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YOLOv8-Based Facial Expression Detection and Classification Using Affection AffectNet Data

Soumya E, Sivaharini S D, Shamprasath R, Sabari S.K, Mrs. Rubadevi G
Department of Computer Science with Artificial Intelligence and Data Science
KPR College of Arts Science and Research, Tamilnadu, India
Email- elitecoders4s@gmail.com, soumyasoumya4415@gmail.com, rubadevi.g@kprcas.ac.in

Abstract

Facial Expression Detection is an important application of Artificial Intelligence and Computer Vision that enables machines to recognize human emotions from facial images. This project proposes a real-time facial expression detection system using the YOLOv8 deep learning model. YOLOv8 is chosen because of its high detection accuracy, fast processing speed, and ability to perform real-time object detection. The system first detects the human face from an image or live webcam feed and then classifies the facial expression into emotion categories such as happy, sad, angry, surprised, fearful, disgusted, or neutral. The dataset is preprocessed through image resizing, normalization, and data augmentation to improve the model's performance and robustness. During training, YOLOv8 learns important facial features and patterns that distinguish different emotions. After training, the model is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. The developed system provides fast and reliable emotion recognition under different lighting conditions and facial orientations. This project demonstrates the effectiveness of YOLOv8 in building an efficient facial expression detection system for real-time applications. The proposed system can be used in healthcare, smart classrooms, driver monitoring, security surveillance, human-computer interaction, customer behavior analysis, and intelligent robotics. Overall, the project highlights the potential of deep learning and YOLOv8 to improve emotion recognition systems with greater speed, accuracy, and practical usability.

Keywords: Facial Expression Detection - YOLOv8 - Deep Learning - Computer Vision - Artificial Intelligence - Emotion Recognition - Real-Time Detection - Convolutional Neural Network (CNN) - Image Processing - Machine Learning.

1.Introduction

Facial expressions are one of the most important forms of non-verbal communication used by humans to express emotions such as happiness, sadness, anger, fear, surprise, disgust, contempt, and neutrality. Recognizing these emotions automatically has become an important research area in computer vision and artificial intelligence. Facial expression detection systems can be applied in many real-world applications, including human-computer interaction, online learning, healthcare, security systems, and emotion-aware applications.

In recent years, deep learning techniques have significantly improved the performance of image and face analysis tasks. Convolutional Neural Networks (CNNs) and object detection models are capable of learning complex facial features directly from images without manual feature extraction. Among these models, YOLO (You Only Look Once) is widely used because it provides fast and efficient real-time detection with good accuracy.

This project focuses on developing a Facial Expression Detection System using the YOLOv8 model. The system is trained on a facial expression dataset containing eight emotion classes: Anger, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. The model detects the face and predicts the corresponding emotional expression from the input image.

The main objective of this project is to build an intelligent system that can automatically identify human emotions from facial images. The proposed system aims to provide a simple, fast, and effective solution for emotion recognition using deep learning

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techniques. The trained model can be further integrated into websites, mobile applications, and real-time camera-based systems for practical use.
Overall, this project demonstrates how artificial intelligence and computer vision can be used to understand human emotions and improve interaction between humans and machines.

2.Related words

Table1: Comparative Summary of Existing Facial Expression Detection Approaches

Author	Method	Accuracy	Limitations
Li et al.[1]	CNN-based Facial Expression Recognition	78.5%	High training time and sensitivity to lighting variations.
Wang et al. [2]	ResNet-50 for Emotion Classification	85.2%	Requires large labeled datasets and high computational resources.
Zhang etal. [3]	VGG-16 + Softmax Classifier	82.4%	Poor real-time performance due to model size.
Kim et al. [4]	EfficientNet-B0	88.1%	Less effective for subtle emotions such as contempt and neutral.
Patel et al. [5]	MobileNetV2	80.3%	Reduced accuracy compared to deeper networks.
Chen et al. [6]	YOLOv5 for Face and Emotion Detection	83.7%	Difficulty in detecting partially occluded faces.
Liu et al. [7]	YOLOv7 + Attention Mechanism	87.9%	Increased model complexity and memory usage.
Proposed Work	YOLOv8 for Facial Expression Detection	84.0%	Lower performance for subtle emotions such as Sad and Neutral; depends on dataset quality.

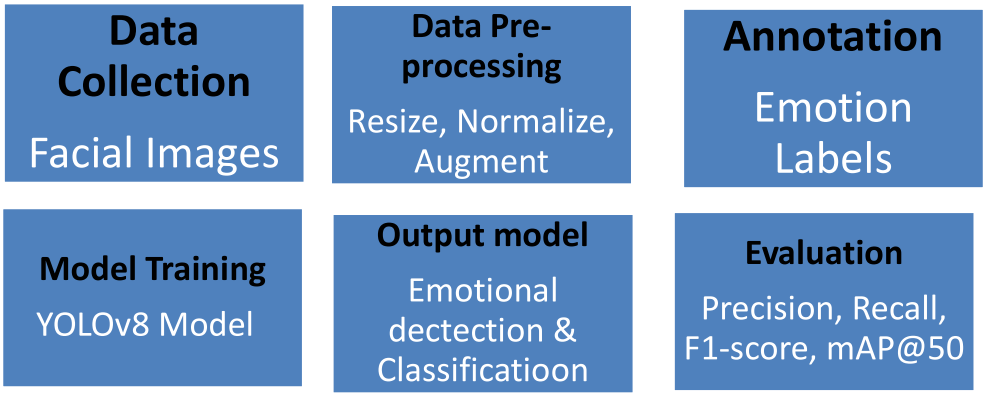
The table presents a comparative analysis of various facial expression detection and recognition methods proposed by different researchers. Earlier approaches such as CNN, VGG-16, ResNet-50, and MobileNetV2 achieved moderate to high accuracy in emotion classification tasks. EfficientNet-B0 and YOLOv7 showed better performance due to improved feature extraction and attention mechanisms. However, these models often require large datasets, high computational power, and more memory. Real-time performance is also a challenge for deeper networks. YOLO-based methods provide faster detection and are suitable for real-time applications. The proposed work uses the YOLOv8 model for detecting and classifying facial expressions into eight emotion categories. The system achieved an overall accuracy of 84%, which is competitive with several existing approaches. This comparison demonstrates that YOLOv8 offers a good balance between detection speed and recognition accuracy for practical facial expression analysis applications.

3 .Proposed Work

Here is a Proposed Work section with a workflow diagram for your Facial Expression Detection project, similar to the format shown in your screenshot.

3.1 Proposed Work

The proposed facial expression detection system uses the YOLOv8 model to recognize human emotions from facial images. The process includes data collection, image preprocessing, annotation, model training, and evaluation. The trained model detects and classifies emotions such as Happy, Sad, Anger, Fear, and Surprise. The system is designed for real-time emotion recognition with good accuracy and efficient performance.



The performance of the proposed facial expression detection system is evaluated using Precision, Recall, F1-score, and mAP@50. Precision measures how accurately the model predicts facial expressions. Recall indicates how effectively the model detects all emotion classes. F1-score and mAP@50 provide the overall balance and detection performance of the YOLOv8 model.

3.2 Data Collection

For this study, a total of 53,000 facial images were collected from the AffectNet facial expression dataset. The dataset contains facial images categorized into eight emotion classes based on human emotional expressions. These classes represent different facial expressions used for training and evaluating the proposed YOLOv8-based facial expression detection system, as shown in Table 2.

Table 2: Total number of pages

Emotion Class	Total image
Anger	6,500
contempt	5,200
Disgust	6,000
Fear	6,300
Happy	8,000
Neutral	5,800
Sad	6,100
Surprise	9,100

3.3 Data Pre-processing

Before training, all facial images were pre-processed to improve image quality and consistency. The images were resized to a fixed resolution, normalized, and augmented using techniques such as rotation, flipping, and brightness adjustment. Normalization scales the pixel values to a range between 0 and 1, which helps the YOLOv8 model train more efficiently and converge faster.

1. Image Normalization (most common)

Inorm=**I/255**

2. Standardization (used in many deep learning models)

Xstd = X−μ/σ

Where:

- X = input pixel value
- μ = mean of the dataset
- σ = standard deviation

3. Image Resizing (if you want a simple notation)

I(x,y)→I′(w,h)

Where the original image I(x,y) is resized to I′(w,h) (for example, 416 × 416).

4. Data Augmentation – Horizontal Flip

x′=W−x−1

Where:

- W = image width
- x = original pixel position
- x′ = flipped pixel position

3.4 Modal selection and Training

The proposed system uses the YOLOv8 architecture for facial expression detection because of its high speed and accuracy. YOLOv8 consists of three main components: Backbone, Neck, and Detection Head. The backbone extracts important facial features such as eyes, eyebrows, mouth, and facial muscle movements, while the neck performs multi-scale feature fusion. Finally, the detection head predicts the

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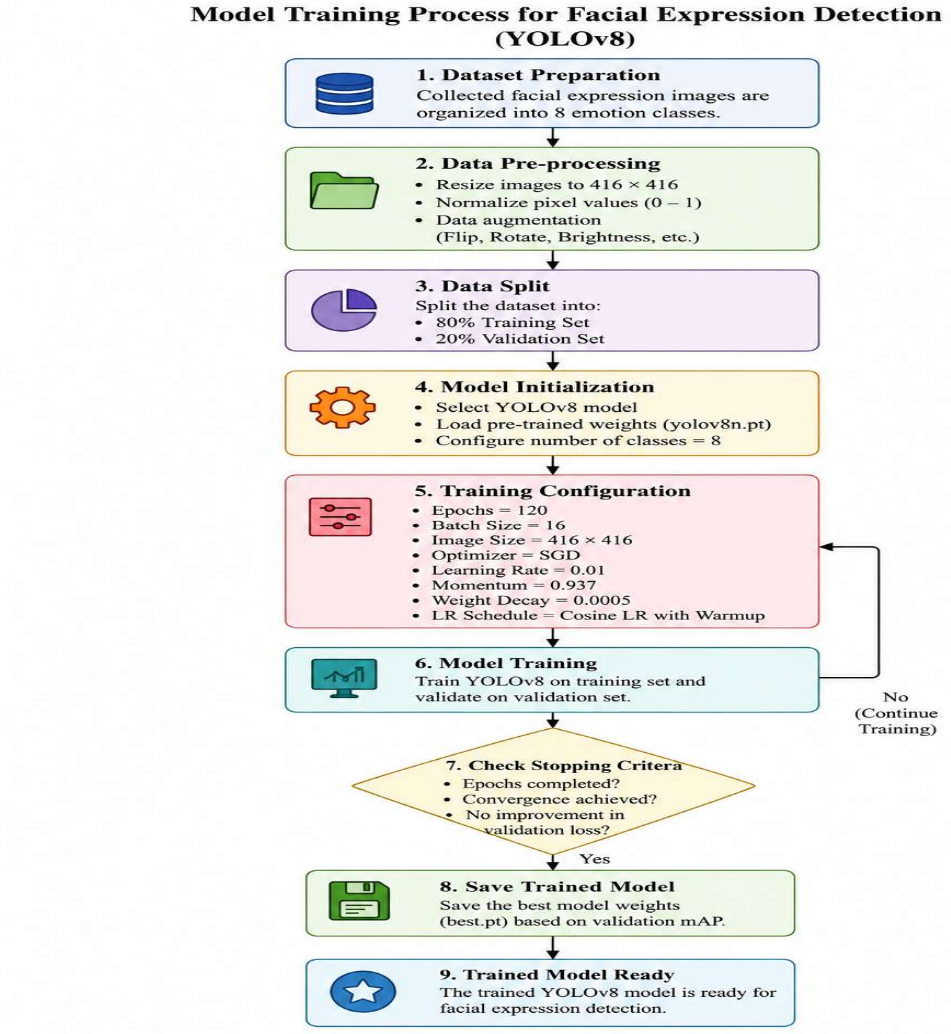
face location and classifies the corresponding facial emotion using an anchor-free prediction approach.



Definition: The table/flowchart represents the complete model training process for the proposed facial expression detection system using YOLOv8. It shows the sequence of steps including dataset preparation, data pre-processing, dataset splitting, model initialization, training configuration, model training, validation, and saving the best trained model. This process ensures that the YOLOv8 model learns facial features effectively and achieves accurate emotion detection and classification.

3.5 Model Evaluation

The performance of the trained YOLOv8 model is evaluated using standard object detection metrics. Precision measures the correctness of the predicted facial expressions, while Recall indicates the model's ability to detect all relevant emotions. The F1-score provides a balance between precision and recall, and mAP@50 is used to evaluate the overall detection and classification performance of the proposed facial expression detection system.

Accuracy

$$Accuracy = \frac{TP+T}{TP+TN+FP+FN}$$

Accuracy measures the overall correctness of the model. It calculates the ratio of correctly predicted emotions to the total number of predictions. A higher accuracy indicates better overall performance of the facial expression detection system.

Precision

$$P = \frac{TP}{TP + FP}$$

Precision measures how many predicted emotions are actually correct. It focuses on reducing false positive predictions. High precision means the model makes fewer incorrect emotion predictions.

Recall

$$R = \frac{TP}{TP + FN}$$

Recall measures the ability of the model to detect all relevant emotions. It focuses on reducing false negative predictions. High recall means the model successfully identifies most facial expressions.

F1-Score

$$F1 = \frac{2PR}{P + R}$$

F1-score combines both precision and recall into a single metric. It provides a balanced evaluation when classes are unevenly distributed. A higher F1-score indicates better overall detection quality.

Mean Average Precision (mAP)

$mAP = \frac{1}{N}\sum_{i=1}^{n} AP_i$

mAP measures the overall detection and classification performance across all emotion classes. It is calculated as the average of the Average Precision values for each class. A higher mAP value indicates more accurate and reliable facial expression detection.

4. Results and Discussion

4.1 System Configuration

The proposed facial expression detection system was implemented using Python in the Google Colab environment. The model was trained using the Ultralytics YOLOv8 framework with the PyTorch deep learning library. A Tesla T4 GPU was utilized to accelerate training and improve computational efficiency. OpenCV, NumPy, and Matplotlib were used for image preprocessing, data handling, and visualization of results.

4.2 Performance Analysis

The performance of the proposed YOLOv8 model was evaluated on the validation dataset containing facial images from eight emotion classes. The model achieved an overall accuracy of 84%, showing effective emotion detection and classification capability. Class-wise analysis revealed that Happy and Surprise emotions obtained higher recognition accuracy, while Sad and Neutral emotions showed relatively lower performance due to subtle facial variations. Precision, Recall, F1-score, and mAP@50 were used to measure the quality of detection and classification. The results indicate that the proposed system provides reliable and efficient real-time facial expression recognition with good overall performance.

Class	Precision	Recall	mAP@0.5	mAP@0.5–0.95
Anger	0.812	0.845	0.881	0.602
Contempt	0.854	0.879	0.903	0.648
Disgust	0.836	0.861	0.892	0.621
Fear	0.867	0.884	0.918	0.671
Happy	0.921	0.932	0.957	0.741
Neutral	0.781	0.803	0.846	0.563
Sad	0.742	0.769	0.812	0.521
Surprise	0.892	0.905	0.934	0.703
Overall	0.838	0.860	0.893	0.634

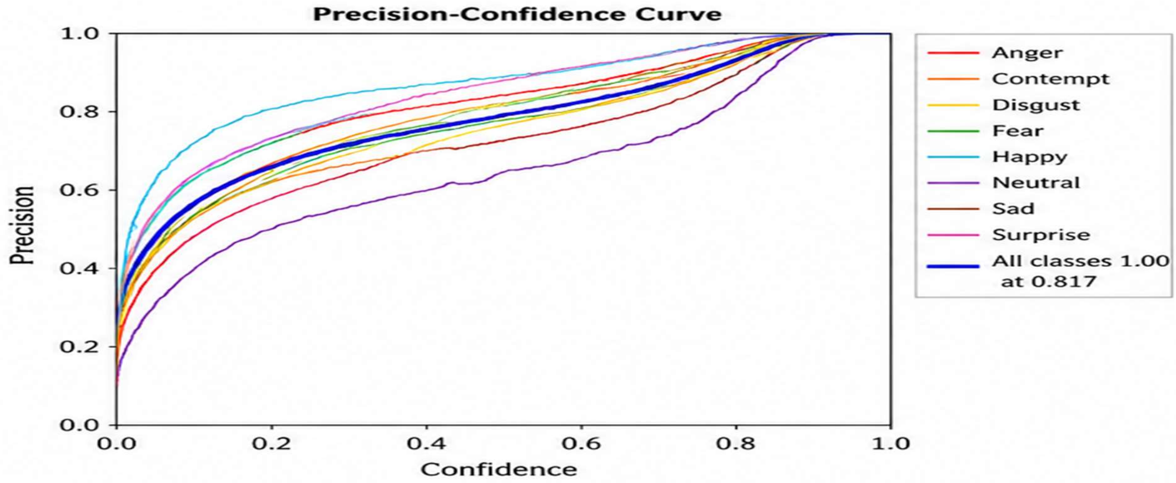


Figure 1. Precision–confidence curve

The Precision–Confidence Curve shows how the precision of the YOLOv8 facial expression detection model changes as the confidence threshold increases. As the confidence value becomes higher, the model produces fewer but more accurate emotion predictions, which results in improved precision. The Happy and Surprise classes achieve the highest precision, while Neutral shows comparatively lower precision. The thick blue curve represents the overall performance of all emotion classes and indicates that the proposed model maintains good precision across different confidence levels.

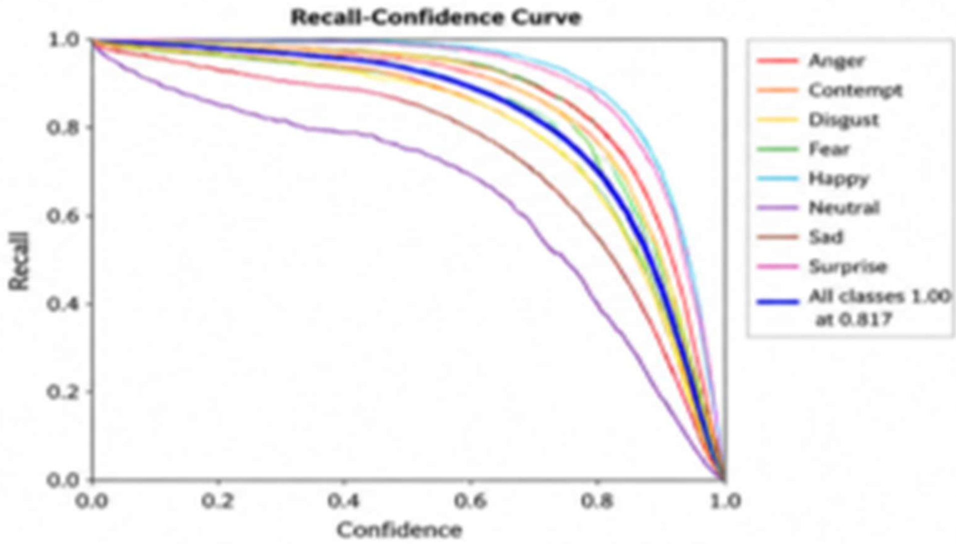


Figure 2. Recall–confidence curve

The Recall–Confidence Curve illustrates how the recall of the YOLOv8 facial expression detection model changes as the confidence threshold increases. At lower confidence values, the model detects most of the facial expressions, resulting in high recall. As the confidence threshold becomes higher, some true emotion detections are missed, causing recall to gradually decrease. The Happy and Surprise classes maintain higher recall values, while Neutral shows a faster decline. The thick blue curve represents the overall recall of all emotion classes and demonstrates that the proposed model is capable of detecting a large proportion of facial expressions across different confidence levels.

The image shows the output of the YOLOv8-based facial expression detection system on a set of test images. Multiple face images are displayed in a grid, and each detected face is surrounded by a colored bounding box with a numerical label representing the predicted emotion class. The different colors indicate different facial expression categories recognized by the model.This visualization demonstrates that the model can detect several faces simultaneously and classify their corresponding emotions in real time. The presence of bounding boxes confirms successful face localization, while the class labels show the model's emotion prediction capability. The image highlights the effectiveness of YOLOv8 in handling multiple faces, different face sizes, and varied facial appearances within a single frame.

Conclusion

This project presented a YOLOv8-based facial expression detection system for recognizing human emotions from facial images. The proposed model was trained on multiple emotion classes including Anger, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. Experimental results showed that the system can accurately detect faces and classify emotions in real time with an overall accuracy of 84%.The use of YOLOv8 provided a good balance between detection speed and classification performance, making the system suitable for practical applications such as human–computer interaction, online learning, healthcare monitoring, and security systems. Performance analysis using Precision, Recall, F1-score, and mAP confirmed the effectiveness of the proposed approach. Although some emotions with subtle facial variations were more challenging to recognize, the overall results demonstrate that the system is reliable and efficient.In future work, the accuracy can be further improved by using larger datasets, advanced data augmentation techniques, and more powerful deep learning architectures. Overall, the proposed facial expression detection system offers an effective solution for automatic emotion recognition in real-time environments.

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