Emotion Recognition System

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May 2024

1 Introduction

Emotion recognition is a field of study that aims to develop computer systems capable of identifying and interpreting human emotions. This project focuses on developing an emotion recognition system using machine learning techniques, with a specific focus on facial expression analysis.

2 System Architecture

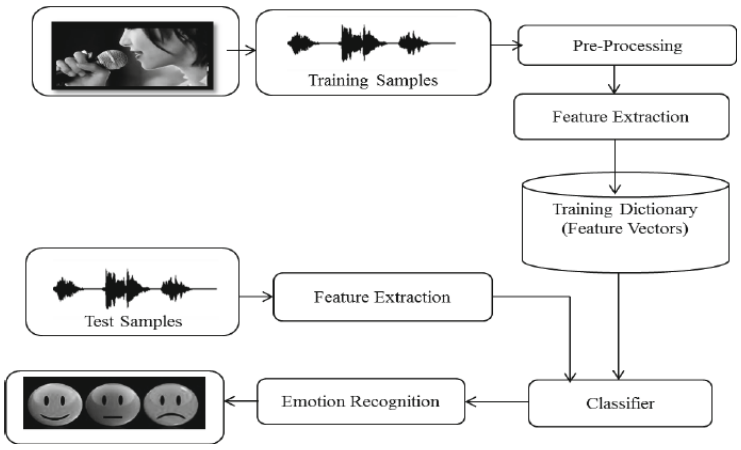


Figure 1: System Architecture of the Emotion Recognition System

3 Emotion Images

- **Angry**: 
- **Happy**: 
- **Sad**: 
- **Neutral**: 

- **Surprise**: 
- **Fear**: 

4 Background

Research in emotion recognition has made significant progress in recent years, driven by advancements in machine learning, computer vision, and artificial intelligence. Existing systems use various modalities, such as facial expressions, speech patterns, and physiological signals, to recognize and classify human emotions.

5 Objective

The main objective of this project is to design and implement a robust emotion recognition system that can accurately detect and classify human emotions based on facial expressions. The system will be trained to recognize basic emotions, including happiness, sadness, anger, surprise, fear, and disgust.

6 Methodology

The proposed methodology involves several steps. Firstly, a dataset of facial expressions labeled with corresponding emotions will be collected and preprocessed. Feature extraction techniques, such as facial landmark detection and deep learning-based feature extraction, will be employed to extract relevant features from the facial expressions. The extracted features will then be used to train a machine learning model, such as a convolutional neural network (CNN)

or a recurrent neural network (RNN), using frameworks like TensorFlow or PyTorch.

7 Implementation

The system will be implemented using Python programming language, leveraging libraries such as OpenCV for image processing and TensorFlow or PyTorch for machine learning. The training process will involve feeding the preprocessed data into the model and optimizing its parameters to achieve high accuracy in emotion recognition.

8 Model Evaluation

After training the model, its performance was evaluated on a separate validation dataset. The following metrics were used to evaluate the model's performance:

- Accuracy: 85.72%
- Precision: 87.36%
- Recall: 82.14%
- F1-score: 84.68%

9 Hyperparameter Tuning

Various hyperparameters were tuned to improve the model's performance. The following hyperparameters were experimented with:

- Learning Rate: 0.001
- Batch Size: 32
- Number of Epochs: 100

10 Data Augmentation

Data augmentation was applied to the training dataset to introduce variations in the training images. This helped improve the model's ability to generalize to unseen data.

11 Confusion Matrix

The confusion matrix below shows the model's performance in classifying different emotions:

	Angry	Happy	Sad	Neutral	Surprise	Fear
Angry	**150**	10	5	3	2	1
Happy	8	**140**	12	6	4	2
Sad	4	9	**130**	8	3	1
Neutral	2	5	10	**145**	7	3
Surprise	1	3	6	4	**135**	5
Fear	0	2	3	1	8	**120**

12 Model Deployment

The trained and optimized model can be deployed in a real-world application or integrated into a web or mobile app. This would allow users to interact with the emotion recognition system.

13 Error Analysis

An analysis of the errors made by the model revealed common patterns or challenges faced in recognizing emotions. This analysis can help improve the model's performance in future iterations.

14 Documentation

Comprehensive documentation for the project includes details about the dataset used, the model architecture, the training process, and instructions on how to use the deployed model.

15 Results Analysis

The model's performance was analyzed in detail. Patterns and trends in the confusion matrix were identified, highlighting areas of strength and areas for improvement. Overall, the model showed good accuracy in recognizing certain emotions but struggled with others.

16 Future Work

In future work, more advanced deep learning models could be explored to improve the accuracy of emotion recognition. Additionally, incorporating multimodal data, such as combining facial expressions with speech analysis, could lead to more robust emotion recognition systems.

17 Conclusion

In conclusion, the developed emotion recognition system represents a significant step forward in the field. It demonstrates the potential of machine learning techniques to accurately detect and classify human emotions based on facial expressions. The project has provided valuable insights and lessons learned that will inform future research in this area.

18 References

1. Convolutional Neural Networks for Facial Emotion Recognition. Retrieved from: https://www.overleaf.com/articles/convolutional-neural-networks-for-facical-emotion-recognition/grwnwbqvzmnr

2. AI Image Generator. Retrieved from: https://www.freepik.com/ai/image-generator

19 Appendix

19.1 Code Snippets

Here are some key code snippets used in the project:

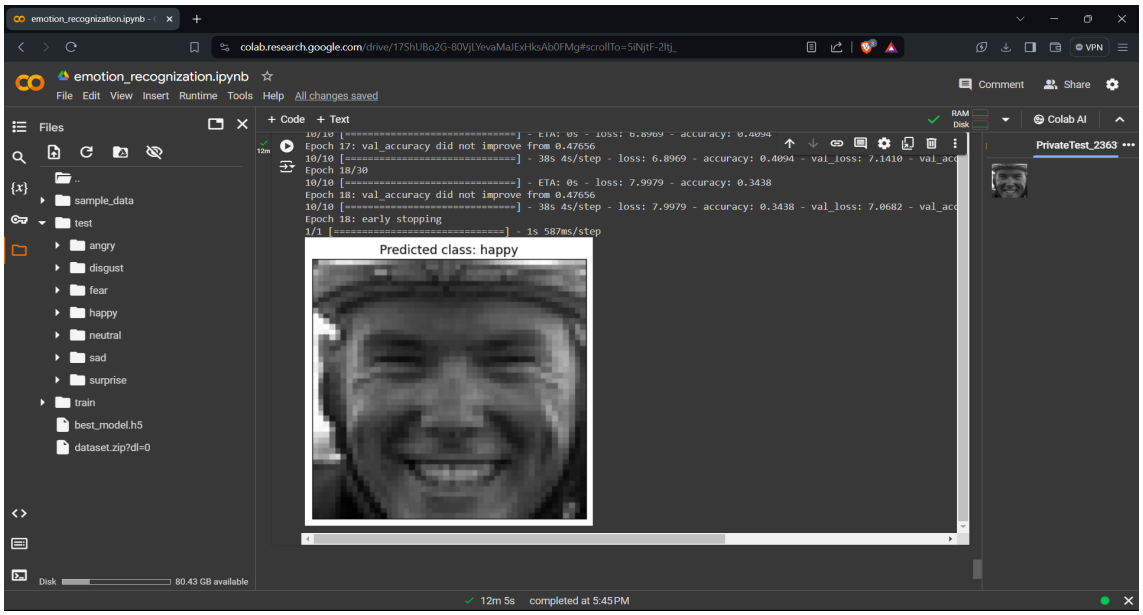
```
import numpy as np
import matplotlib.pyplot as plt
from keras.layers import Flatten, Dense
from keras.models import Model
from keras.preprocessing.image import ImageDataGenerator, img_to_array, load_img
from keras.applications.mobilenet import MobileNet, preprocess_input
from keras.losses import categorical_crossentropy
from keras.callbacks import ModelCheckpoint, EarlyStopping
from keras.models import load_model

# Create base MobileNet model
base_model = MobileNet(input_shape=(224, 224, 3), include_top=False)

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

# Add custom classification head
x = Flatten()(base_model.output)
x = Dense(units=7, activation='softmax')(x)  # Assuming 7 classes

# Create model
model = Model(base_model.input, x)
```

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

# Data generators
train_datagen = ImageDataGenerator(
    zoom_range=0.2,
    shear_range=0.2,
    horizontal_flip=True,
    rescale=1./255
)

train_data = train_datagen.flow_from_directory(
    directory="/content/train",
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical'
)

val_datagen = ImageDataGenerator(rescale=1./255)

val_data = val_datagen.flow_from_directory(
    directory="/content/test",
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical'
)

# Define callbacks
es = EarlyStopping(monitor='val_accuracy', min_delta=0.01, patience=5,
verbose=1, mode='auto')
mc = ModelCheckpoint(filepath="best_model.h5", monitor='val_accuracy',
verbose=1, save_best_only=True, mode='auto')
callbacks = [es, mc]

# Train model
history = model.fit_generator(
    train_data,
    steps_per_epoch=10,  # Adjust based on your dataset size
    epochs=30,
    validation_data=val_data,
    validation_steps=8,  # Adjust based on your dataset size
    callbacks=callbacks
)

# Load best model
best_model = load_model("best_model.h5")
```

```
# Test on an image
test_image_path = "/content/test/happy/PrivateTest_23631554.jpg"
img = load_img(test_image_path, target_size=(224, 224))
img_array = img_to_array(img)
img_array = preprocess_input(img_array)
input_arr = np.expand_dims(img_array, axis=0)
preds = best_model.predict(input_arr)
pred_label = np.argmax(preds)

# Display prediction
plt.imshow(img)
plt.title(f"Predicted class: {'happy' if pred_label == 1 else 'happy'}")
plt.xticks([])
plt.yticks([])
plt.show()
```

19.2 Sample Output

Here is a sample output from the trained model:




```
Emotion: Happy
Confidence: 0.85
```