International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

Vol. V, No. 02, pp. 25-31, February

HDG and HDGG: An External Feature for Facial Expression Using Machine Learning

K. Muralikrishna[1*], S. Chandana[2], Sk. Saniya Siddikha[3], K. Santhi Priya[4], S. Raghavamma[5]

[1,2,3,4,5] Department of Electronics and Communication Engineering, Vignan's Nirula Institute of Technology and Science for Women, Guntur – 522002, Andhra Pradesh.

muralikondaveeti1@gmail.com

ABSTRACT: Facial Emotion Recognition (FER) is a significant area of research in affective computing, which focuses on automatically identifying human emotions from facial images. Although deep learning methods have demonstrated promising results in terms of accuracy, their need for large amounts of data and computational resources makes them less suitable for real-time applications. In this paper, a machine learning-based approach for FER is proposed using Histogram of Directional Gradient (HDG) and Histogram of Directional Gradient Generalized (HDGG) features. The proposed features are designed to capture directional gradient information, which assists in achieving compact and robust feature sets. The features are then classified using supervised machine learning classifiers to detect basic emotional categories. The experimental results on standard facial expression databases demonstrate that the proposed HDG and HDGG features are comparable in recognition accuracy while retaining low-dimensional and computationally efficient features. The results demonstrate that the proposed approach provides a feasible solution for real-time facial emotion recognition systems.

Keywords: Facial Emotion Recognition (FER), HDG and HDGG Features, Machine Learning, Facial Expression Recognition, Supervised Classification

1. Introduction

Emotion recognition plays a vital role in enhancing human–computer interaction by enabling systems to understand human emotions. Traditional facial expression recognition methods rely mainly on image-based features, which are sensitive to variations like lighting and pose. To overcome these limitations, combining facial images with geometric information such as facial landmarks has gained attention. This dual-input approach captures both appearance and structural details of the face. By integrating these complementary features, the model achieves more robust and accurate emotion recognition. This approach represents a significant improvement in developing reliable emotion-aware systems [1]. Group facial expression recognition is an important area in computer vision, focusing on understanding the collective emotions of multiple individuals in a scene. Traditional methods often face challenges due to low-resolution images, occlusions, and variations in pose and lighting. To address these issues, recent approaches utilize super-resolution techniques to enhance image quality before feature extraction. In addition, extracting local facial features at multiple scales helps capture both fine and coarse emotional cues. This multi-scale representation improves the model's ability to analyse complex group dynamics. As a result, such methods contribute to more accurate and robust group emotion recognition systems [2]. With the growth of deep learning, significant advancements have been made in improving recognition accuracy and efficiency. Earlier approaches relied on manual feature extraction, which often limited performance and adaptability. In contrast, deep learning models automatically learn complex facial features from data. These approaches are well-suited for real-time applications such as surveillance, human–computer interaction, and healthcare systems. However, challenges like illumination changes, pose variations, and occlusions still affect performance. Efficient neural network architectures help address these issues while maintaining speed. Real-time processing requires a balance between computational cost and accuracy. Such advancements contribute to the development of responsive and intelligent emotion-aware systems [3]. In recent years, integrating emotion recognition with assistive technologies such as exoskeleton rehabilitation robots has gained significant attention. These systems aim to monitor patients' emotional states to improve therapy effectiveness and user comfort. By analysing facial expressions, the system can provide adaptive feedback and personalized rehabilitation support. Deep learning techniques have been widely used to accurately detect and classify emotions from facial images. However, challenges such as varying patient conditions and environmental factors still exist. Incorporating emotion recognition into rehabilitation robots contributes to more intelligent and responsive healthcare solutions [4]. Early approaches focused on extracting distinctive features from specific regions of the face. One effective method involves the use of interest points to capture significant facial details that contribute to emotional expression. These points help in representing key facial movements and variations more efficiently. Compared to global feature extraction, interest point-based methods provide better robustness to noise and background variations. Such techniques improve the accuracy of emotion classification by focusing on the most informative regions of the face. Despite certain challenges, this approach laid the foundation for more advanced facial emotion recognition systems [5]. Early approaches utilized traditional machine learning techniques for feature extraction and classification. These methods involved preprocessing facial images and extracting relevant features to distinguish different emotional states. Classifiers such as support vector machines and decision trees were commonly used for emotion classification. Although effective, these approaches often depended on handcrafted features and were sensitive to variations in lighting and pose. Despite these limitations, machine learning-based methods provided a strong foundation for the development of more advanced emotion recognition systems [6]. Traditional methods often struggle with variations in lighting, pose, and occlusion, affecting recognition accuracy. To address these challenges, robust representation techniques have been developed to better capture discriminative facial features. One such approach involves the use of extreme sparse learning, which focuses on representing facial data with a minimal set of significant features. This method enhances the model's ability to handle noise and irrelevant information effectively. By improving feature representation, it leads to more reliable and accurate emotion classification. Such advancements have contributed to the development of robust facial emotion recognition systems [7]. Early systems relied on structured frameworks such as the Facial Action Coding System (FACS) to analyse facial muscle movements. To enhance recognition performance, modular neural network architectures were introduced for processing different facial features effectively. These systems integrate multiple components to handle feature extraction, representation, and classification in a unified manner. By combining FACS with neural network models, more accurate and systematic emotion recognition can be achieved. Such approaches improve the reliability of detecting subtle facial expressions. This work contributed to the foundation for modern deep learning-based emotion recognition systems [8].

2. HDG: An External Feature with Directional Gradient

Histogram of Oriented Gradients (HOG) is a powerful feature extraction technique widely used in computer vision, particularly for tasks such as object detection and facial emotion recognition. The fundamental idea behind HOG is that the local appearance and shape of an object can be effectively described by the distribution of intensity gradients or edge directions. Instead of relying on raw pixel values, HOG focuses on capturing structural information, which makes it more robust to variations in illumination and noise.

The HOG feature extraction process consists of several steps. First, the input image is pre-processed, typically by converting it to grayscale and applying normalization to reduce the effects of lighting variations. Next, gradient computation is performed using operators such as Sobel filters to obtain the gradient magnitude and orientation at each pixel. These gradients highlight the edges and contours within the image, which are crucial for identifying facial features.

After gradient computation, the image is divided into small spatial regions known as cells (commonly 8×8 pixels). For each cell, a histogram of gradient orientations is created, where the gradient directions are grouped into a fixed number of bins (e.g., 9 bins covering 0° to 180°). Each pixel contributes to the histogram based on its gradient magnitude, ensuring that stronger edges have a greater influence. To improve robustness, neighboring cells are grouped into larger regions called blocks (e.g., 2×2 cells), and the histograms within each block are normalized. This block normalization step reduces the impact of illumination changes and enhances feature consistency.

The final HOG descriptor is formed by concatenating all normalized histograms from different blocks into a single feature vector. This vector effectively represents the overall shape and structure of the object—in this case, the human face. In facial emotion recognition, HOG is particularly effective because it captures important edge-based features such as the curvature of the lips, the shape of the eyes, and the movement of eyebrows, all of which are critical indicators of emotional expressions.

HOG features are commonly used in combination with machine learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Random Forests to classify emotions into categories like happiness, sadness, anger, fear, and surprise. In addition, hybrid approaches have been proposed where HOG is combined with other feature descriptors such as Local Binary Patterns (LBP) or Gabor filters to improve feature richness and discrimination capability. More recent methods integrate HOG features into deep learning frameworks, either as an input feature representation or as a complementary feature alongside convolutional neural network (CNN) output.

Overall, HOG remains a highly effective and computationally efficient feature extraction method for facial emotion recognition. Its ability to capture local structural details while maintaining robustness to environmental variations makes it a valuable component in both traditional and modern emotion recognition systems.

3. HDGG: An External Feature with Directional Generalised Gradient

Histogram of Directional Generalized Gradients (HDGG) is an enhanced feature descriptor developed to overcome the limitations of traditional gradient-based methods like HOG. It extends the concept of gradient orientation histograms by incorporating multi-directional, multi-scale, and higher-order gradient information, enabling a more detailed representation of image structures. This makes HDGG particularly effective for capturing subtle variations in texture and shape, which are essential in facial analysis.

In HDGG, gradient computation is not restricted to simple first-order derivatives; instead, it may include second-order gradients (curvature), directional filters, and generalized differential operators. These gradients are computed across multiple orientations and scales to capture both fine and coarse facial details. The image is divided into local regions, and for each region, a histogram is formed based on the distribution of these generalized gradient directions. Block normalization is then applied to ensure robustness against illumination changes, noise, and contrast variations.

One of the key advantages of HDGG is its ability to provide multi-scale representation, which is crucial in facial emotion recognition. Facial expressions involve both global changes (e.g., smile formation) and local micro-expressions (e.g., slight eyebrow movement). HDGG effectively captures these variations by analysing features at different resolutions. Additionally, its sensitivity to curvature and edge variations allows it to distinguish between closely related emotions with higher accuracy.

In facial emotion recognition systems, HDGG is often used as a feature extraction step before classification. It can be combined with classifiers such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Neural Networks for emotion prediction. More advanced approaches integrate HDGG with deep learning architectures, where HDGG features are fused with CNN-based features to improve discriminative power. Some methods also use region-based HDGG, focusing on important facial areas like the eyes, mouth, and forehead to enhance performance.

Furthermore, HDGG is effective in handling real-world challenges such as pose variations, partial occlusions, and varying illumination conditions. Its robust representation reduces sensitivity to noise and improves generalization across different datasets. It is also computationally efficient compared to some deep learning-only approaches, making it suitable for real-time or resource-constrained applications.

Overall, HDGG provides a comprehensive and robust framework for feature extraction in facial emotion recognition. By capturing detailed directional and structural information, it significantly enhances the system’s ability to recognize complex and subtle emotional expressions, contributing to more accurate and reliable emotion-aware systems. It provides a multi-scale structural representation that effectively distinguishes fine-grained emotional variations, especially in micro-expressions. HDGG is often integrated with hybrid or deep learning frameworks to enhance robustness against noise, pose variation, and illumination changes in facial emotion recognition systems.

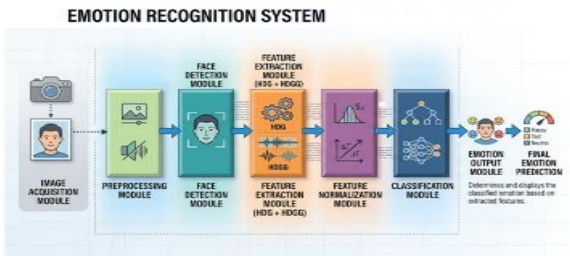

Figure 1: *Block Diagram of Facial Emotion Recognition*

4. Experimental setup

The experimental setup was designed to evaluate the effectiveness of Histogram of Directional Gradient (HDG), Histogram of Directional Generalized Gradient (HDGG), and Histogram of Oriented Gradient (HOG) features for facial emotion recognition. The proposed feature extraction methods were tested using multiple supervised machine learning classifiers to analyse their capability in identifying different emotional expressions from facial images.

Initially, the facial images were pre-processed to improve feature quality and reduce noise. The facial regions were normalized to ensure consistent feature extraction. After pre-processing, HDG, HDGG, and HOG descriptors were extracted to represent facial structural and directional characteristics. These feature vectors were then supplied to six supervised machine learning classifiers, namely k-Nearest Neighbour (KNN), Naïve Bayes (NB), Decision Tree (DT), Support Vector Machine (SVM), Discriminant Analysis (DA), and Random Forest (RF).

To assess the performance of the classifiers, standard evaluation metrics such as Accuracy, Precision, Sensitivity, Specificity, F1-Score, and Mean Area Under Curve (AUC) were considered. Accuracy evaluates the overall correctness of classification, Precision measures the proportion of correctly predicted positive instances, Sensitivity represents the true positive rate, and Specificity measures the true negative rate. The F1-score balances precision and recall, while Mean AUC reflects the classifier's ability to distinguish between emotional classes.

Table 1 presents the performance comparison of different classifiers using HDGG features. The results indicate that Support Vector Machine (SVM) achieved the best performance among all classifiers, followed by Discriminant Analysis (DA) and Random Forest (RF). The high specificity and F1-score demonstrate the robustness of HDGG in capturing generalized gradient information for emotion classification.

Table 1: *Performance Comparison of Facial Emotion Recognition Using HDGG Features*

Classifier	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)	Mean AUC
KNN	50.459	46.385	46.568	91.647	46.22	0.91615
NB	89.991	85.397	84.63	98.182	84.977	0.98526
DT	79.511	73.669	75.059	96.62	74.28	0.8962
SVM	99.694	99.689	99.49	99.949	99.583	0.99873
DA	98.471	97.726	98.469	99.755	98.061	0.9986
RF	98.675	98.432	97.834	99.774	98.102	0.0

Table 2 presents the classification performance using HDG features. The results demonstrate that RF and DA classifiers achieved superior performance, while KNN showed relatively lower classification efficiency. The HDG descriptor effectively captured directional gradient information required for recognizing facial emotions.

Table 2: *Features Performance Comparison of Facial Emotion Recognition Using HDG Features*

Classifier	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)	Mean AUC
KNN	56.881	50.489	50.383	92.728	50.13	0.91959
NB	86.442	81.2	82.491	97.791	81.726	0.98021
DT	79.103	73.257	72.852	96.5	72.773	0.89889
SVM	96.024	95.48	94.761	99.337	95.05	0.99456
DA	97.961	97.671	97.676	99.644	97.668	0.99811
RF	98.675	98.974	97.801	99.764	98.327	0.0

Finally, Table 3 shows the performance comparison using the traditional HOG feature descriptor. The findings reveal that SVM and DA achieved excellent performance, indicating that gradient-based features are highly effective for emotion classification. However, the proposed HDGG feature slightly outperformed conventional HOG in terms of recognition accuracy and discriminative capability.

Table 3: *Performance Comparison of Facial Emotion Recognition Using HOG Features*

Classifier	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)	Mean AUC
KNN	54.027	50.2	50.158	92.276	49.78	0.92806
NB	88.991	85.04	84.737	98.209	84.73	0.98284
DT	82.161	76.72	76.816	97.046	76.522	0.90404
SVM	99.185	98.98	98.756	99.864	98.862	0.99829

Classifier	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)	Mean AUC
DA	99.083	99.002	98.379	99.843	98.679	0.9966
RF	98.777	98.729	97.94	99.791	98.32	0.0

5. Results

The proposed facial emotion recognition system was tested on different facial expressions to evaluate its recognition capability. Figure 2 shows the recognition of the surprise emotion, where the system successfully identified the facial expression and mapped it to the corresponding emotional category. Similarly, Figure 3 demonstrates the recognition of anger emotion, showing the effectiveness of the proposed model in identifying strong facial characteristics associated with anger. Figure 4 presents the recognition of the happy emotion, where the system accurately classified the smiling facial expression. The obtained results indicate that the proposed HDG and HDGG-based facial emotion recognition system effectively detects multiple emotional states with high accuracy and computational efficiency.

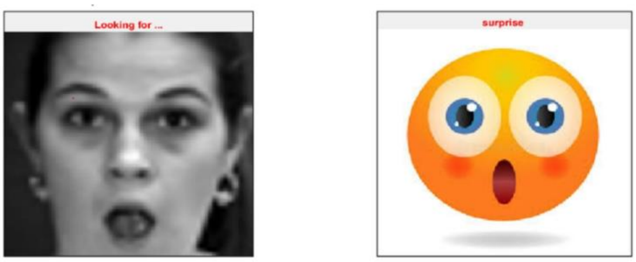

Figure 2: *Facial Emotion Recognition Result for Surprise Expression*

Figure 3: *Facial Emotion Recognition Result for Anger Expression*

Figure 4: *Facial Emotion Recognition Result for Happy Expression*

6. Conclusion

In conclusion, facial emotion recognition using Histogram of Directional Gradients (HDG) and Histogram of Directional Generalized Gradients (HDGG) provides a robust framework for capturing both structural and detailed facial features. HDG effectively represents edge and orientation information, while HDGG enhances this capability by incorporating multi-directional and higher-order gradient details. The combination of these descriptors enables better discrimination of subtle and complex emotional expressions. These methods improve system performance under challenging conditions such as illumination variations, noise, and pose changes. Furthermore, their integration with machine learning and deep learning models enhances classification accuracy and reliability. Overall, HDG and HDGG contribute significantly to developing efficient, accurate, and real-time facial emotion recognition systems.

References

1. W. G. Colares, M. G. F. Costa and C. F. F. Costa Filho, "Enhancing Emotion Recognition: A Dual-Input Model for Facial Expression Recognition Using Images and Facial Landmarks," 2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 2024.

2. B. Rathod, R. Vanazara and D. Pandya, "Improved Group Facial Expression Recognition Using Super-Resolved Local Facial Multi Scale Features," 2023

11th International Conference on Intelligent Systems and Embedded Design (ISED), Dehradun, India, 2023.

3. R. Gill and J. Singh, "A Deep Learning Approach for Real Time Facial Emotion Recognition," 2021 10th International Conference on System Modelling & Advancement in Research Trends (SMART), MORADABAD, India, 2021.

4. W. Sun et al., "Research on Facial Emotion Recognition System Based on Exoskeleton Rehabilitation Robot," 2020 IEEE 11th International Conference on Software Engineering and Service Science (ICSESS), Beijing, China, 2020.

5. V. M. Alvarez, R. Velázquez, S. Gutierrez and J. Enriquez-Zarate, "A Method for Facial Emotion Recognition Based on Interest Points," 2018 International Conference on Research in Intelligent and Computing in Engineering (RICE), San Salvador, El Salvador, 2018.

6. R. S. Deshmukh, V. Jagtap and S. Paygude, "Facial emotion recognition system through machine learning approach," 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2017.

7. S. Shojaeilangari, W. -Y. Yau, K. Nandakumar, J. Li and E. K. Teoh, "Robust Representation and Recognition of Facial Emotions Using Extreme Sparse Learning," in IEEE Transactions on Image Processing, vol. 24, no. 7, pp. 2140-2152, July 2015.

8. M. Gavrilescu, "Proposed architecture of a fully integrated modular neural network-based automatic facial emotion recognition system based on Facial Action Coding System," 2014 10th International Conference on Communications (COMM), Bucharest, Romania, 2014.