(test_gen_new.class_indices.keys()),
yticklabels=list(test_gen_new.class_indices.keys()))
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```




```python
from tensorflow.keras.applications import VGG19
from tensorflow.keras.models import Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense,
Dropout, BatchNormalization, GaussianNoise, Input, MultiHeadAttention,
Reshape
from tensorflow.keras.optimizers import Adam
import tensorflow as tf

def create_vgg19_model(input_shape):

    inputs = Input(shape=input_shape)

    base_model = VGG19(weights='imagenet', input_tensor=inputs,
include_top=False)

    for layer in base_model.layers:
```

```
        layer.trainable = False

    x = base_model.output

    height, width, channels = 7, 7, 512
    x = Reshape((height * width, channels))(x)

    attention_output = MultiHeadAttention(num_heads=8,
key_dim=channels)(x, x)

    attention_output = Reshape((height, width, channels))
(attention_output)

    x = GaussianNoise(0.25)(attention_output)
    x = GlobalAveragePooling2D()(x)

    x = Dense(512, activation='relu')(x)
    x = BatchNormalization()(x)
    x = GaussianNoise(0.25)(x)
    x = Dropout(0.25)(x)

    outputs = Dense(14, activation='softmax')(x)

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

    return model

input_shape = (224, 224, 3)
cnn_model = create_vgg19_model(input_shape)

cnn_model.compile(optimizer=Adam(learning_rate=0.0001),
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])

history = cnn_model.fit(
    train_gen_new,
    validation_data=valid_gen_new,
    epochs=5,
    callbacks=[early_stopping],
    verbose=1
)
```

```
Epoch 1/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 24s 179ms/step - accuracy: 0.3077 - loss:
2.1396 - val_accuracy: 0.2800 - val_loss: 2.3190
Epoch 2/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 9s 102ms/step - accuracy: 0.5888 - loss:
1.2940 - val_accuracy: 0.2743 - val_loss: 2.1177
Epoch 3/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 10s 105ms/step - accuracy: 0.6390 - loss:
1.1083 - val_accuracy: 0.4057 - val_loss: 1.7282
```

```
Epoch 4/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 10s 107ms/step - accuracy: 0.7429 - loss:
0.8452 - val_accuracy: 0.5886 - val_loss: 1.3326
Epoch 5/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 10s 107ms/step - accuracy: 0.7924 - loss:
0.6552 - val_accuracy: 0.5829 - val_loss: 1.3261

plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```


```
test_labels = test_gen_new.classes
predictions = cnn_model.predict(test_gen_new)
predicted_classes = np.argmax(predictions, axis=1)
```

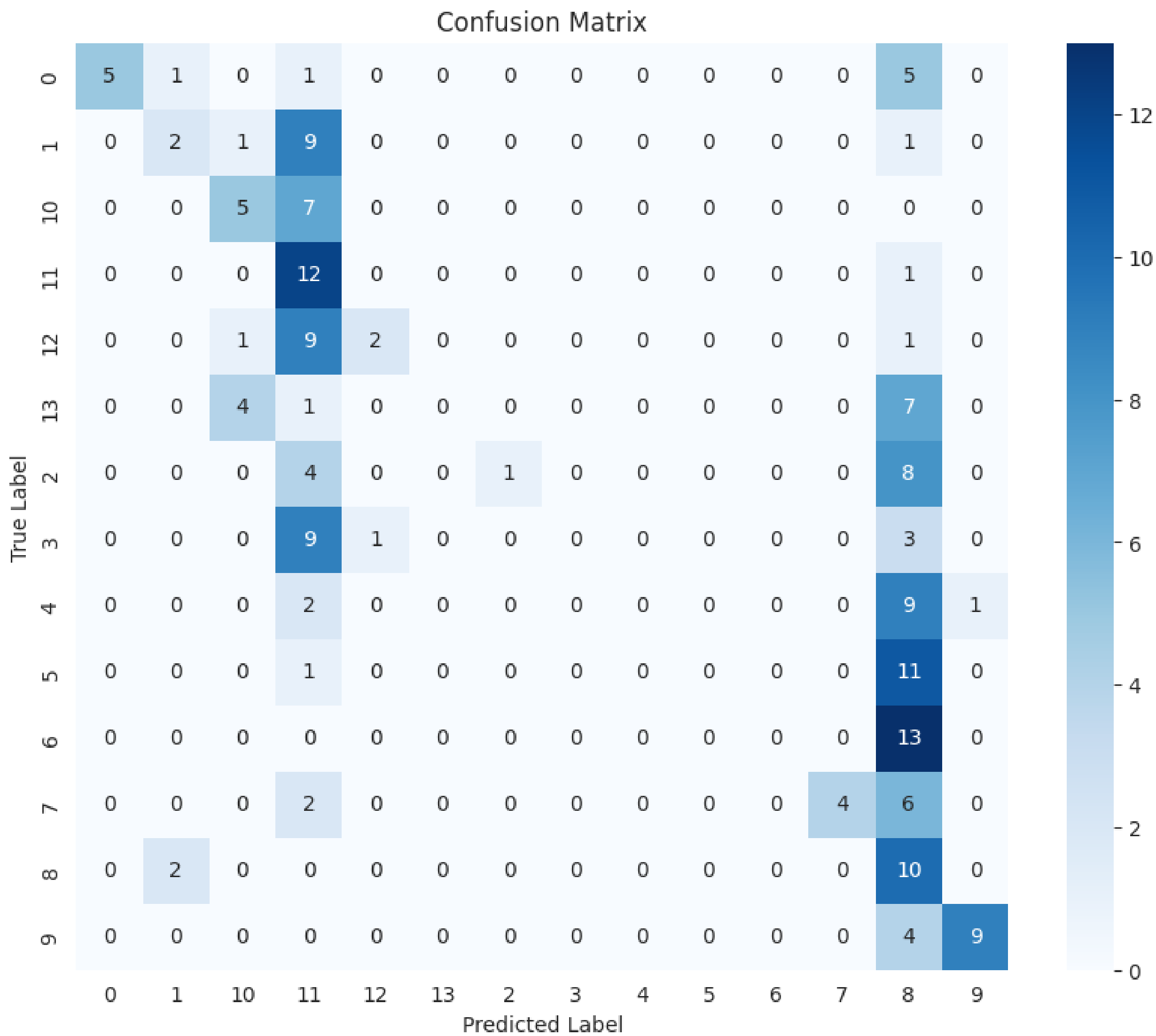
```
11/11 ━━━━━━━━━━━━━━━━━━━━ 2s 142ms/step
```

```
report = classification_report(test_labels, predicted_classes,
target_names=list(test_gen_new.class_indices.keys()))
print(report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.42      0.59        12
           1       0.40      0.15      0.22        13
          10       0.45      0.42      0.43        12
          11       0.21      0.92      0.34        13
          12       0.67      0.15      0.25        13
          13       0.00      0.00      0.00        12
           2       1.00      0.08      0.14        13
           3       0.00      0.00      0.00        13
           4       0.00      0.00      0.00        12
           5       0.00      0.00      0.00        12
           6       0.00      0.00      0.00        13
```

```
           7       1.00      0.33      0.50        12
           8       0.13      0.83      0.22        12
           9       0.90      0.69      0.78        13

    accuracy                           0.29       175
   macro avg       0.41      0.29      0.25       175
weighted avg       0.41      0.29      0.25       175
```

```python
conf_matrix = confusion_matrix(test_labels, predicted_classes)

plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=list(test_gen_new.class_indices.keys()),
yticklabels=list(test_gen_new.class_indices.keys()))
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



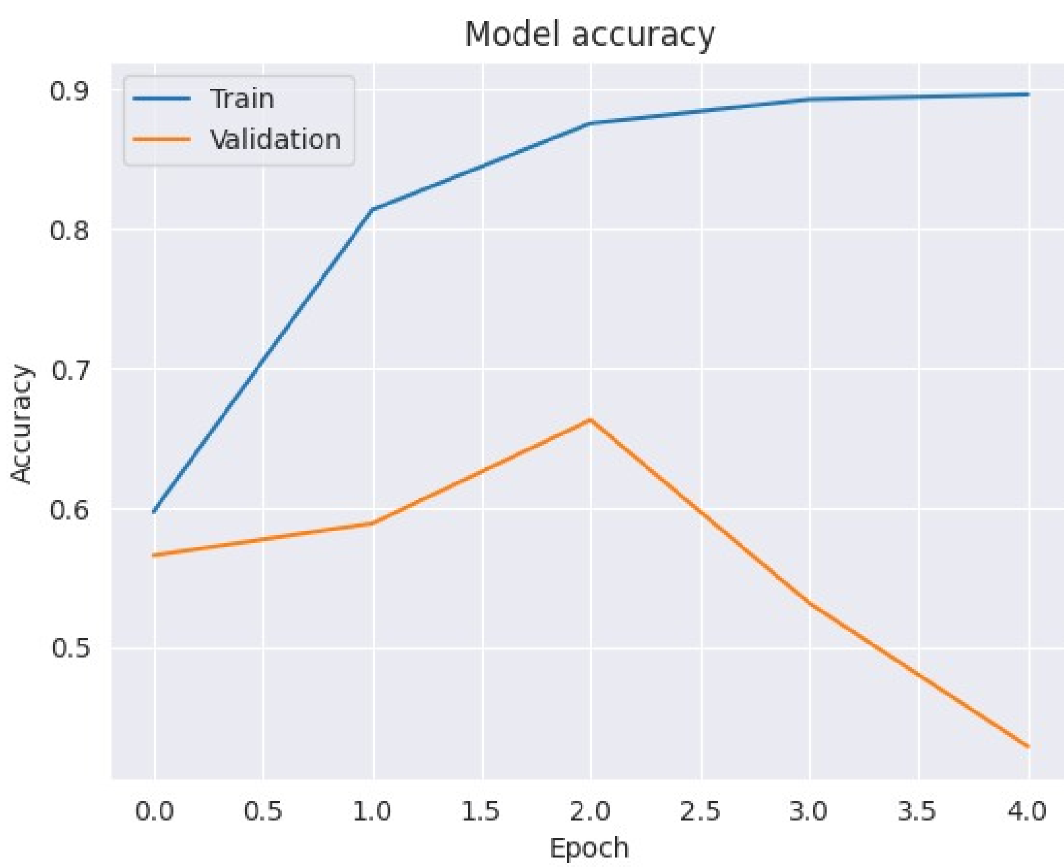

```python
from tensorflow.keras.applications import InceptionV3
from tensorflow.keras.models import Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense,
Dropout, BatchNormalization, GaussianNoise, Input, MultiHeadAttention,
Reshape
from tensorflow.keras.optimizers import Adam
import tensorflow as tf

def create_inceptionv3_model(input_shape):

    inputs = Input(shape=input_shape)

    base_model = InceptionV3(weights='imagenet', input_tensor=inputs,
include_top=False)

    for layer in base_model.layers:
```

```
        layer.trainable = False

    x = base_model.output

    height, width, channels = 5, 5, 2048
    x = Reshape((height * width, channels))(x)

    attention_output = MultiHeadAttention(num_heads=8,
key_dim=channels)(x, x)

    attention_output = Reshape((height, width, channels))
(attention_output)

    x = GaussianNoise(0.25)(attention_output)
    x = GlobalAveragePooling2D()(x)

    x = Dense(512, activation='relu')(x)
    x = BatchNormalization()(x)
    x = GaussianNoise(0.25)(x)
    x = Dropout(0.25)(x)

    outputs = Dense(14, activation='softmax')(x)

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

    return model

input_shape = (224, 224, 3)
cnn_model = create_inceptionv3_model(input_shape)

cnn_model.compile(optimizer=Adam(learning_rate=0.0001),
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])

history = cnn_model.fit(
    train_gen_new,
    validation_data=valid_gen_new,
    epochs=5,
    callbacks=[early_stopping],
    verbose=1
)
```

```
Epoch 1/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 48s 340ms/step - accuracy: 0.4807 - loss:
1.9312 - val_accuracy: 0.5657 - val_loss: 1.7963
Epoch 2/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 12s 129ms/step - accuracy: 0.8081 - loss:
0.6570 - val_accuracy: 0.5886 - val_loss: 1.4472
Epoch 3/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 12s 131ms/step - accuracy: 0.8700 - loss:
0.4519 - val_accuracy: 0.6629 - val_loss: 1.2109
```

```
Epoch 4/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 12s 131ms/step - accuracy: 0.8957 - loss:
0.3675 - val_accuracy: 0.5314 - val_loss: 2.7913
Epoch 5/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 12s 129ms/step - accuracy: 0.9102 - loss:
0.3699 - val_accuracy: 0.4286 - val_loss: 3.7984
```

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```




```
test_labels = test_gen_new.classes
predictions = cnn_model.predict(test_gen_new)
predicted_classes = np.argmax(predictions, axis=1)
```

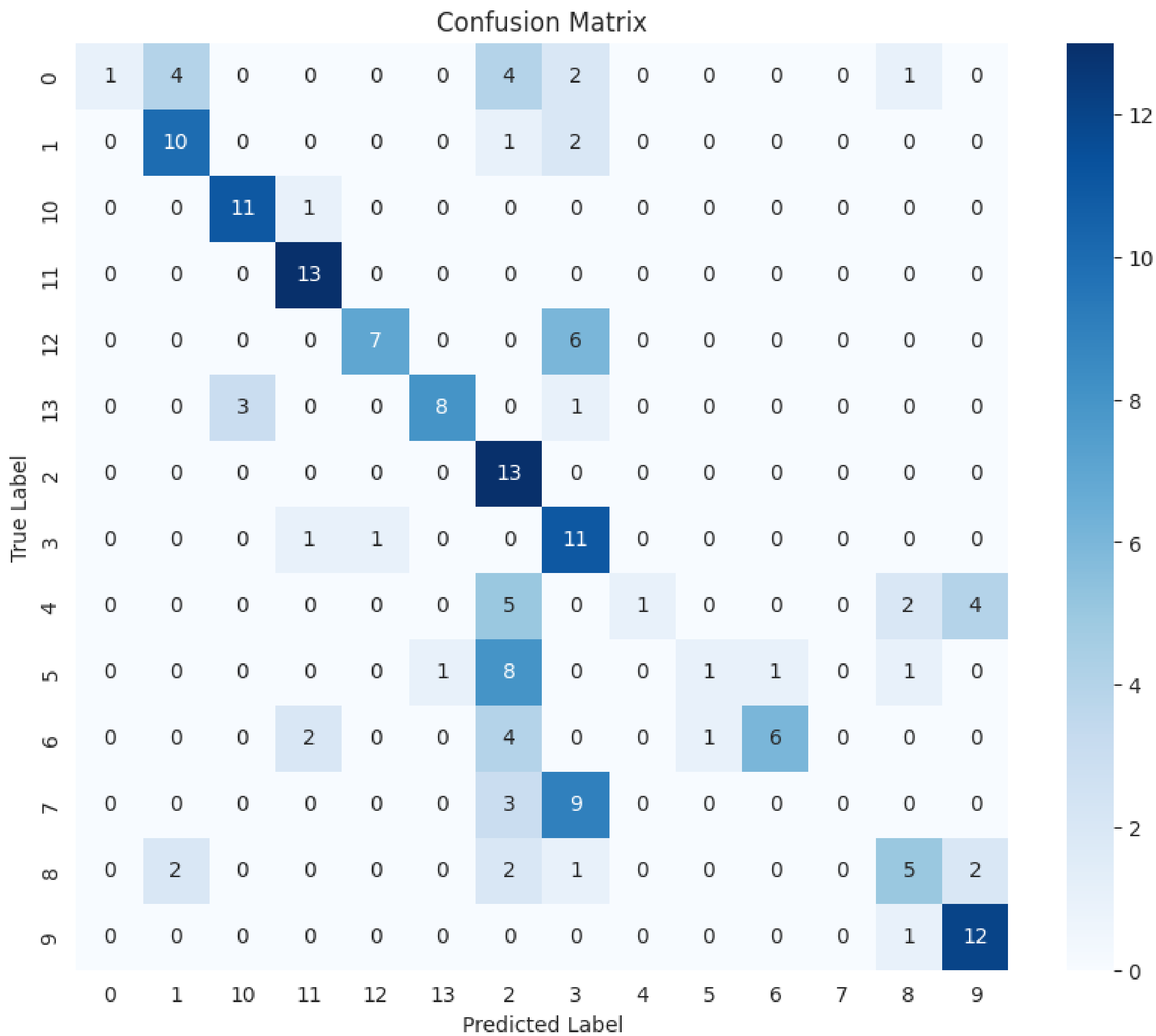
```
11/11 ━━━━━━━━━━━━━━━━━━━━ 11s 570ms/step
```

```
report = classification_report(test_labels, predicted_classes,
target_names=list(test_gen_new.class_indices.keys()))
print(report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.08      0.15        12
           1       0.62      0.77      0.69        13
          10       0.79      0.92      0.85        12
          11       0.76      1.00      0.87        13
          12       0.88      0.54      0.67        13
          13       0.89      0.67      0.76        12
           2       0.33      1.00      0.49        13
           3       0.34      0.85      0.49        13
           4       1.00      0.08      0.15        12
           5       0.50      0.08      0.14        12
           6       0.86      0.46      0.60        13
```

```
           7       0.00      0.00      0.00        12
           8       0.50      0.42      0.45        12
           9       0.67      0.92      0.77        13

    accuracy                           0.57       175
   macro avg       0.65      0.56      0.51       175
weighted avg       0.65      0.57      0.51       175
```

```python
conf_matrix = confusion_matrix(test_labels, predicted_classes)

plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=list(test_gen_new.class_indices.keys()),
yticklabels=list(test_gen_new.class_indices.keys()))
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

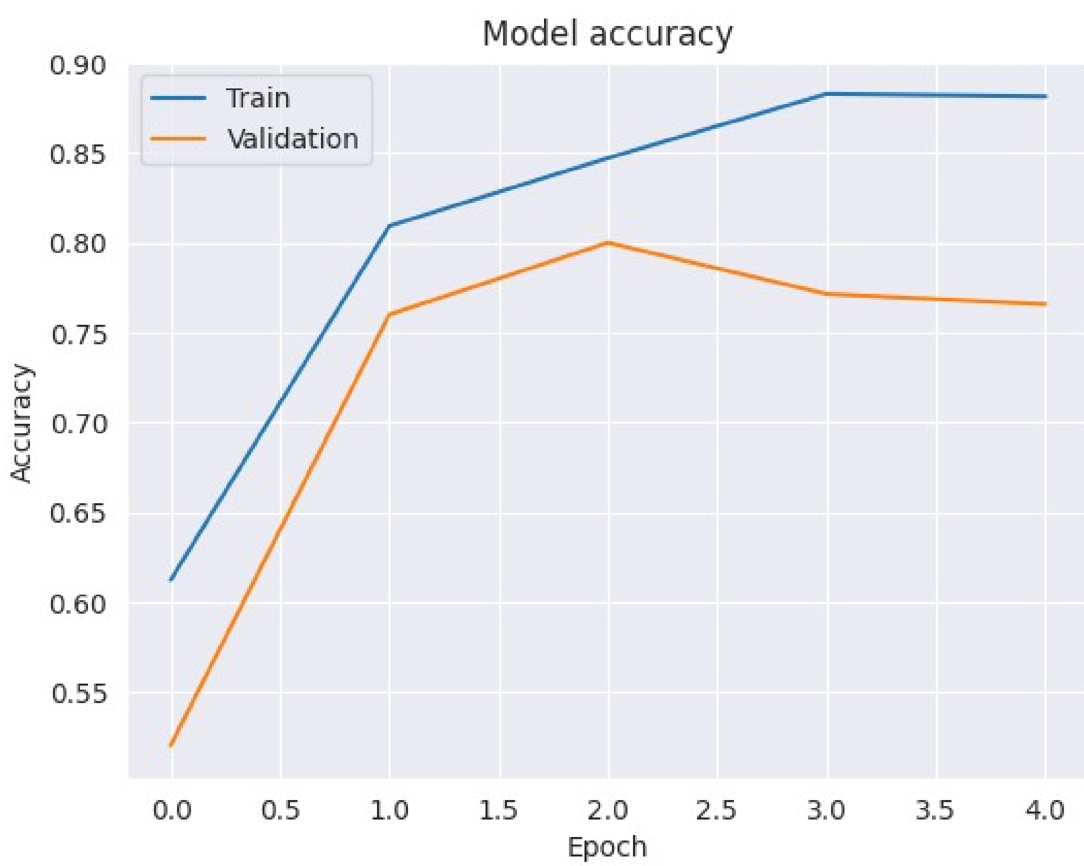


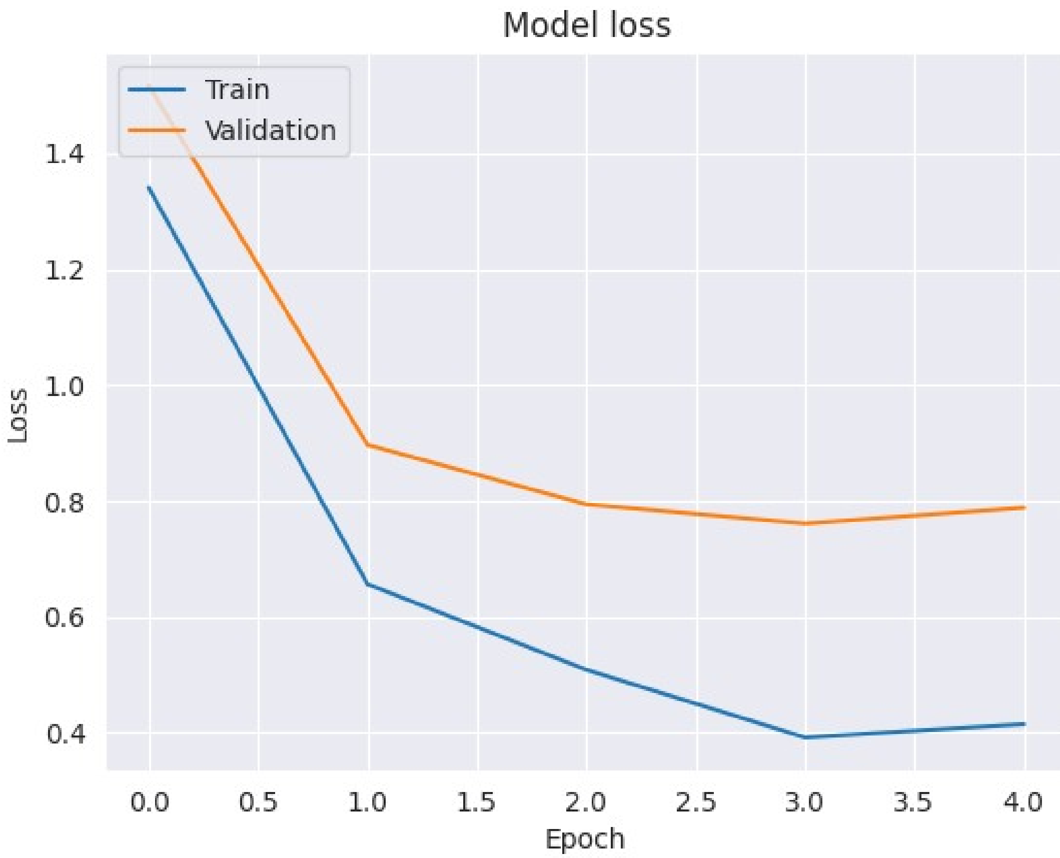

```
from tensorflow.keras.applications import Xception
from tensorflow.keras.models import Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense,
Dropout, BatchNormalization, GaussianNoise, Input, MultiHeadAttention,
Reshape
from tensorflow.keras.optimizers import Adam
import tensorflow as tf

def create_xception_model(input_shape):

    inputs = Input(shape=input_shape)

    base_model = Xception(weights='imagenet', input_tensor=inputs,
include_top=False)

    for layer in base_model.layers:
```

```
        layer.trainable = False

    x = base_model.output

    height, width, channels = 7, 7, 2048
    x = Reshape((height * width, channels))(x)

    attention_output = MultiHeadAttention(num_heads=8,
key_dim=channels)(x, x)

    attention_output = Reshape((height, width, channels))
(attention_output)

    x = GaussianNoise(0.25)(attention_output)
    x = GlobalAveragePooling2D()(x)
    x = Dense(512, activation='relu')(x)
    x = BatchNormalization()(x)
    x = GaussianNoise(0.25)(x)
    x = Dropout(0.25)(x)
    outputs = Dense(14, activation='softmax')(x)

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

    return model

input_shape = (224, 224, 3)
cnn_model = create_xception_model(input_shape)

cnn_model.compile(optimizer=Adam(learning_rate=0.0001),
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])

history = cnn_model.fit(
    train_gen_new,
    validation_data=valid_gen_new,
    epochs=5,
    callbacks=[early_stopping],
    verbose=1
)
```

```
Epoch 1/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 43s 345ms/step - accuracy: 0.5023 - loss:
1.7452 - val_accuracy: 0.5200 - val_loss: 1.5167
Epoch 2/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 21s 238ms/step - accuracy: 0.8033 - loss:
0.6875 - val_accuracy: 0.7600 - val_loss: 0.8965
Epoch 3/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 21s 232ms/step - accuracy: 0.8390 - loss:
0.5244 - val_accuracy: 0.8000 - val_loss: 0.7940
Epoch 4/5
```

```
88/88 ━━━━━━━━━━━━━━━━━━━━ 20s 226ms/step - accuracy: 0.8884 - loss: 
0.3722 - val_accuracy: 0.7714 - val_loss: 0.7607
Epoch 5/5
88/88 ━━━━━━━━━━━━━━━━━━━━ 20s 218ms/step - accuracy: 0.8929 - loss: 
0.3921 - val_accuracy: 0.7657 - val_loss: 0.7880

plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```






```
test_labels = test_gen_new.classes
predictions = cnn_model.predict(test_gen_new)
predicted_classes = np.argmax(predictions, axis=1)
```

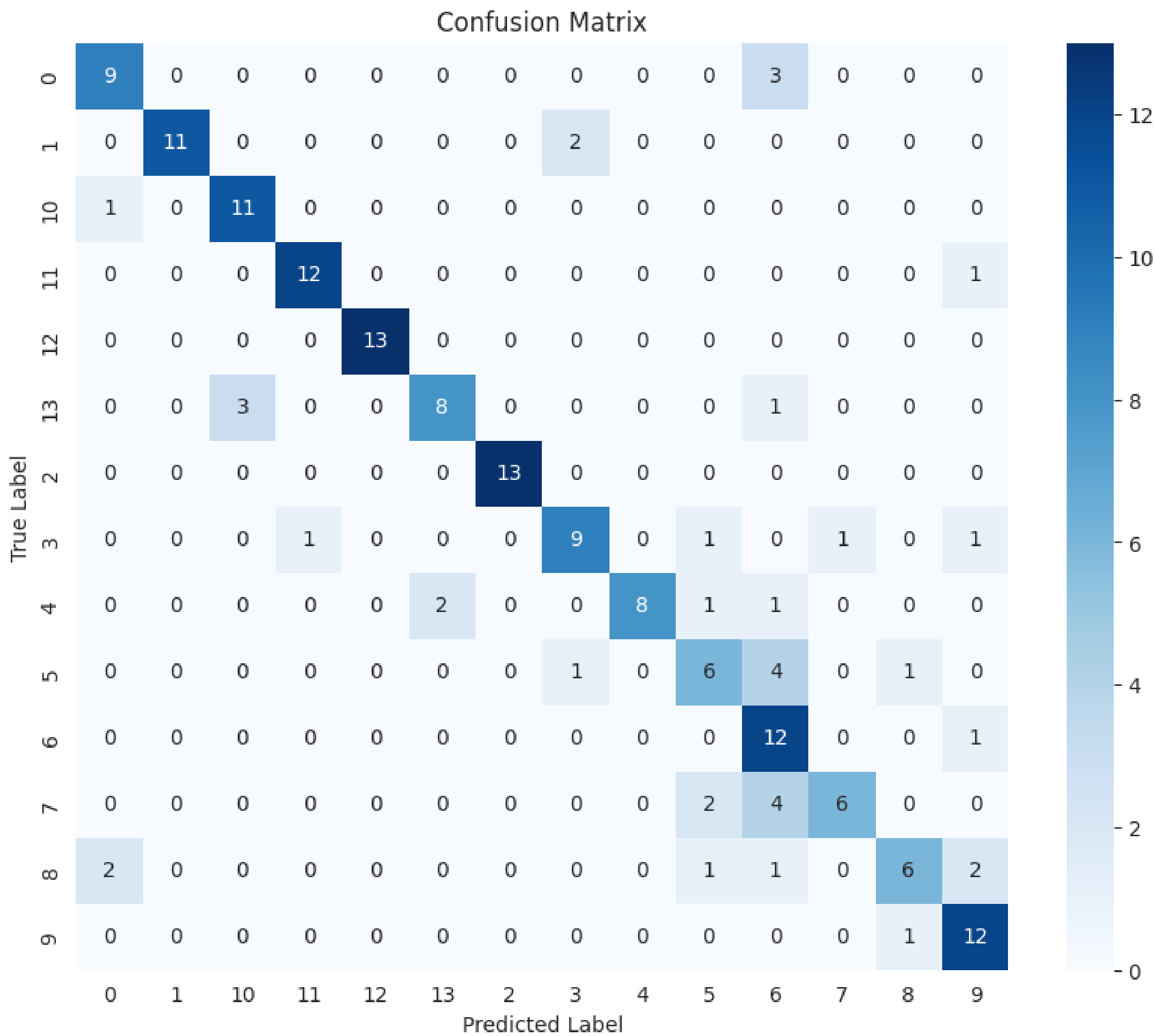
```
11/11 ━━━━━━━━━━━━━━━━━━━━ 6s 335ms/step
```

```
report = classification_report(test_labels, predicted_classes,
target_names=list(test_gen_new.class_indices.keys()))
print(report)
```

```
              precision    recall  f1-score   support

           0       0.75      0.75      0.75        12
           1       1.00      0.85      0.92        13
          10       0.79      0.92      0.85        12
          11       0.92      0.92      0.92        13
          12       1.00      1.00      1.00        13
          13       0.80      0.67      0.73        12
           2       1.00      1.00      1.00        13
           3       0.75      0.69      0.72        13
           4       1.00      0.67      0.80        12
           5       0.55      0.50      0.52        12
           6       0.46      0.92      0.62        13
```

```
             7       0.86      0.50      0.63        12
             8       0.75      0.50      0.60        12
             9       0.71      0.92      0.80        13

      accuracy                           0.78       175
     macro avg       0.81      0.77      0.78       175
  weighted avg       0.81      0.78      0.78       175
```

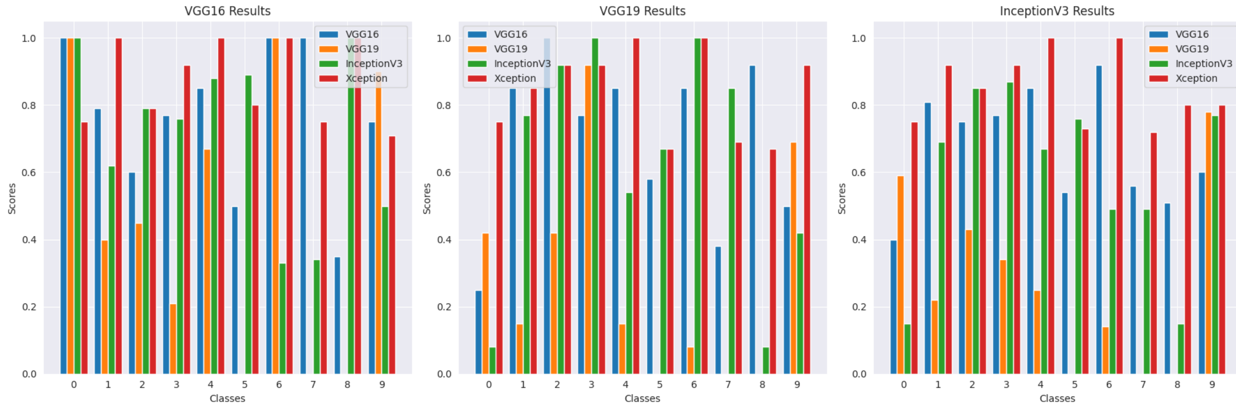
```
conf_matrix = confusion_matrix(test_labels, predicted_classes)

plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=list(test_gen_new.class_indices.keys()),
yticklabels=list(test_gen_new.class_indices.keys()))
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```




```python
import matplotlib.pyplot as plt
import numpy as np

labels = [str(i) for i in range(10)]

vgg16_precision = [1.00, 0.79, 0.60, 0.77, 0.85, 0.50, 1.00, 1.00,
0.35, 0.75]
vgg16_recall = [0.25, 0.85, 1.00, 0.77, 0.85, 0.58, 0.85, 0.38, 0.92,
0.50]
vgg16_f1 = [0.40, 0.81, 0.75, 0.77, 0.85, 0.54, 0.92, 0.56, 0.51,
0.60]

vgg19_precision = [1.00, 0.40, 0.45, 0.21, 0.67, 0.00, 1.00, 0.00,
0.00, 0.90]
vgg19_recall = [0.42, 0.15, 0.42, 0.92, 0.15, 0.00, 0.08, 0.00, 0.00,
0.69]
```

```
vgg19_f1 = [0.59, 0.22, 0.43, 0.34, 0.25, 0.00, 0.14, 0.00, 0.00,
0.78]

inceptionv3_precision = [1.00, 0.62, 0.79, 0.76, 0.88, 0.89, 0.33,
0.34, 1.00, 0.50]
inceptionv3_recall = [0.08, 0.77, 0.92, 1.00, 0.54, 0.67, 1.00, 0.85,
0.08, 0.42]
inceptionv3_f1 = [0.15, 0.69, 0.85, 0.87, 0.67, 0.76, 0.49, 0.49,
0.15, 0.77]

xception_precision = [0.75, 1.00, 0.79, 0.92, 1.00, 0.80, 1.00, 0.75,
1.00, 0.71]
xception_recall = [0.75, 0.85, 0.92, 0.92, 1.00, 0.67, 1.00, 0.69,
0.67, 0.92]
xception_f1 = [0.75, 0.92, 0.85, 0.92, 1.00, 0.73, 1.00, 0.72, 0.80,
0.80]

fig, ax = plt.subplots(1, 3, figsize=(18, 6))

models = ['VGG16', 'VGG19', 'InceptionV3', 'Xception']
precision_data = [vgg16_precision, vgg19_precision,
inceptionv3_precision, xception_precision]
recall_data = [vgg16_recall, vgg19_recall, inceptionv3_recall,
xception_recall]
f1_data = [vgg16_f1, vgg19_f1, inceptionv3_f1, xception_f1]

x = np.arange(len(labels))
width = 0.2

for i, model in enumerate(models):
    ax[0].bar(x + i * width - 1.5 * width, precision_data[i], width,
label=model)

for i, model in enumerate(models):
    ax[1].bar(x + i * width - 1.5 * width, recall_data[i], width,
label=model)

for i, model in enumerate(models):
    ax[2].bar(x + i * width - 1.5 * width, f1_data[i], width,
label=model)

for i in range(3):
    ax[i].set_xlabel('Classes')
    ax[i].set_ylabel('Scores')
    ax[i].set_title(f'{models[i]} Results')
    ax[i].set_xticks(x)
    ax[i].set_xticklabels(labels)
    ax[i].legend()
```

```
plt.tight_layout()
plt.show()
```




# Thanks !!!