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Face Recognition Based on Deep Learning: A Comprehensive Review

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Abstract

Face recognition technology has undergone transformative changes with the advent of deep learning techniques. This review paper provides a comprehensive examination of the development and current state of face recognition techniques influenced by deep learning. We begin by discussing the fundamental deep learning models that have dramatically enhanced the accuracy and efficiency of face recognition, highlighting pivotal architectures such as convolutional neural networks (CNNs) and autoencoders. Subsequent sections delve into the application of these models in various environments and challenges, such as different lighting conditions, occlusion, and facial expressions. We also address the integration of deep learning with emerging technologies such as 3D facial reconstruction and multimodal biometrics. Furthermore, the review explores the ethical, privacy, and bias concerns inherent in facial recognition systems, focusing on the need for responsible and fair practices in AI. Finally, future directions are suggested, focusing on the need for robust, adaptable, and ethical face recognition systems. This paper aims to provide an important resource for researchers and practitioners in the field of computer vision, providing insight into the technological advances and ongoing challenges in deep learning-based face recognition.

A. Introduction

The technology for recognizing human facial features is called face recognition. Its many benefits include initiative, lack of aggression, and ease of use[1]. Specifically, facial recognition works better than fingerprint, iris, and gait recognition technologies. The process of identifying the input facial image or video is known as facial recognition[1]. Modern biometric systems rely heavily on facial recognition technology, which has rapidly evolved from simple image processing methods to complex artificial intelligence (AI)-based solutions[2]. Essentially, facial recognition uses a person's facial features taken from a photo or video to identify or confirm that person's identity. There are many uses for this technology, from improving security systems to enabling seamless user authentication on various digital devices [3].

Facial recognition technologies are essential for many applications, including security systems and consumer electronics. Using each person's unique biometric characteristics to identify and verify their identity[4]. The incorporation of neural networks has greatly improved the ability of facial recognition systems, allowing them to manage complex real-life situations with changes in lighting, pose, and facial emotions. However, despite these advances, it is still very difficult to recognize faces correctly in low-resolution images or inappropriate settings such as low light and irregular situations[5]. These types of situations are common in surveillance footage or images taken from a distance, where noise and lack of information can significantly impair the effectiveness of facial recognition systems[6].The crux of the problem is how difficult it is to extract and match facial features in situations where they are not clearly defined or where noise or blur effects degrade image quality[1].

With a focus on integrating deep learning-based models, this research seeks to explore the evolution of face recognition technologies.
This paper aims to demonstrate how deep learning can be used to overcome the inherent limitations of traditional face recognition systems, opening the door to more reliable and effective identification processes in an increasingly digital world. This will be achieved through a comprehensive analysis of recent developments and methodologies.

The remainder of this paper is structured as follows: Section B discusses face recognition. Section C discusses the structure of face recognition. Section D discusses the convolutional neural networks. A summary of related works (Literature Review) and related work table are presented in Section E, Discussion ensues in Section F . Finally, in Section G the paper ends with a conclusion.

B. Face Recognition

Facial recognition is a biometric technology that uses patterns based on the characteristics of a person's face to identify or confirm an individual's identity [7]. In this procedure, the face is captured in a photo or video, important aspects of the facial area are extracted - such as the distance between the eyes, the contour of the lips, and the curvature of the cheekbones - and these features are then identified against a database of recognized faces [8][9]. There are many uses for it, such as access control, identity verification in financial transactions, security and monitoring, and access to personal devices [10]. Facial recognition systems process and analyze facial data using advanced algorithms and neural networks, allowing the technology to work accurately even under challenging conditions including changing lighting, poses, and expressions [11].

C. Structure of Face Recognition System

Face detection, preprocessing, feature extraction, and face recognition are the four modern basic steps in building any biometric recognition system [11]. As shown in Figure 1, it helps in the identification and authentication of people [12]. the image is first acquired using a video camera or imported from a database. It then undergoes additional processing at different stages.

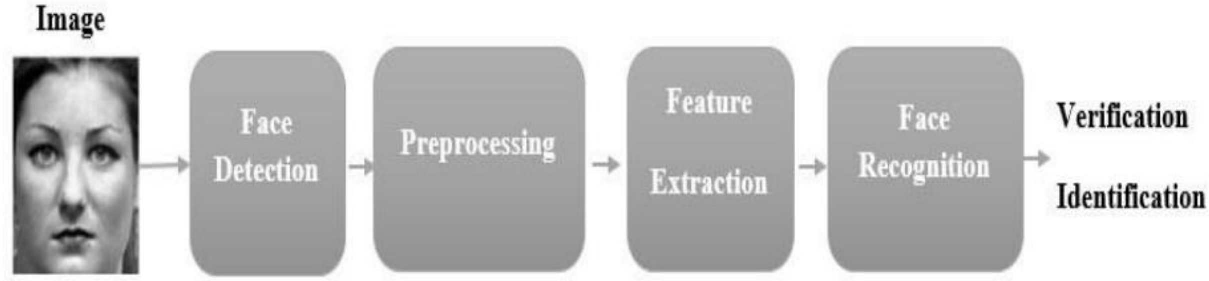

Figure 1. Structure of Face Recognition System [12]

1. Face Detection Phase

The primary task of this stage is believed to be to identify the image of the target face from a captured image or an image selected from a database. In fact, determining whether a given image contains a face image region or not is the primary goal of the face detection procedure [13]. After the target facial region or region of concern has been fully detected and segmented, the output will be sent to a preprocessing stage so that additional developments can be made [14].

. Preprocessing Phase

The three main modules that make up the image preprocessing steps are typically histogram equalization, edge detection, and token matching. These modules are used to enhance image quality and identify the edge point in the digital image and then perform the removal and normalization using pre-defined algorithms[14][15]. All unwanted image effects, such as noise, distortion, blur, shadow, or filters, can be eliminated through pre-processing techniques[16]. This normalizes the image to produce a smooth face image as output, which is then used in the extraction phase [16][17]as shown in Figure 2.

Figure 2. Typical Preprocessing Method[14]

3. Feature Extraction Phase

The selected face image area will be entered in this step. All facial features, including separations between features on the nose, lips, and eyes, will be efficiently retrieved from the facial region through the use of feature extraction algorithms [18]. The primary goals of the feature extraction process are to perform certain tasks, such as saliency extraction, denoising, and information bagging operations [19]. The acquired data is then converted into a vector for use in the next step, which involves comparing the acquired feature with the data that has been stored [20].

4. Face Recognition Phase

This final stage is used to accomplish automatic identification and authentication of people. In order to achieve this, every face recognition system needs a face database containing all the features derived from faces[21]. Multiple images must be collected for each person, and the extracted features must then be kept in this specific database[22].Thus, Figure 3 shows how the feature information extracted from the previous stage will be compared with each face category maintained in the database in order to perform authentication, identify the individual and make the algorithm re-identify[23].

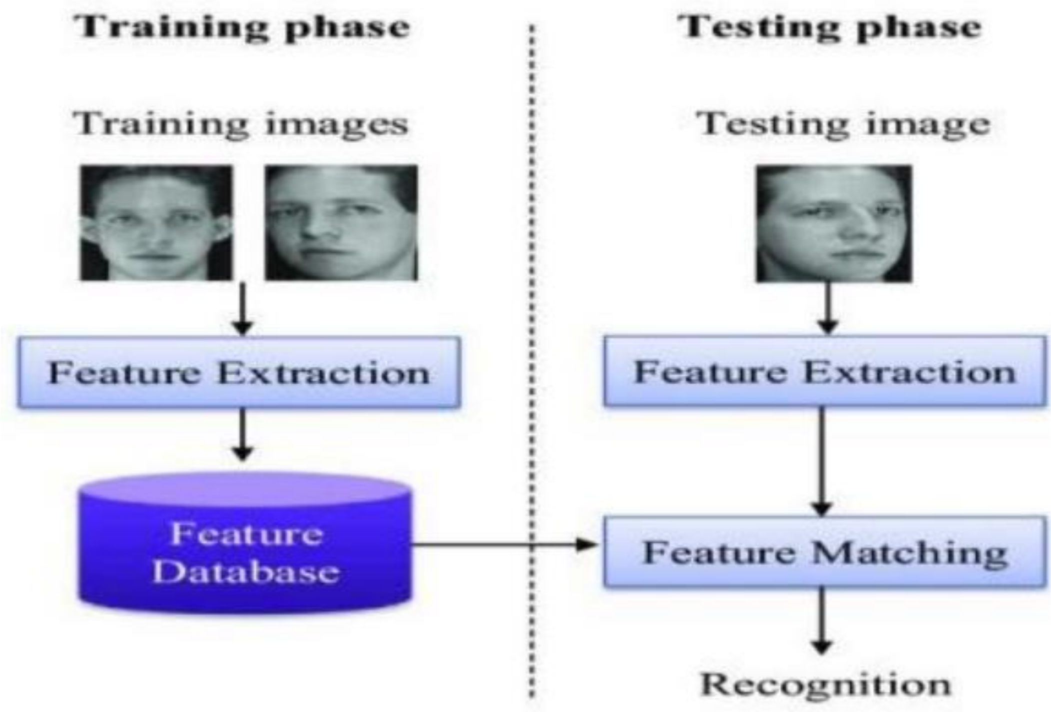

Figure 3. Feature Extraction

D.Convolutional neural networks

Convolutional neural networks are a type of feedforward neural network with deep architecture and convolutional computation and are a major approach in deep learning [24]. The term "translation-invariant artificial neural network" refers to a convolutional neural network, which is also capable of representation learning, continuous translation, and classification of input values based on its distinct capabilities [25]. Weight sharing, space pooling, and local receptive field are the three basic concepts of convolutional neural networks [26]. The size of the local region mapped by a point on the output feature map in the input image is known as the local receptive field [27]. The fundamental basis of weight-sharing theory is the local properties of the spatial correlation between images. The neurons in each image only need to sense the immediate region of the image because the images are locally connected. Space assembly possesses these qualities. Maintain rotation, translation, and expansion constant while cutting parameters significantly [28]. The input layer, convolutional layer, pooling layer, fully connected layer, and output layer make up the majority of the convolutional neural network architecture [29]. Figure 4 depicts the architecture of a convolutional neural network [30].

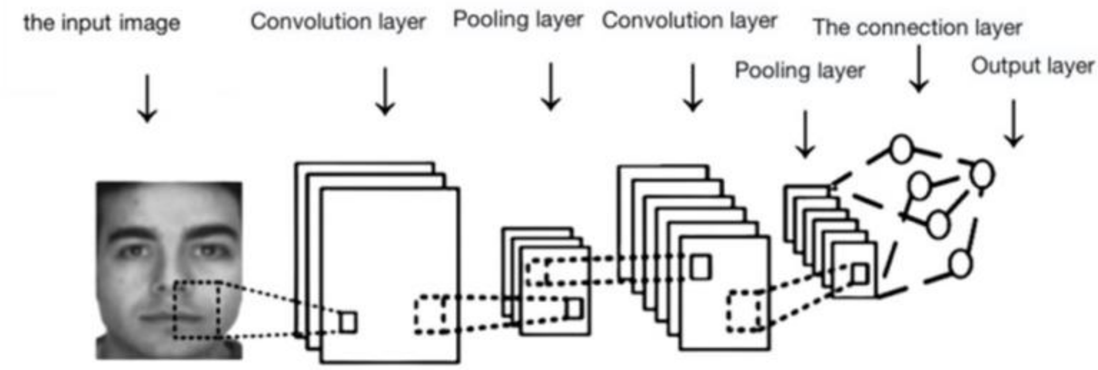

Figure 4. Schematic diagram of convolutional neural network structure [32]

1. Convolution layer

An important function in the entire neural network is performed by the convolutional layer. The input of each node is simply the unit volume of a convolutional box of the neural network from the layer before it, and there is a small block in the convolutional layer known as the set box volume. This convolutional box often measures 3 x 3 or 5 x 5 (usually odd). To extract more abstract features, the convolutional layer will analyze each small component of the neural network in detail[31]. The depth of the node matrix following the convolutional layer will usually increase because the node matrix processed by the convolutional layer will generally become deeper[32].

2.Pooling layer

One way to visualize the clustering procedure is to convert a higher-resolution image to a lower-resolution image; The size of the three-bit array has been reduced, but its depth has not changed. The goal of minimizing parameters throughout the neural network can be achieved via the pooling layer, which further reduces the number of nodes in the final fully connected layer[33].

3.Fully Connected layer

One or two fully connected layers often provide the final classification result of the convolutional neural network after multiple rounds of convolutional layer and pooling layer processing. The original image can be stripped down to an image containing more integrated data after continuous convolution and assembly procedures[34]. Together, convolution and pooling layers can be considered a method for automatically extracting image features in general. Finally, in order to finish the classification, we still need to use the fully linked layer[34][35].

E. Literature Review

In [36], the authors investigated the effectiveness of pre-trained convolutional neural networks (CNNs), namely AlexNet and ResNet-50, in face recognition using transfer learning classifiers and a support vector machine (SVM) to increase accuracy. Their work, conducted on a variety of datasets, showed that CNNs can classify data with a classification accuracy of 94% to 100%, indicating the potential of CNNs in the field of biometric security. The significant advances in face recognition techniques made by CNN architectures are highlighted in this paper.

In [37], the researchers achieved an average recognition rate of 87.5% by developing a face recognition method that combines principal component analysis (PCA) for feature extraction and back propagation neural network (BPNN) for classification. Their approach, which uses facial recognition based on HAR-like features, seeks to simplify the recognition process while providing reliable results in real-time situations. This work improves the accuracy and efficiency of facial recognition systems, advancing the field of biometric security.

In [38], the researchers created a facial recognition system for service robots using CNN, and using the dataset they created themselves, they achieved a high accuracy of 97.63%. This technology demonstrates its suitability for real-world robot interactions by efficiently handling dynamic recognition scenarios. This development improves robotic capabilities for rapid and accurate recognition and detection of human faces.

In [39], the study presented a real-time face recognition system based on a three-layer convolutional neural network (CNN), which achieved an impressive 98.5% accuracy on the University of Essex database. Their technology effectively reduces the recognition process time to less than 0.019 seconds by addressing difficulties caused by differences in lighting, positions, occlusion, and facial emotions. This work establishes a baseline that is on par with the most advanced models currently in use, demonstrating the effectiveness of CNNs in managing complex face recognition tasks in real-time applications.

In [40], the researchers presented a single-stage deep neural network that uses triangular loss and feature pyramids to improve the efficiency of face detection and identification simultaneously. Using the LFW dataset, our new method achieves 212 fps at 640 x 640 resolution and 92.4% accuracy while reducing computational redundancy and memory usage. For real-world uses, the model shows notable gains in recognition accuracy and processing speed.

In [41], the authors aimed to address the shortcomings of traditional algorithms in side view and low-light scenarios by combining ArcFace Loss and a deep residual neural network (ResNet) to create an improved face recognition framework. This new combination dramatically improved accuracy, surpassing previous models and proving the effectiveness of maximizing within-class variation while enhancing between-class discrimination, with an accuracy rate of 97.7% on the LFW dataset. Their study represents a significant development in the field of facial recognition technology.

In [42], the authors created Mixnet, a facial recognition technology that addresses occlusion and angle issues in traditional 2D recognition by combining 2D RGB images with 3D depth maps. Their new method performed better in complex situations, achieving 100% accuracy on the Texas and Bosphorus datasets by incorporating in-depth information. This work highlights the potential of combining 2D and 3D data to improve face recognition accuracy.

In [43], the authors presented a channel-level separable CNN with a dilated convolutional set face recognition model based on deep learning, achieving an accuracy of 97.95% on the LFW dataset. By effectively extracting image features and using SVM and Softmax classifiers to classify images, our method outperforms traditional methods. The software is particularly good at accurately identifying multiple faces in difficult environments, including classrooms where attendance is tracked.

In [44], the writers presented a face recognition system based on convolutional neural networks (CNNs) that achieves noteworthy and accurate results while going beyond traditional eigenface methods. The study used the AT&T face dataset and the Viola-Jones method for face detection, followed by CNN to extract and classify features.

In [45], the study proposed a novel noise-robust low-resolution face recognition algorithm is presented, utilizing a convolutional neural network (CNN) based classification mechanism. The algorithm addresses the challenge of matching low-resolution images with high-resolution gallery images in uncontrolled environments, achieving superior recognition accuracy compared to existing models. Overall, this research significantly advances the field of low-resolution face recognition through innovative algorithms and experimental validation.

In [20], the writers proposed the use of a Convolutional Neural Network (CNN) for face recognition, which has shown an accuracy rate of 97.5%. The paper includes a literature survey on face recognition methods and introduces the CNN approach, which consists of layers such as convolution, rectified linear unit, pooling, and fully connected. The authors also mention the process of face recognition, which involves pre-processing, training, and testing. Overall, the paper highlights the significance of CNN in achieving accurate and reliable face recognition results.

In [46], the authors presented a face recognition technique that increases image contrast by histogram equalization and uses an improved multi-scale convolutional neural network. Their model efficiently combines the retrieved information for classification using a simplified architecture consisting of three convolutional layers, with high accuracy rates of 99.4% on ORL and 98.9% on Yale datasets. This method shows a significant increase in the efficiency of feature extraction and recognition, making it suitable for small datasets and potentially useful in embedded systems.

In [47], the researchers created an autonomous facial recognition access control system with high accuracy and flexibility to changes in lighting and background. The system uses efficient algorithms to overcome computing limitations. Their system, which processed at 5.26 frames per second in real-world scenarios and was 97% accurate on benchmark datasets, used an LBP-AdaBoost architecture for detection and Gaussian derivative filters for recognition. This development emphasizes how the system can be used to provide secure and useful access control solutions.

In [9], the authors used the AlexNet model for feature extraction and classification, and a 25-layer convolutional neural network (CNN) was used to build the face recognition system. Using a dataset of four patients, this method - which included layers including convolution, ReLU, normalization, pooling, and softmax classification achieved 100% accuracy. Their research shows how CNNs, especially deep learning models, can be used to accomplish biometric identification tasks with a high degree of accuracy. This development has a major impact on the field of facial recognition technology.

In [48], the researchers presented a deep convolutional neural network-based face recognition method that produced results on the LFW database with an accuracy of over 97.8%. Their network demonstrated excellent efficiency and utility in intelligent security applications, with its design of 11 convolutional layers and 4 pooling layers. The algorithm's remarkable potential for fast and accurate facial recognition in practical situations is demonstrated by its ability for 1:1 authentication and 1:N recognition.

In [49], the authors improved the accuracy of the LeNet-5 CNN face recognition model to over 98% on ORL and GT datasets by using PReLU activation function and Gabor filter to initialize the initial layer. In addition, the model demonstrated strong performance on the augmented reality dataset for facial occlusion, achieving over 90% accuracy. The issues of low accuracy and slow convergence in traditional CNN training for face recognition are addressed by these improvements.

In [8], the study created a face recognition system for the Raspberry Pi that uses an improved convolutional neural network (CNN) with dropout technology to reduce overfitting and enhance accuracy. Using OpenCV for real-time detection, the system shows over 85% accuracy in face recognition under various scenarios. This portable and affordable method demonstrates how dropout-enhanced CNNs can be used to achieve reliable face recognition in contexts with limited resources.

In [50], the authors described a facial recognition system for virtual currency trading that uses deep learning and a multi-task cascade convolutional network (MTCNN) to overcome obstacles including posture differences and lighting problems. Experiments show that this method extracts facial features from video data with improved accuracy and robustness, superior to traditional face detection techniques. This development provides significant improvements to the security and monitoring of virtual currency transactions.

In [51], the writers created a face recognition method using convolutional neural networks to enhance image recognition. It achieved an accuracy of 98.7% on the LFW dataset and 97.4% on the CUHK Face Sketch database. Their solution significantly outperforms traditional face recognition techniques by employing transfer learning and an adaptive scale local binary pattern extraction method. Security and identification effectiveness are expected to be improved with this innovation for uses such as virtual currency trading.

In [52], the authors enhanced PSNR, SSIM, and AUC metrics of multi-task convolutional neural network (MTCNN) to improve face recognition accuracy under challenging conditions, outperforming faster R-CNN and R-CNN. To generate effective filter box and classification, MTCNN uses cascade networks and works best in settings with large variations in light and complex backgrounds. Facial recognition technology has advanced significantly using this method, providing significant increases in security and resource efficiency.

In [53], the authors focused on addressing the challenge of partial occlusion in face recognition systems. The proposed approach combines a pre-trained deep convolutional neural network with an integrated single-shot multi-box detector. This combination improves the accuracy of recognizing partially occluded faces. The system also incorporates feature pyramids and an image context module to enhance the face detection network's performance. Experimental results show that the proposed method outperforms existing state-of-the-art techniques in detecting and recognizing occluded faces. Overall, this paper provides valuable insights and advancements in improving the effectiveness of face recognition systems.

In [54], the authors created a Siamese Convolutional Neural Network (CNN) using the Kivy framework for facial recognition in mobile applications. Their study used data augmentation to increase the effectiveness of training while solving pose and lighting problems. Their work demonstrates the power of Siamese CNN for biometric authentication in real-world applications, as evidenced by its impressive 98% accuracy on test data.

In [55], the authors unveiled a CNN-based system to improve low-resolution face recognition, focusing on correctly matching high-resolution gallery images with LR probe images despite noise issues. Their method shows higher recognition accuracy on benchmark databases by presenting images in a common feature space and using CNN for classification. This innovation shows great potential for real-time monitoring applications.

In [56], the researchers presented a study on a nine-layer convolutional neural network (CNN) for face recognition. To evaluate the effectiveness of the model under different scenarios, the study uses the LFW dataset as well as additional real-world images acquired. The CNN model shows great accuracy in identifying faces with different lighting and poses due to its multi-layer structure, which includes convolutional and pooled layers. The reliability of CNNs in computer vision tasks has been confirmed by this work, especially in real-time face recognition applications.

In [57], the writers studied how convolutional neural networks (CNNs) improve facial recognition technology, focusing on how well they work in different applications and how their design works. They touch on how high accuracy rates on benchmark datasets show that CNNs are successful at overcoming basic recognition hurdles such as pose and illumination fluctuations. This work demonstrates how CNN-based algorithms can be used to solve real-world face recognition problems, and they are always improving.

In [58], the researchers created an optimized neural network algorithm (ONNA) that combines robust principal component analysis (RPCA) for feature extraction with a weight transfer ideal filter (WTIF) for preprocessing to improve face recognition in different lighting conditions. When tested on the Extended Yale B and CMU-PIE datasets, its technique showed better accuracy and lower error rates than classical SVM and RF algorithms. This new method greatly enhances recognition ability in difficult lighting conditions.

In [59], the study presented two face recognition techniques based on convolutional neural networks to improve accuracy in difficult situations. In the first, overfitting is prevented by a combination of convolution, pooling, Softmax classification, and dropout; In the second, a dual-symmetric LetNet architecture with DCT-LBP processing is used. These techniques outperform traditional models, indicating advances in neural network face recognition applications.

In [60], the authors created a facial recognition technique using DCNN that can handle position changes and maintain high-resolution images without requiring significant downscaling. With an F1 score of 98.53% and an accuracy of 98.67% in the FEI database, their method shows significant improvements over previous approaches. The model works well with limited data sets and recognizes faces in poses up to 180 degrees. This invention has greatly helped the development of biometric identification technology.

In [61], the authors achieved an accuracy rate of 94.5% in face recognition using the Genetic Algorithm (GA) to improve the Convolutional Neural Network (CNN). Their approach significantly improved model performance on a dataset of ninety subjects by automating the fine-tuning of CNN hyperparameters such as filter size and number of filters. The GA-CNN model showed superior performance compared to traditional CNN models, indicating the possibility of integrating evolutionary and deep learning algorithms for complex problems such as face recognition.

In [62], the authors created the AB-FR model, a convolutional neural network-based face recognition system incorporating BiLSTM and attention mechanism, with the aim of increasing accuracy under different conditions. The model performs extremely well, with accuracy rates of up to 99.35% across many datasets, by combining channel-specific information with capturing the temporal dynamics of facial features. This method emphasizes the usefulness of facial recognition technology in difficult situations, representing a major breakthrough in this field.

Related Work Table Summary

Authors, year	**Dataset**	**Methodology**	**Advantage**	**Disadvantage**	**Accuracy**
Almabdy et. al.,2019 [36]	ORL, GTAV, Georgia Tech, FEI, LFW, F_LFW, YTF, DB_Collection	AlexNet with SVM, ResNet-50 with SVM, Transfer Learning AlexNet	High accuracy, effective transfer learning	Potential overfitting, high computational demand	94%-100% across datasets
Sugandi et al., 2019 [37]	5 face images, each taken 100 times; a total 500 images for training	Haar, PCA, BPNN	Reliable, effective, and real-time	Difficulties with lighting and rapid movement	87.5% average recognition rate
Tao et al., 2019 [38]	22 people, 100 images each	CNN, Haar cascade, image optimization	Real-time, efficient, and memory-light	Sensitive to motion and light	97.63% test set accuracy
Yadav et al., 2019 [39]	Essex University, 115 subjects, 20 images each	3-layer CNN, ReLU, Max Pooling	High accuracy and instant processing	Concerns about scalability and flexibility	98.5% accuracy, <0.019 seconds per recognition
Mahmood &Babaei., 2019 [40]	ORL, CTK	SIFT, Neural Network, Kepenekci	Robust for image changes	Unmet computational demand	80.71%-92.2%

Zhenzhou & Ding., 2019 [41]	CAS-PEAL, LFW, ORL	Enhanced ResNet, ArcFace Loss	High resolution and depth degradation have been addressed	Complex two-step training procedures	97.7% on LFW
Zhang et al., 2020 [42]	Texas, Bosphorus	Mixnet, 2D/3D fusion	Overcomes clogging and corner problems	Challenges in collecting 3D data	100% accuracy.
Vijay M et al., 2020 [43]	LFW	Channel-wise separable CNN, SVM, Softmax	Superior precision and efficient handling	Significant computational resources are required.	97.95% accuracy
Shrestha &Panday., 2020 [44]	AT&T Faces	Viola-Jones, shallow CNN	Clearer model with high accuracy	Constrained by shallow mesh depth	Recall 0.992, precision 99.4%
Rajput & Arya., 2020[45]	CMU PIE, Yale-B	CNN classification	Effective in situations with limited accuracy	Potential level of computational complexity	Best AUC 97.56%, highest PSNR, SSIM
Swapna et al., 2020[20]	ORL faces	Proposed CNN	High rate of recognition	Potential need for computing power	97.5% accuracy
Liu et al., 2020 [46]	ORL, Yale	Improved multiscale CNN	Simple structure, excellent precision, and efficiency	It may perform worse on larger data sets	99.4% ORL, 98.9% Yale
Lee et al., 2020 [47]	E-face, XM2VTS, indoor	LBP-AdaBoost, Gaussian filters	Reliable for lighting and easy to use	Potential difficulties in measurement	97.27%-99.06% accuracy
Borra et al., 2020 [9]	Custom (4 subjects)	CNN (AlexNet)	Excellent accuracy and efficient complexity management	Training speed limitations in MATLAB	100%
Xu et al., 2020 [48]	CASIA-WebFace, LTW	CNN with 11 convolutional layers, 4 pooling layers	High accuracy and effectiveness	Complexity and resource intensity of training	>97.8% on LTW
Dai et al., 2020[49]	ORL, GT, AR with occlusion	Gabor-LeNet CNN, PReLU activation	Clogging-resistant and highly accurate	Unsolved arithmetic and generalization problems	>98% on ORL, GT; >90% on AR
Ning et al., 2021 [8]	ORL, WIDER FACE	Improved CNN, Raspberry Pi	Affordable, portable	Processing restrictions	>85% for static and dynamic images

Wei, 2021 [51]	Wider_face, CelebA, AR	MTCNN, KPCANet, weighted voting	Flexibility in occlusion and expressions	Insatiable computational requirements	>95.6% detection, high recognition
Fan et al., 2021[52]	LFW, CUFS	Adaptive scale LBP, transfer learning	High productivity and effective transfer of learning	Computational complexity and unresolved adaptability issues	98.7% LFW, 97.4% CUFS
Ge et al., 2021[53]	50 faces	MTCNN vs. R-CNN, Faster R-CNN	Improved facial recognition that corrects blemishes	Unresolved computational and scalability issues	Best AUC 97.56%, highest PSNR, SSIM
Tsai et al., 2021[54]	CelebA, UID, LFW	SSHD, CNN, feature pyramids	Efficient polyhedron identification	Unprocessed computational scalability	212 FPS, 92.4% LFW
Aufar et al., 2022[55]	Custom, LFW, CUFS	Siamese CNN, data augmentation	Effective for all facial types, mobile implementation	Unmet computational requirements and generalization	98.7% LFW, 97.4% CUFS
Mirghani et al., 2022[50]	FDDB, AFW, PASCAL, ORL, Yale-B	CNN reviews for face recognition	Excellent accuracy and adaptability	Resource intensive, difficult to adapt	Varied; some near 100%
Liu, 2022[56]	LFW	9-layer CNN	Effective and accurate identification	Possibility of data loss	>90%
Liyakat et al., 2022[57]	Yale Face Database	PCA and Feed Forward Neural Network	Works well with glasses in a variety of positions	Only able to recognize faces facing the camera	Up to 96%
Lakshmi et al., 2022[58]	Yale-B, CMU-PIE	ONNA, WTIF, RPCA	Improved accuracy in a variety of lighting conditions	Unprocessed arithmetic density	0.95 Yale-B, 0.97 CMU-PIE
Huang, 2022 [59]	AR face database	Enhanced CNN, DCT-LBP	Increased accuracy and effectiveness	Unaddressed computational complexity	Up to 98.43% recognition
Abdulameer et al., 2023[60]	FEI face database	Convolutional Neural Network (CNN)	Excellent accuracy with a small data set	Layers increase in complexity.	Best accuracy of 98.67%, F1_score of 98.53%
Karlupia et al., 2023[61]	Robotics Lab (90 subjects)	GA-CNN	Efficient adjustment of hyperparameters	High computation cost	94.50%

Qi et al., 2023[62]	CASIA-FaceV5, LFW, MTFL, CNBC, ORL	AB-FR model, CNN with BiLSTM, attention	High accuracy and flexibility for various conditions	Increase in calculation complexity	96.46%-99.35% across dataset

F. Discussion

The face recognition technology landscape has witnessed significant evolution, marked by a move from traditional models such as Haar cascades and principal component analysis (PCA) to more sophisticated deep learning methods such as convolutional neural networks (CNNs), modifications of ResNet with SVM (support vector machines) and AlexNet. These advances have pushed the field forward, achieving remarkable levels of accuracy across a wide range of datasets, including ORL, LFW (Featured Faces in the Wild), Georgia Tech, the University of Essex, and others. A notable trend is the focus on overcoming specific challenges such as occlusion, motion, illumination variability, and computational demand. For example, [49]a study using a Gabor-LeNet CNN model demonstrated resilience against occlusion at high accuracy rates on datasets with occlusion. This is in keeping with the industry's general quest for models that can operate effectively under diverse and less-than-ideal conditions. Despite these successes, the studies reviewed indicate a continuing struggle with balancing accuracy, computational efficiency, and generalizability. Models that achieve high accuracy rates, such as a 100% recognition rate by [42]through Mixnet 2D/3D fusion, often face significant computational requirements or data collection challenges. This highlights a critical area for future research: developing models that maintain high accuracy while also being computationally efficient and able to generalize across diverse conditions. Furthermore, the emergence of transfer learning and data augmentation techniques, as observed in works [36], respectively, indicates a growing recognition of the value of leveraging pre-existing models and synthetically expanded datasets to enhance model performance. In conclusion, the field of facial recognition technology is advancing rapidly, driven by deep learning innovations that offer promising solutions to historical challenges. However, the trade-off between accuracy, computational efficiency, and adaptability remains a pivotal focus. Future research directions may include exploring lightweight models that do not compromise accuracy or exploring new datasets that challenge existing models to adapt to unprecedented real-world conditions.

G. Conclusion

As we summarize the developments in face recognition supported by deep learning technologies, especially convolutional neural networks (CNNs), it is clear that the landscape has changed profoundly. These developments have not only enhanced accuracy and efficiency, but also expanded the applicability of facial recognition across various sectors, including security, authentication, and personalized user experiences. Despite these advances, the technology faces notable challenges such as computational requirements, scalability, and the ability to adapt to real-world variations in lighting, pose, and expression. Furthermore, ethical considerations surrounding privacy, data security, and potential biases embedded in AI algorithms highlight the need for a balanced approach toward innovation and implementation. Looking to the future, the path to further innovation in facial recognition technologies is to address these challenges through research focused on improving deep learning models to achieve greater efficiency and ethical integrity. Emphasizing the development of ethically conscious and computationally sustainable models will ensure the continued relevance and acceptance of facial recognition technologies in our increasingly digital world. The next phase of progress will likely be characterized by efforts to align technical excellence with ethical responsibility, steering the future of facial recognition toward a safer and more equitable horizon.

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