[Journal of Soft Computing and Computer Applications](https://jscca.uotechnology.edu.iq/jscca)

Volume 2 | Issue 1 Article 1017

2025

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Recommended Citation

Razoqi, Zahraa Naji; Ogla, Raheem; and Rahma, Abdul Monem S. (2025) "Modern Face Recgognition Systems: A Review of Methods and Empirical Findings," *Journal of Soft Computing and Computer Applications*: Vol. 2: Iss. 1, Article 1017.
DOI: https://doi.org/10.70403/3008-1084.1017

REVIEW

Modern Face Recgognition Systems: A Review of Methods and Empirical Findings

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ABSTRACT

The face recognition system is a biometric technique that replaces traditional passwords and personal identification. This research is dedicated to presenting a study of some facial recognition systems. Since it is unlikely to replicate and is more stable over time, the domain of facial feature extraction has proven to be more effective in attaining exact facial recognition, which is important, especially in intelligent security surveillance systems. Face recognition systems encounter several challenges, primarily related to pose variations, illumination conditions, and occlusions such as hair, glasses, and so on. To address these challenges, enhance performance, and boost the accuracy and speed of identification, a wide range of mechanisms were developed to carry out the face recognition function, which converts the face image into a digital feature that allows for effective comparison and storage. This survey highlights more than 25 face recognition systems. The review analyzed the systems based on performance metrics, classifier efficiency, and feature extraction techniques, as well as their strengths, weaknesses, and suitability for real-time applications. It also described the most popular databases used to test the performance of face recognition systems. Additionally, recommendations for future research directions in face recognition have been offered.

Keywords: Biometric identification, Face feature extraction, Face recognition, Face detection

1. Introduction

Biometric measures refer to physical and behavioral characteristics employed for discriminating individuals. These measures include unique traits, such as fingerprints, facial features, iris patterns, voiceprints, and even gait recognition. Biometric systems are an

Received 24 April 2024; revised 4 April 2025; accepted 7 April 2025.
Available online 14 June 2025

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https://doi.org/10.70403/3008-1084.1017

effective security solution in scenarios where properties cannot be replicated, stolen, misplaced, or forgotten. Since these measures rely on behavioral and physical characteristics to identify and differentiate individuals, there is an increased reliance on biometrics for identification systems, which are considered more reliable and intelligent by leveraging inherent human characteristics. These systems not only enhance security but also improve convenience, as users do not need to remember complex passwords or carry identification tokens [1, 2].

Among all biometric features, the human face is the most important for social interactions because it is the main point of attention. It helps express both identity and emotions. People can recognize thousands of faces in their lifetime, even after years of not seeing someone. This ability remains strong despite changes in appearance due to aging, facial expressions, lighting, or accessories like glasses, beards, or different hairstyles. Making facial recognition technology more reliable in these situations improves accuracy, thereby becoming beneficial for security, law enforcement, unlocking phones, and online banking [3, 4].

There are many challenges in face recognition systems which can be summarized as follows:

a. Posture and lighting: Face recognition accuracy diminishes when individuals modify their posture or change the lighting environment because these factors create contrasting light effects on their appearance. The creation of a 3D face model using frontal images obtained from multiple positions then normalization functions together with deep learning applications are used to address lighting inconsistencies [5].
b. Occlusions: Some facial attributes become partially hidden by occlusions which include glasses along with masks as well as hats and hair. The solution to this issue involves implementing training methodologies that identify visible surface features [6].
c. Expression Variations: The modification of expression makes identification more challenging because facial key features shift in appearance. A solution requires developing models with stable performance under diverse changes and using datasets with extensive expression variations [7].
d. Privacy: The privacy of users becomes an issue when they are uncertain about how their facial data is handled and protected. User privacy needs protection against security threats which must also maintain identification accuracy and guarantee secure storage and data transmission for biometric information [8].
e. Bias: Biased datasets create incorrect recognition outcomes as they induce inaccuracies in the identification procedure. Different datasets are employed during training so the system can accurately identify members of various populations [9].

This paper contributes to the field of face recognition systems by explaining the general face recognition process and the essential stages for understanding the intricate details of various face recognition techniques. Also, it highlights the main challenges that these systems encounter and provides a comprehensive comparison of each system, which, in turn, can help to improve the robustness of face recognition systems.

The remainder of this paper is structured as follows: Section 2 explains the general face recognition system. Section 3 describes common face datasets. Section 4 presents various face recognition systems, while Section 5 provides a discussion of these systems. Finally, Section 6 summarizes the conclusions along with recommendations for future work.

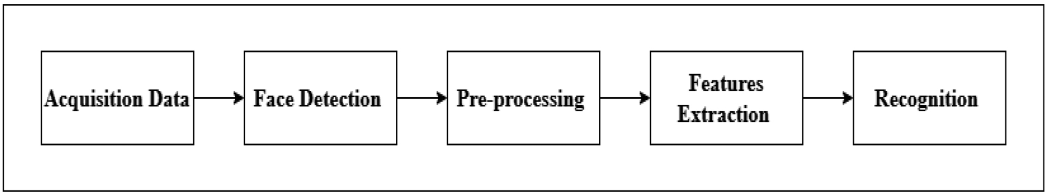

Fig. 1. Face recognition tasks [16].

2. Generic face recognition system

Fig. 1 illustrates the algorithm flow regarding the face recognition tasks. Generally speaking, face recognition and the recognition of moving persons in natural environments need a set of visual tasks to be performed robustly [10]. Those tasks comprise:

a. Acquisition data: The quality of the captured images, whether photo, video, or life-stream, depends on choosing the right sensor from existing sensors. The sensor should offer comfort and an intuitive interface to facilitate quick user adaptation, thereby collecting high-quality face samples from the person. Additionally, it could be designed to be self-contained and capable of autonomously performing the entire biometric verification process [11].
b. Face detection and tracking of these image patches in dynamic scenes to thoroughly examine the picture, and identify the existence of faces in the image. These steps are crucial as they extract pertinent data while filtering out irrelevant information, thus ensuring accurate biometric analysis [12].
c. Pre-processing including alignment, segmentation, and normalization regarding the face image entails separating the image or signal of interest from the background. A failure to segment indicates that the system cannot identify the existence of the relevant biometric feature in the face image [13].
d. Features extraction is the process of extracting relevant and eminent features from a face pattern using any method. The resultant representation is utilized as an input in recognition, which primarily affects the matching process's output. This process creates a template that could be stored in a database and is crucial to recognition systems [14].
e. Recognition of the modeling and representation regarding identified face images and the relation of identified face images with known models, from which an inference about the subject's identity is drawn based on the degree of matching [15].

3. Face recognition datasets

In face recognition systems, face datasets are essential for training, testing, and performance comparison. These datasets typically include diverse facial images collected under varying conditions to ensure the system can generalize well. Below are some popular face dataset commonly used in face recognition research:

a. **Labeled Faces in the Wild (LFW):** LFW contains over 13,000 images of faces collected from the web, with variations in lighting, pose, and expressions. LFW is widely used for performance measurement but is considered obsolete for modern Deep Learning (DL) models due to limited diversity and quality [17].

b. **Aleix and Robert (AR) Face Database:** Contains over 4,000 images of 126 people with control over lighting, expression, and occlusion variations. Although the AR face database is small in size, it is valuable for studying specific challenges in face recognition [18].
c. **Chinese Academy of Sciences (CASIA-WebFace):** A large-scale dataset of over 10,000 identities and 500,000 face images. CASIA-WebFace is challenging due to the differences in pose, expression, and occlusion, making it suitable for deep-learning research [19].
d. **Olivetti Research Laboratory (ORL) Dataset:** Contains 400 grayscale images of 40 individuals, with 10 images for each person. The variety of poses, expressions, and lighting makes it ideal for traditional methods. While too small for modern DL models, it is still suitable for testing new algorithms. [20].
e. **Yale Face Dataset:** The original Yale dataset includes 165 grayscale images of 15 individuals. Extended versions (Yale B and Extended Yale B) have 38 individuals with controlled lighting variations. Yale datasets are excellent for evaluating robustness against illumination changes. Limited diversity and scale make them unsuitable for training deep neural networks [21].
f. **Faces94:** Includes images of 153 individuals with neutral expressions, captured under consistent conditions. Separate versions include female, male, and children subsets. Faces94 is popular for educational purposes and small-scale experiments. Its controlled setup lacks the diversity required for real-world applications [22].
g. **Controlled Access Research Laboratory (CARL) Dataset:** Designed for studying biometric systems. CARL includes face images with various occlusions and controlled environmental conditions. It is often used for developing robust systems but lacks variability in environmental conditions [23].
h. **DroneFace:** A dataset captured using drones, containing face images from aerial perspectives. Features include varying distances, angles, and environmental conditions. DroneFace addresses challenges like low resolution, extreme angles, and motion blur. It is valuable for surveillance applications but requires high computational resources for processing [24].

4. Literature review

Although people recognize faces well, the exact process of how the human brain encodes or decodes a face is still limited. Since faces are intricate, multi-dimensional visual inputs, creating a computational model for face identification is very challenging. Thus, face recognition represents a highly advanced computer vision task [25]. The following briefly explains some of the methods of face recognition systems:

Okumura et al. [26] proposed a system for identity-verification face recognition to enhance the security and efficiency of verifying ticket holders at large-scale events. This system carries out face recognition after the attendant's check-in using their membership cards. This includes ensuring that attendees face the camera directly and have their eyes open during the photo capture process. The system captures two images of each attendee with a brief interval to increase the likelihood of obtaining a clear photo. The system achieved 93% face recognition accuracy and reduced the average verification time to 2.7 seconds per person during a trial with 1,547 attendees.

The verification system described by Rozner et al. [27] depended on a basic neural model for face authentication. Researchers developed a method where assigning individual neural networks to each user leads to lower model complexity and less needed parameters thus producing accurate results on different datasets. The authors presented K-means Centered Sampling (KCS) as a new method for hard negative mining, allowing the model to create feature-based clusters to learn more distinctive characteristics.

Zhang et al. established a system which integrates remote sensing detection of biometric information through a framework [28]. The new detection approach unifies gait signals with facial picture data to establish better methods for accuracy improvement alongside robustness enhancement. The signals become integrated before transmission for further processing and then subsequent remote identification. The detection experiment achieved a precision rate of 95.2% according to the experimental findings.

Ismael et al. established a real-time face recognition solution that operated using deep learning techniques. The recognition of digital images relied on a Histogram of Oriented Gradients (HOG) for facial identification. The process estimated customized facial landmarks for building five facial sections which were subsequently sent to a trained face processing model. The system generated 128 embeddings, which enabled the Support Vector Machine (SVM) to identify which face appeared in the image.

Chauhan et al. [30] developed a face recognition system which employs deep learning methods in an IoT-based cloud platform. This system utilizes a deep learning technology built on tree structures for face recognition. The design of this model ensures high operational efficiency in cloud environments. The feature extraction process uses a combination of single and parallel trees functionally. This structure efficiently displays facial characteristics while running operations at optimal speeds.

Boutros et al. [31] developed a face recognition system which relied on ElasticFace loss functionality. The system resolves the drawbacks present in current margin-based losses, such as ArcFace and CosFace to improve face recognition model efficiency. The ElasticFace loss is tested through the implementation of deep neural networks that use ResNet-100 architectures. Facial recognition infrastructure nowadays widely utilizes this design architecture.

George et al. [32] developed a face recognition network which borrowed its principles from EdgeFace and its dual-model structure of EdgeNeXt. ElasticFace network implements a lightweight design which enables successful implementation on mobile devices along with embedded systems. The low-rank linear layer inside EdgeFace helps decrease both computational expenses and storage space requirements.

Vu et al. [33] introduced a face recognition technique which combines deep learning methods with Local Binary Patterns (LBP) technology. A RetinaFace model performs multi-task learning of face detection as it incorporates Euclidean-distance-based loss and triplet loss functions to optimize feature extraction processes. LBP serves as a technique to extract unique features from chosen areas of scanned images.

Opanasenko et al. [34] developed a face recognition system that operates across several recognition levels to handle situations with partial face obstruction. Under this framework, a face provides distinctive features including eyes, nose, and mouth which operate at different levels of detail. The recognition system develops a full-face depiction by bringing together different extracted features. A local classifier model operated by the system uses combination methods to generate effective results for facial recognition duties.

A face recognition method designed for mobile devices was proposed by Opanasenko et al. [35]. The basic algorithm splits into two core components which include a recognition operator together with a decision rule. The recognition operator determines distance measurements for tested objects relative to different classes and the decision rule applies these measurements to identify objects. The recognizing operators collection organizes as a structured linear polynomial framework and specialists use multiparameter optimization methods to enhance its parameters.

Pecolt et al. [36] outlined a facial recognition system utilizing a Haar cascade classifier and the AdaBoost machine learning algorithm. The system leverages characteristic facial measurable features used to identify and differentiate faces within images. The average recognition time was 10.5 seconds.

Chakraborty et al. [37] presented a system for face recognition to automate the process of marking attendance in educational settings. This system uses Local Binary Patterns Histograms (LBPH) to capture local features of the face, and a Principal Component Analysis (PCA) for the data dimensionality reduction while preserving as much variance as possible. Artificial Neural Networks (ANN) are used to classify the extracted features.

Hamandi et al. [38] introduced a method for face recognition based on mixed of shape moment invariants in both thermal and visible vision. The Affine, Hu, and Zernike moments equations are calculated for each training image, including thermal and grey. Then, Sequential Forward Feature Selection (SFFS) is performed to find the best combination of features that gives the highest result. ANN is used as a classification model. Using two datasets, the performance of each moment descriptor on images is evaluated.

Sharma and Jethani [39] proposed a system for face recognition. This system used the PCA method for feature extraction. The PCA starts by selecting the most important eigenvalues from the images after converting them into a 1D vector, and then projecting all images to the PCA space.

Hamandi et al. [40] presented a method that uses three different techniques of moment invariance: algebraic affine moments, geometric Hu moments, and orthogonal moments. These techniques are used to extract features from various parts of the face, such as images of the left and right eyes, face, mouth, and nose. The best feature subsets are chosen with the highest accuracy by using the SFFS method. SFFS calculation uses a bottom-up approach, starting with an empty list and gradually adding features based on an evaluation process to minimize the Mean Squared Error (MSE). A feed-forward neural network is trained using selected features, categorizing identified faces into one of the fundamental faces within the database.

Hu et al. [41] suggested a technique for mapping cross-modal images to the subspace of VISual (VIS) neutral face based on Dual Face Alignment Learning (DFAL). The DFAL involves three parts: Feature-level Face Alignment (FFA), Image-level Face Alignment (IFA), and Cross-domain compact Representation (CdR). This technique has proven effective when tested on challenging databases.

Ogla et al. [42] proposed a hybrid face recognition system that deploys invariant moments and LBPs. Through the combination of LBPs with the Histogram Oriented Gradient (HOG) descriptor histograms, it becomes possible for the effective extraction of the features. The method calculated various important parameters, including first-order moments, normalized central moments, and central moments. Those parameters were utilized as classifiers and descriptors to identify faces in images.

Obaida et al. [43] presented a real-time face detection system from digital video. The Viola-Jones method is utilized to extract human faces. Witnesses' images need to be captured from various angles to train the CNN classifier. This classifier will then be utilized to detect the witness's face. The Kanade-Lucas-Tomasi (KLT) algorithm is employed to track the witness's face in various video frames.

Abusham et al. [44] introduced a secure face recognition system based on encryption. The encryption is performed on dataset images using XOR operation and Cellular Automata (CA), and then the feature is extracted from the encrypted image using LDA. The random forest method is employed for classification in this work.

Nanduri and Chellappa [45] developed a face recognition system based on semi-supervised cross-spectral in the context of very small training datasets using large pre-trained models. This technique allows the model to leverage both labeled and unlabeled data during training. The training process incorporates two specific loss functions: the first is crystal loss, which is applied to the labeled source and target data, helping to refine the model's predictions based on the available labeled examples. The second is the entropy loss, which is used on the unlabeled data, where the classifier aims to maximize the entropy, while the feature extractor minimizes it.

Ahmed and Halil [46] established a model for face recognition based on the Indepthnet19 architecture with 64 filters. Data transformation and augmentation address challenges in online training data. SVM was used for classification tasks and enhanced performance in real-time. The system performance was evaluated using four datasets.

Mohsen et al. [47] outlined a technique to enhance Unmanned Aerial Vehicle (UAV) capabilities for face detection and recognition. Face detection localizes faces using a deep CNN model for recognition. Convolutional layers extract features from images using multiple filters.

Mahmoud et al. [48] presented a system that utilizes face recognition to monitor attendance. The system integrates Multi-Task Cascaded Convolutional Neural Networks (MTCNN) for face detection, Visual Geometry Group Face (VGGFace) for feature extraction, and SVM for classification.

Shivalila et al. [49] proposed a technique to detect and recognize faces based on the face mesh. The dataset of Labeled Wild Face (LWF) is used to train the deep neural network. This technique can also handle non-frontal images of faces of all ages and races.

Sefik and Alper [50] introduced a lightweight hybrid framework for face recognition that integrates various state-of-the-art models, allowing for flexibility in switching between them during the recognition process. This framework consists of four stages: detect, align, represent, and verify, which are handled in the background.

Landry et al. [51] propose a Thermal to RGB Generative Adversarial Network (TRGAN) to automatically synthesize face images captured in the thermal domain, to their RGB counterparts, to improve cross-modal facial recognition.

5. Discussion

Table 1 shows the comparison of different feature extraction techniques, classifiers, and recognition rates for different face datasets:

As seen in Table 1, the recognition system based on face features can get a high rate for person identification and verification processes. Some of the researchers resorted to using more than one method for feature extraction, such as Moments and SFFS in [40], and LBP and HOG in [42]. Although this approach can improve the recognition rate by combining the advantages of different techniques and capturing more information from the face image, this leads to high computation costs to train and recognize for these systems.

Table 2 shows the comparison of the main strengths and weaknesses of each work, whether the model is suitable for real-time applications or not, and whether the technique is traditional, machine learning, deep learning methods, or hybrid.

As shown in Table 2, DL, especially through the use of CNNs and transformer techniques, has advanced the field of face recognition. CNNs provide a basis for hierarchical feature extraction and handling variations, while transformers provide powerful attention and contextual understanding mechanisms. Together, these play a main role in highly achieving performance and more secure systems by learning robust and discriminative features from the face image to get high performance for the different steps of biometric systems like pre-processing, feature extraction, as well as classification.

Table 1. Recognition rate comparison.

Ref.	Method	Classifier	Dataset	Recognition Rate(%)
[29]	HOG and CNN	SVM	Polytechnic University PolyU	96.88
[30]	tree-based approach	residual function	ORL, FEI, and LFW	98.65%, 99.19%, and 95.84
[31]	DNN	softmax	Microsoft 1Million Version2 (MS1MV2)	98.73
[32]	DNN	EdgeNeXt	LFW, Intelligence Janus Benchmark (IJB)-B, and IJB-C	99.73, 92.6, and 94.85
[33]	deep ensemble model and LBP	Not available	Essex dataset and special dataset	98 and 87
[34]	ANN	Neural Network, Bayesian, and Log-Linear	Face Recognition Technology (FERET)	97.3, 94.5, and 95.4
[35]	Algorithms for Calculating Estimates (ACE)	Not available	ORL and Laboratory Data Processing Systems (LABDPS)	93.57, 89.28, 95.31, and 91.43
[36]	Haar-like features	AdaBoost	Special dataset	Not available
[37]	LBPH and PCA	ANN	Yale dataset	90
[38]	Moment Shape Descriptors	ANN	CARL and Imaging, Robotics, and Intelligent System (IRIS)	98.1 and 81.2 for thermal and grey images
[39]	PCA	Manhattan distance	Special dataset	Not available
[40]	Moment and SFFS	Feed-forward Neural Network (FNN)	CARL	99.92
[41]	DFAL	Student Encoder (StEn)-CNNs	CASIA Near Infra-Red VISual (NIR-VIS) 2.0, Oulu-CASIA NIR-VIS, and Beihang University of Aeronautics and Astronautics (BUAA) NIR-VIS	99.1, 100, and 100
[42]	LBP and HOG	Moments	ORL	98.78
[43]	Viola-Jones supported by CNN	CNN	Special dataset	99.5
[44]	LDA	LDA with random forest	ORL	96.25
[45]	Semi-supervised learning	DNN	Intelligence Advanced Research Projects Activity (IARPA) Janus Benchmark Multi-domain Face dataset	96.84
[46]	CNN	SVM	Face94, Face95, Face96, and Grimace.	100, 99.86, 99.54, and 100
[47]	CNN	full connection layer	DroneFace	100
[48]	VGGFace	SVM	Special dataset	95
[49]	Viola-Jones and computing the Haar value.	Face mesh	LWF	94.23
[50]	FaceNet, VGG-Face, OpenFace, and DeepFace	CNN	Wild dataset	98.57
[51]	VGG-Face	TR-GAN	TUFTS	88.65

Table 2. Comparison of the strengths and weaknesses points.

Ref.	Strength	Weakness	Real-time	Techniques
[26]	• High Accuracy. • Effective in real-world scenarios.	• The system's performance heavily relies on obtaining clear facial images.	Yes	Deep Learning (DL)
[27]	• The reduction in model computational requirements makes the approach suitable for deployment on resource-constrained devices. • The use of KCS for hard negative mining is a novel contribution that enhances the model's ability to learn from challenging examples.	• Complexity in Implementation. • The use of personalized models for each user could lead to overfitting.	Yes	DL
[28]	• The system achieves a high detection accuracy of 95.2% with increasing training data. • Remote sensing capability.	• The complexity of the system may increase with multiple biometrics. • The use of biometric data in remote sensing raises privacy issues.	Yes	Hybrid
[29]	• High performance. • Better alignment of facial features.	• Complex to implement and requires significant computational resources.	Yes	Hybrid
[30]	• High accuracy in face recognition tasks.	• The accuracy of the recognition is significantly influenced by the number of training images per individual. • Complexity in implementation.	No	DL
[31]	• Effectiveness and robustness in real-world scenarios. • An elastic margin loss is an advancement over traditional fixed-margin methods.	• The effectiveness of the ElasticFace loss may be contingent on the availability of large-scale datasets for training.	No	DL
[32]	• The EdgeFace lightweight design makes it particularly well-suited for deployment in resource-constrained environments.	• The performance may be heavily reliant on the quality and diversity of the input images.	Yes	DL
[33]	• Effective feature extraction and classification. • High accuracy.	• Focusing on the eyebrows and forehead is beneficial, it may overlook other important facial features.	No	Hybrid
[34]	• This technique used feature reduction, improving the speed and performance of the neural network. • The system overcomes limitations associated with partial occlusion, leading to higher accuracy and reliability.	• Complexity in implementation. • The effectiveness of the system may be influenced by the quality of the biometric data collected.	Yes	DL
[35]	• The ability to function under various conditions. • High recognition accuracy.	• Requires significant computational resources.	No	Machine learning
[36]	• High performance. • Effective in various scenarios.	• Complexity in implementation. • The performance may be heavily reliant on the quality and diversity of the input images.	No	Machine learning
[37]	• Ease to use. • The system can recognize individuals quickly.	• An unauthorized person may use a photo or video to gain access. • System performance is affected by factors such as lighting, orientation, and distance from the camera.	Yes	Hybrid

(Continued)

Table 2. Continued.

Ref.	Strength	Weakness	Real-time	Techniques
[38]	• High accuracy in face identification. • Extracting robust facial features.	• Require significant processing time. • Complexity of feature selection.	No	Hybrid
[39]	• Strong performance in identifying faces accurately.	• Complexity in implementation. • The varying image sizes and quality affect the accuracy of recognition.	Yes	Hybrid
[40]	• Robust facial feature extraction. • High recognition accuracy.	• Challenges in real-world applications due to different conditions.	No	Hybrid
[41]	• The method was tested on multiple challenging databases, demonstrating its effectiveness in real-world applications.	• Complexity in implementation.	No	Hybrid
[42]	• Effective feature extraction. High accuracy in face recognition tasks.	• Combining the two techniques may introduce complexity in the implementation process. • With the use of multiple features, there is a risk of overfitting the model to the training data.	No	Traditional
[43]	• Effective in practical applications. • Improve speed and accuracy by combining the Viola-Jones algorithm with CNN.	• Training a CNN is a resource-intensive and time-consuming process.	Yes	Hybrid
[44]	• Effective in real-world applications.	• Complicate the implementation process.	No	Traditional
[45]	• Innovative approach which can be used in many real-world applications.	• The approach relies on adapting pre-trained networks, which may not always be feasible or effective in all scenarios.	Yes	DL
[46]	• The model utilizes advanced techniques, enhancing processing speed and robust feature extraction. • Effective in real-world applications.	• Challenges related to dataset diversity and performance in unconstrained environments.	Yes	DL
[47]	• The model can be adaptable to large-scale datasets. • Accurate face detection with a small number of trainable parameters.	• Difficulty recognizing faces at large angles may affect performance. • Difficulty identifying faces in dynamic environments.	Yes	DL
[48]	• Strong performance in facial recognition tasks. • Track multiple faces simultaneously.	• Implementing the system requires significant computational resources and expertise.	Yes	DL
[49]	• Handle non-frontal images. • Effective in real-world applications.	• Expression, illumination, and pose can significantly affect the performance.	Yes	Hybrid
[50]	• Allows users to switch between various state-of-the-art models, enhancing flexibility in face recognition tasks.	• Complexity in implementation. • Require significant processing time.	No	DL
[51]	• Enhance the accuracy of cross-modal face recognition. • The model utilizes the VGG-Face recognition system without retraining.	• The performance relies on the quality of the datasets used for training. • Challenges due to similarities in facial heat maps.	No	DL

On the other hand, some researchers use a multi-model that integrates the face with other biometrics, such as fingerprint or iris, to enhance recognition accuracy. Also, many parameters affect the time and performance of the system, such as the quality and number of images in the dataset used for training the system, the technique, and the number of features extracted from the face images, etc.

Cross-modal face recognition has attracted a lot of attention. This typically involves matching a face image captured in one modality (such as a visible light photograph) with a face image captured in another modality (such as an infrared image, sketch, or 3D model). This capability is essential in scenarios where different types of imaging technologies are used, or where data is available in varied formats, allowing for more versatile and robust face recognition systems. This is achieved by addressing the challenges of feature variance, data diversity, and alignment, and leveraging advanced DL techniques.

Recent advancements in face recognition have explored unsupervised learning techniques, such as contrastive learning and clustering-based approaches, to reduce dependency on labeled datasets and improve scalability. Additionally, transformer networks, initially developed for natural language processing, have been successfully adapted to face recognition.

6. Conclusion

Different mechanisms have been proposed for performing face recognition, and this paper provides a brief overview of some of these systems. The face recognition system can recognize a person's identity utilizing unique facial patterns, whether in photos, videos, or in real-time through feature extraction techniques. These techniques are pivotal in transforming raw input data into a comprehensible and manageable digital feature that allows storage and comparison.

The findings reveal that while current systems excel in controlled environments with consistent lighting, static poses, and neutral expressions, their performance is significantly affected by variations in lighting, pose, and expression. This indicates a need for more advanced feature extraction techniques to enhance robustness in real-world applications. Employing advanced machine learning models, such as deep CNNs trained on diverse datasets, could help systems generalize better to different conditions. Additionally, the trade-off between computational complexity and accuracy remains a critical challenge, particularly for real-time applications.

For future work, use more than one technique to extract face features and train an ANN to choose the appropriate one for the input image, especially in scenarios with variations in lighting, pose, and expression. Furthermore, employing more than one sample can generate a robust feature, which could significantly improve system performance.

Acknowledgment

The authors thank the Department of Computer Science, University of Technology-Iraq, for administering this study.

Conflict of interest

The authors declare no conflict of interest.

Author contributions

Zahraa Naji Razoqi: Analysis, investigation, writing, review and editing. Raheem Ogla: Methodology and review. Abdul Monem S. Rahma: Conceptualization.

Data availability

No dataset has been used in this study.

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