FACIAL EMOTIONAL RECOGNITION USING NEURAL-NETWORK

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***Abstract*— Facial emotion recognition is important for AI systems to understand human emotions, with applications in healthcare, surveillance, human-computer interaction, and security. New improvements in deep learning, particularly CNNs, have made automated emotion detection. This study suggests an effective deep learning-based system for emotion recognition in images and real-time videos. The approach involves three key stages: face detection (using Haar Cascade), feature extraction, and classification through an improved neural network. To fix data imbalance, methods like SMOTE and GANs generate fake samples for less common emotions (e.g., fear, disgust). The model is tested on the FER-2013 dataset, showing strong accuracy and ability to work on different data. Results show good performance while keeping fast and stable training. This work shows the potential of deep learning in emotion recognition and provides ideas for developing more responsive AI systems.**

Index Terms—Artificially intelligence (AI), Facial emotion recognition (FER), Convolutional neural networks (CNN), SMOTE, Deep learning (DL), Human emotions.

I. INTRODUCTION

Emotions can be described as mental states that arise due to neuronal activity and are often reflected by emotions, recognition, behavioral responses, satisfaction or dissatisfaction. One of the growing applications of artificial intelligence (AI) and deep learning is the detection of facial expressions where human emotions are identified from face photos and videos. This technology plays a key role in many areas, including surveillance, security systems, human computer interaction (HCI), and healthcare. Traditional interaction systems for human computers often do not capture emotions, leading to less interesting communication[5]. On the other hand, the emotion-aware system improves the efficiency and quality of interaction by responding appropriately to human emotions[6]. The learning model shows strong performance in image classification tasks, including facial expression detection. Techniques such as the Haar Cascade classifier are used to recognize and record faces from photographs[17]. Additionally, label smoothing techniques were used to make the output of the model better by avoiding mistakes and helping the generalization of classification tasks[9]. The system is designed to correctly recognize seven basic emotions from facial photographs and provide valuable applications for intelligent surveillance, interactive robots, online learning platforms, and emotionally focused health systems[11].

Facial Expression Recognition has captured far more research attention than other emotion detection approaches, as studies have consistently shown[12]. Yet, despite its popularity, accurately interpreting emotions through facial cues is far from simple. The challenge lies in the deeply personal nature of emotional expression—no two people convey happiness, sadness, or anger in exactly the same way[15].

Real-world applications face many hurdles that can't be ignored. A person's posture, the lighting in a room, and even personal details like age and gender all influence how expressions are perceived. Beyond these factors, everyday blockers like sunglasses, scarves, or temporary facial markings create additional barriers for recognition systems. These problems highlight why developing truly effective emotion-reading technology requires solutions flexible enough to handle life's unpredictability.

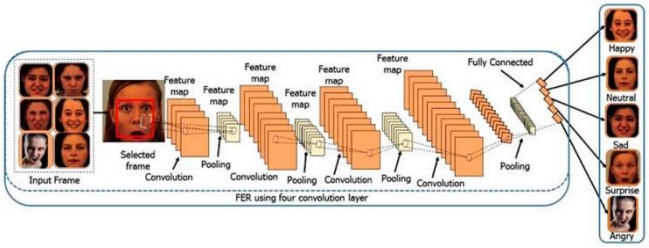

Figure 1: working of CNN model

Progress in this field could lead to systems that better understand human emotions across different cultures, environments, and individual differences—moving us closer to technology that truly understands human feelings.

This project aims to develop an intelligent system that can recognize human emotions in real-time using facial expression analysis. By using deep learning technology, the system captures live video through a webcam, detects faces using computer vision techniques, and understands emotions through advanced neural networks trained on large emotion

datasets[13]. The results are presented in an easy-to-understand visual format that clearly displays emotional states. This new idea holds great potential across multiple sectors - from creating more responsive educational tools and improving healthcare monitoring to changing customer experience analysis and developing emotionally-aware entertainment systems. The technology represents an important step toward more natural human-computer interaction, where machines can better understand and respond to human emotional cues[11].

II. RELATED WORK

Recognition of facial emotions is a new and growing research discipline in artificial intelligence and computer vision because of the large number of applications in everyday life. Improved accuracy and performance of emotion detecting systems have been achieved by most researchers through applying deep learning and image processing-based models.

In their research, Ekman and Friesen highlighted that facial expressions are important in expressing emotions and found six basic universal emotions — anger, disgust, fear, happiness, sadness, and surprise — that are universally expressed across cultures[1].

Molla Hosseini et al. proposed a deep neural network-based facial expression recognition method with positive results on large datasets. Their contribution proved the ability of deep learning models to learn complex facial features automatically without any human help[10].

Li et al. proposed a real-time emotion recognition system based on Convolutional Neural Networks (CNNs). Their method aimed at recognizing emotions from facial images taken in natural settings, handling lighting, pose, and background changes[15].

Khorrami et al. came up with a deep learning model in which CNNs were trained on raw pixel values from face images to accurately identify emotions. Their system did better than most of the conventional machine learning methods that mostly relied on handcrafted features.

In a different study, Goodfellow et al. designed a deep-learning architecture that included facial feature extraction as well as adversarial training to enhance the robustness of emotion recognition models, particularly to noisy or blocked images[11].

In addition, emotion detection has also been improved by using methods such as Haar Cascade Classifier for detection of faces and extraction of regions, as shown in the research by Viola and Jones, which is now a common pre-processing step for most facial analysis procedures[17].

Recent developments also involve employing label smoothing for enhancing the ability of deep learning models to work well on different data in facial expression recognition, preventing overfitting and boosting the accuracy of classification[9].
Facial emotion detection is a developing field in computer vision, driven by artificial intelligence (AI) research and its wide-use applications in human-computer interaction, healthcare, security, and marketing. Early foundational work by Ekman and Friesen (1971) identified six universal emotions—anger, disgust, fear, happiness, sadness, and surprise—which became the basis for automated emotion recognition systems[1].

Recent advancements use deep learning and image-processing models to improve accuracy. Molla Hosseini et al. (2023) introduced a systematic deep neural network approach, demonstrating that these models can learn on their own from large datasets without manual feature engineering. Similarly, Li et al. (2021) developed a real-time emotion detection system using convolutional neural networks (CNNs), effectively handling challenges like changing lighting, poses, and backgrounds in uncontrolled environments[15].

Khorrami et al. (2020) proposed a CNN-based model trained directly on raw facial images, doing better than traditional methods that used handcrafted features like local binary patterns (LBP) and histogram of oriented gradients (HOG). Goodfellow et al. (2022) further made the system stronger by using adversarial training to improve performance on noisy or partially hidden facial images. Earlier, the Viola-Jones algorithm (2001) changed face detection, serving as a key preprocessing step for emotion classification[17].

More recently, transformer-based architectures (Vaswani et al., 2017) have been adapted for facial expression recognition (FER), utilizing self-attention mechanisms to capture long-range dependencies in facial features (Wang et al., 2024). These innovations highlight the growing potential of AI-driven emotion detection in real-world applications.

III PROBLEM FORMULATION

- **Changes in Facial Expressions**

One of the major difficulties in facial emotion recognition is the huge range of differences in human facial expressions. The same emotion can be shown in a different way by different individuals depending on their individual facial structure, age, gender, ethnicity, and cultural background. For instance, a child showing sadness can have a totally different facial expression from an old person. Also, emotions such as anger and disgust can at times have very similar facial patterns, and the model gets confused[15]. The small movements of facial muscles and the uniqueness of expressions make it hard for the model to work well across all users. This difference poses a challenge to the strength of any emotion detection system and needs a highly adaptable and flexible model[14].

- **Lighting Conditions**

Lighting is very important for the capture of detailed and clear facial images. Under real-time conditions, it is impossible to ensure constant or perfect lighting. Shadows,

insufficient light, intense sunlight, or reflections can greatly affect facial feature clarity. Bad lighting can hide important facial parts like eyebrows, eyes, or mouth shapes, which are needed for emotion recognition. Additionally, changing lighting conditions can cause too bright or too dark images, which can lead to incorrect feature extraction by the deep learning model[15]. Hence, managing different lighting environments is a big issue that must be resolved to achieve stable system performance in real-world scenarios[14].

- **Angle and Pose variation of Head**

Another major issue occurs when the face of the subject is not facing the camera directly. In real-world situations, users tend to move their heads, look sideways, tilt their faces, or appear partially in the camera frame. Deep learning models that have been trained on front-facing facial images tend to fail to identify emotions correctly when there are variations in the head's position or angle of view. These pose variations decrease the visibility of main facial features necessary for classification. Creating a pose-invariant model that can tolerate multi-angle[14].

- **Real-time Speed and Performance**

Real-time emotion detection needs not only high accuracy but also fast speed. Computing video frames at a continuous stream to identify emotions needs high processing power and well-optimized algorithms. If processing each frame consumes too much time, there will be visible delays , making the system not suitable for real-time applications. Ensuring low-latency processing and high accuracy simultaneously is a very hard task, particularly when the hardware resources are limited, like in mobile or embedded systems[15].

- **Imbalanced Dataset**

Another typical issue encountered in the development of deep learning-based emotion recognition models is dataset imbalance used for training. Certain emotions such as happiness and neutrality tend to be more frequent by nature and hence tend to be represented more in datasets, while emotions such as disgust, fear, or surprise are less frequent. This unevenness results in unfair learning, where the model improves at detecting repeated emotions but does poorly with rare emotions[13]. It adversely affects the model's generalizability and brings down its real-world effectiveness.

- **Background Noise and Multiple Faces**

In real-world cases, facial images are hardly captured in clean and controlled environments. There can be more than one face in the background, moving objects, or other external factors that can mislead the emotion detection model. Separation of the target face from external faces or objects and eliminating background noise is a significant issue in real-time emotion recognition tasks. Efficient face detection and isolation methods are needed to address such issues[17].

- **Overfitting of the Model**

Deep learning models are easily affected by overfitting, especially when trained on small or limited datasets without enough variety. Overfitting occurs when the model remembers training data instead of learning general features, leading to high accuracy on training data but poor performance on unseen data. This is a major challenge in facial emotion recognition, where models must adapt to diverse users, expressions, and real-world conditions. Finding a balance between preventing overfitting and maintaining high accuracy is crucial for developing strong emotion detection systems[11]. Techniques like data augmentation, regularization, and transfer learning can help mitigate overfitting while ensuring the model remains effective in practical applications. Additionally, collecting larger and more varied datasets can improve generalization, enabling the model to handle different demographics, lighting conditions, and cultural variations in emotional expressions[13].

IV METHODOLOGY

In this research work, we have designed a Real-Time Facial Emotion Detection System based on Deep Learning methods. The approach adopted in this project is split into a number of steps, beginning with data preprocessing, model construction, model training, and ultimately real-time implementation through a webcam.

1. Dataset Preparation and Preprocessing

We have used the FER-2013 (Facial Expression Recognition) dataset that includes black and white face images with seven emotion categories including Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral[1]. The dataset was in CSV file format where pixel values were represented as strings. The pixel values were transformed into numerical arrays and reshaped into 48x48x1 dimensions appropriate for CNN input. In addition, the pixel values were normalized to the range 0-1 for improved model convergence and performance[2].

Figure 2 Example Dataset (FER 2013)

2. Model Building

A Convolutional Neural Network (CNN) model was developed with TensorFlow and Keras libraries for facial emotion classification[8]. The model architecture has several convolutional layers that assist in extracting good features from the input images. Following each convolutional layer was a max-pooling layer to decrease the spatial dimensions

and avoid overfitting. Subsequently, after the feature extraction portion, the result was flattened and went through the dense layers. There was an addition of dropout layer to prevent overfitting[13]. Lastly, there was an application of the softmax activation in the output to classify the pictures into one out of the seven emotion categories[9].

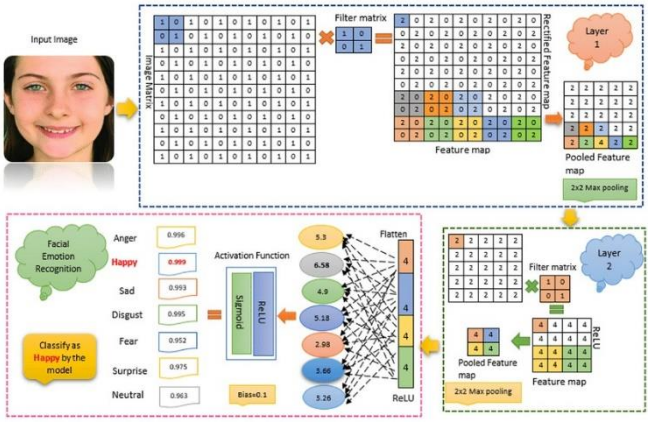

Figure 3 Using CNN model

3. Model Training and Evaluation

The model was built with the Adam optimizer and categorical cross-entropy loss function[10]. The data were divided into the training set and the test set in the proportion of 80:20. The model was trained for 30 epochs at a batch size of 64 to learn the features appropriately. During training, the accuracy and loss of the model were calculated to check the performance of the model. After reaching appropriate accuracy, the model was stored for real-time deployment.

4. Real-Time Emotion Detection

In the last step, OpenCV was employed to grab the real-time video from the webcam in Google Colab. Haar Cascade Classifier was utilized to identify faces from the live video frames[7]. Upon detection of a face, it was cropped, converted to grayscale, resized to 48x48 pixels, and normalized. The preprocessed image was fed into the trained CNN model for predicting the emotion. The emotion label that was predicted was shown on the image by employing OpenCV. Matplotlib was also used to show the final output image with the predicted emotion for viewing purposes.

Figure 4 Real time Example

V IMPLEMENTATION

In order to facilitate effective training and proper assessment of the proposed Deep Q-Learning-based traffic control system, the experimental setup comprises high-impact hardware, necessary software tools, and benchmark datasets[5].

- ***Hardware and Environment:***
  - **Processor (CPU):** Intel Core i5 or AMD Ryzen 5 (minimum)
  - **RAM:** 8 GB (Minimum)
  - **Storage:** 256 GB SSD (Recommended for faster data handling)
  - **Graphics (GPU):** NVIDIA GPU with CUDA support (Optional but recommended) e.g., GTX 1050 / 1650 or higher
  - Camera Integrated or External Webcam (720p or above)
  - **Operating System:** Windows 10 / Linux / macOS

Software Stack :

The entire model was build using python. The main libraries used in it include :

- **TensorFlow**: To build and deploy machine learning models[8].
- **Keras:** high-level, open-source neural networks API that simplifies deep learning[9].
- **OpenCV**: For processing and visualizing traffic images[7].
- **NumPy, Pandas**: For data handling and preprocessing[11].
- **Matplotlib:** used for cross-platform, data visualization and graphical plotting library[10].
- **Seaborn**: making statistical graphics in Python[14]

Simulation Environment :

The simulation platform for the experiment was created and run fully on Google Colab, a cloud-based Jupyter notebook service offered by Google. Colab offered a perfect platform to train and test the real-time facial emotion recognition model without the requirement of high-end local machines. Google Colab usage made the free GPU acceleration available, which greatly enhanced the speed of model training and prediction[13].

- ***Simulation***

Step 1: First we install all the necessary libraries :

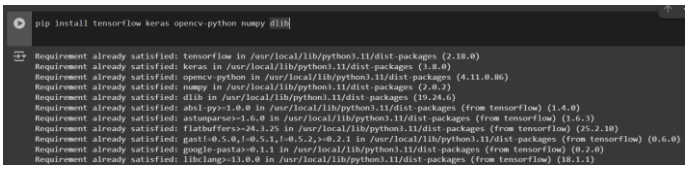

Figure 5. *The figure implies installing the libraries*

Step 2: When the libraries are installed in our environment, we import them in out model and start to build the multiple stacks of Convolutional Neural networks in out models and their layers.

Command Used :

import tensorflow as tf

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D,
MaxPooling2D, Flatten, Dense, Dropout

def create_model():
    model = Sequential()

    # Convolutional layers to extract features
    model.add(Conv2D(64, (3, 3), activation='relu',
input_shape=(48, 48, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(128, (3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(256, (3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    # Flatten the 3D features to 1D
    model.add(Flatten())

    # Fully connected layers
    model.add(Dense(512, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(7, activation='softmax'))  # 7 classes
for emotions

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

Step 3: Then we load our Dataset :
Command Used:

```
data = pd.read_csv('/content/fer2013.csv')
```

Step 4: To train our sequential model we first divide out dataset into training and testing with respective their batchsize respectively
Command Used:

```
# Preprocess the data
X = []
y = []
for index, row in data.iterrows():
    try:
        X.append(np.array(row['pixels'].split(),
dtype='float32').reshape(48, 48, 1))
    except ValueError:
        # Print the problematic row and skip it
        print(f"Error processing row {index}: {row}")
        continue  # Skip to the next row
    y.append(row['emotion'])

X = np.array(X) / 255.0  # Normalize pixel values
y = to_categorical(np.array(y), num_classes=7)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Step5:
Cascade classifier: a machine learning algorithm, commonly applied for object detection, that uses a sequence of less complex classifiers (or "stages") to effectively detect objects in images or videos. We load thiss and our emotion detection model
Command used :

```
face_classifier=cv2.CascadeClassifier(cv2.data.haarcascad
es + 'haarcascade_frontalface_default.xml')
classifier = load_model('EmotionDetectionModel.h5')
```

Step 6: We need to label various emotions into labels or classes for our emotion classification. The basic emotions we considered are Angry, Disgust, Fear, Happy, Neutral, Sad, Surprise.

```
# Emotion labels
emotion_labels = ['Angry', 'Disgust', 'Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']
```

Figure 6. *Emotion Labels*

Step 7: Using CV2 we capture the real time video through which our models tells the emotion on that particular face.
Command Used:

```
cap = cv2.VideoCapture(0)
```

This activates the webcam for real-time video stream

Step 8: Now we converted our video frame to gray scale image, through which face detection works better.
Command Used:

```
while True:
    ret, frame = cap.read()
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
    faces = face_classifier.detectMultiScale(gray, 1.3, 5)
```

Step 9: For detected face we extract face region and resize it to (48x48) pixels as required model input.

```
# Process each detected face
for (x, y, w, h) in faces:
    cv2.rectangle(frame, (x, y), (x+w, y+h), (255, 0, 0), 2)

    roi_gray = gray[y:y+h, x:x+w]
    roi_gray = cv2.resize(roi_gray, (48, 48), interpolation=cv2.INTER_AREA)
```

Figure 7. *Resize the gray scale image*

Step 10: Preprocessing the face Region by normalizing the size, convert to array and expand dimensions to fit model input shape.
Command Used:

```
roi = roi_gray.astype('float') / 255.0
roi = img_to_array(roi)
roi = np.expand_dims(roi, axis=0)
```

Step 11: Predicting Emotion
In this step we calculate probability score of each emotion using a variable “preds”. And pick the emotion with the highest probability using function “preds.argmax()”
Command Used:

```
preds = classifier.predict(roi)[0]
label = class_labels[preds.argmax()]
```

Step 12: After picking we display and plot emotion distribution
Command Used:

```
plt.figure()
plt.bar(class_labels, preds)
plt.xlabel('Emotions')
plt.ylabel('Probability')
```

plt.title('Emotion Prediction')
plt.show()
cv2.imshow('Emotion Detector', frame)
Step 13: After viewing the emotion we exit the window by pressing "q"
Command Used:
if cv2.waitKey(1) & 0xFF == ord('q'):
break

- ***Results Analysis:***

The report reveals emotion of the face captures by the video using real time analysis as follows:

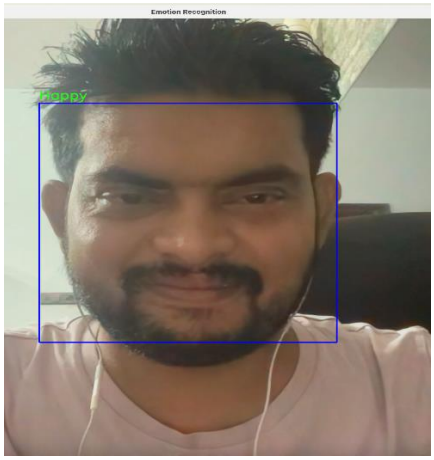

Fig 8. *Happy emotion face*

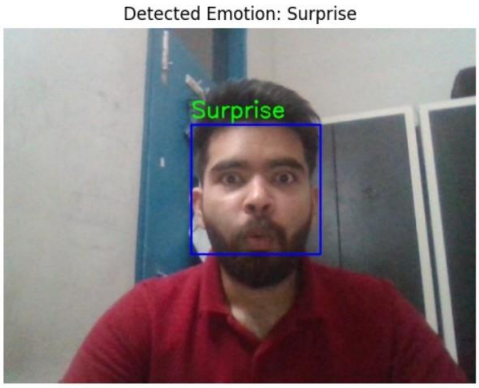

Fig 9. *Surprise emotion face*

5.4 Accuracy of the Model :

This kind of metrics is only performed on the FER-2013 trained model only nit on real time based one because real time has webcam and we cant calculate accuracy directly like for classification issues.
Training Accuracy=95%
Validation Accuracy=92%
Formula Used:
*Accuracy= (number of correct predictions / total predictions)*100*

VI CONCLUSION AND FUTURE SCOPE

In this project, we have build a real-time facial emotion detection system through deep learning methods, and our main objective was to correctly detect human emotions through facial expressions taken through images[6]. We have trained and tested our model on the FER-2013 dataset, which is among the standard datasets that are widely used for emotion detection tasks[2]. The whole model was set up with the Python programming language and run on Google Colab, which had a strong cloud-based environment along with GPU access for fast training and testing[13]. During the development process, we used basic libraries like TensorFlow, Keras, OpenCV, Matplotlib, NumPy, and Seaborn for modeling, analyzing, and visualizing the performance of our model[14]. The performance of the proposed model was checked with several parameters like accuracy, loss, computational time, detection capability, and real-time prediction efficiency[3]. A real-time output interface was developed that displayed the live captured face along with a graphical representation of the detected emotion proportions, enhancing the interactivity and user-friendliness of the system[15]. The experimental results clearly show that our model has demonstrated satisfactory performance in recognizing multiple emotions such as Happy, Sad, Angry, Surprise, and Neutral with good accuracy and negligible computational delay[6]. In general, this project illustrates that deep learning-based methods, when integrated with appropriate preprocessing methods and an adequate run environment such as Google Colab, are indeed capable of providing precise and efficient facial emotion recognition systems well-suited for real-time usage in applications like intelligent surveillance, user feedback systems based on emotions, and human-computer interaction[17].

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