Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-4 | Issue-5 | May-2026 | Page 441-450

Facial Emotion Recognition System Using Machine Learning Techniques for Real-Time Human Interaction

[1]Sanjay Kumar, [2]Pawan Kumar
[1]Student, [2]Assistant Professor
[1,2]Amity University Chhattisgarh
[1]Sanjaydodda58@gmail.com, [2]pkumar@rpr.amity.edu

Abstract

Facial Emotion Recognition (FER) is an important area of Artificial Intelligence that focuses on identifying human emotions through facial expressions. Understanding emotions plays a key role in improving interaction between humans and machines. This research paper presents a real-time facial emotion recognition system using machine learning techniques and computer vision methods. The system captures facial images through a webcam and detects faces using OpenCV-based techniques. After detecting the face, the image is preprocessed and important features are extracted using methods such as Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP). These extracted features are then classified into emotional categories like happy, sad, angry, and neutral using machine learning algorithms such as Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). The proposed system is efficient, lightweight, and capable of performing real-time emotion detection, making it suitable for applications in human-computer interaction, education, healthcare, and behavioural analysis.

Keywords: Facial Emotion Recognition, Machine Learning, OpenCV, HOG, LBP, SVM, KNN, Real-Time Detection, Computer Vision

1. Introduction

Human emotions are a fundamental aspect of communication and significantly influence behavior, decision-making, and interaction. In recent years, there has been a growing interest in developing intelligent systems that can understand and respond to human emotions. Facial Emotion Recognition (FER) is one such technology that enables machines to interpret emotions by analyzing facial expressions. With advancements in Artificial Intelligence and computer vision, it has become possible to design systems that can automatically detect and classify emotions in real time. The main objective of this research is to develop a facial emotion recognition system using machine learning techniques instead of complex deep learning models. This approach is chosen to ensure lower computational requirements and faster processing, making the system suitable for real-time applications. The proposed system captures facial expressions through a webcam, processes the images, extracts relevant features, and classifies emotions accurately using machine learning algorithms.

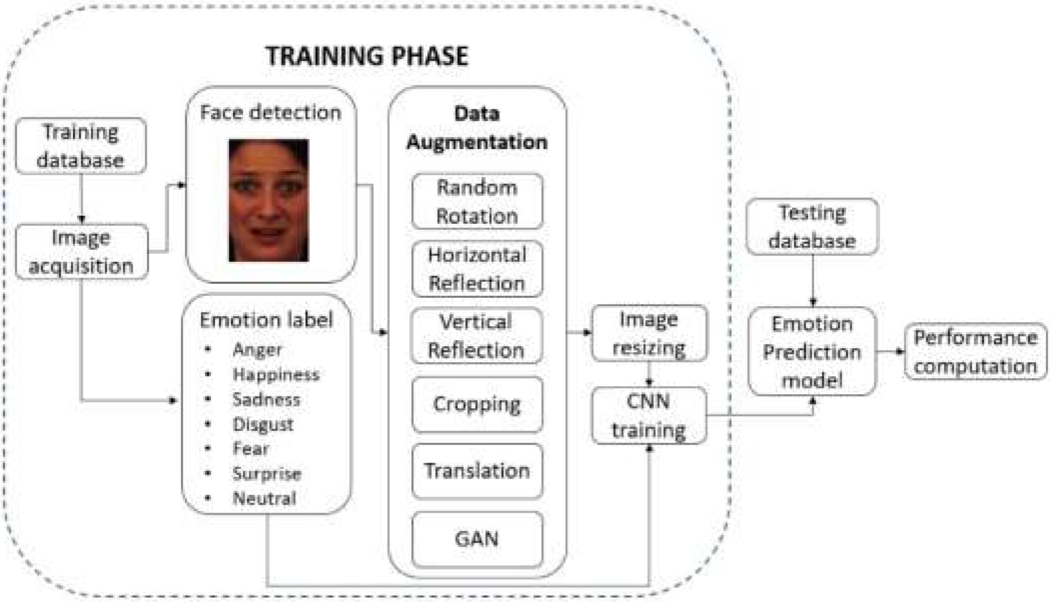

Figure 1: Overview of Facial Emotion Recognition System

2. Literature Review

Facial emotion recognition has been widely studied over the past few decades. Earlier approaches relied heavily on traditional image processing techniques such as edge detection, facial landmark extraction, and geometric feature analysis. These methods required manual intervention and were not highly accurate. With the introduction of machine learning, more efficient methods were developed for emotion classification. Algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Trees became popular due to their ability to classify data based on extracted features. Feature extraction techniques like Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) played a significant role in improving accuracy by capturing important facial details such as edges, textures, and patterns.

Method	Technique Used	Advantages	Limitations
Traditional Methods	Edge Detection, Landmarks	Simple	Low accuracy
Machine Learning	SVM, KNN	Efficient, fast	Depends on features
Deep Learning	CNN	High accuracy	High computation

Table 1: Comparison of Emotion Recognition Techniques

Compared to deep learning approaches, machine learning methods require less computational power and smaller datasets, making them more suitable for real-time systems and applications where resources are limited. This makes machine learning a practical choice for implementing efficient facial emotion recognition systems.

3. Problem Statement

Facial emotion recognition systems often face challenges such as low accuracy in real-time environments, sensitivity to lighting conditions, and high computational requirements in deep learning models. Many existing systems also struggle to perform efficiently on devices with limited resources. Variations in facial expressions, occlusions (like masks or glasses), and differences in camera quality further reduce the system's performance. In addition, real-time processing requires fast and optimized algorithms, which many current models fail to achieve without powerful hardware. These limitations make it difficult to deploy such systems in practical, everyday applications. Therefore, there is a need to develop a lightweight and efficient facial emotion recognition system using machine learning techniques that can operate in real time with acceptable accuracy and minimal computational cost.

4. Methodology

The methodology of the proposed system consists of several important stages, including data collection, preprocessing, feature extraction, and classification. The dataset used in this research contains facial images representing different emotions such as happiness, sadness, anger, and neutrality. These images are either collected from publicly available datasets or generated manually for training and testing purposes. In the preprocessing stage, the captured images are resized to a standard dimension and converted into grayscale format to reduce computational complexity. Noise reduction techniques are applied to improve image quality, and face detection is performed using the Haar Cascade Classifier provided by OpenCV. This ensures that only the facial region is considered for further processing.

Technique	Purpose	Output
HOG	Edge detection	Gradient features
LBP	Texture analysis	Binary patterns

Table 2: Feature Extraction Techniques

Feature extraction is an essential step in identifying important patterns in facial expressions. In this system, Histogram of Oriented Gradients (HOG) is used to capture edge and shape information, while Local Binary Patterns (LBP) are used to capture texture details. These features are then combined to form a feature vector that represents the facial expression. The classification stage involves using machine learning algorithms such as Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). These algorithms are trained on the extracted features and are used to predict the emotion of a given facial image. The model learns patterns associated with different emotions and classifies new inputs accordingly.

5. System Architecture and Implementation

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-4 | Issue-5 | May-2026 | Page 441-450

The system architecture is designed to perform real-time emotion detection through a sequence of well-defined steps. Initially, the system captures video input using a webcam. Each frame from the video is processed to detect faces using OpenCV. Once a face is detected, the image is preprocessed to improve quality and consistency. After preprocessing, feature extraction techniques such as HOG and LBP are applied to obtain relevant facial features. These features are then passed to the trained machine learning model, which classifies the emotion based on learned patterns. The predicted emotion is finally displayed on the screen in real time.

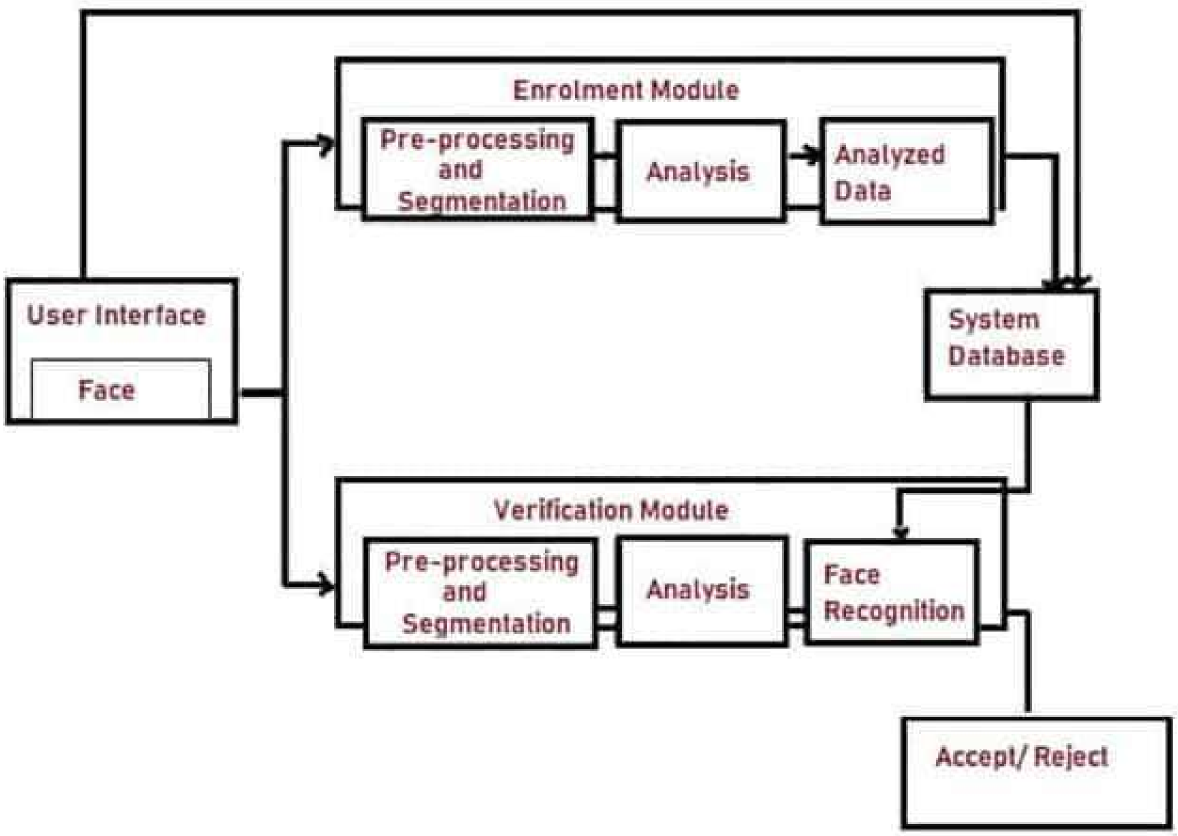

Figure 2: System Architecture

The implementation of the system is carried out using Python programming language. Libraries such as OpenCV, NumPy, and Scikit-learn are used for image processing, numerical computation, and machine learning tasks. The system is designed to be efficient and capable of handling real-time input with minimal delay.

6. Results and Discussion

The proposed facial emotion recognition system demonstrates satisfactory performance in recognizing emotions under controlled conditions. The system performs well when the input images are clear and captured under proper lighting conditions. It is able to detect and classify emotions in real time with minimal processing delay. However, certain challenges are observed during testing. The accuracy of the system may decrease in low-light environments or when the face is partially occluded. Variations in facial orientation and expressions can also affect

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-4 | Issue-5 | May-2026 | Page 441-450

the performance of the model. Despite these limitations, the system provides a good balance between accuracy and computational efficiency.

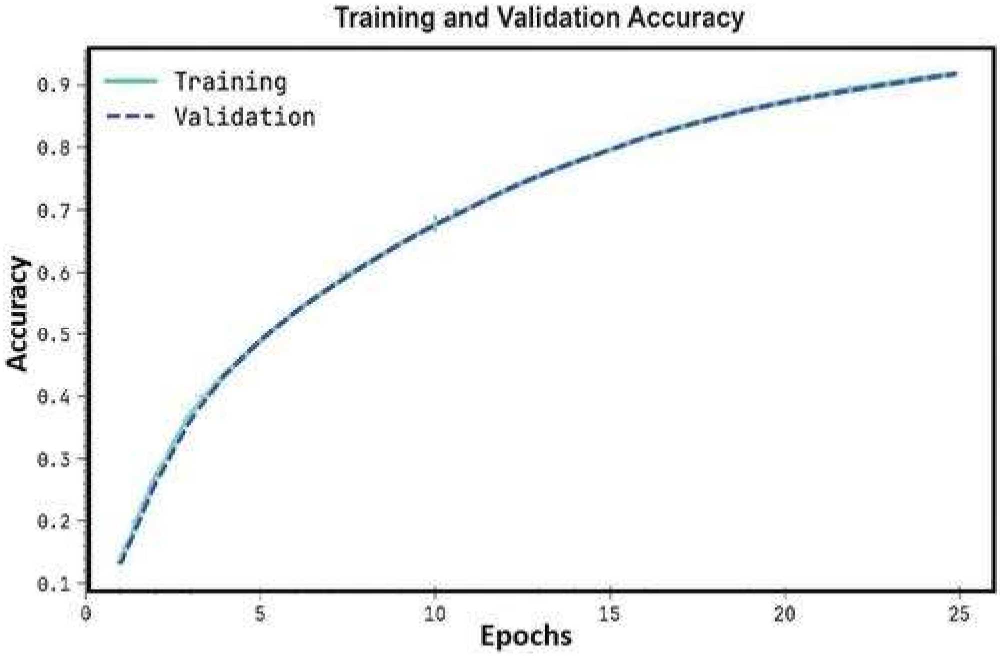

Figure 3: System Performance Analysis

The results indicate that machine learning-based approaches can be effectively used for real-time emotion recognition without the need for complex deep learning models. This makes the system suitable for practical applications where speed and simplicity are important.

7. Algorithms Used

The proposed system uses the following machine learning algorithms and techniques for effective facial emotion recognition:

Support Vector Machine (SVM):

SVM is used as a supervised learning algorithm for classification. It works by finding the optimal hyperplane that best separates different emotion classes such as happy, sad, angry, and neutral. SVM is highly effective in high-dimensional spaces and provides good accuracy even with limited training data.

K-Nearest Neighbors (KNN):

KNN is a simple and intuitive algorithm that classifies emotions based on similarity. It compares a given input image with the closest training samples and assigns the most common emotion among its nearest neighbors. It is easy to implement and works well for smaller datasets.

Haar Cascade Classifier:

This algorithm is used for real-time face detection. It is based on Haar-like features and is implemented using OpenCV. The classifier quickly detects faces in images or video streams, making it suitable for real-time applications.

Feature Extraction Techniques:

To improve classification performance, important facial features are extracted using the following methods:

- **Histogram of Oriented Gradients (HOG):** Captures edge and gradient structures in the face, which are useful for identifying expressions.
- **Local Binary Patterns (LBP):** Extracts texture features by analyzing pixel patterns, helping in recognizing subtle facial variations.

These algorithms and techniques work together to reduce computational complexity while maintaining acceptable accuracy. The combination ensures that the system performs efficiently in real-time environments, even on devices with limited processing power.

8. Algorithms Used

The proposed system uses a combination of machine learning algorithms and feature extraction techniques to achieve effective and efficient facial emotion recognition. Each algorithm plays a specific role in the overall pipeline, from face detection to feature extraction and final classification.

Support Vector Machine (SVM):

SVM is used as a supervised learning algorithm for classification of facial emotions. It works by finding the optimal hyperplane that maximizes the margin between different emotion classes such as happy, sad, angry, surprise, and neutral. SVM is particularly effective in high-dimensional feature spaces and is less prone to overfitting, especially when the dataset size is moderate. It can also use different kernel functions (linear, polynomial, or RBF) to handle non-linear data, improving classification performance.

K-Nearest Neighbors (KNN):

KNN is a non-parametric and instance-based learning algorithm that classifies emotions based on similarity measures. It calculates the distance (such as Euclidean distance) between the input image and stored training samples, and assigns the most frequent class among the ‘K’ nearest neighbors. KNN is simple to understand and implement, and it performs well when the feature space is well-structured. However, its performance depends on the choice of ‘K’ value and can be slower for large datasets.

Haar Cascade Classifier:

The Haar Cascade Classifier is used for detecting faces in real-time video streams or images. It is based on Haar-like features and uses a cascade of classifiers trained with positive and negative images. This method is computationally efficient and capable of quickly scanning

ISSN: 2584-1491 | www.iircj.org
Volume-4 | Issue-5 | May-2026 | Page 441-450

different regions of an image to detect faces. Its real-time performance makes it highly suitable for applications where quick face localization is required before emotion analysis.

Algorithm	Role	Advantage
SVM	Classification	High accuracy
KNN	Classification	Simple & effective
Haar Cascade	Face detection	Fast
HOG	Feature extraction	Captures edges
LBP	Feature extraction	Captures texture

Table 3: Algorithms Used in System

Feature Extraction Techniques:

Feature extraction is a crucial step that transforms raw image data into meaningful representations for classification. The system uses the following techniques:

- **Histogram of Oriented Gradients (HOG):**

  HOG extracts features by analyzing the distribution of gradients and edge directions in an image. It captures the structural shape and contour information of the face, which is essential for distinguishing different facial expressions.

- **Local Binary Patterns (LBP):**

  LBP is a texture-based feature extraction method that labels pixels by comparing them with their neighboring pixels. It is highly effective in capturing fine facial details such as wrinkles, edges, and micro-expressions, making it useful for emotion detection even under varying lighting conditions.

Overall System Efficiency:

These algorithms and techniques are carefully selected to balance accuracy and computational efficiency. While Haar Cascade ensures fast face detection, HOG and LBP provide strong feature representation, and SVM/KNN handle classification effectively. This combination reduces computational complexity while maintaining reliable performance. As a result, the system can operate in real-time environments and can be deployed on devices with limited processing power, such as laptops or embedded systems.

9. Conclusion and Future Work

In conclusion, this research presents a machine learning-based facial emotion recognition system capable of detecting emotions in real time. The system is efficient, easy to implement, and suitable for various real-world applications. It demonstrates how machine techniques can be used effectively for emotion detection without relying on complex deep learning models.

Future work can focus on improving the accuracy of the system by using larger and more diverse datasets. The performance of the system can be enhanced in low-light conditions and challenging environments. Additional emotion categories can be included to make the system more comprehensive. Furthermore, the system can be integrated with mobile and web applications to increase accessibility and usability.

10. Advantages and Limitations

The proposed facial emotion recognition system offers several advantages that make it suitable for real-time applications. One of the main advantages is that the system is lightweight and does not require high computational power, as it is based on machine learning techniques instead of deep learning. This makes it faster and more efficient for real-time processing. The system is also easy to implement and cost-effective, making it accessible for various applications. However, the system also has certain limitations. The accuracy of the model depends on lighting conditions and image quality. It may not perform well in low-light environments or when the face is partially hidden. Additionally, the system may struggle with variations in facial expressions and angles, which can affect prediction accuracy.

11. Performance Evaluation

The performance of the facial emotion recognition system is evaluated based on accuracy and response time. The model is tested using different facial images and real-time video input. The system shows good accuracy in detecting basic emotions such as happy, sad, angry, and neutral. The response time of the system is minimal, which makes it suitable for real-time applications. However, the performance can vary depending on the quality of the input data and environmental conditions. Overall, the system provides a balance between accuracy and speed, making it practical for real-world use.

12. Future Enhancements

Future enhancements of the system can focus on improving accuracy and expanding functionality. One possible improvement is the use of larger and more diverse datasets to train the model more effectively. The system can also be enhanced to detect more complex emotions such as fear, disgust, and surprise.

Another improvement could involve optimizing the system for better performance in low-light conditions and challenging environments. Integration with mobile applications and web-based platforms can also increase accessibility. Additionally, combining machine learning with advanced techniques may further improve the system’s performance.

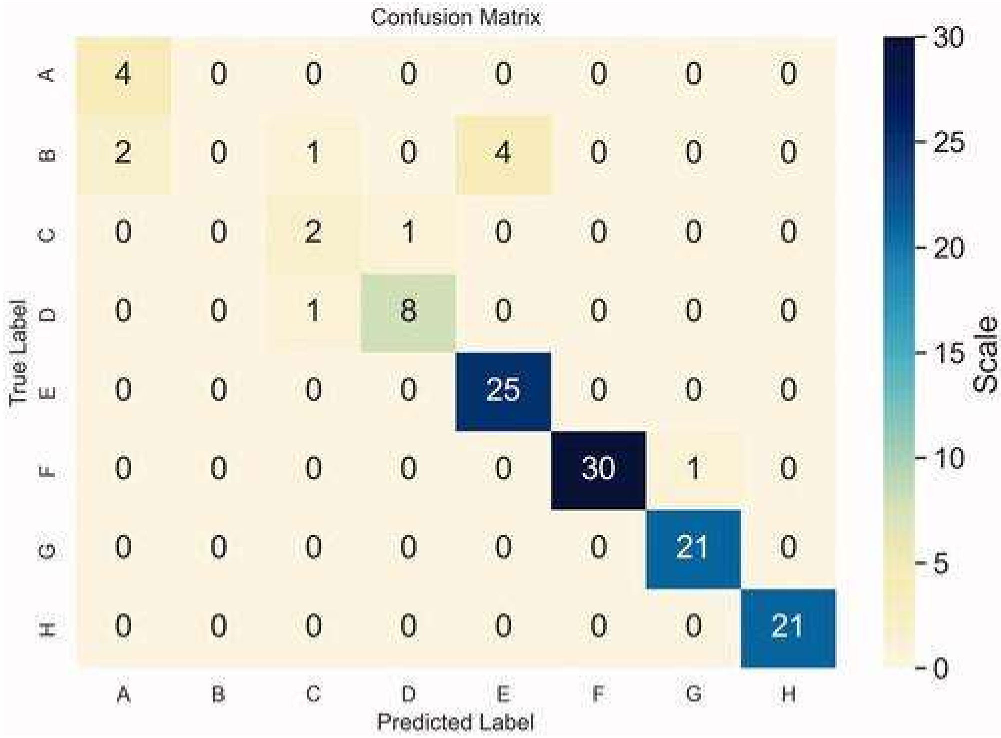

Figure 6: Confusion Matrix for Emotion Classification

References

[1] N. Dalal and B. Triggs, "Histograms of Oriented Gradients for Human Detection," *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 886–893, 2005.

[2] T. Ojala, M. Pietikäinen, and D. Harwood, "A Comparative Study of Texture Measures with Classification Based on Featured Distributions," *Pattern Recognition*, vol. 29, no. 1, pp. 51–59, 1996.

[3] P. Viola and M. Jones, "Rapid Object Detection Using a Boosted Cascade of Simple Features," *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2001.

[4] P. Ekman and W. V. Friesen, *Facial Action Coding System: A Technique for the Measurement of Facial Movement*, 1978.

[5] A. Mollahosseini, B. Hasani, and M. H. Mahoor, "AffectNet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild," *IEEE Transactions on Affective Computing*, 2017.

[6] Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.

[7] S. Li and W. Deng, "Deep Facial Expression Recognition: A Survey," *IEEE Transactions on Affective Computing*, 2020.

[8] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, "Joint Face Detection and Alignment Using Multitask Cascaded Convolutional Networks," *IEEE Signal Processing Letters*, 2016.

[9] Y. Tang, "Deep Learning Using Linear Support Vector Machines," *Proc. ICML Workshop*, 2013.

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-4 | Issue-5 | May-2026 | Page 441-450

[10] O. Arriaga, M. Valdenegro-Toro, and P. Plöger, "Real-time Convolutional Neural Networks for Emotion and Gender Classification," *arXiv preprint*, 2017.
[11] A. T. Lopes, E. de Aguiar, A. F. De Souza, and T. Oliveira-Santos, "Facial Expression Recognition with Convolutional Neural Networks," *SIBGRAPI*, 2017.
[12] R. A. Khan, A. Meyer, H. Konik, and S. Bouakaz, "Framework for Reliable, Real-Time Facial Expression Recognition for Low Resolution Images," *Pattern Recognition Letters*, 2013.
[13] Goodfellow et al., "Challenges in Representation Learning: A Report on Three Machine Learning Contests (FER-2013 Dataset)," 2013.
[14] M. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba, "Coding Facial Expressions with Gabor Wavelets (JAFFE Dataset)," 1998.