Facial Emotion Detection

A Real-Time Research Project Report

Submitted to

Jawaharlal Nehru Technological University

Hyderabad

In partial fulfillment of the requirements for the

award of the degree of

BACHELOR OF TECHNOLOGY

in

ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

By

B.Rachana (23VE1A6609)

T.Siri (23VE1A6650)

U.Ramya Sri (23VE1A6654)

V.Anshu Sri (23VE1A6655)

Under the Guidance of

Mrs.D.Nagasri

Assistant Professor

SREYAS
INSTITUTE OF ENGINEERING AND TECHNOLOGY
AUTONOMOUS

DEPARTMENT OF CSE (ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

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Certificate

This is to certify that the Real-Time Research Project Report on ***"Facial Emotion Detection"*** submitted by **B.Rachana, T.Siri, U.Ramya Sri, V.Anshu Sri** bearing Hall Ticket No's.**23VE1A6609, 23VE1A6650, 23VE1A6654, 23VE1A6655** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Artificial Intelligence & Machine Learning** from Jawaharlal Nehru Technological University, Kukatpally, Hyderabad for the academic year 2023-24 is a record of bonafide work carried out by him / her under our guidance and Supervision.

Internal Guide	**Head of the Department**
Mrs.D.Nagasri	**Dr. A. Swathi**
Asst. Professor	

Project Coordinator	**Signature of the External Examiner**

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DECLARATION

We **B.Rachana, T.Siri, U.Ramya Sri, V.Anshu Sri**, bearing Roll No's **23VE1A6609, 23VE1A6650, 23VE1A6654, 23VE1A6655** hereby declare that the Project titled "***Facial Emotion Detection***" done by us under the guidance of **Mrs.D.Nagasri**, which is submitted in the partial fulfillment of the requirement for the award of the B.Tech degree in **Artificial Intelligence & Machine Learning** at **Sreyas Institute of Engineering & Technology** for Jawaharlal Nehru Technological University, Hyderabad is our original work.

B.Rachana	**23VE1A6609**
T.Siri	**23VE1A6650**
U.Ramya Sri	**23VE1A6654**
V.Anshu Sri	**23VE1A6655**

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B.Rachana 23VE1A6609

T.Siri 23VE1A6650

U.Ramya Sri 23VE1A6654

V.Anshu Sri 23VE1A6655

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ABSTRACT:

A smart system that uses artificial intelligence and computer vision to recognize human emotions just by analyzing facial expressions. We also employ a tool known as DeepFace to enable more accurate face recognition. We save time and resources by using pre-trained models on large datasets, yet still achieve a good outcome. The system is also made to perform effectively even in real-time, to analyze facial emotions from video or camera feed in an instant. To increase the reliability of the system, we incorporate deep learning with other methods such as facial landmark detection. The landmarks are special points on the face, which guide the system in understanding facial expressions in better way. Particularly when faces are not fully visible or are partially hidden. This is when we are detecting emotions on individuals wearing glasses or masks. The program is developed using software such as OpenCV for image processing and TensorFlow/Keras for deep learning. It can run on both computers and smartphones, so it is versatile enough to suit various kinds of users. We also make a minimalistic interface so users can quickly identify the emotions recognized in real-time. Some potential applications of this system are monitoring mental health, enhancing online education through monitoring of student emotions, or assisting visually impaired individuals to interpret the emotions of individuals around them. We benchmark the system against various emotion databases and test its accuracy and speed. The experiments prove that the system performs very well, even in challenging scenarios such as lighting, or variations in facial positions. We also ensure that it is relatively unbiased against various ages, genders, and cultures. In short, this project demonstrates how contemporary AI can be employed to recognize human emotions quickly and precisely. The system is intended to be practical, dependable, and simple to use in real-world scenarios. It takes us one step closer to more intelligent and human-like computers that can comprehend and react to the way we feel.

Key words: Convolutional Neural Networks , Real-time Analysis, Human-Computer Interactions, Pre-trained Models, Facial Expressions

CHAPTER 1

INTRODUCTION

It is crucial to understand human emotions when it comes to enhancing the way we interact with technology. Emotions inform us about how a person feels—whether they are happy, sad, angry, surprised, afraid, or disgusted. Facial expressions are one of the most natural forms of expressing emotions, and with the technology we have today, computers can also learn to identify these expressions. All this is possible due to artificial intelligence (AI) and deep learning. Computers can now "read" faces and interpret emotions. Facial emotion detection is the term used for this. It enables machines to know people better and respond more like humans. Facial emotion detection is already being utilized in various fields, like education, healthcare, marketing, and security.The manner in which humans convey emotions with their face is the same in most places on earth, and therefore the facial expressions are an international way to interpret the feelings. For instance, a smile indicates happiness, and frowning may indicate sadness or anger. Scientists and engineers have thus developed computer systems that can learn to identify these expressions and equate them with the appropriate emotions.Early systems employed basic image processing methods, but today we employ something known as deep learning—a form of AI that can learn automatically from patterns in data, such as how a particular expression appears. These systems are far more accurate and quicker at detecting emotions. One significant form of deep learning model employed is known as Convolutional Neural Network (CNN). It works by examining small sections of a face and learning what shapes or patterns correspond to each emotion.In recent times, there been significant work in developing real-time emotion detection system. These can be used with a webcam or camera, and provide results on the spot. This is quite useful in actual application. Suppose a student feels bored in an online class, the system will notify the instructor. If a customer appears frustrated while operating a product, the company can easily enhance their experience.Training these emotion detection systems is achieved through large datasets—collections of thousands of images or videos of individuals exhibiting various emotions. These datasets consist of individuals from various countries, skin colors, ages, and genders so the system can learn to detect emotions in a balanced and unbiased manner. Also, to make things quicker, developers tend to employ pretrained models, i.e., models that someone else trained in the past and then fine-tuned for certain tasks such as emotion recognition.With tools such as OpenCV, TensorFlow, and Keras, these systems are now easier and quicker to create. Ready-made models such as DeepFace are also available, which can identify faces and emotions with high accuracy. All these tools enable systems that can run on computers and mobile phones and are thus more accessible to the masses. Emotion detection has numerous useful applications. In medicine, it can monitor how patients feel and assist individuals with depression or anxiety. In education, it can assist teachers in knowing whether students are puzzled or not attending. In retail and marketing, it assists in comprehending how customers feel about a product. In security, it can assist in identifying abnormal behavior. These instances illustrate how useful emotion detection can be in daily life. But with this influential technology also come significant issues. Individuals are concerned about privacy—what happens to their facial information—and if these systems discriminate against all individuals equally. The developers now are working to make these systems more transparent(so individuals know how they function) and fair (so they don't discriminate on the basis of race, gender, or age). Open guidelines and ethical standards are being adhered to in order to keep individuals secure and uphold their rights. In a nutshell, emotion recognition through facial expressions is a rapidly emerging field of AI that is getting smarter, faster, and more accurate. It's no longer merely about face recognition—it's about sensing emotions and leveraging that to enhance human-computer interactions. From assisting physicians with patient care to enhancing virtual assistants, this tech can transform the lives and workplaces of everyone!Facial Emotion Detection is the powerful application of artificial intelligence and computer vision for identifying human emotions through facial expressions. This project use deep learning techniques, mainly convolutional neural networks (CNNs), in analyzing facial features and to classify emotions as happiness,sadness,anger,surprise,fear, or disgust. Facial expressions are very important in the communication of emotions, motivations, and intent. Thus, emotion detection is a very important area of research in AI. This project is used to recognize emotion using DeepFace,a Deep learning framework developed by Facebook. DeepFace uses convolutional neural networks (CNNs) to pull out facial features and classify emotions accurately. The system captures real-time video from a webcam, detects faces, and predicts emotions, displaying labels directly on the video frames. The methodology used involved pre-processing of images for uniform facial features and then feature extraction using DeepFace. Then it classified emotions within predefined categories. The model trained on large datasets of facial emotion ensured that high accuracy and robustness are exhibited in real-world applications. Facial emotion detection has a wide variety of applications. It is used for human-computer interaction, customer experience analysis, mental health monitoring, and security systems. By enabling machines to respond and recognize to human emotion, the project enhances user experience in all other various domains. Experimental results show that DeepFace is capable of distinguishing facial emotions with high precision, which makes it a very useful tool which work as real-time emotion analysis. This project demonstrates the potential of AI-driven emotion recognition in improving interactions between humans and technology.

Project Overview :

This project involves using AI and deep learning to recognize all the human emotions through facial expression. It employs deep learning software called DeepFace, which is created by Facebook. DeepFace applies a new type of model (CNNs) to scan the face, select pertinent features, and classify the emotion. The system extracts live video from a webcam, recognizes the face of the person, and prints the emotion onto screen in real time. The face images are first cleaned and standardized so that every image is of the same shape and size before emotion detection takes place. DeepFace then removes features from the face and compares them to an emotion category, such as happy,sad,angry,etc.The computer was also taught using a vast collection of face images that are already labeled as emotion, and therefore it already has an idea of how to identify patterns based on the look of various emotions. It's because of this that it works so well in everyday life and is able to determine how someone feels. These sorts of technologies have many uses. It will make machines better understand people and provide them with experiences that are more personal and meaningful—whether in school, hospitals, online shopping, or airport security.Facial emotion detection in DeepFace and CNNs proves to be swift, accurate, and useful with the project. It shows that AI can be used to create smarter systems that understand human feelings and make technology more human-focused. This project involves making an intelligent system that will be able to know a person's emotions just by observing their faces. It takes a live video through a webcam and then observes the facial expressions of the person to see how they feel—such as happy, sad, angry, or surprised. The system relies on a strong tool known as DeepFace coupled with artificial intelligence (AI) and deep learning to achieve this. One of the main advantages is that the system works in real time, meaning it can detect emotions as soon as someone shows them. It doesn’t take a long time to respond. It also uses models that were already trained using thousands of images, so it doesn’t need to learn from scratch. This saves both time and effort. Before the system verifies the emotion, it first cleans and adjusts the image-for example, by resizing the face and turning the picture into black and white. This makes the system remain as accurate as possible even when working with other people or under varied lighting conditions. The project is designed in such a way that it can easily be modified or upgraded in the future. Even, it is possible to merge it with other software like speech recognition. Furthermore, all the processing is done on the device of the user, so no information is transferred online. This makes people's privacy secure.In total, the project demonstrates how computers can become more human-centric through assisting them to identify and respond to emotions, and this can be of much assistance in schools, hospitals, customer services, etc.

CHAPTER 2

LITERATURE SURVEY

Emotion detection is a key feature for promoting human-computer interaction and numerous applications such as healthcare, security, and assistive technology. Several studies have focused on facial emotion detection using deep learning approaches. Venkatesan et al. (2023) examined real-time emotion detection with DeepFace and AI and attained 94% accuracy through the extraction of 26 facial landmarks. Gautam and Seeja (2023) combined hand-crafted features with convolutional neural networks (CNNs) to improve emotion detection accuracy, whereas Awana et al. (2023) employed a live emotion detection system using DeepFace. Mohammadpour et al. (2017) demonstrated the strength of CNNs in extracting subtle facial features for facial emotion recognition, and Valstar et al. (2011) hosted the first Facial Expression Recognition and Analysis Challenge, providing benchmark datasets and evaluation metrics. With the increase in the use of face masks, recognition of emotions from masked faces is a problem now. Mukhiddinov et al. (2023) employed a deep learning approach using facial landmarks which were specifically targeted for visually impaired individuals and achieved a 69.3% accuracy rate using the AffectNet dataset. Emotion recognition based on facial expressions is not the only recognition; speech recognition has also been given sufficient attention. Kakuba et al. (2022) suggested a speech emotion recognition model using deep learning that is based on multi-level fusion of concurrent features to improve robustness. Sariyanidi et al. (2014) provided a survey of facial affect analysis, including facial recognition methods, while studies from 2000 to 2011 mentioned various classifiers and feature extraction techniques for speech emotion recognition. Some of survey papers and challenge have assisted in standardizing emotion recognition research. Karnati et al. (2023) provided a comprehensive overview of deep learning techniques for emotion recognition, including datasets, models, and performance metrics, while Sariyanidi et al. (2014) provided an overview of different methodologies for automatic facial affect analysis. Valstar et al. (2011) provided a benchmark challenge that set a precedent for the testing of facial expression recognition algorithms. The work that has been surveyed demonstrates significant advancement in emotion recognition depend on AI and deep learning across different categories such as facial expressions and speech. There is a need for future research to improve accuracy for recognizing masked faces, real-time deployment, and multimodal detection of emotions in order to enhance user experience in applications.

Author et al. [Ref No.]	**Year of Production**	**Algorithm**	**Implementation Details**	**Evaluation Parameters**	**Comments**
Venkatesan et al.[1]	2023	DeepFace, AI	Extracted 26 facial landmarks for emotion classification	Accuracy(94%)	Focuses on real time emotion detection
Mukhiddinov et al.[2]	2023	Facial landmarks, Deep learning	Designed for maskedface emotion recognition for visually impaired individuals	Accuracy (69.3%)	Tackles emotion recognition despite occlusion
Gautam & Seeja [3]	2023	Handcrafted features + CNN	Hybrid approach using traditional feature extraction with CNNs	Accuracy improvements over standalone CNN	Bridges traditional and deep learning approaches
Awana et al. [4]	2023	DeepFace	Implemented live emotion detection system	Real-time performance metrics	Applied in human-computer interaction
Kakuba et al. [5]	2022	Deep Learning,	Speech emotion recognition	Robustness improvements,	Enhances speech-based

		Multi-level feature fusion	using concurrent feature fusion	performance metrics	emotion recognition
Lian et al.[6]	2023	Multimodal Deep Learning	Conducted a survey on deep learning-based multimodal emotion recognition, focusing on speech, text, and facial expressions	Comparative evaluation of various models across multiple datasets.	Provides insights into the integration of multiple modalities for enhanced emotion recognition accuracy.
Joseph et al.[7]	2024	ResNet50, CNN for Audio	Developed models for audio and visual emotion detection using ResNet50 for facial recognition and a CNN-based model for speech emotion detection.	Achieved accuracies of 70% (speech) and 63.5% (visual) on combined SAVEE and RAVDESS datasets.	Emphasizes the importance of integrating multiple modalities for improved emotion detection in human-robot interaction.
Roy, Arnab Kumar, et al.[8]	2024	ResEmoteNet (CNN-based)	Developed a deep learning model that improve accuracy	Achieved high accuracy with optimized training.	Focuses on balancing accuracy and loss reduction.

Gaddam, Dharma Karan Reddy, et al.[9]	2022	CNN, Deep Learning	Implemented a CNN based model for emotion detection	High accuracy achieved with deep learning techniques.	Applied in real-world emotion analysis scenarios
Karnati et al. [10]	2023	Survey of Deep Learning methods	For recognition reviewed deep learning technique	Dataset comparisons, model evaluation	Comprehensive review of AI-based recognition

Table 1: Summary Table of Recent Emotion Recognition Approaches

CHAPTER 3

SYSTEM DESIGN

3.1 WORKFLOW OF FACIAL EMOTION DETECTION

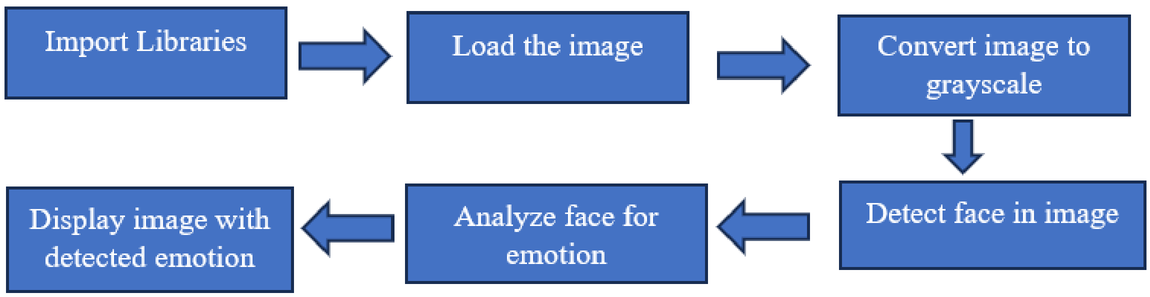

Fig-1

The facial emotion recognition process begins by importing all the required Python libraries. These libraries are useful for image processing, face detection, and deep learning. OpenCV is used for image and video processing and DeepFace for face detection. Libraries like TensorFlow or Keras are used to run deep learning models. Once the environment is set, an image is read from a file path or from a camera stream. The system takes this image as input to process. The image is first converted into grayscale mode to be processed. This reduces colour complexity and emphasizes intensity values. This is significant as it speeds up detection and makes it more accurate by removing redundant colour information. As the image is converted, the system subsequently scans the image to determine whether there are faces of humans or not. Face detection is a critical process, and Haar cascade classifiers or Multi-task Cascaded Convolutional Networks (MTCNN) are typically use to identify the presence and position of a face in the frame. If a face is identified, the region is then processed further. Facial features such as the eyes, eyebrows, mouth, and nose are now analyzed at this stage. These features possess minute variations that signify an individual's emotional state. The analysis is carried out by a convolutional neural network (CNN), which has been pre-trained on large sets of facial expressions in order to recognize different emotional patterns. After analyzing the facial features, the system concludes the most likely emotion from a given list of categories. These classes normally cover basic human feelings .The prediction is then overlaid on the initial image, along with a label indicating the emotion that was detected, normally near the face identified for easier visual interpretation. The end output does not just show the emotion but may also include other details such as confidence levels or face bounding boxes around them. This entire process happens quickly and can be extended to live video streams as well, which makes it handy for live emotion tracking in various types of applications. The system can be used in a various of fields like virtual classes, customer service platforms, surveillance systems, and mental health products and so on.That gives machines the capacity to understand and respond to emotional signals from humans more effectively.

3.2 System Architecture

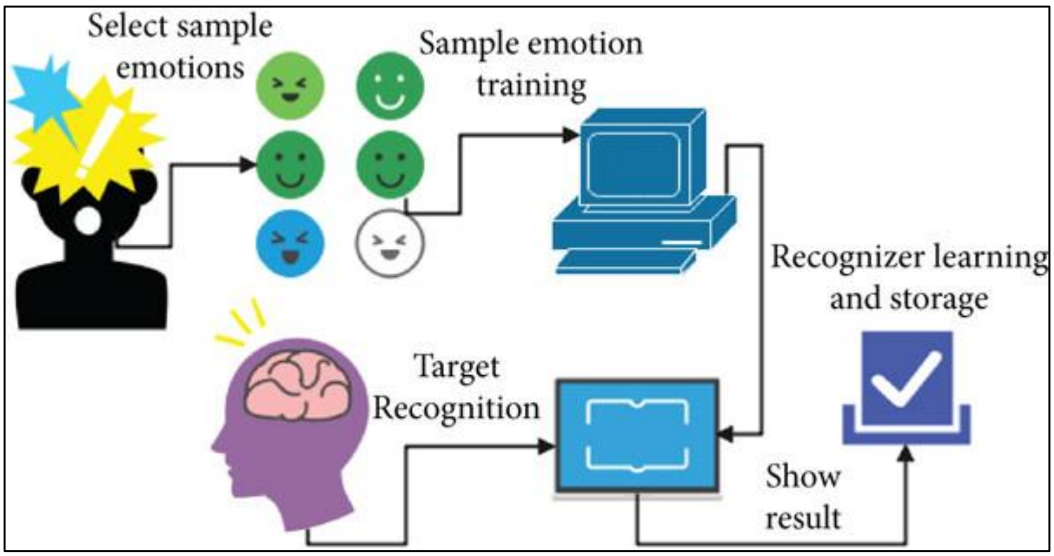

Fig-2: System Architecture of Facial Emotion Detection

The facial emotion detection system architecture is planned to recognize and detect human emotional expressions in real-time employing artificial intelligence and deep learning methods. The system is separated into multiple steps ranging from data preparation to the display of the final output. The diagram provides the high-level architecture view of the system and how each of the components collaborates to provide accurate and effective emotion detection.The Sample Emotion Selection is the initial step in constructing the system to define the set of target emotions that will be identified by the model. In this system, fundamental human emotions are chosen from psychological research. These categories are a reductionist but efficient method of interpreting facial expressions.At Training with Sample Emotions step, a collection of many face images with their respective emotional states tagged on them is utilized for the training of a deep model. Most commonly, datasets like FER-2013 or AffectNet are utilized for this purpose. To train, one utilizes convolutional neural networks (CNNs) to pull feature information like lip curvature, positions of the eyebrows, eye openness, and other facial landmark that correspond to various emotions. These patterns are acquired by the model from where it fine-tunes its internal parameters (weights) to enhance classification accuracy over time.After training is finished, the generated model architecture and weights are saved for deployment. Such files (e.g., `.json` for architecture and `.h5` for weights) contain the recognizer — a pre-trained model to identify emotions in new faces. Retained knowledge during being trained is guaranteed at this stage such that the model does not need to be retrained from scratch. Instead, it is made available to use for inference tasks of real applications.In this live mode of operation, the system takes live video feed from a webcam or other camera-capturing devices. Employing OpenCV's Haar cascade classifier, the system recognizes faces in each frame. The recognized facial area is then preprocessed — resized to 48x48 pixels, converted to grayscale, and normalized — so that it fits the input format that the model requires. The pre-processed image is then input to the model to forecast the likely emotion. The prediction is made on the basis of probabilities calculated for each class of emotions.Once the emotion is anticipated, the outcome is presented visually in the form of superposition of the emotion label over the video frame close to the detected face. The system refreshes automatically for every incoming new frame and offers a real-time experience. This enables the system to have a real-time response to changes of facial expressions and thus appropriate for interactive applications like virtual support, mental monitoring, games, and customer feedback analysis.One of the most significant benefits of this architecture is that all processing is done on the user's device locally. Facial data does not need to be uploaded to cloud servers, providing enhanced privacy and data protection. This makes the system more reliable and in accordance with data protection law, particularly in fields such as healthcare or education, where this is crucial**.**

CHAPTER 4

IMPLEMENTATION

4.Methodology

The methodology of the facial emotion detection system is designed to ensure efficient, real-time, and accurate recognition of human emotions using facial expressions. The entire process is composed of several integrated stages, each critical to the overall performance of the system. This pipeline includes data collection, model selection, face detection, image preprocessing, feature extraction, classification, and visualization.

Our approach emphasizes modular design — where each stage can be independently improved or replaced — allowing for scalability, customization, and future integration with other modalities such as speech or gesture recognition.

4.1 Data Collection and Pretrained Model Usage

Instead of training a model from scratch, which is often computationally expensive and time-consuming, this project leverages a pre-trained Convolutional Neural Network (CNN) model trained on large and diverse facial emotion datasets such as **FER-2013**. These datasets consist of thousands of labeled facial images representing universal emotions like happiness, sadness, anger, surprise, fear, disgust, and neutrality. Their diversity in terms of age, gender, ethnicity, and lighting conditions enables the model to generalize effectively across a wide range of real-world scenarios. The pre-trained models used in this project are stored in .json format for the model architecture and .h5 format for the model weights. This approach, based on transfer learning, not only reduces development time but also delivers higher accuracy, as the models have been extensively fine-tuned and validated by the research community. Specifically, the project employs DeepFace, a powerful facial recognition and emotion detection library developed by Facebook. DeepFace abstracts away the complexities of low-level facial analysis and integrates state-of-the-art CNN architectures internally. These pretrained models enable real-time inference, making it possible to implement a responsive and efficient system capable of live emotion detection using webcam input.

4.2 Tools and Libraries

To build the facial emotion detection system, a variety of open-source tools and libraries were used, each playing a vital role in the project pipeline. Python served as the primary programming language due to its simplicity, readability, and the extensive availability of libraries for artificial intelligence and computer vision. OpenCV (Open Source Computer Vision Library) was employed for real-time video capture from the webcam, frame manipulation, and face detection using Haar cascades. It also facilitated several preprocessing tasks such as resizing images, converting them to grayscale, and drawing bounding boxes around detected faces. For the deep learning component, Keras with a TensorFlow backend was used to build and deploy the CNN model. This combination allowed access to powerful features such as GPU acceleration and cross-platform support, making the model efficient and scalable. To simplify facial feature analysis and emotion classification, the project integrated DeepFace, a high-level face recognition and analysis library that wraps around multiple pre-trained models. Lastly, NumPy was used extensively for numerical operations, managing image data in array format, reshaping input tensors, and normalizing pixel values for model input.

4.2.1 Face Detection

To detect human faces in each video frame we have used "Haar Cascade Classifier" .It is implemented by OpenCV. This algorithm scans the input grayscale image to locate face regions by comparing Haar features.

4.2.2 Image Preprocessing

Detected face regions are transform to grayscale (simplified complexity), the size of 48x48 pixels,Normalized(normalized pixel values from 0 to 1),Reshaped to 4D tensor for inputting into the CNN model.

4.2.3 Feature Extraction and Emotion Classification

The pre-processed face is sent into a CNN-based model, which will look for distance among various features, like shape of eyes, movement of the eyebrow, curvature of mouth, etcThe class with high probability will be taken as predicted emotion.

4.2.4 Real-Time Visualization

For each frame:A bounding box is placed around faces that are detected.The forecasted emotion label is visible near the face.The video feed is continuously updated to include new emotions as they are detected, with instant feedback.

4.3 Sample Code

```
import cv2
from keras.models import model_from_json, Sequential
import numpy as np

# Load model architecture
with open("facialemotionmodel.json", "r") as json_file:
    model_json = json_file.read()

model = model_from_json(model_json, custom_objects={'Sequential': Sequential})
model.load_weights("facialemotionmodel.h5")

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

# Function to preprocess face image
def extract_features(image):
    image = np.array(image).astype('float32') / 255.0
    image = image.reshape(1, 48, 48, 1)
    return image

# Labels
labels = {
    0: 'angry', 1: 'disgust', 2: 'fear',
    3: 'happy', 4: 'neutral', 5: 'sad', 6: 'surprise'
}

# Start webcam
webcam = cv2.VideoCapture(0)
if not webcam.isOpened():
    print("[ERROR] Cannot access camera.")
    exit()

print("[INFO] Starting webcam. Press 'q' to quit.")

while True:
    ret, frame = webcam.read()
    if not ret:
        print("[ERROR] Failed to grab frame.")
        break

    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
    faces = face_cascade.detectMultiScale(gray, scaleFactor=1.3, minNeighbors=5)
```

```python
    for (x, y, w, h) in faces:
        face = gray[y:y + h, x:x + w]
        if face.shape[0] < 48 or face.shape[1] < 48:
            continue  # skip small faces

        face_resized = cv2.resize(face, (48, 48))
        face_features = extract_features(face_resized)
        predictions = model.predict(face_features, verbose=0)
        pred_idx = np.argmax(predictions)
        label = labels[pred_idx]
        prob_percent = int(predictions[0][pred_idx] * 100)

        display_text = f"{label} {prob_percent}%"

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

    # Show frame
    cv2.imshow("Facial Emotion Detection", frame)

    # Break loop on 'q' key
    if cv2.waitKey(1) & 0xFF == ord('q'):
        print("[INFO] Quitting...")
        break

# Cleanup
webcam.release()
cv2.destroyAllWindows()
```

CHAPTER 5

RESULTS

5 Result:

OUTPUT IMAGES OF REAL-TIME FACIAL EMOTION DETECTION

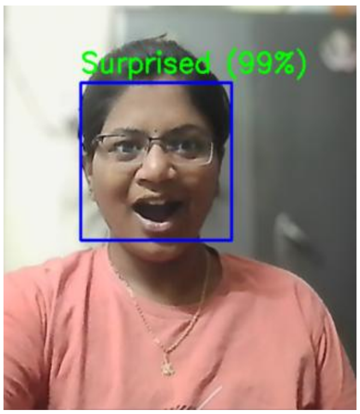

Fig-3

Fig-4

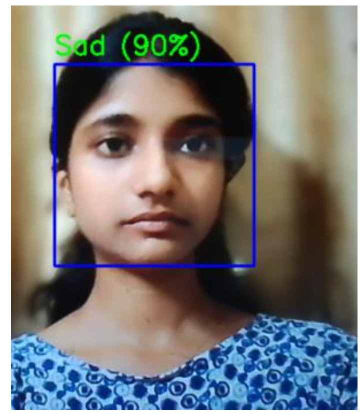

Fig-5

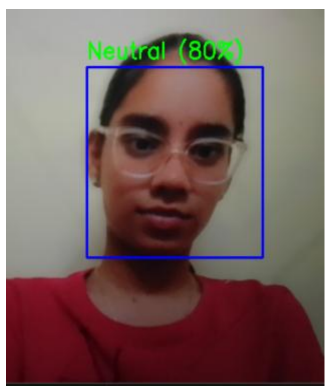

Fig-6

The images depict the outcome of a realtime facial emotion recognition system. The system utilizes a webcam for capturing faces and then predicting the emotion of the person, i.e., whether happy, sad, surprised, or fearful. It employs artificial intelligence (AI) and computer vision for the purpose. The identified faces are highlighted by a colored box, and the predicted emotion accompanied with a percentage (confidence level) is displayed at the top. A larger percentage indicates the system is more confident in that emotion.

In fig 3 and fig 4, we can observe two different individuals. The left person is expressing a surprised face, and the system accurately identifies it as "surprise" with a high confidence score. The individual at the right has a smile, and the system picks up the feeling as "happy." This indicates that the model can perform well on various individuals, not only on one individual. It is able to recognize emotions even if individuals wear various attires, in varying light sources, or have varying facial shapes. The boxes are correctly positioned around the faces, and the predictions are readable and understandable.

In fig5 and fig 6, once more two individuals are depicted. The individual on the left is the same as in the second figure, but here she is not smiling. Her emotion is identified by the system as "sad." This indicates that it can identify even minor changes in expression. The individual on the right has a calmer or more serious face, and the model identifies it as "neutral." These are the kinds of results that indicate the model does not guess indiscriminately – rather, it examines the face very carefully and makes an educated estimate based on the features.

This type of system can be applied to various useful domains. For instance, in e-learning, it will inform teachers whether students are bored or confused. In medicine, it will track an individual's mood over a period of time. In customer support, it will indicate how frustrated or pleased a customer is while conversing. It functions in real-time, meaning that the emotions are displayed live, similar to a video call. Although the system functions well, we have to keep in mind it's not always accurate. At times it may not get the true emotion because individuals portray feelings differently. Additionally, utilizing such systems should be done with care to safeguard individuals' privacy. Individuals ought to be kept aware and request permission if they're being monitored regarding their emotions.

Overall, the pictures prove that the system can operate on various individuals and recognize a variety of emotions in an accurate way. The outcome is evident, quick, and useful for lots of applications.

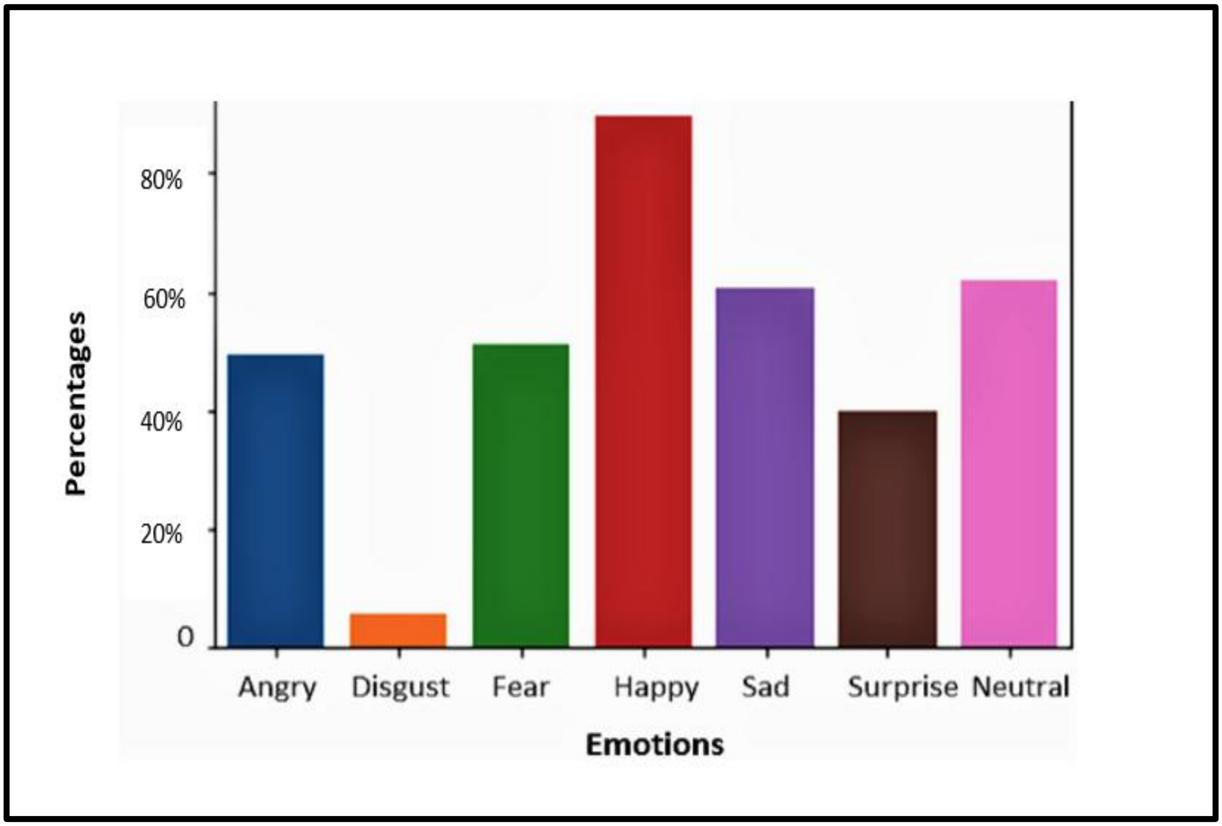

Fig 9: Graph that shows the accuracy of each emotion

The bar graph displayed above represents the collected results of detecting facial feelings, which is using a firm neural network (CNN) trained to classify human facial expressions into seven infrastructure. These emotions are among universal manifestations recognized in cultures and are usually used in emotional recognition systems.

From the graph, it is clear that the "Happy" is the most prominent spirit, which is a percentage of more than 90%, followed by neutral, depressed and fear, between 40%to 65%. This means that the a person has maintained a positive or neutral expression for most of the time during webcam capture. High values for "happy" often indicate smiling, which is firmly associated with high confidence scores in the CNN-based emotion model due to the specific nature of the smile in facial muscle patterns.

On the other hand, "disgust" is the lowest percentage, almost negligible, indicating that this expression was not strongly detected throughout the session. This corresponds to the behavior of the real world, as the expression of hatred is usually less frequent and difficult until it is deliberately expressed.

As a whole, the graph shows how the emotion identification model handles and calculates facial information in real time. These figures are the product of real-time video capture and analysis, whereby the emotional potential is computed frame-by-frame and subsequently averaged or accumulated to yield an aggregate scene. Such visual sentiment-component systems, human-computers interactions (HCIs), and behavioral studies are useful in studies, which help to explain emotional trends in individuals or groups.

Finally, this graph valid the effectiveness of the model in detecting facial expressions and presents a clear approach to emotional distribution, which exposes the prominence of happiness and neutrality in the captured session.

CHAPTER 6

CONCLUSION

Using deep learning and artificial intelligence, detecting facial feelings (FED) marks a significant progress in increasing the way to interact with humans. By taking advantage of techniques such as convene neural networks and framework, the project effectively captures, analyzes and interprets emotional expressions from facial characteristics in real time. The use of pre-educated models and large emotion dataset not only accelerates growth, but also ensures high accuracy and generalization in various demographics. The ability of a system of efficient functioning even in challenging scenarios such as poor lighting, or masked users show its adaptability and strength in real -world settings.One of the major powers of the system lies in its real -time performance and comprehensive application scope. Implementation can be originally integrated into educational platforms to monitor the student's engagement in healthcare systems for basic health evaluation, or to track customer satisfaction in customer service. In addition, privacy-centered architecture, where all facial data is processed locally, strengthens the moral integrity of the system by reducing the risk of misuse of data. It not only creates the user trust, but also ensures compliance with data safety rules that receive both technical and socially viable solutions.

In short, this project is a powerful example of how AI can be used to create machines that are emotionally intelligent and human-focused. It brids the gap between emotional signals and machine reaction, enabling more natural, sympathetic interactions. Like -technology develops

CHAPTER 7

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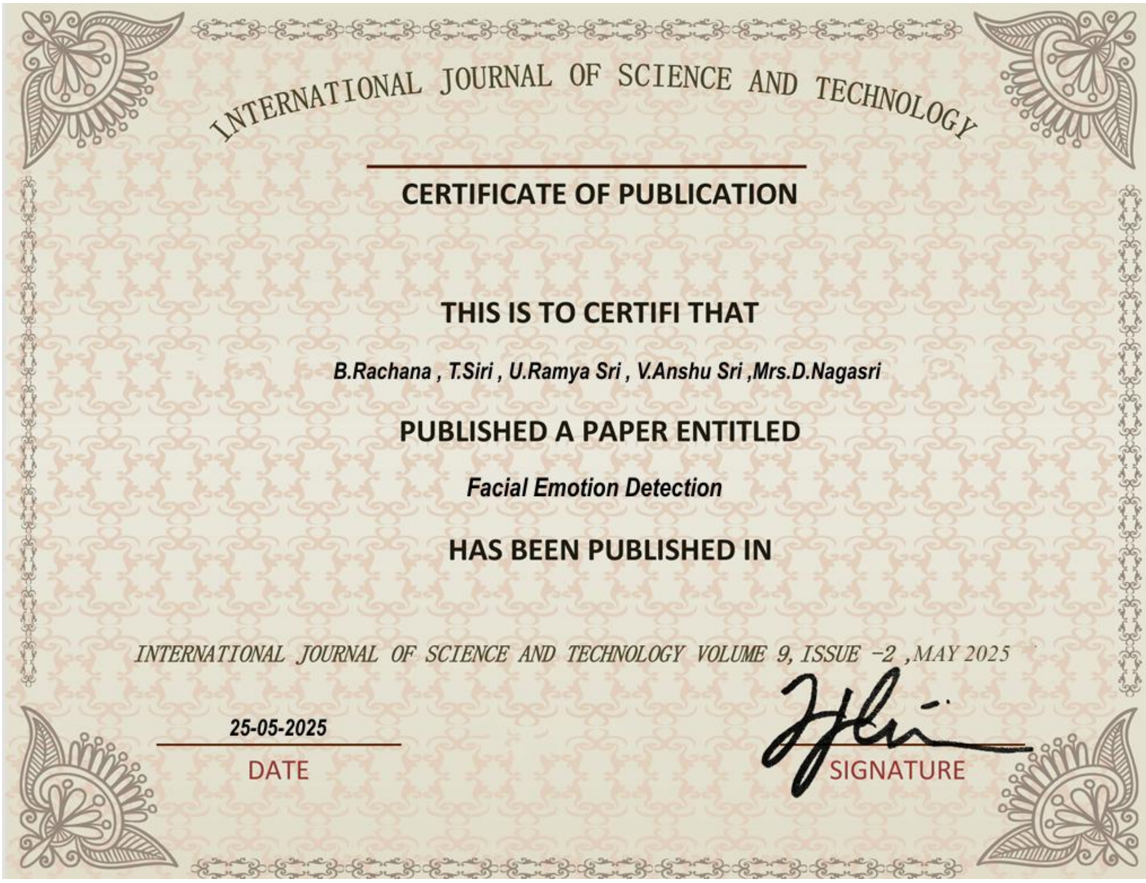

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