Emotion Recognition Classification Task

```
#Python's operating system interface
import os
#Python time-related functions
import time
#Python module for manipulating dates and times
import datetime
#a Python numerical computing library
import numpy as np
#a Python data manipulation and analysis library
import pandas as pd
#a Python package for making visualisations
import matplotlib.pyplot as plt


#a Python package that provides several machine learning methods and tools
import sklearn


#Google's open-source platform for developing and training machine learning models
%tensorflow_version 2.x
#Python API for high-level neural networks that runs on top of TensorFlow and other lower-
import tensorflow as tf
#Python module that provides numerous functions for interacting with functions
from tensorflow import keras

%load_ext tensorboard

#Python module that provides numerous functions for interacting with functions
from functools import partial
#Python module for making statistical graphics
import seaborn as sns

#a Keras class that generates batches of enhanced picture data during training
from tensorflow.keras.preprocessing.image import ImageDataGenerator
'''Dense is a neural network layer that is fully connected.
A model's input shape is defined by input.
Dropout is a regularisation technique that helps to avoid overfitting.
Flatten is a function that converts the output of a convolutional layer into a vector.
Conv2D is a 2D convolutional layer used in image processing and computer vision for featur
from tensorflow.keras.layers import Dense, Input, Dropout,Flatten, Conv2D
'''BatchNormalization is a Keras layer that is used to normalise inputs to a layer.
Activation is a Keras layer that specifies the activation function.
MaxPooling2D is a Keras layer that implements maximum pooling.'''
from tensorflow.keras.layers import BatchNormalization, Activation, MaxPooling2D
'''It imports the Model and Sequential classes from TensorFlow's tensorflow.keras.models m
from tensorflow.keras.models import Model, Sequential
```

```
#a stochastic gradient descent Keras optimizer
from tensorflow.keras.optimizers import Adam
'''This piece of code imports two callback classes from TensorFlow's tensorflow.keras.call
from tensorflow.keras.callbacks import ModelCheckpoint, ReduceLROnPlateau
#import plot_model from tensorflow.keras.utils
from tensorflow.keras.utils import plot_model
#importing Sequential class from keras.model
from keras.models import Sequential
#importing Reshape to reshape the images
from keras.layers import Dense, Activation, Convolution2D, Reshape, Flatten, MaxPooling2D,
#NumPy-to-Keras data transformation.
from keras.utils import np_utils

#Importing TensorFlow machine learning library.
import tensorflow as tf
import pandas as pd

```

```
Colab only includes TensorFlow 2.x; %tensorflow_version has no effect.
```

```
#Importing visualization functions from Matplotlib.
from matplotlib import pyplot
```

```
'''This code block installs PyDrive and imports the modules required to access Google Driv
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
link = 'https://drive.google.com/file/d/1za6RekuOq7IHDUmiVgsIDqf7YhLTD4hK/view?usp=share_l
id = link.split("/")[-2]

downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('my_emotion_train.csv')

 #This line of code reads a CSV file named'my_emotion_train.csv' and saves the contents as
df = pd.read_csv('my_emotion_train.csv')
print(df)
```

```
          id  emotion                                             pixels
0       9415        6  29 16 18 18 18 20 19 18 17 17 17 18 17 18 17 1...
1      19109        3  126 154 167 181 188 194 195 194 196 195 198 20...
2      21523        2  169 220 218 208 184 144 72 73 143 183 203 210 ...
3       2076        3  60 64 72 80 83 83 80 82 89 106 114 125 125 127...
4      13957        3  174 148 121 97 78 70 62 57 54 54 42 58 40 64 1...
```

```
...      ...      ...                                                    ...
28995   7926        5  54 49 35 32 27 32 39 41 61 85 100 107 114 121 ...
28996  21200        3  101 107 111 90 95 129 134 139 152 132 126 135 ...
28997   1097        3  133 113 120 151 178 199 209 215 216 221 221 22...
28998   4186        3  65 63 63 54 58 58 49 54 62 60 56 61 57 57 58 5...
28999   8701        2  23 19 22 21 21 22 24 24 26 27 28 32 38 57 74 7...

[29000 rows x 3 columns]
```

```

#These two lines of code are initializing the 'labels' and 'pixels' variables for further
labels=df['emotion']
pixels=np.zeros((df.shape[0], 48*48))
```

```
#This line allocates the DataFrame 'df''s 'pixels' column to a variable called 'tem'.
tem=df['pixels']
```

```
#This function converts the pixel values from string to integer format and stores them in
for ix in range(pixels.shape[0]):
    t = tem[ix].split(' ')
    for iy in range(pixels.shape[1]):
        pixels[ix, iy] = int(t[iy])
```

```
#This will return the array pixels' form. The shape will be a tuple of the form (n, m), wh
pixels.shape
```

```
(29000, 2304)
```

```
#This is the process of standardising or normalising a pixel array to have a zero mean and
pixels -= np.mean(pixels, axis=0)
pixels /= np.std(pixels, axis=0)
```

```
#Reshape pixels array to 4D for CNN input.
pixels=pixels.reshape(29000,48,48,1)
```

```
#Convert labels to categorical format.
labels=labels.astype('category')
```

```
#This code splits the data into training and validation sets.
X_train=pixels[:27000]
y_train=labels[:27000]
X_val=pixels[27000:]
y_val=labels[27000:]

```

```
#Returns the shape of y_val.
y_val.shape
```

```
(2000,)
```

```
#Converts labels to one-hot encoded arrays.
y_train = tf.one_hot(y_train, depth=7)
y_val=tf.one_hot(y_val,depth=7)
y_train=np.array(y_train)
y_val=np.array(y_val)
```

```
#The geometry of the numpy array X_train is returned by this code snippet.
X_train.shape
```

```
(27000, 48, 48, 1)
```

```
#X_train and X_val arrays are reshaped to 4D arrays with dimensions (number of samples, he
X_train = np.reshape(X_train,(-1,48,48,1))

X_val = np.reshape(X_val,(-1,48,48,1))

```

```
#Displays shape of X_val array.
X_val.shape
```

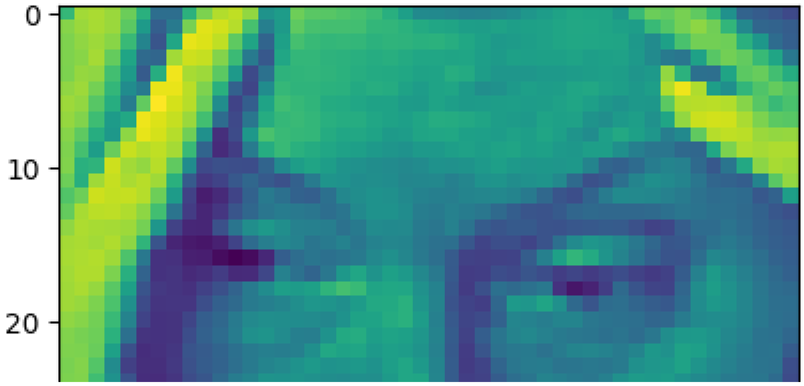
```
(2000, 48, 48, 1)
```

```
##Displays shape of y_val array.
y_val.shape
```

```
(2000, 7)
```

```
#Displays the image of the third sample.
from matplotlib import pyplot
pyplot.imshow(pixels[2])
```

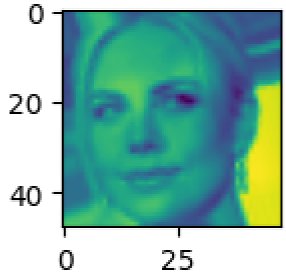
```
<matplotlib.image.AxesImage at 0x7ff966b47970>
```




```
#The shape of pixels[2] is (48, 48).
pixels[2].shape
```

```
(48, 48, 1)
```

```
#This programme develops an image data generator, fits it to the training data, generates
datagen = ImageDataGenerator(rotation_range=90)
datagen.fit(X_train)
for X_batch, y_batch in datagen.flow(X_train,y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch[i].reshape(48, 48, 1))
        pyplot.show()
    break
```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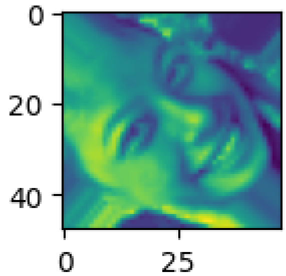
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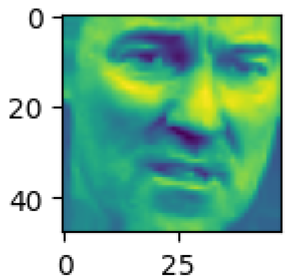
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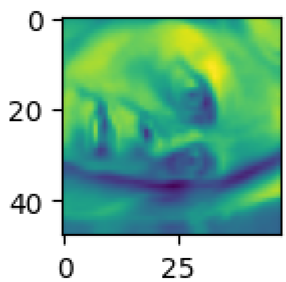
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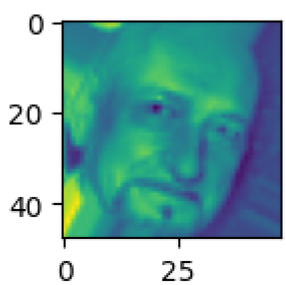
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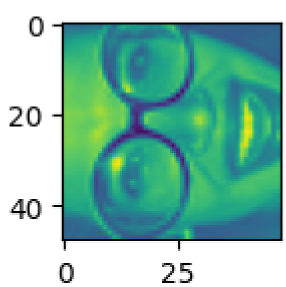
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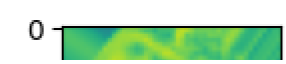
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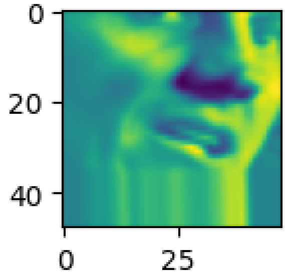
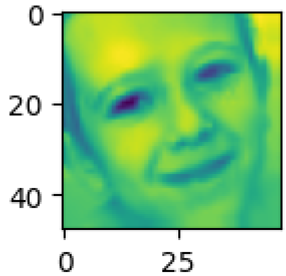
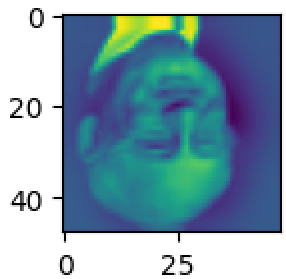
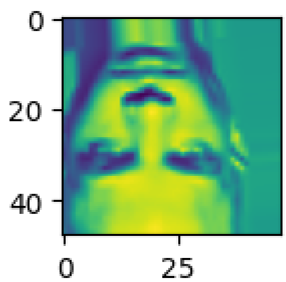
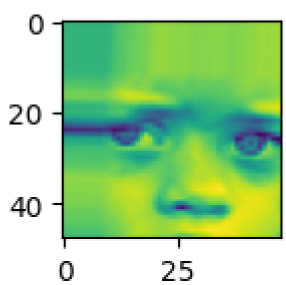
```
#This code employs Keras' ImageDataGenerator function to build augmented images from train
from matplotlib import pyplot
datagen = ImageDataGenerator(rotation_range=5,
        width_shift_range=0.2,
        height_shift_range=0.2,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
        vertical_flip=True,
        fill_mode='nearest')
datagen.fit(X_train)
for X_batch1, y_batch1 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch1[i].reshape(48, 48, 1))
        pyplot.show()
    break
```





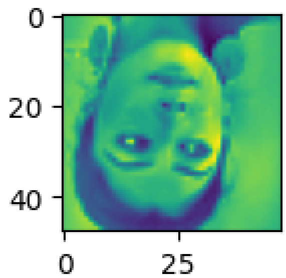


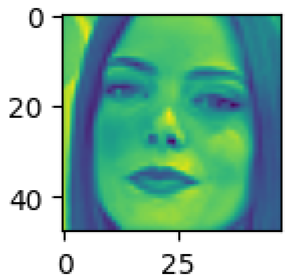


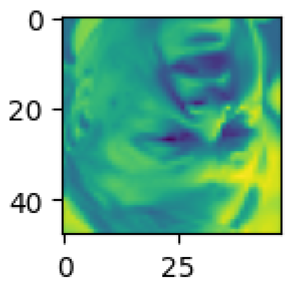



```
'''The ImageDataGenerator function from the Keras package is used in this code to suppleme
from matplotlib import pyplot
datagen = ImageDataGenerator(horizontal_flip=True, vertical_flip=True)
datagen.fit(X_train)
for X_batch2, y_batch2 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch2[i].reshape(48, 48, 1))
```

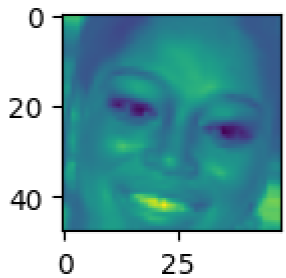
```
        pyplot.show()
    break
```








```
'''This method generates batches of augmented data with random rotations applied to them b
datagen = ImageDataGenerator(rotation_range=30)
datagen.fit(X_train)
for X_batch5, y_batch5 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch5[i].reshape(48, 48, 1))
        pyplot.show()
    break
```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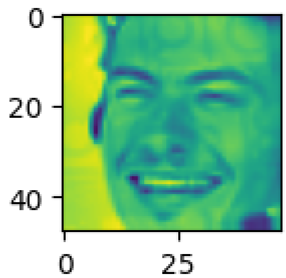
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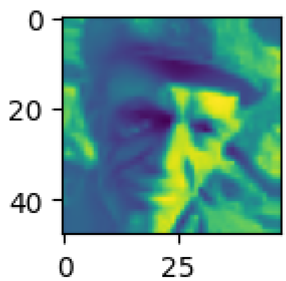
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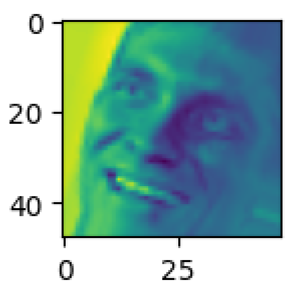
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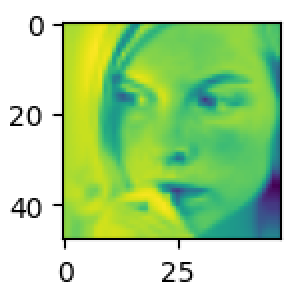
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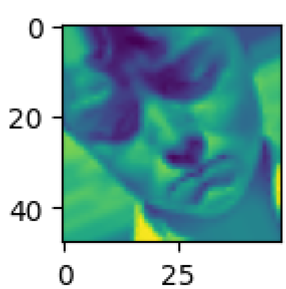
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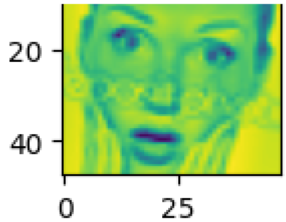
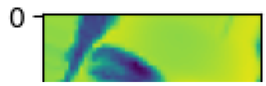
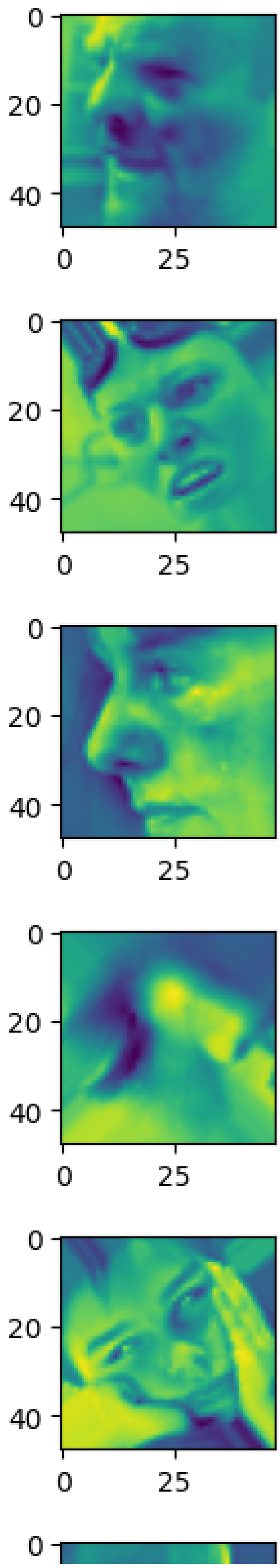


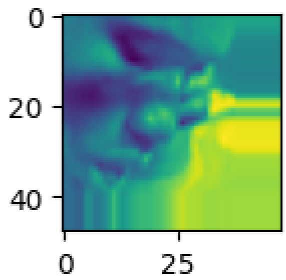


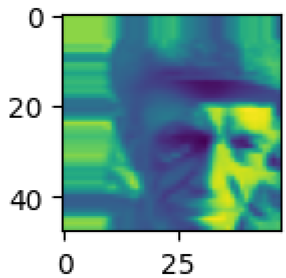

```
#Using ImageDataGenerator, this code augments the picture data by rotating the images at a
datagen = ImageDataGenerator(rotation_range=45)
datagen.fit(X_train)
for X_batch6, y_batch6 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch6[i].reshape(48, 48, 1))
        pyplot.show()
    break
```

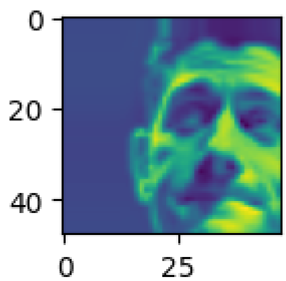


```
#This code defines an image data generator that applies random horizontal and vertical shi
datagen = ImageDataGenerator(width_shift_range=0.3, height_shift_range=0.3)
datagen.fit(X_train)
for X_batch7, y_batch7 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch7[i].reshape(48, 48, 1))
```

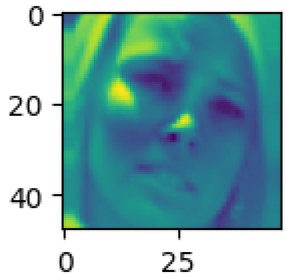
```
        pyplot.show()
    break
```








```
#Using the zoom_range option of the ImageDataGenerator function, this code zooms in on the
from matplotlib import pyplot
datagen = ImageDataGenerator(zoom_range=0.2)
datagen.fit(X_train)
for X_batch8, y_batch8 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch8[i].reshape(48, 48, 1))
        pyplot.show()
    break
```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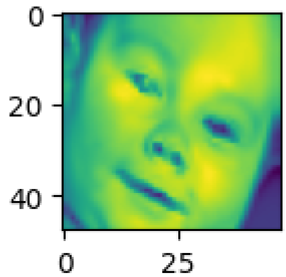
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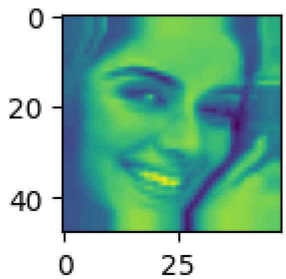
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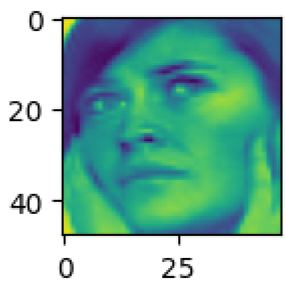
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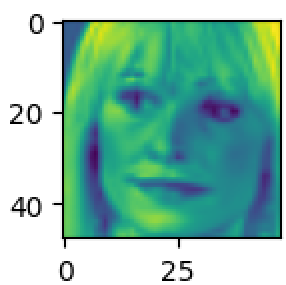
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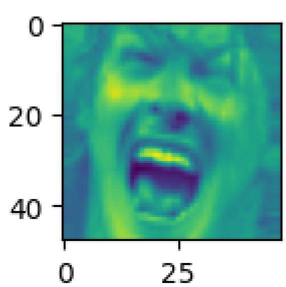
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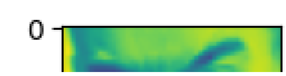
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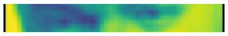
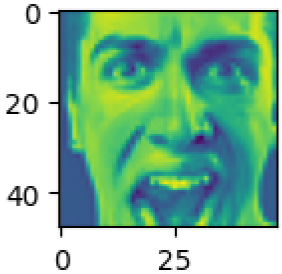
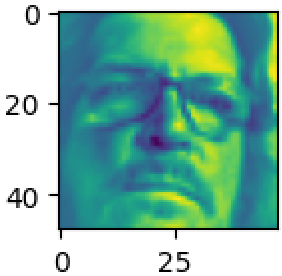
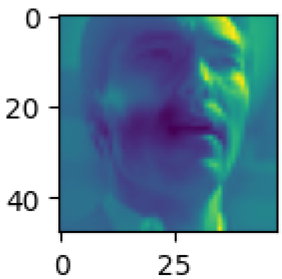
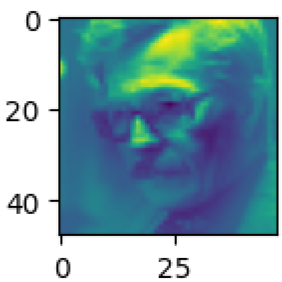


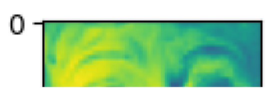
```
#Image brightness augmentation.
from matplotlib import pyplot
datagen = ImageDataGenerator(brightness_range=[0.5,1])
datagen.fit(X_train)
for X_batch9, y_batch9 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch9[i].reshape(48, 48, 1))
        pyplot.show()
    break
```



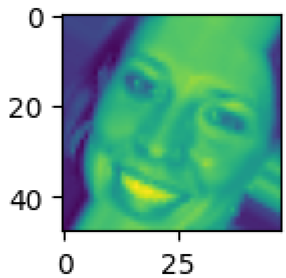









```
#This code creates an ImageDataGenerator that rotates images randomly up to 125 degrees, f
datagen = ImageDataGenerator(rotation_range=125)
datagen.fit(X_train)
for X_batch10, y_batch10 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch10[i].reshape(48, 48, 1))
        pyplot.show()
    break
```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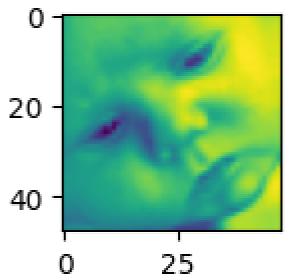
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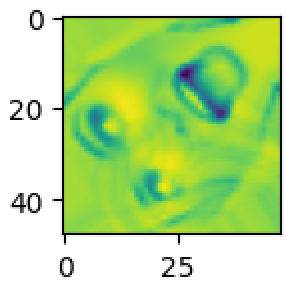
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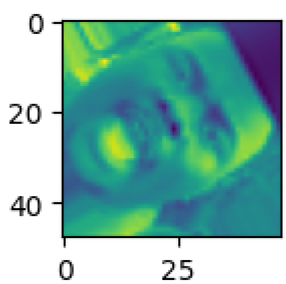
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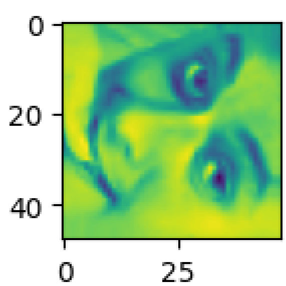
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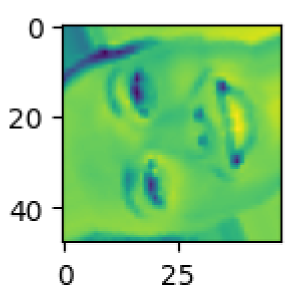
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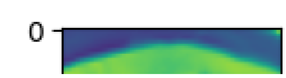
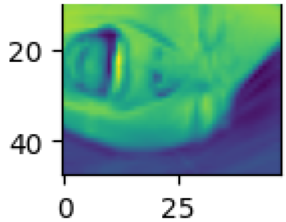
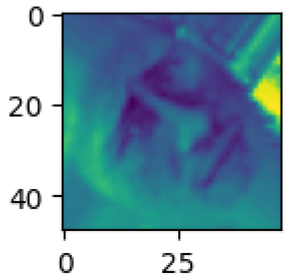
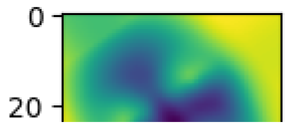
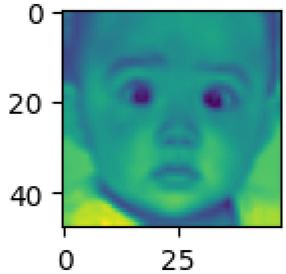

0








```
#This code creates an instance of ImageDataGenerator with horizontal and vertical shift ra
datagen = ImageDataGenerator(width_shift_range=0.1, height_shift_range=0.1)
datagen.fit(X_train)
for X_batch11, y_batch11 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch11[i].reshape(48, 48, 1))
        pyplot.show()
    break
```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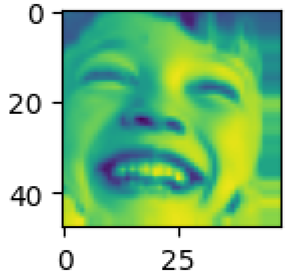
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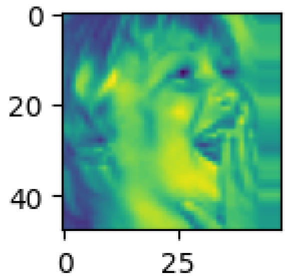
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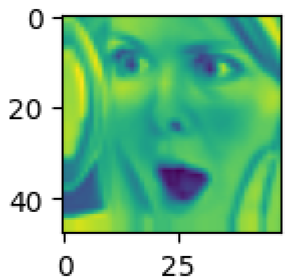
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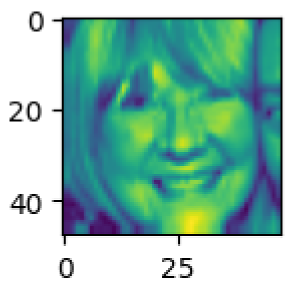
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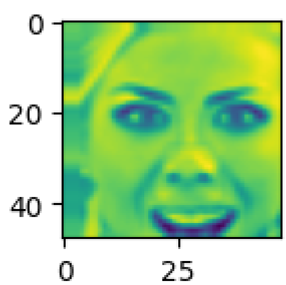
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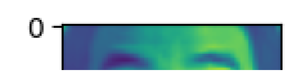
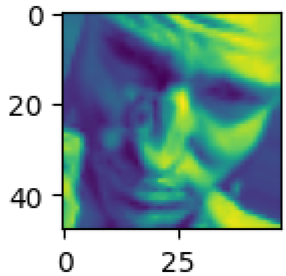
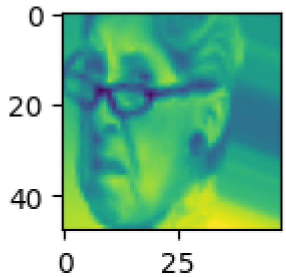
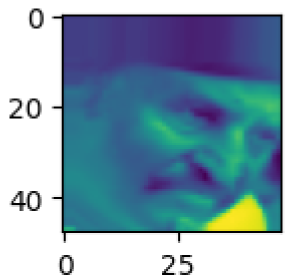
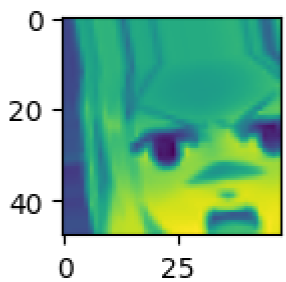

0

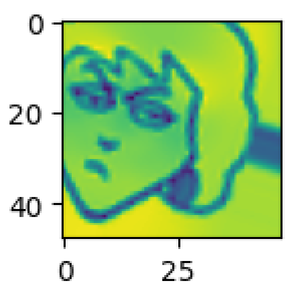
```

#Several data augmentation approaches are used in this code, which makes use of Keras' Ima
datagen = ImageDataGenerator(rescale=1./255,
      rotation_range=40,
      width_shift_range=0.2,
      height_shift_range=0.2,
      shear_range=0.2,
      zoom_range=0.2,
      horizontal_flip=True,
      fill_mode='nearest')
datagen.fit(X_train)
for X_batch12, y_batch12 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch12[i].reshape(48, 48, 1))
        pyplot.show()
    break
```





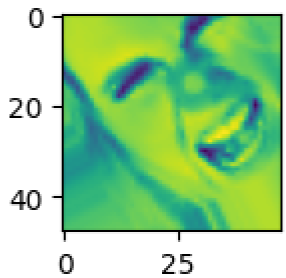


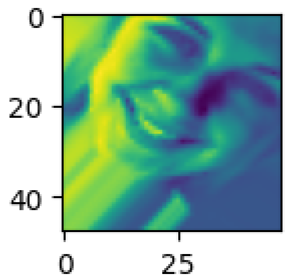


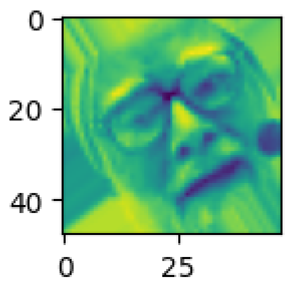


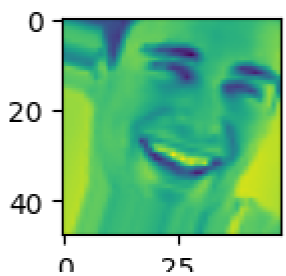
```
#ImageDataGenerator is used in the code to apply data augmentation techniques to the train
datagen = ImageDataGenerator(rescale=1./255,
      rotation_range=62,
      width_shift_range=0.1,
      height_shift_range=0.1,
      shear_range=0.4,
      zoom_range=0.2,
      horizontal_flip=True,
```

```
      fill_mode='nearest')
datagen.fit(X_train)
for X_batch13, y_batch13 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch12[i].reshape(48, 48, 1))
        pyplot.show()
    break
```

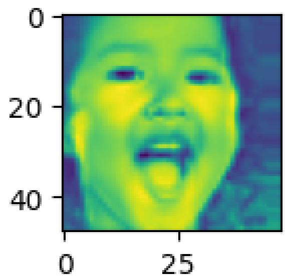









```
#The code creates an ImageDataGenerator object that includes data augmentation parameters
datagen = ImageDataGenerator(rescale=1./255,
      rotation_range=12,
      width_shift_range=0.1,
      height_shift_range=0.05,
      shear_range=0.6,
      zoom_range=0.05,
      horizontal_flip=True,
      fill_mode='nearest')
datagen.fit(X_train)
for X_batch15, y_batch15 in datagen.flow(X_train, y_train, batch_size=100000):
    for i in range(0, 9):
        pyplot.subplot(330 + 1 + i)
        pyplot.imshow(X_batch15[i].reshape(48, 48, 1))
        pyplot.show()
    break
```


0
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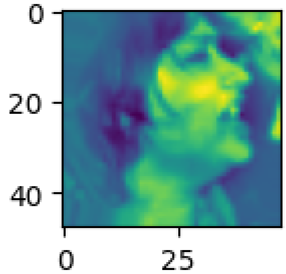
0
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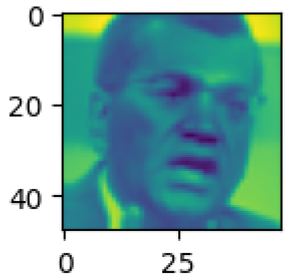
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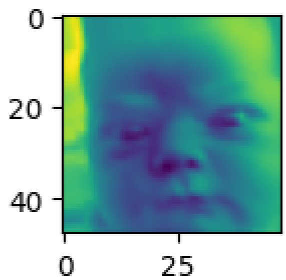
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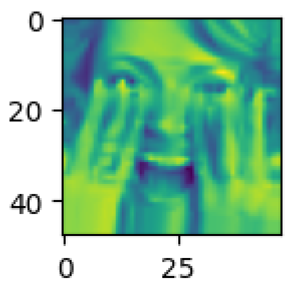
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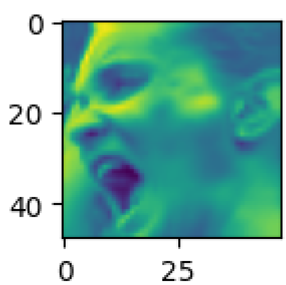
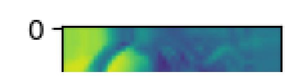
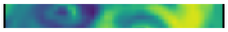

0
20
40
0
25


0

```
#This code concatenates four arrays along the first axis, X_train, X_batch1, X_batch2, and
X_train2=np.concatenate((X_train,X_batch1,X_batch2,X_batch15))
```

```
X_train2.shape
```

    (108000, 48, 48, 1)



```
#This function concatenates the original training labels y_train with the labels created b
y_train2=np.concatenate((y_train,y_batch1,y_batch2,y_batch15))
```

```
#Concatenates multiple batches of image data to the training set along the first axis.
X_train1=np.concatenate((X_train,X_batch1,X_batch2,X_batch5,X_batch6,X_batch7,X_batch8,X_b
```

```
#Returns array dimensions.
X_train1.shape
```

    (351000, 48, 48, 1)

```
#y_train1 is formed by concatenating y_train with batches.
y_train1=np.concatenate((y_train,y_batch1,y_batch2,y_batch5,y_batch6,y_batch7,y_batch8,y_b
```

```
#Create learning rate reduction and early stopping callbacks.
lrd = ReduceLROnPlateau(monitor = 'val_loss',patience = 2,verbose = 1,factor = 0.50, min_l



es = tf.keras.callbacks.EarlyStopping(verbose=1, patience=20)
```

```
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import numpy as np
from sklearn.metrics import mean_squared_error

# build MLP model
model = MLPClassifier(hidden_layer_sizes=(128, 64), activation='relu', solver='adam', max_

# reshape input data to have 2 dimensions
x_train = X_train2.reshape(X_train2.shape[0], -1)
x_test = X_val.reshape(X_val.shape[0], -1)

# train model
model.fit(x_train,y_train2)

# evaluate model on test set
```

```
y_pred = model.predict(x_test)
# accuracy = accuracy_score(x_test, y_val)
# print('Test accuracy:', accuracy)
mse = mean_squared_error(y_pred, y_val)
print('Mean Squared Error:', mse)
```

```
Mean Squared Error: 0.1439285714285714
/usr/local/lib/python3.9/dist-packages/sklearn/neural_network/_multilayer_perceptron.py
  warnings.warn(
```

```
#Normal CNN
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
l2 = tf.keras.regularizers.L2
l1=tf.keras.regularizers.L1
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=10)
kernel_init = tf.keras.initializers.GlorotNormal()

# Define input shape
input_shape = (48, 48, 1)

# Define the model architecture
model = keras.Sequential([


    layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer=tf.keras.initializers.
    layers.MaxPooling2D((2, 2)),
    layers.BatchNormalization(),

    layers.Conv2D(128, (3, 3), activation='relu',kernel_initializer=tf.keras.initializers.
    layers.MaxPooling2D((2, 2)),
    layers.BatchNormalization(),



    layers.Conv2D(256, (3, 3), activation='relu',kernel_initializer=tf.keras.initializers.
    layers.MaxPooling2D((2, 2)),
    layers.BatchNormalization(),




    layers.Conv2D(512, (3, 3), activation='relu',kernel_initializer=tf.keras.initializers.
    layers.MaxPooling2D((2, 2)),
    layers.BatchNormalization(),
    layers.Dropout(0.4),


    layers.Flatten(),
```

```
    layers.Dense(512, activation='relu',kernel_initializer=tf.keras.initializers.GlorotUni
    layers.Dropout(0.4),

    layers.Dense(256, activation='relu',kernel_initializer=tf.keras.initializers.GlorotUni
    layers.Dropout(0.2),

    layers.Dense(7, activation='softmax')
])

# Compile the model with categorical cross-entropy loss and Adam optimizer
optimizer=tf.keras.optimizers.experimental.Adam(learning_rate=0.001)
model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['accuracy'])
model_CNN=model
# Print model summary
#model_CNN.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 46, 46, 64)        640

 max_pooling2d (MaxPooling2D  (None, 23, 23, 64)       0
 )

 batch_normalization (BatchN  (None, 23, 23, 64)       256
 ormalization)

 conv2d_1 (Conv2D)           (None, 21, 21, 128)       73856

 max_pooling2d_1 (MaxPooling  (None, 10, 10, 128)      0
 2D)

 batch_normalization_1 (Batc  (None, 10, 10, 128)      512
 hNormalization)

 conv2d_2 (Conv2D)           (None, 8, 8, 256)         295168

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 256)        0
 2D)

 batch_normalization_2 (Batc  (None, 4, 4, 256)        1024
 hNormalization)

 conv2d_3 (Conv2D)           (None, 2, 2, 512)         1180160

 max_pooling2d_3 (MaxPooling  (None, 1, 1, 512)        0
 2D)

 batch_normalization_3 (Batc  (None, 1, 1, 512)        2048
 hNormalization)

 dropout (Dropout)           (None, 1, 1, 512)         0
```

```
 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 512)               262656

 dropout_1 (Dropout)         (None, 512)               0

 dense_1 (Dense)             (None, 256)               131328

 dropout_2 (Dropout)         (None, 256)               0

 dense_2 (Dense)             (None, 7)                 1799

=================================================================
Total params: 1,949,447
Trainable params: 1,947,527
Non-trainable params: 1,920
_________________________________________________________________
```

```
model_CNN.fit(X_train2,y_train2,validation_data=(X_val,y_val),epochs=5,verbose=1,callbacks
```

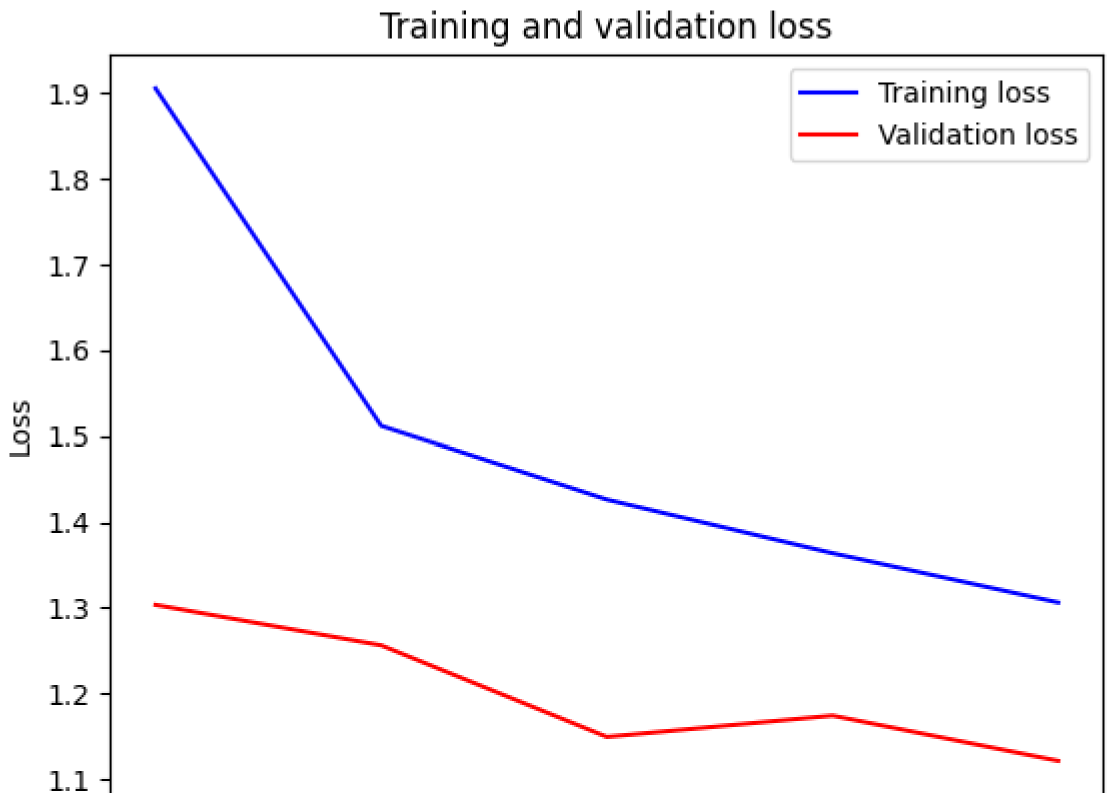
```
Epoch 1/5
3375/3375 [==============================] - 24s 6ms/step - loss: 1.9051 - accuracy: 0.3
Epoch 2/5
3375/3375 [==============================] - 21s 6ms/step - loss: 1.5117 - accuracy: 0.4
Epoch 3/5
3375/3375 [==============================] - 21s 6ms/step - loss: 1.4262 - accuracy: 0.4
Epoch 4/5
3375/3375 [==============================] - 24s 7ms/step - loss: 1.3636 - accuracy: 0.4
Epoch 5/5
3375/3375 [==============================] - 21s 6ms/step - loss: 1.3061 - accuracy: 0.5
<keras.callbacks.History at 0x7f2b0a5c90a0>
```

```
# Extract losses from model training history
train_loss = model_CNN.history.history['loss']
val_loss = model_CNN.history.history['val_loss']

# Plot training and validation loss
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

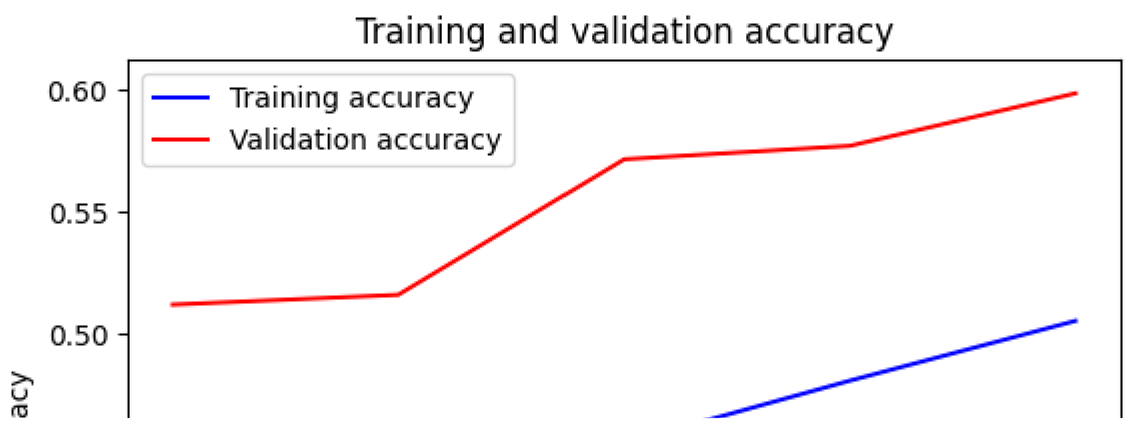



```
# Extract accuracies from model training history
train_loss = model_CNN.history.history['accuracy']
val_loss = model_CNN.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```




```
import pandas as pd
import numpy as np

# Evaluate model_CNN on training and testing data
train_scores = model_CNN.evaluate(X_train2, y_train2, verbose=0)
test_scores = model_CNN.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)

```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  1.167382  1.167382      0.0
1  Training Accuracy  0.564472  0.564472      0.0
2       Testing Loss  1.121507  1.121507      0.0
3   Testing Accuracy  0.598500  0.598500      0.0
```

```
from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.models import Sequential
import tensorflow as tf

# Define the model architecture
model = Sequential()

# Add a convolutional layer with 32 filters, 3x3 kernel size, and relu activation function
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(48,48,1)))
# Add a batch normalization layer
model.add(BatchNormalization())
# Add a second convolutional layer with 64 filters, 3x3 kernel size, and relu activation f
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
# Add a second batch normalization layer
model.add(BatchNormalization())
# Add a max pooling layer with 2x2 pool size
model.add(MaxPooling2D(pool_size=(2, 2)))
# Add a dropout layer with 0.25 dropout rate
model.add(Dropout(0.25))

# Add a third convolutional layer with 128 filters, 3x3 kernel size, and relu activation f
model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
# Add a third batch normalization layer
model.add(BatchNormalization())
# Add a fourth convolutional layer with 128 filters, 3x3 kernel size, and relu activation
model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
# Add a fourth batch normalization layer
model.add(BatchNormalization())
# Add a max pooling layer with 2x2 pool size
model.add(MaxPooling2D(pool_size=(2, 2)))
# Add a dropout layer with 0.25 dropout rate
model.add(Dropout(0.25))

# Add a fifth convolutional layer with 256 filters, 3x3 kernel size, and relu activation f
model.add(Conv2D(256, kernel_size=(3, 3), activation='relu'))
# Add a fifth batch normalization layer
model.add(BatchNormalization())
# Add a sixth convolutional layer with 256 filters, 3x3 kernel size, and relu activation f
model.add(Conv2D(256, kernel_size=(3, 3), activation='relu'))
# Add a sixth batch normalization layer
model.add(BatchNormalization())
# Add a max pooling layer with 2x2 pool size
model.add(MaxPooling2D(pool_size=(2, 2)))
# Add a dropout layer with 0.25 dropout rate
model.add(Dropout(0.25))

# Flatten the output of the convolutional layers
model.add(Flatten())
# Add a dense layer with 256 neurons and relu activation function
model.add(Dense(256, activation='relu'))
```

```
# Add a seventh batch normalization layer
model.add(BatchNormalization())
# Add a dropout layer with 0.5 dropout rate
model.add(Dropout(0.5))
# Add a dense layer with 7 neurons (one for each class) and softmax activation function
model.add(Dense(7, activation='softmax'))

# Compile the model with categorical cross-entropy loss, adam optimizer, and accuracy metr
model.compile(loss="categorical_crossentropy", optimizer= tf.keras.optimizers.Adam(lr=0.00
model_deep=model
model_deep.summary()
```

```
 conv2d_5 (Conv2D)           (None, 44, 44, 64)        18496

 batch_normalization_5 (Batc  (None, 44, 44, 64)       256
 hNormalization)

 max_pooling2d_4 (MaxPooling  (None, 22, 22, 64)       0
 2D)

 dropout_3 (Dropout)         (None, 22, 22, 64)        0

 conv2d_6 (Conv2D)           (None, 20, 20, 128)       73856

 batch_normalization_6 (Batc  (None, 20, 20, 128)      512
 hNormalization)

 conv2d_7 (Conv2D)           (None, 18, 18, 128)       147584

 batch_normalization_7 (Batc  (None, 18, 18, 128)      512
 hNormalization)

 max_pooling2d_5 (MaxPooling  (None, 9, 9, 128)        0
 2D)

 dropout_4 (Dropout)         (None, 9, 9, 128)         0

 conv2d_8 (Conv2D)           (None, 7, 7, 256)         295168

 batch_normalization_8 (Batc  (None, 7, 7, 256)        1024
 hNormalization)

 conv2d_9 (Conv2D)           (None, 5, 5, 256)         590080

 batch_normalization_9 (Batc  (None, 5, 5, 256)        1024
```

```
 batch_normalization_10 (Bat  (None, 256)              1024
 chNormalization)

 dropout_6 (Dropout)         (None, 256)               0

 dense_4 (Dense)             (None, 7)                 1799

=================================================================
Total params: 1,394,183
Trainable params: 1,391,943
Non-trainable params: 2,240
```

```
model_deep.fit(X_train2,y_train2,validation_data=(X_val,y_val),epochs=5,verbose=1,callback
```

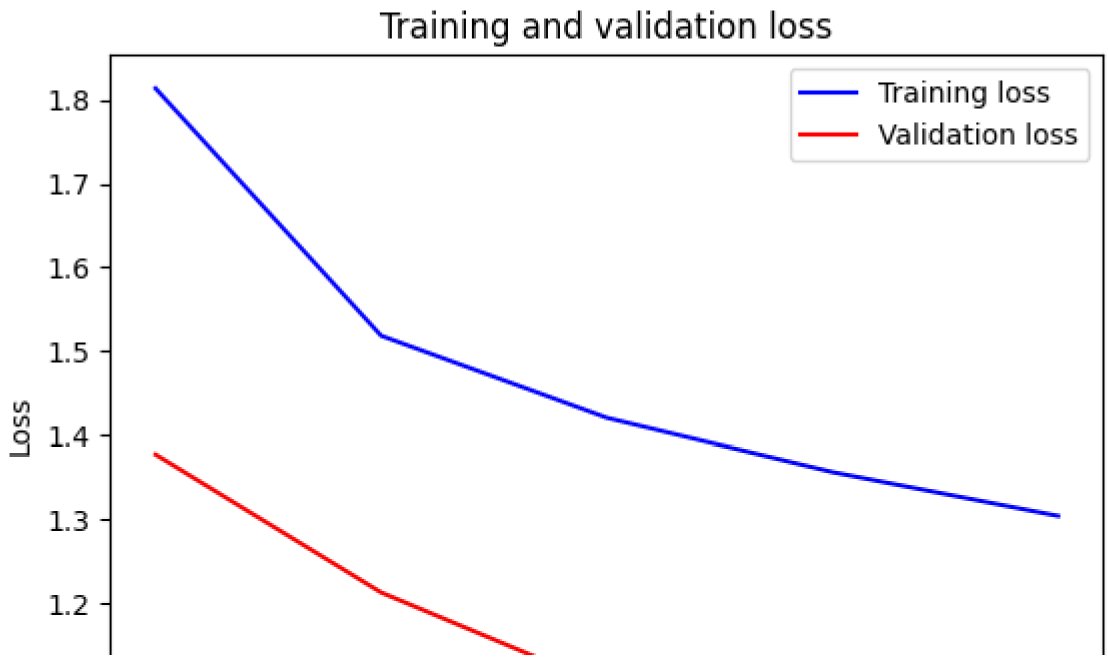
```
Epoch 1/5
3375/3375 [==============================] - 41s 8ms/step - loss: 1.8137 - accuracy: 0.2
Epoch 2/5
3375/3375 [==============================] - 27s 8ms/step - loss: 1.5185 - accuracy: 0.3
Epoch 3/5
3375/3375 [==============================] - 27s 8ms/step - loss: 1.4207 - accuracy: 0.4
Epoch 4/5
3375/3375 [==============================] - 27s 8ms/step - loss: 1.3563 - accuracy: 0.4
Epoch 5/5
3375/3375 [==============================] - 27s 8ms/step - loss: 1.3041 - accuracy: 0.4
<keras.callbacks.History at 0x7f49a063b280>
```

```
# Extract losses from model training history
train_loss = model_deep.history.history['loss']
val_loss = model_deep.history.history['val_loss']

# Plot training and validation loss
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

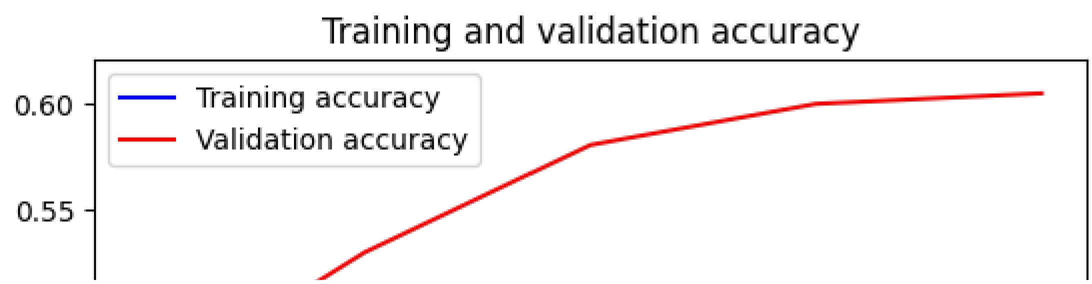



```
# Extract accuracies from model training history
train_loss = model_deep.history.history['accuracy']
val_loss = model_deep.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```




```
import pandas as pd
import numpy as np

# Evaluate model_CNN on training and testing data
train_scores = model_deep.evaluate(X_train2, y_train2, verbose=0)
test_scores = model_deep.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)
```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  1.169493  1.169493      0.0
1  Training Accuracy  0.546759  0.546759      0.0
2       Testing Loss  1.011950  1.011950      0.0
3   Testing Accuracy  0.605000  0.605000      0.0
```

```
#Bayesian Optimization


!pip install keras-tuner
import tensorflow as tf
```

```
from tensorflow import keras
from tensorflow.keras import layers
from kerastuner.tuners import BayesianOptimization

def build_model(hp):
    model = keras.Sequential()

    # Add a convolutional layer with variable number of filters, kernel size and padding
    model.add(layers.Conv2D(
        filters=hp.Int('conv_1_filters', min_value=32, max_value=128, step=16),
        kernel_size=hp.Choice('conv_1_kernel', values=[3,5]),
        padding='same',
        activation='relu',
        input_shape=(48, 48, 1)
    ))



    # Add a batch normalization layer
    model.add(layers.BatchNormalization())

    # Add another convolutional layer with variable number of filters, kernel size and pad
    model.add(layers.Conv2D(
        filters=hp.Int('conv_2_filters', min_value=64, max_value=512, step=32),
        kernel_size=hp.Choice('conv_2_kernel', values=[3,5]),
        padding='same',
        activation='relu'
    ))

    model.add(layers.BatchNormalization())

    # Add a max pooling layer with variable pool size
    model.add(layers.MaxPooling2D(
        pool_size=hp.Choice('pool_1_size', values=[2,3]),
        strides=2
    ))

    model.add(Dropout(hp.Choice('dropout_1_rate',values=[0.2,0.6])))

    model.add(layers.Conv2D(
        filters=hp.Int('conv_3_filters', min_value=64, max_value=512, step=32),
        kernel_size=hp.Choice('conv_3_kernel', values=[3,5]),
        padding='same',
        activation='relu'
    ))

    model.add(layers.BatchNormalization())
    model.add(layers.Conv2D(
        filters=hp.Int('conv_4_filters', min_value=64, max_value=512, step=32),
        kernel_size=hp.Choice('conv_4_kernel', values=[3,5]),
        padding='same',
```

```
        activation='relu'
    ))
    model.add(layers.BatchNormalization())

    model.add(layers.MaxPooling2D(
        pool_size=hp.Choice('pool_2_size', values=[2,3]),
        strides=2
    ))
    model.add(Dropout(hp.Choice('dropout_2_rate',values=[0.2,0.6])))

    model.add(layers.Conv2D(
        filters=hp.Int('conv_5_filters', min_value=64, max_value=512, step=32),
        kernel_size=hp.Choice('conv_5_kernel', values=[3,5]),
        padding='same',
        activation='relu'
    ))

    model.add(layers.BatchNormalization())
    model.add(layers.Conv2D(
        filters=hp.Int('conv_6_filters', min_value=64, max_value=512, step=32),
        kernel_size=hp.Choice('conv_6_kernel', values=[3,5]),
        padding='same',
        activation='relu'
    ))
    model.add(layers.BatchNormalization())

    model.add(layers.MaxPooling2D(
        pool_size=hp.Choice('pool_3_size', values=[2,3]),
        strides=2
    ))

    model.add(Dropout(hp.Choice('dropout_3_rate',values=[0.2,0.6])))






    # Flatten the output of the convolutional layers
    model.add(layers.Flatten())

    model.add(Dense(hp.Int('Fully_connected_dense', min_value=64, max_value=512, step=32),
# Add a seventh batch normalization layer
    model.add(BatchNormalization())
# Add a dropout layer with 0.5 dropout rate
    model.add(Dropout(hp.Choice('dropout_3_rate',values=[0.2,0.6])))



    # Add an output layer with 7 units (one for each emotion category) and softmax activat
    model.add(layers.Dense(7, activation='softmax'))
```

```

    # Compile the model with categorical cross-entropy loss, adam optimizer, and accuracy
    model.compile(
        optimizer=tf.keras.optimizers.Adam(
            hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])
        ),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )

    return model

tuner = BayesianOptimization(
build_model,
objective='val_accuracy',
max_trials=5
)

tuner.search(X_train2, y_train2, epochs=7, validation_data=(X_val, y_val))
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

model_bayes = build_model(best_hps)
model_bayes.compile(loss='categorical_crossentropy',
optimizer=Adam(best_hps.get('learning_rate')),
metrics=['accuracy'])
model_bayes.fit(X_train2, y_train2, epochs=5, validation_data=(X_val, y_val))
```

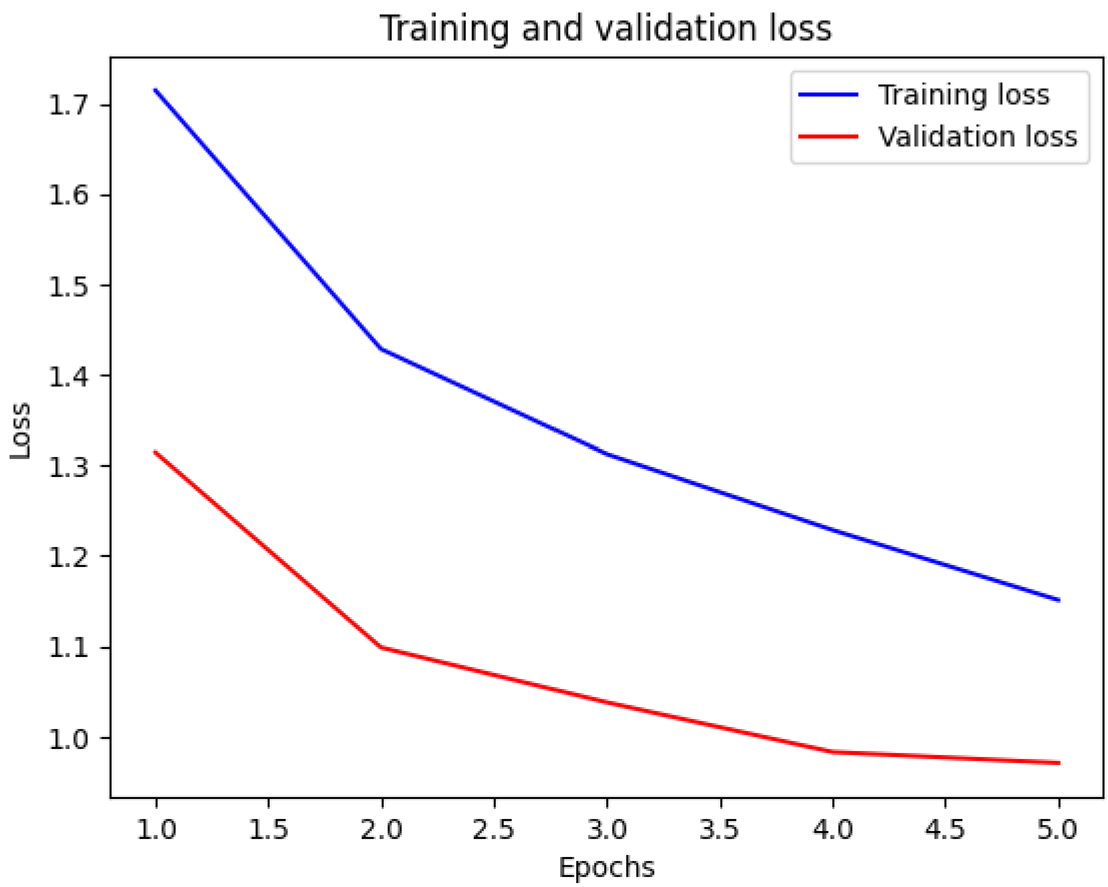
```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
Requirement already satisfied: keras-tuner in /usr/local/lib/python3.9/dist-packages (1
Requirement already satisfied: kt-legacy in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: requests in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: packaging in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (f
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packa
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dis
<ipython-input-46-8455132e9ec9>:8: DeprecationWarning: `import kerastuner` is deprecated
  from kerastuner.tuners import BayesianOptimization
Epoch 1/5
3375/3375 [==============================] - 100s 28ms/step - loss: 1.7147 - accuracy: 0
Epoch 2/5
3375/3375 [==============================] - 93s 28ms/step - loss: 1.4284 - accuracy: 0
Epoch 3/5
3375/3375 [==============================] - 93s 28ms/step - loss: 1.3125 - accuracy: 0
Epoch 4/5
3375/3375 [==============================] - 93s 28ms/step - loss: 1.2286 - accuracy: 0
Epoch 5/5
3375/3375 [==============================] - 93s 28ms/step - loss: 1.1512 - accuracy: 0
<keras.callbacks.History at 0x7f494826a5e0>
```

```
# Extract accuracies from model training history
train_loss = model_bayes.history.history['loss']
val_loss = model_bayes.history.history['val_loss']


# Plot training and validation loss
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



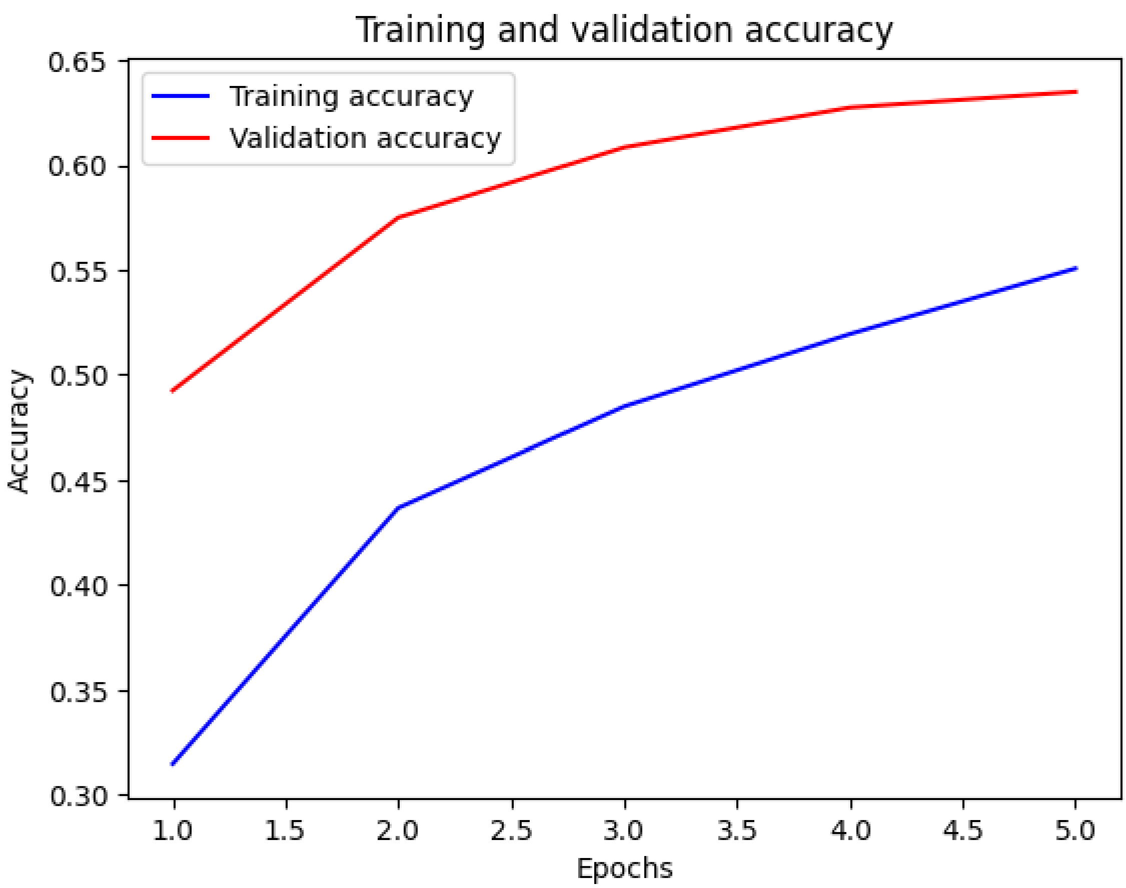

```
# Extract accuracies from model training history
train_loss = model_bayes.history.history['accuracy']
val_loss = model_bayes.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
```

```
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```




```
import pandas as pd
import numpy as np

# Evaluate model_CNN on training and testing data
train_scores = model_bayes.evaluate(X_train2, y_train2, verbose=0)
test_scores = model_bayes.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
```

```
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)
```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  0.974819  0.974819      0.0
1  Training Accuracy  0.624278  0.624278      0.0
2       Testing Loss  0.970960  0.970960      0.0
3   Testing Accuracy  0.635000  0.635000      0.0
```

```
#Ensemble
nets = 10
model = [0] *nets
for j in range(nets):
    model[j] = Sequential()
    model[j].add(Conv2D(32, kernel_size = 3, activation='relu', input_shape = (48, 48, 1))
    model[j].add(BatchNormalization())
    model[j].add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
# Add a second batch normalization layer
    model[j].add(BatchNormalization())
# Add a max pooling layer with 2x2 pool size
    model[j].add(MaxPooling2D(pool_size=(2, 2)))
# Add a dropout layer with 0.25 dropout rate
    model[j].add(Dropout(0.25))

# Add a third convolutional layer with 128 filters, 3x3 kernel size, and relu activation f
    model[j].add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
# Add a third batch normalization layer
    model[j].add(BatchNormalization())
# Add a fourth convolutional layer with 128 filters, 3x3 kernel size, and relu activation
    model[j].add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
# Add a fourth batch normalization layer
    model[j].add(BatchNormalization())
# Add a max pooling layer with 2x2 pool size
    model[j].add(MaxPooling2D(pool_size=(2, 2)))
# Add a dropout layer with 0.25 dropout rate
    model[j].add(Dropout(0.25))

# Add a fifth convolutional layer with 256 filters, 3x3 kernel size, and relu activation f
    model[j].add(Conv2D(256, kernel_size=(3, 3), activation='relu'))
# Add a fifth batch normalization layer
    model[j].add(BatchNormalization())
```

```
# Add a sixth convolutional layer with 256 filters, 3x3 kernel size, and relu activation f
  model[j].add(Conv2D(256, kernel_size=(3, 3), activation='relu'))
# Add a sixth batch normalization layer
  model[j].add(BatchNormalization())
# Add a max pooling layer with 2x2 pool size
  model[j].add(MaxPooling2D(pool_size=(2, 2)))
# Add a dropout layer with 0.25 dropout rate
  model[j].add(Dropout(0.25))

# Flatten the output of the convolutional layers
  model[j].add(Flatten())
# Add a dense layer with 256 neurons and relu activation function
  model[j].add(Dense(256, activation='relu'))
# Add a seventh batch normalization layer
  model[j].add(BatchNormalization())
# Add a dropout layer with 0.5 dropout rate
  model[j].add(Dropout(0.5))
# Add a dense layer with 7 neurons (one for each class) and softmax activation function
  model[j].add(Dense(7, activation='softmax'))

# Compile the model with categorical cross-entropy loss, adam optimizer, and accuracy metr
  model[j].compile(loss="categorical_crossentropy", optimizer= tf.keras.optimizers.Adam(
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use th
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use th
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WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use th
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use th
```

```
#Ensemble(Same deep model 10 times)
models=model
model_input = tf.keras.Input(shape=(48, 48, 1)) #takes a list of tensors as input, all of
model_outputs = [model(model_input) for model in models] #collects outputs of models in a
ensemble_output = tf.keras.layers.Average()(model_outputs) #averaging outputs
ensemble_model = tf.keras.Model(inputs=model_input, outputs=ensemble_output)
ensemble_model.compile(loss="categorical_crossentropy", optimizer= tf.keras.optimizers.Ada

```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use th
```

```
ensemble_model.fit(X_train2,y_train2,validation_data=(X_val,y_val),epochs=5,verbose=1,call
```

```
Epoch 1/5
3375/3375 [==============================] - 256s 60ms/step - loss: 1.7968 - accuracy: 0
```

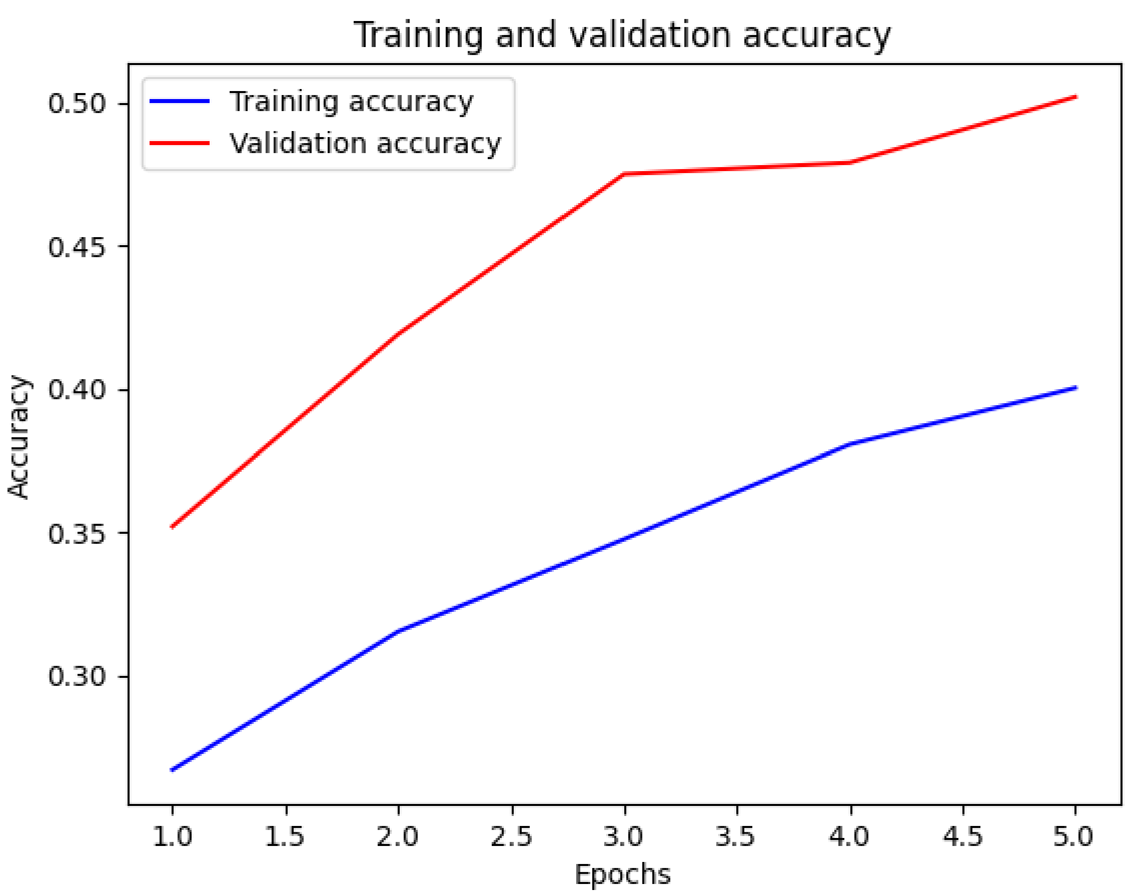
```
Epoch 2/5
3375/3375 [==============================] - 200s 59ms/step - loss: 1.7250 - accuracy:
Epoch 3/5
3375/3375 [==============================] - 199s 59ms/step - loss: 1.6682 - accuracy:
Epoch 4/5
3375/3375 [==============================] - 200s 59ms/step - loss: 1.6161 - accuracy:
Epoch 5/5
3375/3375 [==============================] - 199s 59ms/step - loss: 1.5780 - accuracy:
<keras.callbacks.History at 0x7f2bad393940>
```

```
# Extract accuracies from model training history
train_loss = ensemble_model.history.history['accuracy']
val_loss = ensemble_model.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



```
import pandas as pd
import numpy as np

# Evaluate model_CNN on training and testing data
train_scores = ensemble_model.evaluate(X_train2, y_train2, verbose=0)
test_scores = ensemble_model.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)
```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  1.537355  1.537355      0.0
1  Training Accuracy  0.420824  0.420824      0.0
2       Testing Loss  1.384540  1.384540      0.0
3   Testing Accuracy  0.502000  0.502000      0.0
```

```
#Transfer learning Inception
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
l2 = tf.keras.regularizers.L2
l1=tf.keras.regularizers.L1
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=10)
kernel_init = tf.keras.initializers.LecunUniform()

# Define input shape
input_shape = (48, 48, 1)

```

```
# Define the base model
base_model = tf.keras.applications.InceptionV3(
    input_shape=(75,75,3),
    include_top=False,
    weights='imagenet'
)
base_model.trainable = False

# Define the model architecture
model = keras.Sequential([
    layers.Lambda(lambda x: tf.image.grayscale_to_rgb(x), input_shape=input_shape),
    layers.experimental.preprocessing.Resizing(75, 75),
    base_model,

    layers.GlobalAveragePooling2D(),
    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(7, activation='softmax'),

])

# Compile the model with categorical cross-entropy loss and Adam optimizer
optimizer=tf.keras.optimizers.experimental.Adam(learning_rate=0.001)
model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['accuracy'])

# Print model summary
model.summary()
inception=model

```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 lambda (Lambda)             (None, 48, 48, 3)         0         
                                                                 
 resizing (Resizing)         (None, 75, 75, 3)         0         
                                                                 
 inception_v3 (Functional)   (None, 1, 1, 2048)        21802784  
                                                                 
 global_average_pooling2d (G  (None, 2048)             0         
 lobalAveragePooling2D)                                          
                                                                 
 flatten_3 (Flatten)         (None, 2048)              0         
                                                                 
 dense_7 (Dense)             (None, 256)               524544    
                                                                 
 dropout_11 (Dropout)        (None, 256)               0         
                                                                 
 dense_8 (Dense)             (None, 7)                 1799      
                                                                 
=================================================================
```

```
Total params: 22,329,127
Trainable params: 526,343
Non-trainable params: 21,802,784
_________________________________________________________________
```

```
inception.fit(X_train2,y_train2,validation_data=(X_val,y_val),epochs=5,verbose=1,callbacks
```

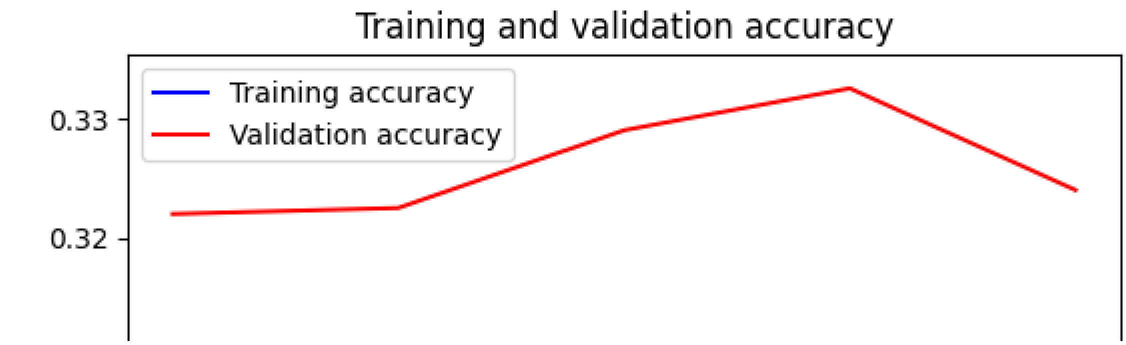
```
Epoch 1/5
3375/3375 [==============================] - 43s 11ms/step - loss: 1.7772 - accuracy: 0
Epoch 2/5
3375/3375 [==============================] - 37s 11ms/step - loss: 1.7373 - accuracy: 0
Epoch 3/5
3375/3375 [==============================] - 35s 10ms/step - loss: 1.7247 - accuracy: 0
Epoch 4/5
3375/3375 [==============================] - 36s 11ms/step - loss: 1.7148 - accuracy: 0
Epoch 5/5
3375/3375 [==============================] - 35s 11ms/step - loss: 1.7066 - accuracy: 0
<keras.callbacks.History at 0x7f4920fbc880>
```

```
# Extract accuracies from model training history
train_loss = inception.history.history['accuracy']
val_loss = inception.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```

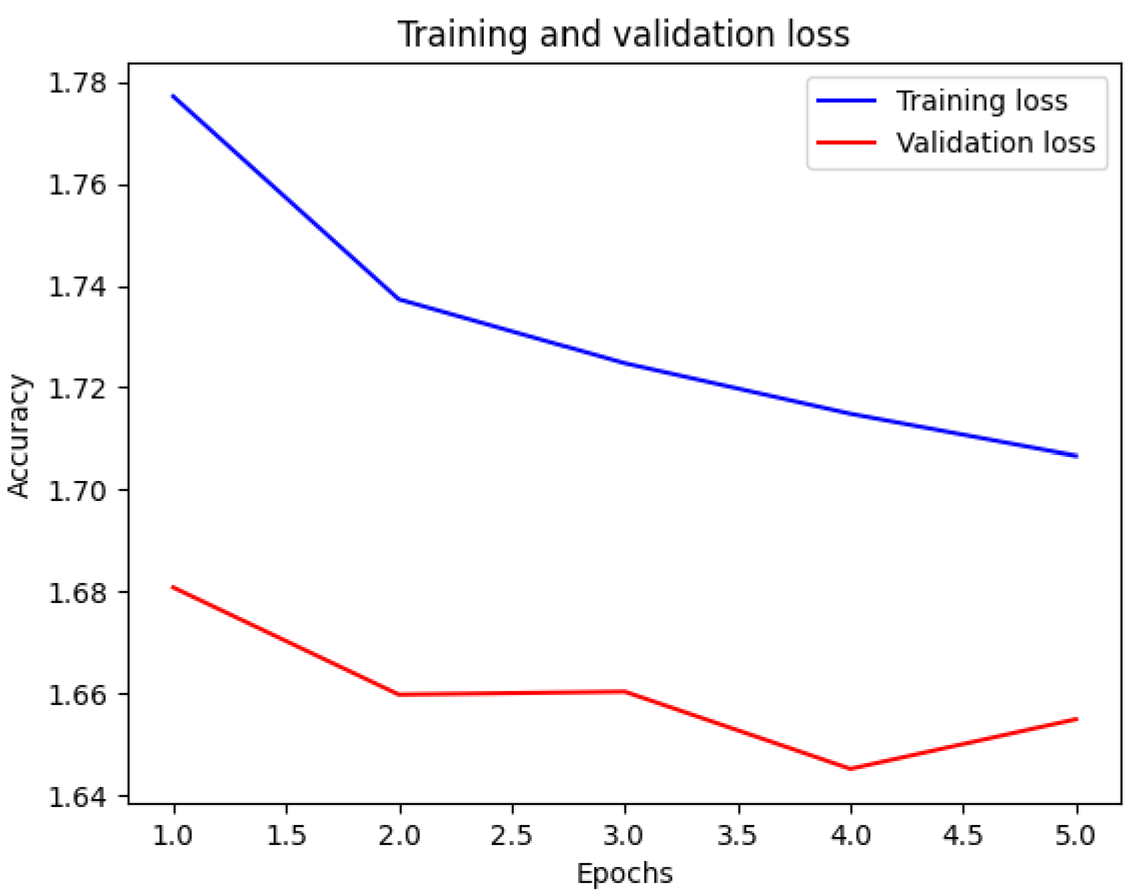



```
# Extract accuracies from model training history
train_loss = inception.history.history['loss']
val_loss = inception.history.history['val_loss']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



```
import pandas as pd
import numpy as np

# Evaluate model_CNN on training and testing data
train_scores = inception.evaluate(X_train2, y_train2, verbose=0)
test_scores = inception.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)
```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  1.658386  1.658386      0.0
1  Training Accuracy  0.331380  0.331380      0.0
2       Testing Loss  1.644682  1.644682      0.0
3   Testing Accuracy  0.344500  0.344500      0.0
```

```
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
from tensorflow.keras.applications.resnet50 import ResNet50
#Resnet
# Create ResNet50 base model with pretrained weights
base_model = ResNet50(include_top=False, weights='imagenet', input_shape=(224, 224, 3))

# Freeze base model layers
for layer in base_model.layers:
    layer.trainable = False

# Build model architecture on top of base model
```

```
model = Sequential()
model.add(layers.Lambda(lambda x: tf.image.grayscale_to_rgb(x), input_shape=(48,48,1)))
model.add(layers.Lambda(lambda image: tf.image.resize(image, (224, 224))))
model.add(base_model)
model.add(layers.GlobalAveragePooling2D())
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(7, activation='softmax'))

# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Print model summary
model.summary()
resnet=model
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lambda_3 (Lambda)           (None, 48, 48, 3)         0

 lambda_4 (Lambda)           (None, 224, 224, 3)       0

 resnet50 (Functional)       (None, 7, 7, 2048)        23587712

 global_average_pooling2d_1   (None, 2048)             0
 (GlobalAveragePooling2D)

 flatten_5 (Flatten)         (None, 2048)              0

 dense_13 (Dense)            (None, 256)               524544

 dropout_15 (Dropout)        (None, 256)               0

 dense_14 (Dense)            (None, 7)                 1799

=================================================================
Total params: 24,114,055
Trainable params: 526,343
Non-trainable params: 23,587,712
_________________________________________________________________
```

```
resnet.fit(X_train2,y_train2,validation_data=(X_val,y_val),epochs=5,verbose=1,callbacks=[l
```

```
Epoch 1/5
3375/3375 [==============================] - 109s 31ms/step - loss: 1.7890 - accuracy: (
Epoch 2/5
3375/3375 [==============================] - 103s 30ms/step - loss: 1.7579 - accuracy: (
Epoch 3/5
```

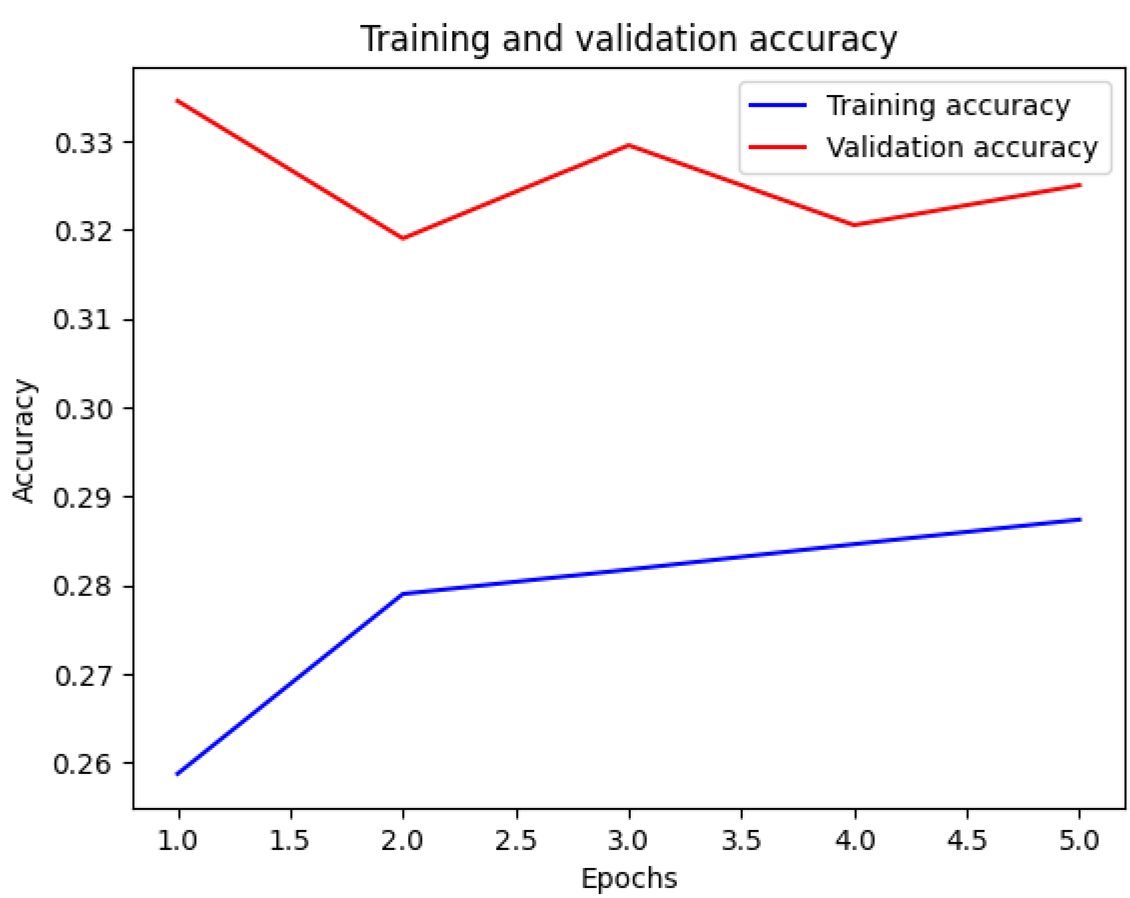
```
3375/3375 [==============================] - 103s 30ms/step - loss: 1.7490 - accuracy: 0
Epoch 4/5
3375/3375 [==============================] - 103s 31ms/step - loss: 1.7440 - accuracy: 0
Epoch 5/5
3375/3375 [==============================] - ETA: 0s - loss: 1.7359 - accuracy: 0.2874
Epoch 5: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
3375/3375 [==============================] - 103s 30ms/step - loss: 1.7359 - accuracy: 0
<keras.callbacks.History at 0x7f2ae8b9f3d0>
```

```
# Extract accuracies from model training history
train_loss = resnet.history.history['accuracy']
val_loss = resnet.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```

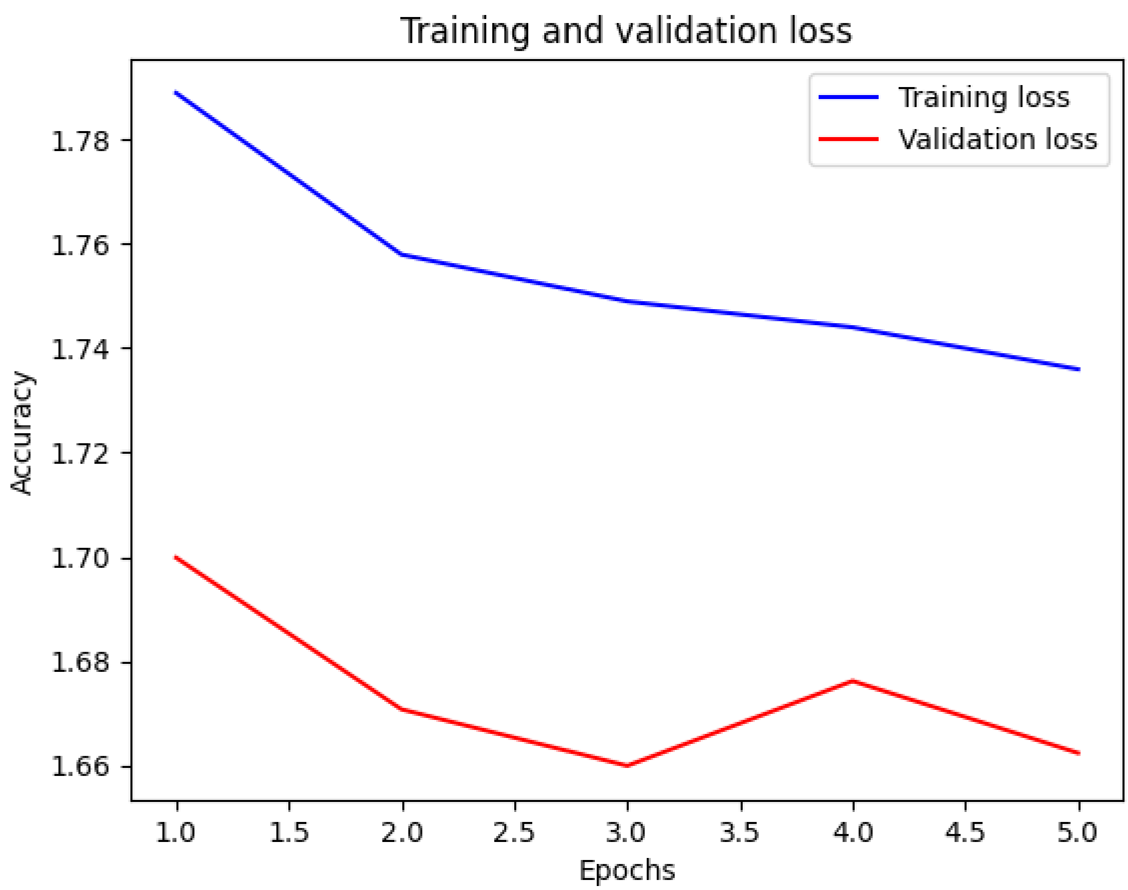


```
# Extract accuracies from model training history
train_loss = resnet.history.history['loss']
val_loss = resnet.history.history['val_loss']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```




```
import pandas as pd
import numpy as np

# Evaluate model_CNN on training and testing data
train_scores = resnet.evaluate(X_train2, y_train2, verbose=0)
test_scores = resnet.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
```

```
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)
```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  1.705958  1.705958      0.0
1  Training Accuracy  0.307083  0.307083      0.0
2       Testing Loss  1.662355  1.662355      0.0
3   Testing Accuracy  0.325000  0.325000      0.0
```

```
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential

#VGG16
base_model = keras.applications.VGG16(include_top=False, weights='imagenet', input_shape=(

# Freeze base model layers
for layer in base_model.layers:
    layer.trainable = False

# Build model architecture on top of base model
model = Sequential()
model.add(layers.Lambda(lambda x: tf.image.grayscale_to_rgb(x), input_shape=(48,48,1)))
model.add(layers.Lambda(lambda image: tf.image.resize(image, (224, 224))))
model.add(base_model)
model.add(Dropout(0.5))
model.add(Flatten())
model.add(BatchNormalization())
model.add(Dense(32,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
```

```
model.add(Dropout(0.5))
model.add(Dense(32,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(32,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dense(7,activation='softmax'))

# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model_VGG=model
# Print model summary
model_VGG.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lambda_1 (Lambda)           (None, 48, 48, 3)         0

 lambda_2 (Lambda)           (None, 224, 224, 3)       0

 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 dropout_12 (Dropout)        (None, 7, 7, 512)         0

 flatten_4 (Flatten)         (None, 25088)             0

 batch_normalization_112 (Ba  (None, 25088)            100352
 tchNormalization)

 dense_9 (Dense)             (None, 32)                802848

 batch_normalization_113 (Ba  (None, 32)               128
 tchNormalization)

 activation_94 (Activation)  (None, 32)                0

 dropout_13 (Dropout)        (None, 32)                0

 dense_10 (Dense)            (None, 32)                1056

 batch_normalization_114 (Ba  (None, 32)               128
 tchNormalization)

 activation_95 (Activation)  (None, 32)                0

 dropout_14 (Dropout)        (None, 32)                0

 dense_11 (Dense)            (None, 32)                1056
```

```
 batch_normalization_115 (Ba  (None, 32)                128
 tchNormalization)

 activation_96 (Activation)  (None, 32)                0

 dense_12 (Dense)            (None, 7)                 231

=================================================================
Total params: 15,620,615
Trainable params: 855,559
Non-trainable params: 14,765,056
_________________________________________________________________
```

```
model_VGG.fit(X_train2,y_train2,validation_data=(X_val,y_val),epochs=5,verbose=1,callbacks
```

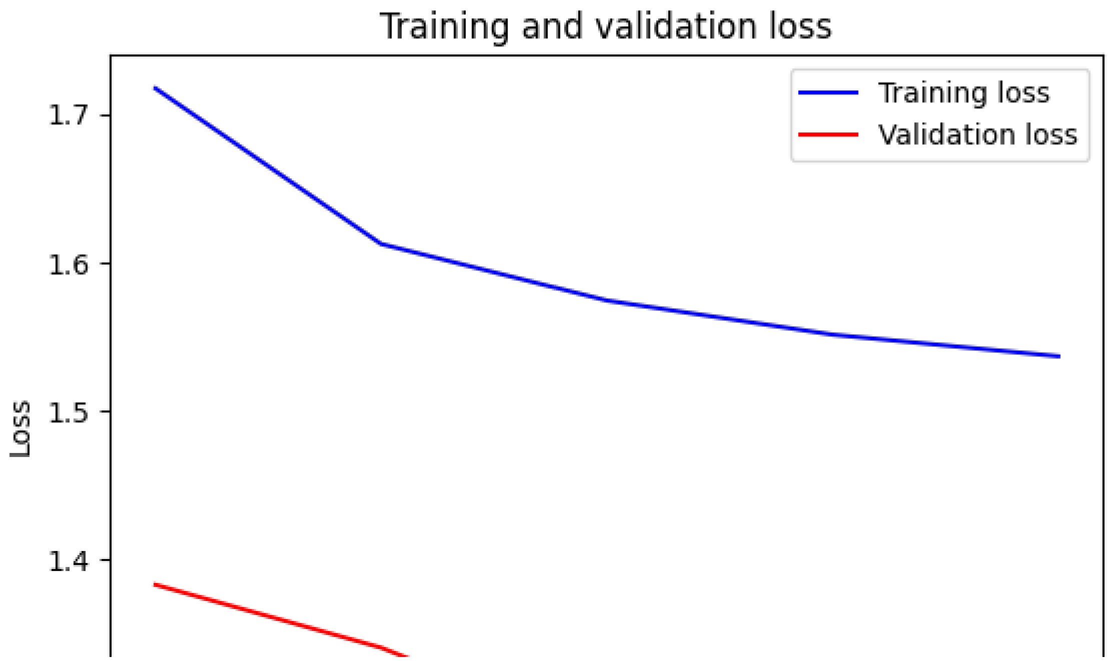
```
Epoch 1/5
3375/3375 [==============================] - 153s 44ms/step - loss: 1.7172 - accuracy: (
Epoch 2/5
3375/3375 [==============================] - 149s 44ms/step - loss: 1.6123 - accuracy: (
Epoch 3/5
3375/3375 [==============================] - 149s 44ms/step - loss: 1.5741 - accuracy: (
Epoch 4/5
3375/3375 [==============================] - 149s 44ms/step - loss: 1.5511 - accuracy: (
Epoch 5/5
3375/3375 [==============================] - 150s 44ms/step - loss: 1.5365 - accuracy: (
<keras.callbacks.History at 0x7f2b94283a00>
```

```
# Extract accuracies from model training history
train_loss = model_VGG.history.history['loss']
val_loss = model_VGG.history.history['val_loss']


# Plot training and validation loss
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

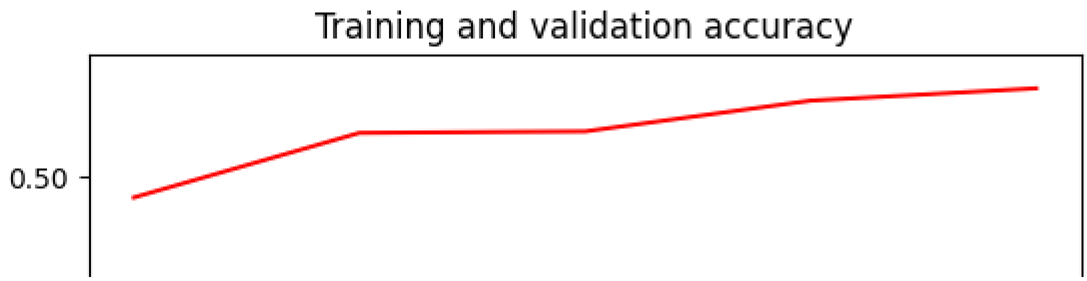



```
# Extract accuracies from model training history
train_loss = model_VGG.history.history['accuracy']
val_loss = model_VGG.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```




```
import pandas as pd
import numpy as np

# Evaluate model_CNN on training and testing data
train_scores = model_VGG.evaluate(X_train2, y_train2, verbose=0)
test_scores = model_VGG.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)
```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  1.393742  1.393742      0.0
1  Training Accuracy  0.471917  0.471917      0.0
2       Testing Loss  1.263955  1.263955      0.0
3   Testing Accuracy  0.529000  0.529000      0.0
```

```
#Ensemble model if you wanna try ensembling different models
models1=[resnet,model_bayes,model_VGG]
model_input = tf.keras.Input(shape=(48, 48, 1))
model_outputs = [model(model_input) for model in models1] #collects outputs of models in a
```

```
ensemble_output = tf.keras.layers.Average()(model_outputs) #averaging outputs
ensemble_model2 = tf.keras.Model(inputs=model_input, outputs=ensemble_output)
ensemble_model2.compile(loss="categorical_crossentropy", optimizer= tf.keras.optimizers.Ad

```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use th
```

```
#Learning rate reduction and early stopping callbacks.
lrd = ReduceLROnPlateau(monitor = 'val_loss',patience = 2,verbose = 1,factor = 0.50, min_l



es = tf.keras.callbacks.EarlyStopping(verbose=1, patience=20)
```

```
#Fit ensemble model with callbacks.
ensemble_model2.fit(X_train2,y_train2,validation_data=(X_val,y_val),epochs=5,verbose=1,cal
```

```
Epoch 1/5
3375/3375 [==============================] - 341s 101ms/step - loss: 1.3403 - accuracy:
Epoch 2/5
3375/3375 [==============================] - 339s 101ms/step - loss: 1.2809 - accuracy:
Epoch 3/5
3375/3375 [==============================] - 339s 101ms/step - loss: 1.2455 - accuracy:
Epoch 4/5
3375/3375 [==============================] - 339s 100ms/step - loss: 1.2207 - accuracy:
Epoch 5/5
3375/3375 [==============================] - 339s 100ms/step - loss: 1.1971 - accuracy:
<keras.callbacks.History at 0x7f491a299220>
```

```
# Extract accuracies from model training history
train_loss = ensemble_model2.history.history['accuracy']
val_loss = ensemble_model2.history.history['val_accuracy']

# Plot training and validation accuracy
epochs = range(1, len(train_loss) + 1)

plt.plot(epochs, train_loss, 'b', label='Training accuracy')
plt.plot(epochs, val_loss, 'r', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```

```
import pandas as pd
import numpy as np
```

```

# Evaluate model_CNN on training and testing data
train_scores = ensemble_model2.evaluate(X_train2, y_train2, verbose=0)
test_scores = ensemble_model2.evaluate(X_val, y_val, verbose=0)

# Extract loss and accuracy from scores
train_loss = train_scores[0]
train_acc = train_scores[1]
test_loss = test_scores[0]
test_acc = test_scores[1]

# Calculate mean and standard deviation of scores
mean_train_loss = np.mean(train_loss)
mean_train_acc = np.mean(train_acc)
mean_test_loss = np.mean(test_loss)
mean_test_acc = np.mean(test_acc)
std_train_loss = np.std(train_loss)
std_train_acc = np.std(train_acc)
std_test_loss = np.std(test_loss)
std_test_acc = np.std(test_acc)

# Create a pandas DataFrame to present the results in a table
results_df = pd.DataFrame({'Metric': ['Training Loss', 'Training Accuracy', 'Testing Loss'
                           'Score': [train_loss, train_acc, test_loss, test_acc],
                           'Mean': [mean_train_loss, mean_train_acc, mean_test_loss, mean_
                           'Std Dev': [std_train_loss, std_train_acc, std_test_loss, std_t

# Print the results DataFrame
print(results_df)
```

```
              Metric     Score      Mean  Std Dev
0      Training Loss  1.068653  1.068653      0.0
1  Training Accuracy  0.669241  0.669241      0.0
2       Testing Loss  1.093816  1.093816      0.0
3   Testing Accuracy  0.639500  0.639500      0.0
```

```
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.


# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
link1 = 'https://drive.google.com/file/d/1Jr89SBNo8wCq7yTqny4q_Y8toex1zeBE/view?usp=share_
id1 = link1.split("/")[-2]
```