

## NÂNG CAO ĐỘ CHÍNH XÁC TRONG NHẬN DIỆN CẢM XÚC TỪ KHUÔN MẶT BẰNG PCA VÀ ANN

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### TỪ KHÓA

Nhận diện cảm xúc khuôn mặt;  
Phân tích thành phần chính;  
Mạng nơ-ron nhân tạo;  
Trích xuất đặc trưng;  
Phân loại cảm xúc.

### TÓM TẮT

Nghiên cứu này giải quyết thách thức trong việc nhận diện chính xác cảm xúc của con người thông qua biểu cảm khuôn mặt bằng cách sử dụng Phân tích Thành phần Chính (PCA) kết hợp với Mạng Nơ-ron Nhân tạo (ANN). Quy trình đề xuất gồm tiền xử lý ảnh khuôn mặt, trích xuất đặc trưng bằng PCA và phân loại cảm xúc bằng ANN trên hai tập dữ liệu JAFFE và FEI. Trọng tâm của nghiên cứu là đánh giá ảnh hưởng của số lượng hidden neurons đến độ chính xác phân loại trong cùng một quy trình tiền xử lý và trích xuất đặc trưng. Kết quả thực nghiệm cho thấy mô hình PCA-ANN đạt độ chính xác cao nhất là 96,3% trên tập dữ liệu JAFFE với cấu hình 40 hidden neurons và 97,0% trên tập dữ liệu FEI với cấu hình 5 hidden neurons. Các kết quả này cho thấy số lượng hidden neurons là một tham số thiết kế có ảnh hưởng trực tiếp đến độ chính xác nhận diện cảm xúc, đồng thời cấu hình phù hợp có sự khác nhau giữa các tập dữ liệu. Phương pháp đề xuất có ưu điểm là cấu trúc gọn nhẹ, chi phí tính toán thấp và phù hợp với các bối cảnh dữ liệu nhỏ, có kiểm soát. Trong tương lai, mô hình có thể được mở rộng trên các tập dữ liệu đa dạng hơn và các cấu hình cảm xúc phức tạp hơn để đánh giá tốt hơn khả năng tổng quát hóa.

## IMPROVING ACCURACY IN FACIAL EMOTION RECOGNITION THROUGH PCA AND ARTIFICIAL NEURAL NETWORKS

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Feature extraction;  
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### ABSTRACT

This study presents a facial emotion recognition approach based on Principal Component Analysis (PCA) and Artificial Neural Networks (ANN). The proposed pipeline includes facial-image preprocessing, PCA-based feature extraction, and ANN-based emotion classification on the JAFFE and FEI datasets. The main objective of the study is to evaluate the effect of hidden-neuron size on classification accuracy under the same preprocessing and feature-extraction pipeline. Experimental results show that the PCA-ANN model achieves the highest accuracy of 96.3% on the JAFFE dataset with 40 hidden neurons and 97.0% on the FEI dataset with 5 hidden neurons. These findings indicate that hidden-layer size is an influential design parameter in PCA-ANN-based facial emotion recognition and that suitable hidden-neuron settings differ across datasets. The proposed method offers a lightweight structure, low computational cost, and practical suitability for small and controlled datasets. In future work, the framework can be extended to more diverse datasets and more challenging emotion configurations in order to examine its generalizability more thoroughly.

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## 1. INTRODUCTION

Facial emotion recognition (FER) is an important research topic in computer vision and affective computing because it supports a wide range of applications, including human-computer interaction, healthcare support systems, education, assistive technologies, driver monitoring, and intelligent surveillance [1]–[3]. The ability of a computational system to infer emotional states from facial expressions can improve interaction quality, support decision-making, and enhance adaptive system behavior in both academic and real-world environments [1], [2]. For this reason, FER has remained an active and evolving area of research over the last decade [1]–[3].

Recent review studies indicate that FER has developed from conventional handcrafted feature extraction and shallow classifiers toward hybrid and deep-learning-based architectures capable of learning highly discriminative facial representations [1]–[3]. Current FER research includes a broad spectrum of methods, ranging from appearance-based descriptors and geometry-based representations to convolutional neural networks, residual architectures, attention mechanisms, and multimodal frameworks [1]–[3]. These developments have improved recognition capability, particularly under challenging conditions such as pose variation, illumination change, partial occlusion, and real-world background complexity [2]–[5].

At the same time, the increasing complexity of state-of-the-art FER systems has introduced practical tradeoffs. Deep architectures often require large annotated datasets, long training times, substantial computational resources, and careful tuning to avoid overfitting [1]–[3]. Such requirements may be acceptable for large-scale benchmark studies, but they are not always practical in small-data settings or in resource-constrained applications. Consequently, efficient and lightweight FER pipelines remain relevant, especially when the target problem involves controlled datasets, limited training samples, or low computational budgets [2], [3], [9], [10].

Recent representative studies illustrate these two directions clearly. On one hand, modern FER research continues to improve recognition performance using more advanced architectures. Huang et al. proposed a computer-vision-based FER framework that demonstrated the continuing importance of robust facial representation for emotion analysis [4]. Elsheikh et al. developed an improved deep convolutional structure for FER, showing that more refined network designs can increase recognition capability under complex conditions [5]. On the other hand, efficient feature-based and lightweight approaches remain valuable. Yaddaden explored appearance-based fused descriptors for FER [6], Liu et al. investigated hybrid pixel-geometry

features [7], Kim et al. proposed a CNN-SVM hybrid classification framework [8], Tang et al. presented a lightweight continuous emotion-analysis system [9], and Barman and Dutta introduced a reversible neural-network approach for FER [10]. These studies show that practical FER research still benefits from solutions that balance accuracy with simplicity and computational efficiency [6]–[10].

Despite these advances, an important gap remains in the literature. Many recent FER studies prioritize deep architectures and high benchmark performance, but fewer studies provide a careful re-evaluation of lightweight pipelines based on compact feature extraction and simple neural classifiers for controlled datasets [2], [3], [9], [10]. This gap is still meaningful because lightweight methods can be useful in educational settings, prototype systems, small-sample research, and applications where computational resources are limited. In such contexts, dimensionality reduction methods such as Principal Component Analysis (PCA) remain attractive because they reduce redundancy in image data while retaining the dominant variance structure required for classification. Likewise, Artificial Neural Networks (ANNs) remain practical classifiers because they can model nonlinear relationships without the cost associated with much deeper architectures.

From this perspective, combining PCA and ANN is not merely a classical alternative, but a relevant methodological choice for examining the tradeoff between efficiency and recognition capability in FER. PCA can transform high-dimensional facial images into compact feature vectors, thereby lowering computational burden and reducing the risk of overfitting in small datasets. ANN can then operate on these reduced representations to perform nonlinear classification across emotion categories. Although PCA and ANN are both well-established techniques, their integration still deserves systematic analysis when applied to controlled benchmark datasets and compared with other PCA-based classifiers under the same experimental conditions.

Accordingly, this study aims to investigate whether PCA can preserve sufficiently discriminative facial information for emotion recognition on the selected JAFFE and FEI datasets, to determine a suitable ANN configuration for the extracted feature space, and to compare the proposed PCA-ANN model with other PCA-based classifiers under the same experimental setting. The corresponding research questions focus on feature effectiveness, classifier suitability, and comparative performance. More specifically, the study asks whether a compact PCA representation can support reliable facial emotion

recognition, whether ANN is an effective classifier for such reduced representations, and whether the proposed PCA-ANN framework offers a reasonable balance between performance and simplicity when compared with alternative PCA-based classification models.

The main contributions of this study are threefold. First, it develops and evaluates a PCA-ANN framework for facial emotion recognition on controlled benchmark datasets. Second, it systematically examines the effect of hidden-layer size on classification accuracy, thereby identifying suitable ANN configurations for different dataset-specific settings. Third, it shows that, under the same PCA-based feature-extraction pipeline, ANN provides higher classification accuracy than the other evaluated classifiers while maintaining a lightweight and computationally efficient design [2], [9].

## 2. METHODOLOGY

This section describes the methodology used to evaluate the proposed PCA-ANN framework for facial emotion recognition. The overall procedure consists of image preprocessing, PCA-based feature extraction, ANN training, and emotion classification. Two publicly available datasets, JAFFE (Japanese Female Facial Expression) and FEI, were used in the experiments. JAFFE was used as a controlled facial-expression dataset through the selected subset of emotion classes considered in this study, whereas FEI was used through the selected frontal-expression images adopted for the present classification setting. The number of images, class distribution, and selected expression categories for each dataset were determined according to the experimental configuration used in this study. Images from both datasets were preprocessed through grayscale conversion, face alignment, resizing, and normalization to standard dimensions in order to ensure a consistent representation across samples. This preprocessing stage reduced irrelevant variation caused by illumination, scale, and minor positional differences while preserving the dominant facial structure required for feature extraction. PCA was then applied as the core feature-extraction method because of its ability to reduce dimensionality while retaining the most significant facial variations for subsequent ANN-based classification.

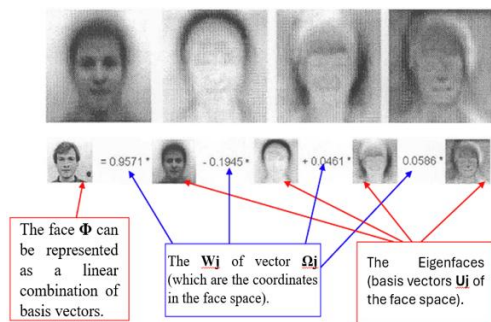


Figure 1. Illustrating Eigenfaces obtained from PCA

The PCA-based feature extraction process involves the following steps and yields a compact representation of each face image for subsequent classification: Compute Covariance Matrix: We calculate the covariance matrix from the training set images to identify primary axes (Eigenvectors) that represent major variations. Eigenvector Selection (Eigenfaces): By solving the Eigen decomposition of the covariance matrix, Eigenvectors corresponding to the highest Eigenvalues are selected as principal components, termed Eigenfaces. These Eigenfaces represent the most discriminative facial features. Projection onto Eigenface Space: Facial images from training and testing sets are projected onto the Eigenface space, generating a set of coefficients that form reduced-dimensional feature vectors. These vectors efficiently encapsulate facial expressions. Through this procedure, the original high-dimensional image data were transformed into a reduced feature space that preserved the principal facial variations relevant to the classification task. This representation reduced computational complexity and improved the suitability of the extracted features for ANN-based learning. The retained number of principal components defined the dimensionality of the ANN input layer in each experiment. By transforming the original image data into a compact feature space, PCA helped stabilize the ANN input representation across experiments. This design allowed the effect of the hidden-layer configuration on classification accuracy to be examined more directly.

ANN was employed because of its effectiveness in pattern recognition tasks and its adaptability to nonlinear data representations. The ANN architecture comprises an input layer matching the PCA feature vector length, one or more hidden layers, and an output layer corresponding to the emotion categories defined for each dataset-specific experiment. Network Architecture: The ANN used is a feed-forward multilayer perceptron with one hidden layer. The input neurons correspond to PCA-derived features, while the output neurons represent the emotion classes defined for each dataset-specific experiment. Training Procedure: The ANN is trained using the backpropagation algorithm, adjusting weights to minimize the error between the predicted output and the actual emotions. A sigmoid activation function is employed in hidden layers to handle non-linear relationships. The ANN architecture was configured as a feed-forward multilayer perceptron whose hidden-layer size was adjusted across experiments in order to identify a suitable balance between model complexity and classification performance. This design allowed the classifier to learn nonlinear decision boundaries from the compact PCA-based feature vectors. The final hidden-layer settings reported in the Results section therefore reflect the empirical tuning process applied to each dataset-specific

experiment. In this study, the hidden-layer size was treated as the main experimental variable in order to examine its effect on classification accuracy. Therefore, the ANN design was evaluated primarily in terms of how different hidden-neuron settings influenced recognition performance under the same preprocessing and PCA feature-extraction pipeline.

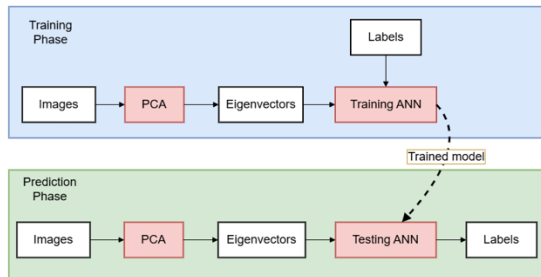


Figure 2. ANN architecture diagram used for emotion classification

Experiments were conducted in MATLAB using the corresponding neural-network toolbox functions. The dataset partitioning strategy was applied to the training, validation, and testing subsets according to the adopted experimental setting. Hyperparameters, particularly the number of hidden neurons, were tuned across multiple trials in order to examine their effect on classification accuracy and to identify a suitable ANN configuration for each dataset. Model evaluation was performed primarily using accuracy together with confusion-matrix analysis. This evaluation strategy was adopted because the main objective of the study was to determine how different hidden-layer settings affected the recognition accuracy of the PCA-ANN framework under the same feature-extraction pipeline.

The overall research procedure of the proposed FER system is illustrated in Figure 2 and consists of the following steps, with the hidden-layer configuration serving as the main experimental variable in the ANN stage:

- (1) Dataset Collection: Facial images were obtained from two publicly available datasets, JAFFE and FEI, according to the dataset-specific class configuration used in each experiment.
- (2) Image Preprocessing: All images were converted to grayscale, aligned, resized, and normalized to reduce noise and ensure consistency across samples before feature extraction.
- (3) Feature Extraction using PCA: Principal Component Analysis was applied to extract the most significant facial features and reduce dimensionality.
- (4) Feature Representation: Each facial image was represented as a feature vector in the Eigenface space.
- (5) ANN Model Training: The extracted PCA feature vectors were used to train a feed-forward ANN model, and

multiple hidden-neuron settings were evaluated to determine a suitable architecture.

(6) Emotion Classification: The trained ANN classified facial expressions into the emotion categories defined for each dataset-specific experiment.

(7) Performance Evaluation: The system performance was evaluated using accuracy and confusion matrices.

To ensure a fair evaluation of the hidden-layer effect, the preprocessing procedure, PCA-based feature extraction, and dataset configuration were kept fixed within each experimental setting. Under this design, changes in classification accuracy can be interpreted primarily as the result of changes in the ANN hidden-layer configuration rather than changes in the input representation.

### 3. RESULTS AND DISCUSSION

This section presents and analyzes the results obtained from applying the proposed PCA-ANN method for FER. The evaluation focuses primarily on classification accuracy across different hidden-neuron configurations, supported by confusion-matrix analysis to illustrate the main class-wise error patterns. In addition, an auxiliary comparison with other PCA-based classifiers is provided to position the ANN model within the same feature-extraction setting. Because the main objective of the study is to examine the effect of hidden-layer size on recognition performance, accuracy is used as the principal metric for comparing ANN configurations on the JAFFE and FEI datasets. Results are detailed as follows:

Table 1. Classification Performance on JAFFE Dataset

Hidden Layer Neural	Trial	Invalid Samples	Accuracy
10	Trial 1	5/27	80%
	Trial 2	5/27	80%
	Trial 3	6/27	77,8%
20	Trial 1	8/27	70,3%
	Trial 2	7/27	74%
	Trial 3	6/27	77,8%
30	Trial 1	5/27	80%
	Trial 2	3/27	88,9%
	Trial 3	5/27	80%
40	<b>Trial 1</b>	<b>2/27</b>	<b>92,6%</b>
	<b>Trial 2</b>	<b>1/27</b>	<b>96,3%</b>
	<b>Trial 3</b>	<b>2/27</b>	<b>92,6%</b>
50	Trial 1	7/27	74%
	Trial 2	8/27	70,3%
	Trial 3	5/27	80%
60	Trial 1	4/27	85%
	Trial 2	5/27	80%
	Trial 3	5/27	80%

Table 2. Classification Performance on FEI Dataset

Hidden Layer Neural	Trial	Invalid Samples	Accuracy
3	Trial 1	4/100	96%
	Trial 2	6/100	94%
	Trial 3	7/100	93%
5	Trial 1	3/100	97%
	Trial 2	4/100	96%
	Trial 3	4/100	96%
10	Trial 1	7/100	93%
	Trial 2	6/100	94%
	Trial 3	6/100	94%
15	Trial 1	7/100	93%
	Trial 2	4/100	96%
	Trial 3	8/100	92%

From Table 1, ANN combined with PCA demonstrated an overall average accuracy of about 81.1% on the JAFFE dataset. The accuracy score was particularly high in tests using 40 hidden neurons, exceeding 92%. Therefore, we propose an ANN structure with a model as shown in Figure 3.

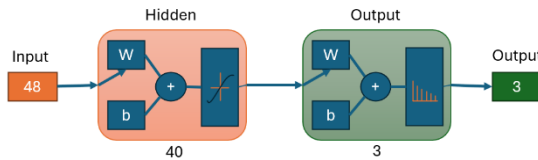


Figure 3. Neural Network Diagram Used for JAFFE Dataset.

Table 2 shows that the FEI dataset achieves consistently high classification accuracy across the evaluated hidden-neuron settings. The best result is obtained with 5 hidden neurons, reaching 97.0% accuracy in Trial 1, while the remaining trials remain relatively close to this level. Compared with JAFFE, the FEI results are more stable, suggesting that the selected FEI classification setting is easier to separate under the same PCA-ANN framework. This result also confirms that the most suitable hidden-layer configuration depends on the dataset-specific classification task. The ANN structure adopted for the FEI dataset is illustrated in Figure 4.

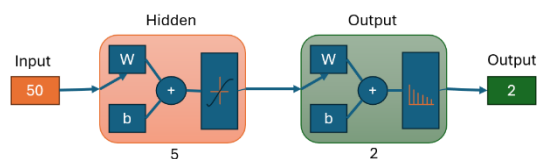


Figure 4. Neural Network Diagram Used for FEI dataset.

Figures 5 and 7 display the confusion matrices for the JAFFE and FEI datasets, respectively.

Output Class	Target Class		
	1	2	3
1	5 29.4%	0 0.0%	0 0.0%
2	1 5.9%	6 35.3%	0 0.0%
3	0 0.0%	0 0.0%	5 29.4%
	83.3% 16.7%	100% 0.0%	100% 0.0%
			94.1% 5.9%

Figure 5. Confusion Matrix for JAFFE Dataset

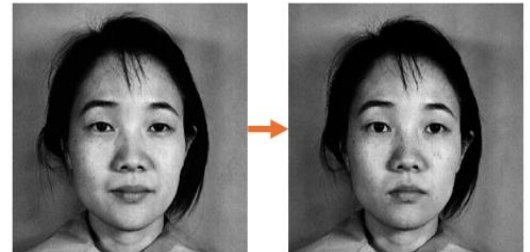


Figure 6. Examples of Misclassified Facial Expressions in the JAFFE Dataset

The confusion matrix for the JAFFE dataset (Figure 5), representing three emotions (label 1: happy, label 2: sad, label 3: surprise), shows clear diagonal dominance, indicating high accuracy in emotion classification. The misclassification between happy and sad expressions may result from overlapping facial feature distributions captured by PCA, indicating that subtle emotional variations might require more sophisticated feature extraction techniques or multi-layer ANN models.

Output Class	Target Class	
	1	2
1	19 42.2%	1 2.2%
2	1 2.2%	24 53.3%
	95% 5.0%	96% 4.0%
		95.6% 4.4%

Figure 7. Confusion Matrix for FEI Dataset

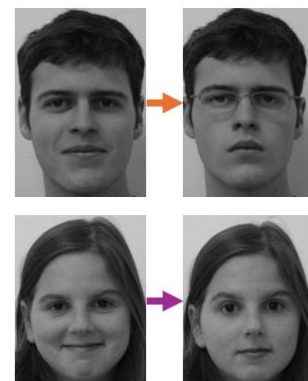


Figure 8. Examples of Misclassified Facial Expressions in the FEI Dataset

The confusion matrix for the FEI dataset (Figure 7), representing two emotions (label 1: happy, label 2: neutral), indicates a higher misclassification rate, particularly between happy and neutral emotions. This may be due to the variation in individual expressions across more faces.

**Table 3.** Comparison of PCA-Based Classifiers

Models	PCA+SV M	PCA+Decisio n Tree	PCA+KN N	PCA+AN N
Accurac y (%)	38.7%	68.6%	86.1%	<b>93.8%</b>

Table 3 provides an additional comparison among the evaluated PCA-based classifiers. The results show that PCA+ANN achieves the highest classification accuracy among the tested models, outperforming PCA+SVM, PCA+Decision Tree, and PCA+KNN under the same feature-extraction setting. This comparison supports the use of ANN as the main classifier in the present study. However, the principal objective of this research is not the general comparison among classifiers, but the analysis of how hidden-layer configurations influence the accuracy of the PCA-ANN model. Therefore, Table 3 is included as a supporting result, while the main discussion remains focused on the effect of hidden-neuron settings reported in Tables 1 and 2.

Overall, the experimental results show that the classification performance of the proposed PCA-ANN framework depends not only on the selected dataset but also on the hidden-layer configuration used in the ANN model. For JAFFE, the highest accuracy is obtained with a larger hidden-layer setting than in FEI, indicating that the optimal ANN structure is related to the complexity of the dataset-specific classification task. This finding supports the main objective of the study, namely that hidden-layer size is not a fixed parameter but an influential design variable in the performance of PCA-ANN-based facial emotion recognition.

From a practical perspective, the proposed framework remains feasible because it combines a compact PCA-based representation with a relatively simple ANN architecture. This design reduces feature dimensionality, limits computational burden, and still produces high recognition accuracy under controlled experimental conditions. At the same time, the present results should be interpreted within the scope of the datasets and class configurations used in this study. Since the experiments were conducted on controlled facial-image datasets with selected expression subsets, the generalizability of the current findings to larger, more diverse, or less constrained datasets remains limited. Nevertheless, the observed relationship between hidden-layer configuration and classification accuracy provides a useful basis for future studies that aim to adapt

PCA-ANN models to broader facial emotion recognition settings.

#### 4. CONCLUSION

This study developed and evaluated a facial emotion recognition framework based on PCA and ANN. The proposed method combines PCA-based feature extraction with ANN classification in order to analyze how hidden-neuron configuration affects recognition accuracy under fixed preprocessing and feature-representation conditions.

Experimental results show that the proposed PCA-ANN framework achieves a highest accuracy of 96.3% on the JAFFE dataset with 40 hidden neurons and 97.0% on the FEI dataset with 5 hidden neurons. These results confirm that hidden-layer size has a direct effect on classification accuracy and that the most suitable ANN configuration depends on the dataset-specific classification setting.

From a practical perspective, the proposed method offers a lightweight structure, reduced computational cost, and suitable performance for small and controlled datasets. These characteristics make the framework a feasible option for experimental and resource-constrained facial emotion recognition settings.

The study contributes by showing that a PCA-ANN pipeline can provide effective facial emotion recognition while also demonstrating that hidden-neuron selection is an important design factor in this framework.

Future work may extend the present study in several directions. First, the proposed PCA-ANN framework should be evaluated on larger and more diverse facial-expression datasets in order to examine whether the hidden-layer patterns observed in this study remain stable under broader variation in subjects, expressions, and imaging conditions. Second, future experiments should investigate additional emotion categories and more challenging classification settings so that the relationship between hidden-layer size and classification accuracy can be analyzed in greater depth. Third, a more systematic strategy for selecting the hidden-layer configuration could be explored, including automated tuning procedures and dataset-adaptive model selection. Finally, the present lightweight PCA-ANN design may be further extended through hybrid feature representations or more complex evaluation settings while preserving the main practical advantage of computational efficiency.

In summary, this study demonstrates that the proposed PCA-ANN framework can achieve promising facial emotion recognition performance under controlled conditions and that the hidden-layer configuration has a direct influence on classification accuracy. The findings confirm that ANN design should be adjusted according to the dataset-specific classification task rather than fixed arbitrarily. This result not only strengthens the

methodological contribution of the study but also provides a practical basis for future work on lightweight and adaptable FER systems.

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