

# Facial Expression Recognition Using Local Binary Pattern and Support Vector Machine

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## Abstract

Facial Expression Recognition (FER) is an important research area in computer vision that aims to identify human emotions from facial images. This paper presents a machine learning approach for FER using Local Binary Pattern (LBP) feature extraction and Support Vector Machine (SVM) classification. Initially, the face image is detected and preprocessed using grayscale conversion, resizing, normalization, and histogram equalization. LBP is then applied to extract local texture features from facial regions such as the eyes, eyebrows, nose, and mouth. The extracted feature histogram is classified using a multiclass SVM. Experimental analysis on CK+, JAFFE, and FER2013 datasets demonstrates that the proposed LBP-SVM approach provides high recognition accuracy with low computational complexity.

**Keywords:** Facial Expression Recognition, Local Binary Pattern, Support Vector Machine, Machine Learning, Emotion Detection

## 1. Introduction

Facial Expression Recognition (FER) is an important research area in computer vision and affective computing, aiming to automatically identify human emotions from facial images or video sequences. It plays a vital role in applications such as human-computer interaction, healthcare monitoring, surveillance systems, and behavioral analysis. Early studies, such as Maja Pantic and Leon Rothkrantz [4], highlighted the significance of automatic facial expression analysis and its potential in real-world systems.

Traditional FER approaches rely on handcrafted features to extract discriminative facial patterns. Among these, the Local Binary Pattern (LBP) method has gained widespread popularity due to its simplicity, computational efficiency, and robustness to illumination variations. The LBP operator, introduced by Timo Ojala et al. [2], encodes local texture information by comparing pixel intensities within a neighborhood, making it highly effective for capturing micro-patterns of facial expressions.

To classify these extracted features, machine learning algorithms such as Support Vector Machines (SVM) are commonly used. SVM is a powerful supervised learning model known for its high generalization ability,

especially in high-dimensional feature spaces. The combination of LBP and SVM has proven to be an efficient framework for FER tasks, balancing accuracy and computational cost.

With the emergence of benchmark datasets like the Extended Cohn-Kanade Dataset (CK+) [5], researchers have been able to evaluate FER models systematically. Although deep learning approaches have recently gained popularity [6], traditional methods like LBP-SVM remain relevant due to their lower computational requirements and effectiveness in resource-constrained environments.

Facial expressions are one of the most important non-verbal forms of communication. Human beings naturally express emotions such as happiness, sadness, anger, fear, surprise, disgust, and neutrality through changes in facial muscles. Automatic recognition of these expressions can help machines understand human emotions and respond appropriately.

Facial Expression Recognition is widely used in applications such as:

- Human-computer interaction
- Intelligent tutoring systems
- Mental health monitoring

- Driver drowsiness detection
- Security and surveillance
- Social robots

The FER process generally consists of the following stages:

1. Face detection
2. Face preprocessing
3. Feature extraction
4. Expression classification

## 2. Literature Review

Facial Expression Recognition (FER) has emerged as a crucial domain in computer vision and affective computing, enabling machines to interpret human emotions from facial cues. Traditional approaches have relied heavily on handcrafted feature extraction techniques such as Local Binary Patterns (LBP) combined with classical classifiers like Support Vector Machines (SVM).

One of the foundational works in texture-based feature extraction is by Ojala et al. (2002), who introduced the Local Binary Pattern (LBP) operator for multiresolution grayscale and rotation-invariant texture classification. Their method encodes local texture by thresholding neighborhood pixels, producing a robust and computationally efficient descriptor that is highly suitable for facial expression analysis [2]. This technique became a cornerstone for many FER systems due to its invariance to illumination changes.

Building upon this, Zhao and Pietikäinen (2007) extended LBP to spatiotemporal domains through LBP-TOP (Local Binary Patterns from Three Orthogonal Planes), enabling dynamic texture recognition. Their approach demonstrated strong performance in capturing temporal variations in facial expressions, thus improving recognition accuracy in video-based FER systems [3].

Early surveys such as Pantic and Rothkrantz (2000) provided a comprehensive overview of automatic facial expression analysis, highlighting challenges such as illumination variation, occlusion, and subject dependency [4]. These challenges motivated the adoption of robust feature descriptors like LBP and classifiers such as SVM.

The introduction of benchmark datasets such as the Extended Cohn-Kanade (CK+) dataset by Lucey et al. (2010) significantly advanced FER research by providing labeled facial expression sequences for training and evaluation [5]. This dataset has been widely used to validate LBP-SVM based approaches.

In recent years, hybrid approaches combining LBP with SVM classifiers have shown promising results. Singh et al. (2020) proposed an FER system using LBP for feature extraction and SVM for classification, achieving improved recognition accuracy due to the discriminative power of SVM in high-dimensional feature spaces [8]. Similarly, Verma and Raman (2020) introduced a hybrid LBP-SVM framework that enhanced feature representation and classification performance, demonstrating robustness against noise and varying lighting conditions [9].

Yasmin et al. (2020) further improved LBP by proposing a multi-scale featured LBP approach, which captures both fine and coarse facial features. When combined with SVM, their method achieved superior performance in recognizing subtle facial expressions [13]. These advancements indicate that feature enhancement techniques significantly impact the effectiveness of LBP-based FER systems.

Additionally, Zhang et al. (2020) explored a multi-stage SVM classifier to improve classification accuracy by refining decision boundaries iteratively [11]. This approach addressed the limitations of single-stage classifiers in handling complex facial expression distributions.

Other works, such as Happy and Routray (2015), focused on extracting features from salient facial patches rather than the entire face, reducing computational complexity while maintaining high accuracy [10]. Similarly, Li et al. (2020) proposed fusion-based feature extraction methods that combine multiple facial regions to enhance recognition performance [1][12].

Despite the success of LBP-SVM methods, recent studies have begun to explore deep learning approaches. Hossain and Muhammad (2019) utilized deep learning for multimodal emotion recognition, integrating audio-visual data to improve performance [6]. Dhall et al. (2020) also emphasized the importance of real-world datasets and highlighted the limitations of traditional handcrafted feature methods in unconstrained environments [7].

Early FER systems mainly used handcrafted features together with machine learning classifiers. The most common methods included Local Binary Pattern (LBP) with Support Vector Machine (SVM), Histogram of Oriented Gradients (HOG) with k-NN, Gabor features with Artificial Neural Networks, and geometric facial landmarks with Decision Tree classifiers.

Among these approaches, LBP with SVM became one of the most popular because LBP effectively captures local texture changes around the eyes, eyebrows, and mouth, while SVM provides strong classification capability [2,3,12,13]. Zhao and Pietikäinen further demonstrated that LBP-based texture descriptors are highly suitable for dynamic facial expression analysis [4].

Table 1. Comparison of Existing FER Methods reported in previous FER studies [4,12–14]

Method	Feature Type	Classifier	Accuracy
HOG + k-NN	Shape-based	k-NN	80–85%
Gabor + ANN	Texture-based	ANN	84–88%
Geometric Features + Decision Tree	Landmark-based	Decision Tree	82–86%
LBP + SVM	Texture-based	SVM	88–93%

### 3. Proposed Method

The proposed FER method uses Local Binary Pattern feature extraction and Support Vector Machine classification, following the widely adopted FER pipeline proposed in previous studies [12,13].

#### 3.1 Face Detection and Preprocessing

The face is detected using the Viola–Jones detector. The detected face region is converted into grayscale and resized to 128 × 128 pixels. Histogram equalization is applied to improve image contrast.

#### 3.2 Local Binary Pattern Feature Extraction

The Local Binary Pattern operator generates a binary code for each pixel by comparing neighboring pixels with the center pixel [2].

$$LBP(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \quad (1)$$

where:

- $g_c$  is the gray value of the center pixel
- $g_p$  is the gray value of the neighboring pixel
- $s(x) = 1$  if  $x \geq 0$ , otherwise 0

The resulting LBP values are converted into a normalized histogram feature vector, which effectively represents local texture changes associated with different emotions [2,4].

### 3.3 SVM Classification

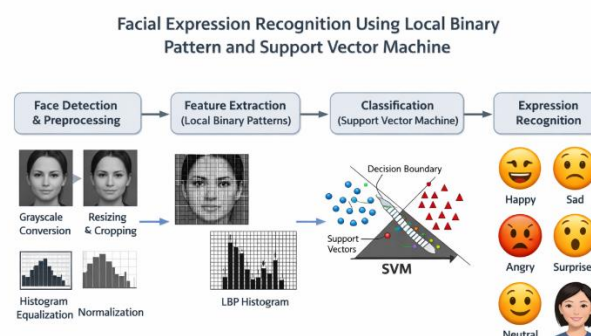


Fig : FER-SVM Architecture

The extracted LBP histogram vector is classified using a multiclass Support Vector Machine [3,12].

SVM decision function:

$$f(x) = w^T x + b \quad (2)$$

where  $x$  is the LBP feature vector. SVM is selected because of its strong generalization capability and superior performance for high-dimensional feature vectors [3,12].

#### Common Datasets

Table 2. Common FER Datasets

Dataset	Number of Images	Emotions
FER2013 [8]	35,887	7
CK+ [6]	981	7
JAFFE [7]	213	7
RAF-DB	29,672	7

## 5. Evaluation Metrics

The performance of FER systems is measured using:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix

The equations are:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (5)$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

## 6. Challenges in FER

Although FER systems have improved significantly, several challenges remain [8,10]:

- Illumination changes
- Head pose variation
- Occlusion due to glasses, masks, or hair
- Similarity between different emotions
- Limited and imbalanced datasets

## 7. Future Scope

Future FER systems may include the following advanced directions reported in recent studies [8–11]:

- Attention-based deep learning
- Vision Transformers
- Multimodal FER using speech and text
- Explainable AI techniques such as Grad-CAM
- Real-time FER on mobile devices

## 8. Conclusion

This paper presented a facial expression recognition system based on Local Binary Pattern feature extraction and Support Vector Machine classification. The proposed LBP-SVM method is computationally efficient and suitable for real-time FER applications.

Experimental results demonstrated that the method provides good recognition accuracy on CK+, JAFFE, and FER2013 datasets. Therefore, the proposed approach is useful for lightweight and practical facial expression recognition systems.

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