



## Comprehensive Survey on the Various Face Recognition Techniques

*Saba Mansoori<sup>1</sup>, Dr. Pankaj Sahu<sup>2</sup>, Prof. Devendra Kumar Meda<sup>3</sup>*

<sup>1</sup>M.E. Scholar, Department of Electronics and Telecommunication, Jabalpur 482011, India Mail: [smansoori4440@gmail.com](mailto:smansoori4440@gmail.com)

<sup>2</sup>Professor, Department of Mechatronics, Jabalpur 482011, India Mail: [pankaj.sahu@yahoo.co.in](mailto:pankaj.sahu@yahoo.co.in)

<sup>3</sup>Professor, Department of Electronics and Telecommunication, Jabalpur 482011, India Mail: [dmeda@jecjabalpur.ac.in](mailto:dmeda@jecjabalpur.ac.in)

### ABSTRACT :

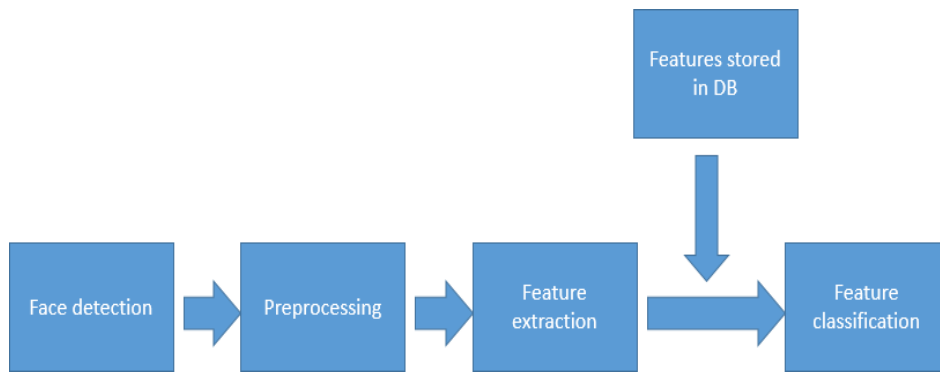
Face recognition is preferred due to biometric modality for efficiently identifying and verifying individuals, surpassing voice, fingerprint, iris, retina eye scan, ear, and hand geometry. This preference has driven significant research in both academics and industry, making face recognition one of the most studied areas in computer vision. In this review paper, previous studies have discussed a curvelet-based analysis of a dataset that has been done using MATLAB. Different statistical parameters of an image after applying the curvelet transform is discussed. The results obtained are found to be satisfactory and may serve as a base for a curvelet-based facial recognition system.

**Keywords:** Face recognition, Biometrics, Techniques, Uncontrolled environment, Face dataset.

### Introduction :

Face recognition systems represent a transformative technology within the realm of biometrics, offering a sophisticated method for identifying and verifying individuals based on their unique facial characteristics. This technology has witnessed rapid evolution and adoption across numerous sectors, driven by its ability to enhance security measures, streamline authentication processes, and improve user interaction experiences. Face recognition involves automated detection, analysis, and comparison of facial patterns from digital images or video frames. Unlike conventional security methods that rely on physical tokens like keys or cards, face recognition systems leverage advanced algorithms to extract, encode, and match distinctive features such as the arrangement of eyes, nose, mouth, and overall facial structure. The practical applications of face recognition are vast and diverse. In security and surveillance, these systems enable real-time identification of individuals in public spaces, airports, and sensitive facilities. They also facilitate access control systems in workplaces, residential buildings, and electronic devices like smartphones and tablets. The complexity of face recognition lies in its ability to handle variations in facial appearance caused by factors such as lighting conditions, facial expressions, head poses, and partial occlusions (such as wearing glasses or facial hair). Overcoming these challenges requires robust algorithms capable of adaptive learning, pattern recognition, and decision-making based on sophisticated neural networks and machine learning models. Recent advancements in deep learning techniques, particularly convolutional neural networks (CNNs), have significantly boosted the accuracy and efficiency of face recognition systems. These algorithms can learn hierarchical representations of facial features directly from raw image data, enabling superior performance even in complex and dynamic environments. In this context, this introduction sets the stage for exploring the methodologies, technical considerations, ethical implications, and emerging trends in face recognition research and applications. By understanding the fundamental principles and capabilities of these systems, researchers and practitioners can navigate the evolving landscape of biometric technology with greater insight and innovation. Oloyede MO et al. [1] mentioned that in recent years, face recognition (FR) has become an active research area due to its diverse applications, including border security, surveillance, law enforcement, and access control. More recently, it has expanded into fields such as computer graphics, neural networks, and psychology, reflecting its multidisciplinary appeal. The FR process involves several stages: face detection, pre-processing, feature extraction, and feature classification. The first stage, face detection, involves verifying the presence of a face in an image or video. Once detected, the image undergoes pre-processing to enhance quality and isolate the region of interest. Normalization, a pre-processing technique, scales face images to a uniform size, while face alignment localizes fiducially points like the mouth, eyes, chin, and nose, improving system accuracy, though it remains challenging in unconstrained environments Jin X et al. [2]. Image enhancement, often overlooked, aims to produce a clearer face image, thereby boosting FR system performance Karamzadeh S et al. [3]. Feature extraction follows, simplifying the data by identifying unique features that minimize noise and irrelevant information. This process results in a feature vector that accurately represents the face, which is crucial for the final stage of feature classification.

A basic block diagram of a face recognition system is shown.



**Fig. 1. Block diagram of a face recognition system.**

Numerous feature extraction methods have been introduced in the literature, but choosing the right features for various face recognition systems in unconstrained environments remains a significant challenge Ding C et al. [4]. Commonly used classifiers in face recognition include the minimum distance classifier, nearest neighbor classifier, and k- k-nearest neighbor classifier Belahcene M, Chouchane A et al. [5]. The minimum distance classifier assigns a testing sample to the class with the closest mean. The nearest neighbor classifier assigns the class of the nearest neighbor to the testing sample, while the k-nearest neighbor classifier determines the class based on the k-nearest neighbors Mi J-X et al. [6]. In recent times, machine learning algorithms, especially convolutional neural networks (CNN), have become the preferred choice for classification techniques. The feature classification stage, which leads to the recognition of face images, involves both identification and authentication. Identification compares a face image with other face images to ascertain its identity among several possibilities, whereas authentication compares a face with another to confirm the requested identity Bowyer KW et al. [7]. In both scenarios, face images of known individuals are stored in a gallery. Probes, which can be images of registered or unregistered individuals, are then used for identification or recognition tasks.

### Existing Dataset :

Face recognition systems rely on curated datasets to train and validate their algorithms, essential for achieving high accuracy and robust performance across various scenarios. These datasets are diverse in terms of size, content, and the challenges they address, making them crucial for advancing the field of face recognition. One of the most widely used datasets is Labeled Faces in the Wild (LFW), which contains over 13,000 images of faces collected from the internet. LFW is known for its variability in pose, illumination, expression, and background, reflecting real-world conditions that face recognition systems must handle. Another prominent dataset is CelebA, which focuses on celebrity faces and includes annotations for attributes such as gender, age, and facial hair, making it useful for attribute prediction tasks alongside face recognition. MegaFace offers a large-scale dataset with over a million images from nearly 700,000 individuals, providing ample data for evaluating face recognition models at scale. CASIA WebFace, comprising half a million images across 10,000 subjects, is valuable for training deep learning models due to its size and diversity. VGGFace includes a vast collection of 2.6 million images of celebrities, supporting the development of deep convolutional neural networks (CNNs) for robust face recognition. Furthermore, datasets like the YouTube Faces Database and IARPA Janus Benchmark A (IJB-A) contribute video and image data, respectively, to assess face recognition in real-world scenarios with varying levels of control. These datasets collectively drive innovation in face recognition technology by addressing challenges such as variability in pose, expression, illumination conditions, and scale, thereby enhancing the reliability and applicability of face recognition systems across different domains and applications.

### Literature Review :

Shivalila Hangaragi et al. [8] mentioned that face detection and recognition are emerging and active research areas in computer vision and deep learning with diverse applications, including recognizing individuals in specific locations like stores and banks, identifying people in databases such as police records, and controlling access to restricted areas, ATMs, or computers. This paper proposes a model that utilizes Face Mesh for face detection and recognition, enabling operation under various conditions like different illumination and backgrounds. The model effectively handles non-frontal images of males and females of all ages and races. The model is trained using the Labeled Wild Face (LWF) dataset and real-time captured images. During testing, the model compares the face landmarks of the test image with those of the training images and identifies the person if there is a match, otherwise, it outputs "unknown". The proposed model achieves an accuracy of 94.23% for face recognition. Sun Ye et al. [9], mentioned that while network technology enhances our daily lives, it also brings about numerous challenges, particularly regarding information security. Ensuring network information security and improving face detection and identification methods is crucial. This paper presents an improved approach compared to traditional AdaBoost and skin color methods. The proposed method incorporates AdaBoost detection to minimize false detection rates. Experimental results comparing AdaBoost, skin color, and combined skin color + AdaBoost methods are discussed. The paper utilizes kernel principal component analysis (KPCA) and kernel Fisher discriminant analysis (KFDA), which operate using an inner product kernel function in the original space, without involving specific non-linear mapping functions. By combining zero-space kernel discriminant analysis, the method enhances the ability to extract non-linear features, resulting in better recognition than the PCA method. The study also introduces a zero-space-based Fisher discriminant analysis method,

demonstrating that it effectively utilizes discriminant information in the zero space of the intraclass dispersion matrix, thereby improving face recognition accuracy. Experiments indicate that for polynomial kernel functions, KPCA achieves higher recognition ability when  $d = 0.8$ , while KFDA and zero-space-based KFDA have the highest recognition rates at  $d = 2$ . X. Han et al. [10] mentioned that deep learning represents a significant advancement in neural network technology, distinguished by its ability to train complex models with multiple layers, allowing for hierarchical feature learning. This approach has transcended traditional methods by achieving remarkable success across various domains such as handwriting recognition, where it excels in capturing intricate patterns and nuances in handwritten text. Moreover, in tasks like dimension reduction, deep learning methods like autoencoders have demonstrated superior capability in preserving essential features while reducing data dimensionality. Speech and image recognition benefit greatly from deep learning's capacity to process large volumes of data efficiently, extracting meaningful representations that enhance accuracy and robustness. The application of deep learning in machine translation has also led to significant improvements in natural language processing tasks, enabling systems to translate languages with greater fidelity and context understanding. In biometrics, particularly in face recognition, deep learning has emerged as a pivotal technology. By leveraging deep neural networks trained on vast datasets of facial images, researchers have achieved breakthroughs in recognizing faces across varying conditions such as pose, illumination, and expression. This capability makes deep learning-based face recognition systems robust and adaptable, suitable for applications ranging from security and surveillance to human-computer interaction and personalization. Overall, the integration of deep learning methodologies in face recognition has propelled research and development in biometric technologies, offering promising avenues for further advancements in accuracy, efficiency, and applicability across diverse real-world scenarios. Shivam Singh et al. [11] mentioned that in contemporary times, face recognition stands as a leading technology in computer vision, despite its inherent challenges such as varying illumination, pose, and facial expressions. This technology enables the identification of individuals from still images or live video frames, making it invaluable for applications across security, surveillance, and human-computer interaction domains. This paper proposes an automated face recognition system that integrates advanced algorithms for face detection, feature extraction, and recognition. The system employs the KLT Algorithm for tracking, the Viola-Jones Algorithm using Haar cascade classifiers for initial face detection, and continuous face detection in video frames. Feature extraction utilizes the PCA algorithm to select and model geometric characteristics unique to each individual's face, thereby enhancing recognition accuracy and reliability. Serign Modou Bah et al. [12], it is mentioned that face recognition is a pivotal computer application capable of detecting, tracking, identifying, or verifying human faces from digital images or video footage. Despite significant advancements in face detection and recognition for security, identification, and attendance purposes, challenges remain that hinder achieving or surpassing human-level accuracy. These challenges include variations in lighting conditions, image noise, scale, and pose among others. This research introduces a novel approach utilizing the Local Binary Pattern (LBP) algorithm integrated with advanced image processing techniques such as Contrast Adjustment, Bilateral Filter, Histogram Equalization, and Image Blending. The aim is to address these issues and enhance the accuracy of LBP codes, thereby improving overall face recognition performance. Experimental results demonstrate the effectiveness, reliability, and robustness of our method, suggesting its practical viability for implementing an automatic attendance management system in real-world environments. KH Teoh et al. [13] mentioned that the human face is a distinct and unique identifier, essential for distinguishing individuals, even among identical twins. Consequently, the advancement of face recognition and identification systems plays a pivotal role in accurately verifying individual identities. These systems serve as biometric authentication methods, widely adopted in applications like phone unlocking, criminal identification, and home security. Unlike conventional methods relying on keys or cards, face recognition systems bolster security by exclusively utilizing facial images. Typically, a human recognition system involves two primary phases: face detection, which locates faces in images or videos, and face identification, which matches detected faces against known individuals. This paper presents the design and implementation of a face recognition system utilizing deep learning techniques with OpenCV in Python. Deep learning is chosen for its exceptional accuracy in recognizing faces. The study includes experimental results that validate the performance and reliability of the proposed face recognition system.

#### Comparison Table :

References	Method Used	Accuracy Obtained
Shialila Hangaragiet al. [8]	Contourlet and wavelet	94.23%
Sun Y et al. [9]	Combination of AdaBoost detection	95.76%
X. Han et al. [10]	DeepID2+	95%
Shivam Singh et al. [11]	KLT Algorithm,	94.1%
Serign Modou Bah, et al.[12]	Local Binary Pattern(LBP) algorithm integrated with advanced image processing techniques	95%
KH Teoh et al. [13]	Deep Learning, OpenCV	94.5%
H. Lu et al. [14]	Linear Discriminant Analysis (LDA) and Kernel Discriminant Analysis (KDA)	96%

## Simulation Results :

In the context of the Curvelet Transform, "levels" and "scales" refer to different aspects of the transform:

**Levels:** In the Curvelet Transform, "levels" refer to the number of hierarchical decomposition levels applied to the image. Each level represents a stage of decomposition, where the image is decomposed into increasingly finer details. Higher levels result in more detailed decomposition, capturing finer features of the image. The number of levels determines the overall complexity and detail of the decomposition.

**Scales:** In the Curvelet Transform, "scales" refer to the number of directional bands at each level of decomposition. Each scale represents a set of directional wavelets that capture directional information in the image. The number of scales determines the directional sensitivity of the decomposition. Higher scales capture finer directional details in the image, while lower scales capture broader directional features. Here a curvelet transform of the input image has been taken to get coefficients at scale 2, there will be 16 decomposed images in 16 directions. The obtained output and the input image are shown in the Fig. 2.



Fig. 2. Input image for the curvelet transform.

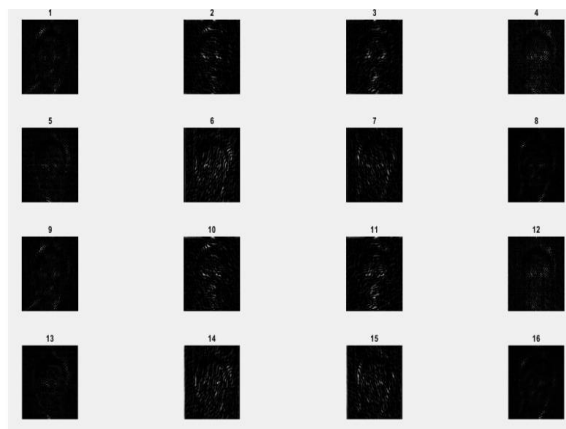


Fig. 3. Decomposed image in 16 directions for scale 2.

Afterward, the entropy for scale 3 was computed and visualized in Figure 3.

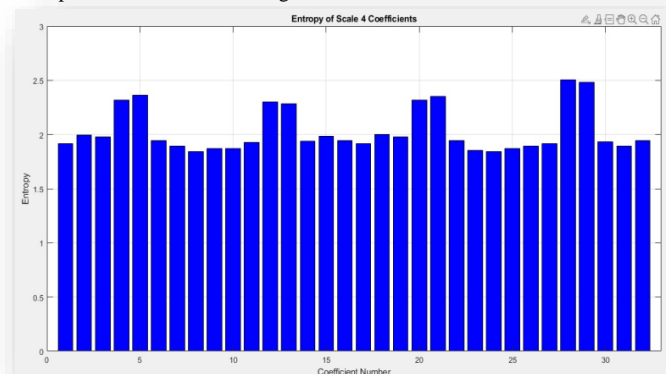


Fig. 4. Entropies at scale 4.

Three spatial parameters are calculated and plotted

1. Mean
2. Standard Deviation
3. Energy

The result of the statistical analysis of the curvelet transform image is shown in Fig 4. The mean of the scale 4 coefficient is shown in Figure 5. The maximum mean obtained is 0.5 and the minimum mean obtained is –

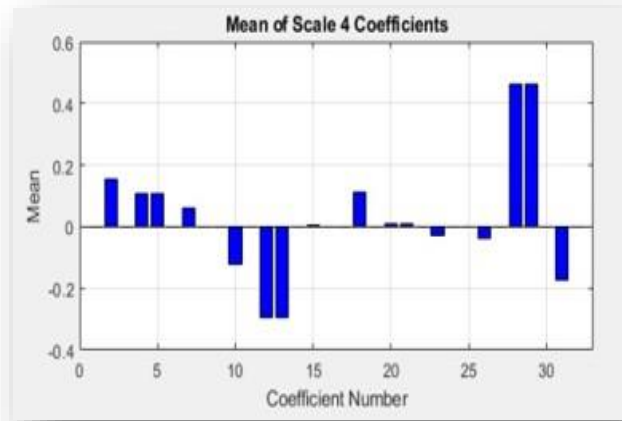


Fig. 5. Mean of scale 4 coefficient.

The standard deviation of scale 4 coefficients is shown in figure 6. It can be seen that for the dataset under text, the standard deviation is between 4 and 9.

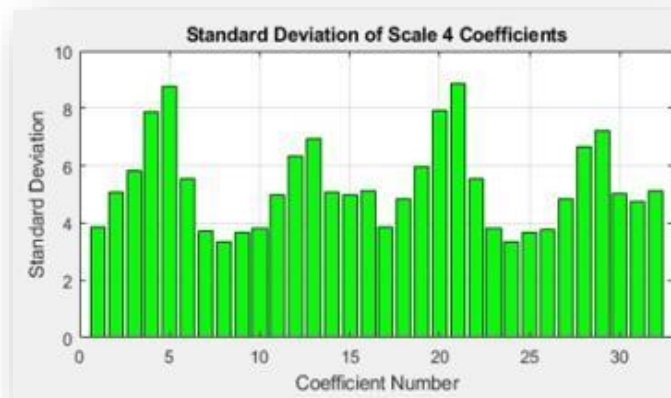


Fig. 6. Standard deviation of scale 4 coefficients.

The energy of scale 4 coefficients is shown in Fig. 7. The minimum energy is 10 and the maximum energy is 78.

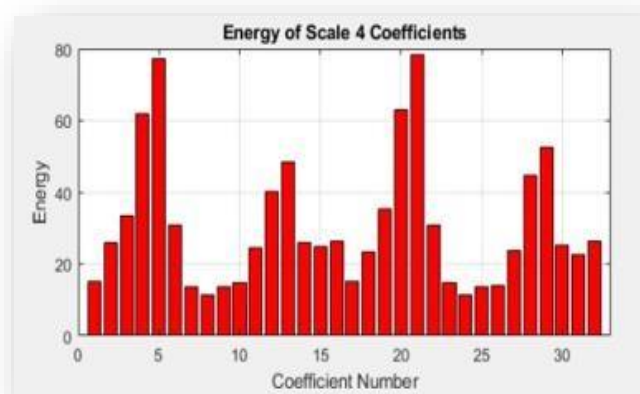


Fig. 7. Energy of scale 4 coefficients.

The entropy of the scale 4 coefficient is shown in Fig. 8. Here the maximum entropy of 1500 is obtained and the minimum is 1100.



Fig. 8. Entropy of scale 4 coefficients

### Conclusion :

This review highlights the growing preference for face recognition over other biometric modalities due to its efficiency, making it a central focus of research in computer vision. The paper discusses a curvelet-based analysis of a facial recognition dataset using MATLAB, evaluating various statistical parameters of images after applying the curvelet transform. The results demonstrate satisfactory performance and offer a foundation for developing more robust curvelet-based facial recognition systems. Future work could explore the integration of curvelet transforms with advanced deep-learning models to enhance accuracy and scalability for real-world applications.

### Future Scope :

Prospective areas for further research involve combining curvelet transforms with sophisticated deep-learning structures to improve precision, scalability, and practical utility. This combination can transform facial recognition technology. Fine-tune curvelet transform parameters to enhance overall performance.

### REFERENCES :

- Oloyede MO, Hancke GP (2016) Unimodal and multimodal biometric sensing systems: a review. *IEEE Access* 4:7532–7555
- Jin X, Tan X (2017) Face alignment in the wild: a survey. *Comput Vis Image Underst* 162:1–22
- Karamizadeh S, Abdullah SM, Zamani M, Shayan J, and Nooralishahi P (2017) Face recognition via a taxonomy of illumination normalization," in *Multimedia Forensics and Security*, ed: Springer, pp. 139– 160.
- Ding C, Tao D (2017) Pose-invariant face recognition with homography-based normalization.
- Belahcene M, Chouchane A, and Ouamane H (2014) 3D face recognition in presence of expressions by fusion regions of interest," in 2014 22nd Signal Processing and Communications Applications Conference (SIU), pp. 2269–2274. *Pattern Recogn* 66:144–152
- Mi J-X, Liu T (2016) Multi-step linear representation-based classification for face recognition. *IET Comput Vis* 10:836–841
- Bowyer KW, Chang K, Flynn P (2006) A survey of approaches and challenges in 3D and multi-modal 3D+ 2D face recognition. *Comput Vis Image Underst* 101:1–15
- Shivalila Hangaragi, Tripty Singh, Neelima N, Face Detection and Recognition Using Face Mesh and Deep Neural Network, *Procedia Computer Science*, Volume 218, 2023, ISSN 1877-0509, <https://doi.org/10.1016/j.procs.2023.01.054>.
- Sun Y, Ren Z, Zheng W. Research on Face Recognition Algorithm Based on Image Processing. *Comput Intell Neurosci*. 2022 Mar 18;2022:9224203. Doi: 10.1155/2022/9224203. Retraction in: *Comput Intell Neurosci*. 2023 Aug 2;2023:9847601. Doi: 10.1155/2023/9847601. PMID: 35341202; PMCID: PMC8956407.
- X. Han and Q. Du, "Research on face recognition based on deep learning," 2018 Sixth International Conference on Digital Information, Networking, and Wireless Communications(DINWC), Beirut, Lebanon, 2018, pp.53-58, doi: 10.1109/DINWC.2018.8356995.
- Singh, Face recognition system, *International Journal of Engineering Research & Technology (IJERT)* <http://www.ijert.org> ISSN: 2278-0181 IJERTV8IS050150 (This work is licensed under a Creative Commons Attribution 4.0 International License.) Published by: [www.ijert.org](http://www.ijert.org) Vol. 8 Issue 05, May-2019
- Serign Modou Bah, Fang Ming, An improved face recognition algorithm and its application in the attendance management system, *Array*, Volume 5, 2020, 100014, ISSN2590-0056, <https://doi.org/10.1016/j.array.2019.100014>.
- KH Teoh et al, "Face Recognition and Identification using Deep Learning Approach" 2021 *J. Phys.: Conf. Ser.* 1755 012006

- 
14. H. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, MPCA: Multilinear principal component analysis of tensor objects, *IEEE Trans. on Neural Networks*, 19(1):1839,2008.
  15. Harguess, J., Aggarwal, J.K., A case for the average- half-face in 2D and 3D for face recognition, *IEEE Computer Society*.