EC9580 COMPUTER VISION
MINI PROJECT
TOPIC SELECTION

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2020/E/050

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SEMESTER 7

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Topic: **Facial Emotion Recognition with Age detection.**

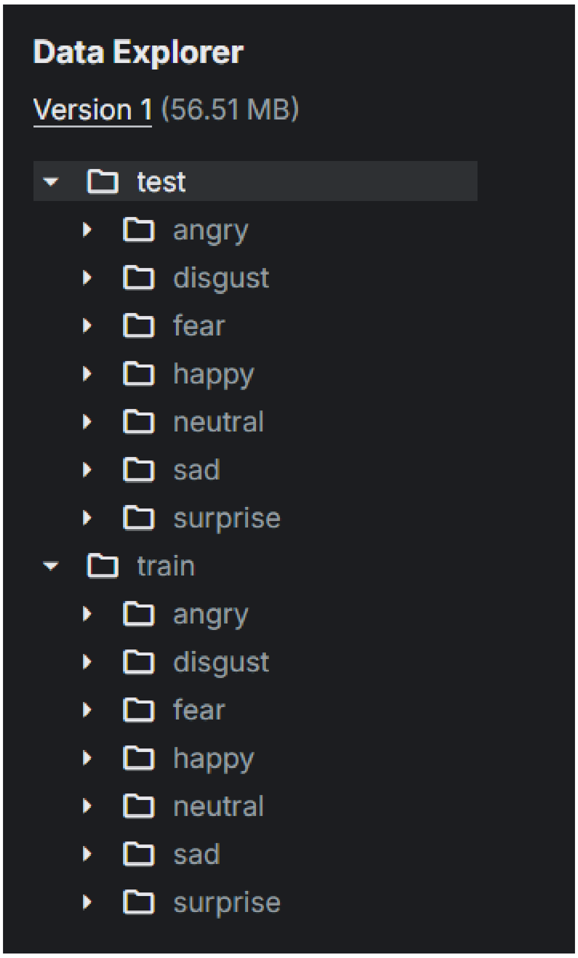
DATA:

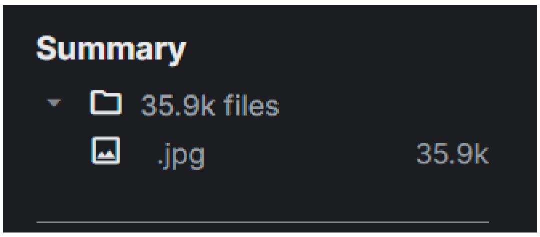
https://www.kaggle.com/datasets/msambare/fer2013/data

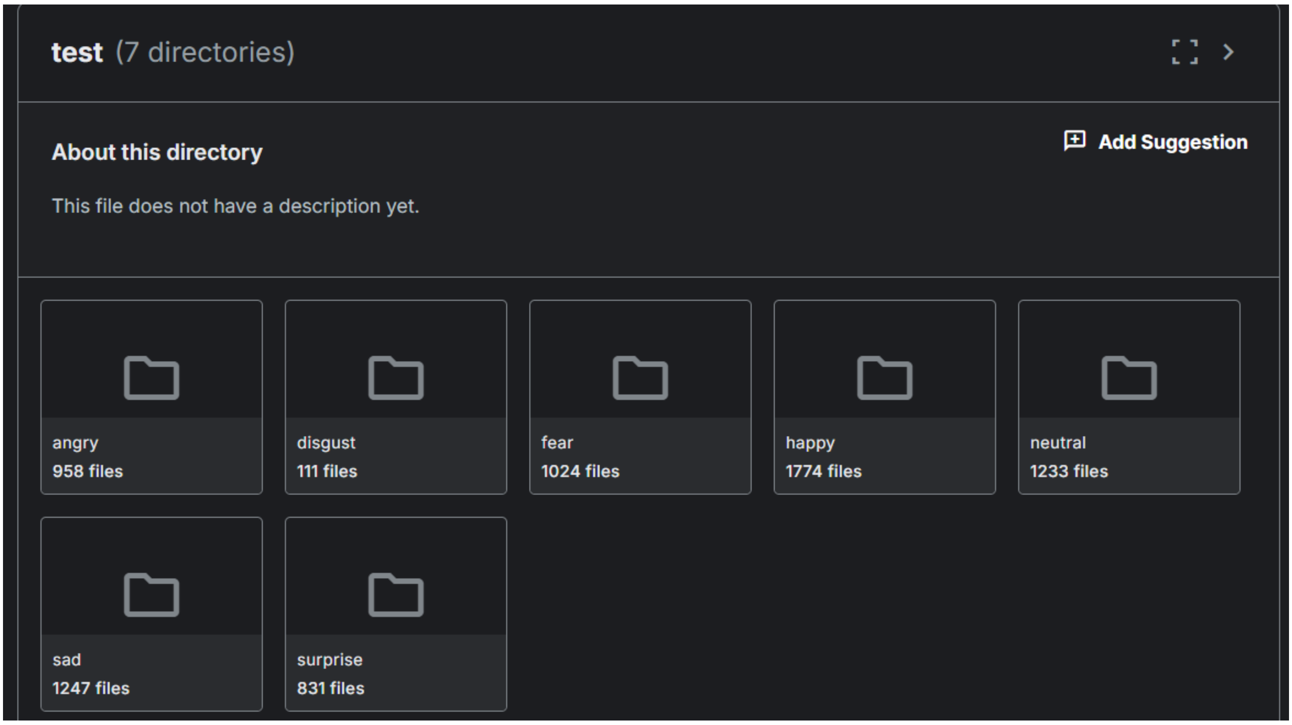
API Command: kaggle datasets download -d msambare/fer2013

API COMMAND :: kaggle datasets download d pkdarabi/cardetection

Name of Classes: Angry, disgust, fear, happy, neutral, sad, surprise







Introduction

In this project, we’re developing a model that can recognize emotions based on facial expressions and classify them into specific categories. The dataset we’re using consists of 48x48 pixel grayscale images of faces, each centered and aligned to ensure uniformity. The task is to identify the emotion being expressed in the image and classify it into one of seven emotions. The dataset includes over 28,000 training images and around 3,500 test images, giving us a good amount of data to work with.

Objective

Our main goal is to build a model that can accurately detect emotions from facial expressions and classify them into one of the following categories:

1. Angry
2. Disgust
3. Fear
4. Happy
5. Sad
6. Surprise
7. Neutral

This model has practical applications, such as:

- Human-Computer Interaction:
  Systems could respond to users' emotions in realtime.
- Customer Sentiment Analysis:
  Businesses could better understand how their customers feel during interactions.
- Security and Surveillance:
  Detecting emotional states in public places could help with public safety.
- Healthcare:

The model could be used to monitor emotional wellbeing or even help diagnose mood disorders.

Dataset Overview

- Image Size: 48x48 pixels, grayscale
- Emotion Categories: Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral
- Training Set: 28,709 images
- Test Set: 3,589 images

Methodology

1. **Data Preprocessing**

   To get the data ready for the model, we will:

- Load and explore the dataset to understand how the different emotion classes are distributed.
- Normalize the image pixel values to a range of [0, 1], making it easier for the model to process and train efficiently.
- Apply data augmentation (like rotating, zooming, and flipping the images) to increase diversity and prevent the model from overfitting, which means we don't want the model to perform well on just the training data but also on new, unseen data.

2. Model Development

- Model Architecture: We will likely use a Convolutional Neural Network (CNN), which is a proven method for handling image data. Alternatively, we might finetune a pretrained model like VGG or Res-Net that has been designed for image classification.
- Framework: The model will be built using either TensorFlow or Py-Torch, both of which are powerful tools for deep learning.
- Loss Function and Metrics: Since this is a multiclass classification problem, we'll use categorical cross-entropy as the loss function and track metrics like accuracy and F1score to evaluate how well the model is performing.

3. Training

We'll train the model using the training set and monitor how it performs on the validation set, making adjustments as needed. Techniques like dropout (which randomly "drops" some neurons during training) and batch normalization (which helps the model train more smoothly) will be applied to improve performance and prevent overfitting.

4. Evaluation

Once training is complete, we'll test the model on the test set to see how well it can recognize emotions from new images. Confusion matrices will be used to visualize which emotions are most often confused with each other, and precision-recall curves will help us understand the model's effectiveness across different emotion categories.

5. Real-Time Testing

Finally, we'll test the model in a real-world scenario by feeding it video input and observing how well it can detect emotions in real-time. This will show us whether the model can be practically applied in settings where live emotion recognition is needed.

Expected Outcomes

- Accurately recognize emotions from facial expressions and classify them into one of seven categories.
- Be used in practical applications, such as improving human-computer interaction, analyzing customer sentiment, and enhancing public safety through emotion detection.

- This project will contribute to creating a reliable system for emotion recognition, which has the potential to bring significant benefits to industries ranging from customer service to healthcare.