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LOCAL FEATURE SELECTION USING THE WRAPPER APPROACH FOR FACIAL-EXPRESSION RECOGNITION

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ABSTRACT

Automatic Facial Expression Recognition (FER) systems provide an important way to express and interpret the emotional and mental states of human beings. These FER systems transform the facial image into a set of features to train a classifier capable of distinguishing between different classes of emotions. However, the problem often posed is that the extracted feature vectors sometimes contain irrelevant or redundant features, which decreases the accuracy of the induced classifier and increases the computation time. To overcome this problem, dimensionality must be reduced by selecting only the most relevant features. In this paper, we study the impact of adding the "Wrapper" selection approach and using the information provided by different local regions of the face such as the mouth, eyes and eyebrows, on the performance of a traditional FER system based on a local geometric feature-extraction method. The objective here is to test and analyze how this combination can improve the overall performance of the original traditional system. The obtained results, based on the Multimedia Understanding Group (MUG) database, showed that the FER system combined with the proposed feature-selection strategy gives better classification results than the original system for all four classification models; namely, K-Nearest Neighbor (KNN) classifier, Tree classifier, NB classifier and Linear Discriminant Analysis (LDA). Indeed, a considerable reduction (up to 50%) in the number of features used and an accuracy of 100%, using the LDA classifier, were observed, which represents a significant improvement in terms of computation time, efficiency and memory space. Furthermore, the majority of relevant features used are part of the "eyebrows' region", which proves the importance of using information from local regions of the face in emotion recognition tasks.

KEYWORDS

Facial expression recognition, Local feature extraction, Feature selection, Wrapper approach, Classification.

1. INTRODUCTION

In the field of FER, which is one of the most important topics in image processing and computer vision, feature selection is a crucial step used to extract the most relevant information from images, thus improving performance of the model in various modalities, including two-dimensional (2D), three-dimensional (3D) and temporal data. For 2D FER, feature selection involves identifying and choosing relevant facial features that capture the information needed for expression recognition while minimizing irrelevant data. Whereas, for complex and diverse data, such as 3D and temporal facial expressions, where different angles and movements must be considered, a specific feature-selection approach tailored to the unique feature of each data type, allows the development of more precise and more robust models having a positive effect on the overall performance of the FER [1]-[2] system.

In the context of the 2D FER, several techniques for feature selection have been proposed in the literature. For example, in [3] the authors used the Relief-F feature-selection method to select the top-ranked features for each facial expression. In this method, features are classified in sequential order based on their variance values. After that, the selected features are used to train and test six classifiers which are Multi-Layer Perceptron (MLP), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Radial Basis Function (RBS). The results given in [3] showed that the KNN classifier is the most accurate classifier among the others with a total accuracy rating equal to 94.93% using the Cohn-Kanade (CK+) database.

Mahmood [4] applied both the Chi-square and Relief-F feature-selection methods to select the top-

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ranked features. The latter ones were then used to distinguish the most accurate classifier among the four classifiers which are the SVM, the KNN, the DT and the RBS. The obtained experimental results, based on the CK+ database, showed that KNN is the most accurate classifier for both feature-selection methods. Indeed, the average accuracy rate, corresponding to the KNN classifier, is 94.18% for the Chi- square method and 94.93% for the Relief-F method.

Ewees et al. [5] proposed an optimization method, called Sine-Cosine Algorithm (SCA) for feature selection. This method, which is a metaheuristic algorithm that utilizes the mathematical forms of sine and cosine functions to perform the optimization problems, was used to improve the performance of a real-time system intended to recognize student's facial expression. The performance of this method was evaluated on a database of Students' Facial Expression (SFE), using various classifiers including KNN, RF and SVM. The experimental results showed that the KNN classifier achieved the best performance with a remarkable reduction in the number of features.

Cossetin et al. [6] proposed a hybrid method to select relevant features and reduce dimensionality as well as computational complexity. In this method, the authors combined the "Filter" approach, in which features were ranked by relevance using techniques such as Correlation-based Feature Selection (CFS), Relief-F and Information Gain (IG), with the "Wrapper" approach. The latter one makes it possible to progressively optimize the sub-set of the most discriminating features for each pair of expressions. The results obtained in [6] demonstrated that this combination overcomes the limitations of existing methods while avoiding reliance on reference points and improving SVM classification accuracy.

Dino and Abdulrazzaq [7] compared different feature-selection methods for FER using multi-classification algorithms such as KNN, MLP, DT (J48) and NB. The comparison here, the main objective is to determine the best classifier capable of achieving an acceptable accuracy rate, is carried out on the basis of three feature-selection techniques; namely, CFS, the Gain Ratio (GR) and IG. The experimental results, based on the CK+ database, showed that the KNN classifier was the best, with an accuracy of 91% using only 30 features.

Wang et al. [8] proposed a feature-fusion model of multiple feature selection, realized by the measure of the RV correlation coefficient, to increase the performance of the FER system. Four kinds of features; namely, Local Binary Patterns (LBP), Pyramid of Histogram of Oriented Gradients (PHOG), Histogram of Oriented Gradients (HOG) and Gabor features are selected for fusion. In addition, Canonical Correlation Analysis (CCA) and Principal Component Analysis (PCA) sub-spaces are used to fuse selected features. The experimental results, based on the Japanese Female Facial Expression (JAFFE) and CK databases (using an SVM classifier) demonstrated that the proposed model improves performance and eliminates feature redundancy.

Li et al. [9] proposed an Iterative Universum Twin SVM (IUTWSVM) using Newton method for the classification of multiclass emotions by means of facial-expression analysis. This innovative approach, which integrates an iterative method, aims to improve feature selection and classification performance while reducing computational costs. To improve Universum's data selection and ensure that it effectively contributes to the classification task, the authors introduced a new system based on information entropy. Experimental results based on benchmark databases demonstrated that the IUTWSVM approach outperforms existing algorithms, in terms of classification accuracy and learning efficiency. This is true for both binary and multiclass facial emotion-recognition tasks.

Talaat et al. [10] developed a real-time emotion-identification system to detect autism spectrum disorders (ASDs) in autistic children. The proposed system integrates an autoencoder-based feature-selection method implemented in a Deep Convolutional Neural Network (DCNN) architecture. The results obtained demonstrated that this autoencoder achieved a remarkable accuracy of 95.23% with the Xception model. Additionally, it improves real-time emotion detection, thus providing an advanced technological solution adaptable on various smart devices.

Always in the context of improving the performance of FER systems, the authors in [11] used Active Shape Models (ASM) proposed by Cootes et al. in [12] to study the positioning of 24 facial landmarks (four marks for the mouth, four marks for each eye and six marks for each eyebrow). At this stage, several classifiers were also used to determine which of them gave the best results in identifying seven emotions; namely, happiness, anger, sadness, surprise, disgust, fear and neutral. The results presented in [11] demonstrated that this approach has advantages in terms of robustness and interpretability. Additionally, it is stable to illumination changes and is invariant to global transformations such as face rotation and scaling.

To sum up, each of the various methods has its own set of limitations. For instance, Relief-F is a supervised method that calculates feature weights based on their relevance to other features, but it may struggle with noisy data. Chi-square measures the relationship between features and the target variable through statistical analysis. Nevertheless, it is less effective for non-linear relationships. The SCA employs mathematical functions for feature selection and global optimization, but can converge to local optima. Splitting a multi-class problem into binary ones simplifies the classification process, but may overlook the relationships between classes. Correlation evaluates the linear relationship between features and the target, but may not capture non-linear associations. GR and IG, which rely on entropy, can detect non-linear relationships, but might favor features with more values. RV correlation is a non-parametric method that captures both linear and non-linear relationships, although it can be computationally intensive. The autoencoder approach, based on neural networks, excels at learning non- linear feature relationships, but requires substantial data and computational resources [13]-[16]. Finally, for ASM-based approach, using the set of all extracted features, without selecting the relevant ones, increases the complexity in terms of computation time and memory space and likely reduces the accuracy caused by the curse of dimensionality.

The aim of this work is to demonstrate the efficiency and impact of adding a feature-selection step to the FER process, on the one hand and to conduct, on the other hand, a study on the effect of local facial regions such as the mouth, eyes and eyebrows on the performance of the FER system. This study will make it possible to determine the local facial regions containing the most important local features to ensure good recognition of facial emotional expressions. To achieve this, in this paper, we propose a modified enhanced FER system based on that given in [11]. In other words, we will integrate a "Wrapper" approach to remove redundant or irrelevant features that can degrade the classification model's performance and processing time. The reminder of this paper is organized as follows. Section 2 presents the related work. Section 3 describes the proposed modified enhanced FER system. In section 4, the experimental results, based on the MUG database, together with a performance comparison are given. We end with a conclusion.

2. RELATED WORK

A schematic overview of the proposed Silva et al. FER [11] system is shown in Figure (1). As illustrated in this figure, the latter system includes three functional blocks. The first one characterizes the face-detection function and the second is facial feature extraction and normalization. Finally, the last functional block represents facial-expression classification.

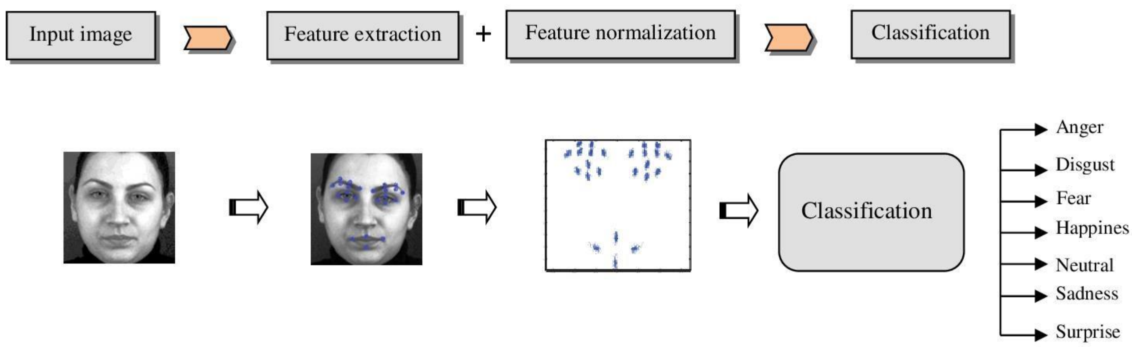


Figure 1. A schematic overview of the traditional FER system proposed in [11].

The principle of each of these blocks is given below.

2.1 Face-detection Block

In [11], faces are located using the algorithm proposed by Viola and Jones [17], which consists of two main steps: Haar-like feature extraction and AdaBoost classification.

2.2 Feature-extraction Block

After the face-detection step, features are extracted using the ASM method proposed by Cootes et al. [12]. ASM is a feature-matching method based on a statistical model [18] comprising two stages. In the first one, each structured object is represented by a set of landmarks manually placed in each image. In the second stage, the landmarks are automatically aligned to minimize the distance between their corresponding points. Then, the ASM creates a statistical model of the facial shape that iteratively deforms to fit the model in a new image [11]. The optimal number of facial landmarks ensuring better facial expression-recognition performance is chosen 24 [11]. This number, which ensures the maximum precision ratio, was chosen after an evaluation test based on 9 sets of facial landmarks containing 4, 12, 20, 24, 27, 35, 39, 55 and 76 landmarks. Table 1 describes the number of landmark points extracted for each facial region utilized.

Table 1. Number of landmark points extracted for each facial region.

Facial region	Number of landmark points
Mouth	4
Left eye	4
Right eye	4
Left eyebrow	6
Right eyebrow	6
Total	**24**

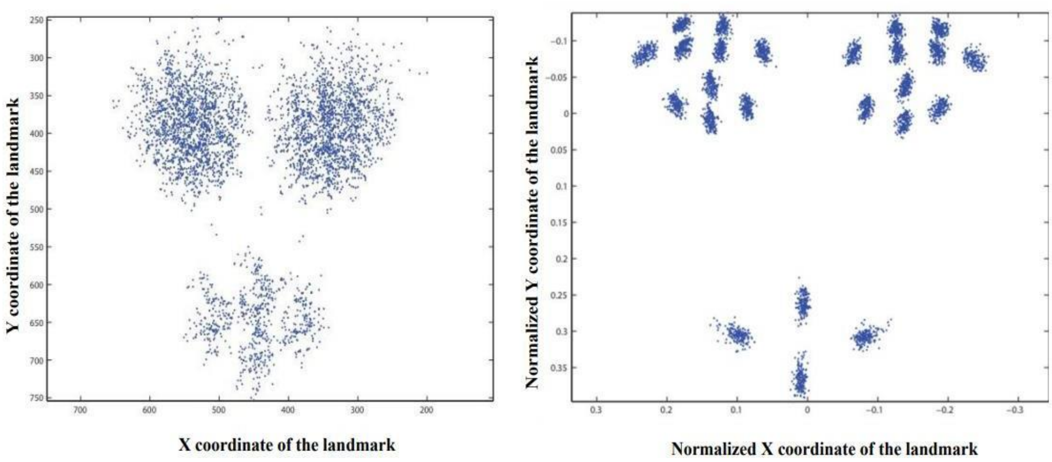
The choice of facial regions is based on the fact that facial expressions are deformations of the main permanent areas of the face (mouth, eyes, …etc.). These local areas contain most of the emotional information [19]-[20], which makes it possible to clearly recognize different emotions according to different deformations.

2.3 Feature-normalization Block

In this step, the Generalized Procrustes Analysis (GPA) is used to accomplish the following:

- Normalizing the extracted landmarks;
- Eliminating the effects of scale, rotation and translation in the landmarks' set;
- Decreasing the variations between the corresponding landmarks and search for the best fit.

GPA is a standard multivariate statistical method widely applied in shape analysis. To find the optimal superposition of two or more configurations, GPA involves three transformations; namely, translation, rotation and scaling [21]. Figure (2) shows the features extracted from the surprise expression using the MUG database. Figure 2(a) shows the raw data and Figure 2(b) shows the data normalized with GPA.



(a) (b)

Figure 2. Landmark normalization: (a) Raw data (b) Normalization with GPA [11].

2.4 Facial-expression Classification Block

The final step of this FER system is the classification of facial expressions, which is achieved in [11] using several classifiers; namely, KNN [22], NB [23], LDA [24] and DT [15] classifiers. First, the KNN algorithm, one of the most popular algorithms for pattern recognition, predicts the test sample's category according to the K training samples that are its nearest neighbors, then determines the category by selecting the one with the highest category probability [25]. Second, NB is a statistical classifier based on Bayes' theorem, assigning the most likely class to a given example described by its feature vector. Third, LDA involves finding the projection hyperplane that minimizes the interclass variance and maximizes the distance between the projected means of the classes [26]. Finally, the DT classification algorithm establishes the relationship between the input attributes and the output attributes to build a model that predicts the desired class with the highest accuracy [27].

3. PRINCIPLE OF THE PROPOSED ENHANCED FER SYSTEM

Figure (3) shows the proposed modified schematic diagram of the FER system. As illustrated in this figure, our main contribution is the adoption of a feature-selection phase for the original FER system to determine how much its overall performance can be improved.

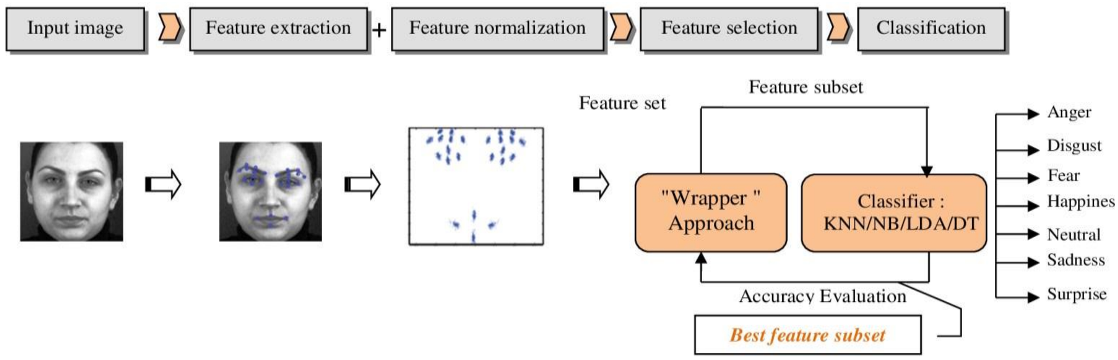


Figure 3. Schematic overview of our proposed modified FER system.

According to this FER system, using both ASM and GPA methods, 48 features (48 = 24 × 2: representing the Cartesian coordinates of 24 landmark points) are extracted from the face image and are also normalized. The feature vector is then constructed according to the following equation:

$$F_{\overrightarrow{i,j}} = (f_1, f_2, \dots\dots, f_n) \tag{1}$$

Where:
i and j denote the i-th landmark set for the j-th facial expression; $n = 24$, is the number of extracted landmarks; $f = (x, y)$, is the Cartesian coordinates for landmark f.

The 48 local features, resulting from the feature extraction, are given as follows:

$$m_{x1}, m_{y1}, m_{x2}, m_{y2}, m_{x3}, m_{y3}, m_{x4}, m_{y4}$$
$$le_{x1}, le_{y1}, le_{x2}, le_{y2}, le_{x3}, le_{y3}, le_{x4}, le_{y4}$$
$$re_{x1}, re_{y1}, re_{x2}, re_{y2}, re_{x3}, re_{y3}, re_{x4}, re_{y4}$$
$$lw_{x1}, lw_{y1}, lw_{x2}, lw_{y2}, lw_{x3}, lw_{y3}, lw_{x4}, lw_{y4}, lw_{x5}, lw_{y5}, lw_{x6}, lw_{y6}$$
$$rw_{x1}, rw_{y1}, rw_{x2}, rw_{y2}, rw_{x3}, rw_{y3}, rw_{x4}, rw_{y4}, rw_{x5}, rw_{y5}, rw_{x6}, rw_{y6}$$

with:
(m_{xi}, m_{yi}) are the Cartesian coordinates of the 4 landmarks positioned on "the mouth"; (le_{xi}, le_{yi}) are the Cartesian coordinates of the 4 landmarks positioned on "the left eye"; (re_{xi}, re_{yi}) are the Cartesian coordinates of the 4 landmarks positioned on "the right eye"; (lw_{xi}, lw_{yi}) are the Cartesian coordinates of the 6 landmarks positioned on "the left eyebrow"; (rw_{xi}, rw_{yi}) are Cartesian coordinates of the 6 landmarks positioned on "the right eyebrow".

After feature extraction and normalization, in our proposed FER system, we integrated a selection approach to select the best relevant features. There are three main approaches to feature selection commonly discussed in the literature: "Filter" approaches, "Wrapper" approaches and "Embedded" approaches [28]-[30]. Filter-based approaches, which select features independently of any classifier, evaluate features based on their statistical properties or correlation with the output variables without considering the interaction with the classifier. These approaches provide a quick and easy way to eliminate irrelevant or redundant features before applying more complex modeling techniques. Wrapper-based approaches involve selecting an optimal sub-set of features by directly minimizing the classification error. Unlike filter approaches, Wrappers approaches evaluate feature sub-sets by using a specific classifier, thus accounting for the interaction between feature sub-sets and the classifier's performance. This iterative process allows for more accurate selection of features that directly contribute to the classifier's performance. Embedded approaches integrate feature selection directly into the model training process, simultaneously optimizing both model parameters and feature selection [5]-[31]. In this work, we propose the use of "Wrapper" approach that can select the most relevant features that are more robust to variations such as changes in angle, illumination and occlusion present in real data [32], as well as inter-individual differences in emotional expression [33]-[34]. In fact, feature relevance can help resolve issues like insufficient feature extraction and inaccurate class representation. It can also mitigate the problem of relying on a single similarity measure by allowing a more exhaustive exploration of the feature space and selecting the feature sets best suited to the specific classification task [35].

"Wrapper" approach can be used dynamically to select the best features at each stage of model training, allowing the model to continually adapt to new data and inter-domain variations that may arise, thus increasing its robustness [36]. In the context of a search strategy, this approach involves selecting an algorithm that searches for the optimal sub-set of features based on a given objective function. This transforms the feature-selection problem into an optimization problem, where the goal is generally to maximize classification accuracy while reducing the size of the corresponding feature sub-set. There are many search strategies that can be used in the "Wrapper" selection approach. These can be grouped into three categories: (i) exponential-complexity strategies, (ii) population-based approach strategies and (iii) sequential-selection strategies [37]. In our study, we introduced a selection approach which combines the principle of exponential-complexity strategies with that of sequential selection strategies. Specifically, we evaluate every probable sub-set of features to pinpoint the optimal sub-set. At the same time, we utilize Sequential Forward Selection (SFS), an iterative method that systematically incorporates features from a candidate set. This dual strategy harnesses the robustness of exponential methods to achieve optimal solutions and leverages the efficiency of sequential strategies to enhance the feature-selection process. In what follows, we will give the principle of our proposed selection algorithm. The flowchart depicted in Figure 4 shows the first three iterations of the feature-selection process integrated in the proposed FER system.

As depicted in this figure, the process begins with an empty set devoid of any features. In each iteration, every feature from the initial set is tested to assess its impact on the system's overall performance. Subsequently, the best-performing feature is added to the empty set and the process continues by testing combinations of this resultant set with the remaining features. The general procedure of this process can be given as follows:

Step 1: Initialization
Parameter Set: Start with an empty set of features, 'S', to be selected from the initial set of features, F';
Set $F \leftarrow$ "Initial set of n features";
$S \leftarrow$ "Empty subset";
Basic Models: KNN, DT, NB, LDA;
Performance Criterion: Accuracy maximization;

Step 2: First feature to be selected

1. Test each feature individually:
   - Train the model with each feature individually;
   - Evaluate the model's performance for each case:

   $\forall f_i \in F$, calculate the accuracy using f_i;
   - Select the feature, '$fs1$', that gives the best performance;
   - Add the best feature 'f_{s1}' to the sub-set 'S' and remove it from the set 'F';
     $F \leftarrow F - \{f_{s1}\}$;
     $S \leftarrow \{f_{s1}\}$.

Step 3: Progressive feature Addition

1. Combination with the best feature:
   - For each feature $f_i$in set F, combine it with the sub-set S;
   - Train the model on the new $S \cup \{f_i\}$ set;
   - Evaluate performance and add the feature that yields the greatest improvement;
2. Repetition of the feature-selection process until all features are tested:
   - Continue adding features one at a time, testing each combination, until all features have been tested.

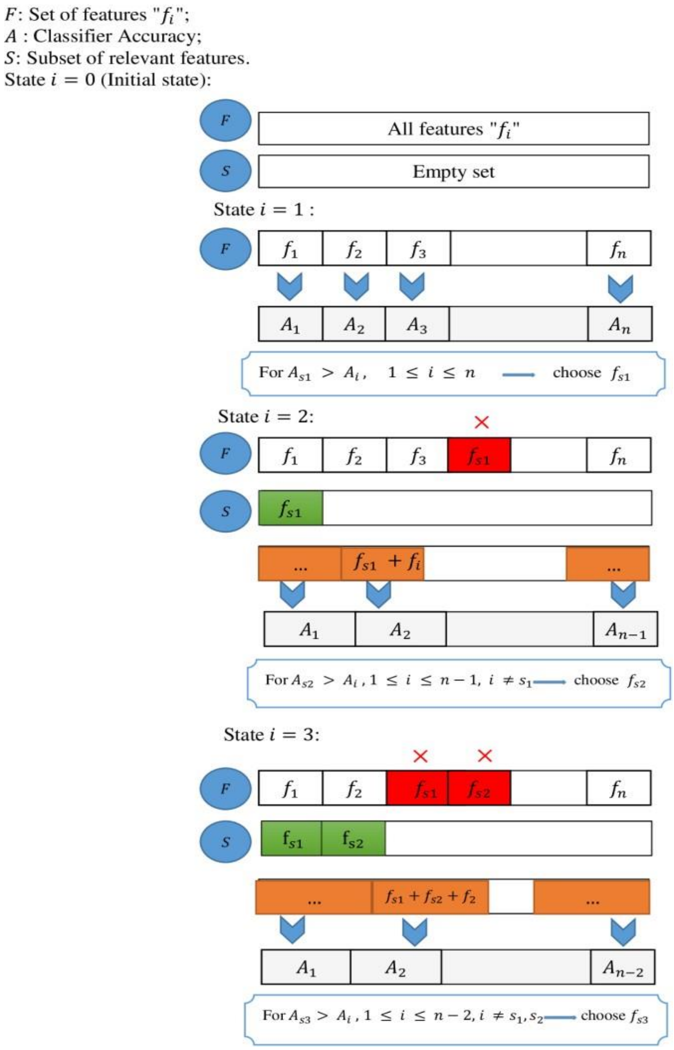


Figure 4. The first three iterations of the feature-selection process integrated in our proposed FER system.

Note here that our proposed Wrapper-based approach carefully selects features during the training phase and applies these same feature columns to the test set without reselecting features for the latter. This approach ensures that the performance metrics obtained during testing reflect the true generalizability of the selected features and the trained model. Consistency in the selection and application of feature columns aims to provide reliable and accurate predictions for unseen data, thereby reinforcing the validity of our method for real-time applications and diverse databases.

For the classification task, we have used KNN, NB, LDA and DT classifiers to find the optimal recognition performance. Although the study in [11] reports that LDA performs better, we decided to test various classifiers, because the effectiveness of our feature-selection approach is directly related to the classifier's performance. Indeed, by systematically eliminating irrelevant or redundant features, our approach could achieve better performance in terms of system response time while maintaining relatively acceptable recognition accuracy when using classifiers other than LDA. Therefore, evaluating the proposed approach using all the classifiers has two advantages:

1. It validates the results reported in [11];
2. It ensures a thorough evaluation of the classifiers to determine the best combination, potentially leading to a more efficient and responsive FER system.

Although most recent work in the field of facial-expression recognition focuses on deep learning-based approaches, our work centers on traditional classification models. The main objective is to assess to what extent our "Wrapper" feature-selection approach can enhance the performance of the recognition system while exploring different model types. Once we have demonstrated the effectiveness of this approach across various classifiers, we can consider generalizing its use to deep learning-based approaches.

In the following section, we will show the contribution of this method to the proposed FER system, by comparing the results obtained before and after its addition.

4. EXPERIMENTAL RESULTS AND DISCUSSION

To test the performance of the proposed modified FER system, it is evaluated on the MUG database. The latter one, proposed by [38], consists of image sequences of 86 subjects (35 women and 51 men), aged from 20 to 35 years and of Caucasian origin, performing facial expressions. Our experimental paradigm is carried out in person-independent mode where no subjects used for testing appear in the training set. Experiments were performed based on 1260 images (180 images for each facial expression), 840 for the training phase (560 images of men and 280 images of women) and 420 for the tests (280 images of men and 140 images of women).

Regarding the work environment, Table 2 outlines the key specifications and software setup of the system used for our work.

Table 2. Technical specifications and environment.

Software/Hardware	Specification details
System	Windows 10 Professional, 64-bit
Processor	Intel (R) Core (TM) i5-4300U at 2.49 GHz
RAM	4 GB
Environment	MATLAB R2023a
Toolbox used	MATLAB's Statistics and Machine Learning Toolbox

The analysis and discussion of the obtained results are divided into three sub-sections, presented below.

4.1 The Impact of Adding a Feature-selection Approach on FER System Performance

As explained earlier in the principle of the proposed FER system, after applying the “Wrapper” feature-selection approach to each feature vector (resulting from the extraction of local features for each image of the database using the ASM method), four classification models are used to classify test images into one of seven universal facial-expression classes. The results, obtained using the most relevant features selected by the KNN, DT, NB and LDA classifiers are presented in Tables 3, 4, 5 and 6, respectively. Here, the performance metric used to evaluate the classification performance is the accuracy, which represents the number of correctly predicted data items among all the data. It is given by:

$$Accuracy = \frac{\sum_{i=1 \dots n, j=1 \dots n}[\text{prediction}(i,j)]|i = j}{\sum_{i=1 \dots n, j=1 \dots n}[\text{prediction}(i,j)]} \times 100 \tag{2}$$

with: i: the predicted class; j: the correct class; n: the number of classes.

The classification, using the KNN classifier, was carried out by measuring the Euclidean distance with different values of the nearest neighbor K.

As shown in Table 3, for the KNN classifier, the best accuracy, with a percentage equal to 85.48%, is obtained for K = 1. The classification results, obtained using the DT classifier (according to different minimum numbers of leaf-node observations), reached a maximum accuracy of 70.48% for a minimum leaf size equal to 3 (see Table 4). Similarly, an accuracy of 69.29% is obtained using the NB classifier with Normal (Gaussian) distribution (see Table 5). Finally, the classification results using LDA (for three discriminant types; namely, linear, diagLinear and diagQuadratic) are shown in Table 6. As shown in this table, the best result, with an accuracy of 100%, is obtained using a linear discriminative function.

Table 3. Classification results using the KNN classifier.

K value	Maximal Accuracy (%)	
	Silva et al. FER system [11]	**Our proposed FER system**
1	75.23%	**85.48**%
3	76.42%	**83.57**%
5	75.71%	**83.57**%
7	75.23%	**84.29**%
9	75.95%	**83.33**%

Table 4. Classification results using the DT classifier.

Minimum number of branch node observations	Maximal Accuracy (%)	
	Silva et al. FER system [11]	**Our proposed FER system**
3	58.09%	**70.48**%
5	58.80%	**68.09**%
8	58.33%	**66.43**%
10	58.57%	**69.52**%
15	58.10%	**70**%

Table 5. Classification results using the NB classifier.

Distribution	Maximal Accuracy (%)	
	Silva et al. FER system [11]	**Our proposed FER system**
Normal	58.33%	**69.29**% (with 16 features)
Kernel	58.57%	**69.28**% (with 18 features)

Table 6. Classification results using the LDA classifier.

Discriminant Type	Maximal Accuracy (%)	
	Silva et al. FER system [11]	**Our proposed FER system**
Linear	99.71%	**100**%
diagLinear	62.34%	**70.48**%
diagQuadratic	60.07%	**69.29**%

A summary of the comparison of the best results between the FER system of Silva et al. [11] and the FER system proposed in this work for the four abovementioned classifiers is shown in Table 7. As shown in this table, the proposed modified FER system provides better performances in all cases. In fact, as illustrated in the same table, by integrating the “Wrapper” feature-selection approach into the traditional system, the proposed modified system achieves an improvement in accuracy between 0.3% and 12%. Moreover, it reduces in the length of the selected feature sub-set which results in a reduction in the number of features between 50% and 77.08%, compared to the original system, for almost identical accuracy or even better.

Simulations utilizing MATLAB tool are performed to evaluate the response time corresponding to the four FER classifiers-based systems before and after incorporating our proposed feature-selection approach. As shown in Table 8, knowing that the NB classifier has the greatest response time (which represents 100%), the results demonstrate the considerable improvement in response time for all evaluated classifiers. Specifically, the KNN classifier's response time decreased from 58.82% to 4.31%, followed by the DT with response time of 4.73% after integrating our feature-selection approach. Similar response times are approximately observed for NB (5.66%) and LDA (4.63%), respectively, illustrating that reducing data complexity through feature selection can significantly speed up classification processes while maintaining comparable performance levels.

Table 7. Performance comparison between the FER system of Silva et al. [11] and the proposed one.

Classifier	Silva et al. FER system [11]		Our proposed FER system		Improvement in accuracy	Rate of reduction in the number of features
	Accuracy (%)	Feature Dimension	Accuracy (%)	Feature Dimension		
KNN	76.42%	48	**85. 48%**	**16**	**9%**	**66. 67%**
DT	58.57%		**70. 48%**	**11**	**11. 91%**	**77. 08%**
NB	58.33%		**69. 29%**	**16**	**10. 96 %**	**66. 67%**
LDA	99.71%		**100%**	**24**	**0. 29%**	**50%**

Table 8. Time-response comparison between the FER system of Silva et al. [11] and the proposed one.

Classifier	Response Time in % (NB: 100%)	
	Silva et al. FER system [11]	Our proposed FER system
KNN	58.82%	**4. 31%**
DT	67.49%	**4. 73%**
NB	100%	**5. 66%**
LDA	74.15%	**4. 63%**

Figure (5) reveals how our proposed FER system outperforms, in terms of accuracy and number of processed features, the original system [11]. In fact, the increase in accuracy can be clearly observed with a reduction in the number of features used in the recognition process. Therefore, we can conclude that feature selection helps improve the recognition accuracy through the removal of redundant and irrelevant features, while also reducing the classifier training time.

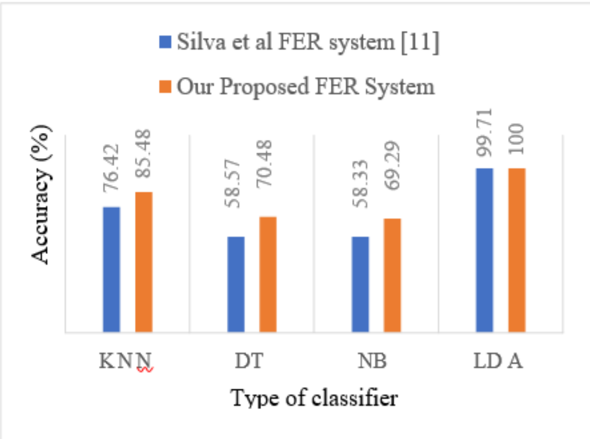


Figure 5. (a) Comparison of the accuracy between the FER system of Silva et al. [11] and the proposed system.

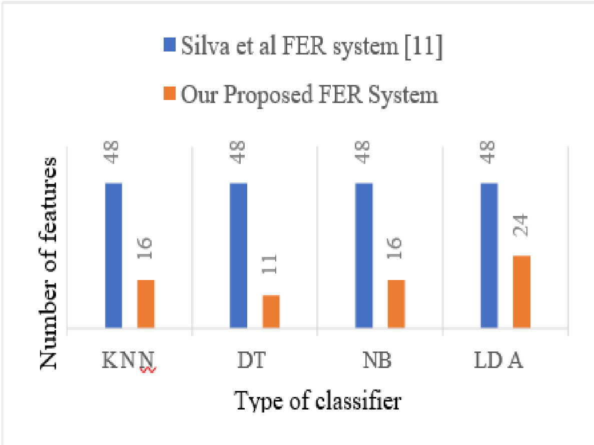


Figure 5. (b) Comparison of feature dimensions between the FER system of Silva et al. [11] and the proposed system.

4.2 Analysis of the Curse of Dimensionality Phenomenon

The term "curse of dimensionality" was introduced, for the first time, by Richard E. Bellman [39] to describe the phenomenon of exponentially increasing the amount of data with dimensionality. From a theoretical point of view, increasing the data dimension adds more information and therefore improves performance. However, in practice, this principle is not always valid. Indeed, in most cases, increasing the dimension leads to increased noise and redundancy during the analysis operation.

In what follows, we will study the impact of this phenomenon on the results of the original FER system. In addition, we will see how the “Wrapper” selection approach can eliminate this phenomenon and thus improve its overall performance. The resulting variations in accuracy, as a function of the number of features, for the four classifiers are shown in Figure (6). In this figure, we represent the response of the FER system, based on each selected feature sub-set Sj (j is the iteration number varying from 1 to 48), using each of the four classifiers.

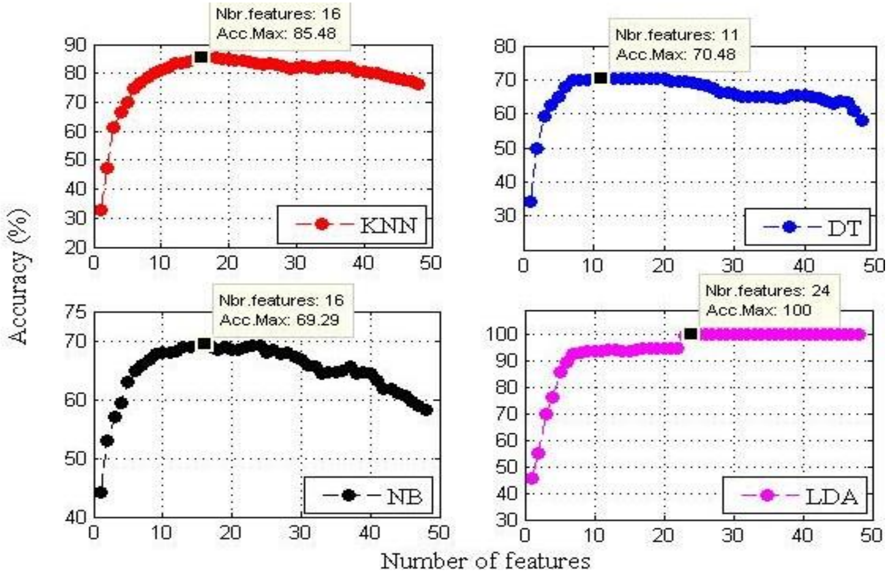


Figure 6. Variation in the accuracy as a function of the number of features:
Top left: KNN classifier ($K = 1$), **Top right:** DT classifier (Number of branch node observations equal to 3), **Bottom left:** NB classifier (Distribution: Normal), **Bottom right:** LDA classifier (Discriminant type: Linear).

As shown in this figure, for the KNN, DT and NB classifiers, each of the corresponding accuracy curves reaches its maximum value, for a specific number of features and then decreases again. This behavior is known as the curse of dimensionality phenomenon or peaking phenomenon. The approach of selecting relevant features makes it possible to overcome this problem and, consequently, improve the performance of the FER system. In fact, as shown in this figure, the FER system, based on the KNN classifier, achieves its maximum accuracy (equal to 85.48%) by exploiting only 16 features. For the DT classifier, this same system achieved a maximum accuracy of 70.48% using only 11 features. Finally, for the NB and LDA classifiers, the FER system achieved values of 69.29% and 100%, respectively, using 16 and 24 features, respectively. For the LDA classifier, as illustrated in this figure, the curve reaches its plateau at 24 selected features with an accuracy of 100%. Therefore, this result demonstrates how the FER system exhibits better performance following the use of the “Wrapper” selection approach and the LDA classifier.

Table 9 provides more details on the feature-selection operation. In particular, it presents the first ten relevant features as well as the recognition accuracy values, corresponding to the different sub-sets Sj, obtained using the LDA classifier. As shown in this table, the selection approach achieved an accuracy of approximately 93% with a dimensional reduction in the feature vector of 83% (8/48), which proves its effectiveness for facial expression-recognition process.

Table 9. The first ten selected features “fsi” and their accuracy values obtained using the LDA classifier for the optimal case.

$\boldsymbol{Accuracy\ max = 100\%}$ **obtained using an optimal number of selected features equal to 24.**										
$\boldsymbol{i}$	1	2	3	4	5	6	7	8	9	10
$\boldsymbol{f_{si}}$	rw_{y5}	m_{y3}	re_{x4}	rw_{y6}	rw_{x2}	rw_{x5}	m_{y1}	m_{y2}	m_{y4}	le_{x4}
Sub-set (Si)	rw_{y5}	S_1+m_{y3}	S_2+re_{x4}	S_3+rw_{y6}	S_4+rw_{x2}	S_5+rw_{x5}	S_6+m_{y1}	S_7+m_{y2}	S_8+m_{y4}	S_9+le_{x4}
Accuracy (%)	45.48%	55.24%	69.52%	75.95%	85.71%	89.05%	92.38%	93.10%	93.57%	93.57%

4.3 Relevance of Local Facial Regions on FER-system Performance

To determine the most important local region of a face, the most relevant local features, allowing the system to achieve maximum accuracy, must be studied.

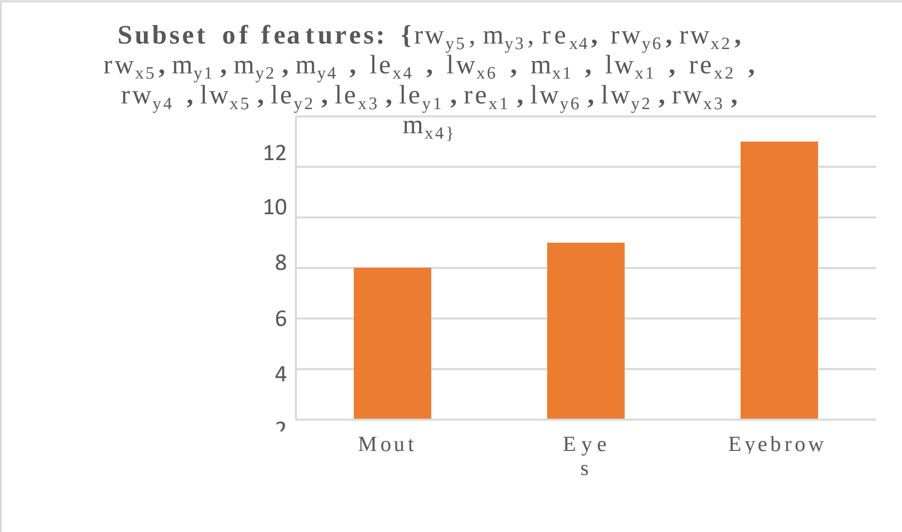


Figure 7. Most relevant features according to their position on the face using LDA classifier.

As shown in Figure (7), after an analysis of the most relevant features (according to their positions on the face), we find that most of them belong to the local "eyebrow" region (with 11 features/24), followed by the "eyes" region (with 7 features/24) and finally the "mouth" region (with 6 features/24). This result shows the importance of the "eyebrows" region in the field of facial-expression recognition. In fact, eyebrows are highly mobile and their movement significantly contributes to expressing various emotions. The position and movement of eyebrows provide subtle cues about a person's intentions and internal state, often preceding changes in other aspects of the face. This nuanced expressiveness underscores the crucial role of eyebrows in non-verbal communication, making them an essential element for understanding and accurately recognizing facial expressions. Despite their importance, this concept has been overlooked by researchers in the field. Typically, studies focus primarily on the three main facial regions: the mouth, nose and eyes. However, future research could enhance algorithms by incorporating eyebrow dynamics, potentially leading to more accurate facial-expression recognition.

4.4 Comparison with State-of-the-Art Methods

When we compare our approach to those proposed in [15], [40]-[44], we observe that each feature-selection approach has its strengths and weaknesses. The choice of a specific approach often depends on the specific application context and practical constraints, such as the trade-off between precision and acceptable computational complexity.

- Our approach demonstrates optimal performance in terms of accuracy by capturing complex interactions between features. This is particularly effective when the number of features is not too high as the computational cost remains moderate. Consequently, our method is particularly suitable when computational resources are available and achieving the highest precision is crucial;
- Relief-F and Minimum Redundancy Maximum Relevance (mRMR) are well suited for managing feature redundancy and noise while being less computationally expensive. They strike a balance between relevance and redundancy, making them efficient for large databases with many features;
- Chi-square, GR and IG are fast and straightforward to implement. However, they may lack the sophistication needed to capture complex interactions between features, which could lead to sub-optimal performance in scenarios where such interactions are critical;
- The SCA and Autoencoder methods offer global exploration capabilities and the ability to capture nonlinear relationships, respectively. Despite their advanced capabilities, these methods require fine-tuning and are computationally intensive, which might limit their practicality for large- scale problems without sufficient computational resources.

Table 10 compares the performance of our proposed FER system to those of the most relevant systems reported in the literature.

Table 10. Comparison between the performance of the proposed FER system and those of the most relevant reported in the literature.

Ref.	Database	Region of interest	No. of emotions	FS Method	Type of approach	Classifier	Accuracy in %
Our work	MUG	Mouth, Eyes and Eyebrows	7	Our proposed FS approach	Wrapper	LDA	**100%**
[3]	CK+	Whole face	8	Relief-F	Filter	KNN	94.93%
[4]	CK+	Whole face	8	Relief-F	Filter	KNN	94.93%
[5]	SFE	Whole face	8	SCA	Wrapper	KNN	97.80%
[6]	TFEID	Whole face divided into regular regions	8	Pairwise FS	Hybrid	SVM	99.63%
[7]	CK+	Left eye regions and half mouth region	8	GR	Filter	KNN	91.01%
[8]	JAFFE	Whole face	7	RV Correlation	Filter	SVM	96.53%
[9]	JAFFE	Whole face	7	IUTWSVM	Embedded	SVM	91.43%
[10]	Xceptio	Whole face	6	Autoencoder	Embedded	DCNN	95.23%

The analysis realized herein reveals that the proposed system, which selects regions of interest (ROIs) such as the mouth, eyes and eyebrows, achieves a remarkable accuracy of 100% using the MUG database. Unlike whole-face analysis, focusing on these key regions makes it possible to better capture emotional nuances, thus improving the robustness and efficiency of the models. Finally, this comparison emphasizes the promising effectiveness of the proposed method, even amidst the variety of existing approaches in this field.

5. CONCLUSION

In this paper, an improved FER system, based on the integration of "Wrapper" selection approach and the use of relevant information provided by local regions of the face, is proposed. This FER system, which is realized in several steps, can be used to achieve more efficient recognition of several facial expressions, namely, happiness, anger, sadness, surprise, disgust, fear and neutral. In its first step, which consists of feature extraction and normalization, ASM was used to extract facial features and GPA was used to normalize the extracted features. Concerning its second step, intended for the selection of features, a "Wrapper" approach was integrated to choose, among the features already extracted, only those that were the most relevant. Here, to determine the recognition accuracy, several classifiers, specifically KNN, DT, NB and LDA, were used. Simulation results, based on the MUG database demonstrated that the proposed FER system outperforms the traditional system in terms of accuracy and response time. Indeed, our approach effectively addresses the curse of dimensionality phenomenon for all four classifiers. Furthermore, the results highlighted that the majority of relevant extracted local features belong to the local "eyebrow" region, underscoring its importance in decoding emotions through facial expressions. Eyebrows play a crucial role in expressive movements, intentional cues and the accentuating facial features, which may explain their significance in FER systems. Recognizing their increasing importance in future research could lead to advancements in recognition algorithms, human- machine interactions and applications in various fields, such as mental health, security and marketing. Integrating this dynamic in FER systems and emotional analysis could provide a richer and more precise understanding of human-machine interactions.

Our approach effectively mitigates challenges in recent FER systems, such as overfitting and handling expression-unrelated variations like lighting and head pose, thereby enhancing accuracy and robustness. However, relying on features extracted by the Cootes and Taylor algorithm may limit the system's ability to capture the full spectrum of facial expressions and nuances. Additionally, the MUG database's constraints, including small sample size, controlled capture environment and lack in ethnicity and age, may limit the generalizability of our findings.

In future work, we aim to integrate deep-learning techniques for feature extraction to enhance captured expressions. We also plan to expand and diversify our database to improve the system's generalization to more varied and naturalistic settings.

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ملخص البحث:

تــوفّر أنظمــة تمييــز تعــابير الوجْــه طريقــةً مهمّــةً للتعبيــر عــن الحالــة النّفســية والعاطفيــة للنّــاس وتفســيرها. وتعمــل هــذه الأنظمــة علــى تحويــل صــورةِ الوجــهِ إلــى مجموعــةٍ مــن السّــمات أو الخصــائص لتــدريب مُصَــنِّفٍ قــادرٍ علــى التّمييــز بــين أصــنافٍ مختلفــةٍ مــن المشــاعِر. ومــع ذلــك، فــإنّ المشــكلة الّتــي تعْتــرض تلــك الأنظمــة تكمــن فــي أنّ مُتّجهــات السِّــمات الّتــي يــتمّ الحصــول عليهــا قــد تحتــوي أحيانــاً علــى ســماتٍ مكــرّرة أو ليســت ذات علاقــة، الأمــر الــذي يــؤدي إلــى تقليــل دقّــة المصــنِّف بالإضــافة إلــى زيــادة زمــن الحســاب. وللتّغلُّــب علــى هــذه المشــكلة، يجــب تقليــل عــدد السِّــمات مــن خــلال انتقــاء السِّــمات ذات العلاقة الأقوى دون غيرها.

فــي هــذه الورقــة، نعمــل علــى دراســةِ أثــر إضــافة انتقــاء السِّــمات بطريقــة "اللّــفّ" واســتخدام المعلومــات التــي توفرهــا منــاطق محليــة مــن الوجْــه، مثــل: الفــم، والعينــين، والرّمــوش، ودراســة أثرهــا علــى أداء الأنظمــة التّقليديــة لتمييــز تعــابير الوجــه. والهــدف هنــا هــو فحــص وتحليــل كيــف يمكــن لهــذه التّوليفــة أن تحسّــن مــن أداءِ النّظــام الأصــلي التّقليدي.

وتبــيّن النّتــائج أنّ نظــام تمييــز تعــابير الوجــه المعــزَّز باســتراتيجية انتقــاء السِّــمات المقترحــة أعطــى نتــائج أفضــل مقارنــةً بالنّظــام الأصــلي لجميــع المصــنِّفات المســتخدمة. وفــي الواقــع، لــوحظ الحصــول علــى تقليــلٍ معتبَــر لعــدد السِّــمات (حتــى 50%) ودقّــة بلغــت (100%) عنــد اســتخدام مصــنِّف التّحليــل التّمــايُزي الخطّــي (LDA)، الأمــر الّــذي يُعــدّ تحسيناً ملحوظاً من حيث زمن الحسابات والفاعلية و حجم الذّاكرة.

بالإضــافة إلــى ذلــك، كانــت غالبيــة السِّــمات المســتخدمة جــزءاً مــن "منطقــة الرُّمــوش"، الأمــر الّــذي يثبــت أهميــة اســتخدام معلومــاتٍ مــن منــاطق محليــة معينــة مــن الوجــه فــي المهامّ المتعلّقة بتمييز المشاعِر.