Image Recognition with IBM Cloud Visual Recognition

Emotion Recognition in Image Captioning Emotion recognition adds a new dimension to image captioning by detecting and expressing the emotions depicted in the image. With the help of advanced algorithms, images can be analyzed to identify emotions such as joy, sadness, sur prise, and more.

Project Update.

We have created a website to upload and display Images

Future Development of the Project:

The website will be AI generated to caption the emotions in the uploaded image

Source Code.

HTML Code

```
#DOCTYPE html

fhtml lang="eri">

fhead

fineta charset="UTF-8"

fitle*Image Uploads/title

fineta rel="stylesheet" href="stylecss">

fhead

fody

for class="container">

file*Image Uploads/h1>

form id="upload-form" encty pe="multi part/form-data">

form id="upload-form" encty pe="multi part/form-data">
```

CSS Code

```
body l
font-family Arial, sans-serif:
}

container l
max-width: 400 px;
margin: 0 auto;
text-align center;
}

h1 l
margin-to a 20 px;
}
```

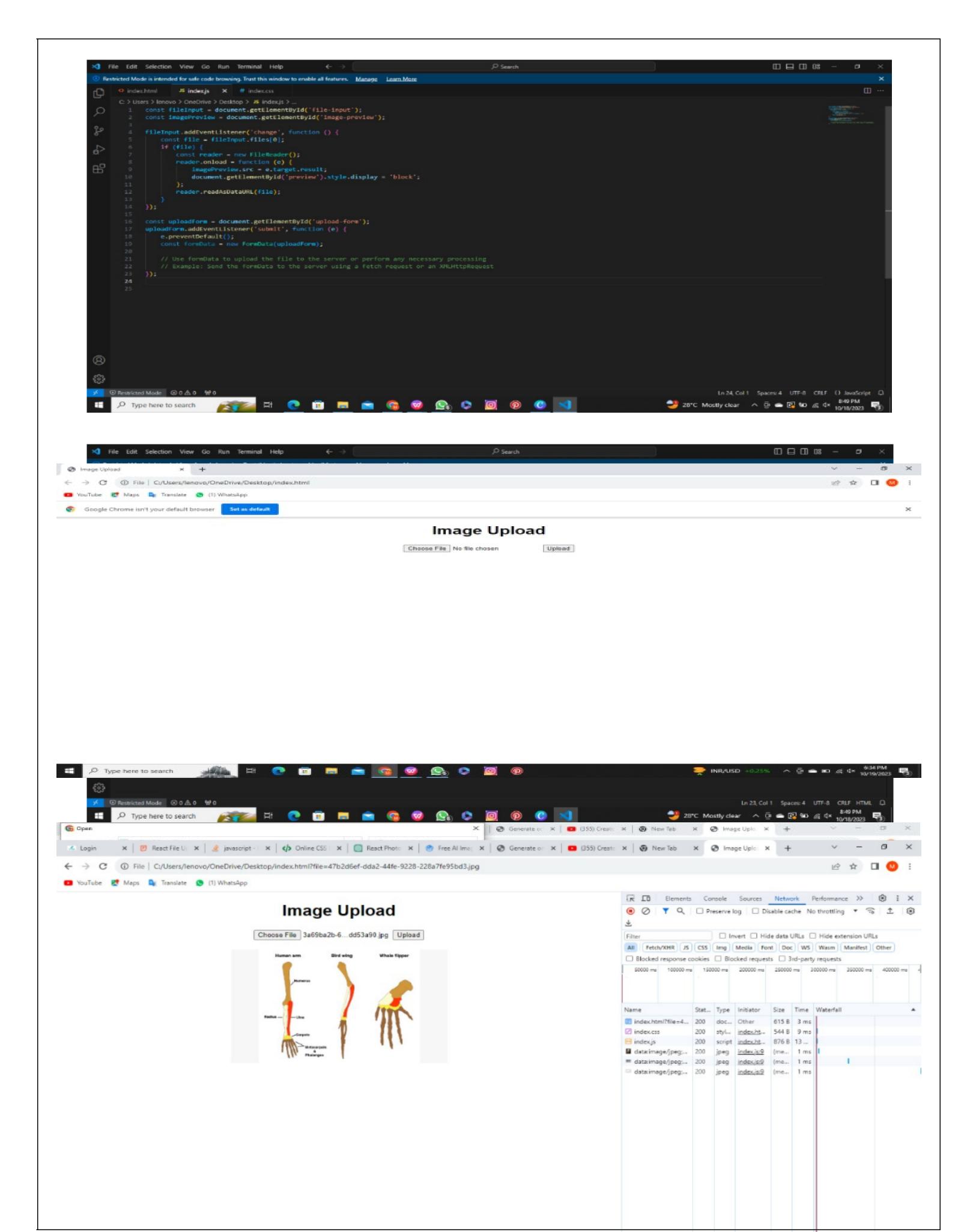
```
form {
   margin: 20 px 0;
input[type="file"] {
   display: none;
button (
   padding: 10 px 20 px;
   background-color: #007BFF;
   color: #fff;
   border: none,
   cursor: pointer;
buttonhover (
   background-color: #0056b3;
}
#preview (
   display: none;
   margin-top: 20px;
```

```
#image-preview {
max-width: 100%;
```

```
Javascript Code
const fileInput = document.getElementById('file-input');
const imagePreview = document.getElementByIdCimage-preview');
fileInput.addEventListenerCchange, function () {
   const file = fileInput.files[0];
   if (file) {
      const reader = new FileReader();
      reader.onload = function (e) {
         imagePreview.src = e.target.result;
         document.getElementById('preview').style.dis.play = 'block';
      };
      reader.readAsDataURL(file);
3);
const u plogdForm = document.getElementByIdCu plogd-form');
u plocdForm.cddEventListener('submit', function (e) {
   e.preventDefgult();
```

```
const formData = new FormData(u_ploadForm);
   // Use formData to upload the file to the server or perform any necessary processing
   // Example: Send the formData to the server using a fetch request or an XMLHttpRequest
3);
const fileIn put = document.getElementById('file-in put');
const imagePreview = document.getElementByIdCimage-preview');
fileInput.addEventListenerCchange, function () {
   const file = fileInput.files[0];
   if (file) {
      const reader = new FileReader();
      reader.onload = function (e) {
         imagePreview.src = e.target.result;
         document.getElementById('preview').style.dis.play = 'block';
      };
      reader.readAsDataURL(file);
});
const u plogdForm = document.getElementByIdCu plogd-form');
```

u plogdForm.gddEventListener('submit', function (e) {
e.preventDefgult();
const formData = new FormData(u.ploadForm);
// Use formData to u pload the file to the server or perform any necessary processing
// Example: Send the formData to the server using a fetch request or an XMLHttpRequest
3);



Type here to search

6 requests 2.0 kB transferred 102 kB resources Finish: 5.9 min DOMContentLoaded: 36 ms

Step 2: Setting up Data for the AI Model

Before running the scripts for the image recognition project, it's crucial to set up the required datasets. Collecting the dataset for emotion captioning includes several steps,

1.define your emotion Categories

2.Data source selection

3.Data collection

4. Emotion labeling

1.Define your emotion Categories:

The set of distinct emotional states or labels used to categorize and describe human emotions based on their characteristics and expressions.

The seven primary emotion categories are.

neutral

happy

sur prise

sad

angry

disgust

fear

2.Data source selection

SOURCE:

https://www.kaggle.com/datasets

DESCRIPTION: Kaggle Datasets serves as a valuable resource for data enthusiasts, offering detailed descriptions, documentation, and metadata to assist in dataset selection.

htt ps://github.com/microsoft/FERPlus

DESCRIPTION: FERPlus is an extension of the FER-13 dataset, providing a more refined annotation of emotions. It includes additional labels, offering improved granularity in emotion recognition.

COCO Dataset

DESCRIPTION: The COCO Dataset is a widely recognized and extensively used dataset in the field of computer vision and machine learning. It is designed for various computer vision tasks, including object detection, image segmentation, and captioning.

3.Data collection.

To run the image recognition scripts successfully, we should follow these steps,

Download the CK+, FER-13, and FERPlus datasets from their respective sources.

Organizing the dataset files according to our project's directory structure.

The collection of data could be facial images, text, audio recordings, or any other relevant data.

REORGANIZATION OF DATA:

Images are transferred from the original FERPlus directory structure to match the FER-2013 structure.

Images are categorized into training and test sets based on the "Usage" attribute in the CSV file. EXECUTION:

The Python script appears to be related to data preprocessing and reorganizing image data from two different datasets: the "FERPlus" dataset and the "FER-2013" dataset, which are used in the context of facial expression recognition.

```
import os
import shutil

import cv2
import numpy as np
import pandas as pd

def get_best_emotion(list_of_emotions) emotions):

best_emotion = npargmax(emotions)
if best_emotion = "neutral" and sum(emotions(1:1)) 0:
emotions(best_emotion) = 0
best_emotion = npargmax(emotions)
```

```
return list_of_emotions[best_emotion]
def read_and_clean_csv(path):
   # we read the csv and we delete all the rows which contains NaN
   df = pd.read_csv(path)
   df = df.dropng()
   return df
def rewrite_image_from_df(df);
   print("Moving images from FERPlus inside FER-2013")
   # we setup an accumulator to print if we have finished a task
   GCC = <sup>111</sup>
   emotions = [
      "neutral",
      "happy",
      "sur prise",
      "sad",
      "angry",
      "disgust",
      "fear",
      "contempt",
      "unknown",
      "NF",
   # we rewrite all the image files
   for row in range(len(df)):
      item = df.iloc[row]
      if item["Usage"] not in ["", acc]:
```

```
print(f"litem['Usage']) done")
      if (item['Usage'] == "Training"):
         image = cv2.imread(f"./FERPlus/out.put/FER2013Train/litem['Image name']")
      elif item['Usage'] == "PublicTest":
         image = cv2.imread(f'./FERPlus/output/FER2013Valid/litem['Image name'])")
      else:
         image = cv2.imread(f'./FERPlus/output/FER2013Test/litem['Image name'])")
      gcc = item["Usage"]
      if acc == "Training":
         cv2.imwrite(
            f"./FER-2013/train/lget_best_emotion(emotions, item[2::])}/litem['Image name']}",
            image,
         )
      else:
         cv2.imwrite(
            f"./FER-2013/test/(get_best_emotion(emotions, item[2::])}/(item['Image name'])",
            image,
if __name__ == "__main__":
   os.systemCpython./FERPLUS/src/generate_training_data.py -d./FERPLUS/output -fer./FER-2013/fer2013.csv -ferplus.
/FERPLUS/fer2013new.csv')
   df = read_and_clean_csv("./FERPlus/fer2013new.csv")
   rewrite_image_from_df(df)
```

4.Emotion labeling:

The FERPlus dataset provides emotion labels in a detailed format.

SEVEN PRIMARY CATEGORIES:

neutral, happy, surprise, sad, angry, disgust, and fear.

SORTING OF IMAGES BASED ON EMOTION:

Sorting images into subfolders based on the dominant emotion category they represent is a common practice in organizing image datasets for emotion recognition and other image classification tasks.

```
<?xml version="1.0"?>
<opencv_storage>
<cascade type_id="o pencv-cascade-classifier"><stageType>BOOST</stageType>
 'featureType'HAAR'/featureType'
 \height\24\/height\
 \uidth\24\/width\
 <stageParams
  'maxWeakCount'211\'/maxWeakCount'\'/stageParams'
 <fectureParams>
  'maxCatCount'\0\/maxCatCount\\/featureParams'

<stageNum
25</stageNum
)
</pre>
 (stages)
   \_>
    'maxWeakCount'\9\/maxWeakCount'\
    \stageThreshold -5.0425500869750977e+004 stageThreshold
    (weakClassifiers)
      (<u>)</u>
       (internalNodes)
         0 -1 0 -3.1511999666690826e-02\/internalNodes\
       (leafValues)
         2.0875380039215088e+00 -2.2172100543975830e+00\(\legfV\) clues\(\left\)
      (_)
       (internalNodes)
         0 -1 1 12396000325679779e-02\/internalNodes\
       (leafValues)
         -1.8633940219879150e+00 1.3272049427032471e+00\(\legfV\) clues\(\left\)
      (_)
       (internalNodes)
         0-1 2 2.1927999332547188e-02\/internalNodes\
       (leafValues)
         -1.5105249881744385e+00 10625729560852051e+00/leafValues\\_\)
```

```
\_>
    (internalNodes)
      0-1 3 5.7529998011887074e-03\(\internalNodes\)
    (leafValues)
      -8.7463897466659546e-01 1.1760339736938477e+00/leafValues\\_\
   ⟨_>
    (internalNodes)
      0 -1 4 15014000236988068e-02\/internalNodes\
    (leafValues)
      -7.7945697307586670e-01 1.2608419656753540e+00/legfVglues×/_>
   \_>
    (internalNodes)
      0 -1 5 9.9371001124382019e-02\/internalNodes\
    (leafValues)
      5.5751299858093262e-01 -1.8743000030517578e+00/legfVglues\/_>
   \_>
    (internalNodes)
      0 -1 6 2.7340000960975885e-03\/internalNodes\
    (leafValues)
      -1.6911929845809937e+00 4.4009700417518616e-01\(\legfV\) clues\(\left\)
   \_>
    (internalNodes)
      0 -1 7 -1.8859000876545906e-02\/internalNodes\
    (leafValues)
      -1.4769539833068848e+00 4.4350099563598633e-01\(\legfValues\)
   ⟨_>
    (internalNodes)
      0 -1 8 5.9739998541772366e-03/internalNodes
    (leafValues)
      -8.5909199714660645e-01 8.5255599021911621e-01<br/>//leafValues×/_×/weakClassifiers×/_>
⟨_>
 'maxWeakCount'16\/maxWeakCount'
  \verb| 'stageThreshold' - 4.9842400550842285e + 00 \verb| '/stageThreshold' | \\
```

```
(weakClassifiers)
 ⟨_>
   (internalNodes)
    0 -1 9 -2.1110000088810921e-02\/internalNodes\
  (leafValues)
    1.2435649633407593e+00 -1.5713009834289551e+00\(\legfV\) clues\(\left\)
 ⟨_>
  (internalNodes)
    0 -1 10 2.0355999469757080e-02\/internalNodes\
  (leafValues)
    -1.6204780340194702e+00 1.1817760467529297e+00/legfVglues×/_>
 ⟨_⟩
   (internalNodes)
    0 -1 11 2.1308999508619308e-02\(\internalNodes\)
  (leafValues)
    -1.9415930509567261e+00 7.0069098472595215e-014/legfValues×/_>
 ⟨_>
   (internalNodes)
    0 -1 12 9.1660000383853912e-02\/internalNodes\
  (leafValues)
    -5.5670100450515747e-01 17284419536590576e+00/leafValues×/_>
 \_>
   (internalNodes)
    0 -1 13 3.6288000643253326e-02\/internalNodes\
  (leafValues)
    2.6763799786567688e-01 -2.1831810474395752e+00\(\legfV\) clues\(\left\)
 ⟨_⟩
   (internalNodes)
    0 -1 14 -1.9109999760985374e-02\( \internal \text{Nodes} \)
   (leafValues)
    -2.6730210781097412e+00 4.5670801401138306e-01\(\legfV\)clues\(\legf\)
 <u>\_</u>>
   (internalNodes)
```

```
0 -1 15 8.2539999857544899e-03\(\internal\)Nodes\
 (leafValues)
   -1.0852910280227661e+00 5.3564202785491943e-01/legfVglues×/_>
⟨_⟩
 (internalNodes)
   0 -1 16 1.8355000764131546e-02\/internalNodes\
 (leafValues)
   -3.5200199484825134e-01 9.3339198827743530e-01/legfValues\/_\
<u>\_</u>>
 (internalNodes)
   0 -1 17 -7.0569999516010284e-03\(\internalNodes\)
 (leafValues)
   9.2782098054885864e-01 -66349899768829346e-014leafValues×/_>
⟨_>
 (internalNodes)
   0 -1 18 -9.8770000040531158e-03\(\internalNodes\)
 (leafValues)
   1.1577470302581787e+00 -2.9774799942970276e-01/leafValues\/_>
(_)
 (internalNodes)
   0 -1 19 15814000740647316e-024/internalNodes
 (leafValues)
   -4.1960600018501282e-01 1.3576040267944336e+00\(\leafValues\\/\_\)
⟨_>
 (internalNodes)
   0 -1 20 -2.0700000226497650e-02\/internalNodes\
 (leafValues)
   1.4590020179748535e+00 -19739399850368500e-01/legfValues\/_>
\_>
 (internalNodes)
   0 -1 21 -1.3760800659656525e-01\/internalNodes\
 (leafValues)
   1.1186759471893311e+00 -5.2915501594543457e-01\(\legfValues\(\l)\)
```

```
\_>
    (internalNodes)
      0-1 22 1.4318999834358692e-02\/internalNodes\
    (leafValues)
      -3.5127198696136475e-01 1.1440860033035278e+00\(\leafValues\\/_\)
   \_>
    (internalNodes)
      0 -1 23 10253000073134899e-02\/internalNodes\
    (leafValues)
      -6.0850602388381958e-01 7.7098500728607178e-01/leafValues\/_>
   ⟨_>
    (internalNodes)
      0 -1 24 9.1508001089096069e-02\/internalNodes\
    (leafValues)
      3.8817799091339111e-01 -15122940540313721e+00\/leafValues\/_\/\/weakClassifiers\/_\
⟨_>
 'maxWeakCount'>27/maxWeakCount'>
  \verb| (stageThreshold) - 4.6551899909973145e + 00 | \textit{(stageThreshold)} \\
 (weakClassifiers)
   ⟨_>
    (internalNodes)
      0 -1 25 6.9747000932693481e-02\internalNodes\
    (leafValues)
      -1.0130879878997803e+00 14687349796295166e+00\(\legfV\) clues\(\left\)
   ⟨_>
    (internalNodes)
      0-1 26 3.1502999365329742e-02\/internalNodes\
    (leafValues)
      -1.6463639736175537e+00 1.0000629425048828e+00/leafValues\\_\
   ⟨_>
    (internalNodes)
      0 -1 27 1.4260999858379364e-024/internalNodes
    (leafValues)
```

```
4.6480301022529602e-01 -1.5959889888763428e+001/leafValues\/_>
<u>\_</u>>
 (internalNodes)
   0-128 14453000389039516e-02\/internalNodes\
 (leafValues)
   -6.5511900186538696e-01 8.3021801710128784e-01/leafValues\/_>
⟨_>
 (internalNodes)
   0 -1 29 -3.0509999487549067e-03\/internalNodes\
 (leafValues)
   -1.3982310295104980e+00 4.2550599575042725e-01/leafValues\/_>
⟨_>
 (internalNodes)
   0-1 30 3.2722998410463333e-02\/internalNodes\
 (leafValues)
   -5.0702601671218872e-01 1.0526109933853149e+00x/legfValuesx/_>
⟨_>
 (internalNodes)
   0 -1 31 -7.2960001416504383e-03\(\internalNodes\)
 (leafValues)
   3.6356899142265320e-01 -1.3464889526367188e+00/leafValues\/_>
\_>
 (internalNodes)
   0 -1 32 5.0425000488758087e-024/internalNodes
 (leafValues)
   -3.0461400747299194e-01 1.4504129886627197e+00/legf/glues×/_>
\_>
 (internalNodes)
   0 -1 33 4.6879000961780548e-02\/internalNodes\
 (leafValues)
   -4.0286201238632202e-01 1.2145609855651855e+00/legfValues×/_>
<u>\_</u>>
 (internalNodes)
```

```
0-134-6.9358997046947479e-02\/internalNodes\
       (leafValues)
         1.0539360046386719e+00 -4.5719701051712036e-01/leafValues*/_>
      ⟨_>
       (internalNodes)
         0-135-4.9033999443054199e-024/internalNodes
       (leafValues)
         -1.6253089904785156e+00 1.5378999710083008e-01/leafValues\/_>
      \_>
       (internalNodes)
         0-13684827996790409088e-021/internalNodes
       (leafValues)
         2.8402999043464661e-01 -1.5662059783935547e+00\(\legfV\) clues\(\left\)
(30000 lines in between)
<u>\_</u>>
    (rects)
      (_)
       0 13 18 3 -1./_>
      <u>\_</u>>
       0 14 18 1 3./_x/rectsx/_>
   <u>\_</u>>
    (rects)
     \_>
      15 17 9 6 -14/_>
      <u>\_</u>>
       15 19 9 2 3.4_x/rectsx/_>
   <u>\_</u>>
    (rects)
      <u>\_</u>>
       0 17 9 6 -1.4_>
```

```
<u>\_</u>>
     0 19 9 2 3./_x/rectsx/_>
\_>
  (rects)
   ⟨_>
    12 17 9 6 -1./_>
   \_>
    12 19 9 2 3.4_\(\text{/_x}\)
\_>
 (rects)
   <u>\_</u>>
    3 17 9 6 -1.4_>
   ⟨_>
    3 19 9 2 3./_x/rectsx/_>
<u>\_</u>>
 (rects)
   <u>\_</u>>
    16 2 3 20 -14/_>
   <u>\_</u>>
     17 2 1 20 3.4_x/rects\/_>
<u>\_</u>>
 (rects)
   <u>\_</u>>
     0 13 24 8 -1.4_>
   <u>\_</u>>
     0 17 24 4 2\(\lambda\)/rects\(\lambda\)
<u>\_</u>>
 (rects)
   <u>\_</u>>
    9 1 6 22 -1.4_>
   <u>\_</u>>
    12 1 3 11 242
   <u>(_</u>)
```

9 12 3 11 24/_x/rectsx/_x/featuresx/cascade

(/opencv_storage)

EXECUTION

The provided XML code represents a Haar Cascade Classifier, a machine learning model used for detecting frontal faces in images. Haar Cascade Classifiers are a type of object detection algorithm commonly used in computer vision for recognizing objects, such as faces, within images.

Developing and Fine-Tuning Deep Learning Models for Emotion Recognition:

The central focus is on the development and fine-tuning of deep learning models for precise emotion recognition, outlining the essential steps in the process,

DATA PREPROCESSING:

The role of data pre-processing in training emotion recognition models. It highlights the use of techniques like data augmentation, specifically leveraging Keras' ImageDataGenerator. Data augmentation is employed to improve the model's capacity to identify emotions from diverse facial expressions.

ARCHITECTURE SELECTION:

The readers introduce range of pre-trained architectures, such as VGG16, ResNet50, Xception, and Inception, which form the basis for emotion recognition models.

Fine-Tuning for Optimal Performance:

The importance of fine-tuning in model development, emphasizing its role in adapting the model for a specific task. It discusses the process of selecting and configuring the layers that require retraining to achieve optimal model performance.

Monitoring and Evaluation.

The use of Matplotlib for visualizing training and validation metrics, enabling developers to gain insights into the model's progress and effectiveness.

Saving and Reusing Models:

Developers are guided on saving their trained models for future use, enabling them to deploy these models in various applications with consistent performance.

```
from glob import glob
from kergs import Model
from keras.callbacks import EarlyStopping
from keras.layers import Flatten, Dense
from keras.models import save_model
from kergs.o ptimizer_v2.gradient_descent import SGD
from keras_pre processing.image import ImageDataGenerator
def get_data(parameters, pre process_input: object) -> tuple.
  image_gen = ImageDataGenerator(
      # rescale=1 / 127.5,
      rotation_range=20,
      zoom_range=0.05,
      shear_range=10,
      horizontal_flip=True,
      fill_mode="necrest",
      validation_split=0.20,
      preprocessing_function=preprocess_input,
   )
   # create generators
   train_generator = image_gen.flow_from_directory(
      parameters["train_path"],
      target_size=parameters["sha pe"],
      shuffle=True,
      batch_size= parameters["batch_size"],
   )
   test_generator = image_genflow_from_directory(
      parameters["test_path"],
      target_size=parameters["sha pe"],
```

```
shuffle=True,
      batch_size= parameters["batch_size"],
   )
   return (
      glob(f'{parameters['train_path']}/*/*.jp*g"),
      glob(f'iparameters['test_path']}/*/*.jp*g"),
      train_generator,
      test_generator,
   )
def fine_tuning(model: Model, parameters):
   # fine tuning
   for layer in model.layers[: parameters["number_of_last_layers_trainable"]]:
      layer.trainable = False
   return model
def create_model(architecture, parameters):
   model = architecture(
      in put_shape= parameters["shape"] + [3],
      weights="imagenet",
      include_top=False,
      classes=parameters["nbr_classes"],
   )
   # Freeze existing VGG already trained weights
   for layer in model.layers[: parameters["number_of_last_layers_trainable"]]:
      layer.trainable = False
   # get the VGG output
   out = model.out.put
```

```
# Add new dense layer at the end
   x = Flatten(Xout)
   x = DenseCparameters["nbr_classes"], activation="softmax")XX
   model = Model(inputs=model.input, outputs=x)
   opti = SGDC
      lr=parameters["learning_rate"],
      momentum=parameters["momentum"],
      nesterov=parameters["nesterov"],
   )
   model.com pile(loss="categorical_crossentro.py", o.ptimizer=o.pti, metrics=["accuracy"])
   # model.summary()
   return model
def fit(model, train_generator, test_generator, train_files, test_files, parameters):
   early_stop = EarlyStop.ping(monitor="val_accuracy", patience=2)
   return model.fit(
      train_generator,
      validation_data=test_generator,
      epochs=parameters["epochs"],
      ste.ps_per_e poch=len(train_files) // parameters["batch_size"],
      validation_ste.ps=len(test_files) // parameters["batch_size"],
      callbacks=[early_stop],
def evaluation_model(model, test_generator):
```

```
score = modeLevoluate_generator(test_generator)

print("Test loss", score[0])

print("Test accuracy", score[1])

return score

def soveModel(filename, model):

sove_model(model=model, file_path=f"/trained_models/lfilename!")

model.sove_weights(f"/trained_models/lfilename!h5")
```

Conclusion.

In the fifth phase of our image recognition development, we focused on as pects of data pre-paration, Haar Cascade Classifier for face detection, and the creation and fine-tuning of deep learning models for emotion recognition. We recognized the foundational importance of well-organized and pre-processed datasets in training accurate image recognition models. The exploration of the Haar Cascade Classifier highlighted its efficiency in detecting faces in images, making it a valuable tool for a wide range of computer vision applications. It also involved the development of powerful deep learning models, utilizing pre-trained architectures like VGG16, ResNet50, Xce ption, and Inception, and adapting them for emotion recognition. These models are poised to deliver impressive levels of accuracy.

