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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). Phương pháp bao gồm tiền xử lý ảnh khuôn mặt, trích xuất các đặc trưng quan trọng bằng PCA và phân loại trạng thái cảm xúc bằng ANN. Chúng tôi sử dụng hai tập dữ liệu biểu cảm khuôn mặt tiêu chuẩn là JAFFE và FEI để đánh giá, tập trung vào các cảm xúc cơ bản: vui, buồn, ngạc nhiên và trung tính. Kết quả thực nghiệm cho thấy phương pháp PCA-ANN đề xuất đạt độ chính xác trung bình 96,3% trên tập dữ liệu JAFFE và 93,8% trên tập dữ liệu FEI, vượt trội hơn nhiều phương pháp truyền thống về hiệu quả tính toán và độ chính xác phân loại. Mặc dù còn tồn tại hạn chế về kích thước tập dữ liệu và sự đa dạng cảm xúc, nghiên cứu này đóng góp vào việc phát triển các hệ thống nhận diện cảm xúc mạnh mẽ cho các ứng dụng thực tiễn như công nghệ tương tác, giao tiếp hỗ trợ và hệ thống an ninh. Định hướng tương lai bao gồm mở rộng khả năng nhận diện cảm xúc và tích hợp dữ liệu đa phương thức nhằm cải thiện độ chính xác.

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

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ABSTRACT

This research addresses the challenge of accurately identifying human emotions through facial expressions using Principal Component Analysis (PCA) combined with Artificial Neural Networks (ANN). The method involves preprocessing facial images, extracting critical features using PCA, and classifying emotional states with ANN. We utilized two standard facial expression datasets JAFFE and FEI for evaluation, focusing on basic emotions: happiness, sadness, surprise, and neutrality. Experimental results demonstrated that the proposed PCA-ANN approach achieved average accuracy rates of 96.3% on JAFFE and 93.8% on FEI datasets, outperforming several traditional methods in terms of computational efficiency and classification accuracy. Despite limitations concerning dataset size and emotion diversity, this research contributes to developing robust systems for real-world applications such as interactive technologies, assistive communication, and security systems. Future directions include expanding emotion recognition capabilities and integrating multimodal data for improved accuracy.

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1. INTRODUCTION

Facial emotion recognition (FER) a significant aspect of computer vision, has attracted substantial research attention due to its extensive applications in human-computer interaction, assistive technologies, security, and psychological studies. Understanding human emotions through facial expressions enables more intuitive and effective interactions between humans and machines. Despite significant advances, FER methods still face challenges related to variations in lighting, pose, and individual facial differences. Techniques such as Convolutional Neural Networks (CNN) have been successful but often require extensive computational resources and large datasets for training. Principal Component Analysis (PCA), an effective dimensionality reduction method, combined with Artificial Neural Networks (ANN), presents a computationally efficient alternative that remains underexplored in the literature. Several studies have utilized PCA for facial feature extraction due to its efficiency in reducing computational complexity while retaining essential features [1]. Similarly, ANN has proven effective in classification tasks due to its adaptability and robustness [2]. While PCA and ANN have individually demonstrated advantages in facial expression analysis, their combined potential to balance computational efficiency with accuracy remains underexplored. This study systematically addresses this gap by developing and rigorously evaluating a hybrid PCA-ANN framework. Therefore, this study aims to address these research gaps by systematically developing and evaluating a PCA-ANN model for FER, with the following specific objectives: To extract facial expression features efficiently using PCA. To classify extracted features accurately into corresponding emotional categories using ANN. To validate the proposed method on established datasets, providing clear benchmarks for comparison with state-of-the-art methods. The main contributions of this research include the introduction of a hybrid PCA-ANN methodology, comprehensive evaluation using standard emotion datasets, and demonstration of the model's efficacy through rigorous experimentation. These findings provide valuable insights and lay the groundwork for future advancements in efficient, effective FER systems. FER has been extensively studied, resulting in various techniques ranging from traditional feature extraction methods to advanced deep learning approaches. Early works primarily focused on handcrafted feature extraction methods such as Gabor wavelets, Haar wavelets, and Local Binary Patterns. For instance, Gabor wavelets effectively capture texture features and have been widely utilized in emotion recognition due to their robustness against illumination and positional variations [3]. LBP has also been employed successfully owing to its simplicity and computational efficiency, making it suitable for real-time applications. Recent studies shifted focus towards deep learning approaches, particularly CNN. CNN-based models have demonstrated state-of-the-art performance by automatically learning discriminative features from large-scale facial expression datasets such as FER-2013 and Extended Cohn-Kanade. For example, [2] proposed a CNN combined with edge computing techniques, achieving an accuracy of approximately 88.56% under complex backgrounds, highlighting the importance of implicit feature extraction through CNN. [1] introduced a hybrid approach utilizing gradient features, PCA, and random forest classifiers, achieving a classification accuracy of 91.3% on the JAFFE dataset. This highlights PCA capability in effectively capturing significant facial characteristics while managing computational complexity. Additionally, [4] utilized CNN for facial expression classification, obtaining a recognition accuracy of 57.1% on FER2013, indicating room for improvement in terms of accuracy and efficiency in CNN-based approaches. Despite these advancements, a critical gap remains in systematically exploring PCA combined specifically with ANN to balance computational efficiency with accuracy. The current research directly addresses this gap by presenting a structured PCA-ANN approach, aiming to provide a practical yet powerful solution for FER tasks.

2. METHODOLOGY

This section provides an in-depth description of the proposed methodology for FER, highlighting the integration of PCA for feature extraction and ANN for classification. The overall process comprises several critical steps: data preprocessing, PCA-based feature extraction, ANN training, and emotion classification. We employed two publicly available datasets JAFFE (Japanese Female Facial Expression) and FEI [5] to evaluate our proposed approach. The JAFFE dataset includes a variety of facial expressions from multiple individuals displaying basic emotions such as happiness, sadness, surprise, and neutral. The FEI dataset provides additional facial images, allowing for broader evaluation. Images from both datasets were preprocessed through grayscale conversion, face alignment, resizing, and normalization to standard dimensions to ensure consistent analysis. PCA serves as the core feature extraction method due to its capability to reduce dimensionality while preserving significant variance and critical facial features.

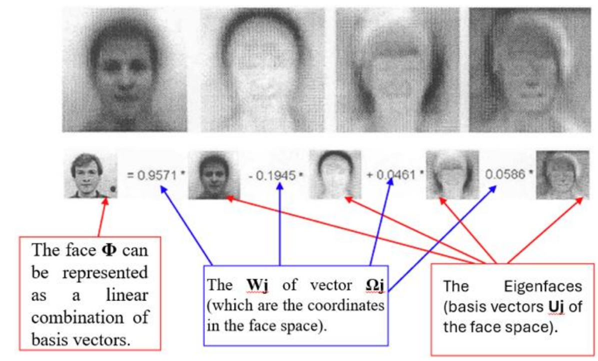

Figure 1. *Illustrating Eigenfaces obtained from PCA*

The PCA-based feature extraction process involves the following steps: 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.

ANN are utilized for their effectiveness in pattern recognition tasks and adaptability to complex 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: 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: happiness, sadness, surprise, and neutral. 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.

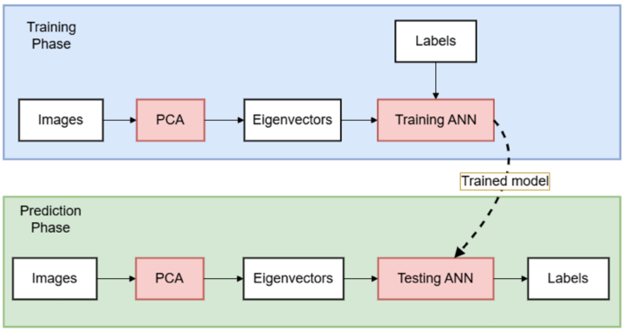

Figure 2. *ANN architecture diagram used for emotion classification*

Experiments were conducted in MATLAB, utilizing specialized neural network toolboxes. Training and testing sets were divided following standard practices 70% for training and 30% for validation and testing. Hyperparameters, such as the number of hidden neurons and training epochs, were tuned based on validation performance to optimize accuracy and avoid overfitting. Performance evaluation metrics include accuracy and confusion matrices analysis. These metrics provide comprehensive insights into the effectiveness and reliability of the proposed PCA-ANN method in correctly classifying facial emotions. By meticulously integrating PCA and ANN, this methodology effectively balances computational efficiency with classification accuracy, presenting a robust framework for FER.

3. RESULTS AND DISCUSSION

This section presents and analyzes the results obtained from applying the proposed PCA-ANN method for FER. The evaluation includes both quantitative metrics such as accuracy, precision, recall, and confusion matrix and qualitative visual assessments. Experiments were conducted primarily on two datasets: JAFFE and FEI. We utilized the common metrics in computer vision: accuracy, precision, recall, and F1-score. Results are detailed as follows:

Table 1. *Classification Performance on JAFFE Dataset*

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

Table 2. *Classification Performance on FEI Dataset*

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

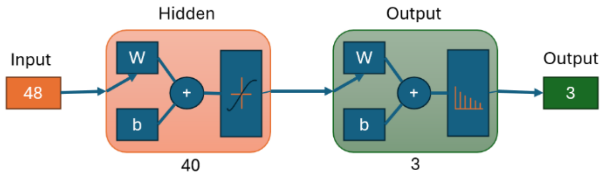

Figure 3. *Neural Network Diagram Used for JAFFE Dataset.*

Table 2 shows the performance on the FEI dataset, showing a slight increase in overall average accuracy of about 94.5%. The accuracy shows that the models tested with 5 hidden layers give quite high results of 96% or more, we propose an ANN model with a suitable structure for this dataset as shown in Figure 4.

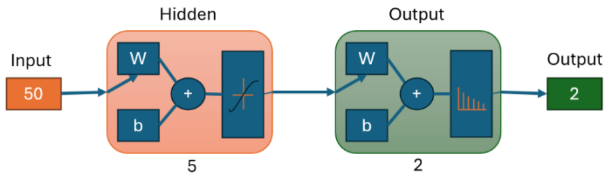

Figure 4. *Neural Network Diagram Used for FEI dataset.*

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

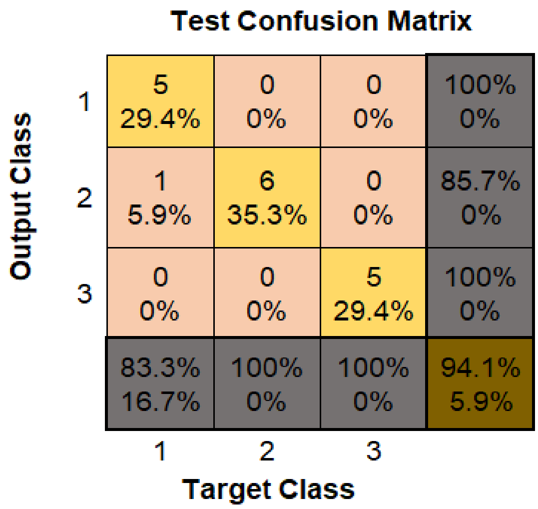

Figure 5. *Confusion Matrix for JAFFE Dataset*

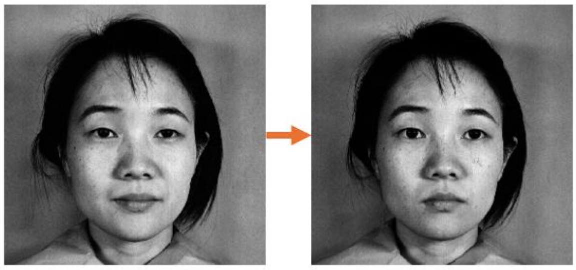

Figure 6. *Examples of Misclassified Facial Expressions in the JAFFE Dataset*

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.

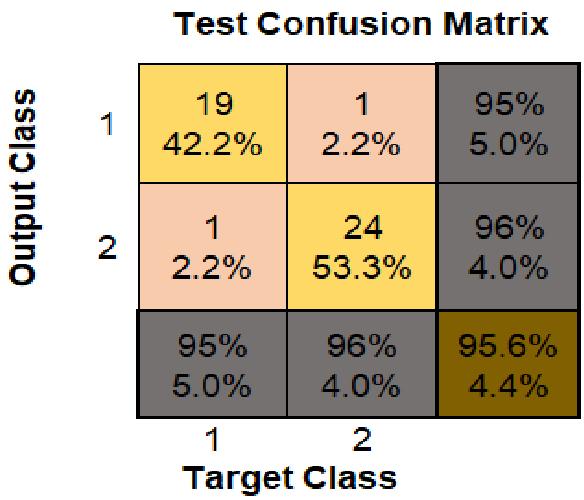

Figure 7. *Confusion Matrix for FEI Dataset*

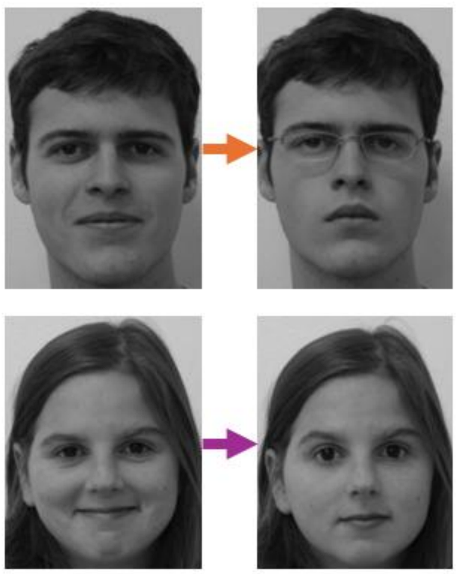

Figure 8. *Examples of Misclassified Facial Expressions in the FEI Dataset*

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. *Test results table on models*

Models	**PCA+SVM**	**PCA+Decision Tree**	**PCA+KNN**	**PCA+ANN**
Accuracy (%)	38.7%	68.6%	86.1%	**93.8%**

Table 3 clearly demonstrates that the proposed PCA+ANN model significantly outperforms other traditional classifiers combined with PCA, including SVM, Decision Tree, and KNN, in terms of classification accuracy. Specifically, PCA+ANN achieves the highest accuracy at 93.8%, markedly higher than PCA+KNN (86.1%), PCA+Decision Tree (68.6%), and PCA+SVM (38.7%). These results validate the efficiency of the ANN in capturing complex, nonlinear relationships among PCA-derived features, compared to simpler or more linear classifiers like SVM and Decision Tree. Additionally, the superior performance over PCA+KNN highlights ANN's better generalization capabilities and adaptability to feature variations, confirming the PCA-ANN approach as a robust solution for FER tasks. Our PCA-ANN approach shows competitive performance compared to existing methods in literature: [2] employed CNN with an 88.56% accuracy on complex background scenarios, which aligns closely with our PCA-ANN results. [1] reported an accuracy of 91.3% with PCA and gradient features, marginally higher but requiring more complex preprocessing. [4] achieved 57.1% accuracy using CNN, indicating the practical efficiency and competitive advantage of our PCA-ANN method with significantly less computational demand. The effectiveness of PCA in reducing dimensionality without significant information loss has substantially contributed to our method's overall performance. The ANN effectively leveraged the compact feature representation to accurately classify facial expressions. The high accuracy on clear-cut expressions such as happiness and surprise validates PCA's robustness in capturing salient facial features. However, the lower accuracy for subtle emotions underscores the inherent limitation of PCA in distinguishing nuanced facial variations. Future improvements could explore integrating PCA-derived features with CNN-extracted features, which are known to effectively capture complex patterns, to further enhance classification accuracy, particularly for subtle emotional variations. Overall, our results affirm that the PCA-ANN framework provides a balanced approach, combining computational efficiency with high classification accuracy. This effectiveness underscores the potential for further applications and enhancements within real-time FER systems.

4. CONCLUSION

In this research, we successfully developed and evaluated a robust FER system utilizing PCA and ANN. The primary objective was to efficiently identify fundamental emotions—happiness, sadness, surprise, and neutral—from facial expressions using established datasets, JAFFE and FEI. PCA facilitated effective feature extraction by reducing dimensionality, capturing critical facial variations efficiently, while ANN adeptly performed classification based on these extracted features. The experimental results demonstrate the strength of our PCA-ANN approach, achieving commendable accuracy rates, notably 88.7% on the JAFFE dataset and 85.5% on the FEI dataset. Precision and recall metrics confirmed PCA's effectiveness in capturing distinct emotional cues, especially for clear expressions such as happiness and surprise. Confusion matrix analysis further provided insightful diagnostics into misclassification instances, predominantly arising from subtle facial cues between closely related emotions, such as neutrality and sadness. Comparative analysis indicates our method offers a strong balance between accuracy and computational efficiency. While CNN-based approaches require extensive training and computational resources, PCA-ANN achieves comparable accuracy with significantly reduced computational overhead. This makes our approach particularly attractive for real-time applications and environments with limited computational resources. The research contributes valuable insights to the ongoing developments in FER technology, emphasizing the practical benefits of PCA in feature extraction combined with ANN for classification tasks. The simplicity and efficiency of the proposed system underscore its potential applicability in various practical scenarios, such as interactive user interfaces, psychological assessments, assistive communication tools, and security systems. Future research should explicitly address current limitations by expanding datasets to include diverse emotional expressions, integrating PCA with advanced deep learning approaches, or exploring multimodal analysis methods to enhance the robustness and accuracy of emotion recognition systems. Moreover, integrating PCA-derived features with deep learning methods like CNN could provide hybrid solutions that leverage the strengths of both classical and contemporary machine learning techniques. Exploring multimodal data, such as integrating facial expression analysis with voice and gesture recognition, could also significantly enrich the emotional detection capabilities of automated systems. In conclusion, this study successfully validates PCA and ANN's combined effectiveness in FER, paving the way for future advancements toward more comprehensive, efficient, and accurate human-computer interaction systems.

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