IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

AN EFFICIENT FACIAL EMOTION DETECTION

Anjanadevi. B, Vanapalli Santosh, Sura Kavya, Guduru Naveen Chowdary, Sannapu Bunni

Associate Professor, Student, Student, Student, Student

Department of Information Engineering & Computational Technology

MVGR College of Engineering (A), Vizianagaram, Andhra Pradesh, India.

ABSTRACT

Facial Emotion Detection is an important application of computer vision and deep learning that enables computers to understand human emotions from facial expressions. This project focuses on developing an intelligent system capable of detecting human emotions automatically using deep learning techniques. The proposed system uses Convolutional Neural Networks (CNN) to analyse facial expressions and classify them into different emotion categories such as happy, sad, angry, surprise, fear, disgust, and neutral. The system is trained using well-known datasets such as **CK+** (Extended Cohn-Kanade) which contain thousands of labelled facial expression images. The images are first pre-processed using techniques such as face detection, grayscale conversion, normalization, and resizing. The deep learning model then extracts important facial features automatically and learns patterns associated with different emotions. After training, the model is capable of predicting emotions from real-time facial images captured using a webcam. The developed system demonstrates good accuracy and performance in recognizing facial emotions and can be applied in various fields such as human-computer interaction, mental health monitoring, smart surveillance, and interactive gaming systems.

I. INTRODUCTION

Facial Emotion Detection is a computer vision application that enables machines to recognize human emotions by analysing facial expressions. Human emotions play a crucial role in communication, detecting emotions can improve interaction between humans and machines. This project aims to develop a deep learning based facial emotion detection system using **CK+ dataset**. These datasets contain thousands of facial images labelled with different emotional states. By training a deep learning model on these datasets, the system learns to recognize patterns and features associated with different emotions. proposed system uses **RESNET-18**, which are widely used in image recognition tasks. The **RESNET-18** model automatically extracts important facial features such as eyes, eyebrows, mouth, and facial muscle movements that represent different emotional states. The system first detects the face from an input image or webcam frame using computer vision techniques. The detected face is then pre-processed and fed into the trained deep learning model. The model analyses the facial features and predicts the corresponding emotion. The system can be integrated into various real-world applications such as smart classrooms, healthcare systems, driver monitoring systems, and customer experience analysis.

II. LITERATURE SURVEY

In order to improve the accuracy and efficiency of facial emotion recognition systems, recent research has focused on deep learning–based computer vision techniques and benchmark facial expression datasets. Traditional machine learning approaches showed limitations in handling complex facial variations under different lighting conditions and head poses. The proposed system utilizes deep convolutional neural networks and the CK+ dataset to overcome these limitations. The following section presents some significant research works carried out in this domain.

[1] This research presents one of the earliest structured facial expression datasets for emotion recognition. It provides labelled facial image sequences representing different emotional transitions. The dataset supports supervised learning approaches for expression classification. However, it has limited diversity compared to modern large-scale datasets.
[2] This book explains the fundamentals of deep learning architectures such as convolutional neural networks used for image classification tasks. CNN models automatically extract hierarchical image features and improve classification accuracy compared to traditional machine learning techniques. However, deep learning models require large datasets and higher computational resources.
[3] Deng This survey reviews various deep learning techniques used for facial emotion recognition, including CNN and residual network architectures. It highlights the effectiveness of deep neural networks in extracting discriminative facial features. However, the performance of these systems depends heavily on dataset quality and preprocessing techniques.

[4] This research introduces the Haar Cascade classifier for real-time face detection. It enables efficient detection of facial regions before performing emotion classification. Although it works well in real-time applications, it may fail under extreme lighting variations and occlusions.

[5] This book provides a comprehensive overview of computer vision techniques such as image preprocessing, feature extraction, and object recognition. These techniques are essential for facial emotion detection systems. However, traditional feature extraction approaches are less effective compared to deep learning methods.

[6] This research demonstrates the effectiveness of deep convolutional neural networks for recognizing facial expressions. The study shows that deeper architectures improve classification performance compared to shallow networks. However, deeper models increase training complexity and computational requirements.

[7] This research introduces TensorFlow as a scalable machine learning framework for implementing deep learning models. supports efficient training and deployment of neural network architectures such as ResNet-18. However, the framework requires optimized hardware resources for faster execution.

[8] This book explains practical implementation of deep learning algorithms using Python libraries such as Kera's and TensorFlow. It provides methods for building image classification models applicable to facial emotion detection. However, model performance depends on dataset preprocessing and hyperparameter tuning.

[9] This work explains the implementation of computer vision applications using OpenCV and Python. It provides techniques for face detection, image preprocessing, and real-time video analysis used in emotion detection systems. However, OpenCV alone cannot perform high-level feature extraction without deep learning integration.

[10] This documentation describes various computer vision functions such as image processing, face detection, and video capture used in real-time facial emotion recognition systems. It supports efficient preprocessing before deep learning classification. However, it requires integration with neural network models for improved prediction accuracy.

III. PROPOSED METHODOLOGY

The proposed system aims to detect human facial emotions using a deep learning–based approach. The system utilizes the **ResNet-18 convolutional neural network architecture** for accurate emotion classification and the **CK+ dataset** for model training. The methodology consists of multiple stages including data preprocessing, face detection, feature extraction, emotion classification, and real-time prediction.

First, the CK+ dataset is collected and pre-processed by resizing facial images and converting them into a suitable format for training the deep learning model. Data augmentation techniques are applied to improve model performance and reduce overfitting.

Next, face detection is performed using the **OpenCV Haar Cascade classifier**, which identifies facial regions from input images or live webcam video. The detected face is then passed to the trained ResNet-18 model.

The ResNet-18 architecture extracts deep facial features through residual learning blocks, which help overcome the vanishing gradient problem and improve classification accuracy. These extracted features are then used to classify emotions such as happiness, sadness, anger, surprise, fear, disgust, and neutral.

Finally, the trained model is integrated with a real-time webcam interface to detect and display emotions dynamically. The predicted emotion label along with confidence score is shown on the screen.

Thus, the proposed system provides an efficient and accurate solution for real-time facial emotion recognition using deep learning techniques. The ResNet-18 architecture extracts deep facial features through residual learning blocks, which help overcome the vanishing gradient problem and improve classification accuracy. These extracted features are then used to classify emotions such as happiness, sadness, anger, surprise, fear, disgust, and neutral.

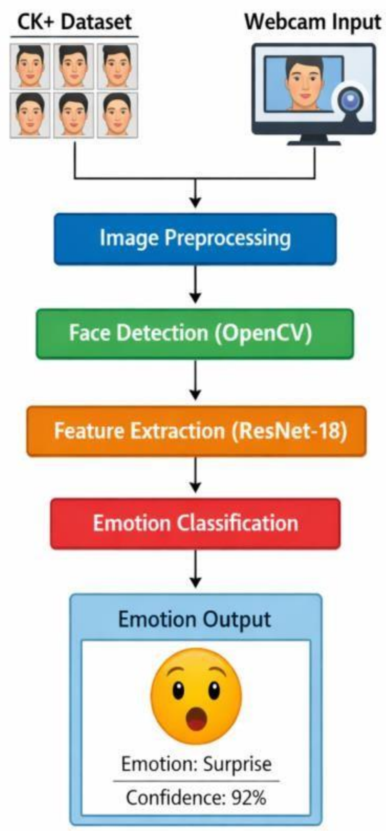


Fig 1: Working Methodology

The block diagram represents the working methodology of the facial emotion detection system. First, facial images are collected from the CK+ dataset or webcam input. The images are then preprocessed and faces are detected using OpenCV Haar Cascade. The detected face is passed to the ResNet-18 deep learning model for feature extraction and emotion classification. Finally, the system predicts emotions such as happy, sad, angry, surprise, fear, disgust, and neutral, and displays the result with confidence level.

Flowchart

The flowchart represents the working process of the facial emotion detection system. First, the system captures facial images either from the CK+ dataset during training or from webcam input during real-time execution. The captured images are then preprocessed by resizing and normalizing them to improve image quality and ensure consistency. After preprocessing, the system detects the facial region using the OpenCV Haar Cascade classifier. The detected face is then passed to the ResNet-18 deep learning model for feature extraction. Based on the extracted features, the system classifies the facial expression into emotion categories such as happy, sad, angry, fear, surprise, disgust, and neutral. Finally, the predicted emotion along with the confidence score is displayed as the output.

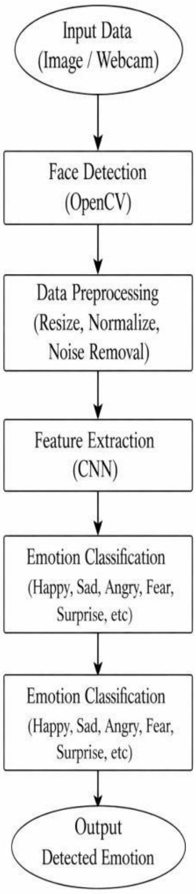
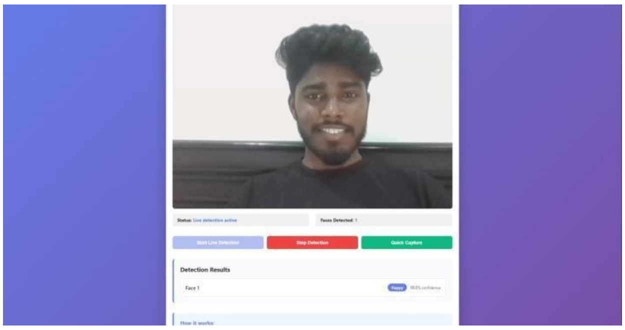


Fig 2: Process flow chart

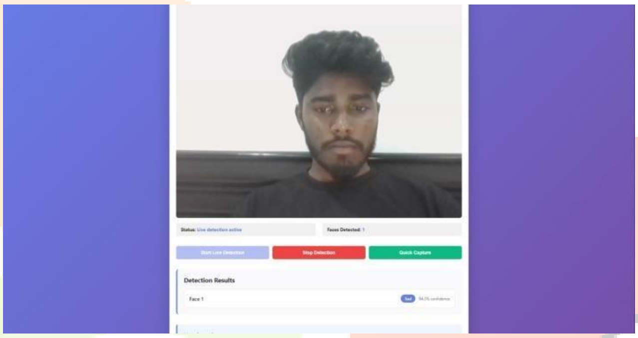
IV. RESULTS

The proposed facial emotion detection system was implemented using the ResNet-18 deep learning architecture and evaluated using real-time webcam input. The system successfully detects human facial expressions and classifies them into predefined emotional categories such as happy, sad, angry, fear, surprise, disgust, and neutral with high accuracy.

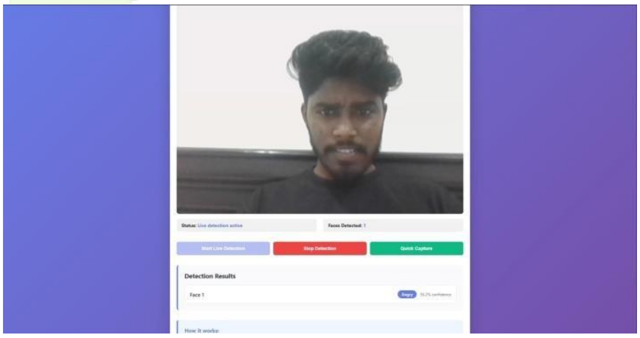


The experimental results demonstrate that the system is capable of detecting emotions dynamically under real-time conditions. The Open Haar Cascade classifier effectively identifies facial regions from webcam frames, and the ResNet-18 model extracts deep facial features to perform emotion classification.

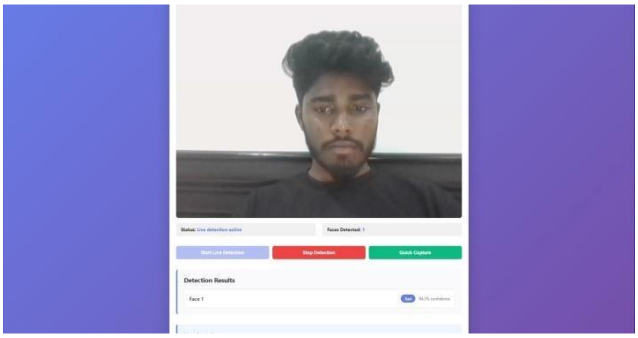
During testing, different facial expressions were captured and analyzed by the system. The model produced accurate predictions with confidence scores displayed alongside the detected emotion labels. For example, the system correctly identified the **sad emotion with a confidence score of 94.3%,** the **angry emotion with a confidence score of 55.2%**, and the **happy emotion with a confidence score of 99.8%** under live detection conditions**.**



The experimental observations indicate that the system performs highly accurate predictions for clear facial expressions such as happiness, while moderate confidence values are observed in expressions such as anger due to variations in lighting conditions, facial orientation, and expression intensity.



The developed system provides efficient real-time emotion recognition performance and demonstrates the effectiveness of deep residual learning techniques in extracting meaningful facial features. The integration of the CK+ dataset and ResNet-18 architecture improves classification reliability and supports practical deployment in human–computer interaction applications.



V. LIMITATIONS

- The model is trained on the CK+ dataset, which is relatively small and may lead to overfitting.
- The dataset consists of posed expressions captured in controlled environments, limiting real-world generalization. Performance is sensitive to lighting conditions, face orientation, and occlusions.
- Haar Cascade face detection is less robust compared to modern deep learning-based methods. Only basic emotions are recognized, lacking complex emotional understanding.

VI. FUTURE SCOPE

- Integrate larger and more diverse datasets such as FER2013 and Affect Net. Train models on real-world (in-the-wild) datasets for better generalization. Optimize models for faster inference using lightweight architectures.
- Extend to multimodal emotion detection systems. Deploy the system on cloud, mobile, or edge platforms.
- The system can also be extended for multi-face detection, mobile deployment, and integration into healthcare monitoring, driver safety, and intelligent human–computer interaction applications.

CONCLUSION

In future, the system can be improved by using larger and more diverse datasets to increase the accuracy and performance of the model. Real-time emotion detection can be enhanced with more advanced deep learning architectures and optimized processing techniques. The system can also be integrated with applications such as online learning platforms, mental health monitoring systems, and smart surveillance systems. Additionally, combining facial emotion detection with voice recognition and gesture analysis can help create more intelligent and interactive human–computer systems.

REFERENCES

[1] T. Kanade, J. F. Cohn, and Y. Tian, "Comprehensive Database for Facial Expression Analysis," IEEE International Conference on Automatic Face and Gesture Recognition, 2000. https://doi.org/10.1109/AFGR.2000.840611

[2] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016. https://www.deeplearningbook.org

[3] S. Li and W. Deng, "Deep Facial Expression Recognition: A Survey," IEEE Transactions on Affective Computing, 2020. https://doi.org/10.1109/TAFFC.2020.2981446

[4] P. Viola and M. Jones, "Rapid Object Detection Using a Boosted Cascade of Simple Features," IEEE CVPR, 2001.

Available: https://doi.org/10.1109/CVPR.2001.990517

[5] R.

Szeliski,

Computer

Vision:

Algorithms

and

Applications,

Springer,

2010.
Available: https://szeliski.org/Book/

[6] A. Molla Hosseini, D. Chan, and M. H. Mahoor, "Going Deeper in Facial Expression Recognition Using Deep Neural Networks," IEEE Winter Conference on Applications of Computer Vision, 2016.
Available: https://doi.org/10.1109/WACV.2016.7477450

[7] M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems," 2016.
Available: https://arxiv.org/abs/1603.04467

[8] "Deep Learning with Python" (2017). F.Chollet.

[9] "Practical Python and OpenCV" (2019), A. Rosebrock.

[10] "Open-Source

Computer

Vision

Library"

(

2024), OpenCV Documentation.

[11] P. Lucey et al., "The Extended Cohn-Kanade Dataset (CK+): A Complete Dataset for Action Unit and Emotion-Specified Expression,"IEEE CVPR Workshops,2010.
https://doi.org/10.1109/CVPRW.2010.5543262.