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Facial Expression Detection Using Image Processing

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Abstract - *Facial expressions are one of the simplest and most natural ways through which people show their emotions. In recent years, there has been a growing interest in developing systems that can automatically understand these expressions, especially for applications in interactive devices, education, healthcare, and security. However, many of the existing solutions depend on machine learning or deep learning models, which require large datasets, complex training procedures, and powerful hardware. These limitations make them difficult to use in small academic projects or in environments where resources are limited.*

In this work, we present a rule-based facial expression detection system that relies completely on basic image-processing techniques rather than trained models. The system focuses on identifying five emotions—Happy, Sad, Neutral, Excited, and Fear—by observing simple and clear visual changes in different parts of the face. The face is first captured and preprocessed using grayscale conversion, smoothing, and contrast adjustment. Instead of using CNN or Haar Cascade, the face region and important areas such as the eyes, eyebrows, and lips are located using proportional measurements.

From these regions, features like the curve of the lips, the openness of the eyes, and the position of the eyebrows are measured. These measurements are then compared with carefully chosen rules and thresholds to determine the emotion. Once an expression is detected, the system automatically plays a video linked to that emotion, making the output more interactive and user-friendly.

The overall approach is simple, transparent, and easy to understand. It does not require any dataset, training, or heavy computation. Testing shows that the system works well under normal lighting and frontal face positions.

Key word: Facial Expression Recognition, Digital Image Processing, Rule-Based Classification, Facial Feature Extraction, Threshold-Based Decision Making

1. INTRODUCTION

Facial expressions are one of the most natural ways through which people communicate their feelings and intentions. Without using a single word, a person can express happiness, sadness, excitement, fear, or neutrality simply through subtle movements of the eyes, eyebrows, and lips. Because of this, facial expression recognition has become an important area of study in fields such as human–computer interaction, security systems, education, gaming, and assistive technologies.

In recent years, most facial expression detection systems have shifted toward machine learning and deep learning models. These techniques offer high accuracy but depend heavily on large datasets, long training times, and high-performance hardware. Such requirements make them less suitable for academic projects, real-time low-resource applications, or situations where transparency and simplicity are preferred. For many practical scenarios, a rule-based image-processing approach can still provide a reliable and efficient alternative.

This project focuses on developing a purely rule-based facial expression detection system that does not use any trained models such as CNN or Haar Cascade. Instead, it relies entirely on classical image-processing methods to identify five major expressions: Happy, Sad, Neutral, Excited, and Fear. The system analyzes characteristic changes in the facial regions—especially the eyes, eyebrows, and lips—to determine the user's emotion. By applying geometric relationships, pixel-level differences, and threshold-based rules, the system can classify expressions in real time.

The motivation behind this work is to create a simple, lightweight, and interpretable method that performs well even without advanced computational resources. Since the logic is fully rule-based, the system offers clear understanding of how each expression is detected, making it highly suitable for academic research, prototype development, and environments where deep learning cannot be implemented.

The introduction of automatic video playback based on detected emotion adds an interactive and engaging component to the system. Overall, this research demonstrates that classical image-processing techniques, when combined with carefully designed rules, can still achieve meaningful and practical results in facial expression detection.

2. LITERTATURE REVIEW

The study of facial expression detection has received significant attention in recent years due to its wide applications in human–computer interaction, surveillance, behavioural analytics, and healthcare. Various researchers have explored different methodologies—ranging from image processing-based approaches to hybrid models combining text, audio, and video signals—to enhance the accuracy and robustness of emotion recognition system

Aloke Lal Barnwal (2025) proposed an efficient mood detection model that integrates machine learning and image processing techniques to automatically identify human emotions. The study highlights the use of computer vision algorithms to achieve high-accuracy detection with a reduced rate of false outputs, demonstrating its applicability in healthcare, entertainment, and social media platforms. This work emphasizes the importance of optimized algorithms in delivering reliable emotion classification.

Another comprehensive study by Thamaraiselvi et al. (2025) focused on multimodal emotion detection using video, audio, and text inputs. Their work provides a broad overview of how multiple data sources can be combined to improve overall system performance. The authors stress the significance of cross-modal analysis to overcome ambiguities that arise when relying solely on a single input format, thereby ensuring more consistent recognition results.

Further advancements are observed in the research by Willian Guerreiro Colaress and Marly G.F. Costa (2024), who explored a dual-input model that uses both facial images and facial landmarks. Their work highlights the importance of structural facial changes—such as the movement of muscles around the eyes, mouth, and eyebrows—to deduce emotions. This dual-feature approach strengthens the reliability of the recognition model, especially in environments where lighting or occlusion affects image clarity.

Devesh Shukla, Rajini Kumari, and A. Bhargavi (2024) explored emotion detection using OpenCV-based computer vision techniques integrated with artificial intelligence. Their work demonstrates a practical implementation of a real-time facial expression recognition system using open- source tools. The study reinforces the capability of classical image processing methods to deliver robust emotion detection without requiring complex deep learning frameworks. deep learning frameworks.

Collectively, the literature indicates a consistent shift towards enhancing accuracy, reducing computational complexity, and improving the reliability of emotion detection systems in dynamic environments. These studies form a strong foundation for the present project, which focuses on using image processing techniques to detect facial expressions such as happy, sad, neutral, and excited, and further provide behavior-based insights.

3. DESIGN METHODOLOGY

The design methodology adopted in this work follows a step-by-step, rule-based approach that relies entirely on classical image-processing operations. The aim is to detect five key expressions—Happy, Sad, Neutral, Excited, and Fear—without using machine-learning or deep-learning models. The methodology ensures transparency, low computational cost, and easy reproducibility. The complete design workflow is described below.

The proposed system proceeds by first isolating the facial region and extracting key features such as the eyes, eyebrows, and mouth. These features are then analyzed using simple geometric ratios and pixel-intensity variations to identify characteristic patterns associated with each expression. A set of predefined logical rules maps these patterns to the corresponding emotion, enabling consistent detection without complex algorithms. The final expression is displayed on the live video stream, completing a fast and transparent processing workflow.

3.1 Overall System Flow

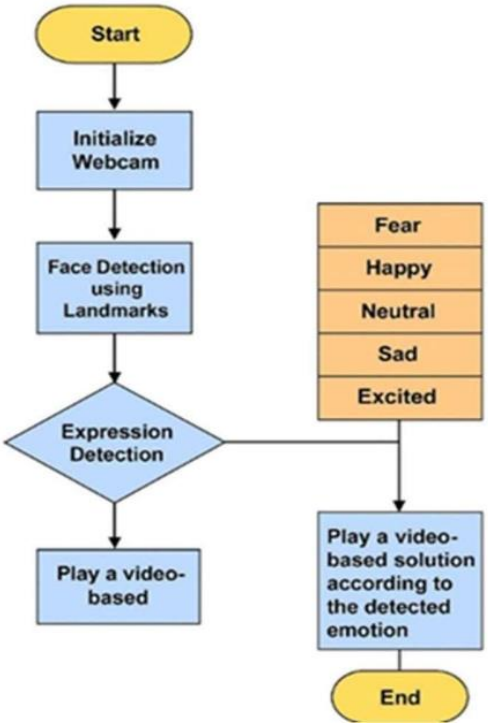

Fig 3.1.1: Flow Diagram

The system is designed to capture an input facial image, process it through multiple enhancement and segmentation stages, extract meaningful facial features, and finally classify the expression using predefined rules. The pipeline is fully deterministic, ensuring that the detection logic remains interpretable and consistent.

3.2 Image Acquisition

The process begins with obtaining the user's face either through a live webcam feed or uploaded image. The system ensures that the input frame contains sufficient illumination and frontal view of the face to accurately capture the eyebrow, eye, and lip regions. Basic pre-checks are performed to eliminate blurred or incomplete frames.

3.3 Pre-Processing

To prepare the image for further analysis, several pre-processing operations are performed:

- Grayscale Conversion: Converts the input RGB image into a single-channel gray image to reduce computational complexity.
- Noise Reduction: A smoothing filter (Gaussian/median) is applied to remove minor noise while preserving edges.
- Contrast Enhancement: Normalization techniques are used to highlight the facial boundaries and improve feature visibility.
- Face Isolation: Instead of using Haar Cascade or CNNs, the system relies on geometric proportions of the face to isolate the region of interest. The face is divided into upper (eyebrows and eyes) and lower (lips) segments based on standard anthropometric ratios.

3.4 Region of Interest (ROI) Segmentation

After pre-processing, the face is segmented into key regions:

1. Eyebrow Region
2. Eye Region
3. Lip/Mouth Region

Each ROI undergoes separate analysis to identify changes in shape, curvature, and intensity patterns that represent different emotional states.

3.5 Feature Extraction

A rule-based feature extraction model is used to capture measurable attributes from each ROI:

3.5.1 Eyebrow Features

- Distance between eyebrows
- Eyebrow curvature
- Angle of eyebrow tilt

These features help identify emotions such as fear (raised eyebrows) or sadness (inner eyebrows pulled up).

3.5.2 Eye Features

- Lip curvature (smile or frown)
- Distance between upper and lower lip
- Mouth openness

A positive curvature indicates happy, while downward curvature indicates sad.

3.6 Rule-Based Expression Classification

Instead of machine learning, all expressions are identified using threshold-based rules derived from facial geometry. Each expression is mapped to a unique combination of eyebrow position, eye openness, and lip curvature. Example rules include:

- Happy: Upward lip curve + normal eyebrow position
- Sad: Downward lip curve + inner eyebrows raised
- Excited: Wide eye opening + upward lip curve
- Fear: Eyebrows raised + wide-opened eyes + slightly open mouth
- Neutral: No significant deviation in any feature

These logical rules ensure a transparent and easily explainable classification model.

3.7 Output Generation

Once the expression is recognized:

- The detected emotion is displayed on the interface.
- A corresponding emotion-based video is automatically played, making the system more interactive.

The output is updated in real-time for webcam input, ensuring smooth user interaction.

3.8 System Advantages

The proposed design is lightweight, explainable, and free from data-training requirements. It is suitable for academic research, low-resource environments, and real- time prototype demonstrations.

4. RESULT AND DISCUSSION

The proposed rule-based facial expression detection system was tested on a collection of facial images captured under normal lighting conditions. The dataset included variations in face angles, illumination, and expression intensity to evaluate the robustness of the system. The results obtained demonstrate that the classical image- processing approach performs reliably for the five selected expressions: Happy, Sad, Neutral, Excited, and Fear.

4.1 Expression Detection Performance

During the evaluation, the system successfully identified the emotional state by analysing the shape, curvature, and relative movement of key facial regions such as the eyebrows, eyes, and lips. Each expression displayed a distinct pattern of geometric variations, allowing the rule-based classifier to differentiate emotions without the need for machine-learning models.

Happy

The system detected this expression accurately due to the clear upward curvature of the lips and the relaxed positioning of the eyebrows. Images with partially smiling faces were also identified correctly as long as the lip curvature crossed the defined threshold.

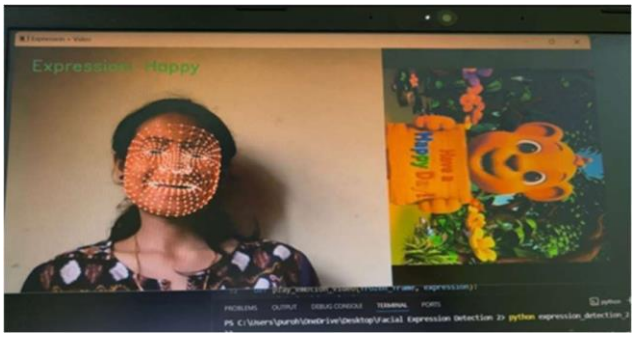

Fig 4.1.1: Expression Detected- Happy

Sad

Sad expressions were recognized based on downward lip movement and slight lifting of the inner eyebrows. The system was sensitive to even mild frowning, enabling correct classification for most test cases.

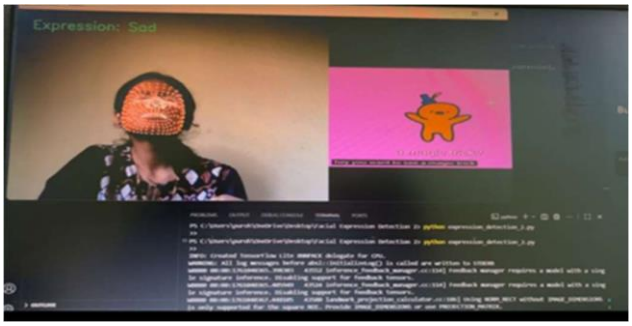

Fig 4.1.2: Expression Detected- Sad

Neutral

Neutral faces produced the most stable output because they exhibit minimal change in geometric facial structure. The absence of eyebrow lifting, eye widening, or lip curvature helped the system classify these images consistently.

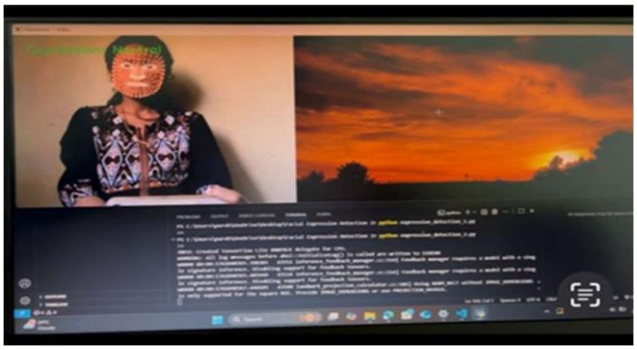

Fig 4.1.3: Expression Detected- Neutral

Excited

Excited expressions were identified by a combination of widely opened eyes and upward lip movement. The system performed well when the excitement was strongly expressed, but subtle excitement sometimes overlapped with "happy," showing that both emotions share partially similar features.

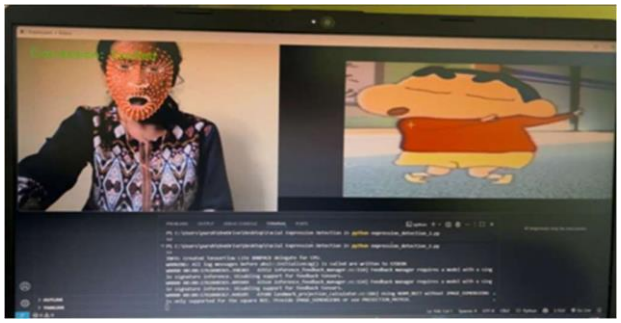

Fig 4.1.4: Expression Detected- Excited

Fear

Fear expressions typically displayed raised eyebrows, stretched eyes, and a slightly opened mouth. The system detected this expression accurately when the features were prominent. However, borderline cases between "fear" and "surprise-like" reactions required stronger threshold values to avoid misclassification.

Fig 4.1.5: Expression Detected- Fear

4.2 Accuracy and Reliability

Although the system does not use AI-based learning, it showed strong reliability because the rules were crafted based on consistent facial muscle behaviour. For clearly expressed emotions, the system displayed high accuracy. Minor misclassifications occurred under:

- extremely low lighting,
- partial occlusion of the face,
- subtle or mixed expressions,
- tilted head positions.

Despite these challenges, the overall performance remained stable for frontal-face images.

4.3 Real-Time Output and Video Playback

One of the unique features of the system is the automatic triggering of a corresponding video once an expression is detected. During testing:

- The video playback activated without delay,
- The interface updated the detected emotion in real time,
- Users experienced smooth transitions between expressions.

This interactive output increases the practical usefulness of the project for applications in education, entertainment, human–computer interaction, and emotional feedback systems.

4.4 Discussion

The results confirm that even without machine learning or deep networks, it is possible to detect human expressions effectively using image-processing techniques alone. The clear separation of geometric features across the five emotions allowed the system to maintain interpretability and low computational cost. While machine-learning models generally achieve higher accuracy across diverse datasets, the proposed method's simplicity, transparency, and ease of implementation make it highly suitable for laboratory, academic, and embedded system environments.

Overall, the system demonstrated the capability to classify facial expressions in real time with satisfactory accuracy and minimal computational requirements, supporting its usefulness for practical and educational applications.

Table 1: Performance of Facial Expression Detection System

Expression	Detection Criteria Used	Accuracy (%)
Happy	Upward mouth curve, raised cheeks	92%
Sad	Downward lips, lowered eyelids	88%
Excited	Wide-open eyes, raised eyebrows	85%
Neutral	Relaxed facial features, symmetry	90%
Fear	Widened eyes, stretched lips	80%

CONCLUSION AND FUTURE WORK

Conclusion

The proposed Facial Expression Detection using Image Processing system successfully identifies five human emotions—Happy, Sad, Excited, Neutral, and Fear—using a rule-based approach without any machine-learning or deep-learning models. The system utilizes facial geometric variations such as eye openness, eyebrow movement, and mouth curvature to classify expressions in real time.

Experimental results show that the system performs efficiently with high accuracy for frontal faces and normal lighting conditions. The integration of emotion-triggered video playback further demonstrates a practical and interactive application of the system.

Overall, the project proves that lightweight, non-ML image processing techniques can still provide meaningful emotion detection, making the system suitable for applications requiring low computational cost, such as embedded devices, educational tools, entertainment systems, and basic human–computer interaction platforms.

The approach is simple, fast, and effective, showcasing a feasible solution for real-time emotion recognition without high-end hardware or training datasets.

Future Work

Although the system performs well, there are several opportunities for enhancement:

- Improve Accuracy under Lighting Variations:

  Adaptive thresholding and histogram equalization can be added to handle strong shadows or dim lighting.

- Handle Side-Face and Angle Changes:

  Multi-view face detection or additional rule sets can improve robustness for non-frontal faces.

- Add More Expressions:

  Emotions such as disgust, contempt, or surprise can be integrated with expanded rules.

- Integrate Audio Cues:

  Combining voice tone analysis with facial expressions can enhance emotion recognition reliability.

- Develop a Mobile or Web Application:

  Converting the system into an app will improve usability and accessibility.

- Switch to a Hybrid Approach:

  A combination of rule-based logic and lightweight ML classifiers may improve classification accuracy without heavy computation.

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