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Real-Time Emotion Detection and Recommendation System

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Abstract- Emotion recognition plays a crucial role in enhancing human–computer interaction by enabling systems to understand and respond to user emotions effectively. This paper presents a real-time facial emotion detection and intelligent recommendation system using deep learning techniques. The proposed system utilizes a Convolutional Neural Network (CNN) trained on grayscale facial images to classify emotions into four categories: Angry, Happy, Neutral, and Sad. The model is trained on a balanced dataset to ensure unbiased learning across all classes. Extensive preprocessing and data handling techniques are applied to improve model generalization. The system captures real-time video input, detects facial features, and predicts emotions dynamically, followed by generating appropriate recommendations based on the detected emotional state. Experimental results demonstrate a significant improvement in model performance, achieving an accuracy of 75%, compared to an earlier baseline of 68%, highlighting the effectiveness of the proposed approach. The system is efficient, scalable, and suitable for real-world applications such as mental health monitoring, personalized user interaction, and smart assistive systems

I. INTRODUCTION

Emotion recognition has become an important research area in artificial intelligence and computer vision, particularly in improving human–computer interaction [1]. Human emotions are commonly expressed through facial expressions, speech, gestures, and body language. Among these modalities, facial expressions provide one of the most direct and reliable indicators of a person's emotional state [6]. With the rapid advancement of deep learning techniques, especially Convolutional Neural Networks (CNNs), significant progress has been achieved in automatic facial emotion recognition systems [3].

Despite these advancements, many existing emotion recognition systems focus primarily on offline emotion classification and lack efficient real-time implementation [7]. Additionally, most systems only detect emotions without providing meaningful responses or recommendations based on the detected emotional state [8]. These limitations reduce their practical usability in real-world applications such as mental health monitoring, smart assistants, interactive learning systems, and personalized user interfaces [5].

To address these challenges, this work proposes a Real-Time Facial Emotion Detection and Intelligent Recommendation System using Deep Learning. The proposed system utilizes a CNN-based model trained on grayscale facial images to classify emotions into four categories: Angry, Happy, Neutral, and Sad [3] . The system processes real-time video input through a webcam, detects faces, and predicts emotions dynamically. Based on the predicted emotion, an intelligent recommendation module generates appropriate suggestions to enhance user interaction [4]. Experimental results demonstrate an improvement in accuracy from 68% to 75%, highlighting the effectiveness of the proposed data preprocessing and model optimization techniques.

II. RELATED WORK

Emotion recognition has been widely studied across multiple domains including facial expressions, speech analysis, sentiment detection, and physiological signal processing. Mohammad and Banchs explored multimodal emotion recognition approaches and demonstrated how machine learning techniques can improve recognition accuracy across

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different data types such as text, speech, and images [9]. Their work highlights the growing importance of intelligent systems capable of understanding human emotions in real-world applications.

A major foundation in facial emotion recognition was established by Ekman and Friesen through the Facial Action Coding System (FACS), which systematically maps facial muscle movements to specific emotions [6]. This framework remains one of the most influential contributions in the field and is widely used in modern emotion recognition datasets and classification systems. In addition, the FER-2013 dataset has become one of the most commonly used benchmark datasets for facial expression recognition. It contains 35,887 grayscale facial images categorized into seven emotions and is extensively used for training deep learning models [10].

Further advancements in the field include machine learning-based approaches for automatic emotion classification. Halder et al. developed a system using image processing and neural network techniques to classify six primary human emotions, showing improved accuracy and efficiency [11]. Similarly, Chanel et al. studied emotion recognition through physiological signals and EEG data, demonstrating that combining multiple modalities can provide deeper emotional analysis [12]. In recent years, Convolutional Neural Networks (CNNs) have become the dominant approach for facial emotion recognition due to their ability to automatically learn relevant image features directly from raw data, significantly improving classification performance [3].

III. SYSTEM ARCHITECTURE

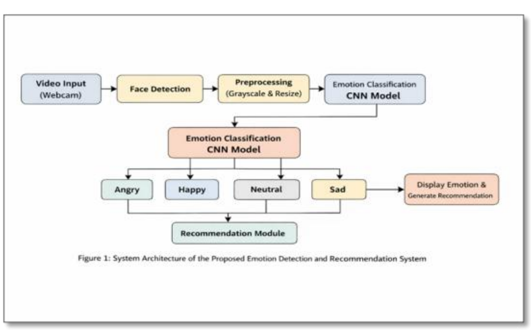

Fig.1 System Architecture

IV. METHODOLOGY

The proposed system aims to detect human emotions in real time using facial expressions and provide intelligent recommendations based on the detected emotional state. The methodology consists of several stages including data collection, preprocessing, model training, real-time emotion detection, and recommendation generation. The overall workflow of the system ensures efficient emotion recognition using deep learning techniques.

3.1 Data Collection and Dataset Preparation

The dataset used in this study is a combination of publicly available facial emotion datasets including FER-based datasets and additional labeled images collected from online repositories such as Roboflow. The dataset contains facial images categorized into four emotion classes: Angry, Happy, Neutral, and Sad.

To improve model performance and reduce bias, the dataset was organized into separate training and testing sets. The training set contains approximately 45,808 images, while the testing set includes 11,351 images distributed across the four emotion categories. Proper class distribution was maintained to ensure balanced learning during the training process.

3.2 Data Preprocessing

Before training the model, several preprocessing steps were applied to improve the quality and consistency of the dataset. All images were converted into grayscale format to reduce computational complexity while preserving essential facial features. Each image was resized to a fixed resolution of 48 × 48 pixels, which is a commonly used size for facial emotion recognition tasks.

In addition, data augmentation techniques were applied to increase dataset diversity and improve model generalization. These techniques included small rotations, horizontal flipping, and width/height shifts. Pixel values were also normalized by rescaling them to a range between 0 and 1.

3.3 CNN Model Architecture

A Convolutional Neural Network (CNN) was used to classify facial emotions from input images. CNNs are

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particularly effective for image-based tasks because they can automatically extract important spatial features from images[3].

The proposed CNN architecture consists of multiple convolutional layers followed by Batch Normalization, ReLU activation functions, and Max Pooling layers to capture important facial features. Dropout layers were incorporated to reduce overfitting during training. The final layers include a Global Average Pooling layer and fully connected dense layers with a Softmax activation function, which outputs the probability distribution for the four emotion classes.

3.4 Model Training
The emotion classification model was trained using a Convolutional Neural Network (CNN) architecture designed to learn facial expression features from grayscale images. The dataset was divided into training and testing sets to evaluate the model's performance. The model was trained for 50 epochs using the Adam optimizer with a learning rate of 0.0001. The categorical cross-entropy loss function was used to perform multi-class emotion classification for the four emotion categories: Angry, Happy, Neutral, and Sad.

To address class imbalance in the dataset, class weighting techniques were applied during training using the compute_class_weight method. This helped ensure that the model did not become biased toward classes with more samples.For real-time emotion detection, Haar Cascade Classifiers were used to detect faces from the webcam video stream[13]. The detected face region was then converted to grayscale, resized to the required input size, and passed to the trained CNN model for emotion prediction.

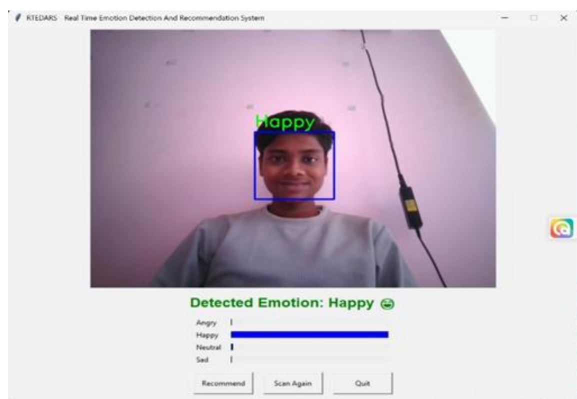
3.5 Real-Time Emotion Detection
For real-time emotion detection, the trained CNN model was integrated with a webcam-based video capture system. Each video frame is processed to detect faces using a face detection algorithm. The detected face region is then preprocessed and fed into the trained CNN model to predict the emotional state. The predicted emotion is displayed on the screen along with the detected face bounding box. This allows the system to dynamically analyze emotions from live video input.

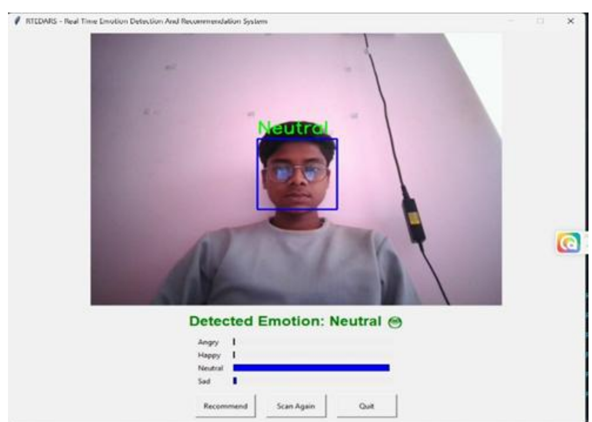
3.6 Recommendation System
After detecting the emotion, the system generates suitable recommendations based on the emotional state of the user. For example:

- Happy: Suggest productive or engaging activities
- Sad: Recommend relaxing content or motivational suggestions
- Angry: Suggest calming activities or stress relief methods
- Neutral: Provide general recommendations or positive engagement activities

This recommendation module enhances the practical usability of the system by making it interactive and user-oriented.

V. RESULTS





The performance of the proposed Real-Time Facial Emotion Detection and Intelligent Recommendation

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System was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score[13]. The model was tested on a dataset containing 11,351 test images across four emotion categories: Angry, Happy, Neutral, and Sad.

The trained CNN model achieved an overall accuracy of 75%, which represents a noticeable improvement over the earlier baseline accuracy of 68%. This improvement was achieved through dataset refinement, class balancing techniques, data augmentation, and optimization strategies during model training.

The confusion matrix shown in Figure 4.1 illustrates the classification performance of the model across different emotion categories. Most of the predictions are concentrated along the diagonal of the matrix, indicating correct classifications. The model performs particularly well in detecting the Happy emotion, which achieved the highest number of correct predictions. However, some misclassifications are observed between Neutral and Sad as well as Angry and Sad, which is expected due to the similarity of facial expressions between these emotional states.

Figure 4.1 Confusion Matrix of the Proposed Emotion Detection Model

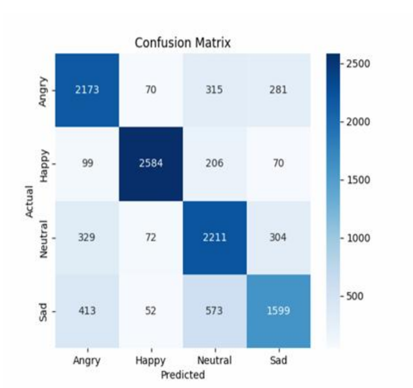

Fig 4.1 Confusion Matrix

To further evaluate the classification performance, precision, recall, and F1-score metrics were calculated for each emotion class. The results are illustrated in Figure 4.2.

Figure 4.2 Precision, Recall, and F1 Score Comparison for Each Emotion Class

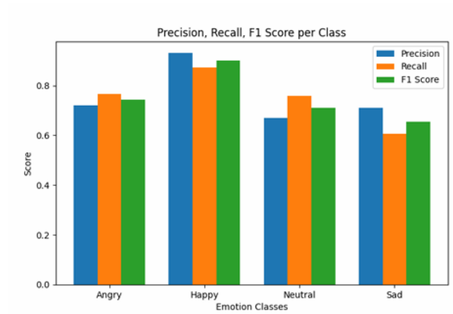

Fig 4.2 Precision, Recall, and F1-Score Analysis

The evaluation results indicate that the model performs best for the Happy emotion class, achieving the highest precision, recall, and F1-score values. The Angry and Neutral classes show moderate performance, while the Sad class exhibits slightly lower recall due to misclassification with other similar emotional states. Overall, the results demonstrate that the proposed CNN-based model effectively learns facial emotion patterns and performs reliably in real-time emotion detection scenarios.

VI. CONCLUSION

This paper presents a Real-Time Facial Emotion Detection and Intelligent Recommendation System using deep learning. The proposed CNN-based model successfully detects human emotions from live webcam input and classifies them into Angry, Happy, Neutral, and Sad categories. With the help of preprocessing, data augmentation, and optimization techniques, the model achieved an accuracy of 75%, showing a significant improvement over the previous 68% baseline. The integrated recommendation module further enhances user interaction by providing suitable emotion-based suggestions.Overall, the system proves to be effective, practical, and user-oriented, making it suitable for applications such as mental health monitoring, smart assistive systems, personalized learning platforms, and interactive user interfaces. Although the system performs well in real-time conditions, there is future scope for improvement by using larger and more diverse datasets, advanced

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deep learning architectures, and multimodal inputs such as speech and text to further improve accuracy and reliability.

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