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Facial Expression Recognition Techniques and Comparative Analysis Using Classification Algorithms

Gamze BALLIKAYA[1*], Duygu KAYA[2]

[1] *Bitlis Eren University, Faculty of Engineering-Architecture, Department of Electrical-Electronics Engineering, Bitlis/TURKEY*
[2] *Firat University, Faculty of Engineering, Department of Electrical-Electronics Engineering, Elazig/TURKEY*
(ORCID: 0000-0001-7380-1181) (ORCID: 0000-0002-6453-631X)

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Abstract
With the development of technology and hardware possibilities, it has become possible to analyze the changes that occur as a result of the reflection of emotional state on facial expression with computer vision applications. Facial expression analysis systems are used in applications such as security systems, early diagnosis of some diseases in the field of medicine, human-computer interaction, and safe driving. Facial expression analysis systems developed using image data consist of 3 basic stages. These are; extracting the face area from the input data, extracting the feature vectors of the data and classifying the feature vectors. In this study, a hybrid method for facial expression analysis is proposed. The method aims to combine the ability of deep learning models in feature extraction with the ability of machine learning to classify small datasets. Multi Task Cascaded Convolutional Network (MTCNN) has been used to detect the face region in the input data. The features extracted from the fully connected layer of the AlexNet model, which achieves successful results in classification problems, have been classified with K-Nearest Neighborhood (KNN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) algorithms. Machine learning and deep learning methods are widely used in facial expression analysis systems proposed in the literature. In this study, the performances of LDA, SVM and KNN algorithms have been analyzed using JAFFE dataset without data augmentation. With LDA, SVM and KNN algorithms, 89.2%, 88.3% and 87.8% accuracy has been achieved respectively.

1. Introduction

Facial expressions that appear as a result of the change in emotional state can variety in different cultures. However, as a result of the study achieved by Ekman and Friesen in 1971, 6 emotion expressions were universally accepted all around the world [1]. As a result of experiments in different parts of the world, the 6 basic emotions universally defined are happiness, sadness, surprise, fear, anger and disgust.

It is known that the effect of nonverbal communication tools is higher than nonverbal communication tools in interpersonal communication [2]. In addition to the importance of facial expressions in communication, it is used in research subjects such as mental health diagnosis in psychiatry, early diagnosis of autism spectrum disorder and Parkinson's diseases, behavioral analysis of delinquent people in the field of security [3]–[5]. It is used in various application areas by classifying emotions with information obtained from text data, brain wave activities, audio data or image data [6]-[8].

*Corresponding author: *gballikaya@beu.edu.tr*
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Facial expression analysis systems using image data consist of 3 basic stages. Firstly, the face area is detected to remove the unnecessary parts. Then, the features of the face area are extracted in order to reduce the size of the data and highlight the robust features. In the last stage, the class of the test data is estimated with the extracted features. The general flow diagram of facial expression analysis systems is shown in Figure 1.

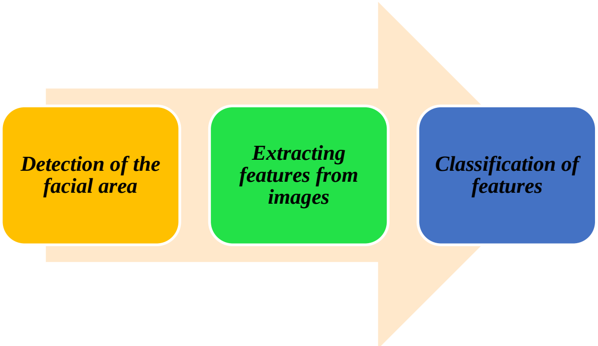

Figure 1. Main steps of facial expression analysis systems.

The systems proposed for facial expression analysis can be classified under two headings: traditional and deep learning-based. In traditional-based approaches, features are manually acquired and classified. However, in deep learning-based approaches with end-to-end learning, the network acquires the attributes of the data through its layers. Deep learning-based approaches require more training data than traditional-based approaches.

Suk et al. [9] proposed a system to classify 7 emotions. In this proposed system, Active Shape Model is used to extract feature vectors from input images, and support vector machine (SVM) is used to classify features. Extended Cohn Kanade (CK+) data set was used in the study. As a result of the study, 86% accuracy in theoretical tests and 72% accuracy in real-time applications was achieved.

Nicolai et al. [10] used image processing methods to extract features of the face area. An accuracy of 78.8% was obtained by using fuzzy logic-based approach in classification. The Japanese Female Facial Expression (JAFFE) dataset was used in the study.

Fatima Zahra et al. [11] proposed a geometric-based approach for feature extraction. In the study, in which JAFFE and Cohn Kanade (CK) datasets were used, decision trees algorithm, one of the supervised machine learning algorithms, was used. Accuracy of 89.20% for JAFFE dataset and 90.61% for CK dataset was achieved.

In the study by Ju et al. [12], emotion analysis was performed using the JAFFE dataset. Principal component analysis was used for feature extraction and random forest algorithm was used for classification of extracted features. In the study, in which 8 emotional states were classified, an average accuracy rate of 77.1% was achieved with the proposed method.

Gonzalez et al [13] proposed a system in which 6 different data sets are combined at different rates for the recognition of facial expressions and micro expressions. Convolutional neural networks (CNN) were used for feature extraction in the proposed facial expression recognition system. The proposed facial expression recognition system has achieved a success rate of 92%.

The methods that are frequently used in traditional based approaches for facial expression recognition systems are shown in Figure 2.

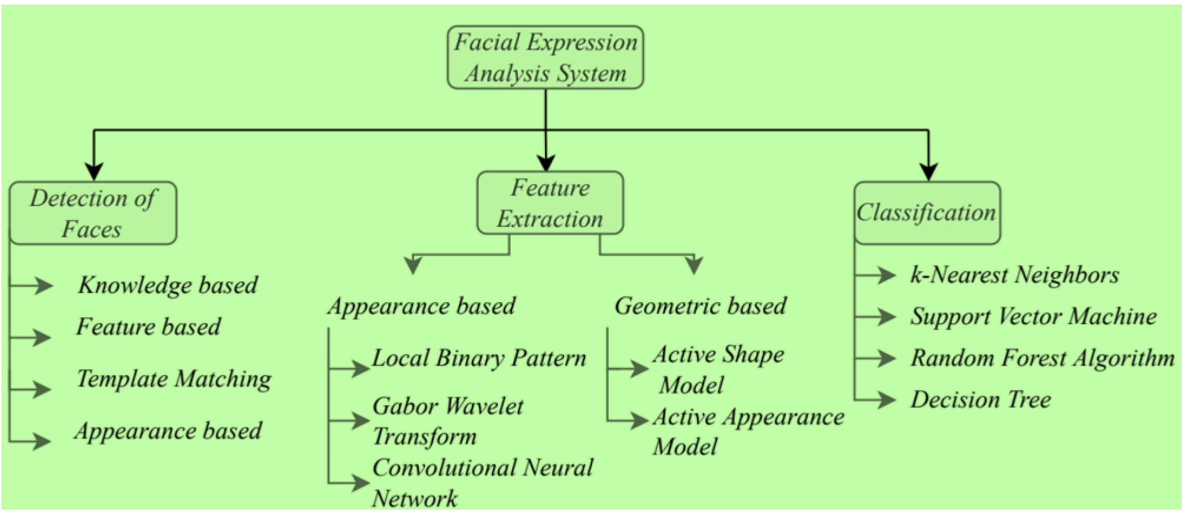

Figure 2. Approaches frequently used in facial expression analysis systems.

In recent years, following the proven success of deep learning models in classification problems [14]-[16], deep learning based methods have been proposed for facial expression analysis in addition to the traditional based approach given above.

Shervin et al. [17] proposed a deep learning-based attentive CNN model that can focus on important parts of the face with robust features. FER2013, FERG, JAFFE and CK+ datasets were used in the study, where a new visualization technique was proposed to take attention to distinct facial regions in different emotions. Accuracy values of 70.02%, 99.3%, 92.8% were obtained in the applications performed on the listed datasets, respectively.

Barman et al. [18] used landmarks to accurately detect facial expressions. In the face region, 3 points for eyebrows, 4 points for eyes, 3 points for nose and 4 points for mouth region were considered. A grid was created with these points. The distance and shape information obtained from the grid is normalized. The features obtained from the distance and shape pair were classified with a multilayer classifier. In the study performed on JAFFE, CK+, MMI and MUG datasets, accuracy between 90.1% and 100% was achieved.

Deepak et al. [19] offered suggestions to eliminate the negative effects of illumination and pose variation on facial expression recognition systems. In the study, a multi-angle optimal model-based deep learning method consisting of 5 main processes was used. After removing the background from the input image, the resulting image is isolated from illumination and pose variations. This deep learning based method achieved 74.4%, 91.34%, 84.32%, 94.62%, 86.19%, 98.7% accuracy for anger, disgust, fear, happiness, sadness and surprise expressions in the CK dataset, respectively.

In this study, 7 basic emotions such as happiness, sadness, fear, anger, surprise, disgust and normal were determined from facial images. The JAFFE dataset prepared in the laboratory environment, which is frequently used in facial expression analysis systems, was used [20]. Multistage convolutional neural networks (MTCNN) were used to detect the face area and CNN architecture was used to obtain features. In order to examine the effects on system performance, the features were classified with different supervised machine learning algorithms. In the study, the highest accuracy rate was achieved when the features extracted with the AlexNet model were classified by Discriminant Analysis.

2. Material and Method

In this study, MTCNN architecture is used to detect the faces in the JAFFE dataset. The input data were resized in accordance with the input layer of the CNN architecture. The extracted feature vectors were classified using machine learning algorithms and their performances were compared. The proposed approach is shown in Figure 3.

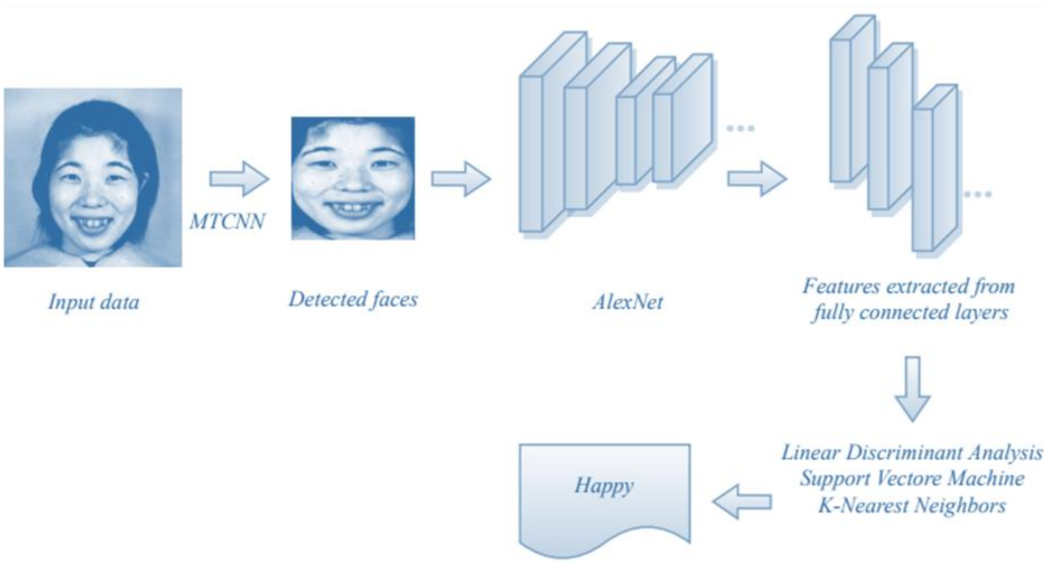

Figure 3. Proposed facial expression analysis system.

The hybrid approach of feature extraction and machine learning involves extracting valuable features from the data and then classifying them with machine learning algorithms. In the deep learning approach, multilayer neural networks are used to automatically learn from the raw data. The network is trained using large amounts of data and features are learned end-to-end.

The hybrid method preferred in this study aims to achieve the highest accuracy without augmenting the dataset. The success of the hybrid system created by combining the feature extraction success of deep learning models with machine learning algorithms is evaluated.

2.1. Dataset

For the development of facial expression analysis systems, datasets are available for researchers to perform comparative and detailed experiments [20]-[23]. In this study, the Japanese Female Facial Expression (JAFFE) dataset published by researchers from the ATR Human Computing Laboratory and the Department of Psychology at Kyushu University has been used.

Facial expression analysis systems can use deep learning models to directly classify facial expressions. However, deep learning models require more data and more computing power than machine learning. For this reason, this study examines the classification performance of a hybrid system with the JAFFE dataset containing 213 data. It is believed that considering the amount of data, the results of the study are comparable to the results obtained with deep learning-based systems in the literature. The dataset contains data on 7 different emotions: happiness, sadness, surprise, anger, fear, disgust and normal. The class distributions of the JAFFE dataset are shown in Figure 4.

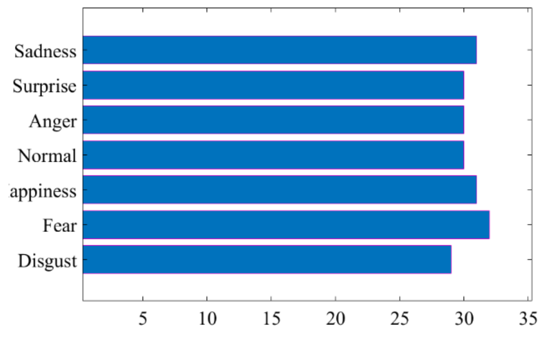

Figure 4. JAFFE dataset class distributions

2.2. Multitask Cascaded Convolutional Network (MTCNN)

Face detection has some difficulties in real-time applications. Many different methods have been proposed in the literature to overcome these difficulties. The proposed MTCNN architecture for face detection consists of 3 models: Proposal Network (P-Net), Refine Network (R-Net), Output Network (O-Net).

In the first stage, the input image is scaled and sent to P-Net. Here, the regions candidate to be faces and the bounding boxes are quickly identified. Then, R-Net rejects frames that do not contain faces from the selected candidate regions. In the third stage, the positions of some critical points on the face are determined with O-Net and the results are improved. In addition to providing the detection of the face region in the frame by obtaining the positions of the critical points of the MTCNN architecture, a solution is also offered to the face alignment problem [24].

2.3. Convolutional Neural Network (CNN)

CNN [25], one of the most basic neural network types in the field of deep learning, has been successfully applied in problems such as image classification, object identification, face recognition, autonomous vehicle technology. Researchers can solve various problems by using open-source datasets with CNNs [26,27]. Unlike machine learning algorithms, CNN does not require an additional processing step for feature extraction. CNN uses the knowledge obtained from the training set for classification due to the convolution layers it contains.

In the 2012 ImageNet Large Scale Visual Recognition Competition, the AlexNet model [16] proposed by Alex Krizhevskyi et al. has achieved significant success in object classification. The proposed model consists of 7 layers, 5 convolutional layers and 2 fully connected layers named FC6 and FC7. The convolutional layers contain 11×11, 5×5 and 3×3 filters.

The AlexNet model provides faster learning and higher accuracy rates due to the use of ReLU activation functions [16]. The model is also trained on the ImageNet dataset. Training with this very large dataset allows the model to extract features more efficiently [16]. For this reason, the AlexNet model is selected in this study in order to extract precious features from the dataset.

The feature vector obtained from the FC7 layer of the AlexNet model consists of 1000 columns. For 213 input images, 1000 feature vectors are obtained. In the feature extraction step, both valuable features of the data are extracted and the size of the image data is reduced indirectly.

2.4. Linear Discriminant Analysis (LDA)

LDA is a technique used to classify datasets with 2 or more classes. Two different types of classification can be used: class-dependent transformation and interclass transformation. The choice of classification type depends on the type of dataset and the classification problem [28]. Class-dependent transformation aims to maximize the ratio of the variance between classes to the variance within the class, while class-independent transformation aims to maximize the ratio of the overall variance to the variance within the class. It is also used to reduce the number of features in datasets. In this process, uncorrelated features are preserved as much as possible.

2.5. Support Vector Machine (SVM)

Support vector machine is a supervised machine learning algorithm often used in classification and regression problems [29]. It can also be used in problems that cannot be linearly separated with different kernel functions. SVMs can use sigmoid, polynomial or Gaussian kernel functions.

Linear SVMs are used for datasets consisting of linearly separable classes. In the SVM algorithm, the decision boundary that separates the classes is basically created. When determining the decision boundary, the aim is to maximize the distance of the decision boundary to the samples belonging to the classes. For example, in a 2-class problem, the samples belonging to the classes can be separated from each other as in equation (1).

$$f(x) = w.x + b = 0 \quad (1)$$

2.6. K-Nearest Neighbor (k-NN)

KNN which is an easy-to-implement machine learning algorithm, is frequently used in classification and regression problems. In the algorithm, the class of the test data is decided according to the similarity between the examples in the training set [30]. Basically, the algorithm evaluates the class labels of the k samples that are nearest to the test data. The class of the test data is determined by evaluating the majority of the class labels of these samples.

In the k-NN algorithm, which is based on feature similarity, the selection of the k parameter is critical. In the classification problem given in Figure 5, if k parameter is selected 3, the decision will be made according to the class information of the 3 nearest neighbors. In this case, it will be decided that the test data belongs to class 1. On the other hand, if k parameter is selected 7, it will be decided that the test data belongs to class 2.

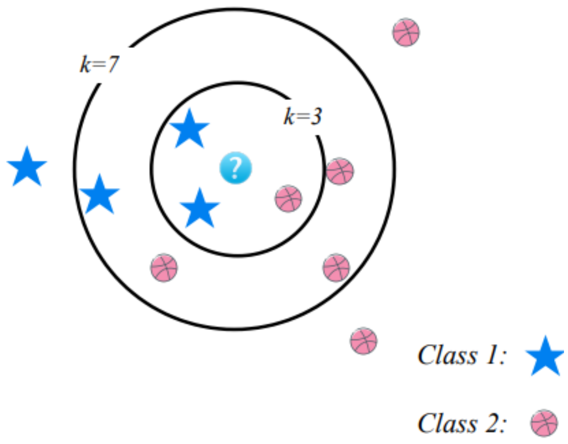

Figure 5. Selection of parameter k in k-NN algorithm.

3. Results and Discussion

The classification performances of different machine learning algorithms for emotion analysis were analyzed using image data. In this study, all experiments were performed in MATLAB R2019B environment with Intel Core CPU at 1.5 GHz, 8 GB RAM and NVIDIA GeForce MX330 graphics card. In this study, we used Classification Learner, an application used in MATLAB. This application allows the user to build classification models using the dataset and evaluate the performance of these models. The application provides various graphs and metrics to evaluate the performance of the generated models. In addition, optimizable models are used to efficiently classify the data and to find the most appropriate parameters.

Facial areas were detected using the MTCNN architecture to remove the unnecessary background in the input images and reduce the size of the image. The process is shown in Figure 6.

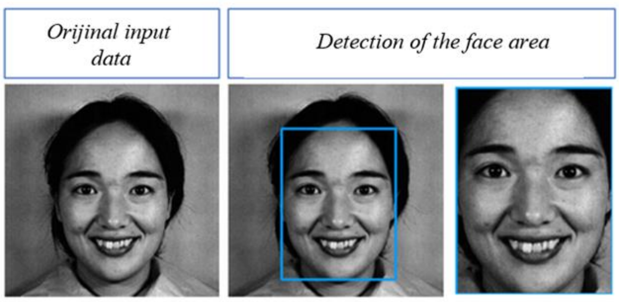

Figure 6. Face area detection from input images.

An object containing the weights and other parameters of the pre-trained AlexNet model was created and used.

Facial expression analysis using image data, LDA, SVM and KNN classifiers have been performed 50 iterations with 10-fold cross-validation technique on the JAFFE dataset. The optimized parameters of the classifiers, training times and total misclassification costs have been recorded. These values are given in Table 1 and Figure 7.

Table 1. Classification results.

	Accuracy	**Iterations**	**Training time (sec.)**	**Total misclassification cost**	**Optimized hyperparameters**	
LDA	%89,2	50	733,99	23	Discriminant type	Linear
					Optimizer type	Bayesian
SVM	%88,3		2383,8	25	Kernel function	Gaussian
					Kernel scale	151,21
KNN	%87,8		679,19	26	Number of neighbors	1
					Distance metric	Correlation

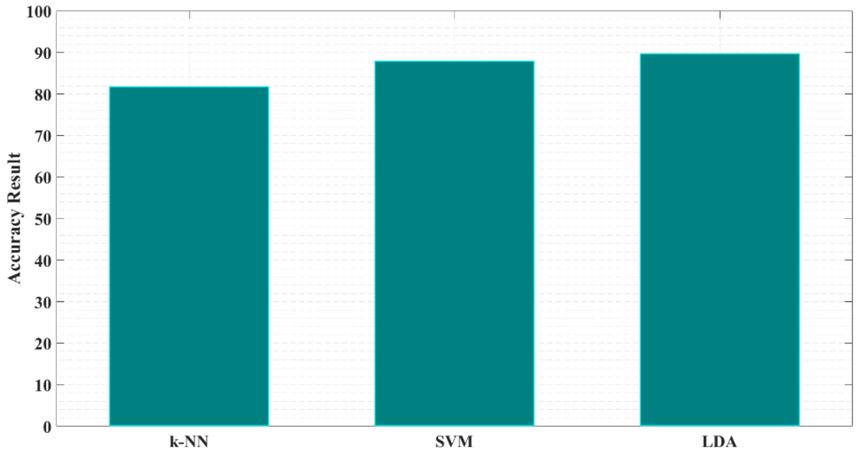

Figure 7. Accuracy scores of classifiers.

According to Table 1, the highest performance in facial expression analysis using the JAFFE dataset has been 89.2% with LDA, while the lowest performance has been 87.8% with the KNN classifier. Training time of the classifiers is analyzed and it is seen that the SVM classifier takes considerably more time compared to the other methods. During the training of the classifiers, optimal parameters are defined as the parameters with minimum error. In Figure 8, the confusion matrices of the models and Figure 9, the minimum classification error graphs of the classifiers are shown. For LDA, SVM and KNN classifiers respectively, the confusion matrix parameters and performance metrics for the emotion states are shown in Tables 2,3,4,5,6,7.

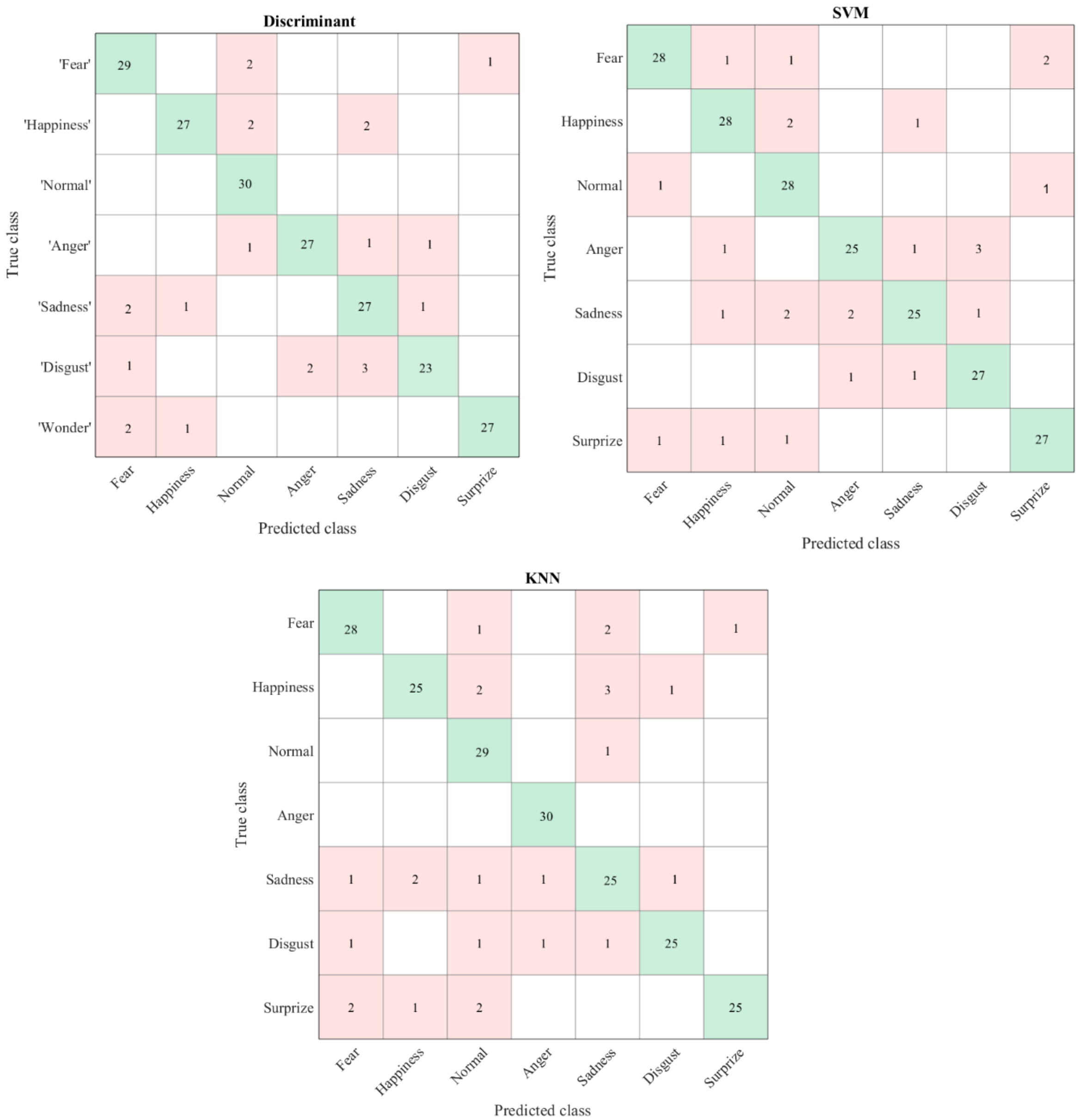

Figure 8. Confusion matrices of classifiers.

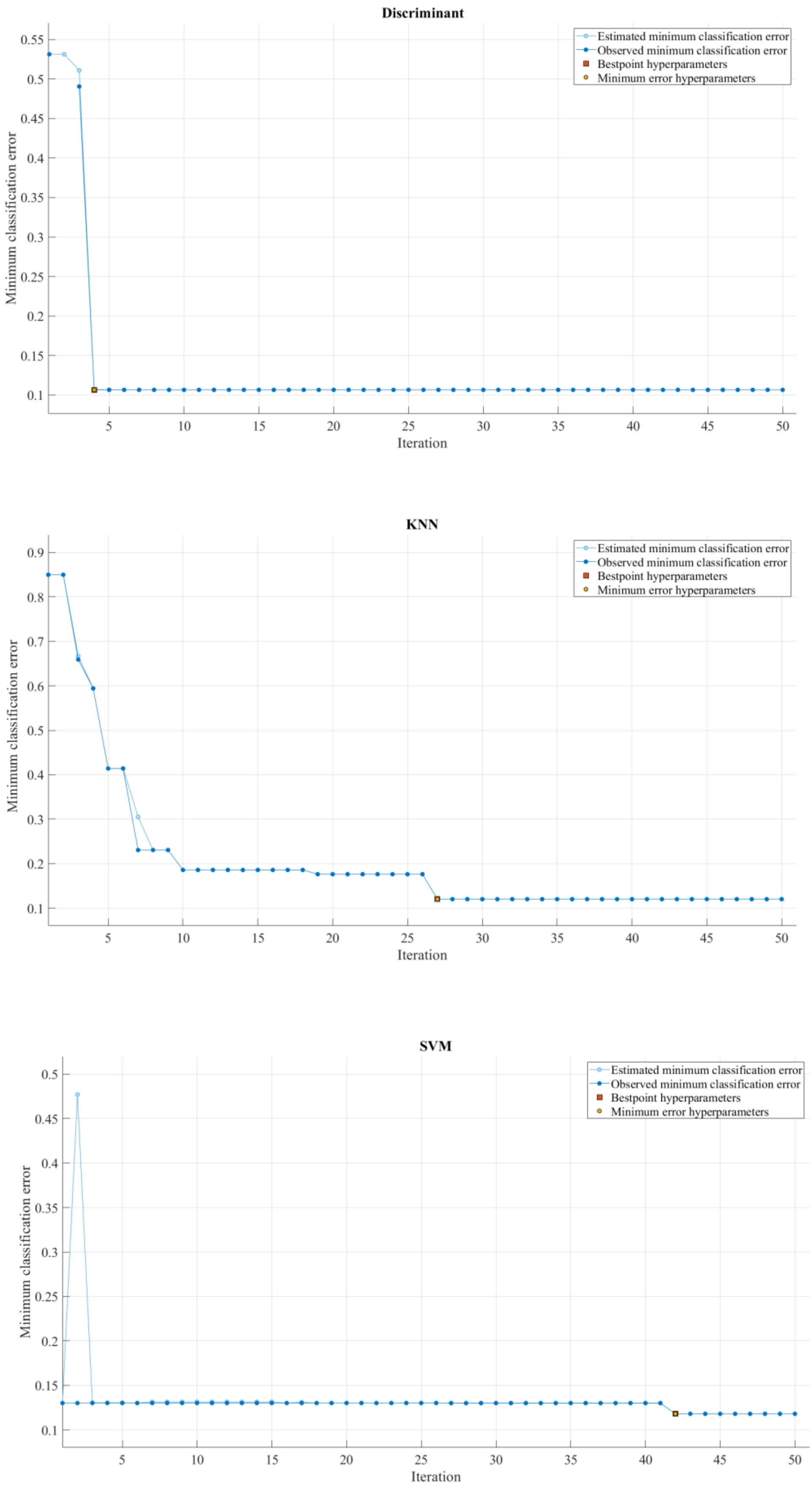

Figure 9. Minimum classification error graphs of classifiers.

Table 2. Confusion matrix parameters of emotions for AlexNet+LDA

	Fear	Happiness	Normal	Anger	Sadness	Disgust	Surprise
TP	29	27	30	27	27	23	27
TN	176	180	178	181	176	182	182
FN	3	4	0	3	4	6	3
FP	5	2	5	2	6	2	1

Table 3. Performance metrics of emotions for AlexNet+LDA

	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Fear	0,96	0,85	0,91	0,97
Happiness	0,97	0,93	0,87	0,99
Normal	0,98	0,86	1,00	0,97
Anger	0,98	0,93	0,90	0,99
Sadness	0,95	0,82	0,87	0,97
Disgust	0,96	0,92	0,79	0,99
Surprise	0,98	0,96	0,90	0,99

Table 4. Confusion matrix parameters of emotions for AlexNet+SVM

	Fear	Happiness	Normal	Anger	Sadness	Disgust	Surprise
TP	28	28	28	25	25	27	27
TN	179	178	177	181	179	180	180
FN	4	3	2	4	6	2	3
FP	2	4	6	3	3	4	3

Table 5. Performance metrics of emotions for AlexNet+SVM

	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Fear	0,99	0,93	0,88	0,99
Happiness	0,97	0,88	0,90	0,98
Normal	0,96	0,82	0,93	0,97
Anger	0,97	0,89	0,86	0,98
Sadness	0,96	0,89	0,81	0,98
Disgust	0,97	0,87	0,93	0,98
Surprise	0,97	0,90	0,90	0,98

Table 6. Confusion matrix parameters of emotions for AlexNet+KNN

	Fear	Happiness	Normal	Anger	Sadness	Disgust	Surprise
TP	28	25	29	30	25	25	25
TN	177	179	176	181	175	182	182
FN	4	6	1	0	6	4	5
FP	4	3	7	2	7	2	1

Table 7. Performance metrics of emotions for AlexNet+KNN

	Accuracy (%)	**Precision (%)**	**Sensitivity (%)**	**Specificity (%)**
Fear	0,96	0,88	0,88	0,98
Happiness	0,96	0,89	0,81	0,98
Normal	0,96	0,81	0,97	0,96
Anger	0,99	0,94	1,00	0,99
Sadness	0,94	0,78	0,81	0,96
Disgust	0,97	0,93	0,86	0,99
Surprise	0,97	0,96	0,83	0,99

The comparison of the proposed facial expression analysis system with other studies using the same dataset is presented in Table 8. When the table is analyzed, Nicolai et al. [10] achieved 78.8% accuracy with Fuzzy classifier using JAFFE dataset, Fatima Zahra et al. achieved 89.2% accuracy with decision trees in a study on JAFFE dataset, and Ju Jia et al. achieved 77.1% accuracy with SVM classifier. In the proposed study, a higher accuracy rate was achieved than the studies performed on the JAFFE dataset in the literature. It is seen that the proposed system with the features extracted with the AlexNet model and the LDA classifier from machine learning algorithms gives higher results compared to other studies using the JAFFE dataset.

Table 8. Comparison of the proposed study with studies using the same data sets.

Author	**Dataset**	**Classifier**	**Success rate (%)**
Nicolai at al. (2015) [10]	JAFFE	Fuzzy classification	%78,8
Fatima Zahra at al. (2016) [11]	JAFFE Cohen-Kanade	Decision tree	%89,2 %90,61
Ju Jia at al. (2016) [12]	JAFFE	Support vector machine	%77,1
Proposed system	**JAFFE**	**Linear discriminant analysis**	**%89,2**

4. Conclusion and Suggestions

In this study, a comparative analysis of the performance of machine learning techniques in expression classification from facial images has been aimed. For this reason, the JAFFE dataset, which has open source access for researchers to perform their studies, has been used. Facial expressions have been classified with LDA, SVM and KNN classifiers, which are frequently used in classification problems. The experimental results show that the LDA classifier is more successful than other methods in facial expression analysis. In addition, considering the training time of the classifiers, SVM has been the classifier which has been trained in the longest time.

The recognition of facial expressions has been used in the early diagnosis of some diseases, behavioral analysis, security systems, and safe driving. In facial expression recognition, which is a multi-class classification problem, it is possible to achieve high success with machine learning methods as well as deep learning methods. According to the results of this study, without any data augmentation, LDA has achieved 89.2% success in the classification of the JAFFE dataset.

There are many challenges in detecting the facial area in computer vision applications with facial images. In addition, many factors directly affect the success of deep learning or machine learning methods. Considering all these challenges, the research on facial expression analysis is expected to continue.

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Contributions of the Authors

The authors' contributions to the paper are equal.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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