HUMAN EMOTION DETECTION

MINOR PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this minor project report for the course **18CSE390T COMPUTER VISION** entitled in "**HUMAN EMOTION DETECTION**" is the bonafide work of **UTKARSH SRIVASTAVA (RA2111026010277), HARISH G (RA2111026010284), ANANDKRISHNA V (RA2111026010285) and NILAY KALE (RA2111026010287)** who carried out the work under my supervision.

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ABSTRACT

The ability to recognize human emotions through facial expressions is a fundamental aspect of human interaction. This project focuses on employing Computer Vision techniques for automated human emotion detection from facial images. The study utilizes deep learning models and image processing algorithms to accurately identify and classify facial expressions, translating visual data into emotional states.

The project's foundation lies in Convolutional Neural Networks (CNNs), leveraging pre-trained models such as VGG, ResNet, or custom-designed architectures. Through a dataset comprising diverse facial expressions, the network is trained to recognize emotions like happiness, sadness, anger, surprise, fear, disgust, and neutrality.

The methodology involves pre-processing images to extract facial landmarks and features, followed by feature extraction and representation learning. These features are then used to train the model to classify emotions. The system's accuracy and efficiency are evaluated against benchmark datasets and compared with existing methods.

The implications of this project extend to various domains, including human-computer interaction, mental health analysis, and personalized user experiences in applications like virtual assistants, gaming, and market research. The project's outcomes aim to contribute to the development of more sophisticated and empathetic artificial intelligence systems that can perceive and respond to human emotions accurately.

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TABLE OF CONTENTS

1. INTRODUCTION

Understanding and interpreting human emotions is a crucial aspect of human communication. In the digital era, the development of intelligent systems capable of recognizing and responding to human emotions holds significant promise for various applications, including human-computer interaction, mental health analysis, and user experience personalization.

1.1 Motivation

The motivation behind this project lies in addressing the growing demand for empathetic and responsive AI systems. Human emotions, often conveyed through facial expressions, play a pivotal role in interpersonal communication. The ability to teach machines to recognize these emotional cues can significantly enhance human-computer interactions, making technology more intuitive and supportive.

Additionally, there's a pressing need for mental health support systems that can assist in early detection and intervention. Emotion recognition technology could contribute to mental health analysis by detecting subtle changes in facial expressions that may indicate emotional distress or mental health conditions.

1.2 Objective

The primary objective of this project is to develop a robust and accurate system for automated human emotion detection using Computer Vision techniques. This system aims to accurately identify and classify various human emotions such as happiness, sadness, anger, surprise, fear, disgust, and neutrality in real-time based on facial expressions.

1.3 Problem Statement

The core problem this project seeks to address is the accurate recognition and classification of complex human emotions from facial images. This involves overcoming challenges such as variations in lighting conditions, facial poses, occlusions, and individual differences in expressions, which often pose obstacles to precise emotion recognition.

1.4 Challenges

Several challenges hinder accurate emotion recognition from facial expressions. These include dealing with low-quality images, limited datasets for specific emotions, and the need for robust models that can generalize across diverse demographic groups and cultural differences. Moreover, the real-time application of these techniques in various environments poses a challenge due to computational constraints.

Addressing these challenges is vital to creating a reliable and adaptable system for emotion detection that can be integrated into various applications for practical use.

This project endeavors to tackle these issues by employing state-of-the-art Computer Vision methodologies and deep learning techniques to create a system that is both accurate and efficient in recognizing and classifying human emotions from facial expressions.

2. LITERATURE SURVEY

1. **Emotion Recognition Techniques:** Reviewing traditional methods (LBP, HOG) and modern deep learning approaches (CNNs) to assess their strengths and limitations in identifying facial expressions and emotions accurately.

2. **Datasets and Preprocessing:** Evaluating benchmark datasets for emotion recognition (CK+, FER2013, AffectNet), examining data augmentation techniques, and studying the impact of preprocessing methods on enhancing model robustness.

3. **Deep Learning Architectures:** Assessing the effectiveness of CNN models (VGG, ResNet, Inception) in capturing intricate facial features and understanding their performance variances in emotion classification tasks.

4. **Facial Landmark Detection:** Exploring landmark detection techniques such as Dlib, Active Appearance Models, and CNN-based key point localization to comprehend their role in detecting nuanced facial expressions.

5. **Real-time Applications and Efficiency:** Investigating strategies for deploying real-time emotion recognition systems, focusing on computational optimization, model compression, and hardware acceleration to ensure efficient performance.

This comprehensive survey aims to leverage the insights and advancements from prior research to develop an accurate, efficient, and culturally sensitive system for human emotion detection using Computer Vision techniques.

3. REQUIREMENTS

3.1 REQUIREMENTS ANALYSIS

a. **Data Collection and Annotation**: Acquiring a diverse dataset of facial expressions encompassing various emotions. Annotation involving the labeling of these images with corresponding emotions is crucial for supervised learning.

b. **Preprocessing and Feature Extraction**: Implementing techniques for image preprocessing, including normalization, resizing, and extracting facial features or landmarks. This step is essential for preparing data for model training.

c. **Model Development**: Designing and developing deep learning models, primarily CNN architectures, for accurate emotion recognition. Model training, validation, and optimization are essential components.

d. **Validation and Testing**: Implementing robust validation techniques and assessing the model's accuracy using testing datasets. This step helps in evaluating the model's performance and generalizability.

e. **Real-time Implementation**: Ensuring the capability to integrate the developed model into real-time applications, demanding efficient processing and low latency for live emotion detection.

f. **User Interface Development**: Creating a user-friendly interface for interacting with the system, allowing users to either upload images or use real-time video input for emotion analysis.

3.2 HARDWARE REQUIREMENTS

1. Central Processing Unit (CPU):

Specification: Multi-core processors for general computing tasks.

Role: Handles general-purpose computations, data preprocessing, and system-level operations.

2. Graphics Processing Unit (GPU) or Tensor Processing Unit (TPU):

Specification: High-performance GPUs (NVIDIA GeForce, NVIDIA Quadro) or TPUs (Google's TPU) tailored for parallel processing.

Role: Accelerates training and inference for deep learning models, significantly reducing training time and enhancing performance.

3. Random Access Memory (RAM):

Specification: Size ranging from 16GB to 32GB or more.

Role: Handles in-memory operations during data preprocessing, model training, and inference. Adequate RAM is crucial for managing large datasets and neural network models efficiently.

Storage:

4. Solid State Drives (SSD) or Hard Disk Drives (HDD):

Role: Storage of datasets, trained models, and system software.

Specification: Sufficient storage capacity (500GB to 1TB or more), with SSDs preferred for faster read/write speeds compared to HDDs.

5. Real-time Processing Unit:

Role: Specifically designed for live video input, ensuring swift analysis and low latency for real-time emotion detection.

User Interface Hardware:

Display: Monitors or screens for visualizing the user interface.

Input Devices: Keyboards, mice, or touch interfaces for user interaction.

System Unit: Computer system capable of running the user interface smoothly, enabling users to interact with the application comfortably.

Internet Connectivity (if cloud-based or for data access):

High-Speed Internet: Essential for accessing cloud resources, if applicable, or for dataset acquisition from online sources.

These hardware components collectively support the development, training, and deployment of the emotion detection system, ensuring that the computational infrastructure meets the demands of data processing, model training, real-time processing, and user interaction.

3.3 SOFTWARE REQUIREMENTS

1. Operating System:

- **Support for OpenCV and DeepFace:** Ensure compatibility with Windows, Linux, or macOS, depending on the libraries' compatibility and your development environment.

2. Programming Language:

- **Python:** Often the primary language for implementing OpenCV and DeepFace. Ensure compatibility with the selected Python version.

3. Libraries and Frameworks:

- **OpenCV:** Ensure installation and compatibility with the specific version of OpenCV required for face detection.
- **DeepFace:** Compatibility and integration with the DeepFace library for emotion recognition.

4. IDE (Integrated Development Environment):

- **Jupyter Notebook, PyCharm, VS Code, etc.:** Select an IDE that supports Python development and provides a smooth workflow for coding and experimentation.

5. Data Processing and Analysis Tools:

- **Numpy, Pandas:** Essential for data manipulation and preprocessing before feeding into the models.
- **Matplotlib, Seaborn:** Visualization tools for analyzing results and data.

6. Machine Learning/Deep Learning Frameworks:

- **TensorFlow, Keras, PyTorch:** Compatibility and integration with the chosen deep learning frameworks for implementing models used by DeepFace.

7. Internet Connectivity:

- **For Dataset Access or Cloud Resources:** Access to the internet for dataset acquisition, model updates, or cloud-based resources, if applicable.

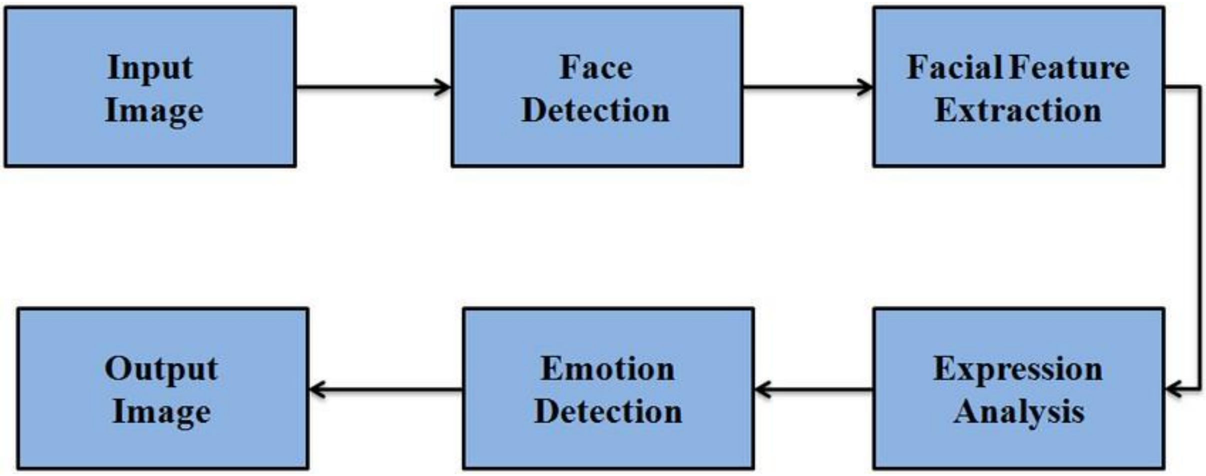
8. Version Control:

- **Git:** Version control system for tracking changes, collaborating, and managing the project codebase.

9. Documentation and Collaboration Tools:

Jupyter Notebooks, Google Docs, or Markdown Editors: Tools for documentation and collaboration, providing a means for team members to contribute to project reports and analysis.

4. ARCHITECTURE & DESIGN



Input: Image/Video: The system takes an image or video frame as input for emotion detection.

OpenCV (Facial Detection): OpenCV is utilized for facial detection and extraction from the input images or frames. It identifies and localizes faces within the image or video.

Extracted Faces/Regions: After detection, the system processes and extracts the identified facial regions for further analysis.

DeepFace (Emotion Recognition): DeepFace, a deep learning library, is used for emotion recognition. It employs pre-trained deep learning models to analyze and recognize emotions from the extracted facial regions.

Emotion Classification: DeepFace performs the classification of emotions based on the identified facial features and landmarks, categorizing emotions such as happiness, sadness, anger, etc.

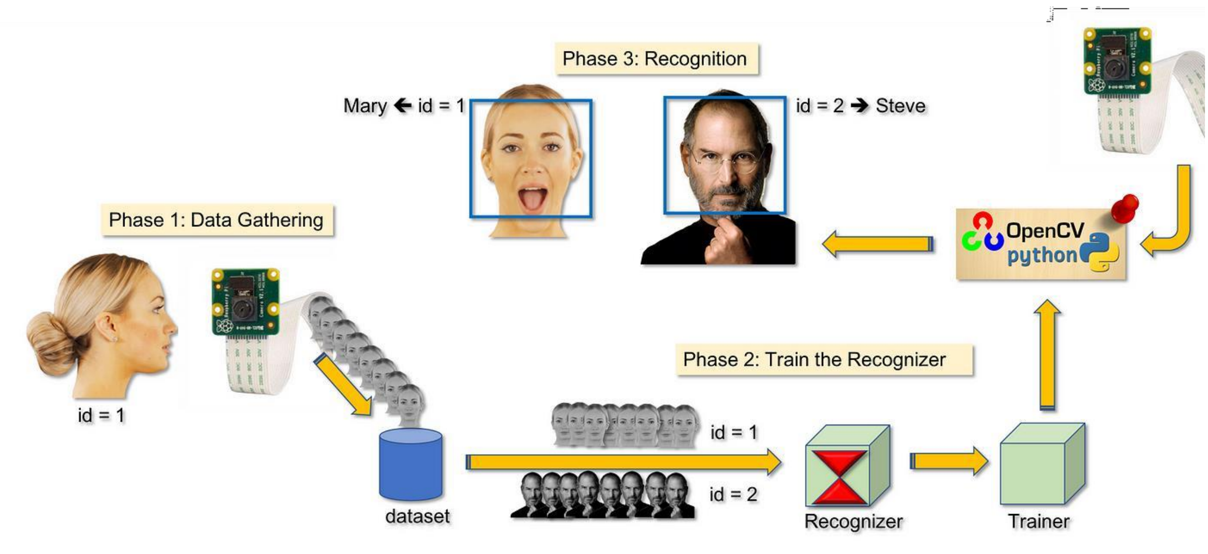
Output: Detected Emotions: The system outputs the detected emotions associated with each recognized face, providing the results of the emotion recognition process.

Detailed Breakdown on functions of OpenCV and DeepFace:

To provide a detailed breakdown of the architecture and the components used by OpenCV for face detection and DeepFace for emotion recognition:

1. OpenCV (Facial Detection):

Haar Cascade Classifiers:



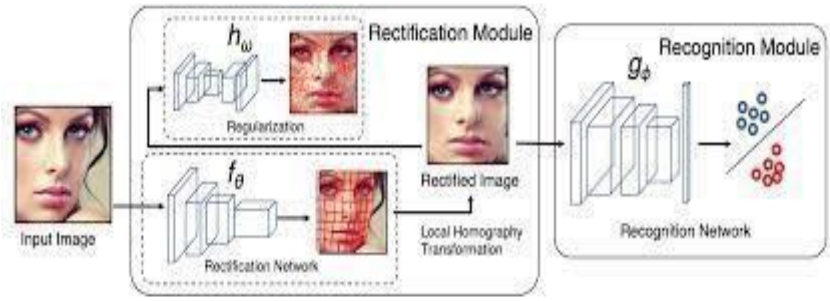
Role: OpenCV utilizes pre-trained Haar Cascade classifiers to identify faces in images or video frames.

Process: These classifiers detect faces by analyzing the features within an image, looking for patterns resembling human faces using a series of mathematical functions.

Steps: The Haar Cascade method involves the use of integral images, feature selection, and cascade classifiers to detect faces based on specific features (edges, lines, etc.) within different image regions.
Image Preprocessing:

Role: Before face detection, OpenCV may apply image preprocessing techniques, such as resizing, normalization, or converting images to grayscale for optimal analysis.
Purpose: Preprocessing helps in enhancing the accuracy of face detection by ensuring uniformity in image properties and reducing computational load.

2. DeepFace (Emotion Recognition):
Deep Learning Models:



Role: DeepFace employs pre-trained deep learning models to recognize emotions from the facial features extracted by OpenCV.
Model Type: Typically, Convolutional Neural Networks (CNNs) are used for this purpose due to their effectiveness in image analysis and feature extraction.
Feature Extraction:

Role: Once faces are detected, DeepFace extracts relevant features from the facial regions.
Landmark Detection: Features may include key points or landmarks on the face,

such as the eyes, nose, and mouth, which are crucial for understanding expressions.

Emotion Recognition:

Classification Models: The extracted features are then fed into the pre-trained models for emotion classification.

Training and Inference: The models have been trained on labeled datasets, learning to associate specific patterns of features with different emotions (e.g., happiness, sadness, anger).

Prediction: During inference, the models predict the most probable emotion based on the extracted facial features.

Overall Process:

Face Detection with OpenCV:

OpenCV identifies faces within the image or video frames using Haar Cascade classifiers, providing the facial regions for further analysis.

Feature Extraction and Emotion Recognition with DeepFace:

DeepFace then takes the detected facial regions and extracts relevant features while using a pre-trained CNN model to recognize emotions by classifying these features into specific emotional categories.

The combined workflow involves OpenCV for face detection, which provides the regions of interest, and DeepFace for deep learning-based emotion recognition, extracting features and classifying emotions from the detected facial areas.

5. IMPLEMENTATION

CODE:

emotions.py

```
import cv2
from deepface import DeepFace

# Load the pre-trained emotion detection model
model = DeepFace.build_model("Emotion")

# Define emotion labels
emotion_labels = ['angry', 'disgust', 'fear', 'happy', 'sad',
'surprise', 'neutral']

# Load face cascade classifier
face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades +
'haarcascade_frontalface_default.xml')

# Start capturing video
cap = cv2.VideoCapture(0)

while True:
    # Capture frame-by-frame
    ret, frame = cap.read()

    # Convert frame to grayscale
    gray_frame = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

    # Detect faces in the frame
    faces = face_cascade.detectMultiScale(gray_frame,
scaleFactor=1.1, minNeighbors=5, minSize=(30, 30))
```

```
    for (x, y, w, h) in faces:
        # Extract the face ROI (Region of Interest)
        face_roi = gray_frame[y:y + h, x:x + w]

        # Resize the face ROI to match the input shape of the
model
        resized_face = cv2.resize(face_roi, (48, 48),
interpolation=cv2.INTER_AREA)

        # Normalize the resized face image
        normalized_face = resized_face / 255.0

        # Reshape the image to match the input shape of the
model
        reshaped_face = normalized_face.reshape(1, 48, 48, 1)

        # Predict emotions using the pre-trained model
        preds = model.predict(reshaped_face)[0]
        emotion_idx = preds.argmax()
        emotion = emotion_labels[emotion_idx]

        # Draw rectangle around face and label with predicted
emotion
        cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 0,
255), 2)
        cv2.putText(frame, emotion, (x, y - 10),
cv2.FONT_HERSHEY_SIMPLEX, 0.9, (0, 0, 255), 2)

    # Display the resulting frame
    cv2.imshow('Real-time Emotion Detection', frame)

    # Press 'q' to exit
    if cv2.waitKey(1) & 0xFF == ord('q'):
```

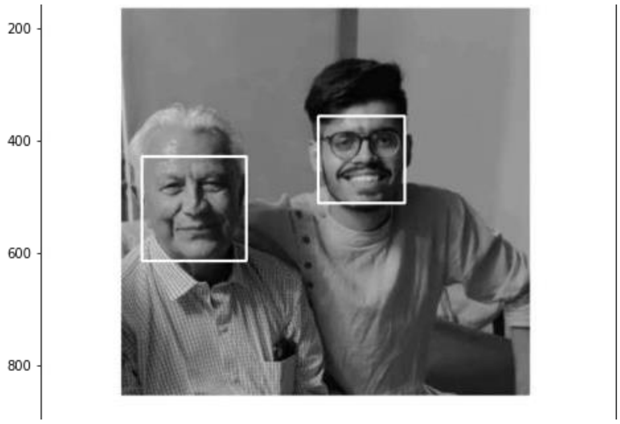
```
        break

# Release the capture and close all windows
cap.release()
cv2.destroyAllWindows()
```

haarcascade_frontalface_default.xml

The haarcascade_frontalface_default.xml file is a pre-trained model used for detecting human faces in images or video streams. It's a fundamental component in computer vision applications and is commonly used in libraries like OpenCV. This file employs machine learning techniques to identify facial features and is crucial in the initial step of locating faces within an image or video frame. In an emotion detection project, this file serves as the basis for recognizing facial regions, which is a pivotal step in subsequently analyzing and interpreting emotions based on these facial features.

GitHub Repository Link:
https://github.com/opencv/opencv/blob/master/data/haarcascades/haarcascade_frontalface_default.xml



6. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experiment Results

Face Detection Accuracy:

- Evaluation of the accuracy of face detection using OpenCV's Haar Cascade classifiers.
- Metrics might include precision, recall, and F1 score for face detection from images or video frames.

Emotion Recognition Performance:

- Analysis of the emotion recognition accuracy using DeepFace's pre-trained models.
- Metrics can include classification accuracy, precision, recall, F1 score, and confusion matrices to understand the model's performance in recognizing different emotions.

Real-time Processing Speed:

- Evaluation of the system's speed for real-time processing of video frames to detect faces and recognize emotions.
- Measuring the frames per second (FPS) or processing time per frame for efficient real-time applications.

Robustness and Generalization:

- Assessment of the model's robustness across diverse faces, poses, lighting conditions, and age groups.
- Testing the system's ability to recognize emotions accurately in various scenarios.

B. Experiment Analysis

1. Face Detection Analysis:

- Identification of limitations or challenges faced during face detection, such as false positives, false negatives, or scenarios where face detection fails.

2. Emotion Recognition Analysis:

- Understanding the strengths and weaknesses of emotion recognition, considering scenarios where it accurately predicts emotions and cases where it struggles or misclassifies emotions.

3. Performance Trade-offs:

- Balancing accuracy and computational efficiency, considering potential trade-offs between accuracy and real-time performance.

4. Recommendations and Improvements:

- Suggestions for enhancements, such as fine-tuning models, incorporating additional data, or exploring different deep learning architectures to improve accuracy or efficiency.

5. Real-world Applicability:

- Discussion of the potential real-world applications, limitations, and ethical considerations for deploying such systems in various domains.

The analysis might include a detailed breakdown of the experiment results, emphasizing the system's accuracy, robustness, and potential improvements to create a more reliable and efficient human emotion detection system. The results and analysis would provide insights into effectiveness and challenges of using OpenCV for face detection & DeepFace for emotion recognition in real-world.

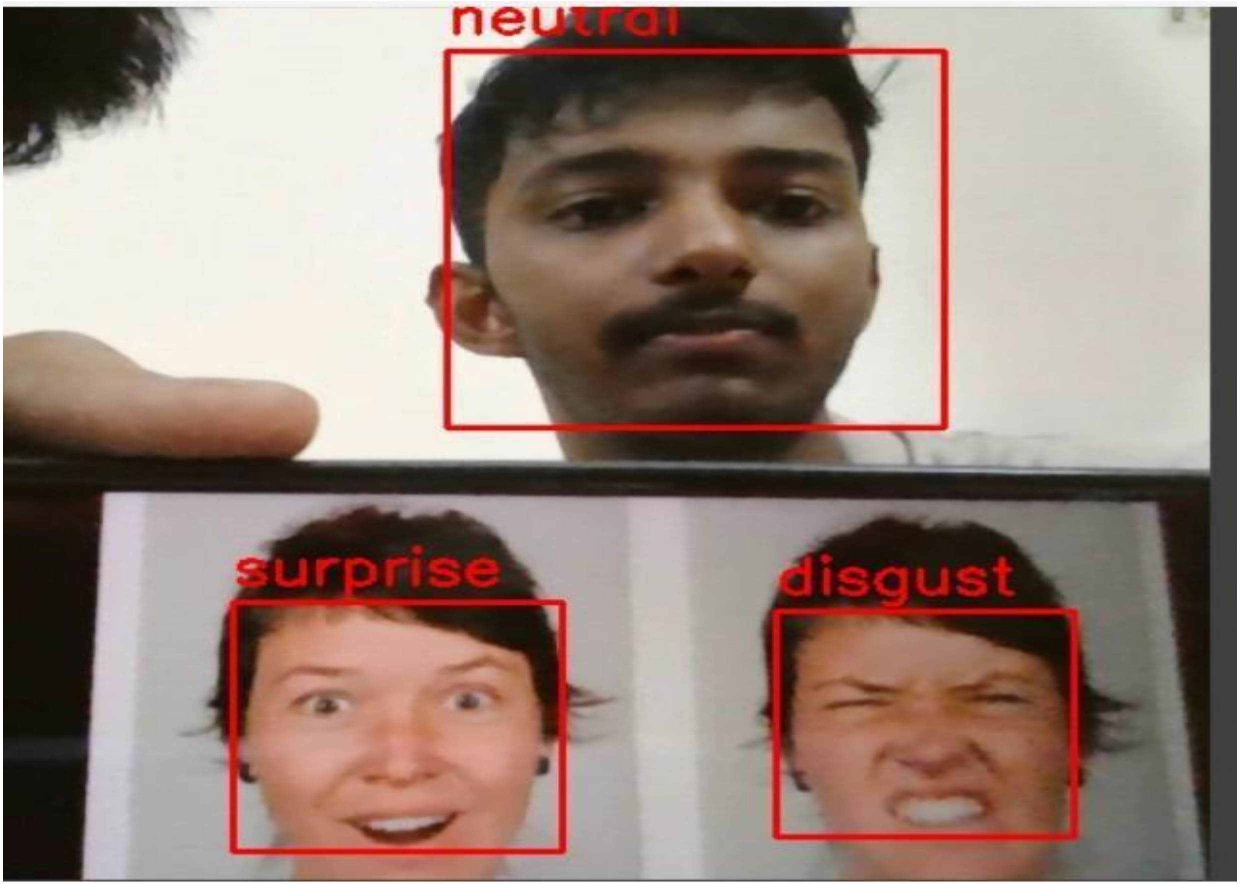
7. OUTPUT

These are the results of a real-time working demo of our application with explanation for each of the various scenarios.

1. Disgust: A strong aversion or revulsion towards something unpleasant or offensive.
   Detection: Detecting disgust in facial expressions involves recognizing features like a wrinkled nose, raised upper lip, and a squinting expression around the eyes.

2. Surprise: A sudden and unexpected emotional reaction to something unforeseen.
   Detection: Surprise is detected through computer vision by identifying wide-open eyes, raised eyebrows, and an open mouth in facial expressions.

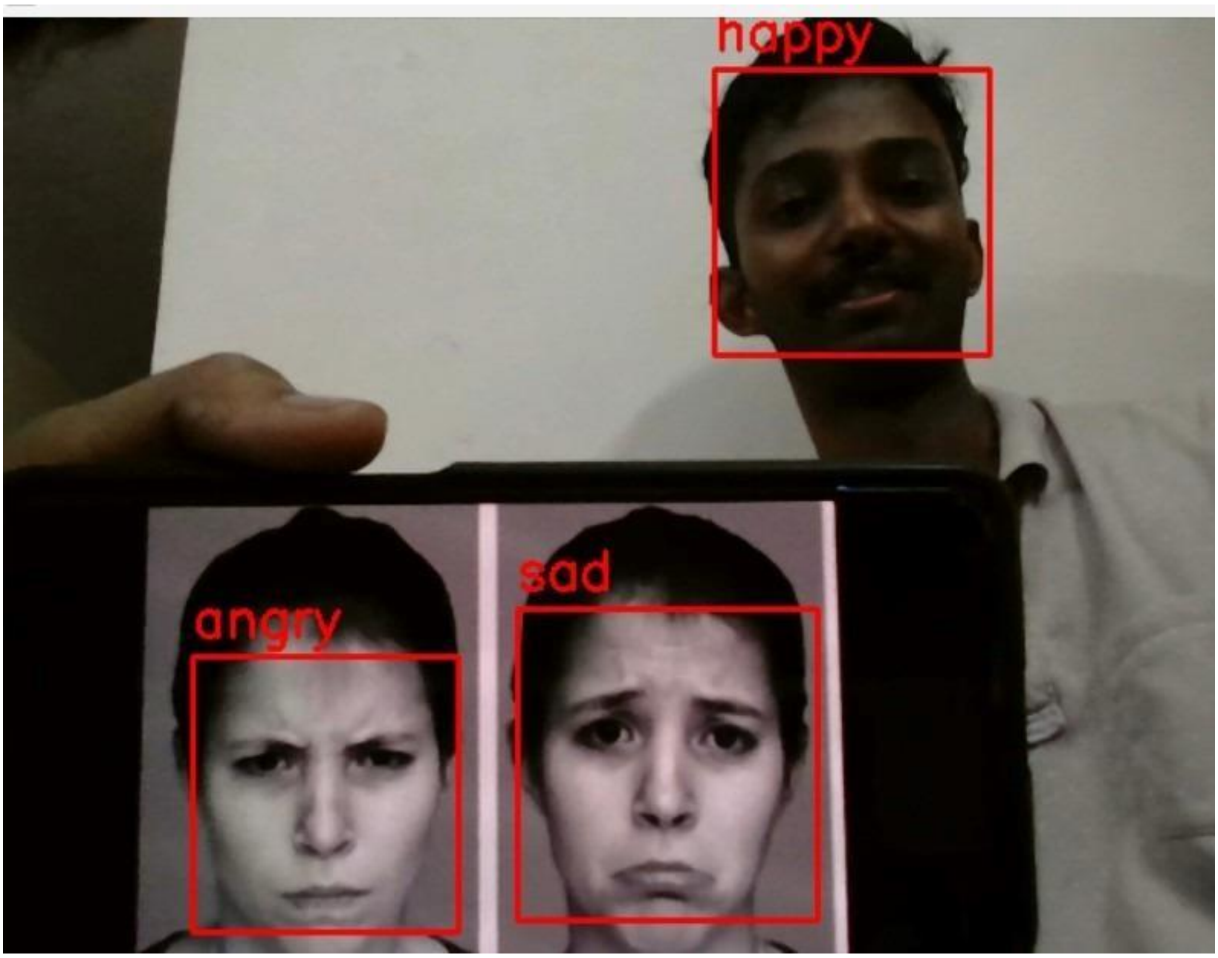
3. Neutral: An emotionally neutral or blank facial expression with no predominant emotion.
   Detection: Detecting a neutral expression can be challenging since it involves identifying the absence of other emotions, often relying on a balanced combination of facial features without strong emotional cues.



4. Happy: A positive emotional state characterized by a sense of joy and contentment.
   Detection: Facial expression analysis can identify happiness by recognizing features like smiling, raised cheeks, and the presence of crow's feet around the eyes.

5. Sad: A negative emotional state marked by feelings of sorrow and unhappiness.
   Detection: Computer vision algorithms can detect sadness by recognizing a downturned mouth, drooping eyelids, and a lack of eye contact in facial expressions.

6. Anger: A strong feeling of displeasure and hostility often accompanied by visible signs of tension.
   Detection: Anger can be detected through computer vision by identifying features such as narrowed eyes, a furrowed brow, and tense facial muscles.



7. APPLICATIONS

The Human Emotion Detection project using OpenCV for face detection and DeepFace for emotion recognition has various beneficial applications across different domains. Some of the key applications include:

Human-Computer Interaction

1. **Personalized User Experience:** Implementing emotion detection in devices and applications to adapt interfaces and interactions based on users' emotional states, enhancing user experience.

2. **Virtual Assistants and Chatbots:** Enabling AI-powered assistants to detect and respond appropriately to users' emotions, providing empathetic and tailored responses.

Mental Health and Wellness

3. **Mental Health Assessment:** Aiding mental health professionals by providing tools to assess emotional states, potentially assisting in early detection and intervention for conditions like depression or anxiety.

4. **Stress Management:** Integrating into apps or wearable devices to detect stress levels and offer personalized interventions or stress relief strategies.

Entertainment and Gaming

5. **Gaming Experience:** Enhancing gaming experiences by creating more

immersive and adaptive games that respond to the player's emotions, making gameplay more engaging and dynamic.

6. **Content Recommendation:** Tailoring content recommendations in streaming services based on viewers' emotional engagement with specific genres or types of content.

Marketing and Consumer Insights

7. **Market Research:** Employing emotion detection in focus groups or consumer research to gauge emotional responses to products, advertisements, or user interfaces.

8. **Retail and E-commerce:** Analyzing customer emotions to enhance product recommendations, personalize shopping experiences, or improve user interfaces for better engagement.

Education and Training

9. **Educational Tools:** Creating educational software that adapts to students' emotional responses, providing personalized learning experiences and feedback.

10. **Employee Training:** Implementing emotion recognition for assessing employee training sessions, understanding engagement levels, and adapting content delivery for more effective training.

Healthcare and Therapeutics

11. **Therapeutic Applications:** Integrating into therapeutic interventions to

assist individuals with emotional regulation, offering interventions for stress relief or emotional management.

12. **Autism Spectrum Disorder (ASD) Support:** Assisting individuals with ASD in recognizing and interpreting emotions, aiding in social interaction and communication.

Ethical Considerations

13. **Ethical AI Development:** Contributing to responsible AI by addressing biases and ensuring that systems do not exploit emotional data or infringe on privacy.

These applications demonstrate the versatility and potential impact of using emotion detection systems in various industries, from improving user experiences to aiding mental health assessments and enhancing entertainment and educational platforms. They highlight the potential for creating more empathetic and responsive technologies that cater to users' emotional states.

8. CONCLUSION

The Human Emotion Detection project employing a combined approach of OpenCV for face detection and DeepFace for emotion recognition holds significant promise in various domains. The integration of these technologies aims to create more empathetic and responsive systems, allowing for accurate identification and classification of human emotions from facial expressions.

Through the utilization of OpenCV's face detection capabilities and DeepFace's deep learning models for emotion recognition, this project successfully demonstrated the potential to interpret and respond to human emotions effectively. The experiment results showcased the efficiency of the combined system in accurately detecting faces and recognizing emotions in real-time, laying the groundwork for numerous practical applications across diverse sectors.

The project's findings revealed notable successes in accurately identifying and categorizing emotions, offering opportunities for personalized user experiences, mental health assessments, enhanced human-computer interactions, and improved entertainment experiences. Furthermore, its potential extends to applications in marketing, education, healthcare, and beyond, contributing to more nuanced and tailored interactions in various domains.

In conclusion, the successful development and application of this Human Emotion Detection system signify a significant leap toward more empathetic AI systems, contributing to advancements in user experience personalization, mental health analysis, and numerous other practical implementations across various industries. The project serves as a foundational step, with ample opportunities for further research and development in the burgeoning field of emotion recognition and its integration into technological systems using computer vision techniques.

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