

# Pose Invariant Face Recognition System: Integrating PCA and SVM for improved identification

Pragya baluni<sup>1\*</sup>, Devendra Singh<sup>2</sup>, Bhumika Gupta<sup>3</sup>

<sup>1</sup> (Email id: [pragya.uniyal115@gmail.com](mailto:pragya.uniyal115@gmail.com))

<sup>1</sup>Research Scholar, IFTM University, Moradabad, India.

<sup>2</sup>Associate professor, IFTM University, Moradabad India.

<sup>3</sup>Associate professor, GBPIET, Pauri Garhwal.

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## ABSTRACT

**Introduction:** Face recognition from online sources and other media has become a prominent research area. Advancements in face recognition and computer vision are continually sought in biometrics, banking, national identity systems, and law enforcement. However, many face recognition algorithms struggle with multi-constraint models. The field of computer vision and image processing is constantly evolving, with new research leading to modifications in existing techniques. Face recognition technology has progressed from basic methods to more sophisticated techniques and mathematical representations for face matching and image analysis. Achieving accurate face recognition with pose variations remains a challenge. This study explores face recognition and identification approaches using dimensionality reduction for pose-invariant datasets, examining techniques like PCA, LDA, and SVM. Computational complexity and time are crucial factors for accuracy and efficiency. This paper outlines the goals of face recognition applications and addresses associated complexities. PCA emerges as a strong dimensionality reduction technique, particularly when combined with SVM for classification. PCA reduces data dimensionality while preserving key features. With modifications, the algorithm can be designed for faster and more accurate face recognition, regardless of pose and color. While frontal face recognition is relatively straightforward, creating an accurate and efficient system for pose-invariant cases is a significant challenge.

**Keywords:** Face recognition, Image analysis, Pose invariant, PCA.

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## INTRODUCTION

Human face recognition involves identifying faces within a database, distinguishing between human faces and unknown faces. Face recognition and identification analyze images stored and trained within a database. Face detection and recognition are closely related tasks. Face recognition can be categorized into verification and identification. Face identification in image processing is complex and challenging due to factors like pose, illumination, and pose variation. Current applications often struggle to identify individuals at different angles [1, 2]. Face identification is crucial in computer vision and image processing research and is increasingly used across various fields. Face recognition is a non-intrusive technique applicable with digital cameras and CCTV. Progress has been made in recognizing faces from various perspectives, including overcoming challenges related to brightness. Face identification systems process captured images, comparing them to a stored database. Faces in the database are classified as recognized or identified. Unknown faces prompt further algorithm training. Facial features (eyes, nose, cheeks, etc.) are analyzed. Image processing and identification are achieved through various methodologies. Facial structure and alignment are critical for accurate image analysis. Numerous algorithms address the challenges of face structuring and analysis [3]. This study examines and evaluates various face identification methods, comparing and assessing different approaches.

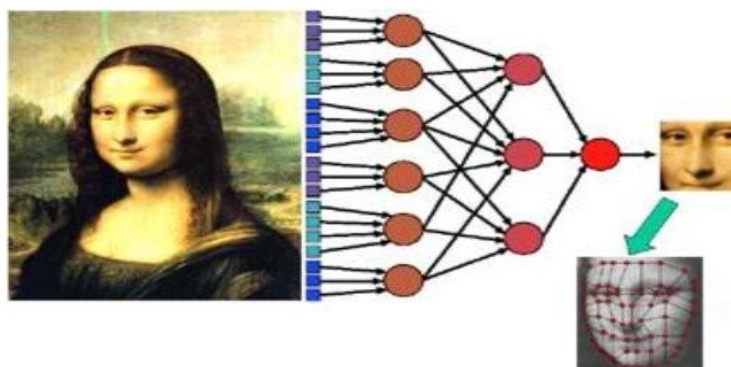
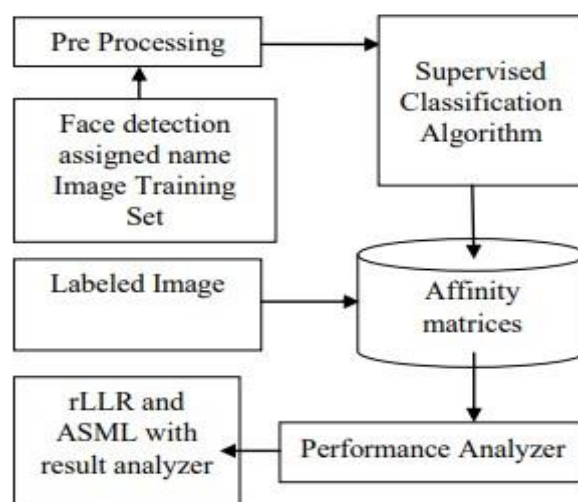
**Figure1: Face recognition Model**

Image feature extraction is fundamental. This paper uses a video dataset, extracting image frames from short clips. Dimensionality reduction algorithms and classification techniques are then applied.

**Figure 2: System Architecture**

## RELATED WORK

This section summarizes recent image/face identification research. Park et al. developed the "key point method" for increased accuracy and efficiency using a large dataset. Cassio et al. investigated whether a subject was present in a face gallery, focusing on sample size, scalability, and accuracy. Their methods were evaluated on FRGC and Pub fig83 databases [9]. Another study used LBP histograms for face identification based on sample size, considering non-alignment and pose variations. Sharma et al. suggested pose-invariant face identification methods, evaluating older techniques like Fisherface and Eigenface, which performed well in specific situations. Curtis dissimilarity was used for remote features. Shyam et al. presented a multimodal biometric system, combining traditional and feature-based matching scores. PCA uses Eigenfaces with eigenvectors, requiring covariance matrix computation. Eigenvectors represent variations, and a face is represented by a linear combination of Eigenfaces. Only the "best" eigenvectors with the largest eigenvalues are used for approximation. The authors reported approximately 90%, 80%, and 64% accuracy for light effects, image angle, and size variations, respectively, using a database of 2,500 images of 16 individuals. The dataset included images with backgrounds. It was noted that effective deployment requires more than just a full face [29], with pose, lighting, and other factors being crucial. The Eigenfaces approach [13] typically requires illumination normalization [27]. Support vector machines were used to handle classification-based learning to produce a predictive learning approach. SVM was regarded as the finest of all the strategies that were evaluated because of its increased efficiency and accuracy rate. An additional method for classifying picture data sets is the edge

feature. However, morphological edge detection is a more effective method. The methods are used to video-based detections in traffic situations. When a vehicle is present, edge detection is used to identify it, and histogram processing is then used [14].

In a study by Nagarkar Raviraj Prakash and Kazi Kutubuddin Sayyad Liyakat, PCA and neural network was used for pose invariant recognition system [31]. The study suggested that optimization using advanced normalisation techniques along with arbitration methods can improve accuracy for pose invariant face recognition. Neural network worked out better as compared to other conventional training methods using a variety of techniques, features are identified in order to process and identify the image [26]. Deep learning has become an increasingly prominent topic of research in recent years. The method that is usually used for face identification is the convolutional neural network. Depending on the classification that needs to be done, it can contain categories like basic CNN or the other CNN categories. Human face recognition through computer vision has advanced to a new level thanks to CNN's performance, which incorporates deep face, deep ID, and other features[27]. In previous years, algorithms such as LBP and Viola Jones were created. The algorithms have produced impressive results in terms of accuracy and efficiency [28]. The algorithm's performance in feature extraction has been outstanding. Support vector machines can be used for classification. It is the supervised learning method. SVM is implemented as final step after application of PCA so that classification can be achieved.



**Figure 3: Face naming after face recognition**

**Table 1: The list and description of the general factors for face recognition**

Factor	Description
Illumination	The illumination variation has been widely discussed in many faces' detection and recognition research. This variation is caused by various lighting environments and is mentioned to have larger appearance difference than the difference caused by different identities [16].
Pose	The pose variation results from different angles and locations during the image acquisition process. This variation changes the spatial relations among facial features and causes serious distortion on the traditional appearance-based face recognition algorithms such as eigenfaces and fisher faces.
Expression	Humans use different facial expressions to express their feelings or tempers.
Cluttering	In addition to the above four variations which result in changes in facial appearances, we also need to consider the influence of environments and backgrounds around people in images. The cluttering background affects the accuracy of face detection, and face patches include the background. Also, it diminishes the performance of face recognition algorithms [17].
Occlusion	The occlusion is possibly the most difficult problem in face recognition and face detection. It means that some parts of human faces are unobserved, especially the facial features.

## TECHNIQUES

This section involves the studies about numerous face recognition technologies and algorithms. These are mostly applied on images with front facial position. All the studied and mentioned techniques include some pros and cons.

These methods are divided into two major categories: first is face identification and second is face recognition.

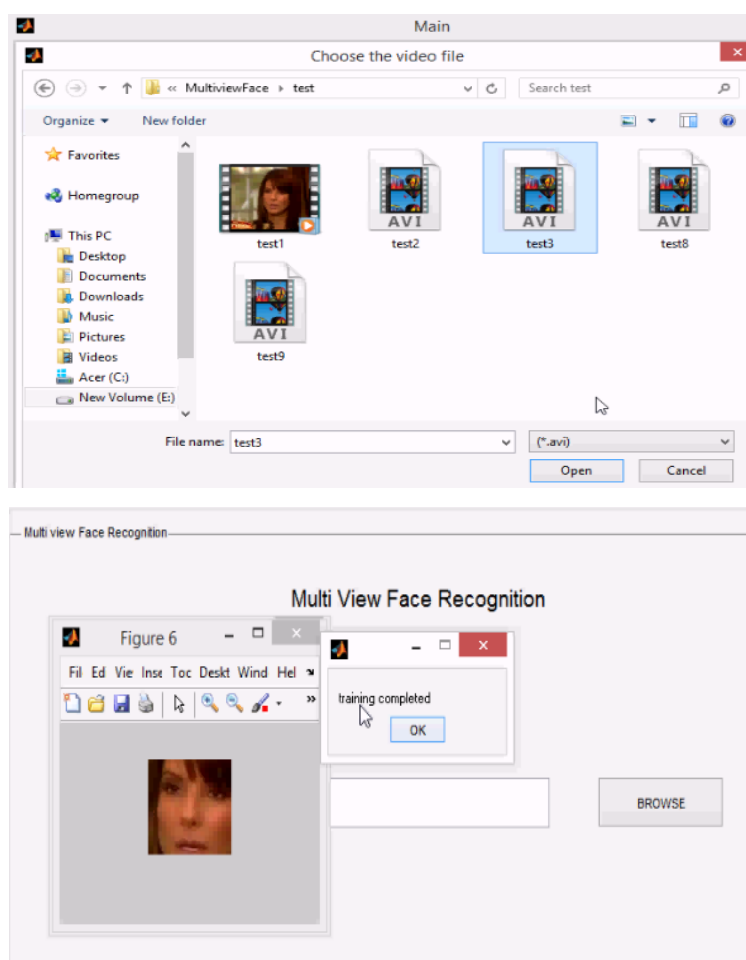
We can categorize these methods in two categories. Former methods use holistic texture features that are applied to either whole-face or specific regions in a face image whereas latter methods employ shape and texture of the face. Earlier holistic based features and methods were mostly used. The algorithm which can do detection along with identification are called as fully automatic algorithm. The dataset with faces which are facing the camera or frontal images are easy to identify and recognize. The real challenge comes when faces with invariant poses are to be recognized. It becomes difficult to generate a system with great accuracy for face detection in different pose of faces for the same person.

### Face recognition methodologies:

#### 3.1 Appearance-based Face Recognition Methods

The space searching problem is a technique used in face recognition. PCA and LDA are commonly used appearance-based techniques. PCA uses projection vectors to retain important information resembling the original dataset [6]. PCA and LDA have demonstrated good accuracy in face detection [7].

Below is an implemented model for multiple view of faces using PCA.



**Figure 4: GUI of an implemented model.**

#### 3.2 Model-based Face Recognition Methods

This approach constructs a human face model for efficient face detection, extracting facial features. Supervised classification is used for face recognition modeling [Shyam et al.]. Feature-based matching derives distance and relative position features from internal facial elements (e.g., eyes). Wiskott et al. developed a feature graph matching

technique integrating shape and texture, while Cootes et al. developed a 2D face model learning face variations [8]. Explicitly modeling face variations (pose, illumination, expression) enables handling these variations. Automatically and robustly extracting facial feature points is challenging. A hybrid technique combining AdaBoost and neural networks improved face detection speed and ignored non-human faces/objects, representing a real-time approach. However, combining algorithms can have drawbacks. Fuzzy logic can be combined with algorithms like genetic algorithms for enhanced results, but this might affect recognition speed, requiring careful consideration of speed and efficiency.

### 3.3 Feature Based Approaches

These approaches detect fiducial points and use distance-based techniques for feature extraction. A study [15] using Euclidean distance for matching 15 feature vectors (extracted from a database of 30 samples with 5 photos per person) achieved approximately 70% performance. Feature-based tracking identifies objects by tracking key points, aiding in object detection and analysis.

**Table 2: Various Techniques for face recognition along with classification**

S No	Author	Year	Techniques	Output	Drawback/Challenges
1	Joseph Mensah, Justice Kwame Appati, Elijah Kwaku Adutwum Boateng, Eric Ocran	2024	PCA, SVM, Euclidean Distance	About 85 % accuracy with occlusion	Higher complexity observed .
2	W Jhao. R Chellapa, P Jonathon Phillips, Azriel Rosenfeld	2013	PCA, LDA, Emphasis is on discriminant functions.	LDA performed with accuracy rate of 78% whereas PCA executed with the accuracy rate of 96%	Inaccuracy was observed in case of different pose
3	Jagdeep Kaur <sup>1</sup> , Er. Navneet Kaur <sup>2</sup>	2024	PCA, DCT	PCA overperformed DCT for dimensionality reduction on selected dataset.	Database with images with different poses and age based had difficulty in face recognition.
4	Amal. E. Aswis, Dr. M. Morsy	2015	DCT, PCA	94% accuracy was observed with PCA whereas DCT had the accuracy rate of 95%	Occlusion was a challenge for face recognition
5	Shiqian Wu Weilong Chen, Meng Joo Er,	2014	LDA, PCA	PCA was observed with better accuracy rate of 92% in comparison to LDA with accuracy rate of 89%	PCA was observed inaccuracy in case of coloured image dataset
6	Bhawani Singh <sup>1</sup> and Prabakaran S <sup>2</sup>	2017	PCA, LDA	Unique Hybrid approach was used to improve efficiency.	LDA could not give better results for pose variant images.

7	Gurleen Kaur, H. Kaur	2016	PCA, LDA	Feature extraction was improved with PCA and LDA using Euclidean distance.	Matrix generation can be modified for better recognition results.
8	H. L. Gururaj 1, B. C. Soundarya 1, S. Priya1, J. Shreyas 1, And Francesco Flammini2	2024	PCA	better accuracy with 90% accuracy	Accuracy was affected in case of different positions
9	M Karpagam, R. Beaulah Jeyavathana,S athiya Kumar Chinnappan,K. V. Kanimozhi, M. Sambath	2022	Eigen vector, Eigenface	Improved Dimensionality reduction algorithm	Dimensionality reduction algorithm needs to be optimised for different pose images and occlusion.
10	Manju Da * and Radha V	2019	Viola Jones, HOG, PCA	better accuracy with PCA	Images with multiple faces could not be accurately identified.
11	Kiransing Pratapsing Paradeshi, Deepak Bhimrao Kadam, Kishor Pandyaaji	2022	PCA, ANN	2 layered neural network is used to enhance accuracy	Images with noisy data were not identified with greater accuracy
12	Savitha G1, Keerthi	2019	CNN	SVM and NN used in videos for better image recognition	SVM performed with better results as compared to CNN for selected dataset
13	Meiqing Wang et al	2021	PCA, CNN	accuracy to 92%	Computation time was higher
14	Rashmirekha Mohanty, Chandrakanti Malik, Gayatri Barik3	2023	PCA, LDA , CNN,HAAR CASCADE	PCA with SVM executed with accuracy of 96.2 %	Difficult to achieve good accuracy with low dimensional data
15	S. V. Tathe, A. S. Narote	2016	Gabor filter, eigen face	accuracy attained to 95% with optimised algorithm	Poor accuracy and high computation time.
16	Nima Khairdoost, S. Amirhassan Monadjemi, Kamal Jamshidi	2014	PCA, LDA, KNN, GABOR	97 % accuracy using integrated approach of Gabor, PCA and LDA	Low efficiency was observed

17	Muhammad Deo Pratama, Khoirin Nisa, La Zakaria, Mona Arif Muda	2024	PCA, ANN	91% accuracy could be achieved with multi layers ANN	Difficulty in achieving face recognition in pose invariant dataset.
18	Hamid Reza Yazdani, Ali Reza Shojaeifard	2023	Eigenfaces, PCA	Fast computation rate	Works efficiently on only frontal images.

The studies suggested that combining Principal component analysis with optimized techniques is giving results with around 95 % and more accuracy in case of pose invariant approach[32].

### CHALLENGES

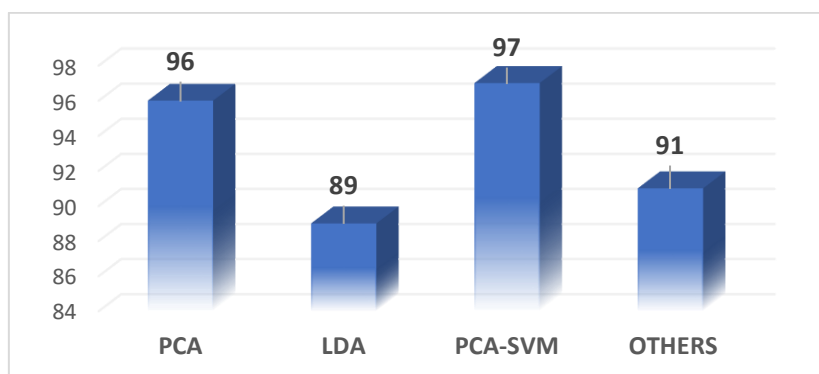
Several factors affect real-time application performance:

1. **3D Head Pose Variations:** Faces are rarely frontal, leading to challenges. Differentiating between the same face with multiple poses and multiple faces with the same pose is complex.
2. **Illumination Variations:** Skin color and illumination/radiance create variations, hindering real-time face identification. Background light adds complexity, especially with pose variations.
3. **Facial Expression:** Facial expressions can cause significant facial deformation, posing a challenge for face recognition algorithms.
4. **Occlusion:** Faces captured at different angles or obstructed are difficult to identify.
5. **Time Delay:** Human faces change over time due to factors like makeup, facial hair, or glasses.

### RESULTS AND CONCLUSION

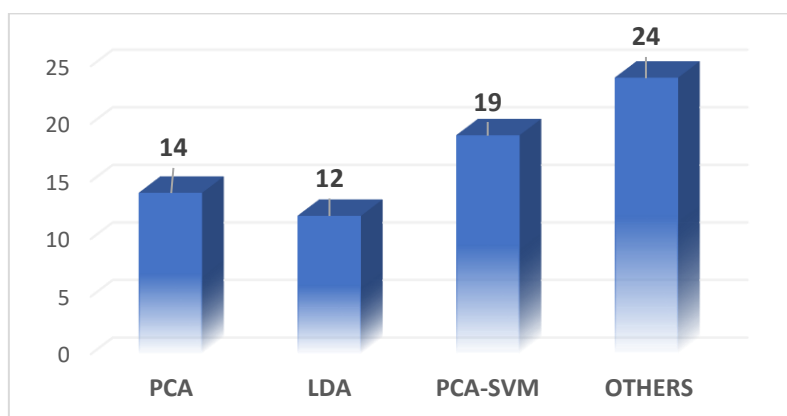
Face recognition and identification are current focal points in computer vision research. While progress has been made, a robust and reliable system is still needed. Further research in computer vision and image processing is essential. Challenges remain, including makeup, hairstyles, image blur, and achieving target accuracy levels. These results can guide new algorithm development and advance human-computer interaction. Future modifications can further reduce false detections for improved accuracy and efficiency. Frontal face images are easier to identify than pose-invariant images. Algorithms struggle with varying poses. Dimensionality reduction algorithms combined with optimized approaches show better accuracy. It was common finding after doing research that faces with frontal view are easier to identify as compared to pose invariant images. The algorithms are not achieving accuracy with faces of different poses. The dimensionality reduction algorithms have been performing with better accuracy rate if combined with optimized approach.

The dimensionality reduction algorithms work best to reduce the size of the data. Algorithms must be designed so that not much of the information is lost and important information remains intact with the image.



**Figure 5: Graph representing accuracy of commonly used techniques**

Also, in the study results shows that PCA gives results with good accuracy but implementation must be carefully done so as keep the necessary information intact with the image. The factors like occlusion, pose and many other factors can be ruled out if dimension reduction algorithm are implemented with careful feature extraction. The application of PCA with SVM gives results for lower dimensionality data but with improved accuracy. The pose constrained related to image identification can be removed with this integrated approach. The co variance matrix generated plays an important role because the generated matrix is used for the identification and recognition.



**Figure 6: Journal wise status of techniques used**

The above graphs represent the status of commonly used techniques in various journals. PCA-SVM can be optimized to get better results for various poses-based dataset.

The study shows that PCA if integrated with SVM for classification can give results with better accuracy and efficiency. Also, with optimized algorithm for classification, the computation time can also be reduced and problem related to pose invariant face recognition can be solved. Hence PCA along with SVM can be used to build up a strong and robust face recognition system with pose invariant factor. For future purpose occlusion as a factor can be considered for face recognition.

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