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Facial Expressions Recognition Using Machine Learning Classifiers Based HOG Features

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Abstract - **Facial Expression Recognition (FER) is a critical area of research in computer vision and human-computer interaction. This paper presents a comprehensive study on the use of Histogram of Oriented Gradients (HOG) and machine learning algorithms for FER. We explore the effectiveness of HOG features in capturing facial expressions and evaluate the performance of various machine learning classifiers, including Support Vector Machines (SVM), Random Forests, and Neural Networks, in recognizing facial expressions. Our experiments are conducted on widely used JAFFE dataset. The results demonstrate that HOG features, when combined with SVM, achieve high accuracy in recognizing facial expressions, outperforming other feature extraction methods. This paper also discusses the challenges and future directions in FER systems, emphasizing the need for robust feature extraction and classification techniques in managing high-dimensional feature spaces and its appropriateness for facial expression recognition tasks. Note that SVM was used and we obtained results of 86%, and we used RF and obtained results of 81%. Future studies may focus on combining deep learning methods with hybrid feature extraction methods to improve performance on more complex datasets.**

Keywords: Facial expression; Machine learning classification; HOG features, ML, classification.

I. INTRODUCTION

Facial Expression Recognition (FER) has garnered significant attention in artificial intelligence due to its broad applications in human-computer interaction, security, healthcare, and psychological assessment [1]. FER aims to enable machines to interpret human emotions through the analysis of facial expressions, a complex and dynamic form of non-verbal communication. Despite substantial progress, FER systems face challenges including variability in individual expressions, lighting conditions, and environmental settings, which impact their performance [2, 3].

Existing FER methodologies often rely on feature extraction techniques such as Histogram of Oriented Gradients (HOG), Gabor wavelets, and Local Binary Patterns (LBP) to capture structural and textural data [4]. These features are then processed using machine learning classifiers such as Support Vector Machines (SVM), Naïve Bayes, and K-Nearest Neighbors (KNN) [3, 5]. This paper provides a comprehensive evaluation of FER approaches, including an analysis of key datasets, feature extractors, and classifiers. Furthermore, it explores how the integration of various methods can address existing challenges and enhance FER systems for diverse practical applications.

1.1 Datasets for FER

A critical component of any FER system is the dataset used for training and testing the models. Datasets provide a collection of labeled facial expression images, each associated with an emotional state [1, 6] Several datasets have been widely used to benchmark FER systems:

JAFFE: The Japanese Female Facial Expression (JAFFE) dataset consists of 213 images of 10 female subjects, each displaying seven facial expressions: anger, disgust, happiness, fear, neutrality, sadness, and surprise [3].

Figure 1: Japanese Female Facial Expression (JAFFE) Database

Fer2013: About 30,000 face RGB photos of various emotions, limited in size to 48 by 48 pixels, are included in Fer2013. Its primary labels may be categorized into seven types: 0 denotes anger, 1 disgust, 2 fear, 3 happiness, 4 sadness, 5 surprise, and 6 neutralities. While the other categories contain around 5,000 samples apiece, the disgust emotion has the fewest images 600 [7].

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Figure 2: Selected examples of the original FER2013 dataset

CK+: The Cohn-Kanade (CK+) dataset provides over 500 sequences of facial expressions of 123 subjects, covering a range of emotions and offering high-quality images for action unit coding [4, 8].

Figure 3: Samples from the CK+48 dataset

1.2 Feature Extraction Techniques

Feature extraction is a crucial step in FER systems as it transforms raw pixel values into a set of characteristics that the machine learning algorithm can process. Several techniques have been used for feature extraction:

Histogram of Oriented Gradients (HOG): This technique computes the gradient direction distribution in localized portions of the image, capturing information about the shape and appearance of facial components [1]. HOG features are widely used due to their robustness to photometric and geometric transformations [8-10].

Gabor Wavelets: Gabor wavelets are used on the facial images to capture information regarding texture and frequency. These are useful in capturing detailed facial features representative of emotions [11].

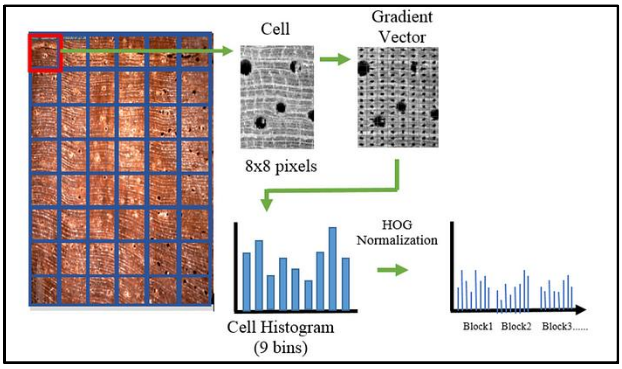

Figure 4: HOG feature process

Principal Component Analysis: PCA is primarily applied to reduce the dimensions of the feature space by retaining only the most important features and excluding the noise in the data, thereby enhancing performance with reduced computational cost [1, 4, 12].

1.3 Machine Learning Algorithms for FER

Once facial features are extracted, machine learning algorithms are employed to classify facial expressions. Below are some of the key algorithms commonly used in FER:

K-Nearest Neighbors (KNN): K-Nearest Neighbors (KNN) is a non-parametric algorithm that assigns the label of a test sample based on the majority vote from its 'k' closest neighbors in the feature space. KNN uses a distance metric (often Euclidean) to measure similarity between samples [13, 14].

Algorithm Steps:

1. Select the value of 'k' (number of neighbors).
2. Calculate the distance between the new input data point and all points in the training dataset.
3. Identify the 'k' nearest neighbors based on the calculated distances.
4. Assign the label based on the majority class among these neighbors.

Mathematical Equation: The distance d between two points x and y in an n-dimensional space is typically calculated using the Euclidean distance formula:

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Naïve Bayes: A probabilistic classifier based on Bayes' theorem; Naïve Bayes assumes that the features are independent given the class label. Despite this simplifying assumption, Naïve Bayes has proven effective for FER in high-dimensional data, especially when datasets are small [15, 16].

Algorithm Steps:

1. Calculate the prior probability for each class.
2. For each feature, compute the conditional probability of the feature given the class.
3. Use Bayes' theorem to compute the posterior probability for each class.
4. Assign the class with the highest posterior probability to the test sample.

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Mathematical Equations: Given a feature vector X= (x1, x2, xn) and a class C, the probability of C given X is calculated as:

$$P(C\backslash X) = \frac{P(C).P(X\backslash C)}{P(X)}$$

Where:

P(C|X) is the posterior probability of class C given X.
P(C) is the prior probability of class C
P(X|C) is the likelihood of the features given the class.
P(X) is the evidence or the probability of observing X, often ignored in the classification.

Under the independence assumption:

$$P(X\backslash C) = \prod_{i=1}^{n} P(X_i\backslash C)$$

Support Vector Machine (SVM): SVM is a supervised learning algorithm that aims to find the optimal hyperplane separating different classes with the maximum margin. SVM is well-suited for high-dimensional feature spaces and typically performs well on complex datasets with a high number of features [1, 17].

Algorithm Steps:

1. Identify a hyperplane that separates the data points of different classes.
2. Maximize the margin between the hyperplane and the nearest data points of each class.
3. Assign new points to a class based on which side of the hyperplane they fall.

Mathematical Equations: For a dataset with classes +1 and −1, SVM tries to find a hyperplane represented as:

$$w.x + b = 0$$

Where:

w is the weight vector orthogonal to the hyperplane.
b is the bias term.

To maximize the margin, SVM solves the following optimization problem:

$$\min_{w,b} \frac{1}{2} ||w||^2 subject\ to\ y_i(w.x_i + b) \geq$$

Where yi are the class labels (+1 or −1).

When the data is not linearly separable, kernel functions (e.g., radial basis function) are introduced to map the data to a higher-dimensional space where a hyperplane can separate them.

1.4 Comparative Analysis of Classifiers

Challenges and Advancements

While FER systems have made significant progress, several challenges remain [18, 19]:

Pose and Head Orientation: Variations in head position and facial pose are very different in real-world scenarios when head movements are dynamic [20].

Lighting and Occlusion: Lighting changes and partial occlusions (e.g., facial hair, glasses) can reduce the accuracy of emotion classification systems.

Table 1: Comparative analysis of classifiers

Classifier	Advantages	Disadvantages	Typical Use Cases
K-Nearest Neighbors	Simple, intuitive, works well with smaller datasets, robust to noisy data	Computationally expensive during testing, sensitive to irrelevant features	Small-scale emotion recognition tasks
Naïve Bayes	Fast, efficient, works well with high-dimensional data, good for small datasets	Assumes independence between features, may struggle with complex dependencies	Quick emotion classification with small datasets
Support Vector Machine	Effective in high-dimensional spaces, robust to overfitting, handles large datasets	Computationally expensive, requires careful tuning of parameters	High-performance emotion recognition in complex datasets

- Real-Time Processing: FER systems need to be optimized for real-time applications, especially in interactive environments where immediate feedback is crucial [21].
- Recent deep learning methods, especially Convolutional Neural Networks, have proved to yield much better accuracy for improving FER performance. CNN learns the hierarchical features automatically from raw pixel data, which brought a big performance boost compared to traditional methods of feature extraction [4].

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1.5 Future Directions

- Multimodal Emotion Recognition: Future FER systems may integrate facial expression analysis with other modalities such as voice, body language, and physiological signals to improve accuracy.
- Cross-Cultural Recognition: FER systems must be trained with more diverse datasets to handle cultural differences in emotional expression.
- Unsupervised Learning and Transfer Learning: These techniques could reduce the need for large labeled datasets by enabling models to learn from unannotated data or transfer knowledge across different emotion recognition tasks.

II. RELATED WORKS

Paper [22] reviews three main active features extraction techniques, namely Gabor, LBP, and HOG, used in computer vision for the emotion recognition tasks conducted on FE datasets like JAFFE and CK+. By using the simple classifier k-Nearest Neighbor, the responses come fast enough. Moreover, this work proved the efficiency of Gabor filters in the processing of binary images to enhance them, hence making the model reliable for various applications such as ATMs, passport verification, and security. This study emphasizes that, while computationally burdensome, Gabor filters recognize with higher accuracy compared to simpler ones. Future work could consider alternative techniques for feature extraction in order to maintain efficiency with no loss of accuracy.

Following the work presented in Paper [22], in Study [23] a facial expression recognition model was implemented through HOG descriptors combined with the RF classifier. For the JAFFE dataset, this was tested to show improvements to the more traditional handcrafted approaches which are, unfortunately, less consistent against diverse image variances and partial faces. This research underlines the precision and robustness of the methodology since, using the HOG descriptor, only relevant characteristics are extracted that later can be classified by RF. This evidences the potential of combinations of HOG-RF on facial expression recognition tasks.

Paper [24] further extends the search for the most efficient feature extraction methodology in facial expression recognition by a comparison approach that identifies features with the highest impact. With the use of a well-trained face expression recognition system on a controlled dataset, and the application of several feature extraction techniques, each transforming into the sparse representation domains, a total number of 14 combinations were tested. The results indicate that LPQ features yield the most reliable improvements to expression classification with 83%, HOG features with 82%, and RAW features with 82%. This paper emphasizes the fact that specific features might represent some expressions better.

Building upon the feature extraction insights, research [25] investigates pragmatic approaches toward FER using HOG and Gabor filters to capture the details of facial regions such as the eyes, brow, and lips. For classification, Support Vector Machines (SVM) are employed; this methodology tries to address sensitivities related to facial deformations, which gives a classification performance of 63.82%. The contribution here is related to the fine-tuning approach toward handling texture recognition and classification in the FER area, providing specific benefits, notably in applications related to object deformation management.

This paper [25] pushes the investigation one step further by comparing machine learning algorithms in FER tasks using SVM, Random Forest, and Convolutional Neural Networks on the FER2013 dataset. Results show CNN has the highest performance with 65% accuracy in the classification of FER tasks. The study supports the use of deep learning architectures, specifically CNNs, in handling complex emotion classification challenges over simpler models.

Researchers [26] then address dynamic aspects of FER, introducing FlowCorr and Dyn-HOG descriptors for interpreting emotions. These descriptors analyze intra-class similarity and inter-class variance, enhancing recognition accuracy across datasets like CK+ and KDEF-dyn. This study contributes to the dynamic descriptors' literature, indicating that FlowCorr and Dyn-HOG offer competitive performance against state-of-the-art methods in dynamic human-computer interaction contexts.

The subsequent study [27] proposes a simplified framework for pattern recognition by extracting fusion features from salient facial areas. Utilizing LBP and HOG, it applies dimensionality reduction with Principal Component Analysis (PCA) and a softmax classifier for expression classification [1]. By defining and normalizing salient areas, the framework achieves high performance on CK+ and JAFFE databases, demonstrating improved recognition rates and streamlined model architecture.

This paper [28] further refines the FER field by introducing a cascade framework (McRiHOG) for multi-threaded FER across data categories. Tested on popular FER databases, McRiHOG extends the use of cascade learning to broader applications in imaging industries. This model illustrates the scalability of cascade frameworks and suggests future research on minimizing feature representation error in FER frameworks.

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Pioneering novel methods, paper [29] integrates convolutional neural networks (CNNs) and HOG features in a unique framework for Video-based FER (VFER). By addressing issues like displacement, scale, and deformation invariance, this method enhances feature comprehensiveness and achieves superior performance on RML, CK+, and AFEW5.0 databases. The study calls for future research to reduce parameter count without compromising accuracy, underscoring the potential of hybrid CNN-HOG models.

Shifting focus to non-verbal communication, research [30] combines shape and texture features to develop a discriminative FER model using Local Phase Quantization, LBP, and HOG. Achieving a 94.2% recognition rate on CK+ and 93.7% on KDEF, the study demonstrates the utility of multi-feature approaches for accurate emotion recognition. This work supports the integration of discriminative feature distribution in FER to maximize recognition rates across diverse datasets.

Continuing from the previous studies, paper [31] introduces a face recognition algorithm using HOG features paired with an SVM classifier, directly comparing its performance against the standard Eigen-based PCA algorithm. By extracting Histogram of Oriented Gradient features for both test and training images, this approach achieves an 8.75% improvement over PCA on the ORL database, showcasing its effectiveness across seven other face datasets. It thus further emphasizes the combinations of HOG-SVM in face recognition, which are much stronger than the more traditional PCA approaches.

Paper [32] presents a dual-method approach for FER using Principal Component Analysis and Linear Discriminant Analysis. It uses LDA for linear discriminant analysis after reducing the facial features to lower dimensions, which enhances the ability of the model to distinguish different classes. This is tested on face databases such as FERET and CAS-PEAL and proves that the combination of PCA with LDA is effective in boosting both feature extraction performance and overall classification performance.

First, after dimensional reduction was explored, the research in [33] uses a Machine Learning approach to emotion recognition by converting 600 digital images into grayscale, obtains relevant statistical features, and optimizes those through a best-first search algorithm. Afterward, it deployed this optimized dataset across different ML classifiers, noted higher accuracy with Boosting and Decision Tree algorithms. This therefore brings out the fact that feature optimization is very important in high-accuracy performance, especially with the application of boosting techniques and decision trees.

With the emphasis on specific facial expressions, [34] presented a novel interpretation scheme for frowns by using PSO with patch-based Gabor features. Indeed, this was more powerful than point-based Gabor features which could be extended for domains like patient monitoring, driver fatigue detection, and intelligent tutoring. The technique, which embeds mGA within PSO for local aspect analysis, performs better than traditional PSO variants and classical GA, thus finding applications in real-time uses for expression-specific detection.

The paper [35] extends FER, introducing HOG features into ESRs in order to enhance emotion recognition. It describes an improved HOG-ESR methodology enhancing the features extracted and reducing generalization error, increasing the robustness of the system, especially under challenging conditions, such as those seen outdoors with variable lighting. The work has been tested on the FER2013 dataset, and it advocates for possible future research about the use of image data under different light conditions with the purpose of expanding the model adaptability across a different environmental context.

In other words, all the papers discussed above have contributed to the progress of face expression recognition systems. Advantages and disadvantages are given about different machine learning algorithms and features-extracting methods. This evolution from the traditional approaches employing PCA and LBP to higher-end hybrid models of CNN-HOG, and even feature combination approaches like HOG-ESR, signifies innovation in the area. As the FER research goes on, further studies on improving parameter efficiency, variety in lighting, and other environmental issues should be designed in the future. Further areas of application could be in extending applications in human-computer interaction, security, and personalized education.

A look back at the earlier facial expression recognition (FER) systems shows a progression from mostly feature extractions to a combination of hybrid and deep learning models. In their earlier efforts, Paper [22] combined Gabor, LBP, and HOG filters with k-nearest neighbor (kNN) classifiers and established that Gabor filters were more accurate, although they were computationally intensive. In Study [22], this was taken a step further with the incorporation of HOG descriptors and random forest (RF) improving performance especially on the JAFFE dataset. Expanding on the features comparison study, Study [24] employed several extraction techniques and concluded that LPQ, HOG, and RAW could be utilized satisfactorily for expression classification which is consistent with the postulation that some features work better for certain emotions. In research [25] Gabor and HOG filters were used with SVM, and in

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Study [36] the focus shifted to comparing machine learning algorithms on FR2013 dataset with CNN performing the best among them in most accuracy measures. Moreover, in Study [26], novel dynamic descriptors were presented, FlowCorr and Dyn-HOG, to reflect facial expressions that varied with time. works such as [27] focused on the simplification of the recognition frameworks by fusing features using dimensional reduction techniques and achieved high accuracies on CK+ and JAFFE databases.

Innovations continued with a multithreaded cascade framework called McRiHOG in Study [28], followed by a CNN-HOG model in Study [29]. Thus, these models enhanced feature comprehensiveness for Video-based FER tasks. Later, features that combined LPQ and LBP with HOG realized high accuracy on both CK+ and KDEF in Study [30]. More recently, hybrid methods, such as the HOG-ESR model in Study [35], which surmounted the lighting change difficulties, shows the adaptability FER methods can assume. These studies collectively show that FER is biased towards traditional and modern approaches, feature improvement, classification accuracy, and the adaptability of a system across real-world conditions.

Table 2: Comparison of previous studies

Ref	**year**	**Database**	**Feature Extraction Algorithms**	**Classification Algorithms**	**Accuracy**
[22]	2023	CK+, JAFFE	Gabor, LBP, HOG	K-Nearest Neighbors (kNN)	Gabor: 94.8%, LBP: 88.2%, HOG: 55.2%
[23]	2024	JAFFE	HOG	Random Forest	High
[24]	2022	CK+, JAFFE	LPQ, HOG, RAW, Gabor	Ensemble Classifiers	LPQ: 83%, HOG: 82%, RAW: 82%
[25]	2022	FER2013	HOG, Gabor	Support Vector Machine (SVM)	63.82%
[36]	2023	FER2013	None	SVM, Random Forest, CNN	CNN: 65%
[26]	2020	CK+, KDEF	FlowCorr, HOG	Multi-class SVM	Competitive with SOTA
[27]	2017	CK+, JAFFE	LBP, HOG	Softmax	State-of-the-art on CK+, JAFFE
[28]	2015	CK+, MMI, AFEW	Rotation-invariant HOG	Multithreading Cascade, AdaBoost	Outperformed SOTA
[29]	2020	RML, CK+, AFEW5.0	CNN, HOG	Support Vector Machine (SVM)	High performance
[30]	2022	CK+, KDEF, JAFFE	LPQ, LBP, HOG	Multi-class SVM	CK+: 94.2%, KDEF: 93.7%
[31]	2016	ORL	HOG	SVM	Improved over PCA by 8.75%
[32]	2018	Cohn-Kanade, MMI	LVP, Gabor	PSO, mGA-embedded PSO	High performance on selected datasets
[33]	2020	Taiwan Facial Expression	Texture, histogram, binary features	J48 Decision Tree, Random Forest	97.05% with J48
[34]	2021	FERET, CAS-PEAL	HOG, PCA, LDA	PCA and LDA combined	Improved feature extraction performance
[35]	2021	FER2013	HOG, Ensembles with Shared Representations (ESRs)	Convolutional Neural Network (CNN)	Improved accuracy on FER2013 dataset

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The balance between computational complexity and accuracy is crucial in FER systems, especially when considering their deployment in real-world applications. This analysis highlights the trade-offs among the commonly used feature extraction and classification techniques discussed in the referenced papers.

2.1 Insights from the Analysis

1. Gabor Filters: Achieve the highest accuracy for FER tasks on controlled datasets but suffer from high computational demands, making them less practical for real-time or resource-constrained environments.
2. HOG Descriptors: Offer a good trade-off between complexity and accuracy, particularly when combined with classifiers like Random Forest or SVM. This makes them suitable for applications requiring reasonable accuracy and faster computations.
3. LBP: Provides the least computational complexity but compromises accuracy on datasets with high variability, limiting its use to simpler applications or as a complementary method.
4. CNNs: Represent the gold standard in accuracy due to their ability to learn complex feature hierarchies [37]. However, their computational requirements limit their practicality in low-power or real-time systems without specialized hardware (e.g., GPUs).
5. LPQ and Hybrid Models: Combining LPQ or HOG with advanced classifiers offers a balanced approach, achieving robust performance while managing computational costs better than Gabor or CNNs alone.

Table 3: Comparison of methods

Technique	Accuracy	Computational Complexity	Strengths	Weaknesses
Gabor Filters	High (e.g., 94.8% on CK+)	High (due to convolution operations on multiple scales)	Accurate feature representation; robust against noise and lighting variation.	Computationally intensive; less efficient for real-time applications.
HOG	Moderate (e.g., 82% on JAFFE)	Moderate	Efficient feature extraction; invariant to geometric transformations.	Sensitive to noise; lower performance on complex datasets.
LBP	Moderate (e.g., 88.2% on CK+)	Low	Fast and computationally inexpensive; works well on texture-rich images.	Limited ability to capture spatial relationships; less effective for diverse datasets.
LPQ	High (e.g., 83% on CK+)	Moderate	Effective for capturing fine-grained details; robust to small distortions.	Computationally heavier than LBP but less robust than Gabor for large variations.
SVM with HOG	High (e.g., 63.82% on FER2013)	High	Handles high-dimensional data well; performs better on well-defined features.	Requires careful parameter tuning; computationally expensive during training.
Random Forest with HOG	High (e.g., improved JAFFE performance)	Moderate	Robust to overfitting; handles feature importance effectively.	Less efficient than simpler classifiers for real-time processing.
CNN (Deep Learning)	Very High (e.g., 65% on FER2013)	Very High (due to deep layer computations)	Automatically extracts hierarchical features; state-of-the-art accuracy.	Extremely resource-intensive; requires large labeled datasets.

III. CONCLUSION

The achievements in FER indicate that machine learning contributions in this arena play a huge role in enhancing the classification of emotions from a wide dataset range under difficult conditions. Feature extraction methods such as HOG and Gabor filters proved competent, while machine learning algorithms, especially SVM and KNN, have been highly responsible for pushing the limits of FER. Despite these successes, real-time processing, changes in lighting, and cultural differences remain challenges to be dealt with. Thus, future studies should look toward multimodal methods that combine audio, gestures, and physiological signals with the hope of coming closer to a more genuinely holistic understanding of human emotions. Second, expanding the datasets across cultures and exploiting transfer learning can further improve the robustness and applicability of models to a variety of environments. Cumulatively, these enhancements

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will ensure FER systems play an imperative role in applications related to security, health care, and personalized interaction in intelligent systems.

REFERENCES

[1] S. R. Kay, A. Fiszbein, and L. A. Opler, "The Positive and Negative Syndrome Scale (PANSS) for schizophrenia," *Schizophrenia Bulletin*, vol. 13, no. 2, pp. 261–276, Jan. 1987, doi: 10.1093/schbul/13.2.261.

[2] Z. Song, "Facial Expression Emotion Recognition model integrating philosophy and machine learning theory," *Frontiers in Psychology*, vol. 12, Sep. 2021, doi: 10.3389/fpsyg.2021.759485..

[3] R. A. Elsheikh et al., "Improved facial emotion recognition model based on a novel deep convolutional structure," *Scientific Reports*, vol. 14, no. 1, p. 29050, 2024.

[4] R. A. Elsheikh, M. A. Mohamed, A. M. Abou-Taleb, and M. M. Ata, "Improved facial emotion recognition model based on a novel deep convolutional structure," *Scientific Reports*, vol. 14, no. 1, Nov. 2024, doi: 10.1038/s41598-024-79167-8.

[5] L. Alharbawee and N. Pugeault, "A benchmark of dynamic versus static methods for facial action unit detection," *The Journal of Engineering*, vol. 2021, no. 5, pp. 252–266, 2021, doi: 10.1049/tje2.12001.

[6] S. Van Hoy, "Facial Expression Perception and Psychological Changes During Space Analogs," *Aerospace Medicine and Human Performance*, vol. 95, no. 12, pp. 913–918, 2024, doi: 10.3357/amhp.6504.2024.

[7] N. Raut, "Facial emotion recognition using Machine learning," 2018. doi: 10.31979/etd.w5fs-s8wd.

[8] F. M. A. Mazen, A. A. Nashat, and R. A. A. A. A. Seoud, "Real Time Face Expression Recognition along with Balanced FER2013 Dataset using CycleGAN," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, Jan. 2021, doi: 10.14569/ijacsa.2021.0120617.

[9] S. Xie and H. Hu, "Facial expression recognition using hierarchical features with deep comprehensive multipatches aggregation convolutional neural networks," *IEEE Transactions on Multimedia*, vol. 21, no. 1, pp. 211–220, Jun. 2018, doi: 10.1109/tmm.2018.2844085.

[10] P. N. Maraskolhe and A. S. Bhalchandra, "Analysis of Facial Expression Recognition using Histogram of Oriented Gradient (HOG)," *2019 3rd International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, pp. 1007–1011, Jun. 2019, doi: 10.1109/iceca.2019.8821814.

[11] N. M. Kh. Hussien and N. F. M. Ramo, "Facial expression using Histogram of Oriented Gradients and Ensemble Classifier," *Tikrit Journal of Pure Science*, vol. 27, no. 2, pp. 52–56, Nov. 2022, doi: 10.25130/tjps.v27i2.67.

[12] N. L. Shen and N. S. Jia, "Three-Dimensional Gabor Wavelets for Pixel-Based Hyperspectral Imagery classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 12, pp. 5039–5046, Jun. 2011, doi: 10.1109/tgrs.2011.2157166..

[13] C. Goodall and I. T. Jolliffe, "Principal component analysis," *Technometrics*, vol. 30, no. 3, p. 351, Aug. 1988, doi: 10.2307/1270093..

[14] M. R. Islam, A. R. M. Kamal, N. Sultana, R. Islam, M. A. Moni, and A. Ulhaq, "Detecting depression using K-Nearest Neighbors (KNN) classification technique," *2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2)*, pp. 1–4, Feb. 2018, doi: 10.1109/ic4me2.2018.8465641..

[15] Z. Deng, X. Zhu, D. Cheng, M. Zong, and S. Zhang, "Efficient kNN classification algorithm for big data," *Neurocomputing*, vol. 195, pp. 143–148, Feb. 2016, doi: 10.1016/j.neucom.2015.08.112..

[16] H. Chen, S. Hu, R. Hua, and X. Zhao, "Improved naive Bayes classification algorithm for traffic risk management," *EURASIP Journal on Advances in Signal Processing*, vol. 2021, no. 1, Jun. 2021, doi: 10.1186/s13634-021-00742-6..

[17] B. S. Gandhi, D. A. Megawaty, and D. Alita, "Aplikasi Monitoring dan PenentuanPeringkatKelasMenggunakan Naive Bayes Classifier," *JurnalInformatika Dan RekayasaPerangkat Lunak*, vol. 2, no. 1, pp. 54–63, Apr. 2021, doi: 10.33365/jatika.v2i1.722.

[18] A.Kurani, P. Doshi, A. Vakharia, and M. Shah, "A comprehensive comparative study of Artificial Neural Network (ANN) and Support Vector Machines (SVM) on stock forecasting," *Annals of Data Science*, vol. 10, no. 1, pp. 183–208, Jun. 2021, doi: 10.1007/s40745-021-00344-x.

[19] X. Zhao, J. Zhu, B. Luo, and Y. Gao, "Survey on Facial Expression Recognition: history, applications, and challenges," *IEEE Multimedia*, vol. 28, no. 4, pp. 38–44, Aug. 2021, doi: 10.1109/mmul.2021.3107862..

[20] K. Patel et al., "Facial Sentiment Analysis Using AI Techniques: State-of-the-Art, Taxonomies, and Challenges," *IEEE Access*, vol. 8, pp. 90495–90519, Jan. 2020, doi: 10.1109/access.2020.2993803..

[21] L. Alharbawee and N. Pugeault, "Generative adversarial networks for facial expression recognition in the wild," *International Journal of Computing and*

ISSN (online): 2581-3048
Volume 9, Issue 5, pp 457-465, May-2025
https://doi.org/10.47001/IRJIET/2025.905052

Digital Systems, vol. 15, no. 1, pp. 1259–1282, Jun. 2024, doi: 10.12785/ijcds/160193..

[22] M. R. Koujan, L. Alharbawee, G. Giannakakis, N. Pugeault, and A. Roussos, "Real-time Facial Expression Recognition 'In The Wild' by Disentangling 3D Expression from Identity," *2021 16th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2021)*, pp. 24–31, Nov. 2020, doi: 10.1109/fg47880.2020.00084..

[23] S. Subudhiray, H. K. Palo, and N. Das, "K-nearest neighbor based facial emotion recognition using effective features," *IAES International Journal of Artificial Intelligence*,vol. 12, no. 1, p. 57, Oct. 2022, doi: 10.11591/ijai.v12.i1.pp57-65..

[24] V. A. Saeed, "A framework for recognition of facial expression using HOG features," *International Journal of Mathematics Statistics and Computer Science*, vol. 2, pp. 1–8, May 2023, doi: 10.59543/ijmscs.v2i.7815.

[25] P. D. Marrero-Fernandez, J. M. Buades-Rubio, A. Jaume-I-Capó, and T. I. Ren, "An approach for selecting the most explanatory features for facial expression recognition," *Applied Sciences*, vol. 12, no. 11, p. 5637, Jun. 2022, doi: 10.3390/app12115637..

[26] Z. F. Hasan, "An improved facial expression recognition method using combined hog and gabor features," *Science Journal of University of Zakho*, vol. 10, no. 2, pp. 54–59, Jun. 2022, doi: 10.25271/sjuoz.2022.10.2.897..

[27] S. Anthwal and D. Ganotra, "Dynamic features based on Flow-Correlation and HOG for recognition of discrete facial expressions," *Revue D Intelligence Artificielle*, vol. 34, no. 5, pp. 585–594, Nov. 2020, doi: 10.18280/ria.340508..

[28] Y. Liu, Y. Li, X. Ma, and R. Song, "Facial Expression Recognition with Fusion Features Extracted from Salient Facial Areas," *Sensors*, vol. 17, no. 4, p. 712, Mar. 2017, doi: 10.3390/s17040712..

[29] J. Chen, T. Takiguchi, and Y. Ariki, "Facial expression recognition with multithreaded cascade of rotation-invariant HOG," *in 2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*, IEEE, 2015, doi: 10.1109/ACII.2015.7344665.

[30] X. Pan, "Fusing HOG and convolutional neural network spatial–temporal features for video-based facial expression recognition*," IET Image Processing*, vol. 14, no. 1, pp. 176–182, Oct. 2019, doi: 10.1049/iet-ipr.2019.0293..

[31] N. K. H. N, A. S. Kumar, G. P. M. S, and M. A. Shah, "Automatic facial expression recognition combining texture and shape features from prominent facial regions," *IET Image Processing*, vol. 17, no. 4, pp. 1111–1125, Nov. 2022, doi: 10.1049/ipr2.12700..

[32] H. S. Dadi and G. K. M. Pillutla, "Improved face recognition rate using HOG features and SVM classifier," *IOSR Journal of Electronics and Communication Engineering*, vol. 11, no. 04, pp. 34–44, Apr. 2016, doi: 10.9790/2834-1104013444.

[33] V. Ramalingam, A. Pandian, and L. Jayakumar, "Facial emotion recognition system–a machine learning approach," *in Journal of Physics: Conference Series, IOP Publishing*, 2018, doi: 10.1088/1742-6596/1000/1/012140.

[34] A.Ali et al., "Machine Learning Based Statistical Analysis of Emotion Recognition using Facial Expression," *RADS Journal of Biological Research & Applied Sciences*, vol. 11, no. 1, pp. 39–46, Sep. 2020, doi: 10.37962/jbas.v11i1.262.

[35] Y. Li, R. Lu, R. Huang, and W. Zhang, "Research on face recognition algorithm based on HOG feature," *Journal of Physics Conference Series*, vol. 1757, no. 1, p. 012099, Jan. 2021, doi: 10.1088/1742-6596/1757/1/012099..

[36] Y. Zhong, L. Sun, C. Ge, and H. Fan, "HOG-ESRs face Emotion Recognition Algorithm based on HOG feature and ESRS Method," *Symmetry*, vol. 13, no. 2, p. 228, Jan. 2021, doi: 10.3390/sym13020228.

[37] P. Viola and M. J. Jones, "Robust Real-Time Face Detection," *International Journal of Computer Vision*, vol. 57, no. 2, pp. 137–154, Jan. 2004, doi: 10.1023/b:visi.0000013087.49260.fb.

[38] M. C. Younis and E. Keedwell, "Semantic segmentation on small datasets of satellite images using convolutional neural networks," *Journal of Applied Remote Sensing*, vol. 13, no. 04, p. 1, Nov. 2019, doi: 10.1117/1.jrs.13.046510.

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