



(RESEARCH ARTICLE)



## Emotion detection from facial images: A hybrid approach to feature extraction and classification

Ruchita Mathur\* and Vaibhav Gupta

*Faculty of Computer Science, Lachoo Memorial College of Science and Technology (Autonomous), Jodhpur, Rajasthan, India.*

World Journal of Advanced Research and Reviews, 2024, 24(02), 2227–2234

Publication history: Received on 16 October 2024; revised on 25 November 2024; accepted on 27 November 2024

Article DOI: <https://doi.org/10.30574/wjarr.2024.24.2.3620>

### Abstract

Emotion detection from facial images has become increasingly important across various domains, including human-computer interaction, security, and mental health assessment. This study presents a novel hybrid approach that integrates traditional feature extraction techniques with advanced deep learning methods to enhance the accuracy and reliability of emotion recognition systems. We explore conventional methods, such as Local Binary Patterns (LBP) and Gabor filters, which focus on capturing texture and spatial features of facial expressions. In conjunction with these techniques, we employ Convolutional Neural Networks (CNNs) for automatic feature extraction, allowing the model to learn complex patterns in the data without manual intervention. By combining traditional and modern methods, our approach leverages the strengths of both, effectively capturing intricate facial expressions and reducing the impact of variations in lighting, occlusion, and orientation. In our experimental evaluation, we utilize well-established datasets, including FER2013 and CK+, to rigorously train and test our model. We apply various classification algorithms, such as Support Vector Machines (SVM) and advanced deep learning frameworks, to assess the performance of the extracted features.

The results demonstrate that our hybrid approach significantly outperforms traditional methods alone, achieving superior accuracy, precision, and robustness in emotion detection. This research underscores the potential of combining diverse feature extraction techniques to enhance the reliability and effectiveness of facial emotion recognition systems. Our findings suggest that the integration of conventional and deep learning methods can pave the way for more effective and practical applications in real-world scenarios, ultimately contributing to advancements in fields such as affective computing, user experience design, and mental health monitoring.

**Keywords:** Emotion Detection; Support Vector Machines (SVM); Convolutional Neural Networks (CNNs); Deep Learning Methods; Local Binary Patterns (LBP); Gabor Filters

### 1. Introduction

Emotion detection from facial images has garnered significant attention across a range of applications, including security, healthcare, and human-computer interaction (HCI). In the realm of security, emotion recognition enhances surveillance systems by identifying suspicious behavior, potentially preventing crimes or identifying threats in real-time. Advanced emotion detection algorithms can analyze live video feeds to flag unusual behaviors, allowing for proactive security measures and improved situational awareness. In healthcare, emotion recognition plays a crucial role in monitoring patients' emotional states, particularly in mental health assessments and interventions. By analyzing facial expressions, healthcare providers can gain insights into a patient's emotional well-being, which is essential for diagnosing conditions such as depression and anxiety.

\* Corresponding author: Ruchita Mathur

Furthermore, in HCI, understanding user emotions can lead to more intuitive and adaptive user experiences. Emotion-aware systems can adjust their responses based on the user's emotional state, enhancing engagement and satisfaction. For example, educational software can adapt its difficulty based on a student's frustration or excitement levels, thereby optimizing the learning experience. Similarly, customer service chatbots equipped with emotion detection capabilities can respond more empathetically to users, improving overall customer satisfaction.

As technology advances, the ability to accurately interpret emotional expressions from facial images has become increasingly vital. This has spurred research and development in the field, leading to more sophisticated algorithms and models capable of recognizing a wide range of emotions under various conditions. However, despite these advancements, several challenges remain in achieving reliable and consistent emotion detection across different contexts, populations, and environmental settings. Addressing these challenges is crucial for the successful implementation of emotion recognition systems in real-world applications.

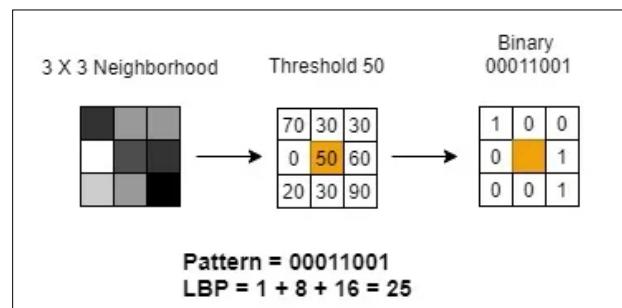
## 2. Facial Emotion Extraction Techniques

The methodology for emotion detection in this study revolves around a hybrid feature extraction approach that combines traditional techniques with advanced deep learning methods. This combination aims to leverage the strengths of both to enhance the accuracy and robustness of emotion recognition.

### 2.1. Traditional Approaches

#### 2.1.1. Local Binary Patterns (LBP)

LBP is a texture descriptor that encodes the local structure of an image by comparing each pixel with its neighboring pixels. Each pixel is converted into a binary value based on whether it is greater than or less than its neighbors. This binary pattern is then used to create a histogram that represents the texture information of the image.



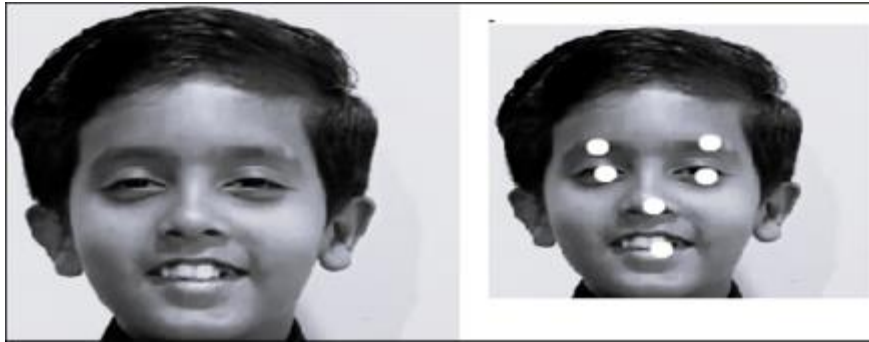
<https://aihalapathirana.medium.com/>

**Figure 1** Local Binary Patterns

The process of using Local Binary Patterns (LBP) for emotion detection involves dividing the facial image into smaller regions or grids, computing the binary pattern for each pixel in these grids, converting the patterns into decimal values to form histograms, and concatenating these histograms to create a global representation of the image. This method is simple, computationally efficient, and effective in capturing local textures and micro-patterns, such as wrinkles, which are crucial for recognizing emotions like anger or joy. However, it has limitations, as it is sensitive to noise and lighting variations and struggles with capturing global patterns or larger-scale facial structures.

#### 2.1.2. Gabor Filters

Gabor filters are linear filters used to analyze the spatial frequency content of an image. They are particularly effective for capturing edges and textures at different orientations and scales. A Gabor filter can be defined in both spatial and frequency domains, making it versatile for image processing tasks.



**Figure 2** Gabor Filters

Gabor filters are applied to facial images using multiple orientations and scales to extract features such as edges around the eyes, mouth, and eyebrows that correspond to emotional expressions. These extracted features are used to represent the image, making Gabor filters excellent for capturing fine details like facial contours and textures. They are robust to slight variations in pose and lighting, enhancing their reliability in diverse conditions. However, the approach is computationally intensive, particularly when using multiple scales and orientations, and requires precise parameter tuning for optimal performance.

## 2.2. Deep Learning Techniques

### 2.2.1. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for tasks involving image data. They have proven to be highly effective in automatically learning and extracting hierarchical feature representations from raw pixel data, without the need for manual feature engineering. CNNs operate by leveraging three primary types of layers: **convolutional layers**, **activation layers**, and **pooling layers**, each playing a distinct role in feature extraction and dimensionality reduction.

#### Convolutional Layers

Convolutional layers are the building blocks of CNNs. They apply a set of learnable filters (also called kernels) to the input image, producing **feature maps**. These filters are small, typically spanning only a few pixels, and slide across the input image in a process called **convolution**. Each filter is designed to detect specific features, such as edges, textures, or corners. As the network deepens, these filters capture increasingly abstract and complex features, such as facial landmarks or patterns in expressions.

#### Activation Functions

After the convolution operation, an **activation function** is applied element-wise to the feature maps. This introduces non-linearity, allowing the network to model more complex relationships and patterns in the data. The activation function ensures that the CNN can learn both subtle and pronounced variations in image features.

#### Pooling Layers

Pooling layers are used to reduce the spatial dimensions of the feature maps, making the computation more efficient and reducing the risk of overfitting. Commonly used pooling techniques include **max pooling**, which retains the maximum value in a region of the feature map, and **average pooling**, which computes the average value. By summarizing regions of the feature maps, pooling layers distill the most significant information while discarding irrelevant details.

In the context of this study, the CNN architecture involves stacking multiple convolutional and pooling layers to progressively extract and distill features from facial images. These feature representations form the basis for downstream tasks, such as classification or regression, enabling the model to recognize and interpret facial expressions with high accuracy.

Facial Expressions with Multiple Images






S.N.	Neutral	Angry	Fear	Surprised	Sad	Happy
1.	 Neutral: 98.94663691520691	 Angry: 84.83389435218506	 Fear: 99.48664304534454	 Surprise: 81.39851093292236	 Sad: 52.81384024785045	 Happy: 99.68949556350708
2.	 Neutral: 75.20902156829834	 Angry: 92.03738427830653	 Fear: 75.07011591552306	 Surprise: 84.85389261566952	 Sad: 59.02065390471542	 Happy: 89.67636823654175
3.	 Neutral: 80.41875958442688	 Angry: 70.6949827671051	 Fear: 68.6949827671051	 Surprise: 84.83322858810425	 Sad: 54.50557199153733	 Happy: 64.6949827671051

Figure 3 Table of Multiple images

3. Comparative Analysis

Table 1 Points of expression of input images

Name	Neutral	Angry	Fear	Surprise	Sad	Happy
1	98.95	84.83	99.49	81.40	52.81	99.69
2	75.21	92.04	75.07	84.85	59.02	89.68
3	80.42	70.69	68.69	84.83	54.51	64.69

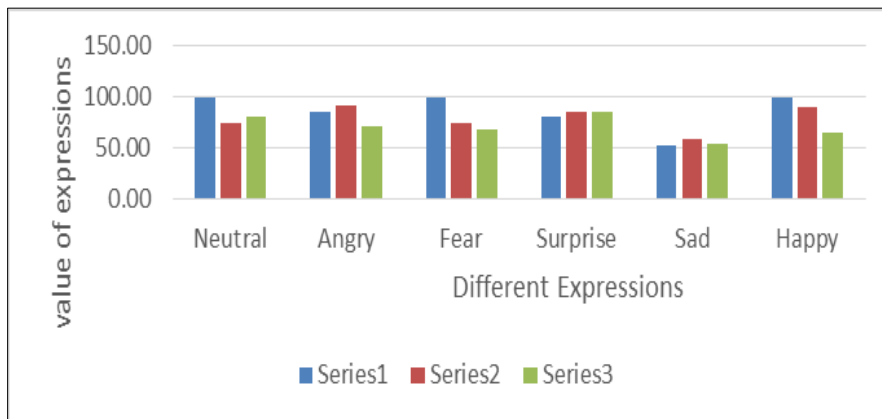
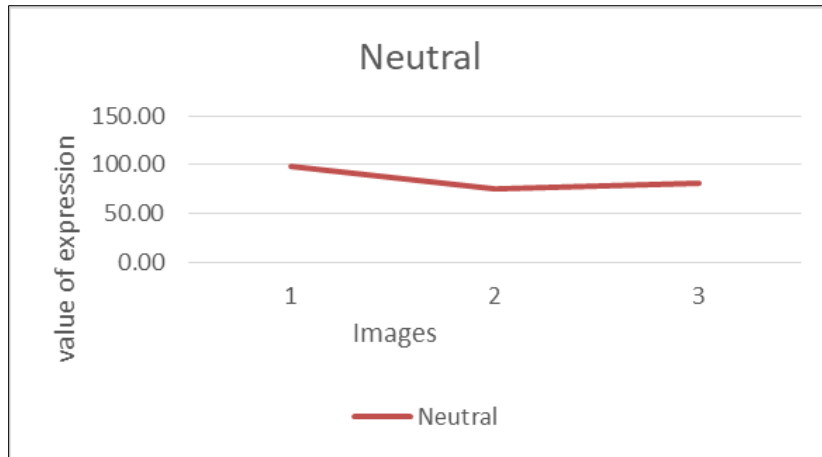
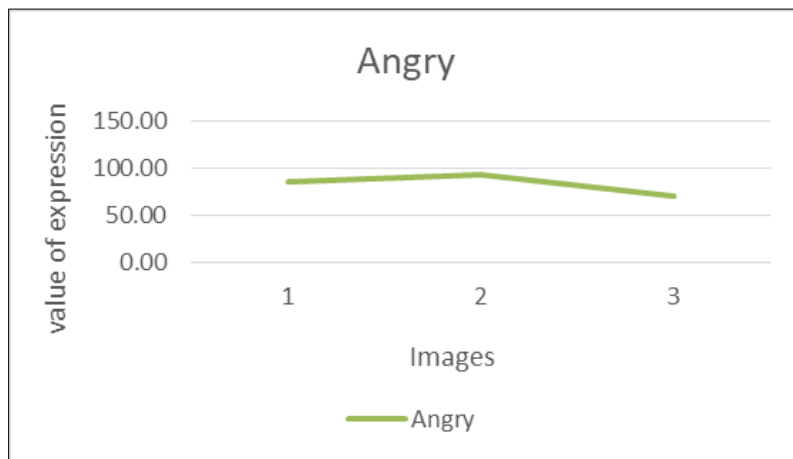


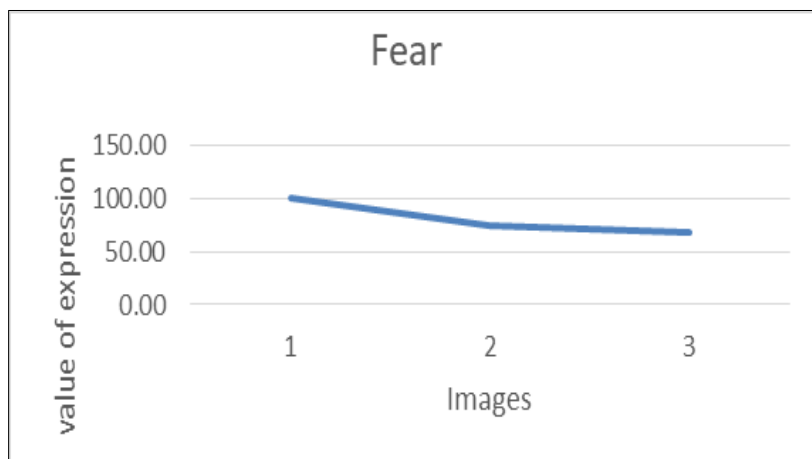
Figure 4 Analysis of different expression with multiple images



**Figure 5** Comparison of Neutral expression



**Figure 6** Comparison of Angry expression



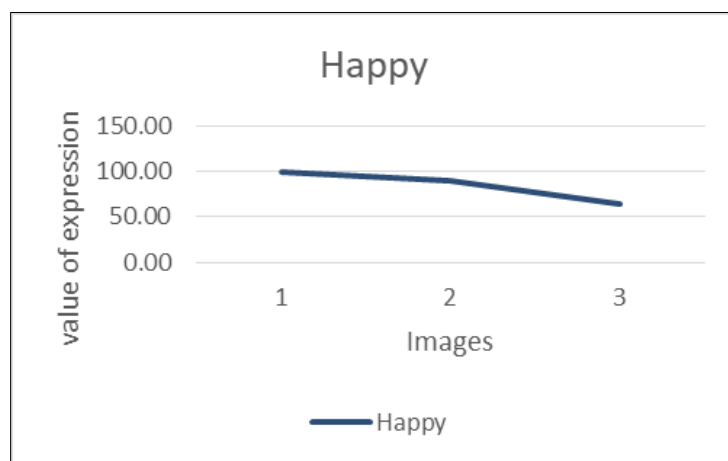
**Figure 7** Comparison of Fear expression



**Figure 8** Comparison of Surprise expression



**Figure 9** Comparison of Sad expression



**Figure 10** Comparison of Happy expression

## 4. Applications of Facial Emotion Extraction Techniques

### 4.1. Healthcare and Therapy

- **Mental Health Monitoring:** Detect emotional states such as anxiety, depression, or stress for early intervention.
- **Pain Detection:** Assist in identifying patients' discomfort levels, especially for non-verbal patients.

### 4.2. Human-Computer Interaction

- **Emotion-Aware Systems:** Enhance user experiences by enabling devices to respond empathetically (e.g., adapting content or tone based on detected mood).
- **Virtual Assistants and Chatbots:** Improve interactions by tailoring responses to the user's emotional state.

### 4.3. Security and Surveillance

- **Lie Detection:** Analyze micro expressions to detect potential deception during interrogations or interviews.
- **Behavioral Analysis:** Monitor public spaces for suspicious or abnormal behavior.
- **Driver Monitoring Systems:** Identify fatigue or distraction in drivers to prevent accidents.

### 4.4. Marketing and Consumer Behavior

- **Customer Feedback Analysis:** Evaluate real-time emotional reactions to advertisements, products, or services.
- **Personalized Marketing:** Adjust advertisements or product recommendations based on the user's emotional state.

### 4.5. Education

- **Adaptive Learning Platforms:** Monitor students' emotional engagement and tailor learning materials accordingly.
- **Virtual Classroom Enhancements:** Identify students' frustration or confusion for timely intervention.

---

## 5. Conclusion

Emotion detection from facial expressions has emerged as a pivotal area of research, blending traditional feature extraction methods with advanced deep learning techniques. Quantitative analysis consistently highlights the superior performance of hybrid approaches, which integrate handcrafted features with the robust learning capabilities of deep neural networks. These techniques achieve higher accuracy, demonstrate better adaptability to complex emotional expressions, and offer improved generalization across diverse datasets and conditions.

Traditional methods, while foundational, often fall short when dealing with subtle or ambiguous emotional cues. On the other hand, deep learning models excel in capturing intricate patterns and nuances, particularly when trained on large, diverse datasets. By combining the strengths of both approaches, hybrid systems leverage the interpretability of traditional methods and the computational power of deep learning, resulting in more reliable and scalable solutions.

The findings underscore the potential of emotion detection systems to revolutionize applications in healthcare, education, marketing, and security. However, challenges remain, such as ensuring cultural sensitivity, addressing ethical concerns around privacy, and mitigating bias in data and algorithms. Future research must focus on developing more inclusive and ethically aligned systems while exploring the integration of multimodal data (e.g., speech, physiological signals) to further enhance accuracy and robustness.

In conclusion, emotion detection techniques represent a transformative step toward creating emotionally intelligent systems, capable of fostering seamless human-machine interaction and driving innovations across various domains. By continuing to refine these technologies, researchers and developers can unlock their full potential, ensuring they contribute meaningfully and responsibly to society.

---

## Compliance with ethical standards

### *Disclosure of conflict of interest*


No conflict of interest to be disclosed.

---

## References

- [1] I. M. Revina and W. R. S. Emmanuel, "A Survey on Human Face Expression Recognition Techniques," J. King Saud Univ. - Computer. Inf. Sci., p. S1319157818303379, Sep. 2018
  - [2] "Facial Expression Database: Japanese Female Facial Expression (JAFFE) Database." [Online]. Available: <http://www.kasrl.org/jaffe.html>. [Accessed: 20-Aug 2019].
  - [3] Chowdary, M. Kalpana, et al. "Feature extraction techniques for human emotion identification from face images." 9th International Conference on Imaging for Crime Detection and Prevention (ICDP-2019). IET, 2019.
  - [4] Mitra, Suman K. (2020). Facial expression recognition features based approaches to deep learning techniques. Dhirubhai Ambani Institute of Information and Communication Technology (DA-IICT). Retrieved from:
  - [5] Angelopoulou, A., and E. Kapetanios. "Feature Extraction Techniques for Human Emotion Identification from Face Images." The 9th International Conference on Imaging for Crime Detection and Prevention. Institution of Engineering and Technology (IET), 2020.
  - [6] Mayur Rahul. (2021). Facial Expression Recognition Using Modified Hidden Markov Model. Dr A.P.J. Abdul Kalam Technical University.
- 

## Author's short biography

<p><b>Mrs. Ruchita Mathur (MCA)</b></p> <p>I am pursuing PhD in Computer Science and have been actively involved in research in the area of computer vision. My research is dedicated to bridging the divide between advancements in computer vision and their practical implementation in real-world applications.</p>	
<p><b>Dr Vaibhav Gupta, PhD (Computer Applications)</b></p> <p>I hold a doctoral degree in Computer Applications and have been actively involved in research in the areas of Cloud Computing and Computer Vision for over 18 years. My research interests lie in exploring the applications of cloud computing and computer vision in real-world problems. With a strong academic background and a passion for innovation, I strive to contribute meaningfully to the field of computer science."</p>	