International Journal of Computer Trends and Technology
ISSN: 2231–2803 / https://doi.org/10.14445/22312803/IJCTT-V72I11P110

Volume 72 Issue 11, 92-104, November 2024

Review Article

Advancements and Challenges in Face Recognition Technology

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Received: 25 September 2024 Revised: 28 October 2024 Accepted: 17 November 2024 Published: 30 November 2024

Abstract *- Face recognition technology has seen rapid advancement due to improvements in algorithms, computational power, and data acquisition methods. This review provides a comprehensive analysis of key approaches in face recognition: texture-based, deep learning-based, and 3D models. Texture-based methods, like Local Binary Patterns (LBP) and Gradient Orientation-Based techniques, demonstrate resilience against variations in lighting and pose, while hybrid methods and advanced descriptors further enhance their performance. Deep learning has transformed face recognition, with models like DeepFace, FaceNet, and VGGFace achieving high accuracy through advanced feature extraction and matching. Nonetheless, this technology still has challenges, such as occlusions, diverse data sources, aging effects, and changes in facial expressions and poses. 3D recognition models use geometric features and morphable models, making their performance better than 2D systems. However, dataset limitations and the effects of surgical modifications continue to pose obstacles. In addition to technical challenges, privacy and ethical considerations surrounding facial recognition technology are also significant. The widespread use of face recognition raises concerns about unauthorized data collection, surveillance, and the impact on individual privacy. Ethical issues such as fairness, autonomy, and biases in facial recognition systems, particularly against marginalized groups, remain underlying challenges. Furthermore, adversarial attacks on face recognition systems pose a critical threat. Attackers exploit vulnerabilities to deceive or manipulate recognition systems, undermining their reliability and security. The review underscores ongoing research directions and future trends, highlighting the need for further advancements to develop face recognition systems that are both robust and accurate in real-world applications.*

Keywords *- 3D facial recognition models, Deep learning, Face recognition technology, Hybrid approaches, Texture-based methods.*

1. Introduction

Face recognition technology has emerged as a pivotal component in computer vision and Artificial Intelligence (AI), reflecting its extensive applications and continual advancements. Unlike other biometric systems that require direct interaction or cooperation from individuals, face recognition can operate non-intrusively, making it particularly advantageous for surveillance and security applications. This capability of identifying individuals based solely on their facial features has driven significant research and development efforts across various disciplines, including pattern recognition, image processing, and machine learning [1]. The core of face recognition involves a complex sequence of processes: face detection, feature extraction, and face matching. Initially, face detection algorithms identify and locate faces within an image, producing coordinates to outline the facial regions. Subsequently, feature extraction involves capturing and converting distinct facial patterns into data that can be used for recognition. The final step, face matching, compares these extracted features with those stored in a database to verify or identify the individual. Recent advancements in deep learning have greatly enhanced these processes, increasing accuracy and efficiency [1]. Historically, face recognition technology has encountered several challenges, including changes in head orientation, lighting conditions, age, and facial expressions. Additionally, factors like alterations in appearance from makeup, facial hair, or accessories have further complicated the recognition process. Despite these difficulties, face recognition has demonstrated significant effectiveness, with substantial advancements in accuracy and adaptability over the past decade [2]. One major milestone in overcoming these challenges has been the development of advanced algorithms. Innovations in deep learning have played a crucial role in this progress, leading to reduced error rates and enhancing the reliability and efficiency of face recognition systems. For instance, Facebook's DeepFace system employs deep learning techniques to analyze large datasets, improving user profile understanding and overall system performance [1]. Further advancements in face recognition technology have included its integration with multi-factor authentication systems. These systems combine face recognition with additional security measures, highlighting the growing importance and versatility of the technology. Such innovations demonstrate its capacity to enhance accuracy and address emerging security needs. Research in the field has also explored the integration of facial recognition with other biometric methods, such as fingerprints and iris scans. This approach aims to improve overall security and accuracy by combining multiple biometric indicators. Additionally, exploring behavioural biometrics, including analysing facial expressions and emotional states, has expanded the scope of face recognition applications, showcased its adaptability, and broadened its use cases [2]. The versatility of face recognition extends to numerous domains. In security, it is employed for surveillance, border control, and suspect tracking.

In educational and corporate settings, it facilitates attendance marking. Smartphones utilize facial recognition for unlocking devices, and social media platforms use it to enhance user experience through features like tagging and profile management. These applications highlight the broad impact of face recognition technology across various sectors [3]. Despite its advancements, face recognition technology is not without limitations. Distinguishing between individuals with similar features, such as twins or close relatives, remains a significant challenge. Furthermore, the technology must continually adapt to emerging privacy concerns and ethical considerations, particularly in light of increasing surveillance capabilities and data security issues [1]. This review paper intends to deliver a detailed assessment of the existing landscape of face recognition technology. It will explore recent advancements, practical applications, and the inherent challenges faced by the technology. By critically evaluating these aspects, the paper seeks to offer insights into the future directions of face recognition research and its implications for various industries.

2. Background

Face recognition technology has a rich history that spans several fields, including neurology, psychology, and computer science. Despite its challenges compared to more precise biometric methods like iris or fingerprint recognition, face recognition is highly valued for its unique advantages. The face, a fundamental aspect of human identity, offers an intuitive and natural feature for authentication and identification. In practical settings such as access control, facial characteristics allow for easy monitoring and verification of individuals, unlike other methods, which often require specialized expertise. Additionally, facial recognition is nonintrusive, allowing for data capture without physical contact, which enhances user comfort and acceptance. Furthermore, it demands minimal user cooperation, making it especially effective in surveillance scenarios where individuals can be identified without active participation. The origins of face recognition technology trace back to the late 19th century, with the first documented attempt at facial recognition involving the comparison of facial photograph parts in a British court in 1871. This early method laid the groundwork for the technology's role in law enforcement, where it has since become a critical tool in analyzing video footage and photographs from crime scenes. The advent of automated facial recognition systems has greatly enhanced the efficiency of judicial processes by streamlining the comparison of facial images. Automated facial recognition technology has evolved markedly since the 1960s. Early versions of facial recognition were semi-automated, relying on manually pinpointing facial features in photos before calculating distances and ratios for analysis.

The field was pioneered by researchers such as Woody Bledsoe, Helen Chan Wolf, and Charles Bisson, who began their work in the mid-1960s. The 1970s saw 21 distinct facial features, although this method required manual measurement and was thus limited. A pivotal advancement occurred in 1988 with the introduction of Principal Component Analysis (PCA) by Sirvoich and Kirby. This method enabled more accurate encoding and normalization of facial images using fewer than 100 values. Turk and Pentland further improved the technology in 1991 with the Eigenfaces method, which utilized residual error for enhanced reliability, though environmental limitations were still affected. The creation and market release of ZN-Face software in 1997 marked a significant milestone, as it could recognize facial images even with occlusions or non-frontal view [2].

Today, automated facial recognition is a prominent area of research and application in image processing and pattern recognition.Advancements in artificial intelligence have spurred significant progress in facial recognition technology. Early research focused on controlled conditions, where classical methods provided strong performance. However, the field has since shifted toward handling faces in unconstrained environments, with deep learning techniques offering increased robustness against variations that affect recognition accuracy. Current research continues to tackle real-world challenges in facial recognition, including the recognition of side profiles. While accuracy for profile views remains around 50%, recent advancements have significantly improved the sensitivity and specificity of identification using this approach [3]. In 2019, the global facial recognition market was valued at $4.4 billion and is expected to exceed $10.9 billion by 2025, with notable adoption in countries such as China [2].

3. Materials and Methods

The research methodology for this article is based on a systematic literature review, rigorously following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. This approach was chosen to ensure a structured and transparent review process that could effectively summarize the current state of face recognition technology, its advancements, and its challenges. The literature search was conducted across multiple academic databases, including IEEE Xplore, SpringerLink, Scopus, and Google Scholar, to ensure comprehensive coverage of relevant research. Key search terms and phrases such as "face recognition technology," "deep learning in face recognition," "3D face recognition," "face anti-spoofing," "biometric security," and "multi-modal face recognition" were used to identify pertinent studies.

To maintain relevance to recent technological advancements, only articles published in the last ten years were considered for inclusion, covering the period from 2014 to 2024. The selection process began by removing duplicate studies and applying specific inclusion and exclusion criteria. Studies were included if they addressed key themes in face recognition, such as algorithmic improvements, dataset design, loss functions, and performance in unconstrained environments. Exclusion criteria were applied to remove papers focused on unrelated biometric systems or studies that did not present empirical results. A detailed screening of titles and abstracts followed to narrow the selection further. Full-text articles that met these criteria were then thoroughly reviewed.

The PRISMA flow diagram was employed to document the number of articles at each stage—identified, screened, assessed for eligibility, and included in the review. This ensures transparency in the study selection process. For data extraction, a structured approach was used to capture essential elements from each study, including the methods employed, major findings, and contributions to the field of face recognition. Special attention was given to articles focusing on challenges such as recognition in poor lighting, occlusions and pose variations and those exploring cutting-edge techniques like one-shot learning and 3D morphable models. Finally, the results were synthesized to identify overarching trends, technological innovations, persistent challenges, and potential directions for future research in the face recognition domain.

4. Results and Discussion

4.1. Face Detection Technologies: Methods, Key Processes, and Evaluation Metrics

4.1.1. Key Steps in Face Recognition Systems

In face recognition systems, the process is generally divided into three essential steps: face detection, feature extraction, and face recognition. Each step plays a critical role in ensuring accurate and reliable performance.

Face Detection and Normalization

The initial step involves identifying and bounding faces within an image or video frame. A robust face detection system should accurately detect all faces present, regardless of their number, while managing changes in pose, illumination, and scale and minimizing distractions from the background. The Viola-Jones face detector, based on Haar-like features, is a well-known method that performs effectively for detecting frontal faces and operates in real-time [4]. Other methods have incorporated colour information to enhance detection accuracy. Recently, deep learning approaches have shown significant success in face detection. For instance, Faster R-CNN was originally created for object detection. After that, it has been modified for face detection through region proposals. The single shot detector (SSD), another technique originally developed for object detection, has proven effective for face detection [5]. Normalization standardizes the detected face following detection, which helps in subsequent feature extraction and recognition. Techniques such as histogram of oriented gradients (HOG) and principal component analysis (PCA) are employed to improve detection accuracy and prepare the face for alignment and feature extraction [6].

Feature Extraction and Precise Normalization

Once a face is detected, the system proceeds to feature extraction, where a feature vector or "signature" is generated. This vector captures the distinctive attributes of the face, including the shape and positioning of facial features like the eyes, nose, and mouth. Feature extraction aims to create a distinctive representation that can differentiate between individuals. Techniques such as HOG, Independent Component Analysis (ICA), Eigenface, Linear Discriminant Analysis (LDA), Gabor filters, Scale-Invariant Feature Transform (SIFT) and Local Binary Patterns (LBP) are employed to derive these features [7]. Precise normalization during this phase ensures that the extracted features are consistent and comparable despite variations in pose or expression.

An important aspect of feature extraction involves identifying key facial landmarks—such as the corners of the eyes, eyebrows, mouth, and the tip of the nose— which are important for aligning facial features. Positioning faces to a canonical orientation improves the accuracy of subsequent face recognition tasks. Techniques such as the ensemble of regression trees are commonly used for facial landmarking. Various methods for face alignment are categorized into holistic approaches, Constrained Local Model (CLM) methods and regression-based techniques. Recent developments feature multi-task learning techniques that combine face detection and landmark localization with other tasks like pose estimation and gender identification [8].

Classification (Verification or Identification)

The final step involves classification, which can be either verification or identification. In verification, the system performs a one-to-one comparison between the detected face and a stored face in the database to confirm or reject the claimed identity. This process is crucial for security applications where accurate identity verification is required. Verification accuracy is often assessed using metrics such as the True Accept Rate (TAR) and the False Accept Rate (FAR), with ROC analysis providing insights into performance [2]. In contrast, identification involves comparing the test face against multiple faces in the database to find the best match. This one-against-all approach is used in scenarios where screening for potential threats or fraud is necessary. Identification can be evaluated using open-set or closed-set protocols. Open-set identification includes individuals absent in the training set, with metrics like the false Negative Identification Rate (FNIR) and the False Positive Identification Rate (FPIR) measuring performance. Closed-set identification uses the same set of identities for training and testing, with performance assessed using Rank-N metrics and Cumulative Match Characteristic (CMC) curves to determine if the true identity appears within the top N matches [2].

4.1.2. Types of Face Recognition Systems

Face recognition systems are widely used to identify individuals based on distinctive biometric features such as facial features, fingerprints, iris patterns, and body structure. Among these, facial recognition stands out for its broad applications, especially in areas like surveillance, security, and identity verification. Facial recognition systems typically rely on key facial features such as the eyes, lips, nose, and mouth, which can be represented in 2D and 3D dimensions. Below is an overview of the different types of face recognition systems and their respective approaches:

2D Face Recognition

2D face recognition is a traditional and widely utilized method involving a structured four-step process in biometric systems. The first step, face detection, locates and identifies a face within an image. Following this, face alignment standardizes the face's orientation and scale to ensure consistency. Feature extraction then converts facial attributes into high-dimensional vectors based on pixel values, intensity, or texture patterns. Finally, feature matching compares these vectors to a database of known faces to identify or verify an individual.

Techniques such as color-based, intensity-based, and illumination-based methods are commonly used in 2D face recognition. Despite its effectiveness in controlled environments, this approach faces challenges, including variations in facial expressions, lighting conditions, head poses, and occlusions, which can significantly affect performance. As a result, 2D face recognition systems are most reliable in settings where environmental factors are controlled, and they have demonstrated considerable success in applications like identity verification, where conditions are closely regulated [2].

2D-3D Hybrid Face Recognition

To address the limitations inherent in 2D face recognition, hybrid systems that integrate both 2D and 3D data have been developed. These systems enhance the traditional 2D approach by incorporating depth information, significantly improving recognition accuracy. Eigenfaces and stereovision integrate 3D depth data into 2D recognition frameworks. This combination helps mitigate such problems as pose variations and illumination changes [9]. For instance, including 3D data allows the system to model faces from various angles, thus improving accuracy even when head poses vary. Additionally, the 3D model captures geometric details that are less sensitive to changes in lighting, leading to more consistent recognition results. Principal Component Analysis (PCA) is often employed for feature extraction and matching in these hybrid systems, further enhancing their ability to handle diverse conditions by merging 2D visual information with 3D structural data. Hybrid face recognition systems offer greater resilience to external factors that can undermine the performance of 2D-only systems [9].

3D Face Recognition

3D face recognition represents a significant advancement over 2D methods by analyzing facial features in three dimensions. This approach captures detailed depth and surface geometry, offering substantial advantages in robustness and accuracy. Unlike 2D systems, which rely solely on pixel data, 3D face recognition generates a comprehensive face model that includes curves, key points, and surface descriptors. This detailed representation is less affected by pose variations, lighting changes, and occlusions [9]. Recent research has focused on local facial features to improve recognition performance in varied environments further. Techniques such as normalization using bidirectional relighting and correlation metrics enhance the system's ability to handle different lighting and pose conditions.

Furthermore, 3D face recognition demonstrates greater resilience to variations in scale and rotation, yielding consistent results even in difficult conditions. Despite these advantages, the primary challenge for 3D face recognition lies in acquiring 3D training data, which requires specialized hardware such as infrared scanners or multi-camera systems. These acquisition methods are categorized into active methods, which use infrared lasers to map facial structures, and passive methods, which rely on multiple cameras to reconstruct 3D models from different perspectives. Although the acquisition process is complex and costly, 3D face recognition advances as a vital technology for scenarios where 2D systems face limitations, demonstrating superior accuracy and robustness [9].

4.2. Face Recognition Datasets

Benchmark datasets play an important role in developing and evaluating face recognition systems. These data sets provide standardized data that is very helpful for researchers to test the performance of their face recognition system under different conditions. Table 1 comprises information about all the influential data sets for 2D and 3D face recognition. These data sets have evolved with time to meet the growing needs and challenges of face recognition technology. Early data sets like ORL and FERET were mainly focussed on the controlled images, which can be used under limiting variations for algorithm evaluation. Later, more data sets like LFW and CASIA-web face were developed. These data sets have images with diverse conditions to simulate real-world settings. Specialized data sets, such as RMFRD and SMFRD, have also been developed to meet specific needs, such as masked face recognition [10]. Similarly, multimodal data sets such as BANCA and XM2VTS include biometric information such as voice samples for improved security applications. 3D face data sets such as Bosphorus, BU-3DFE, and FRGC add depth information and improve the robustness against the pose and lighting challenges. These data sets mainly include 3D models and capture expressions. Detailed information provided in these data sets helps to train and evaluate the algorithms for handling the complex variations in face recognition. All these available data sets have contributed to advancements in face recognition technology. Despite the availability of these huge data sets, there are still certain biases regarding demographic representation. Most available data sets are not sufficiently diverse as they over present certain age groups, ethnicities or genders, leading to a biased performance in face recognition systems. For example, the LFW dataset has images from Western individuals, giving good results for other groups or communities. This inadequate representation can lead to decreased accuracy and fairness in the face recognition system. These issues have drawn significant criticism and attention for the societal implications of face recognition technology. To address this issue, large datasets like MegaFace and VGGFace2 offer large and more varied collections of faces across different age groups, ethnicities and genders. Moreover, initiatives are being launched to develop new datasets focussed on demographic fairness and robustness across different conditions. Even techniques are being developed to debias the datasets by applying synthetic data augmentation techniques.

4.3. Different Face Recognition Methods

4.3.1. Holistic Method

Holistic or subspace-based face recognition algorithms operate on the principle that facial image collections can be simplified by removing redundancies through tensor decomposition. These methods aim to create a reduced-dimensional subspace of basis vectors that retain the essential characteristics of the original facial images. Each facial image, initially represented as an N×NN times NN×N matrix, is transformed into a vector by aligning its rows. This process involves decomposing a consequential matrix of size (N×N)×M(N times N) times M(N×N)×M to derive non-singular basis vectors. For classification, a new facial image is projected onto this subspace and compared with images in the subspace using distance metrics [2].

One of the most well-known linear techniques is Principal Component Analysis (PCA), or Eigenfaces. PCA projects facial images onto a lower-dimensional space defined by principal components derived from the training data. This approach, initially demonstrated by Turk and Pentland [11], showed that a limited set of eigenfaces could effectively capture and reconstruct facial images, achieving high recognition accuracy despite variations in illumination and orientation. Zhao and Yang [12] proposed using multiple images under different lighting conditions to create a more robust covariance matrix to address performance issues caused by lighting variations.

Additionally, this concept was extended with modular eigenfaces like EigenNose and EigenEyes, which improved stability against appearance variations [13]. Another significant linear method is Linear Discriminant Analysis (LDA), known as FisherFaces, which aims to enhance class separability in the reduced- dimensional space.

Table 1. Data-sets for 2D and 3D face recognition

Dataset	Year	Developers	Subjects	Images	Key Features	2D/3D	Application Focus
ORL Dataset [2]	1992-1994	Olivetti Research Laboratory	40	400	Frontal images, varied expressions, plain background	2D	Basic facial variation testing
FERET Dataset [14]	1993-1996	Dept. of Defense, USA	1,199	14,126	Controlled variations in lighting, pose; duplicates over time	2D	Authentication, forensic use
AR Dataset [2]	1998	Computer Vision Center, Barcelona	116	3,000+	Expressions, occlusions (sunglasses, scarves), varied lighting	2D	Expression and occlusion testing
XM2VTS Database [15]	1999	University of Surrey	295	4 video sessions	Multi-session video, Lausanne protocols for evaluation	2D/3D	Verification with impostor analysis
BANCA Dataset [16]	2003	European BIOMET Project	52	Multi-modal data	Face and voice samples, varied conditions across 12 sessions	2D	Multi-modal biometric testing
FRGC Dataset [17]	2004-2006	University of Notre Dame	466	50,000+	Controlled, uncontrolled, and 3D images; extensive testing protocols	2D/3D	Advanced verification and 3D face

LFW Database [18]	2007	University of Massachusetts Amherst	5,749	13,233	Unconstrained images, multiple alignments (funneled, LFW-A)	2D	Unconstrained face recognition
CMU Multi-PIE [19]	2000-2009	Carnegie Mellon University	337	750,000+	15 viewpoints, 19 lighting conditions, multiple expressions	2D	Pose and lighting variance testing
CASIA-WebFace [20]	2014	Chinese Academy of Sciences	10,575	494,414	Large-scale IMDb-sourced images; unconstrained conditions	2D	Large-scale, unconstrained testing
Bosphorus Dataset [21]	2008	Bogazici University, Turkey	105	4,652 3D scans	3D data with varied poses, expressions, occlusions (e.g., hand-over-face)	3D	3D facial expression recognition
BU-3DFE Dataset [22]	2006	Binghamton University	100	2,500+ 3D expressions	3D face scans across six expressions, four intensity levels	3D	3D expression recognition
Face Warehouse [23]	2013	Microsoft Research	150	3D face scans	High-quality 3D models of varied expressions, speech; age/gender labels	3D	Realistic 3D modeling and expressions
MegaFace [24]	2016	University of Washington	690,000+	1 million+	Large-scale dataset with millions of distractors for scalability testing	2D	Large-scale face recognition, open-set testing
VGGFace2 [25]	2017	University of Oxford	9,131	3.3 million	High diversity in age, ethnicity, pose; images sourced from the web	2D	Diverse and unconstrained face recognition
RMFRD & SMFRD [10]	2020	Wuhan University	525,000+	Masked/ unmasked	Masked face images from COVID-19 era	2D	Masked face recognition

FisherFaces has been shown to outperform Eigenfaces on datasets such as the Harvard and Yale Face Databases. Fisher faces algorithm can attain an accuracy of 99.7% for face detection on the face mask dataset [2]. Independent Component Analysis (ICA) is a significant method to ensure statistical independence among components by applying a linear transformation. It has proven effective in face recognition tasks, particularly when applied to compacted and whitened data. ICA-based approaches, such as Independent Gabor Features (IGFs), demonstrate that combining Gabor features with probabilistic reasoning models can achieve high accuracy in datasets like FERET and ORL. Comparisons with techniques like PCA and SVM indicate that although they perform similarly in terms of accuracy, PCA/SVM offers faster training times.

Other integrated approaches, such as combining PCA, Genetic Algorithms, and SVM, have also achieved remarkable success, with detection rates reaching as high as 99% on databases like Cas-Peal [26]. In addition to ICA, techniques such as Gabor filters, Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT) are commonly used for feature extraction and compression in face recognition. For instance, a fused DWT-DCT algorithm has shown superior performance compared to traditional PCA methods [2], [4]. Non-linear techniques frequently employ kernel-based approaches, with Kernel PCA being an extension of PCA that addresses non-linear data mappings. When combined with SVM classifiers, Kernel PCA has demonstrated reduced error rates compared to traditional methods [27]. Kernel-Based Discriminant Analysis is another approach designed to manage complexities such as variations in emotion, offering better performance than both Kernel PCA and Generalized Discriminant Analysis (GDA) [28]. Locally Linear Discriminant Analysis (LLDA) enhances this process by aligning local structures within a framework of global non-linear data, resulting in lower computational costs than Kernel Linear Discriminant Analysis (KLDA) and GDA.

Additionally, methods like ISOMAP and Locally Linear Embedding (LLE), which learn non-linear manifolds from low-dimensional input spaces, have demonstrated encouraging results in comparison to other non-linear methods [2], [4]. Despite their effectiveness, holistic methods face significant challenges, including sensitivity to context changes and misalignments. These techniques often require precise face cropping and alignment to minimize classification errors, as even minor deviations in face orientation can drastically impact recognition accuracy. This reliance on accurate geometric consistency highlights the limitations of holistic methods, particularly in real-world applications where such precision is difficult to maintain.

4.3.2. Geometric Approach

The geometric technique in face recognition focuses on analysing the spatial relationships and configurations of primary facial characteristics, like the eyes, nose, and mouth. This method utilizes the distinct geometric arrangement of these features to identify individuals, prioritizing structural properties over texture or appearance. The process begins with detecting facial landmarks using algorithms such as the Active Contour Model or Constrained Local Models. Once these landmarks, like the tip of the nose, the corners of the eyes, and the edges of the mouth, are identified, they are used to create a feature vector that captures the distances and angles between these points. Geometric methods use the distribution of landmarks through heuristic rules involving distances, angles, and regions.

Normalization ensures consistency across individuals and conditions by aligning the face based on landmark positions and scaling distances to a standard size. Geometric models, including Procrustes Analysis and Principal Component Analysis (PCA), are then used to represent and compare faces. Elastic Graph Matching (EGM) is a widely recognized geometric method. It involves overlaying a sparse, elastic graph on an image and analysing the response of Gabor wavelets at each graph node. This technique uses stochastic optimization to minimize a loss function by considering jet responses and node deformations. EGM has proven effective in recognizing faces under varying expressions and rotations. The Elastic Bunch Graph-Matching (EBGM) algorithm extends EGM by computing jets for multiple facial expressions and configurations, such as open or closed mouths and eyes, allowing it to handle variations in facial appearance.

Additionally, Morphological Elastic Graph Matching (MEGM) replaces Gabor features with multi-scale morphological features derived from dilation-erosion filtering [2], [4]. Kumar et al. [29] introduced an ensemble face recognition system that employs a new descriptor called Dense Local Graph Structure (D-LGS). This method enhances pixel density through bilinear interpolation and has demonstrated strong performance in constrained and unconstrained environments. Despite their advantages, geometric methods often require perfectly aligned facial images, which can be challenging and labor-intensive. While EGM is less dependent on precise alignment, it remains time-consuming due to the need to examine images at multiple scales. Additionally, variations in lighting present significant challenges to face recognition systems, underscoring the need for ongoing improvements in developing robust and accurate geometric models for facial recognition

4.2.3. Texture-Based Face Recognition

Within the realm of computer vision, texture-based face recognition has become one of the most effective approaches for robust and real-time facial recognition, particularly in unconstrained environments. Texture-based methods focus on local feature descriptors that can handle variations in lighting and grayscale and pose more efficiently than global descriptors. Below, critical methodologies and their advancements in texture-based face recognition are critically analysed.

Local Binary Patterns (LBP)

Local Binary Patterns (LBP) are face detection's most commonly used texture descriptors. LBP divides the facial image into several blocks, with texture features from each block used to create a histogram representing the entire face. This method demonstrated remarkable results in recognition tasks, outperforming classical approaches such as PCA and EBGM with a 97% recognition rate on the FERET database's FB probe set. The success of LBP stems from its robustness to changes in lighting and facial expressions.

However, LBP’s limitations arise when block sizes become too large or too small, leading to either an oversimplification of facial details or a sparse representation of texture. This issue can be addressed by introducing Vector Quantization (VQ), which groups patterns into meaningful clusters, thus improving recognition accuracy and reducing the sparsity problem [2].

Gradient Orientation-Based Methods

Another type of texture-based recognition method involves gradient orientation-based descriptors, such as the Histogram of Oriented Gradients (HOG). HOG captures edge and gradient structures that are crucial for facial feature extraction. This method has shown effectiveness, particularly when combined with classifiers like the nearest neighbour approach. Further developments introduced the Co-occurrence of Oriented Gradients (CoHOG), which enhances recognition by adding weighted sub-regions of the face to the analysis. CoHOG outperforms traditional HOG by incorporating gradient magnitude into its process, resulting in higher recognition rates, as demonstrated in tests on various facial datasets [30].

Hybrid Methods: SIFT and LBP

Hybrid methods have combined orientation-based descriptors with texture features for better accuracy and reduced computational costs. For example, Scale-Invariant Feature Transform (SIFT), known for its robustness against scale and rotation changes, has been paired with LBP. This combination, proposed by Shen and Chiu [31], leveraged the strengths of both methods, reducing computation time by 30% while maintaining high recognition accuracy on the FERET database. The fusion of multiple descriptors offers a balanced approach, addressing weaknesses in individual techniques, such as SIFT's high computational demands and LBP's susceptibility to certain variations.

Advanced Local Descriptors

New local descriptors like Local Gradient Orientation Binary Pattern (LGOBP) and Local Phase Quantization (LPQ) have been developed to overcome the limitations of traditional methods. LGOBP introduced an innovative saliency measure, Generalized Survival Exponential Entropy (GSEE), which more effectively identifies critical facial regions than LBP. Additionally, LPQ substantially improved the recognition of blurred images by encoding local regions using the Fourier phase transform. LPQ has demonstrated impressive resilience to blurring, achieving high recognition rates on various datasets, surpassing LBP in performance [30].

Handling Low-Resolution and Blur

Methods that focus on handling low-resolution images, such as Local Frequency Descriptor (LFD), and blur conditions, like LPQ, have made substantial strides in improving real-world performance. LFD, when combined with phase and magnitude information, can outperform LBP and LPQ, especially on low-resolution datasets like the FERET database. These developments underscore the importance of adapting face recognition systems to work effectively in degraded visual conditions [2], [4].

Learning-Based Methods: BSIF

Binarized Statistical Image Features (BSIF) significantly shifted toward learning-based descriptors. Unlike traditional handcrafted descriptors, BSIF learns filters from training images, making it more adaptable to specific datasets and resilient to image degradations like blur and misalignment. BSIF's competitive performance on the FRGC dataset highlights its potential for broader real-world applications. Texture-based face recognition methods, especially those using local descriptors, have proven highly effective in handling environmental variations like lighting, scale, and misalignment. Techniques such as LBP, HOG, and hybrid approaches combining SIFT and LBP have demonstrated notable success across multiple datasets. New descriptors like LPQ and BSIF continue to push the boundaries of performance under challenging conditions like blur and low resolution [2], [4]. However, challenges remain, especially in handling extreme posture and image quality variations. Future advancements should improve descriptor adaptability and robustness in unconstrained environments, potentially through integrating deep learning with texture-based approaches. With ongoing research, texture-based recognition will continue to play a vital role in developing robust facial recognition systems.

4.3.4. Deep Learning-Based Models for Face Recognition

Since 2014, deep learning has revolutionized face recognition systems, leveraging advances in computational power, large-scale datasets, and sophisticated algorithms. Introducing deep neural networks (DNNs) has substantially enhanced face recognition accuracy and performance. One of the groundbreaking methods, DeepFace, can achieve near-human accuracy (97.35%) on the Labelled Faces in the Wild (LFW) dataset, demonstrating the potential of deep learning in facial recognition. This milestone marked a turning point, leading to the development of subsequent models that pushed accuracy rates even higher.Following DeepFace, models such as DeepID and FaceNet further advanced the field. FaceNet introduced triplet loss to optimize the embedding space, improving impressive accuracy.

FaceNet achieved significant performance gains, reaching over 99% accuracy on the LFW dataset by leveraging a triplet loss function that effectively separates facial features into a discriminative embedding space. Additionally, VGGFace used various CNN architectures to achieve similarly high levels of accuracy. These advancements illustrate the growing effectiveness of deep learning models in face recognition tasks [2], [4]. Deep learning-based face recognition typically involves three critical phases. The first phase, face pre-processing, is essential for handling lighting, pose, and facial expression variations. Techniques like one-to-many augmentation, which generates diverse poses from a single image, and many-to-one normalization, which creates a canonical frontal view from multiple angles, have enhanced model robustness.

Deep CNN architectures such as AlexNet, VGGNet, GoogleNet, and ResNet derive significant features from face images in the second phase of deep feature extraction. These models benefit from specialized loss functions like triplet, centre, and arc face loss, which enhance the discriminative power of the features learned. Such advancements have significantly improved face identification and verification task performance [2], [4]. The third phase, face matching, involves comparing the deep features of test images with those stored in a database. Traditional methods such as cosine and L2 distance are widely used for similarity measurement. However, more advanced techniques, including metric learning and sparse representation-based classifiers, have been introduced to improve matching accuracy. For example, significant margin cosine loss (LMCL) reformulates Softmax loss to optimize features in the angular space, further enhancing face recognition performance. Despite these improvements, deep learning-based face recognition faces challenges, particularly in unconstrained environments. Poor lighting, occlusions, and extreme pose variations can hinder recognition accuracy. Video-based approaches and one-shot learning methods are being explored to address these issues. Some research proposes solutions such as pairwise differential Siamese networks to enhance recognition under occlusions.

Additionally, Wei et al. [32] introduced a Minimum Margin Loss (MML) to enhance discriminative ability by adjusting class margins. Recent efforts also focus on integrating deep learning with sparsity-based methods to overcome limitations. The Sparse Representation-based Classifier (SRC) has shown promise in handling small sample sizes and variations, and combining it with deep CNNs has been suggested to improve performance under challenging conditions. These hybrid approaches aim to leverage the strengths of both techniques for better robustness and accuracy.

4.3.5. 3D Facial Recognition Models

Human face recognition relies on geometric features, even when finer details are obscured, primarily depending on the overall structure and shape of the face. This approach has been fundamental in advancing 3D facial recognition technologies. Researchers have extensively explored geometric attributes such as facial curvature, shape, and surface normal to enhance recognition accuracy. Techniques like discrete Fourier transform, discrete cosine transform, principal curvature directions and nonnegative matrix factorization have been employed to represent facial shapes in 3D. The development of 3D morphable models has been pivotal in creating expression-invariant recognition systems. These models enable the generation of 3D facial representations, which help systems handle variations in facial expressions more effectively.

Research has shown that using a 3D morphable model to generate multiple facial images from a single photograph improves performance with the Fisherface method compared to the traditional Eigenface approach. The enhancement became apparent during trials using the ORL dataset and UMIST face databases [30]. Additionally, dual camera systems combined with Active Appearance Models (AAM) have produced robust 3D face models resilient to facial expression changes and photo spoofing attacks.The Microsoft Kinect, an active acquisition system utilizing structured light technology, has shown promising results in 3D facial recognition. This system comprises an RGB camera, an infrared (IR) camera, an IR projector, a multi-array microphone, and a motorized tilt mechanism. It captures depth images at a resolution of 640×480 pixels at a rate of 30 frames per second, providing detailed depth information crucial for various computer vision tasks, including facial recognition (fps). This can also provide higher resolution images at a lower frame rate. The Kinect's effective RGB-D mapping and multimodal detection capabilities make it a valuable tool for 3D facial recognition [33]. Various 3D facial recognition databases, such as BU-3DFE, FRGC v1.0 and v2.0, CASIA, ND2006, Bosphorus, BJUT-3D, Texas 3DFRD, UMB-DB, and BU-4DFE, have been developed over the years, each providing different types of data including mesh models, depth images, point clouds, and 3D video sequences [30]. However, the limited availability of 3D facial scans presents a challenge for deep learning methods, which require large datasets for effective training. While 2D datasets like FaceNet include around 200 million images, leading 3D datasets contain only a fraction of this amount, affecting the accuracy and reliability of 3D facial recognition. Despite some studies achieving reasonable results, the field faces challenges related to dataset size, preprocessing complexity, and recognition performance [2].

4.4. Key Challenges in Face Recognition Technology

4.4.1. Face Recognition and Occlusion

Face recognition systems face significant difficulties when dealing with occlusions, such as sunglasses, scarves, or objects like hands and phones, which partially obscure facial features. These obstructions distort key facial landmarks, making it harder for the system to match and recognize individuals accurately.

Additionally, occlusions often lead to alignment errors, as the system struggles to properly align and compare obscured facial features with stored templates. This results in increased intra-class variability and decreased recognition accuracy. To address this challenge, advancements in algorithms that can better handle occlusions and improved feature extraction and alignment techniques are needed. Developing methods that simulate occlusions during training can also enhance the system's robustness in real-world scenarios [2], [30].

4.4.2. Heterogeneous Face Recognition

Recognizing faces captured through different imaging modalities, such as infrared or sketches, presents a substantial challenge in face recognition technology. This issue is particularly pressing in legal contexts where images may come from varied sources. The differences in image quality, resolution, and modality make direct comparison difficult, as each modality captures distinct features or representations of a face. Effective fusion of data from these diverse modalities is essential but complex, requiring advanced algorithms to align and integrate the varying data types. To improve accuracy in heterogeneous face recognition, developing robust feature-matching algorithms that can bridge these gaps and integrate data from multiple modalities is crucial [2], [30].

4.4.3. Face Recognition and Aging

Aging significantly impacts facial recognition systems by altering facial appearance through skin texture changes, wrinkles, and shifts in facial proportions. These age-related changes can make it challenging to match images of the same person taken at different times, thereby reducing recognition accuracy. To address this, systems must account for these gradual changes over time, which requires sophisticated modelling of age-related transformations. Techniques such as age-invariant feature extraction, coupled auto-encoders, and longitudinal datasets are essential for improving recognition accuracy despite the effects of aging. Incorporating temporal data to model age progression can further enhance system performance in long-term identification scenarios [2], [30].

4.4.4. Single Sample Face Recognition (SSFR)

Single Sample Face Recognition (SSFR) is particularly challenging as it involves identifying individuals from only one facial image, often in practical applications like passport control or immigration systems. The scarcity of data complicates the training process, as traditional pattern recognition systems typically require extensive datasets to achieve reliable generalization. Although deep learning techniques have shown promise, they often rely on large datasets to perform effectively. Innovations in transfer learning, data augmentation, and advanced feature extraction techniques are needed to overcome this challenge. Methods that leverage prior knowledge or synthetic data can also help improve performance in scenarios where only a single sample is available [2], [30].

4.4.5. Thermal Imaging

Thermal imaging presents its own challenges in face recognition due to environmental factors such as varying illumination and the need for effective multi-feature extraction techniques. The low resolution of thermal images compared to visible light images can make it difficult to accurately capture and recognize facial features. Additionally, integrating data from both visible and thermal infrared images through multi-fusion techniques is crucial to improving recognition accuracy. Advances in feature extraction methods, such as those based on Gabor jet descriptors, and the development of new entropy functions for infrared image recognition are needed to improve the presentation of thermal face recognition systems [2], [30].

4.4.6. Iris Recognition

As part of face biometrics, Iris recognition relies on robust feature extraction techniques, often using Bio-Hashing methods. Ensuring the robustness of iris mapping across different databases is crucial for maintaining high performance. Combining face and iris recognition can improve the reliability of biometric systems, particularly in mobile engagement applications. However, data loss during iris corner extraction and synthesis remains a challenge. To address this, fusion techniques, as demonstrated in experiments using frameworks like CASIA-IRIS, can mitigate data loss and improve overall performance. Continued research into multi-biometrics and high-accuracy fusion technologies is essential for advancing iris recognition systems [2], [30].

4.4.7. Facial Expressions and Poses

Variations in facial expressions and poses add complexity to face recognition systems, as these factors can significantly alter facial features and affect recognition accuracy. Techniques such as expression-invariant 3D face recognition and pose-invariant models have been developed to address these issues. For example, feature and shape matching methods and sparse representation classification can improve recognition performance despite variations in expressions and poses. Advances in multimodal models and local shape descriptors further enhance the system’s ability to handle these variations effectively. Addressing these challenges requires developing robust algorithms that can accurately recognize faces under different expressions and poses [2], [30].

4.4.8. Surgical Modifications

Surgical modifications to facial features present a unique challenge for face recognition systems. Techniques such as coarse-to-fine strategies and half-face matching algorithms have been explored to improve accuracy and robustness in the presence of such modifications. Facial transposition patterns and 3D stereoscopic effects offer more precise holistic extraction, while facial inversion techniques help maintain similar performance across different face detection methods. Advances in GPU integration also enhance 3D face recognition performance. To effectively handle surgical modifications, continued development of algorithms that can adapt to changes in facial features and accurately recognize individuals despite such alterations is essential [2], [30].

4.4.9. Adversarial Attacks in Face Recognition Technology

In recent years, deep learning has improved the face recognition technology with the advancement of complex neural networks. However, Goodfellow et al. [34] have revealed that small targeted image alterations, known as adversarial examples, can mislead face recognition models. This issue presents significant challenges to face recognition systems. Since consistent research is going on to explore adversarial attacks, strategies can be developed to exploit these weaknesses. For example, a research team from Tsinghua University developed special glasses that can bypass face recognition systems, even allowing access to mobile banking. In another approach, perturbation patches are placed on the forehead, deceiving the recognition systems but are easily detectable. In more advanced techniques, adversarial make up is applied to images that resemble with the natural make up [35].

However, it is difficult to maintain this technique's effectiveness in realistic conditions. In addition, 3D adversarial attacks are also being explored. These attacks simulate realistic conditions by incorporating color and depth information from 3D scanners, which offers insights into potential vulnerabilities in presentation attacks. Despite all these breakthroughs, creating an effective adversarial sample for face recognition systems has always been a challenge. The main issue is to balance the attack's success with the image quality. The traditional methods used to modify the images generally cause noticeable distortions, making these attacks easy to detect. To address this issue, new methods are designed to make adversarial samples less visible but more effective. These methods mainly focus on applying changes to complex areas of the face, such as the eyes, mouth and forehead, making the alterations harder to recognize [35]. This targeted approach has two main benefits. It reduces the visibility of adversarial noise and directly alters facial features, increasing attacks' effectiveness against recognition algorithms. Masks for facial features can be created using facial landmark detection and superpixel segmentation. This method combines gradient-based techniques to introduce subtle changes. Experimental results show that this approach creates adversarial samples that look natural and are effective against face recognition [35]. Based on the developments in adversarial attacks, the attacks can be categorized into white box and black box attacks. White box attacks are more successful as they are designed according to the architecture and parameters of the target. Black box attacks operate without any information, which makes them easy to deploy but less effective. Fast Gradient Sign Method (FGSM), the Basic Iterative Method (BIM), and Projected Gradient Descent (PGD) are the most common white box attack methods. FGSM is one of the earliest methods. It calculates the gradients of a neural network to manipulate the input images and attain moderate success rates. BIM is improved upon FGSM by introducing iterative steps. This results in higher success rates and better adversarial images. Further, PGD is built upon BIM by adding random initialization, enhancing adversarial image generation's robustness [35]. Despite these advancements, there are still challenges in creating an effective, discrete and practical adversarial method that can operate in diverse and real-world conditions.

4.5. Privacy, Ethical Considerations, and Societal Impacts of Facial Recognition Technology

The widespread use of facial recognition technology has raised several serious concerns about privacy and ethics, which should be carefully considered [3]. This section examines the privacy risks, ethical concerns and social effects of facial recognition technology.

4.5.1. Privacy Concerns

The use of facial recognition technology in everyday life creates serious privacy risks. Facial recognition systems recognize people by analysing facial features in images and videos, so there is a chance that data will be collected and used without permission. Many people do not realize that their facial data is captured and stored without consent. This leads to major privacy violations. There are also no clear laws around facial recognition technology, making these privacy risks worse. Different countries handle regulations in different ways. In the unites states, there is no national law. Only a few states have laws that leave a gap that can be exploited. In the European Union, however, the General Data Protection Regulation (GDPR) enforces strict rules for processing biometric data, requiring clear consent and people’s right to data protection [3].

4.5.2. Ethical issues

The ethical issues around facial recognition technology are beyond privacy concerns. They include autonomy, fairness and bias. When facial data is used without proper safeguards, people may feel less free to express themselves. Furthermore, it has been observed that facial recognition systems can have built-in biases, particularly affecting women and people of care. This raises concerns about fairness and reliability. Such biases can lead to discrimination, especially against vulnerable groups. It highlights the need for ethical guidelines that promote accountability and fairness in facial recognition technology [3].

4.5.3. Social Impacts

The social effects of facial recognition technology are wide-reaching, particularly when used for surveillance. Widespread use of facial recognition technology in surveillance can lead to more government monitoring and control, potentially weakening democratic values and personal freedom. This type of surveillance may create distrust because people may feel constantly watched. The privacy and ethical problems linked to FRT can also increase social divisions, especially if marginalized groups are more negatively impacted [3]. Thus, it is important to create rules that consider how face recognition technology works and its social, ethical, and legal impacts. This includes building frameworks that protect the rights of people while still allowing technological progress. Bringing together stakeholders from technology, law, ethics, and the public will be essential for creating responsible guidelines that respect human dignity and democratic values.

5. Conclusion and Future Scope

Face recognition technology has advanced significantly across various methodologies, each contributing unique strengths to the field. Texture-based approaches, such as Local Binary Patterns (LBP) and hybrid descriptors, have proven effective in handling local variations in facial features. At the same time, deep learning models have set new benchmarks in accuracy through sophisticated neural network architectures and advanced feature extraction techniques. The development of 3D facial recognition has further enhanced performance by utilizing geometric features to address the limitations of 2D systems. Despite these advancements, significant challenges persist. Issues like occlusions, heterogeneous imaging modalities, aging effects, and variations in facial expressions and poses continue to impact recognition accuracy.

Additionally, integrating multiple biometric modalities and managing surgical modifications present ongoing hurdles. Overcoming these obstacles calls for innovative methods and sustained research efforts to boost the resilience and precision of face recognition systems. The discussion has also highlighted the broader implications of facial recognition technology, including privacy concerns, ethical issues, and societal impacts. Privacy risks and ethical challenges such as data misuse, biases, and potential infringements on personal freedom demand comprehensive regulatory frameworks and ethical standards. The potential for adversarial attacks also poses a critical risk. It underscores the need for advanced protective measures within face recognition systems.

These considerations are essential in shaping this technology's responsible use and governance as it continues to evolve. Looking ahead, research in facial recognition systems should concentrate on several key areas to drive further advancements. One significant focus will be image enhancement techniques, such as super-resolution and 3D image generation, aimed at improving face recognition accuracy, especially with low-resolution images commonly captured by security cameras. Bridging the gap between low-resolution and high-resolution image recognition is crucial for enhancing system performance. Another important area is refining loss functions used in deep learning models. As these functions are critical for maintaining performance under various challenging conditions, introducing novel loss functions is expected to advance the accuracy and reliability of face recognition systems. Research will likely explore new approaches to optimize these functions and adapt them to emerging challenges. Dataset design remains a pivotal aspect of improving face recognition technology. Incorporating a wide range of training images with different lighting conditions, poses, and noise levels can significantly enhance the robustness of deep neural networks. Given the difficulties in acquiring large annotated datasets, methods such as active learning and curriculum learning—where training starts with simpler images and progresses to more complex ones—may improve model generalization. Creating comprehensive multi-modal datasets, including RGB, depth, infrared, and 3D mask data, is essential for advancing face recognition and anti-spoofing technologies. Exploring soft biometrics derived from facial dynamics presents another promising research direction. Although these features alone may not suffice for accurate face recognition, integrating them with traditional methods could improve system performance, especially under adverse conditions. Investigating the role of various facial expressions and dynamics in identity recognition and anti-spoofing could yield valuable insights and enhancements. Face anti-spoofing remains a critical challenge despite the progress made with deep learning. Future research should focus on developing zero-shot anti-spoofing techniques and strengthening the resilience of deep neural networks in contrast to adversarial attacks. Addressing these issues is vital for enhancing the safety and reliability of face recognition systems. Finally, multi-modal and cross-modal face recognition is gaining increased attention. Matching face images across different modalities, such as sketches and photographs, presents significant challenges, particularly in forensic contexts. Future research seeks to develop face recognition systems that rival human vision. This effort will necessitate continuous collaboration between computer vision experts and neuroscientists to develop more advanced and dependable face recognition systems that can operate effectively in a variety of challenging conditions relevance.

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