ASSIGNMENT 2

PRATIK PRASHANT CHOUGULE, ROLL NO- 22123011 , kaggle id- pratik_c09

In [1]:
```
 # INDEX
# 1.importing libraries
# 2.loading of training data
# 3. conversion of training data into pixel format (64*64) and greyscale
# 4. merging of 2 data sets i.e cracked and uncracked
# 5. training simple model of CNN
# 6. training another model of CNN consisting of BatchNormalisation(), dropout e
# 7. VGG model (final model)
# 8. making orediction of new data (for 2000 images)
```

Note: I have tried different models of CNN, to check how accuracy chnanges by using different layers of CNN. the final prediction is based on the best model (VGG16).

In [2]:
```
#  IMPORTING IMPORTANT LIBRARIES
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
```

In [3]:
```
# IMPORTING CRACKED IMAGE DATA FROM SYSTEM(TRAIN DATA)
data_1=os.listdir('C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\cracke
```

In [10]:
```
#IMPORTING UNCRACKED IMAGE DATA FROM SYSTEM (TRAIN DATA)
data_2=os.listdir('C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\uncrac
```

Generating CSV file for cracked images (train)

In [18]:
```
from PIL import Image

# Set the source directory for the images and the output CSV file path
source_dir = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\uncracked'
output_path = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\uncraracke

# Initialize an empty list to store the flattened pixel values
data = []

# Loop over the image files in the directory
for file_name in os.listdir(source_dir):
```

```
    # Open the image and Convert the image to grayscale
    image = Image.open(os.path.join(source_dir, file_name)).convert('L')

    #  resize it to 64x64 pixels
    gray_image = image.resize((64,64))


    # Convert the image to a numpy array and flatten it to a 1D array
    pixels = np.array(gray_image).flatten()
    # Add the flattened array to the list
    data.append(pixels)

# Create a pandas dataframe from the list of pixel values
df = pd.DataFrame(data)
df.insert(0,'label','uncracked')

# Save the dataframe to a CSV file
df.to_csv(output_path, index=False)


#  same is done for the cracked folder


# Set the source directory for the images and the output CSV file path
source_dir = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\cracked'
output_path = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\craracked.

# Initialize an empty list to store the flattened pixel values
data = []

# Loop over the image files in the directory
for file_name in os.listdir(source_dir):
    # Open the image and Convert the image to grayscale
    image = Image.open(os.path.join(source_dir, file_name)).convert('L')

    # resize it to 64x64 pixels
    gray_image = image.resize((64,64))


    # Convert the image to a numpy array and flatten it to a 1D array
    pixels = np.array(gray_image).flatten()
    # Add the flattened array to the list
    data.append(pixels)

# Create a pandas dataframe from the list of pixel values
df = pd.DataFrame(data)
df.insert(0,'label','cracked')

# Save the dataframe to a CSV file
df.to_csv(output_path, index=False)
```

In [19]:
```
import pandas as pd
import numpy as np
# Load the two CSV files into separate Pandas dataframes
df1 = pd.read_csv("C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\crarac
df2 = pd.read_csv("C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\uncrar
```

In [22]:
```
# merged_df = pd.concat([df1, df2], axis=0, ignore_index=True)
merged_df = pd.concat([df1, df2], axis=0, ignore_index=True)
```

```
merged_df.to_csv("C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\merged_
```

In [23]:
```
# Shuffle the rows of the merged dataframe using np.random.permutation method:
shuffled_df = merged_df.reindex(np.random.permutation(merged_df.index))
```

importing all the libraries for CNN model

In [25]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPooling2D, Flatten, Dropout
from keras.optimizers import Adam
from keras.callbacks import EarlyStopping
```

In [71]:
```
#  randomly mixing the 2 CSV files
dff = pd.read_csv("C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\mixed_
```

In [72]:
```
dff.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14968 entries, 0 to 14967
Columns: 4097 entries, label to 4095
dtypes: int64(4096), object(1)
memory usage: 467.9+ MB
```

In [73]:
```
#  check for if there is any null| missing values

null_values = dff.isna().sum()
print(null_values)
```

```
label    0
0        0
1        0
2        0
3        0
        ..
4091     0
4092     0
4093     0
4094     0
4095     0
Length: 4097, dtype: int64
```

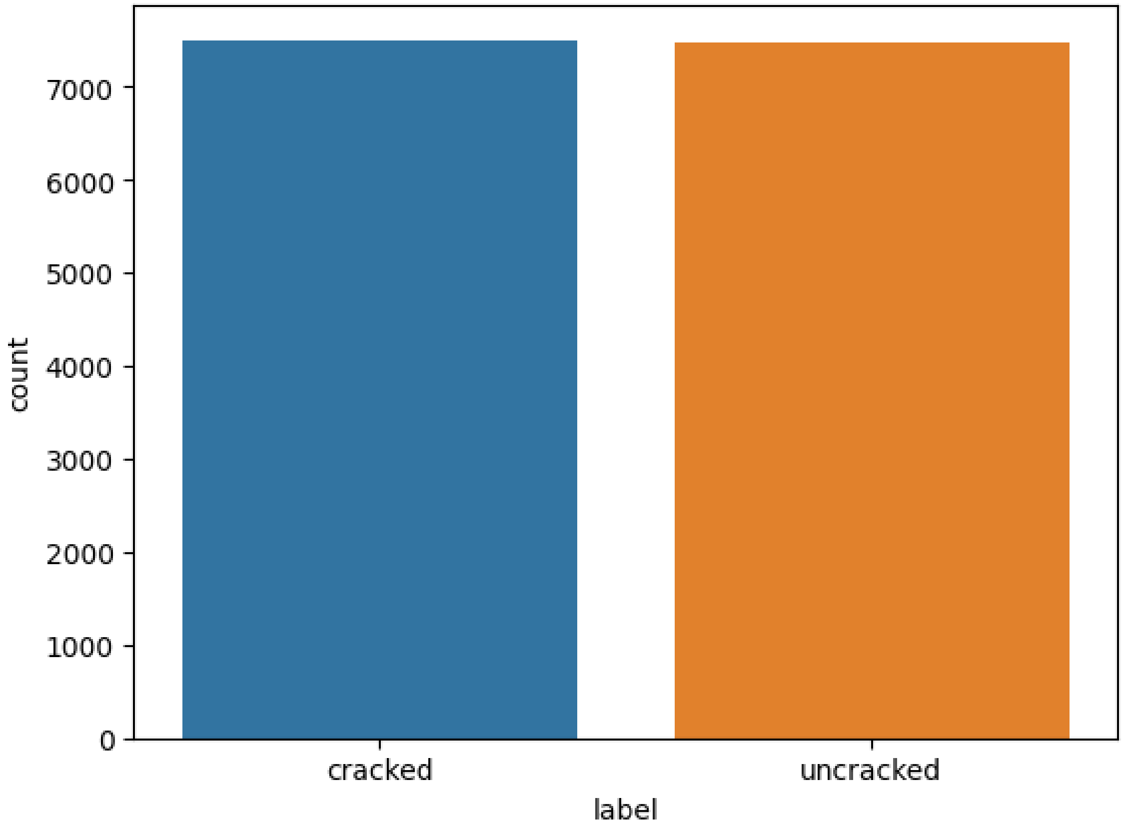
In [74]:
```
missing_values = df.isnull().sum()
print(missing_values)
```

```
label    0
0        0
1        0
2        0
3        0
        ..
4091     0
4092     0
4093     0
4094     0
4095     0
Length: 4097, dtype: int64
```

In [164…

```
# counting the no of datasets available in folder

sns.countplot(x='label', data=dff)
```

Out[164]: <AxesSubplot: xlabel='label', ylabel='count'>



there are approx same no of samples in dataset of "cracked and uncracked " # NO CLASS IMBALANCE

In [48]:

```
# print(dff.drop('label', axis=1).values.shape)
```

```
(14968, 4096)
```

In [75]:

```
y = dff['label']
X=dff.drop(['label'],axis=1)
```

In [76]:

```
y
```

Out[76]:
```
0          cracked
1        uncracked
2          cracked
3          cracked
4        uncracked
           ...
14963      cracked
14964      cracked
14965    uncracked
14966    uncracked
14967    uncracked
Name: label, Length: 14968, dtype: object
```

In [77]:
```
X
```

Out[77]:

	0	1	2	3	4	5	6	7	8	9	...	4086	4087	4088	4089	4090
0	72	74	70	63	62	70	70	69	77	89	...	71	84	82	77	77
1	163	176	174	174	175	177	173	181	176	154	...	166	168	168	164	166
2	156	169	173	174	172	169	171	177	178	171	...	181	181	183	206	185
3	180	190	197	184	192	167	176	189	186	186	...	170	174	181	175	200
4	172	165	165	168	168	167	169	170	167	169	...	160	168	166	167	161
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
14963	179	180	183	181	180	183	183	176	172	172	...	175	172	176	174	174
14964	183	179	184	186	185	186	186	183	181	181	...	192	182	182	187	193
14965	180	180	181	182	182	186	185	186	181	180	...	184	183	186	186	183
14966	101	156	171	178	160	155	144	140	147	136	...	168	168	175	171	168
14967	161	169	148	124	168	167	173	166	151	164	...	154	152	152	154	158

14968 rows × 4096 columns

In [78]:
```
X = dff.drop('label', axis=1).values.reshape(-1, 64, 64, 1)
```

In [79]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
import numpy as np

# Assuming y contains categorical labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
onehot_encoder = OneHotEncoder(sparse=False)
y_onehot = onehot_encoder.fit_transform(y_encoded.reshape(-1, 1))



# # Check the shapes of the arrays
# print("Shape of X_train:", X_train.shape)
# print("Shape of y_train:", y_train.shape)
# print("Shape of X_test:", X_test.shape)
# print("Shape of y_test:", y_test.shape)
```

```
C:\PYTHON 3.10\lib\site-packages\sklearn\preprocessing\_encoders.py:808: Future
Warning: `sparse` was renamed to `sparse_output` in version 1.2 and will be rem
oved in 1.4. `sparse_output` is ignored unless you leave `sparse` to its defaul
t value.
  warnings.warn(
```

In [80]:
```
# # Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y_onehot, test_size=0.2,
```

In [82]:
```
from tensorflow.keras.utils import to_categorical
y_train = to_categorical(y_train)

y_test = to_categorical(y_test)
```

In [92]:
```
y_train
```

Out[92]:
```
array([[[0., 1.],
        [1., 0.]],

       [[1., 0.],
        [0., 1.]],

       [[0., 1.],
        [1., 0.]],

       ...,

       [[0., 1.],
        [1., 0.]],

       [[1., 0.],
        [0., 1.]],

       [[1., 0.],
        [0., 1.]]], dtype=float32)
```

In [93]:
```
X_train
```

```
Out[93]: array([[[[180],
                 [178],
                 [179],
                 ...,
                 [184],
                 [181],
                 [177]],

                [[182],
                 [180],
                 [180],
                 ...,
                 [183],
                 [181],
                 [182]],

                [[181],
                 [181],
                 [181],
                 ...,
                 [176],
                 [179],
                 [178]],

                ...,

                [[180],
                 [180],
                 [178],
                 ...,
                 [174],
                 [176],
                 [173]],

                [[178],
                 [178],
                 [179],
                 ...,
                 [176],
                 [174],
                 [174]],

                [[177],
                 [180],
                 [180],
                 ...,
                 [177],
                 [177],
                 [179]]],


               [[[180],
                 [177],
                 [173],
                 ...,
                 [177],
                 [178],
                 [181]],

                [[183],
```

```
  [174],
  [172],
  ...,
  [178],
  [185],
  [181]],

 [[176],
  [171],
  [174],
  ...,
  [183],
  [179],
  [178]],

 ...,

 [[118],
  [128],
  [132],
  ...,
  [179],
  [180],
  [175]],

 [[109],
  [119],
  [131],
  ...,
  [183],
  [178],
  [185]],

 [[106],
  [118],
  [133],
  ...,
  [184],
  [178],
  [183]]],


[[[170],
  [171],
  [172],
  ...,
  [171],
  [170],
  [170]],

 [[169],
  [169],
  [170],
  ...,
  [170],
  [169],
  [167]],

 [[170],
  [171],
```

```
  [171],
  ...,
  [171],
  [170],
  [169]],

 ...,

 [[176],
  [173],
  [169],
  ...,
  [168],
  [170],
  [161]],

 [[173],
  [172],
  [172],
  ...,
  [170],
  [171],
  [171]],

 [[172],
  [172],
  [172],
  ...,
  [174],
  [174],
  [174]]],


...,


[[[171],
  [171],
  [174],
  ...,
  [179],
  [175],
  [177]],

 [[178],
  [172],
  [172],
  ...,
  [174],
  [177],
  [183]],

 [[179],
  [173],
  [171],
  ...,
  [175],
  [177],
  [185]],
```

```
 ...,

 [[183],
  [186],
  [178],
  ...,
  [167],
  [176],
  [183]],

 [[183],
  [182],
  [179],
  ...,
  [173],
  [171],
  [179]],

 [[185],
  [183],
  [181],
  ...,
  [172],
  [174],
  [176]]],


[[[104],
  [ 73],
  [ 91],
  ...,
  [148],
  [132],
  [132]],

 [[125],
  [ 90],
  [ 88],
  ...,
  [147],
  [138],
  [139]],

 [[129],
  [139],
  [120],
  ...,
  [145],
  [150],
  [144]],

 ...,

 [[129],
  [132],
  [133],
  ...,
  [129],
  [141],
  [145]],
```

```
 [[128],
  [128],
  [133],
  ...,
  [138],
  [125],
  [147]],

 [[127],
  [121],
  [113],
  ...,
  [150],
  [148],
  [150]]],


[[[158],
  [176],
  [172],
  ...,
  [162],
  [160],
  [163]],

 [[158],
  [169],
  [170],
  ...,
  [163],
  [162],
  [166]],

 [[165],
  [157],
  [151],
  ...,
  [161],
  [155],
  [165]],

 ...,

 [[151],
  [169],
  [159],
  ...,
  [163],
  [155],
  [158]],

 [[156],
  [162],
  [162],
  ...,
  [168],
  [162],
  [155]],
```

```
        [[165],
         [154],
         [163],
         ...,
         [162],
         [164],
         [156]]]], dtype=int64)
```

Trying simple model OF CNN

In [111…

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(64, 64,
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(2, activation='sigmoid'))
```

In [112…

```
model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_10 (Conv2D)          (None, 62, 62, 32)        320       
                                                                 
 max_pooling2d_10 (MaxPoolin  (None, 31, 31, 32)       0         
 g2D)                                                            
                                                                 
 conv2d_11 (Conv2D)          (None, 29, 29, 64)        18496     
                                                                 
 max_pooling2d_11 (MaxPoolin  (None, 14, 14, 64)       0         
 g2D)                                                            
                                                                 
 flatten_5 (Flatten)         (None, 12544)             0         
                                                                 
 dense_10 (Dense)            (None, 128)               1605760   
                                                                 
 dropout_5 (Dropout)         (None, 128)               0         
                                                                 
 dense_11 (Dense)            (None, 2)                 258       
                                                                 
=================================================================
Total params: 1,624,834
Trainable params: 1,624,834
Non-trainable params: 0
_________________________________________________________________
```

In [113…

```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy']
# history = model.fit(X_train, y_train, batch_size=32, epochs=10, validation_dat
```

In [115…

```
history = model.fit(X_train, y_train[:,:,1], batch_size=32, epochs=15, validatic
```

```
Epoch 1/15
375/375 [==============================] - 32s 85ms/step - loss: 0.6743 - accur
acy: 0.5500 - val_loss: 0.6982 - val_accuracy: 0.5107
Epoch 2/15
375/375 [==============================] - 32s 86ms/step - loss: 0.6774 - accur
acy: 0.5461 - val_loss: 0.7539 - val_accuracy: 0.5084
Epoch 3/15
375/375 [==============================] - 33s 88ms/step - loss: 0.6755 - accur
acy: 0.5457 - val_loss: 0.7106 - val_accuracy: 0.5217
Epoch 4/15
375/375 [==============================] - 33s 87ms/step - loss: 0.6703 - accur
acy: 0.5501 - val_loss: 0.7073 - val_accuracy: 0.5321
Epoch 5/15
375/375 [==============================] - 33s 89ms/step - loss: 0.6632 - accur
acy: 0.5594 - val_loss: 0.7055 - val_accuracy: 0.5334
Epoch 6/15
375/375 [==============================] - 33s 88ms/step - loss: 0.6625 - accur
acy: 0.5595 - val_loss: 0.7059 - val_accuracy: 0.5251
Epoch 7/15
375/375 [==============================] - 33s 87ms/step - loss: 0.6869 - accur
acy: 0.5225 - val_loss: 0.6985 - val_accuracy: 0.5080
Epoch 8/15
375/375 [==============================] - 33s 88ms/step - loss: 0.6690 - accur
acy: 0.5539 - val_loss: 0.6949 - val_accuracy: 0.5274
Epoch 9/15
375/375 [==============================] - 33s 88ms/step - loss: 0.6633 - accur
acy: 0.5593 - val_loss: 0.7060 - val_accuracy: 0.5321
Epoch 10/15
375/375 [==============================] - 45s 120ms/step - loss: 0.6857 - accu
racy: 0.5578 - val_loss: 0.6919 - val_accuracy: 0.5230
Epoch 11/15
375/375 [==============================] - 39s 103ms/step - loss: 0.6848 - accu
racy: 0.5554 - val_loss: 0.7072 - val_accuracy: 0.5371
Epoch 12/15
375/375 [==============================] - 38s 100ms/step - loss: 0.6648 - accu
racy: 0.5530 - val_loss: 0.7136 - val_accuracy: 0.5274
Epoch 13/15
375/375 [==============================] - 35s 92ms/step - loss: 0.6466 - accur
acy: 0.5734 - val_loss: 0.7383 - val_accuracy: 0.5307
Epoch 14/15
375/375 [==============================] - 33s 87ms/step - loss: 0.6442 - accur
acy: 0.5746 - val_loss: 0.7414 - val_accuracy: 0.5287
Epoch 15/15
375/375 [==============================] - 33s 87ms/step - loss: 0.6404 - accur
acy: 0.5783 - val_loss: 0.7232 - val_accuracy: 0.5354
```

for this model the training and testing accuracy is very low, seems like it is model iss underfitted

another model , introducing batchnormalisation,Droupoutfor the model improvement

In [133…

```
from tensorflow.keras.layers import Dense, BatchNormalization

from keras.callbacks import EarlyStopping

earlystop = EarlyStopping(monitor='val_loss', patience=5, verbose=1, restore_bes

model_1 = Sequential()

model_1.add(Conv2D(32,kernel_size=(3,3),padding='valid',activation='relu',input_
model_1.add(BatchNormalization())
model_1.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))

model_1.add(Conv2D(64,kernel_size=(3,3),padding='valid',activation='relu'))
model_1.add(BatchNormalization())
model_1.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))

model_1.add(Conv2D(128,kernel_size=(3,3),padding='valid',activation='relu'))
model_1.add(BatchNormalization())
model_1.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))

model_1.add(Flatten())

model_1.add(Dense(128,activation='relu'))
model_1.add(Dropout(0.1))
model_1.add(Dense(64,activation='relu'))
model_1.add(Dropout(0.1))
model_1.add(Dense(2,activation='sigmoid'))
```

In [134…

```
model_1.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_22 (Conv2D)          (None, 62, 62, 32)        320       
                                                                 
 batch_normalization_9 (Batc  (None, 62, 62, 32)       128       
 hNormalization)                                                 
                                                                 
 max_pooling2d_21 (MaxPoolin  (None, 31, 31, 32)       0         
 g2D)                                                            
                                                                 
 conv2d_23 (Conv2D)          (None, 29, 29, 64)        18496     
                                                                 
 batch_normalization_10 (Bat  (None, 29, 29, 64)       256       
 chNormalization)                                                
                                                                 
 max_pooling2d_22 (MaxPoolin  (None, 14, 14, 64)       0         
 g2D)                                                            
                                                                 
 conv2d_24 (Conv2D)          (None, 12, 12, 128)       73856     
                                                                 
 batch_normalization_11 (Bat  (None, 12, 12, 128)      512       
 chNormalization)                                                
                                                                 
 max_pooling2d_23 (MaxPoolin  (None, 6, 6, 128)        0         
 g2D)                                                            
                                                                 
 flatten_9 (Flatten)         (None, 4608)              0         
                                                                 
 dense_21 (Dense)            (None, 128)               589952    
                                                                 
 dropout_12 (Dropout)        (None, 128)               0         
                                                                 
 dense_22 (Dense)            (None, 64)                8256      
                                                                 
 dropout_13 (Dropout)        (None, 64)                0         
                                                                 
 dense_23 (Dense)            (None, 2)                 130       
                                                                 
=================================================================
Total params: 691,906
Trainable params: 691,458
Non-trainable params: 448
_________________________________________________________________
```

In [135…

```
# model_1.compile(loss='binary_crossentropy'= for bineary , optimizer='adam', me
model_1.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy']
```

In [136…

```
history = model_1.fit(X_train, y_train[:,:,1], batch_size=32, epochs=25, validat
```

```
Epoch 1/25
375/375 [==============================] - 52s 136ms/step - loss: 0.7389 - accu
racy: 0.6026 - val_loss: 0.6561 - val_accuracy: 0.6186
Epoch 2/25
375/375 [==============================] - 48s 128ms/step - loss: 0.6534 - accu
racy: 0.6298 - val_loss: 0.6714 - val_accuracy: 0.5721
Epoch 3/25
375/375 [==============================] - 49s 131ms/step - loss: 0.6263 - accu
racy: 0.6408 - val_loss: 0.6450 - val_accuracy: 0.6152
Epoch 4/25
375/375 [==============================] - 49s 132ms/step - loss: 0.6025 - accu
racy: 0.6655 - val_loss: 0.6827 - val_accuracy: 0.5341
Epoch 5/25
375/375 [==============================] - 49s 131ms/step - loss: 0.5889 - accu
racy: 0.6738 - val_loss: 0.6664 - val_accuracy: 0.5635
Epoch 6/25
375/375 [==============================] - 50s 133ms/step - loss: 0.5694 - accu
racy: 0.6930 - val_loss: 1.0039 - val_accuracy: 0.5140
Epoch 7/25
375/375 [==============================] - 49s 131ms/step - loss: 0.5360 - accu
racy: 0.7215 - val_loss: 0.7405 - val_accuracy: 0.6096
Epoch 8/25
375/375 [==============================] - 48s 127ms/step - loss: 0.5133 - accu
racy: 0.7374 - val_loss: 0.6403 - val_accuracy: 0.6476
Epoch 9/25
375/375 [==============================] - 48s 129ms/step - loss: 0.4755 - accu
racy: 0.7594 - val_loss: 0.7086 - val_accuracy: 0.6062
Epoch 10/25
375/375 [==============================] - 51s 135ms/step - loss: 0.4420 - accu
racy: 0.7854 - val_loss: 0.6439 - val_accuracy: 0.6389
Epoch 11/25
375/375 [==============================] - 48s 128ms/step - loss: 0.4155 - accu
racy: 0.7968 - val_loss: 0.6308 - val_accuracy: 0.6343
Epoch 12/25
375/375 [==============================] - 52s 139ms/step - loss: 0.3454 - accu
racy: 0.8447 - val_loss: 0.9218 - val_accuracy: 0.6399
Epoch 13/25
375/375 [==============================] - 53s 143ms/step - loss: 0.2808 - accu
racy: 0.8730 - val_loss: 0.6600 - val_accuracy: 0.6877
Epoch 14/25
375/375 [==============================] - 51s 135ms/step - loss: 0.2400 - accu
racy: 0.8989 - val_loss: 0.6874 - val_accuracy: 0.6506
Epoch 15/25
375/375 [==============================] - 48s 129ms/step - loss: 0.1908 - accu
racy: 0.9210 - val_loss: 0.7279 - val_accuracy: 0.6683
Epoch 16/25
375/375 [==============================] - 48s 129ms/step - loss: 0.1597 - accu
racy: 0.9349 - val_loss: 0.7783 - val_accuracy: 0.6483
Epoch 17/25
375/375 [==============================] - 50s 133ms/step - loss: 0.1385 - accu
racy: 0.9481 - val_loss: 0.9421 - val_accuracy: 0.6610
Epoch 18/25
375/375 [==============================] - 49s 131ms/step - loss: 0.1316 - accu
racy: 0.9502 - val_loss: 1.3021 - val_accuracy: 0.6707
Epoch 19/25
375/375 [==============================] - 50s 134ms/step - loss: 0.0948 - accu
racy: 0.9651 - val_loss: 1.0109 - val_accuracy: 0.6396
Epoch 20/25
375/375 [==============================] - 50s 134ms/step - loss: 0.0839 - accu
racy: 0.9697 - val_loss: 1.2067 - val_accuracy: 0.6747
```

```
Epoch 21/25
375/375 [==============================] - 53s 140ms/step - loss: 0.0610 - accu
racy: 0.9788 - val_loss: 1.4061 - val_accuracy: 0.6837
Epoch 22/25
375/375 [==============================] - 53s 142ms/step - loss: 0.0766 - accu
racy: 0.9736 - val_loss: 3.7841 - val_accuracy: 0.6383
Epoch 23/25
375/375 [==============================] - 49s 130ms/step - loss: 0.0578 - accu
racy: 0.9825 - val_loss: 1.1722 - val_accuracy: 0.6787
Epoch 24/25
375/375 [==============================] - 51s 136ms/step - loss: 0.0576 - accu
racy: 0.9790 - val_loss: 1.5043 - val_accuracy: 0.6470
Epoch 25/25
375/375 [==============================] - 48s 128ms/step - loss: 0.0453 - accu
racy: 0.9844 - val_loss: 1.8127 - val_accuracy: 0.6710
```

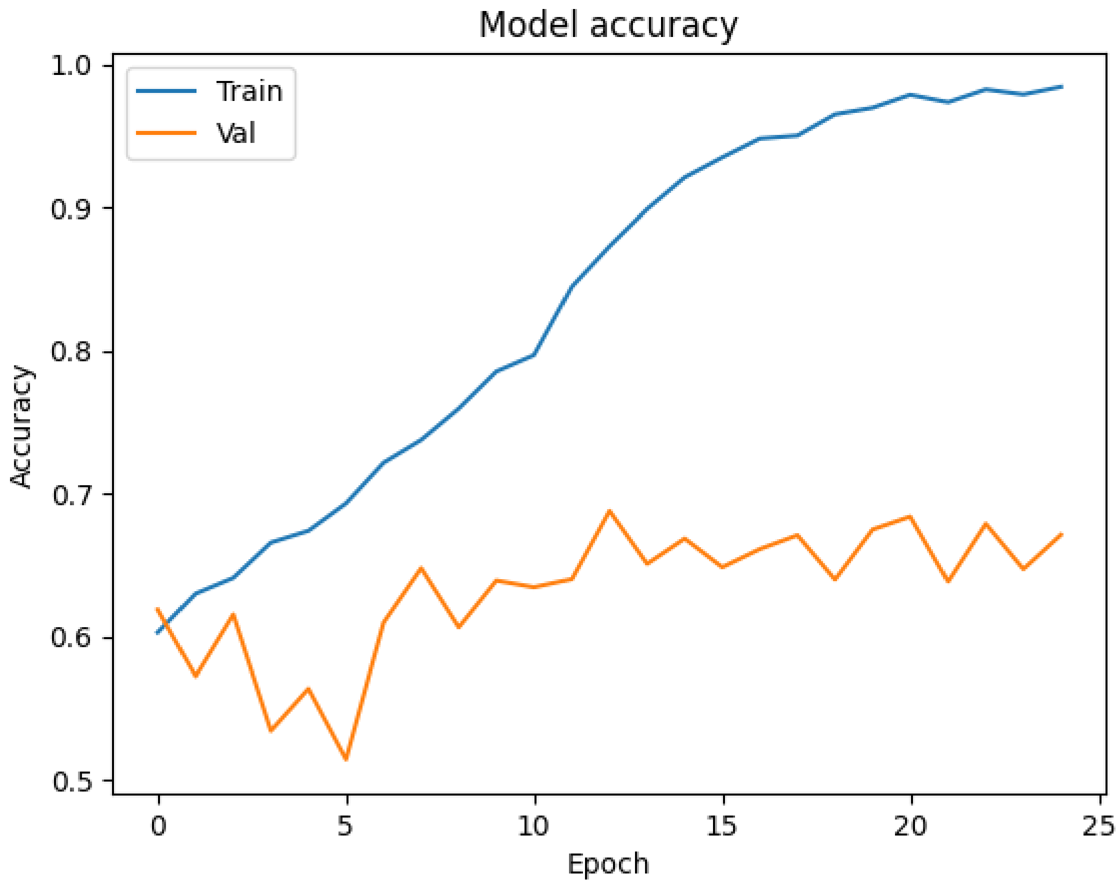
In [182…

```
# Evaluate the model on the test data
test_loss, test_acc = model_1.evaluate(X_test, y_test[:,:,1], verbose=2)

print('Test loss:', test_loss)
print('Test accuracy:', test_acc)
```

```
94/94 - 3s - loss: 1.8127 - accuracy: 0.6710 - 3s/epoch - 32ms/step
Test loss: 1.8126710653305054
Test accuracy: 0.6710087060928345
```

In [137…

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



training accuracy is incresed and test accuracy is very low , this are the signs of OVERFITTED model

VGG16 MODEL

we are using VGG model beacuse,The VGG model of CNN is often used as a feature extractor for transfer learning in computer vision tasks due to its excellent performance on image classification tasks and its simple architecture consisting of stacked convolutional layers with small filters. Its use can lead to better accuracy and faster convergence compared to training a model from scratch, especially when the size of the dataset is limited.

In [6]:
```
import numpy as np
import pandas as pd
from keras.applications.vgg16 import VGG16
from keras.models import Model
from keras.layers import Dense, Flatten, Conv2D, MaxPooling2D
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, OneHotEncoder

# Load data from CSV file
data = pd.read_csv('C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\mixec
X_gray = data.iloc[:, 1:].values.reshape(-1, 64, 64, 1) # reshape to (n_samples,
```

```
X = np.concatenate([X_gray]*3, axis=-1) # duplicate grayscale channel to create
y = data.iloc[:, 0].values

# Convert string labels to numeric labels using label encoding
le = LabelEncoder()
y = le.fit_transform(y)

# Convert numeric labels to one-hot encoding
ohe = OneHotEncoder(sparse=False)
y = ohe.fit_transform(y.reshape(-1, 1))

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Load pre-trained VGG16 model
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(64, 64, 3

# Add custom top layers for grayscale image classification
x = base_model.output
x = Flatten()(x)
x = Dense(256, activation='relu')(x)
x = Dense(128, activation='relu')(x)
predictions = Dense(len(le.classes_), activation='softmax')(x)

# Create a new model with custom top layers
model = Model(inputs=base_model.input, outputs=predictions)

# Freeze pre-trained layers
for layer in base_model.layers:
    layer.trainable = False

# Compile model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accur

# Train model
model.fit(X_train, y_train, batch_size=32, epochs=10, validation_data=(X_test, y

# Evaluate model on test set
score = model.evaluate(X_test, y_test)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
C:\PYTHON 3.10\lib\site-packages\sklearn\preprocessing\_encoders.py:808: Future
Warning: `sparse` was renamed to `sparse_output` in version 1.2 and will be rem
oved in 1.4. `sparse_output` is ignored unless you leave `sparse` to its defaul
t value.
  warnings.warn(
```

```
Epoch 1/10
375/375 [==============================] - 140s 372ms/step - loss: 0.6876 - acc
uracy: 0.7184 - val_loss: 0.5362 - val_accuracy: 0.7285
Epoch 2/10
375/375 [==============================] - 142s 379ms/step - loss: 0.4776 - acc
uracy: 0.7678 - val_loss: 0.4889 - val_accuracy: 0.7655
Epoch 3/10
375/375 [==============================] - 144s 385ms/step - loss: 0.4581 - acc
uracy: 0.7789 - val_loss: 0.5301 - val_accuracy: 0.7341
Epoch 4/10
375/375 [==============================] - 146s 390ms/step - loss: 0.4302 - acc
uracy: 0.7923 - val_loss: 0.5031 - val_accuracy: 0.7672
Epoch 5/10
375/375 [==============================] - 147s 392ms/step - loss: 0.4192 - acc
uracy: 0.7966 - val_loss: 0.5149 - val_accuracy: 0.7502
Epoch 6/10
375/375 [==============================] - 147s 392ms/step - loss: 0.3955 - acc
uracy: 0.8085 - val_loss: 0.5141 - val_accuracy: 0.7715
Epoch 7/10
375/375 [==============================] - 145s 387ms/step - loss: 0.3852 - acc
uracy: 0.8148 - val_loss: 0.5559 - val_accuracy: 0.7515
Epoch 8/10
375/375 [==============================] - 170s 453ms/step - loss: 0.3693 - acc
uracy: 0.8248 - val_loss: 0.5158 - val_accuracy: 0.7796
Epoch 9/10
375/375 [==============================] - 174s 465ms/step - loss: 0.3552 - acc
uracy: 0.8326 - val_loss: 0.5554 - val_accuracy: 0.7589
Epoch 10/10
375/375 [==============================] - 173s 461ms/step - loss: 0.3543 - acc
uracy: 0.8284 - val_loss: 0.5572 - val_accuracy: 0.7605
94/94 [==============================] - 34s 362ms/step - loss: 0.5572 - accura
cy: 0.7605
Test loss: 0.5571762323379517
Test accuracy: 0.7605210542678833
```

Test loss: 0.5571762323379517

Test accuracy: 0.7605210542678833

calculating F1 score .

In [2]:

```
from sklearn.metrics import f1_score

# Predict labels for test set
y_pred = model.predict(X_test)
y_pred = np.argmax(y_pred, axis=1)
y_test = np.argmax(y_test, axis=1)

# Calculate F1 score
f1 = f1_score(y_test, y_pred, average='weighted')
print('F1 score:', f1)
```

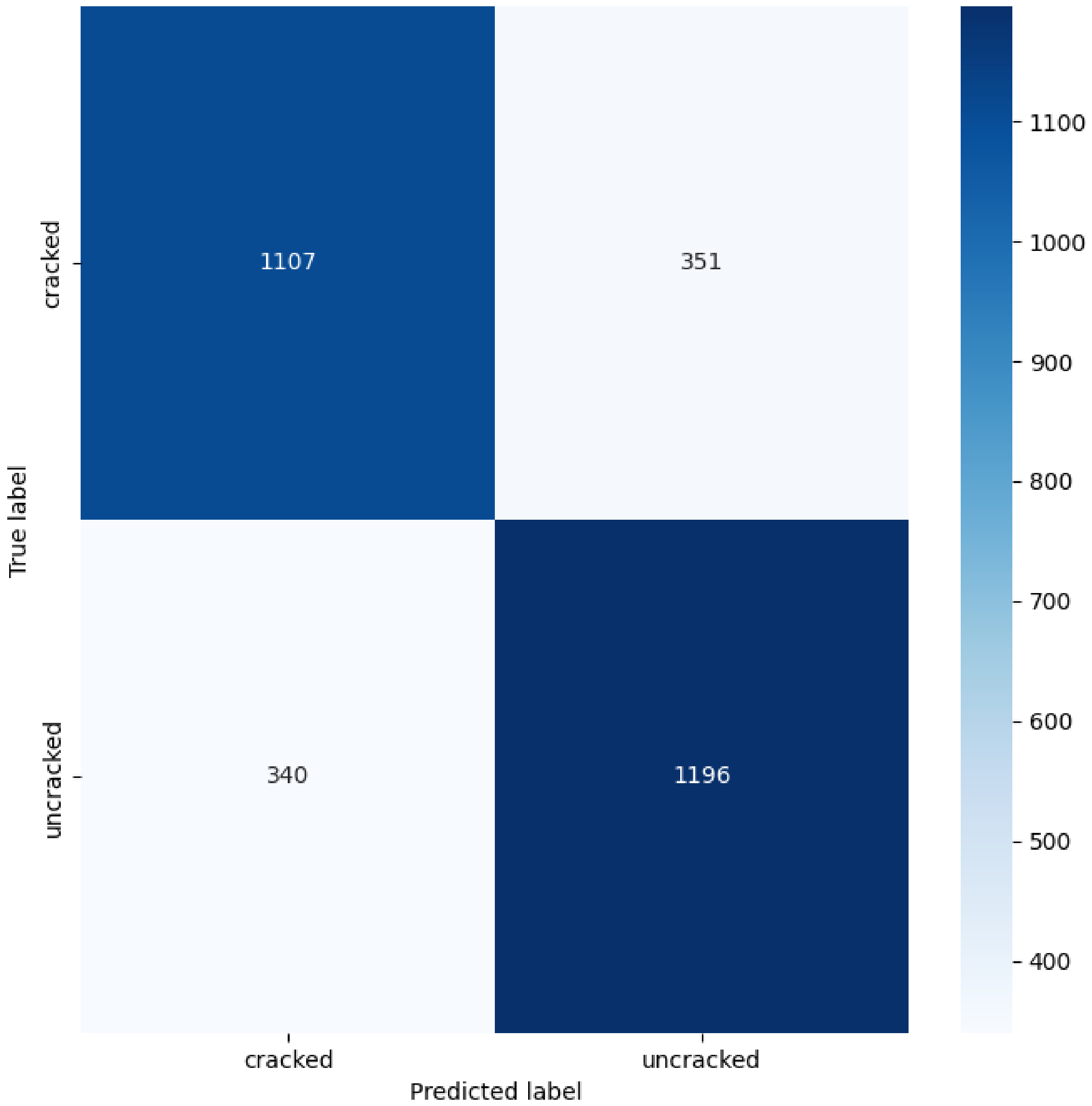
```
94/94 [==============================] - 35s 369ms/step
F1 score: 0.7459576926232551
```

F1 score: 0.75

confusion matrix

In [4]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Predict labels for test set
y_pred = model.predict(X_test)
y_pred = np.argmax(y_pred, axis=1)
y_test = np.argmax(y_test, axis=1)

# Generate confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 8))
sns.heatmap(cm, annot=True, cmap=plt.cm.Blues, fmt='g', xticklabels=le.classes_,
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()
```

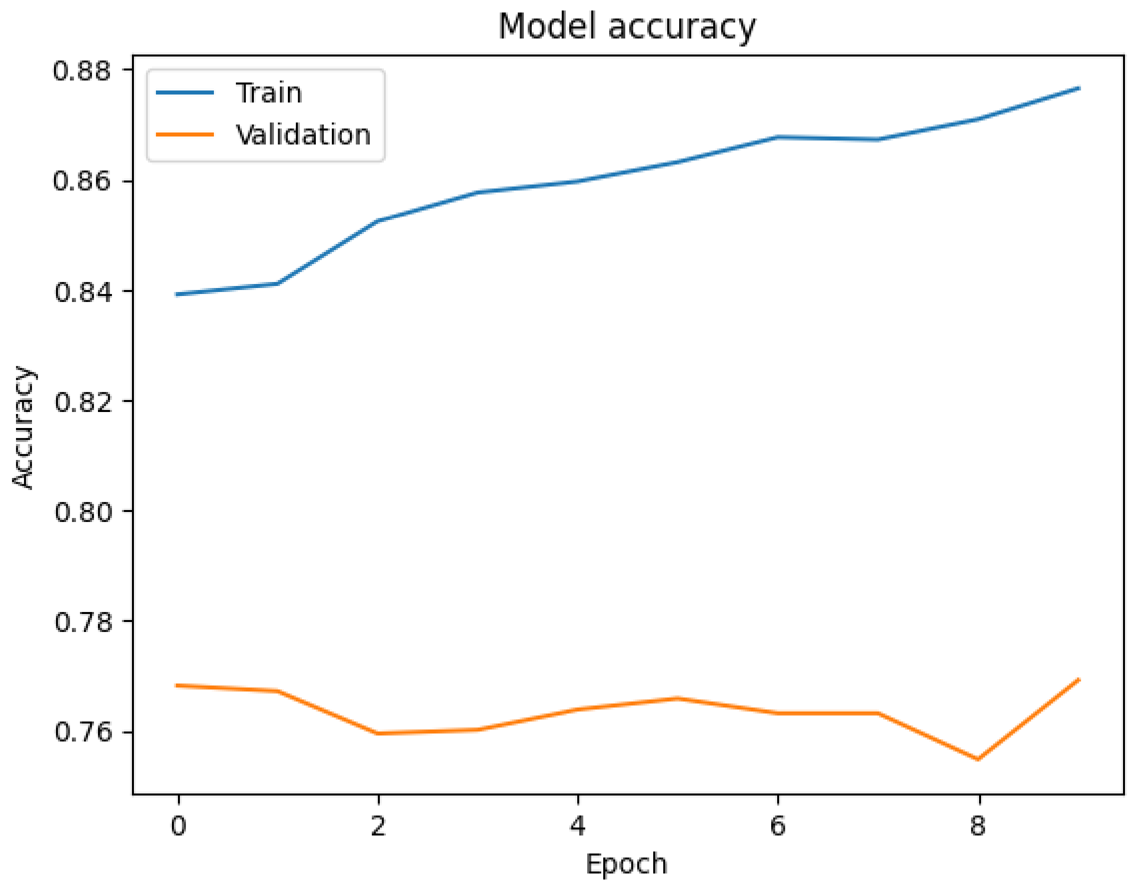
```
94/94 [==============================] - 35s 360ms/step
```

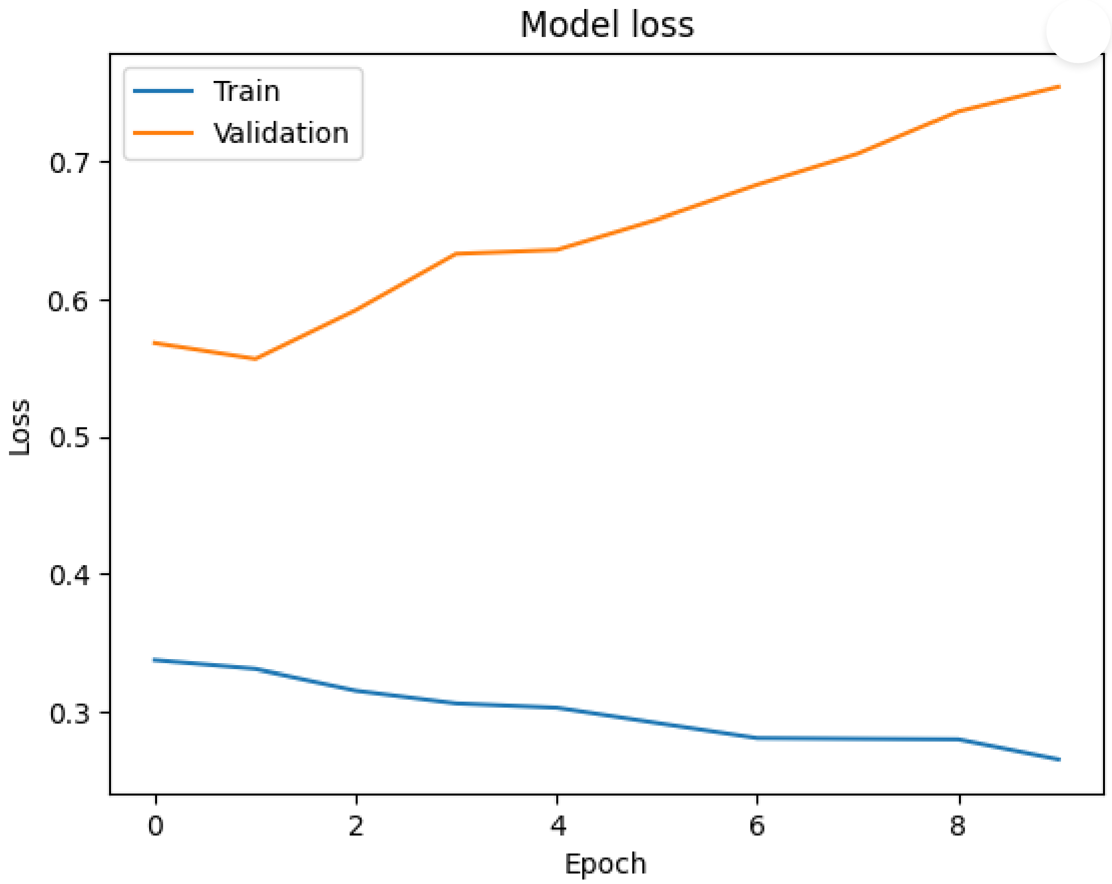


In [8]:

```
import matplotlib.pyplot as plt

# Train model and collect history
history = model.fit(X_train, y_train, batch_size=32, epochs=10, validation_data=

# Plot training and validation accuracy
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()

# Plot training and validation loss
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()
```

```
Epoch 1/10
375/375 [==============================] - 173s 461ms/step - loss: 0.3375 - acc
uracy: 0.8392 - val_loss: 0.5682 - val_accuracy: 0.7682
Epoch 2/10
375/375 [==============================] - 173s 461ms/step - loss: 0.3311 - acc
uracy: 0.8411 - val_loss: 0.5567 - val_accuracy: 0.7672
Epoch 3/10
375/375 [==============================] - 174s 464ms/step - loss: 0.3155 - acc
uracy: 0.8524 - val_loss: 0.5921 - val_accuracy: 0.7595
Epoch 4/10
375/375 [==============================] - 178s 475ms/step - loss: 0.3063 - acc
uracy: 0.8577 - val_loss: 0.6331 - val_accuracy: 0.7602
Epoch 5/10
375/375 [==============================] - 176s 469ms/step - loss: 0.3031 - acc
uracy: 0.8597 - val_loss: 0.6360 - val_accuracy: 0.7639
Epoch 6/10
375/375 [==============================] - 175s 466ms/step - loss: 0.2920 - acc
uracy: 0.8632 - val_loss: 0.6580 - val_accuracy: 0.7659
Epoch 7/10
375/375 [==============================] - 172s 460ms/step - loss: 0.2810 - acc
uracy: 0.8677 - val_loss: 0.6831 - val_accuracy: 0.7632
Epoch 8/10
375/375 [==============================] - 177s 472ms/step - loss: 0.2805 - acc
uracy: 0.8673 - val_loss: 0.7056 - val_accuracy: 0.7632
Epoch 9/10
375/375 [==============================] - 172s 460ms/step - loss: 0.2801 - acc
uracy: 0.8710 - val_loss: 0.7364 - val_accuracy: 0.7548
Epoch 10/10
375/375 [==============================] - 171s 457ms/step - loss: 0.2655 - acc
uracy: 0.8766 - val_loss: 0.7543 - val_accuracy: 0.7692
```





for the above VGG model the training accuracy is almost equal to 85 % and test accuracy is amlost equal to 78 %

In [9]:
```
#  saving our VGG model
model.save('vgg_model.h5')
```

In [10]:
```
from keras.models import load_model

model = load_model('vgg_model.h5')
```

In [31]:
```
# lets convert the prediction images into the grey scale(TEST FOLDER DATA)

from PIL import Image


# Set the source directory for the images and the output CSV file path
source_dir = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\test'
output_path = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\test_data_

# Initialize an empty list to store the flattened pixel values
data = []

# Loop over the image files in the directory
for file_name in os.listdir(source_dir):
    # Open the image and resize it to 64*64 pixels,Convert the image to grayscal
    image = Image.open(os.path.join(source_dir, file_name)).convert('L')
```

```python
    gray_image = image.resize((64,64))


    # Convert the image to a numpy array and flatten it to a 1D array
    pixels = np.array(gray_image).flatten()
    # Add the flattened array to the list
    data.append(pixels)

# Create a pandas dataframe from the list of pixel values
df = pd.DataFrame(data)


# Save the dataframe to a CSV file
df.to_csv(output_path, index=False)
```

In [64]:
```python
# Load the saved model
model = load_model('vgg_model.h5')
```

In [68]:
```python
# # Save the predictions to a CSV file
# df.to_csv('C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\predictions_
```

In [70]:
```python
# Set the source directory for the images and the output CSV file path
source_dir = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\test'
output_path = 'C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\testing_ne

# Initialize an empty list to store the flattened pixel values
data = []

# Loop over the image files in the directory
for i in range(1, 2001):
    # Open the image and resize it to 64*64 pixels
    file_name = f'{i}.jpg'
    image = Image.open(os.path.join(source_dir, file_name)).convert('L')

    # Convert the image to grayscale
    gray_image = image.resize((64,64))

    # Convert the image to a numpy array and flatten it to a 1D array
    pixels = np.array(gray_image).flatten()
    # Add the flattened array to the list
    data.append(pixels)
```

In [79]:
```python
# Create a pandas dataframe from the list of pixel values
df = pd.DataFrame(data)
df.insert(0,'Image',['{}.jpg'.format(i) for i in range(1,2001)])

# Load the model
model = load_model('vgg_model.h5')

# Reshape the data for input to the model
X_gray = df.iloc[:,1:].values.reshape(-1,64,64,1)
X = np.concatenate([X_gray]*3, axis=-1)
```

In [83]:
```python
# Making final  predictions on the test data
predictions = model.predict(X)
labels = ['Cracked' if prediction[0] > prediction[1] else 'Uncracked' for predic
```

```
# Create a Pandas DataFrame with the predictions
df = pd.DataFrame({'Image': df['Image'], 'class': labels})

# Save the predictions to a CSV file
df.to_csv('C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\final_list_2.c
```

```
63/63 [==============================] - 82s 1s/step
```

In [2]:
```
# reding our newly generated file

df = pd.read_csv('C:\\Users\\PRADNYA\\Desktop\\assignment 2 data\\train\\final_l
```

generating count plot using sns librabry to check how many cracked and uncracked images are there according to our model .

In [3]:
```
sns.countplot(x='class', data=df)
plt.show()
```