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A NAVEL APPROACH OF REAL TIME FACIAL EMOTION RECOGNITION USING DEEP LEARNING

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ABSTRACT

The study of Facial Emotion Recognition (FER) has received a lot of attention in the field of Artificial Intelligence, especially when it comes to human-computer interactions and the capability of computers to understand human emotions. Most of the existing emotion recognition techniques are based on static image datasets, which hinders their efficiency in real-time applications. This paper introduces an AI-based emotion recognition framework based on a DCNN that uses Haar cascade face detection algorithm. The proposed system was tested using the FER2013 dataset that includes 35,887 gray-scale facial images classified as seven types of emotions. The training and validation accuracies obtained were 82.56% and 65.68%, respectively, proving that the proposed method generalizes well on unseen data. Unlike most of the existing frameworks, this one works on realtime video feeds and predicts emotions in real time. Differing from traditional approaches, the proposed system will be able to analyze live video feeds obtained via the webcam. Such capability allows the system to perform realtime analysis and predictions regarding people's emotions. By means of DCNN, it is possible to automate the process of learning complicated hierarchies of face features without manual effort.

Keywords

Artificial Intelligence, Deep Learning, Facial Emotion Recognition, Convolutional Neural Networks, Real-Time Systems, Computer Vision

1. INTRODUCTION

Human emotions are essential in the process of communicating with other people and decisionmaking. There are many ways to express one's emotions, and among the most common ones are facial expressions. People use their facial expressions to convey emotions such as joy, sorrow, anger, fear, surprise, and even neutrality. With the fast development of AI technology, computers and robots can now recognize different emotions conveyed by people's facial expressions. Nevertheless, most facial expression recognition systems are based on images, and they cannot be used to analyze dynamic videos. In addition, there are many difficulties when trying to use facial recognition systems in the real world due to such factors as illumination changes, noise backgrounds, and partial occlusions. Therefore, the purpose of this study is to develop a facial expression recognition system for the real-time application with deep learning technology. With regard to the recent advancements in AI, ML, and DL, the methods of interaction between humans and machines have undergone considerable

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transformation. Nowadays, machines are not only designed to follow pre-defined commands but can also learn to understand human behavior, emotions, and intentions. In this regard, human communication methods such as facial expression are extremely effective because emotions are conveyed through this channel quickly, effortlessly, and naturally without verbal communication.

2.LITERATURE REVIEW

1. Goodfellow et al., 2013 Topic/Focus: Emotion Recognition Using CNN Methodology/Tools: CNN, FER2013 Dataset Key Findings: CNN can classify facial emotions efficiently Limitations: Needs a huge dataset and long training time Future Scope: Enhancing accuracy using deep learning techniques

2. **Viola & Jones, 2001 Topic/Focus**: Face Detection Methodology/Tools: Haar Cascade, OpenCV Key Findings: Fast and efficient face detection Limitations: Inaccurate in poor lighting conditions Future Scope: Implementing deep learning-based face detection techniques

3. **Mollahosseini et al., 2016 Topic/Focus**: Deep Learning For Facial Emotion Recognition (FER) Methodology/Tools: DCNN, TensorFlow, Keras Key Findings: DCNN enhances the accuracy of emotion classification Limitations: High computational costs Future Scope: Improving real-time model performance

4. **FER2013 Dataset, 2013 Topic/Focus**: Emotion Dataset Methodology/Tools: Image Preprocessing, labeled Data Key Findings: Provides an emotion dataset to train models Limitations: Low image quality and noisy images Future Scope: Utilizing high-quality datasets

5. **OpenCV, 2020 Topic/Focus: Real-Time Processing Methodology/Tools**: OpenCV, Webcam Key Findings: Real-time face detection and processing Limitations: Dependent on system performance Future Scope: Enhancing processing efficiency

3. METHODOLOGY

3.1 Data Collection

FER2013 dataset is used for the training process of the model. It comprises 35,887 images that are classified into 7 categories: anger, disgust, fear, happiness, sadness, surprise, and neutral emotions.

3.2 Data Pre-processing

- Conversion to grayscale images
- Image resizing to 48×48
- Normalization of pixel intensities
- Division of dataset into training and validation set

3.3 Face Detection

Haar Cascade Classifier is chosen as the face detector because of its high efficiency and speed in real-time application.

3.4 Model Structure

The architecture of the CNN model includes:

- Convolution layers that perform feature extraction
- Pooling layers to reduce dimensionality
- Fully connected layers to classify input data

Softmax layer as an output layer

Future Scope: Optimization of speed and efficiency.

3.5 Training Process

- Loss Function: Categorical CrossEntropy
- Optimization algorithm: Adam
- Evaluation Metrics: Accuracy **3.6 Real-Time Prediction**

Integration with OpenCV to work with live video stream for emotion prediction.

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4. EXPERIMENTAL RESULTS AND ANALYSIS

The performance of the proposed real-time Facial Emotion Recognition (FER) system was evaluated through a series of experiments to analyze the accuracy of the model, realtime detection capability, and robustness under different conditions. The system was tested using live webcam input along with the trained Deep Convolutional Neural Network (DCNN) model.

4.1 Experimental Setup

The system was implemented using Python with libraries such as OpenCV, TensorFlow, and Keras. The DCNN model was trained using the FER2013 dataset, which contains 35,887 grayscale images representing seven different emotions.

Test Environment: The system was executed on a local machine with a webcam for real-time testing.
Input Data: Live video frames captured using OpenCV.
Preprocessing: Images were converted into grayscale and resized to 48×48 pixels. **4.2 Sample Predictions**

The system was tested on multiple users under different conditions such as lighting variations and facial orientations. The model successfully detected faces and classified emotions in real time.

The predicted emotions included:

- Happy
- Sad
- Angry
- Fear
- Surprise
- Disgust
- Neutral

The system showed higher accuracy in detecting common emotions like **happy and neutral**, while slight confusion was observed between similar expressions such as **fear and surprise**.
Table 1: predicted emotions

Expression Input	**Predicted Emotion**	**Confidence Level**	**Notes**
Smiling Face	Happy	High	Clear expression
Neutral Face	Neutral	High	Stable detection
Frowning Face	Sad	Medium	Slight variation
Raised Eyebrows	Surprise	Medium	Sometimes confused with fear
Angry Face	Angry	High	Accurate detection
Distorted Face	Fear	Low	Confusion observed

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Vol 20, Issuse.2 April 2026

4.3 Analysis of Results

Higher accuracy was recorded when recognizing frequent emotions such as happiness and neutral because these emotions have distinct facial expressions. Accuracy for moderate emotions such as sadness and surprise were moderately accurate whereas lower accuracy was recorded in case of fear and disgust as they share similar facial expressions.

The proposed Haar Cascade classifier was able to detect faces in real-time while the DCNN classifier was able to recognize emotions in realtime. However, performance of the system reduced when tested in a low light environment.

4.4 Accuracy Measurement

The following results were obtained for our model:

- Training Accuracy: 82.56%
- Testing Accuracy: 65.68% The difference between the training and validation accuracies indicates that there is some degree of overfitting but even then, the system works efficiently for real-time predictions and offers significant improvement over the static image based techniques.

4.5 Conclusion of Experiments

From the experiments conducted, we conclude that the proposed facial expression recognition system works satisfactorily in terms of both speed and accuracy..

4.6 Real-Time Visualizations and Engagement with the System

The proposed system offers real-time visualization where each detected face and the related predicted emotion are displayed on the video feed. Bounding boxes are used for marking out each face while the respective emotion is labeled above each detected face.

4.7 Conclusion of Experimental Results

The obtained experimental results proved that the proposed real-time facial emotion recognition system was successful and reliable since it showed satisfactory performance with respect to training and validation accuracy rates.

Metrics	Value
Training Accuracy	82.56%
Validation Accuracy	65.68%
Detection Speed	Fast
Prediction Delay	Minimal
Real-Time Processing	Yes

5.CONCLUSION AND FUTURE SCOPE

5.1Conclusion

In this paper, we have developed a real-time facial emotion recognition system by combining Deep Convolutional Neural Networks (DCNN) with the Haar Cascade technique for face detection. Our model was able to accurately detect and classify emotions of humans from

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real-time video input. The application of deep learning allowed us to implement automatic feature extraction and improved performance.

From the results obtained, we can conclude that the developed model functions effectively in real-time scenarios and makes accurate predictions. Although there are certain drawbacks in our system, for instance, susceptibility to light conditions and ambiguity between similar emotions, our model remains an effective one and ready for use.

5.2Future Scope

There are various aspects that can be modified in the proposed system to increase its efficiency. For example, advanced deep neural network architectures like ResNet and EfficientNet can be employed to achieve high accuracy with minimum misclassification of similar emotions. Another aspect is that multiface detection and tracking functionality can be integrated into the system.

Also, implementation of the system on mobile and web interfaces will make it much more practical for real-life use. Finally, additional recognition functionalities can be incorporated to make emotion detection even more accurate, such as adding speech recognition and gesture recognition modules to the system.

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