Here you can find the necessary import

```
import tensorflow as tf
import os
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc, precision_recall_curve, average_precision_sco
re, confusion_matrix
import pandas as pd
import matplotlib.pyplot as plt

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, BatchNormalization, Flatten, D
ense, Input
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import seaborn as sns
```

WARNING:tensorflow:From C:\Users\Faiza Anan Noor\anaconda3\Lib\site-packages\keras\src\lo sses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use t f.compat.v1.losses.sparse_softmax_cross_entropy instead.

In []:

In []:

```
# you need the current working directory NB: works both windows and linux
current_working_directory = os.getcwd()
current_working_directory = os.path.dirname(current_working_directory)

if not os.path.exists(f"{current_working_directory}/Datasets"):
    os.makedirs(f"{current_working_directory}/Datasets")

print(f"[DATASET] PUT THE DATASET here: {current_working_directory}/Datasets")
```

[DATASET] PUT THE DATASET here: C:\Users\Faiza Anan Noor\Computer Vision UTU/Datasets

In []:

```
# get the directory where I want to download the dataset
path_of_dataset = os.path.join(*['...', current_working_directory, 'Datasets', 'pizza_not _pizza'])
print(f"[DIR] The directory of the current dataset is {path_of_dataset}")
```

[DIR] The directory of the current dataset is C:\Users\Faiza Anan Noor\Computer Vision UT U\Datasets\pizza_not_pizza

Data prep

In []:

```
# here let s do some functions that we can re-use also for other assignment
def load_the_data_and_the_labels(data_set_path: str, target_size: tuple or None = None):
    """
    This function help you to load the data dynamically
    :param data_set_path: (str) put the path created in the previous cell (is the dataset
path)
    :param target_size: (tuple) the desired size of the images
    :return:
        - array of images
        - array with labels
        - list of labels name (this is used for better visualization)
    """
    try:
        dataset, labels, name_of_the_labels = list(), list(), list()
```

```
# let s loop here and we try to discover how many class we have
        for class_number, class_name in enumerate(os.listdir(data_set_path)):
            full path the data = os.path.join(*[data set path, class name])
            print(f"[WALK] I am walking into {full path the data}")
            # add the list to nam list
            name of the labels.append(class name)
            for single image in os.listdir(f"{full path the data}"):
                full path to image = os.path.join(*[full path the data, single image])
                # add the class number
                labels.append(class number)
                if target size is None:
                    # let s load the image
                    image = tf.keras.utils.load img(full path to image)
                else:
                    image = tf.keras.utils.load img(full path to image, target size=targ
et_size)
                # transform PIL object in image
                image = tf.keras.utils.img_to_array(image)
                # add the image to the ds list
                dataset.append(image)
      # print(dataset)
       return np.array(dataset, dtype='uint8'), np.array(labels, dtype='int'), name of
the labels
    except Exception as ex:
       print(f"[EXCEPTION] load the data and the labels throws exceptions {ex}")
```

Load the data

```
In [ ]:
# load the data
dataset, labels, label names=load the data and the labels(path of dataset, (224,224))
[WALK] I am walking into C:\Users\Faiza Anan Noor\Computer Vision UTU\Datasets\pizza not
pizza\not pizza
[WALK] I am walking into C:\Users\Faiza Anan Noor\Computer Vision UTU\Datasets\pizza not
pizza\pizza
In [ ]:
print(labels)
print(label names)
[0 0 0 ... 1 1 1]
['not_pizza', 'pizza']
In [ ]:
label names[0]
Out[]:
'not pizza'
```

Normalize the data

In this step, we normalize the dataset by dividing the matrix that containts the image pixel values by 255.0

```
In []:
# normalize the data
```

Split the data use the train_test_split function

We divide the data into train and test labels and targets using the train_test_split function defining the test size as 30% of the whole data.

```
In [ ]:
# split the data in train and test sets
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(dataset, labels, test_size=0.3, rand
om state=42)
# Print the shape of the training and testing sets for verification
print("X_train shape:", X_train.shape)
print("X test shape:", X test.shape)
print("y train shape:", y train.shape)
print("y test shape:", y test.shape)
X train shape: (1376, 224, 224, 3)
X test shape: (590, 224, 224, 3)
y train shape: (1376,)
y test shape: (590,)
In [ ]:
#X train, X test, y train, y test = X train[:500], X test[:200], y train[:500], y test[:2
\#X train, X test, y train, y test = X train[:50], X test[:20], y train[:50], y test[:20]
#X_train, X_test, y_train, y_test = X_train, X_test, y_train, y_test
```

Create the CNN according the instruction:

- a. Input layer
- b. Data augmentation, with random flip (horizontal and vertical) and random rotation (0.2).
- c. Two hidden layers each composed with the following characteristics: 16 conv 2d units, max pooling 2d and batch normalization, the second one should have 24 conv2d units max pooling 2d and batch normalization.
 - d. After this, add a flatten layer and a dense layer with 8 units
- e. Add the final classifier (a dense layer) with the correct number of output and activation

In the following code snippet, we create the CNN model according to the instructions above. We defined the input shape as (224,224, 3) as target size of the images use (224, 224) and has 3 color channels. Then we defined Sequential model in which we defined layers and actions according to the instructions. To do Data Augmentation(Synthetic Data creation for robust model building, we used the ImageDataGenerator Class in which we passed in necessary random flips(horizontal and vertical both) and defined a random rotation as 0.2 and passed in these parameters into the ImageDataGenerator object called datagen.

Afterwards, we defined two hidden layers. For the first one, we defined 16 conv2d units, max pooling 2d and batch normalization, and also the second one has 24 conv2d units max pooling 2d and batch normalization. After this, we added a flatten layer and a dense layer with 8 units. Finally, we add the final classifier (a dense layer) with the correct number of output and activation, which in our case, the correct number of output is 1 and activation function is sigmoid because we will be working with binary classification(pizza and not pizza).

```
In [ ]:

# Creation of the cnn
# Definition of the input shape (3 channels for color images)
```

```
input\_shape = (224, 224, 3)
# Initialization of the model
model = Sequential()
# a) Input layer
model.add(Input(shape=input shape))
# b) Data augmentation, with random flip and random rotation.
datagen = ImageDataGenerator(
   # rescale=1./255,
   horizontal flip=True,
   vertical flip=True,
    rotation range=0.2
# c) Two hidden layers
# 1st hidden layer
model.add(Conv2D(16, (3, 3), activation='relu', input_shape=input_shape))
# Implementation of MaxPool2d
model.add(MaxPooling2D((2, 2)))
model.add(BatchNormalization())
# 2nd hidden layer
model.add(Conv2D(24, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(BatchNormalization())
# d Flatten layer and a dense layer
model.add(Flatten())
model.add(Dense(8, activation='relu'))
# e) Final classifier (dense layer)
# We Replaced 'num classes' with the correct number of output classes which is 1 in our c
ase
num classes = 1
# Sigmoid is typically used for binary classification problems.
# For multi, softmax is used. Since ours is binary we used sigmoid
# # Only 1 output neuron. It will contain a value from 0-1 where 1 for 1 class ('pizza')
and 0 for the other ('not pizza')
model.add(Dense(num classes, activation='sigmoid'))
```

WARNING:tensorflow:From C:\Users\Faiza Anan Noor\anaconda3\Lib\site-packages\keras\src\backend.py:873: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default graph instead.

WARNING:tensorflow:From C:\Users\Faiza Anan Noor\anaconda3\Lib\site-packages\keras\src\la yers\pooling\max_pooling2d.py:161: The name tf.nn.max_pool is deprecated. Please use tf.n n.max pool2d instead.

compile the model

We Compile the model with Adam optimizer and binary cross entropy as loss function. We also defined the metric to define the model effectiveness as accuracy, and when defining the optimizer, we gave a learning rate of 3e-5. And also we printed out the model summary for our first model.

```
In [ ]:
```

```
# compile the CNN
model.compile(
   loss = tf.keras.losses.BinaryCrossentropy(from_logits = True),
   optimizer = tf.keras.optimizers.Adam(learning_rate = 3e-5),
   metrics =["accuracy"],
   )
# Print the model summary
model.summary()
```

Model: "sequential"

Layer (type)	Output	Shape	Param #
conv2d (Conv2D)	(None,	222, 222, 16)	448
max_pooling2d (MaxPooling2 D)	(None,	111, 111, 16)	0
batch_normalization (Batch Normalization)	(None,	111, 111, 16)	64
conv2d_1 (Conv2D)	(None,	109, 109, 24)	3480
max_pooling2d_1 (MaxPoolin g2D)	(None,	54, 54, 24)	0
<pre>batch_normalization_1 (Bat chNormalization)</pre>	(None,	54, 54, 24)	96
flatten (Flatten)	(None,	69984)	0
dense (Dense)	(None,	8)	559880
dense_1 (Dense)	(None,	1)	9

We also used Callback to periodically save the Keras model or model weights.

The ModelCheckpoint callback is utilized in combination with model.fit() training to save a model or weights at regular intervals (in a checkpoint file). This allows the model or weights to be loaded at a later time to resume training from the saved state.

```
In [ ]:
```

Then using fit() function, we trained the model for 28 epochs, batch size 64 and passed in our callbacks, validation data and defined where the data will flow for training using X_train, y_train(targets and labels).

In []:

```
### Train the model with 128 epochs and 64 batch size batch_size=64
epochs=128
batch_size=64

# Train the model
history = model.fit(
    datagen.flow(X_train, y_train, batch_size=batch_size),
    epochs=epochs,
    validation_data=(X_test, y_test),
    callbacks=[cp_callback],
    verbose=1
)
```

Epoch 1/128

```
duced by a Sigmoid activation and thus does not represent logits. Was this intended?
  output, from_logits = _get_logits(

WARNING:tensorflow:From C:\Users\Faiza Anan Noor\anaconda3\Lib\site-packages\keras\src\ut
  ils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.co
  mpat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\Faiza Anan Noor\anaconda3\Lib\site-packages\keras\src\en
  gine\base_layer_utils.py:384: The name tf.executing_eagerly_outside_functions is deprecat
  ed. Please use tf.compat.v1.executing_eagerly_outside_functions instead.
```

22/22 [=============] - 38s 2s/step - loss: 0.7493 - accuracy: 0.6265 -

22/22 [===========] - 30s 1s/step - loss: 0.3716 - accuracy: 0.8343 -

Epoch 1: saving model to training_first_model\cp.ckpt

Epoch 2: saving model to training first model\cp.ckpt

Epoch 3: saving model to training first model\cp.ckpt

Epoch 4: saving model to training_first_model\cp.ckpt

Epoch 5: saving model to training first model\cp.ckpt

Epoch 6: saving model to training_first_model\cp.ckpt

Epoch 7: saving model to training_first_model\cp.ckpt

Epoch 8: saving model to training first model\cp.ckpt

Epoch 9: saving model to training_first_model\cp.ckpt

Epoch 10: saving model to training first model\cp.ckpt

Epoch 11: saving model to training first model\cp.ckpt

Epoch 12: saving model to training_first_model\cp.ckpt

val loss: 0.6831 - val accuracy: 0.5254

val_loss: 0.6778 - val_accuracy: 0.6441

val loss: 0.6788 - val accuracy: 0.6136

val loss: 0.6737 - val accuracy: 0.6085

val_loss: 0.6833 - val_accuracy: 0.5102

val loss: 0.6619 - val accuracy: 0.6678

val loss: 0.6536 - val accuracy: 0.6492

val loss: 0.6438 - val accuracy: 0.6458

val loss: 0.6515 - val_accuracy: 0.6169

val loss: 0.6469 - val accuracy: 0.5864

val_loss: 0.6264 - val_accuracy: 0.6305

val loss: 0.6959 - val accuracy: 0.5424

Epoch 2/128

Epoch 3/128

Epoch 4/128

Epoch 5/128

Epoch 6/128

Epoch 7/128

Epoch 8/128

Epoch 9/128

Epoch 10/128

Epoch 11/128

Epoch 12/128

Epoch 13/128

```
Epoch 13: saving model to training_first_model\cp.ckpt
val loss: 0.6310 - val accuracy: 0.6237
Epoch 14/128
Epoch 14: saving model to training first model\cp.ckpt
val loss: 0.6490 - val accuracy: 0.6000
Epoch 15/128
Epoch 15: saving model to training_first_model\cp.ckpt
val loss: 0.6304 - val accuracy: 0.6237
Epoch 16/128
Epoch 16: saving model to training_first_model\cp.ckpt
val loss: 0.6613 - val_accuracy: 0.6119
Epoch 17/128
Epoch 17: saving model to training first model\cp.ckpt
val loss: 0.6348 - val accuracy: 0.6356
Epoch 18/128
Epoch 18: saving model to training first model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.2721 - accuracy: 0.8924 -
val_loss: 0.6917 - val_accuracy: 0.6085
Epoch 19/128
Epoch 19: saving model to training first model\cp.ckpt
22/22 [============ ] - 31s 1s/step - loss: 0.2726 - accuracy: 0.8888 -
val loss: 0.6686 - val accuracy: 0.6271
Epoch 20/128
Epoch 20: saving model to training first model\cp.ckpt
22/22 [===========] - 31s 1s/step - loss: 0.2600 - accuracy: 0.9077 -
val_loss: 0.6621 - val_accuracy: 0.6458
Epoch 21/128
Epoch 21: saving model to training first model\cp.ckpt
val loss: 0.6426 - val accuracy: 0.6661
Epoch 22/128
Epoch 22: saving model to training_first_model\cp.ckpt
val loss: 0.6190 - val accuracy: 0.6780
Epoch 23/128
Epoch 23: saving model to training first model\cp.ckpt
val loss: 0.6232 - val accuracy: 0.6881
Epoch 24/128
Epoch 24: saving model to training_first_model\cp.ckpt
val loss: 0.5858 - val accuracy: 0.7288
Epoch 25/128
Epoch 25: saving model to training first model\cp.ckpt
22/22 [============= ] - 28s 1s/step - loss: 0.2143 - accuracy: 0.9259 -
val loss: 0.6069 - val accuracy: 0.7169
Epoch 26/128
Epoch 26: saving model to training first model\cp.ckpt
val loss: 0.6283 - val accuracy: 0.7136
Epoch 27/128
Epoch 27: saving model to training first model\cp.ckpt
```

```
- - - - <u>- - - - </u>
val loss: 0.5896 - val accuracy: 0.7390
Epoch 28/128
Epoch 28: saving model to training first model\cp.ckpt
val_loss: 0.6118 - val accuracy: 0.7271
Epoch 29/128
22/22 [============== ] - ETA: 0s - loss: 0.1823 - accuracy: 0.9440
Epoch 29: saving model to training_first_model\cp.ckpt
val loss: 0.6242 - val accuracy: 0.7254
Epoch 30/128
Epoch 30: saving model to training first model\cp.ckpt
val loss: 0.6345 - val_accuracy: 0.7186
Epoch 31/128
Epoch 31: saving model to training first model\cp.ckpt
val loss: 0.6176 - val accuracy: 0.7288
Epoch 32/128
Epoch 32: saving model to training first model\cp.ckpt
val loss: 0.6372 - val accuracy: 0.7305
Epoch 33/128
Epoch 33: saving model to training first model\cp.ckpt
val loss: 0.6512 - val accuracy: 0.7322
Epoch 34/128
Epoch 34: saving model to training first model\cp.ckpt
val_loss: 0.6515 - val_accuracy: 0.7271
Epoch 35/128
Epoch 35: saving model to training first model\cp.ckpt
val loss: 0.6454 - val accuracy: 0.7322
Epoch 36/128
Epoch 36: saving model to training first model\cp.ckpt
val loss: 0.6810 - val accuracy: 0.7068
Epoch 37/128
Epoch 37: saving model to training_first_model\cp.ckpt
val loss: 0.6732 - val accuracy: 0.7203
Epoch 38/128
Epoch 38: saving model to training first model\cp.ckpt
22/22 [============ ] - 28s 1s/step - loss: 0.1332 - accuracy: 0.9717 -
val_loss: 0.6841 - val_accuracy: 0.7339
Epoch 39/128
Epoch 39: saving model to training first model\cp.ckpt
val loss: 0.6856 - val accuracy: 0.7441
Epoch 40/128
Epoch 40: saving model to training first model\cp.ckpt
22/22 [============ ] - 27s 1s/step - loss: 0.1203 - accuracy: 0.9760 -
val loss: 0.6753 - val accuracy: 0.7339
Epoch 41/128
Epoch 41: saving model to training first model\cp.ckpt
22/22 [=========== ] - 28s 1s/step - loss: 0.1206 - accuracy: 0.9746 -
val loss: 0.6842 - val accuracy: 0.7373
```

Epoch 42/128

```
Epoch 42: saving model to training first model\cp.ckpt
val loss: 0.6797 - val accuracy: 0.7441
Epoch 43/128
Epoch 43: saving model to training first model\cp.ckpt
val_loss: 0.6923 - val_accuracy: 0.7356
Epoch 44/128
Epoch 44: saving model to training first model\cp.ckpt
val loss: 0.7000 - val accuracy: 0.7339
Epoch 45/128
Epoch 45: saving model to training first model\cp.ckpt
val loss: 0.7222 - val_accuracy: 0.7254
Epoch 46/128
Epoch 46: saving model to training_first_model\cp.ckpt
val loss: 0.7228 - val accuracy: 0.7288
Epoch 47/128
Epoch 47: saving model to training_first_model\cp.ckpt
22/22 [===========] - 30s 1s/step - loss: 0.0932 - accuracy: 0.9847 -
val loss: 0.7019 - val accuracy: 0.7305
Epoch 48/128
Epoch 48: saving model to training first model\cp.ckpt
22/22 [=========== ] - 29s 1s/step - loss: 0.0928 - accuracy: 0.9847 -
val loss: 0.7148 - val_accuracy: 0.7390
Epoch 49/128
Epoch 49: saving model to training first model\cp.ckpt
val loss: 0.7259 - val accuracy: 0.7305
Epoch 50/128
Epoch 50: saving model to training first model\cp.ckpt
22/22 [============= ] - 31s 1s/step - loss: 0.0922 - accuracy: 0.9826 -
val_loss: 0.7229 - val accuracy: 0.7339
Epoch 51/128
Epoch 51: saving model to training_first_model\cp.ckpt
val loss: 0.7311 - val accuracy: 0.7373
Epoch 52/128
Epoch 52: saving model to training first model\cp.ckpt
val loss: 0.7282 - val_accuracy: 0.7356
Epoch 53/128
Epoch 53: saving model to training_first_model\cp.ckpt
22/22 [============] - 30s 1s/step - loss: 0.0790 - accuracy: 0.9898 -
val loss: 0.7416 - val accuracy: 0.7424
Epoch 54/128
Epoch 54: saving model to training first model\cp.ckpt
val_loss: 0.7351 - val_accuracy: 0.7339
Epoch 55/128
Epoch 55: saving model to training first model\cp.ckpt
val loss: 0.7220 - val accuracy: 0.7339
Epoch 56/128
Epoch 56: saving model to training first model\cp.ckpt
```

```
val loss: 0.7428 - val accuracy: 0.7305
Epoch 57/128
Epoch 57: saving model to training first model\cp.ckpt
val_loss: 0.7228 - val_accuracy: 0.7373
Epoch 58/128
Epoch 58: saving model to training first model\cp.ckpt
val loss: 0.7341 - val accuracy: 0.7339
Epoch 59/128
Epoch 59: saving model to training first model\cp.ckpt
val_loss: 0.7294 - val_accuracy: 0.7339
Epoch 60/128
Epoch 60: saving model to training_first_model\cp.ckpt
val_loss: 0.7456 - val_accuracy: 0.7254
Epoch 61/128
Epoch 61: saving model to training first model\cp.ckpt
val_loss: 0.7410 - val_accuracy: 0.7441
Epoch 62/128
Epoch 62: saving model to training first model\cp.ckpt
val loss: 0.7588 - val accuracy: 0.7322
Epoch 63/128
Epoch 63: saving model to training first model\cp.ckpt
val loss: 0.7560 - val_accuracy: 0.7254
Epoch 64/128
Epoch 64: saving model to training first model\cp.ckpt
val loss: 0.7563 - val accuracy: 0.7271
Epoch 65/128
Epoch 65: saving model to training first model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.0522 - accuracy: 0.9956 -
val loss: 0.7383 - val accuracy: 0.7407
Epoch 66/128
Epoch 66: saving model to training_first_model\cp.ckpt
val loss: 0.7481 - val accuracy: 0.7356
Epoch 67/128
Epoch 67: saving model to training first model\cp.ckpt
val_loss: 0.7441 - val_accuracy: 0.7356
Epoch 68/128
Epoch 68: saving model to training first model\cp.ckpt
val_loss: 0.7793 - val_accuracy: 0.7322
Epoch 69/128
Epoch 69: saving model to training_first_model\cp.ckpt
val loss: 0.7548 - val accuracy: 0.7288
Epoch 70/128
Epoch 70: saving model to training first model\cp.ckpt
val loss: 0.7498 - val accuracy: 0.7288
```

```
_----
Epoch 71/128
Epoch 71: saving model to training first model\cp.ckpt
val loss: 0.7576 - val accuracy: 0.7305
Epoch 72/128
Epoch 72: saving model to training first model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.0468 - accuracy: 0.9956 -
val loss: 0.7556 - val accuracy: 0.7356
Epoch 73/128
Epoch 73: saving model to training_first_model\cp.ckpt
val loss: 0.7536 - val accuracy: 0.7407
Epoch 74/128
Epoch 74: saving model to training first model\cp.ckpt
22/22 [=========== ] - 30s 1s/step - loss: 0.0423 - accuracy: 0.9956 -
val_loss: 0.7615 - val_accuracy: 0.7356
Epoch 75/128
Epoch 75: saving model to training first model\cp.ckpt
val loss: 0.7636 - val accuracy: 0.7424
Epoch 76/128
Epoch 76: saving model to training_first_model\cp.ckpt
val loss: 0.7522 - val accuracy: 0.7458
Epoch 77/128
Epoch 77: saving model to training first model\cp.ckpt
val_loss: 0.7642 - val_accuracy: 0.7407
Epoch 78/128
Epoch 78: saving model to training_first_model\cp.ckpt
val loss: 0.7702 - val accuracy: 0.7322
Epoch 79/128
Epoch 79: saving model to training first model\cp.ckpt
val loss: 0.7718 - val accuracy: 0.7424
Epoch 80/128
Epoch 80: saving model to training_first_model\cp.ckpt
val loss: 0.7891 - val accuracy: 0.7390
Epoch 81/128
Epoch 81: saving model to training_first_model\cp.ckpt
val_loss: 0.7677 - val_accuracy: 0.7288
Epoch 82/128
Epoch 82: saving model to training first model\cp.ckpt
22/22 [============ ] - 28s 1s/step - loss: 0.0362 - accuracy: 0.9971 -
val loss: 0.7762 - val accuracy: 0.7339
Epoch 83/128
Epoch 83: saving model to training first model\cp.ckpt
22/22 [============ ] - 28s 1s/step - loss: 0.0354 - accuracy: 0.9978 -
val_loss: 0.7679 - val_accuracy: 0.7390
Epoch 84/128
Epoch 84: saving model to training first model\cp.ckpt
val loss: 0.7833 - val accuracy: 0.7424
Epoch 85/128
```

```
Epoch 85: saving model to training_first_model\cp.ckpt
val loss: 0.7786 - val accuracy: 0.7254
Epoch 86/128
Epoch 86: saving model to training first model\cp.ckpt
val loss: 0.7838 - val accuracy: 0.7271
Epoch 87/128
Epoch 87: saving model to training_first_model\cp.ckpt
val loss: 0.7847 - val accuracy: 0.7390
Epoch 88/128
Epoch 88: saving model to training_first_model\cp.ckpt
val_loss: 0.7871 - val_accuracy: 0.7271
Epoch 89/128
Epoch 89: saving model to training first model\cp.ckpt
val loss: 0.7886 - val accuracy: 0.7373
Epoch 90/128
Epoch 90: saving model to training first model\cp.ckpt
22/22 [============= ] - 29s 1s/step - loss: 0.0295 - accuracy: 0.9978 -
val_loss: 0.7901 - val_accuracy: 0.7237
Epoch 91/128
Epoch 91: saving model to training first model\cp.ckpt
val loss: 0.7925 - val accuracy: 0.7390
Epoch 92/128
Epoch 92: saving model to training first model\cp.ckpt
val_loss: 0.8077 - val_accuracy: 0.7407
Epoch 93/128
Epoch 93: saving model to training first model\cp.ckpt
val loss: 0.8149 - val accuracy: 0.7424
Epoch 94/128
Epoch 94: saving model to training_first_model\cp.ckpt
val loss: 0.8042 - val accuracy: 0.7322
Epoch 95/128
Epoch 95: saving model to training first model\cp.ckpt
22/22 [=========== ] - 30s 1s/step - loss: 0.0277 - accuracy: 0.9985 -
val loss: 0.7955 - val accuracy: 0.7458
Epoch 96/128
Epoch 96: saving model to training_first_model\cp.ckpt
val loss: 0.8069 - val accuracy: 0.7373
Epoch 97/128
Epoch 97: saving model to training first model\cp.ckpt
22/22 [============= ] - 30s 1s/step - loss: 0.0261 - accuracy: 0.9971 -
val loss: 0.8075 - val accuracy: 0.7339
Epoch 98/128
Epoch 98: saving model to training first model\cp.ckpt
val loss: 0.8169 - val accuracy: 0.7288
Epoch 99/128
Epoch 99: saving model to training first model\cp.ckpt
```

```
- - - - <u>-</u>
val loss: 0.8104 - val accuracy: 0.7254
Epoch 100/128
Epoch 100: saving model to training first model\cp.ckpt
val_loss: 0.8206 - val accuracy: 0.7322
Epoch 101/128
22/22 [============== ] - ETA: 0s - loss: 0.0244 - accuracy: 0.9985
Epoch 101: saving model to training_first_model\cp.ckpt
val loss: 0.8129 - val accuracy: 0.7288
Epoch 102/128
Epoch 102: saving model to training first model\cp.ckpt
22/22 [============ ] - 29s 1s/step - loss: 0.0226 - accuracy: 0.9978 -
val loss: 0.8050 - val accuracy: 0.7322
Epoch 103/128
Epoch 103: saving model to training first model\cp.ckpt
val loss: 0.8012 - val accuracy: 0.7441
Epoch 104/128
Epoch 104: saving model to training first model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.0228 - accuracy: 0.9985 -
val loss: 0.8139 - val accuracy: 0.7356
Epoch 105/128
Epoch 105: saving model to training first model\cp.ckpt
val loss: 0.8097 - val accuracy: 0.7373
Epoch 106/128
Epoch 106: saving model to training first model\cp.ckpt
val loss: 0.8084 - val_accuracy: 0.7373
Epoch 107/128
Epoch 107: saving model to training first model\cp.ckpt
22/22 [=========== ] - 31s 1s/step - loss: 0.0208 - accuracy: 0.9993 -
val loss: 0.8141 - val accuracy: 0.7339
Epoch 108/128
Epoch 108: saving model to training first model\cp.ckpt
val loss: 0.8035 - val accuracy: 0.7407
Epoch 109/128
Epoch 109: saving model to training first model\cp.ckpt
val loss: 0.8101 - val accuracy: 0.7356
Epoch 110/128
Epoch 110: saving model to training first model\cp.ckpt
val_loss: 0.8165 - val_accuracy: 0.7271
Epoch 111/128
Epoch 111: saving model to training first model\cp.ckpt
val_loss: 0.8145 - val_accuracy: 0.7373
Epoch 112/128
Epoch 112: saving model to training first model\cp.ckpt
22/22 [=========== ] - 31s 1s/step - loss: 0.0197 - accuracy: 1.0000 -
val loss: 0.8189 - val accuracy: 0.7271
Epoch 113/128
Epoch 113: saving model to training first model\cp.ckpt
val loss: 0.8350 - val accuracy: 0.7203
```

Epoch 114/128

```
Epoch 114: saving model to training first model\cp.ckpt
22/22 [============ ] - 31s 1s/step - loss: 0.0167 - accuracy: 0.9993 -
val loss: 0.8252 - val accuracy: 0.7424
Epoch 115/128
Epoch 115: saving model to training first model\cp.ckpt
val loss: 0.8273 - val accuracy: 0.7356
Epoch 116/128
Epoch 116: saving model to training_first_model\cp.ckpt
val loss: 0.8234 - val accuracy: 0.7441
Epoch 117/128
Epoch 117: saving model to training first model\cp.ckpt
val loss: 0.8310 - val accuracy: 0.7424
Epoch 118/128
Epoch 118: saving model to training_first_model\cp.ckpt
22/22 [============ ] - 31s 1s/step - loss: 0.0168 - accuracy: 0.9993 -
val loss: 0.8194 - val accuracy: 0.7373
Epoch 119/128
Epoch 119: saving model to training first model\cp.ckpt
22/22 [=========== ] - 29s 1s/step - loss: 0.0159 - accuracy: 0.9993 -
val loss: 0.8316 - val accuracy: 0.7339
Epoch 120/128
Epoch 120: saving model to training first model\cp.ckpt
22/22 [=========== ] - 28s 1s/step - loss: 0.0162 - accuracy: 0.9985 -
val loss: 0.8335 - val_accuracy: 0.7407
Epoch 121/128
Epoch 121: saving model to training first model\cp.ckpt
val loss: 0.8285 - val accuracy: 0.7390
Epoch 122/128
Epoch 122: saving model to training first model\cp.ckpt
val_loss: 0.8355 - val_accuracy: 0.7441
Epoch 123/128
Epoch 123: saving model to training first model\cp.ckpt
val loss: 0.8352 - val accuracy: 0.7390
Epoch 124/128
Epoch 124: saving model to training first model\cp.ckpt
val loss: 0.8474 - val_accuracy: 0.7373
Epoch 125/128
Epoch 125: saving model to training_first_model\cp.ckpt
22/22 [============ ] - 29s 1s/step - loss: 0.0149 - accuracy: 1.0000 -
val loss: 0.8432 - val accuracy: 0.7373
Epoch 126/128
Epoch 126: saving model to training first model\cp.ckpt
val_loss: 0.8283 - val_accuracy: 0.7373
Epoch 127/128
Epoch 127: saving model to training first model\cp.ckpt
val loss: 0.8329 - val_accuracy: 0.7458
Epoch 128/128
Epoch 128: saving model to training first model\cp.ckpt
```

Evaluate the model and report the accuracy

I evaluated the model using model.evaluate passing in our test labels and targets. And then from that variable containing the evaluation results, we take the index 1 to get the accuracy of our model on the test set.

For our first model, the accuracy is 74.24% which means that our model has quite a decent accuracy and for 74% of the cases it can accurately classify between the pizza and not pizza classes.

Make prediction with the test set and use a threshold of 0.5 as boundaries decision between the classes.

Then we make prediction using the test set(X_test) and the variable "predictions" contains the results. Then we set threshold as 0.5 and make binary predictions variable contain predictions as 1 for values that are above 0.5 and 0 otherwise. And this is used using the "predictions" variable defined above containing the real values for the predictions. Since we do not have binary predictions as we see by printing the predictions array, we convert them to binary labels and predictions using the specified threshold of 0.5

```
In [ ]:
# Since we do not have binary predictions, we convert them to binary labels and predictio
ns using the specified threshold of 0.5
threshold=0.5
predictions=model.predict(X test)
predictions[:9]
19/19 [======== ] - 6s 43ms/step
Out[]:
array([[9.9806821e-01],
       [5.5093551e-01],
       [1.2737493e-03],
       [9.9979383e-01],
       [9.9999976e-01],
       [9.1787595e-01],
       [2.5328493e-01],
       [8.7279412e-05],
       [9.8753053e-01]], dtype=float32)
In [ ]:
binary labels = np.argmax(predictions, axis=1)
```

```
binary_predictions = (predictions > threshold).astype(int)
#binary_predictions
```

show predictions

Then we tried to show some predictions by plotting a test image against our predicted Label Results. We can see that almost 74% of the time, it gets correct results. We tried to plot this a couple of times after this code snippet using different subsets of the test set.

In []:

```
# do it here
def show_some_prediction(number_of_subplot, test_set, predictions, name_of_the_labels):
    for i in range(number_of_subplot):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(test_set[i])
        plt.title(f'{name_of_the_labels[predictions[i]]}')
        plt.axis("off")
    plt.show()
show_some_prediction(9, X_test, binary_predictions.flatten(), label_names)
```



In []:

show_some_prediction(9, X_test[40:60], binary_predictions.flatten()[40:60], label_names)



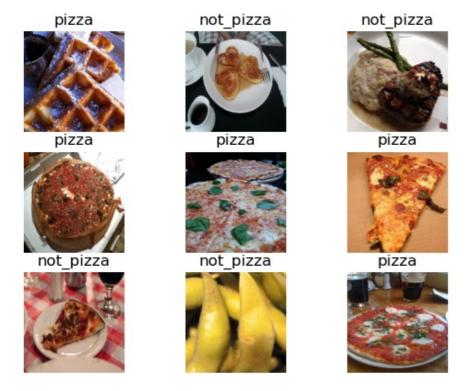






In []:

show_some_prediction(9, X_test[50:60], binary_predictions.flatten()[50:60], label_names)



show metrics like confusion matrix or ROC curve or both (sklearn has already implemented all these stuff)

```
In [ ]:
```

```
print("Confusion Matrix and ROC curve of model 1 is given below : ")
Confusion Matrix and ROC curve of model 1 is given below :
```

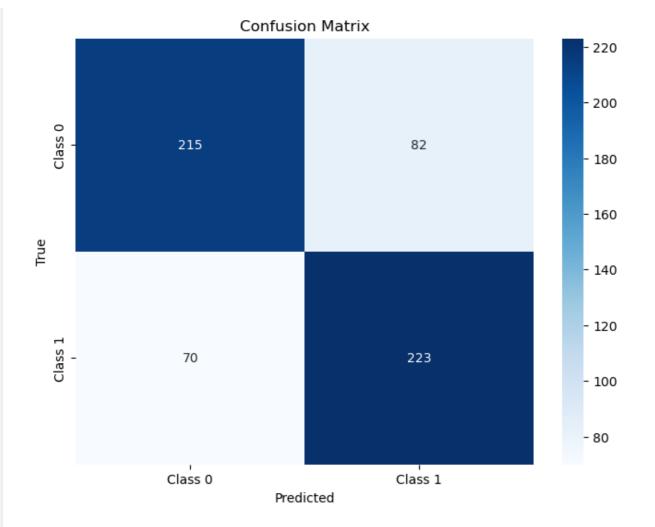
In []:

In []:

```
# Calculate and display the confusion matrix
conf_matrix = confusion_matrix(y_test, binary_predictions.flatten())
print("Confusion Matrix:")
print(conf_matrix)

# Plot Confusion Matrix using Matplotlib
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0', 'Class 1'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

```
Confusion Matrix:
[[215 82]
  [ 70 223]]
```

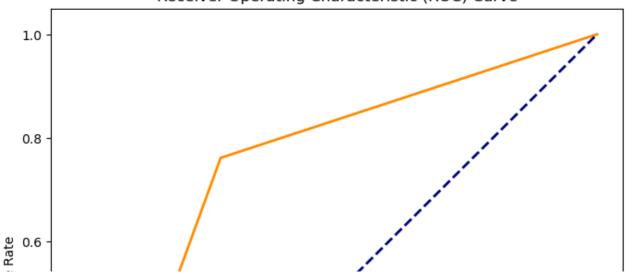


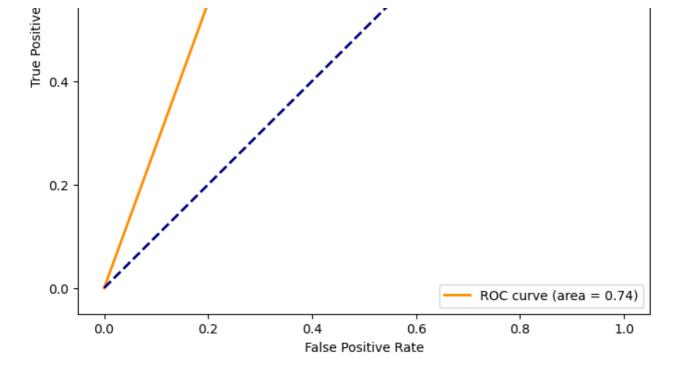
In []:

```
# Plot ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, binary_predictions.flatten())
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

Receiver Operating Characteristic (ROC) Curve





For our first model, the area under the curve is 0.74 which means that our model is pretty efficient in separating the not pizza from the pizza model. The Confusion Matrix shows that our True Positive(TP), True Negative(TN), False Positive(FP), False Negative(FN) for classifying pizza class from not pizza for our first/original model is 215, 223, 82, 70, respectively.

Confusion matrix and ROC curve are common evaluation tools used in classification tasks in machine learning. Here's why they are useful:

Confusion Matrix:

By displaying the numbers of true positive, true negative, false positive, and fals e negative predictions, the confusion matrix offers a thorough analysis of the mode l's performance. In order to evaluate the model's performance for both balanced and unbalanced classes, it is helpful in determining the model's sensitivity (recall), specificity, precision, and accuracy.

ROC Curve (Receiver Operating Characteristic Curve):

The ROC helps visualize the trade-off between sensitivity and specificity by provid ing a graphical depiction of the true positive rate (sensitivity) against the false positive rate (1-specificity) for various threshold values. Greater values indicate greater performance, while the Area Under the ROC Curve (AUC-ROC) offers a single scalar number measuring the model's performance.

Understanding how well the model separates the various classes in the dataset is dependent on these assessment methods. They assist in evaluating many models to determine which is most appropriate for the job at hand, offer insights into the model's advantages and disadvantages, and direct parameter adjustment.

Build another base CNN, but at point c add an extra hidden layer with 32 units of conv2d. Repeat all the other steps. What happened to the accuracy of the model? Why?

Then we built another CNN model called "model2" with the additional hidden layer having Conv2d 32 units and we repeated all the other steps as below:

```
In [ ]:
```

```
# Initialize the model
model2 = Sequential()
input shape = (224, 224, 3)
# Input layer
model2.add(Input(shape=input shape))
# Data augmentation
datagen2 = ImageDataGenerator(
   horizontal flip=True,
   vertical flip=True,
   rotation range=0.2
# Two hidden layers (original)
model2.add(Conv2D(16, (3, 3), activation='relu', input shape=input shape))
model2.add(MaxPooling2D((2, 2)))
model2.add(BatchNormalization())
model2.add(Conv2D(24, (3, 3), activation='relu'))
model2.add(MaxPooling2D((2, 2)))
model2.add(BatchNormalization())
# Extra hidden layer (32 units of Conv2D)
model2.add(Conv2D(32, (3, 3), activation='relu'))
model2.add(MaxPooling2D((2, 2)))
model2.add(BatchNormalization())
# Flatten layer and a dense layer
model2.add(Flatten())
model2.add(Dense(8, activation='relu'))
# Final classifier (dense layer)
num classes=1
model2.add(Dense(num classes, activation='sigmoid'))
# Compile the model
# compile the CNN
model2.compile(
   loss = tf.keras.losses.BinaryCrossentropy(from logits = True),
   optimizer = tf.keras.optimizers.Adam(learning rate = 3e-5),
   metrics =["accuracy"],
# Print the model summary
model2.summary()
```

Model: "sequential 1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 222, 222, 16)	448
<pre>max_pooling2d_2 (MaxPoolin g2D)</pre>	(None, 111, 111, 16)	0
<pre>batch_normalization_2 (Bat chNormalization)</pre>	(None, 111, 111, 16)	64
conv2d_3 (Conv2D)	(None, 109, 109, 24)	3480
<pre>max_pooling2d_3 (MaxPoolin g2D)</pre>	(None, 54, 54, 24)	0
<pre>batch_normalization_3 (Bat chNormalization)</pre>	(None, 54, 54, 24)	96
conv2d_4 (Conv2D)	(None, 52, 52, 32)	6944

```
max pooling2d 4 (MaxPoolin (None, 26, 26, 32)
q2D)
batch normalization 4 (Bat (None, 26, 26, 32)
                                          128
chNormalization)
flatten 1 (Flatten)
                      (None, 21632)
dense 2 (Dense)
                      (None, 8)
                                          173064
dense 3 (Dense)
                      (None, 1)
______
Total params: 184233 (719.66 KB)
Trainable params: 184089 (719.10 KB)
Non-trainable params: 144 (576.00 Byte)
In [ ]:
# Data augmentation
datagen2 = ImageDataGenerator(
  horizontal flip=True,
   vertical flip=True,
   rotation range=0.2
In [ ]:
checkpoint path2 = "training second model/cp.ckpt"
checkpoint dir2 = os.path.dirname(checkpoint path2)
# Create a callback that saves the model's weights
cp callback2 = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint path2,
                                     save weights only=True,
                                      verbose=1)
In [ ]:
# do it here
batch size=64
epochs=128
# Train the model
history = model2.fit(
   datagen2.flow(X train, y train, batch size=batch size),
   epochs=epochs,
   validation data=(X_test, y_test),
   callbacks=[cp callback2],
   verbose=1
Epoch 1/128
C:\Users\Faiza Anan Noor\anaconda3\Lib\site-packages\keras\src\backend.py:5818: UserWarni
ng: "`binary crossentropy` received `from logits=True`, but the `output` argument was pro
duced by a Sigmoid activation and thus does not represent logits. Was this intended?
 output, from_logits = _get_logits(
Epoch 1: saving model to training second model\cp.ckpt
val loss: 0.6884 - val accuracy: 0.5085
Epoch 2/128
Epoch 2: saving model to training second model\cp.ckpt
val_loss: 0.6984 - val_accuracy: 0.5034
Epoch 3/128
Epoch 3: saving model to training_second_model\cp.ckpt
22/22 [============= ] - 32s 1s/step - loss: 0.5873 - accuracy: 0.6904 -
x_{21} logg. 0 6000 - x_{21} logg. 0 5024
```

```
val 1055: 0.0333 - val accuracy: 0.3034
Epoch 4/128
Epoch 4: saving model to training second model\cp.ckpt
val loss: 0.7171 - val accuracy: 0.5034
Epoch 5/128
Epoch 5: saving model to training second model\cp.ckpt
val loss: 0.7036 - val accuracy: 0.5034
Epoch 6/128
Epoch 6: saving model to training second model\cp.ckpt
val_loss: 0.7015 - val_accuracy: 0.5085
Epoch 7/128
Epoch 7: saving model to training second model\cp.ckpt
val loss: 0.7245 - val accuracy: 0.5068
Epoch 8/128
Epoch 8: saving model to training second model\cp.ckpt
val loss: 0.6909 - val accuracy: 0.5373
Epoch 9/128
Epoch 9: saving model to training_second_model\cp.ckpt
val_loss: 0.6842 - val_accuracy: 0.5542
Epoch 10/128
Epoch 10: saving model to training second_model\cp.ckpt
22/22 [============= ] - 31s 1s/step - loss: 0.4906 - accuracy: 0.7718 -
val_loss: 0.6613 - val_accuracy: 0.5881
Epoch 11/128
Epoch 11: saving model to training second model\cp.ckpt
val loss: 0.6543 - val accuracy: 0.6051
Epoch 12/128
Epoch 12: saving model to training second model\cp.ckpt
val loss: 0.6348 - val_accuracy: 0.6186
Epoch 13/128
Epoch 13: saving model to training_second_model\cp.ckpt
val loss: 0.6094 - val accuracy: 0.6627
Epoch 14/128
Epoch 14: saving model to training second model\cp.ckpt
22/22 [===========] - 31s 1s/step - loss: 0.4467 - accuracy: 0.7987 -
val loss: 0.5900 - val accuracy: 0.6780
Epoch 15/128
Epoch 15: saving model to training second model\cp.ckpt
22/22 [============ ] - 31s 1s/step - loss: 0.4323 - accuracy: 0.8016 -
val loss: 0.5965 - val accuracy: 0.6661
Epoch 16/128
Epoch 16: saving model to training second model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.4267 - accuracy: 0.8045 -
val loss: 0.5763 - val accuracy: 0.6814
Epoch 17/128
Epoch 17: saving model to training second model\cp.ckpt
val_loss: 0.5671 - val_accuracy: 0.7017
Epoch 18/128
```

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22/22 [------ - cih; US - 1055; U.4010 - accuracy; U.0217
Epoch 18: saving model to training_second_model\cp.ckpt
val loss: 0.5558 - val accuracy: 0.7034
Epoch 19/128
Epoch 19: saving model to training second model\cp.ckpt
val loss: 0.5572 - val accuracy: 0.7136
Epoch 20/128
Epoch 20: saving model to training_second_model\cp.ckpt
val loss: 0.5444 - val accuracy: 0.7237
Epoch 21/128
Epoch 21: saving model to training second model\cp.ckpt
22/22 [============ ] - 31s 1s/step - loss: 0.3878 - accuracy: 0.8358 -
val loss: 0.5440 - val accuracy: 0.7288
Epoch 22/128
Epoch 22: saving model to training second model\cp.ckpt
22/22 [=========== ] - 30s 1s/step - loss: 0.3693 - accuracy: 0.8401 -
val loss: 0.5345 - val accuracy: 0.7356
Epoch 23/128
Epoch 23: saving model to training second model\cp.ckpt
22/22 [============= ] - 30s 1s/step - loss: 0.3658 - accuracy: 0.8532 -
val_loss: 0.5432 - val_accuracy: 0.7220
Epoch 24/128
Epoch 24: saving model to training second model\cp.ckpt
val_loss: 0.5349 - val_accuracy: 0.7271
Epoch 25/128
Epoch 25: saving model to training second model\cp.ckpt
val loss: 0.5347 - val accuracy: 0.7169
Epoch 26/128
Epoch 26: saving model to training second model\cp.ckpt
val_loss: 0.5355 - val_accuracy: 0.7169
Epoch 27/128
Epoch 27: saving model to training_second_model\cp.ckpt
val_loss: 0.5376 - val_accuracy: 0.7169
Epoch 28/128
Epoch 28: saving model to training second model\cp.ckpt
22/22 [============ ] - 31s 1s/step - loss: 0.3289 - accuracy: 0.8634 -
val_loss: 0.5378 - val_accuracy: 0.7169
Epoch 29/128
Epoch 29: saving model to training second model\cp.ckpt
val loss: 0.5303 - val accuracy: 0.7237
Epoch 30/128
Epoch 30: saving model to training second model\cp.ckpt
val loss: 0.5264 - val accuracy: 0.7339
Epoch 31/128
Epoch 31: saving model to training second model\cp.ckpt
22/22 [=========== ] - 30s 1s/step - loss: 0.3153 - accuracy: 0.8786 -
val_loss: 0.5273 - val_accuracy: 0.7305
Epoch 32: saving model to training second model\cp.ckpt
```

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```
val loss: 0.5260 - val accuracy: 0.7356
Epoch 33/128
Epoch 33: saving model to training_second_model\cp.ckpt
val loss: 0.5279 - val accuracy: 0.7373
Epoch 34/128
Epoch 34: saving model to training_second_model\cp.ckpt
val loss: 0.5284 - val accuracy: 0.7441
Epoch 35/128
Epoch 35: saving model to training second model\cp.ckpt
val_loss: 0.5244 - val_accuracy: 0.7508
Epoch 36/128
Epoch 36: saving model to training second model\cp.ckpt
val loss: 0.5312 - val accuracy: 0.7390
Epoch 37/128
Epoch 37: saving model to training second model\cp.ckpt
val loss: 0.5219 - val accuracy: 0.7424
Epoch 38/128
Epoch 38: saving model to training second model\cp.ckpt
val loss: 0.5170 - val accuracy: 0.7492
Epoch 39/128
Epoch 39: saving model to training second model\cp.ckpt
22/22 [=========== ] - 29s 1s/step - loss: 0.2548 - accuracy: 0.9230 -
val loss: 0.5151 - val accuracy: 0.7525
Epoch 40/128
Epoch 40: saving model to training second model\cp.ckpt
22/22 [============= ] - 31s 1s/step - loss: 0.2571 - accuracy: 0.9004 -
val loss: 0.5211 - val accuracy: 0.7576
Epoch 41/128
Epoch 41: saving model to training second model\cp.ckpt
val_loss: 0.5172 - val_accuracy: 0.7593
Epoch 42/128
Epoch 42: saving model to training second model\cp.ckpt
22/22 [=========== ] - 30s 1s/step - loss: 0.2412 - accuracy: 0.9164 -
val_loss: 0.5225 - val_accuracy: 0.7593
Epoch 43/128
Epoch 43: saving model to training second model\cp.ckpt
val loss: 0.5220 - val accuracy: 0.7576
Epoch 44/128
Epoch 44: saving model to training second model\cp.ckpt
val loss: 0.5292 - val accuracy: 0.7441
Epoch 45/128
Epoch 45: saving model to training_second_model\cp.ckpt
val loss: 0.5274 - val accuracy: 0.7576
Epoch 46/128
Epoch 46: saving model to training_second_model\cp.ckpt
val_loss: 0.5293 - val_accuracy: 0.7593
```

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```
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Epoch 47: saving model to training second model\cp.ckpt
val loss: 0.5280 - val accuracy: 0.7492
Epoch 48/128
Epoch 48: saving model to training second model\cp.ckpt
- val_loss: 0.5319 - val_accuracy: 0.7576
Epoch 49/128
Epoch 49: saving model to training_second_model\cp.ckpt
loss: 0.5327 - val_accuracy: 0.7508
Epoch 50/128
Epoch 50: saving model to training second model\cp.ckpt
- val loss: 0.5373 - val accuracy: 0.7559
Epoch 51/128
Epoch 51: saving model to training second model\cp.ckpt
- val loss: 0.5332 - val accuracy: 0.7610
Epoch 52/128
Epoch 52: saving model to training second model\cp.ckpt
22/22 [===========] - 28s 1s/step - loss: 0.2077 - accuracy: 0.9390 -
val loss: 0.5259 - val accuracy: 0.7593
Epoch 53/128
Epoch 53: saving model to training_second_model\cp.ckpt
val_loss: 0.5237 - val_accuracy: 0.7627
Epoch 54/128
Epoch 54: saving model to training_second_model\cp.ckpt
val loss: 0.5200 - val accuracy: 0.7661
Epoch 55/128
Epoch 55: saving model to training second model\cp.ckpt
val loss: 0.5223 - val accuracy: 0.7627
Epoch 56/128
Epoch 56: saving model to training second model\cp.ckpt
val_loss: 0.5193 - val_accuracy: 0.7593
Epoch 57/128
Epoch 57: saving model to training second model\cp.ckpt
val loss: 0.5228 - val accuracy: 0.7627
Epoch 58/128
Epoch 58: saving model to training second model\cp.ckpt
val loss: 0.5234 - val accuracy: 0.7627
Epoch 59/128
Epoch 59: saving model to training second model\cp.ckpt
val_loss: 0.5198 - val_accuracy: 0.7593
Epoch 60/128
Epoch 60: saving model to training_second_model\cp.ckpt
val_loss: 0.5238 - val_accuracy: 0.7559
Epoch 61/128
Enoch 61. assiss model to training accord model an about
```

```
EPOCH OI: Saving Model to training_second_model(cp.ckpt
val loss: 0.5215 - val accuracy: 0.7644
Epoch 62/128
Epoch 62: saving model to training second model\cp.ckpt
val loss: 0.5224 - val accuracy: 0.7644
Epoch 63/128
Epoch 63: saving model to training second model\cp.ckpt
val_loss: 0.5212 - val_accuracy: 0.7678
Epoch 64/128
Epoch 64: saving model to training second model\cp.ckpt
val_loss: 0.5276 - val_accuracy: 0.7712
Epoch 65/128
Epoch 65: saving model to training second model\cp.ckpt
val loss: 0.5248 - val accuracy: 0.7763
Epoch 66/128
Epoch 66: saving model to training second model\cp.ckpt
val loss: 0.5209 - val_accuracy: 0.7712
Epoch 67/128
Epoch 67: saving model to training_second_model\cp.ckpt
val_loss: 0.5226 - val_accuracy: 0.7797
Epoch 68/128
Epoch 68: saving model to training_second_model\cp.ckpt
val loss: 0.5271 - val accuracy: 0.7729
Epoch 69/128
Epoch 69: saving model to training second model\cp.ckpt
22/22 [=========== ] - 32s 1s/step - loss: 0.1597 - accuracy: 0.9564 -
val loss: 0.5276 - val accuracy: 0.7627
Epoch 70/128
22/22 [============== ] - ETA: 0s - loss: 0.1464 - accuracy: 0.9673
Epoch 70: saving model to training second model\cp.ckpt
val loss: 0.5242 - val accuracy: 0.7729
Epoch 71/128
Epoch 71: saving model to training second model\cp.ckpt
val_loss: 0.5213 - val_accuracy: 0.7712
Epoch 72/128
Epoch 72: saving model to training second model\cp.ckpt
val loss: 0.5244 - val accuracy: 0.7678
Epoch 73/128
Epoch 73: saving model to training second model\cp.ckpt
val_loss: 0.5246 - val_accuracy: 0.7780
Epoch 74/128
Epoch 74: saving model to training second model\cp.ckpt
val_loss: 0.5297 - val_accuracy: 0.7712
Epoch 75/128
Epoch 75: saving model to training_second_model\cp.ckpt
22/22 [============= ] - 31s 1s/step - loss: 0.1313 - accuracy: 0.9753 -
TTAL 1000 - 0 5201 - TTAL 2001720TF 0 7746
```

```
vai 1055: 0.3231 - vai accuracy: 0.7740
Epoch 76/128
Epoch 76: saving model to training second model\cp.ckpt
val loss: 0.5249 - val accuracy: 0.7661
Epoch 77/128
22/22 [============== ] - ETA: 0s - loss: 0.1332 - accuracy: 0.9724
Epoch 77: saving model to training second model\cp.ckpt
22/22 [============= ] - 32s 1s/step - loss: 0.1332 - accuracy: 0.9724 -
val loss: 0.5274 - val accuracy: 0.7661
Epoch 78/128
Epoch 78: saving model to training second model\cp.ckpt
val_loss: 0.5307 - val_accuracy: 0.7746
Epoch 79/128
Epoch 79: saving model to training second model\cp.ckpt
val loss: 0.5345 - val accuracy: 0.7746
Epoch 80/128
Epoch 80: saving model to training second model\cp.ckpt
val loss: 0.5273 - val accuracy: 0.7644
Epoch 81/128
Epoch 81: saving model to training_second_model\cp.ckpt
val_loss: 0.5296 - val_accuracy: 0.7780
Epoch 82/128
Epoch 82: saving model to training second_model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.1244 - accuracy: 0.9760 -
val_loss: 0.5231 - val_accuracy: 0.7763
Epoch 83/128
Epoch 83: saving model to training second model\cp.ckpt
val loss: 0.5347 - val accuracy: 0.7644
Epoch 84/128
Epoch 84: saving model to training second model\cp.ckpt
val loss: 0.5324 - val_accuracy: 0.7610
Epoch 85/128
Epoch 85: saving model to training second model\cp.ckpt
val loss: 0.5340 - val accuracy: 0.7695
Epoch 86/128
Epoch 86: saving model to training second model\cp.ckpt
22/22 [=========== ] - 31s 1s/step - loss: 0.1170 - accuracy: 0.9789 -
val loss: 0.5303 - val accuracy: 0.7780
Epoch 87/128
Epoch 87: saving model to training second model\cp.ckpt
22/22 [=========== ] - 30s 1s/step - loss: 0.1079 - accuracy: 0.9833 -
val loss: 0.5336 - val accuracy: 0.7729
Epoch 88/128
Epoch 88: saving model to training second model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.1074 - accuracy: 0.9826 -
val loss: 0.5320 - val accuracy: 0.7780
Epoch 89/128
Epoch 89: saving model to training second model\cp.ckpt
val_loss: 0.5364 - val_accuracy: 0.7593
Epoch 90/128
```

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22/22 [_____

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22/22 [------ - cim; us - 1055; u.1025 - accuracy; u.3040
Epoch 90: saving model to training_second_model\cp.ckpt
val loss: 0.5330 - val accuracy: 0.7797
Epoch 91/128
Epoch 91: saving model to training second model\cp.ckpt
val loss: 0.5347 - val accuracy: 0.7729
Epoch 92/128
Epoch 92: saving model to training_second_model\cp.ckpt
val loss: 0.5404 - val accuracy: 0.7610
Epoch 93/128
Epoch 93: saving model to training second model\cp.ckpt
22/22 [=========== ] - 30s 1s/step - loss: 0.1112 - accuracy: 0.9797 -
val loss: 0.5356 - val accuracy: 0.7644
Epoch 94/128
Epoch 94: saving model to training second model\cp.ckpt
22/22 [=========== ] - 31s 1s/step - loss: 0.0989 - accuracy: 0.9826 -
val loss: 0.5325 - val accuracy: 0.7780
Epoch 95/128
Epoch 95: saving model to training second model\cp.ckpt
22/22 [============ ] - 30s 1s/step - loss: 0.0992 - accuracy: 0.9826 -
val_loss: 0.5325 - val_accuracy: 0.7797
Epoch 96/128
Epoch 96: saving model to training second model\cp.ckpt
val_loss: 0.5369 - val_accuracy: 0.7593
Epoch 97/128
Epoch 97: saving model to training second model\cp.ckpt
val loss: 0.5394 - val accuracy: 0.7729
Epoch 98/128
Epoch 98: saving model to training second model\cp.ckpt
val loss: 0.5419 - val accuracy: 0.7712
Epoch 99/128
Epoch 99: saving model to training_second_model\cp.ckpt
val_loss: 0.5402 - val_accuracy: 0.7712
Epoch 100/128
Epoch 100: saving model to training second model\cp.ckpt
22/22 [============ ] - 31s 1s/step - loss: 0.0982 - accuracy: 0.9840 -
val_loss: 0.5480 - val_accuracy: 0.7593
Epoch 101/128
Epoch 101: saving model to training second model\cp.ckpt
val loss: 0.5419 - val accuracy: 0.7746
Epoch 102/128
Epoch 102: saving model to training second model\cp.ckpt
val loss: 0.5453 - val accuracy: 0.7695
Epoch 103/128
Epoch 103: saving model to training second model\cp.ckpt
22/22 [=========== ] - 31s 1s/step - loss: 0.0896 - accuracy: 0.9862 -
val_loss: 0.5475 - val_accuracy: 0.7661
Epoch 104: saving model to training second model\cp.ckpt
```

```
val loss: 0.5540 - val accuracy: 0.7678
Epoch 105/128
Epoch 105: saving model to training second model\cp.ckpt
val loss: 0.5435 - val accuracy: 0.7712
Epoch 106/128
Epoch 106: saving model to training second model\cp.ckpt
val loss: 0.5517 - val accuracy: 0.7644
Epoch 107/128
Epoch 107: saving model to training second model\cp.ckpt
22/22 [=========== ] - 31s 1s/step - loss: 0.0783 - accuracy: 0.9927 -
val_loss: 0.5435 - val_accuracy: 0.7780
Epoch 108/128
Epoch 108: saving model to training second model\cp.ckpt
22/22 [============== ] - 31s 1s/step - loss: 0.0761 - accuracy: 0.9927 -
val loss: 0.5441 - val accuracy: 0.7729
Epoch 109/128
Epoch 109: saving model to training second model\cp.ckpt
val loss: 0.5464 - val accuracy: 0.7729
Epoch 110/128
Epoch 110: saving model to training second model\cp.ckpt
val loss: 0.5502 - val accuracy: 0.7746
Epoch 111/128
Epoch 111: saving model to training second model\cp.ckpt
22/22 [=========== ] - 32s 1s/step - loss: 0.0725 - accuracy: 0.9935 -
val loss: 0.5510 - val accuracy: 0.7746
Epoch 112/128
Epoch 112: saving model to training_second_model\cp.ckpt
val loss: 0.5583 - val accuracy: 0.7661
Epoch 113/128
Epoch 113: saving model to training second model\cp.ckpt
val_loss: 0.5497 - val_accuracy: 0.7763
Epoch 114/128
Epoch 114: saving model to training second model\cp.ckpt
val_loss: 0.5655 - val_accuracy: 0.7695
Epoch 115/128
Epoch 115: saving model to training second model\cp.ckpt
val loss: 0.5434 - val accuracy: 0.7746
Epoch 116/128
Epoch 116: saving model to training second model\cp.ckpt
val loss: 0.5531 - val accuracy: 0.7797
Epoch 117/128
Epoch 117: saving model to training second model\cp.ckpt
val loss: 0.5454 - val accuracy: 0.7831
Epoch 118/128
Epoch 118: saving model to training second model\cp.ckpt
val loss: 0.5449 - val accuracy: 0.7831
```

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```
Phocii TT2/TT0
Epoch 119: saving model to training second model\cp.ckpt
22/22 [============= ] - 31s 1s/step - loss: 0.0695 - accuracy: 0.9913 -
val loss: 0.5451 - val accuracy: 0.7797
Epoch 120/128
Epoch 120: saving model to training second model\cp.ckpt
val loss: 0.5450 - val accuracy: 0.7847
Epoch 121/128
Epoch 121: saving model to training second model\cp.ckpt
val_loss: 0.5524 - val_accuracy: 0.7814
Epoch 122/128
Epoch 122: saving model to training second model\cp.ckpt
22/22 [============ ] - 33s 1s/step - loss: 0.0637 - accuracy: 0.9935 -
val loss: 0.5511 - val accuracy: 0.7763
Epoch 123/128
Epoch 123: saving model to training second model\cp.ckpt
22/22 [===========] - 35s 1s/step - loss: 0.0621 - accuracy: 0.9942 -
val loss: 0.5504 - val accuracy: 0.7831
Epoch 124/128
Epoch 124: saving model to training second model\cp.ckpt
22/22 [============] - 32s 1s/step - loss: 0.0606 - accuracy: 0.9956 -
val loss: 0.5554 - val accuracy: 0.7780
Epoch 125/128
Epoch 125: saving model to training second model\cp.ckpt
val loss: 0.5546 - val accuracy: 0.7763
Epoch 126/128
Epoch 126: saving model to training second model\cp.ckpt
val loss: 0.5606 - val accuracy: 0.7797
Epoch 127/128
Epoch 127: saving model to training second model\cp.ckpt
val loss: 0.5568 - val accuracy: 0.7881
Epoch 128/128
Epoch 128: saving model to training second model\cp.ckpt
22/22 [============ ] - 33s 1s/step - loss: 0.0554 - accuracy: 0.9964 -
val_loss: 0.5509 - val_accuracy: 0.7864
In [ ]:
model2.save('Second model.keras')
In [ ]:
model2= tf.keras.models.load model('Second model.keras')
```

Evaluate the model and report the accuracy

I evaluated the model using model.evaluate passing in our test labels and targets. And then from that variable containing the evaluation results, we take the index 1 to get the accuracy of our model on the test set.

```
In []:

eval_result2 = model2.evaluate(X_test, y_test, verbose=1)

# Print the accuracy
accuracy2 = eval_result2[1] * 100 # Accuracy is typically the second element in the eval
```

For our second model, the accuracy is 78.64% which seems to be higher than our first model. This is because of the addition of the extra hidden layer.

Make prediction with the test set and use a threshold of 0.5 as boundaries decision between the classes.

Then we make prediction using the test set(X_test) and the variable "predictions" contains the results. Then we set threshold as 0.5 and make binary predictions variable contain predictions as 1 for values that are above 0.5 and 0 otherwise. And this is used using the "predictions" variable defined above containing the real values for the predictions.

```
In [ ]:
threshold=0.5
predictions2=model2.predict(X test)
binary labels2 = np.argmax(predictions2, axis=1)
binary predictions2 = (predictions2 > threshold).astype(int)
#binary predictions2
In [ ]:
predictions2[:9]
Out[]:
array([[5.7269961e-01],
      [6.5179271e-01],
      [7.8221798e-05],
      [7.9324299e-01],
      [8.3395606e-01],
      [8.5443377e-01],
      [1.6503903e-01],
      [1.2467336e-02],
      [7.1737725e-01]], dtype=float32)
```

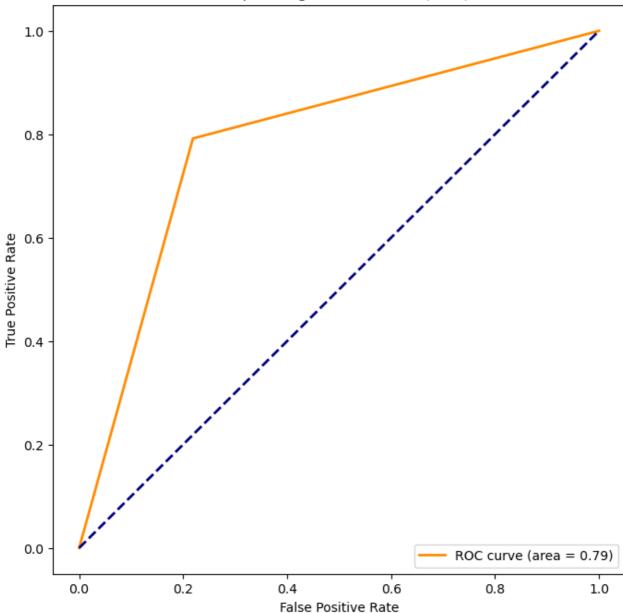
show metrics like confusion matrix or ROC curve or both (sklearn has already implemented all these stuff)

```
In []:
print("Confusion Matrix and ROC curve of model 2 is given below: ")
Confusion Matrix and ROC curve of model 2 is given below:
In []:
# Plot ROC Curve
```

```
fpr, tpr, thresholds = roc_curve(y_test, binary_predictions2.flatten())
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
```

Receiver Operating Characteristic (ROC) Curve



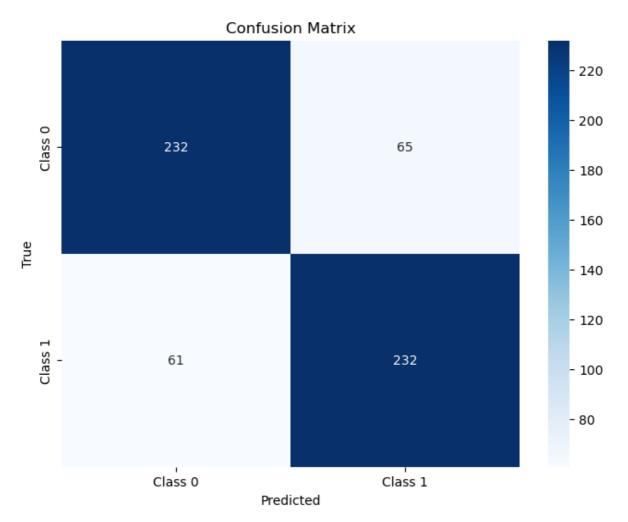
In []:

```
# Calculate and display the confusion matrix
conf_matrix = confusion_matrix(y_test, binary_predictions2.flatten())
print("Confusion Matrix:")
print(conf_matrix)

# Plot Confusion Matrix using Matplotlib
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0', 'Class 1'], yticklabels=['Class 0', 'Class 1'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

Confusion Matrix: [[232 65] 61 23211

.



For our second model, the area under the curve is 0.79 which means that our model is pretty efficient in separating the not pizza from the pizza model and is much better than the first model. Addition of the extra hidden layer seemed to have made it more efficient in distinguishing between the two classes. The Confusion Matrix shows that our True Positive(TP), True Negative(TN), False Positive(FP), False Negative(FN) for classifying pizza class from not pizza for our first/original model is 232, 232, 65, 61, respectively. These results also mean that the model's performance is much better than the first model because the wrongly misinterpretted classes are much less in number and the right ones are more in number.

show predictions

Then we tried to show some predictions by plotting a test image against our predicted Label Results. We can see that almost 78% of the time, it gets correct results.

```
In [ ]:
```

```
def show_some_prediction(number_of_subplot, test_set, predictions, name_of_the_labels):
    for i in range(number_of_subplot):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(test_set[i])
        plt.title(f'{name_of_the_labels[predictions[i]]}')
        plt.axis("off")
    plt.show()
show_some_prediction(9, X_test, binary_predictions2.flatten(), label_names)
```















In []:	
In []:	