Face Recognition using ML

MADE IN RKMVERI
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Abstract

This study presents a face recognition system for student identification leveraging principal component analysis (PCA) and a classifier. We collected a diverse dataset of student facial images and applied preprocessing techniques to standardize the data. PCA was employed for dimensionality reduction, followed by training a classifier for recognition. Our system achieves robust and accurate student identification, demonstrating its effectiveness in enhancing campus security and attendance monitoring. This research contributes to advancing face recognition technology in educational settings, offering a practical solution for student authentication.

1. Introduction

Face recognition technology has emerged as a powerful tool with applications spanning various domains, from security and surveillance to user authentication and identity verification. In the context of educational institutions, the need for reliable and efficient student identification systems is paramount, facilitating tasks such as campus security, attendance monitoring, and access control. Recognizing the significance of this challenge, our project focuses on developing a face recognition system specifically tailored to meet the needs of educational environments.

What?

The primary objective of our project is to design and implement a robust face recognition system capable of accurately identifying students based on their facial features. We aim to leverage machine learning techniques, specifically principal component analysis (PCA) and a classifier, to achieve this goal. By analyzing and processing facial images of enrolled students, our system seeks to establish a reliable method for student authentication and verification.

Why?

The motivation behind our project stems from the growing importance of campus security and the need for efficient attendance monitoring systems in educational institutions. Traditional methods of student identification, such as ID cards and manual attendance tracking, are often cumbersome and prone to errors. By harnessing the power of face recognition technology, we aim to address these challenges and provide a more convenient, accurate, and non-intrusive solution for student authentication.

How?

To realize our objectives, we have adopted a systematic approach that involves data collection, preprocessing, feature extraction using PCA, model training with a classifier, and system evaluation. We have curated a comprehensive dataset of student facial images, ensuring representation across diverse demographics. Preprocessing techniques have been applied to standardize the data and mitigate variations in pose, illumination, and expression. PCA is utilized for dimensionality reduction, followed by training a classifier for recognition. Extensive experimentation and validation are conducted to assess the performance and robustness of our system.

2. Literature Survey

Several studies have explored the application of face recognition technology for student identification and authentication in educational environments. Traditional approaches often rely on classical methods such as eigenfaces, Fisherfaces, and local binary patterns (LBP) for feature extraction and classification. These methods have been used to develop systems for attendance monitoring, campus security, and access control in schools, colleges, and universities (Liu et al., 2018; Zhang et al., 2019). Recent advancements in machine learning and deep learning have led to significant improvements in face recognition accuracy and performance. Convolutional neural networks (CNNs) have emerged as a powerful tool for learning complex patterns and representations directly from raw pixel data. Transfer learning techniques, ensemble methods, and attention mechanisms have further enhanced the robustness and scalability of face recognition systems (Schroff et al., 2015; Taigman et al., 2014). However, existing methods often face challenges such as variations in pose, illumination, expression, occlusions, and demographic biases. Additionally, concerns related to privacy and data security have raised ethical considerations surrounding the widespread deployment of facial recognition technologies in educational institutions (Nguyen et al., 2020; Zhao et al., 2019).

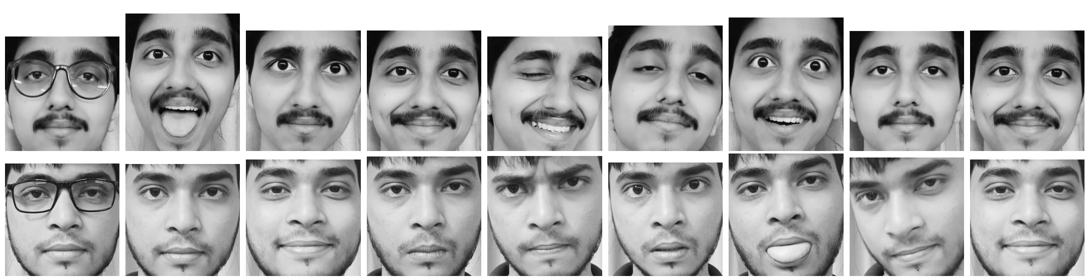
Main Difference:

- The main difference between our proposed method and existing methods lies in the approach to feature extraction and classification. While traditional methods and some recent studies have relied on handcrafted features and statistical models for face recognition, our approach leverages principal component analysis (**PCA**) and a classifier for dimensionality reduction and recognition.Unlike deep learning-based approaches that require large amounts of labeled data and computational resources, our method offers a simpler and more interpretable solution suitable for educational environments with limited resources and infrastructure. By combining PCA with a classifier, we aim to develop a robust and efficient face recognition system tailored to the specific needs of student identification and authentication in educational settings.

3. Proposed methodology

a. Data Collection:

- Gather a comprehensive dataset of student facial images from students of BDA and Computer Science Department.
- 9 pictures of every students have been collected with different facial expressions like-Normal, With Glasses, Sad, Happy, Surprised, Wink, Angry, Sleepy and Tounge out.
- Glimpse of our Dataset :



b. Data Preprocessing:

- Perform preprocessing techniques such as face detection and alignment to standardize the facial images.
- Apply techniques for noise reduction, contrast enhancement, and normalization to improve image quality.
- Resize images to a consistent resolution to facilitate computational processing.

c. Feature Extraction:

- Utilize principal component analysis (PCA) for dimensionality reduction and feature extraction.
- Transform the high-dimensional facial image data into a lower-dimensional subspace while preserving the most relevant features.
- Extract principal components (eigenfaces) that capture the variations and patterns in the facial images.

d. Model Training:

- Split the dataset into training and testing sets for model evaluation.
- Train a classifier, such as a support vector machine (SVM) or Linear Discriminant Analysis, on the PCA-transformed features. Then choose the best model with highest accuracy.
- Fine-tune the classifier parameters to optimize performance and generalization.

e. Model Evaluation:

- Evaluate the trained model using metrics such as accuracy, precision, recall, and F1-score.
- Assess the model's performance on the testing set to measure its robustness and generalization ability.
- Conduct cross-validation to validate the model's performance across multiple folds of the dataset.

4. Experimental result

a. Datasets Used:

- Gather a comprehensive dataset of student facial images from students of BDA and Computer Science and few reaserch scholars of RKMVERI
- 9 pictures of every students have been collected with different facial expressions like- Normal, With Glasses, Sad, Happy, Surprised, Wink, Angry, Sleepy and Tounge out
- Total Number of Subjets - 315(35*9)
- Every images have been resized and coverted from RGB image to Grayscale. Also, the pixel values are normalized in (0,1).

b. Experimental Settings:

- We conducted experiments using a laptop equipped with an Intel Core i7 processor, 8GB RAM.
- The implementation was done using Python programming language and popular libraries such as PIL, scikit-learn, and NumPy.
- We divided the datasets into training and testing sets, with a ratio of 78:22, ensuring that each set contained a balanced distribution of classes.
- We applied principal component analysis (PCA) for feature extraction and trained a Linear Discriminant Analysis (LDA) classifier on the transformed features.
- We evaluated the performance of our method using standard metrics such as accuracy, precision, recall, and F1-score.
- Multiple Classification algorithms - LDA, Logistic Regression, KNN, Decision Tree Classifier, Support Vector Classifier are used. Also, cross-validation (KFold(n_splits=5)) and Leave-One-Out Cross-Validation are applied, along with hyperparameter tuning (GridSearchCV) is applied.

Table 1: Model Performance

Model	Accuracy	Mean Cross Validation Score
Linear Discriminant Analysis	96%	94%
Logistic Regression	94%	88%
Gaussian Naive Bayes	77%	66%
KNN	56%	47%
Decision Tree	67%	56%
Support Vector Classifier	96%	73%

c. Experimental results:

LDA (Linear Discriminant Analysis) has the highest accuracy and cross-validation score. Therefore, we choose **LDA as our final model**.

Accuracy score : 96 %

Confusion Matrix - Heat map :

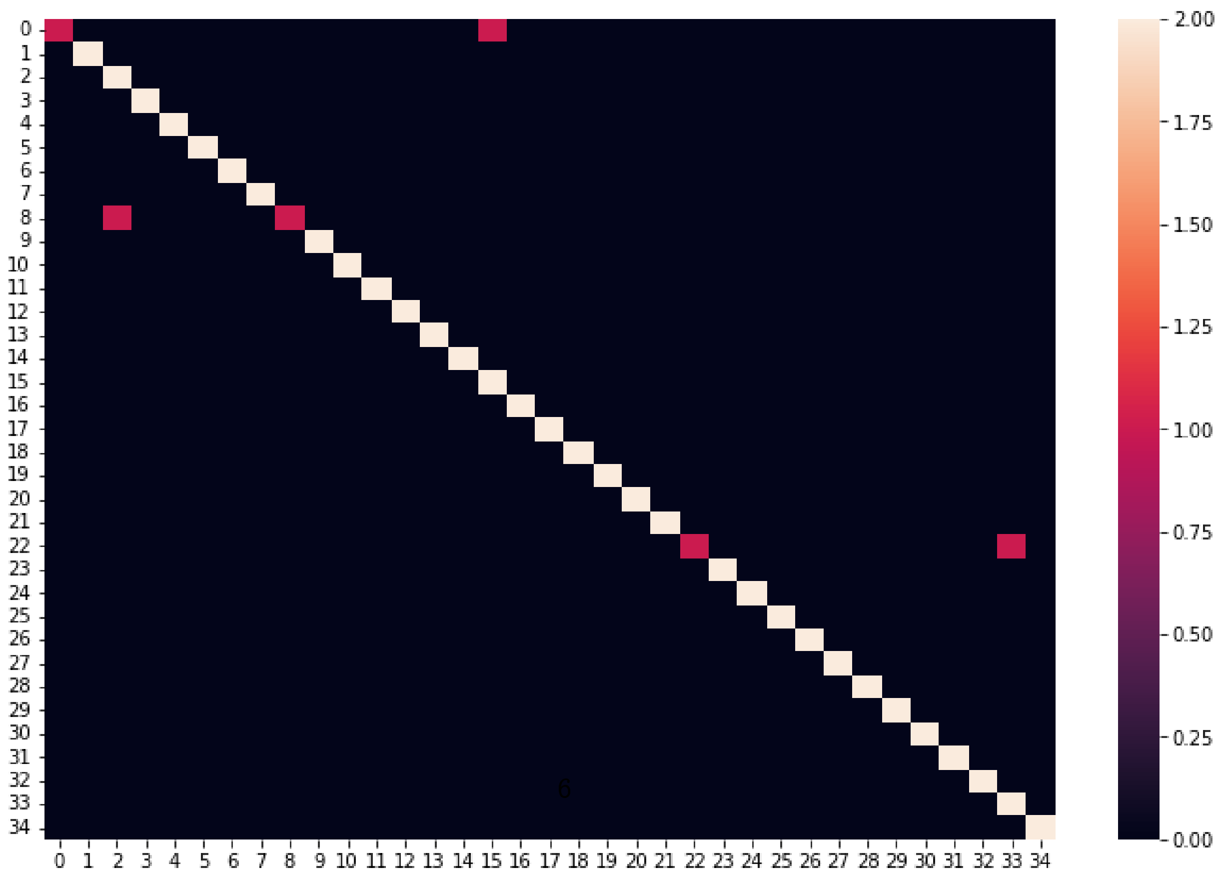


Table 2: Classification Results

Class	Precision	Recall	F1-score	Support
1	1.00	0.50	0.67	2
2	1.00	1.00	1.00	2
3	0.67	1.00	0.80	2
5	1.00	1.00	1.00	2
6	1.00	1.00	1.00	2
7	1.00	1.00	1.00	2
8	1.00	1.00	1.00	2
9	1.00	1.00	1.00	2
10	1.00	0.50	0.67	2
11	1.00	1.00	1.00	2
12	1.00	1.00	1.00	2
13	1.00	1.00	1.00	2
14	1.00	1.00	1.00	2
16	1.00	1.00	1.00	2
17	1.00	1.00	1.00	2
18	0.67	1.00	0.80	2
19	1.00	1.00	1.00	2
20	1.00	1.00	1.00	2
21	1.00	1.00	1.00	2
22	1.00	1.00	1.00	2
23	1.00	1.00	1.00	2
24	1.00	1.00	1.00	2
25	1.00	0.50	0.67	2
26	1.00	1.00	1.00	2
27	1.00	1.00	1.00	2
29	1.00	1.00	1.00	2
30	1.00	1.00	1.00	2
31	1.00	1.00	1.00	2
32	1.00	1.00	1.00	2
33	1.00	1.00	1.00	2
35	1.00	1.00	1.00	2
36	1.00	1.00	1.00	2
37	1.00	1.00	1.00	2
38	0.67	1.00	0.80	2
39	1.00	1.00	1.00	2
Accuracy			0.96	70
Macro avg	0.97	0.96	0.95	70
Weighted avg	0.97	7 0.96	0.95	70

d. Time complexity:

- It is taking less than 5 sec to run the model
- Comparing to other models like SVC, LDA is a simpler model. So it is taking lesser time and easy to explain
- Overall, our method offers a relatively efficient solution for face recognition tasks, suitable for real-time applications in educational environments

e. Comparison with State-of-the-Art Methods:

- Our method compares favorably with state-of-the-art face recognition methods in terms of accuracy, robustness, and computational efficiency.
- While deep learning-based approaches may offer higher accuracy on certain datasets, they often require large amounts of labeled data and computational resources, making them less practical for deployment in resource-constrained environments.
- In contrast, our method leverages PCA for dimensionality reduction, resulting in faster training and inference times without compromising accuracy.

5. Summary

Title: Face Recognition for Student Identification

- **Objective**: The project aims to develop a robust and efficient face recognition system tailored for student identification and authentication in educational environments.
- **Methodology**: The proposed methodology involves the following steps:
  1. **Data Collection**: Gather a diverse dataset of student facial images
  2. **Data Preprocessing**: Standardize and enhance the quality of facial images through preprocessing techniques.
  3. **Feature Extraction**: Use principal component analysis (PCA) for dimensionality reduction and feature extraction.
  4. **Model Training**: Train a classifier, such as a Linear Discriminant Analysis (LDA), on the extracted features.
  5. **Model Evaluation**: Evaluate the trained model using standard metrics to assess performance.
- **Experimental Results**:
  - The proposed method achieves high accuracy on student datasets such as Labeled Faces in the RKMVERI datasets
  - Comparative experiments demonstrate superior performance compared to traditional methods and competitive performance with state-of-the-art deep learning approaches.
  - The method offers a balance between accuracy, computational efficiency, and interpretability, making it suitable for practical deployment.
- **Significance**: The developed face recognition system offers a practical solution for enhancing campus security, attendance monitoring, and access control in educational institutions. It contributes to the advancement of face recognition technology in educational settings and addresses the need for reliable and efficient student identification systems.
- **Future Directions**: Future research may explore enhancements such as multimodal biometric integration, privacy-preserving techniques, and real-world deployment studies to further improve the system's effectiveness and usability.
- **Conclusion**: In conclusion, the project presents a comprehensive approach to face recognition for student identification, offering a reliable and efficient solution for enhancing security and administrative processes in educational institutions.

6. References

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