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REVIEW

A Comprehensive Review of Face Detection/Recognition Algorithms and Competitive Datasets to Optimize Machine Vision

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ABSTRACT: Face recognition has emerged as one of the most prominent applications of image analysis and understanding, gaining considerable attention in recent years. This growing interest is driven by two key factors: its extensive applications in law enforcement and the commercial domain, and the rapid advancement of practical technologies. Despite the significant advancements, modern recognition algorithms still struggle in real-world conditions such as varying lighting conditions, occlusion, and diverse facial postures. In such scenarios, human perception is still well above the capabilities of present technology. Using the systematic mapping study, this paper presents an in-depth review of face detection algorithms and face recognition algorithms, presenting a detailed survey of advancements made between 2015 and 2024. We analyze key methodologies, highlighting their strengths and restrictions in the application context. Additionally, we examine various datasets used for face detection/recognition datasets focusing on the task-specific applications, size, diversity, and complexity. By analyzing these algorithms and datasets, this survey works as a valuable resource for researchers, identifying the research gap in the field of face detection and recognition and outlining potential directions for future research.

KEYWORDS: Face recognition algorithms; face detection techniques; face recognition/detection datasets

1 Introduction

Face recognition (FR) is a biometric technology that recognizes or confirms a person's identification based on visual features [1]. To match the identified face to a known identity, this technique requires analyzing facial traits, including the spacing between the eyes, the nose's shape, and the curves of the face [2]. Face recognition technology is frequently employed for security and authentication purposes, such as unlocking smartphones or entering restricted areas. These activities have grown in significance in fields including surveillance, security, human-computer interaction, and entertainment [3].

The goal of creating biometric applications like facial recognition has gained significance in the context of smart cities. Furthermore, many researchers worldwide have concentrated on developing more reliable and precise techniques and algorithms for these systems and their everyday uses [4]. Every type of security system needs to safeguard personal information. Passwords are the most widely utilized type for recognition.

However, many systems are starting to integrate many biometric factors for recognizing tasks due to the advancements in security algorithms and information technologies [5]. Thanks to these biometric elements, people's identities can be determined by their physiological or behavioral traits. They also offer several benefits. For instance, simply having a person in front of the sensor suffices, and remembering multiple passwords or secret codes is no longer necessary [6]. Recently, many recognition systems based on various biometric characteristics, including face, voice, iris, and fingerprints [7], have been implemented.

Systems that use a person's biological traits to identify them are particularly appealing because they are simple to use. The human face comprises several structures and traits [8]. For this reason, considering its potential in numerous domains and applications (surveillance, home security, border control, and so forth), it has emerged as one of the most popular biometric authentication systems in recent years [9].

Customers can already use facial recognition technology as an ID (identification) outside of phones, such as at concerts, sports stadiums, and airport check-ins [10]. Furthermore, this system can identify people just using photos taken by the camera because it doesn't require human participation. Moreover, many face recognition algorithms with high identification accuracy have been created with various search kinds in mind [11]. Designing new face recognition systems would be fascinating to meet real-time restrictions.

Numerous computer vision techniques, including local, subspace, and hybrid approaches, have been presented to solve face detection or recognition applications with good robustness and discrimination [12]. Despite these advancements, face recognition technology faces challenges in real-world applications, particularly under varying occlusion, lighting conditions, and facial expressions. It is also challenging to detect and recognize the face in the future high-demanding immersive technology in a 360-degree environment due to the loss of facial information caused by merging images taken from different angles, leading to facial features' inconsistencies. The most inventive methods are created to address these difficulties and provide dependable face recognition software. However, they are relatively sophisticated, demand a lot of processing time, and use a lot of memory [13]. Face recognition technology is one of the main technologies because of the quick advancements in digital cameras and portable devices and the growing need for security. The necessity for extensive, diversified datasets that adequately reflect the population is one of the major problems [14]. Concerns about bias and fairness are also raised because many available datasets could only be of some demographic groupings.

Although there is a sizable and constantly expanding number of face detection and identification datasets accessible, it might be difficult for academics and practitioners to discover and select the most suitable dataset for their specific needs.

Although face recognition technology has made significant progress, current algorithms still face difficulties in real-world conditions, such as in lighting changes, facial expressions and poses, and occlusions. In many cases, human perception still outperforms these systems. Additionally, the datasets used for training and evaluating these algorithms differ widely in size, diversity, and applicability. This study provides a comprehensive review of face detection and recognition algorithms developed between 2015 and 2024, explores key datasets, and highlights existing research gaps to support future advancements in the field. This paper's primary contribution is:

- This review paper takes an in-depth look at the most recent face detection and identification methods.
- This work also the face detection/recognition datasets that are currently accessible, considering their size, diversity, and complexity, as well as the specific tasks to which they have been applied.
- Studying these methods, their advantages and disadvantages, and the dataset allows researchers to develop an accurate and efficient algorithm.

2 Challenges and Limitations Faced by Face Detection and Recognition

An effective face detection and recognition algorithm may encounter several constraints when identifying face images. Among these restrictions are:

Pose Variations: Head movements, stance changes, and changes in camera angle may also compromise the efficiency of the face recognition algorithm [1].

Illumination Variation: The image quality and the effectiveness of the algorithms can be obstructed by several environmental factors [5], such as lighting conditions, reflections, and shadows.

Occlusions: Occlusions [7] can complicate and reduce the accuracy of face recognition/detection systems. Examples include hats, mustaches, glasses, etc.

Computational Complexity: Deep learning-based face recognition algorithms can be computationally expensive due to their high memory and processor requirements [11].

Changes in Look: Several parameters, such as aging and haircuts, can affect a person's appearance and make it challenging to match against a database [7].

Limited Training Data: Face recognition algorithms require substantial training data to work effectively [11]. For example, deep learning-based FR algorithms require training on over one million face images.

Specific Dataset: Algorithms for facial recognition are typically only trustworthy on datasets. Other datasets are not recognized by these algorithms [15]. For instance, an algorithm trained to identify photographs of people with lighter skin tones does not recognize a dataset of people with darker skin tones.

Fig. 1 depicts some facial appearances that pose issues for face detection/recognition algorithms.

Figure 1: Facial characteristics that cause challenges for algorithms designed for detecting and recognizing faces

3 Review Methodology

The evaluation procedure begins with an initial screening within the scope of the present effort. As previously stated, this review focused on recent and cutting-edge contributions to face detection/recognition performance and their datasets. The flow diagram of the review methodology is presented in Fig. 2. We have organized the entire review procedure into the sections below.

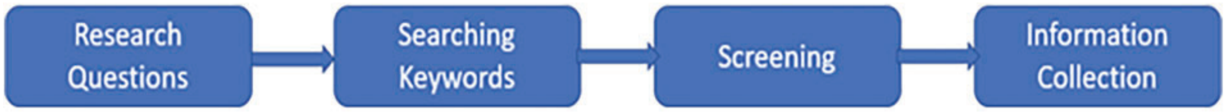

Figure 2: Flow diagram of the review methodology

3.1 Review Process

This work thoroughly evaluates previous investigations using the systematic mapping study provided by Ahmad et al. [16]. The review provides a detailed methodology of previous work that directly or indirectly contributes to face detection/recognition systems and datasets. Furthermore, the study included research questions to highlight the primary aims. These research questions allow users to select an appropriate algorithm/dataset based on their requirements.

3.2 Research Questions

After reviewing the existing face detection/recognition literature, we formulate the research questions carefully. We identified the research gaps by examining the advancements and challenges faced in real-world applications. Moreover, our objective was to develop research questions that explore the performance of face detection/recognition algorithms and their limitations.

- How did face detection and recognition evolve between 2015 and 2024, and what improvements have been made?
- What are the open-source gaps and challenges do modern face recognition/detection algorithms still face?
- How do different published face detection/recognition datasets compare in terms of size, features, and complexity.
- What are the future research directions for researchers in the field of face detection/recognition.

3.3 Searching Keywords

With the default settings, the keywords were searched directly on publisher websites and Google Scholar. We reviewed the articles and selected those that included pertinent findings for further review. Furthermore, the following are the important aspects, subjects, and related studies, including journals, conference proceedings, and book chapters.

Computer vision for face analysis	Limitations of face recognition algorithms
Face detection algorithms	Ethical considerations in facial recognition
Face recognition algorithms	Bias in facial recognition algorithms
Facial biometrics	Facial landmark detection
Deep learning for facial recognition	Face dataset repositories
State-of-the-art face recognition	Cross-database evaluation for face recognition

3.4 Screening

The following terms and criteria govern the screening of studies:

- The team considered peer-reviewed publications (2014–2024) from reputable journals, book chapters, and conference proceedings in the domain of artificial intelligence and biometrics.

- We concentrated on the related title, which has numerous citations in Google Scholar.
- Fast reviews were conducted for additional evaluation and data extraction. We concentrated on the abstract and introduction during the fast review to understand the difficulties, motivations, and contributions.
- Papers having a lack of experimental validations, non-English papers, and studies not directly related to face recognition have been excluded from the study.

3.5 *Information Collection*

Various data were retrieved from the selected publications during the information-gathering process, as indicated in Tables 1–3. Additionally, a spreadsheet was used to capture the various data and further investigate the study's issues. As a result, a comprehensive literature evaluation was conducted to identify potential challenges in forecasting student performance. The research also demonstrates the contributions of prior articles that go beyond the boundaries of artificial intelligence.

Table 1: Face detection algorithms

Ref.	Year	Algorithm	Description	Dataset	Accuracy	Limitations
[25]	2015	Faster Region-CNN (R-CNN)	An object detection algorithm that utilizes a region proposal network and a Fast R-CNN detection network.	WIDER FACE, Pascal VOC	93.4% (WIDER FACE), 73.2% (Pascal VOC)	Limited to frontal faces and medium-sized faces.
[26]	2015	CNN-based	Uses deep neural networks to detect faces in images	WIDER FACE	99%	–
[27]	2018	PyramidBox	A single-stage face detector that uses a pyramid feature extraction module and a scale-aware context aggregation module.	FDDB, WIDER FACE	95.2% (FDDB), 77.0% (WIDER FACE)	Requires high computational power and memory.
[28]	2018	SSH (Single Stage Headless)	A multi-stage face detector that uses a shared feature extraction module and three sub-networks for different scales.	FDDB, WIDER FACE	92.1% (FDDB), 77.1% (WIDER FACE)	Requires high computational power and memory.
[29]	2018	S3FD	A single-shot face detector that uses a scale-sensitive network and a novel anchor-matching strategy.	WIDER FACE, FDDB	79.1% (FDDB), 83.6% (WIDER FACE)	Limited to frontal faces and small faces.
[30]	2019	CenterFace	A unified anchor-free face detection framework that predicts the center point, scale, and aspect ratio of a face in a single shot.	FDDB, WIDER FACE	89.7% (FDDB), 42.5% (WIDER FACE)	Limited to frontal faces, small faces, and low-resolution images.
[21]	2019	DSFD	A multi-task face detector that uses a scale-invariant training strategy and a densely connected network architecture.	WIDER FACE, FDDB	61.3% (FDDB), 93.3% (WIDER FACE)	Limited to frontal faces and medium-sized faces.

(Continued)

Table 1 (continued)

Ref.	Year	Algorithm	Description	Dataset	Accuracy	Limitations
[14]	2020	RetinaFace	A single-stage face detector that uses a multi-task loss function and a novel face prior box initialization.	WIDER FACE, COCO	96.5% (WIDER FACE), 68.2% (COCO)	Requires high computational power and memory.
[31]	2020	EfficientDet-D7x	A family of object detection models that uses an efficient backbone network and a compound scaling method.	WIDER FACE, COCO	91.5% (WIDER FACE), 54.6% (COCO)	Limited to frontal faces and small faces.
[32]	2021	YOLOv5	A state-of-the-art object detection algorithm that achieves high accuracy and speed by using a novel backbone network and a streamlined detection head.	WIDER FACE, COCO, FDDB	92.0% (WIDER FACE), 50.0% (COCO)	Limited to frontal faces and small faces.
[33]	2021	BlazeFace	A lightweight neural network for face detection that uses anchor boxes and a single-stage detection pipeline.	WIDER FACE, COCO	73.1% (WIDER FACE), 38.5% (COCO)	Limited to frontal faces, low-resolution faces, and small faces.
[34]	2022	CNN (Convolutional Neural Networks)	CNN based real-time face detection.	Kaggle dataset and the Face mask dataset	98%	–
[35]	2024	YOLO-FaceV2	Face detector based on the one-stage detector YOLOv5, named YOLO-FaceV2.	WIDER FACE	98.78 (easy), 97.2% (medium) 87.75 (hard)	–

Table 2: Face recognition algorithms

Ref.	Year	Algorithm	Description	Dataset	Accuracy	Speed	Limitations
[1]	2019	PAL	A boosted FR algorithm that recognizes faces with pose, occlusion, and illumination variation under low-resolution images	LFW, CMU Multi-PIE	94% (LFW)	0.4 s per image	Time-consuming
[54]	2021	FaceNet	A deep neural network based on triplet loss for face recognition to improve accuracy with high-dimensional data	LFW, YTF, CPLFW, AgeDB-30, CALFW, CFP-FP	99.63% (LFW)	1.04 s per image	Requires high computational power
[55]	2021	DeepFace	A deep neural network using a multi-task learning framework to improve accuracy under controlled conditions	LFW, YTF	98.87% (LFW)	0.08 s per image	Limited to frontal faces
[56]	2020	ArcFace	A deep neural network based on additive angular margin loss for face recognition to address accuracy	LFW, AgeDB-30, CFP-FP, MegaFace	99.83% (LFW)	0.7 s per image	Requires a large amount of training data

(Continued)

Table 2 (continued)

Ref.	Year	Algorithm	Description	Dataset	Accuracy	Speed	Limitations
[57]	2020	MobileFaceNet	A lightweight face recognition algorithm designed for mobile devices	LFW, YTF, MegaFace	99.55% (LFW)	0.03 s per image	Limited by computational power and memory
[58]	2021	TResNet	A transformer-based residual network for face recognition to improve accuracy	CPLFW, CFP-FP, LFW, CALFW, YTF, and AgeDB-30	99.73% (LFW)	2.2 s per image	Requires high computational power
[59]	2018	CapsNet model	A Capsule Network (CapsNet) based FR algorithm, which employs activity vectors and dynamic routing between capsules to capture spatial hierarchies in data	Yale face database B	95.3%	–	High training time
[60]	2022	Bilateral filtering with expanded capsule network and grey wolf optimization	A FR model which integrates an Enhanced Capsule Network (ECN) with Grey Wolf Optimization (GWO) and a Stacked Autoencoder (SAE)	GTAV face, FEI face, and LFW dataset	99.82% (GTAV), 99.38% (LFW)	0.04 s per image	Increase resource requirements and training time
[61]	2019	CenterFace	A center loss-based deep face recognition algorithm	LFW, CALFW, CPLFW, CFP-FP, AgeDB-30	99.45% (LFW)	0.08 s per image	Limited to frontal faces
[62]	2019	CosFace	A large margin cosine loss for deep frontal face recognition	CPLFW, CFP-FP, LFW, CALFW, MegaFace and AgeDB-30	99.33% (LFW)	0.04 s per image	Limited to frontal faces
[63]	2019	SphereFace	A deep hypersphere embedding for face recognition	CPLFW, CFP-FP, LFW, CALFW, MegaFace and AgeDB-30	99.42% (LFW)	0.07 s per image	Limited to frontal faces
[64]	2019	HFR-GAN	A hierarchical face recognition GAN for pose-invariant face recognition	LFW, Multi-PIE, CASIA-WebFace	99.36% (LFW)	0.3 s per image	Requires a large amount of training data
[65]	2021	Wide Fast Embedded Capsule Network (WFECN)	A modified CapsNet with wider structure to capture richer features and optimized routing to reduce computational overhead	LFW	93.7%	Computational complexity Reduced by 80.6%	Less accuracy
[66]	2020	HRNet	A high-resolution network that uses multi-scale features for face recognition	LFW, MegaFace and AgeDB-30	99.81% (LFW), 98.32% (MegaFace)	0.035 s per image	Limited to frontal faces
[67]	2022	Efficient light-weight attention network	A lightweight attention network that use Efficient fusion attention Module with Pyramid multi-scale module and adaptively spatial feature fusion	LFW, CPLFW, CFP-FP, CALFW, CFP-FF, and VGG2-FP	99.53% (LFW), 95.42% (CALFW)	0.008 s per image	Limited to frontal faces
[68]	2019	Capsule network	Capsule network	LFW dataset	93.7%	–	Computationally expensive
[69]	2022	VGG-16, AlexNet, and ResNet-50	AN efficient Mask face recognition technique	RWMFD and SMFRD	91.3 (RWMFD), 88.9 (SMFRD)	–	–

(Continued)

Table 2 (continued)

Ref.	Year	Algorithm	Description	Dataset	Accuracy	Speed	Limitations
[70]	2023	QMagFace	Quality-aware FR technique	AgeDB, XQLFQ, LFW, and CFP-FP	83.95% (XQLFQ), 99.83 (LFW), 98.50% (AgeDB), and 98.74% (CFP-FP)	–	Occlusion and illumination are not discussed
[71]	2023	CNN with preprocessing	Masked face recognition that recognizes masked faces	VGGFACE2	94.1%	–	–
[15]	2024	EdgeFace	An efficient and lightweight network that combines effectively the strengths of Transformer models, CNN, and a low-rank linear layer to solve the computational and memory issues	LFW, IJB-B, and IJB-C	99.73% (LFW), 92.67% (IJB-B), and 94.85% (IJB-C)	–	–
[72]	2021	Mobile FaceNetsv3	A lightweight face recognition model that uses depth-wise separable convolutions and residual connections for real-time recognition on mobile devices	(LFW)	99.51% (LFW)	200–300 fps (CPU)	–
[73]	2024	MobileFaceNet	A cattle pose invariant face recognition model that uses MobileFaceNet with EEM and EOM	Own collected images	98.69	60 fps	Only tested on high resolution images
[74]	2024	CapsNet-FR	A capsule network-based FR model that uses FLL and preprocessing steps to improve face recognition performance	LFW, COMSATS Face	973.% (LFW), 93.47% (COMSATS face)	–	Not performing well in the occlusion case
[75]	2024	Vision-Transformer	A face recognition model that uses a Vision-Transformer model with a unique loss function to recognize cow faces	Own collected Dataset	96.3%	50 fps	Trained and tested on 7032 images
[76]	2024	AdaBoost and PAL-based FR	A FR model that uses AdaBoost and the PAL algorithm for recognizing cricket player face images on the field and off the field	Own collected dataset	95.6%	0.3 s to 0.6 s per image	Near real-time

Table 3: Commonly used feature extraction techniques

Ref. No.	Feature extraction technique	Description	Use in face detection	Use in face recognition	Advantages
[88]	Haar-like features	Captures intensity differences in rectangular regions.	Used in the Viola-Jones algorithm for efficient face localization.	Rarely used, primarily for detection.	Fast computation, suitable for real-time applications.
[89]	Histogram of Oriented Gradients (HOG)	Computes gradient orientation histograms to detect edges and patterns.	Encodes facial structure for detecting face regions.	Represents facial features for classification tasks.	Robust to lighting variations and noise.

(Continued)

Table 3 (continued)

Ref. No.	Feature extraction technique	Description	Use in face detection	Use in face recognition	Advantages
[90]	Local Binary Patterns (LBP)	Encodes local texture by comparing pixel intensities.	Not commonly used for detection.	Creates feature vectors for texture-based face recognition.	Computationally efficient and robust to lighting changes.
[91]	Scale-Invariant Feature Transform (SIFT)	Extracts key points invariant to scale and rotation.	Rarely used, primarily for matching tasks.	Matches key points for identity verification.	Robust to scale, rotation, and noise.
[92]	Speeded-Up Robust Features (SURF)	A faster alternative to SIFT for extracting key points.	Rarely used, primarily for matching tasks.	Matches key points for identity verification.	Balances speed and accuracy.
[44]	Principal Component Analysis (PCA)	Reduces dimensionality by identifying principal components.	Rarely used, but can reduce features in detection pipelines.	Form basis for Eigenfaces, representing faces as linear combinations.	Reduces complexity and noise in data.
[93]	Deep learning-based features	Uses CNNs to learn hierarchical features directly from raw pixels.	CNN models (e.g., YOLO, SSD) detect face regions.	FaceNet, AlexNet.	High accuracy, handles occlusion, low resolution, and variations.
[94]	Gabor filters	Captures spatial frequency, orientation, and phase information.	Rarely used, mainly supports detection tasks indirectly.	Extracts facial textures for robust recognition.	Effective under varying illumination conditions.

4 Face Detection

In the FR recognition pipeline, face detection is one of the most significant stages. To improve the performance of face detection (FD) [17], several research studies have been conducted, spanning from key point annotation [18] to data augmentation approaches [19]. FR is based on the fundamentals of object detection, and it shares that face detection had the same history as generic object detection before deep learning. Handcrafted characteristics and approaches were used for detection, such as Haar-like characteristics [20]. This gradually evolved into more formalized and complex techniques to minimize variations of Pose, expression, lighting, occlusion, and other difficulties, as presented in Fig. 1. The WIDER FACE dataset [21] has been instrumental in advancing face detection techniques, leading to the emergence of innovative approaches such as PyramidAchors [18], Dual Shot Face Detector (DSFD) [22], and the more recent TinaFace [23], which is among the latest face detection models as of 2021.

Authors in [24] suggested an intriguing technique to handle the issue of spotting small faces. This model can detect hundreds of little faces in a single image. They investigated three components of the little face problem: the effect of scale invariance, picture resolution, and contextual reasoning. In contrast to prior works, they trained distinct detectors for different scales.

The majority of face identification algorithms employ either a feature-based or image-based approach. Feature-based methods involve extracting and comparing image features with a database of known facial features. On the other hand, image-based methods involve comparing training and testing images to find the most suitable match. Tables 1, 2 show the most recently published state-of-the-art face detection and recognition methods. Figs. 3 and 4 compare different face detection approaches tested on the WIDER FACE, and COCO datasets.

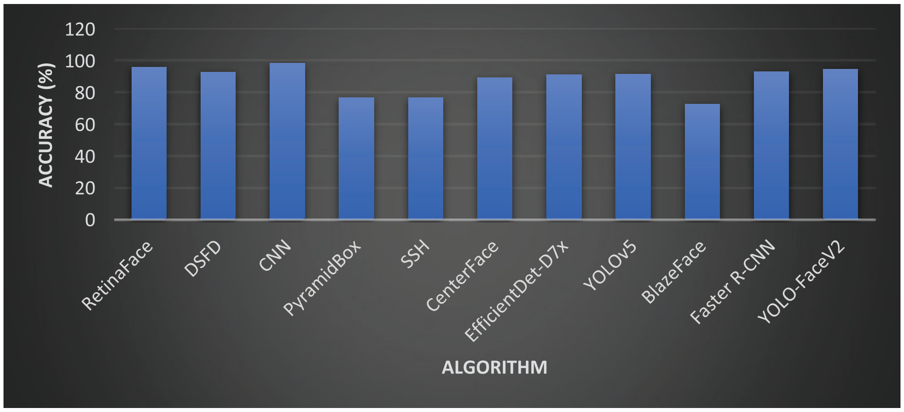

Figure 3: Comparison of different face detection techniques tested on the WIDER FACE dataset

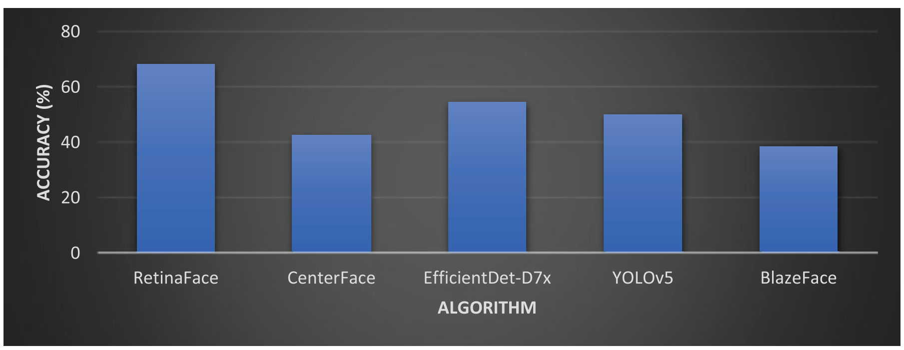

Figure 4: Comparison of different face detection techniques tested based on the COCO dataset

The values for accuracy and speed mentioned here should be considered approximations and subject to change based on the hardware and software setups utilized for testing. Additionally, this list is not complete, and there may be additional cutting-edge face detection algorithms that are not covered. Additionally, the limits indicated are predicated on the information provided in the corresponding study publications. Furthermore, based on the particular use case and requirements, these algorithms may have various strengths and drawbacks [36]. It's critical to thoroughly consider and choose the best algorithm for a certain task. Furthermore, Fig. 5 presents the comparison of several face detection algorithms on the FDDB and PASCAL datasets. These algorithms include DSFD [22], pyramidbox [27], Single shot scale-invariant face detector (S3FD) [29], joint-cascade CNN [37], HyperFace [38], faceness [39], UnitBox [40], DPSSD [41], Selective Refinement Network (SRN) [42], and Joint face detection and facial motion retargeting [43].

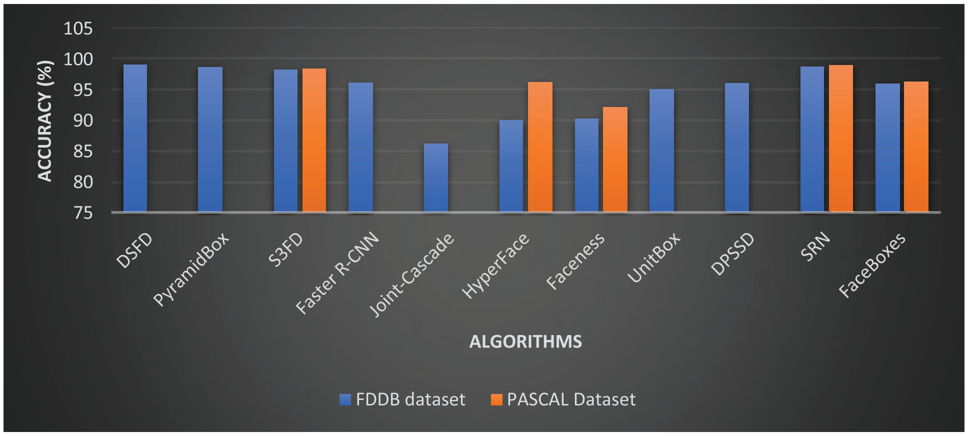

Figure 5: Comparison of different face detection techniques tested based on FDDB and PASCAL datasets

5 Face Recognition

Fig. 6 shows the wide range of FR approaches that have continuously progressed to state-of-the-art DL (Deep Learning) methodologies. Moghaddam et al. [44] released Eigenfaces in the early 90s, one of the most basic approaches utilizing low-dimensional feature-based segmentation, which marked the beginning of significant development in FR. Each face image in the training set is divided into several tiny feature bits known as Eigenfaces using their technique. The variance in the location of each Eigenface for the subject image is calculated by linearly projecting the subject image across the Eigenface feature space. Additional early work that integrates low-dimension feature-based segmentation with holistic techniques is provided by [45,46]. By providing models invariant to both lighting direction and facial expression, Fischerfaces [47] outperformed Eigenfaces. Due to its inability to handle unforeseen facial changes that differ from the variations gathered in the training dataset, scientists looked for novel methods based on manually created local facial feature representations. The early 2000s saw the publication of several important articles, such as a Gabor method for FR based on local features [48], a local binary feature-based approach [49], and a high-dimensional feature-based compression [50]. In terms of FR outcomes, these developments, which mostly concentrated on high-dimensional feature representation, performed better than holistic methods. Their reliance on handcrafted qualities, on the other hand, is partial to their efficiency in practical, diverse, and complex FR scenarios.

Since the limits of handcrafted features have emerged, learning-based techniques have emerged [51]. These approaches, however, perform poorly when confronted with complicated variations in facial appearance that are not recorded in the training data. In response to these problems, the research community boosted its attempts to overcome FR's poor performance under non-linear fluctuations in facial look and expression.

In the last decade, DL has dominated FR research by overcoming the above-mentioned concerns. The functioning of DL imitates the way the human brain processes data and is commonly utilized in CNNs as layered networks. When AlexNet [52] achieved outstanding accuracy in the ImageNet competition 2012, CNNs received attention for image recognition challenges. DeepFace [53] obtained a then-unprecedented FR accuracy of 97.35% on the Labelled Faces in the Wild (LFW) dataset. Table 2 summarizes the evolution chronologically, citing some major works in FR. Fig. 7 presents the accuracy comparison of published FR algorithms tested on the LFW datasets. Fig. 8 concludes the accuracy of the face recognition algorithm on the COMSATS face dataset.

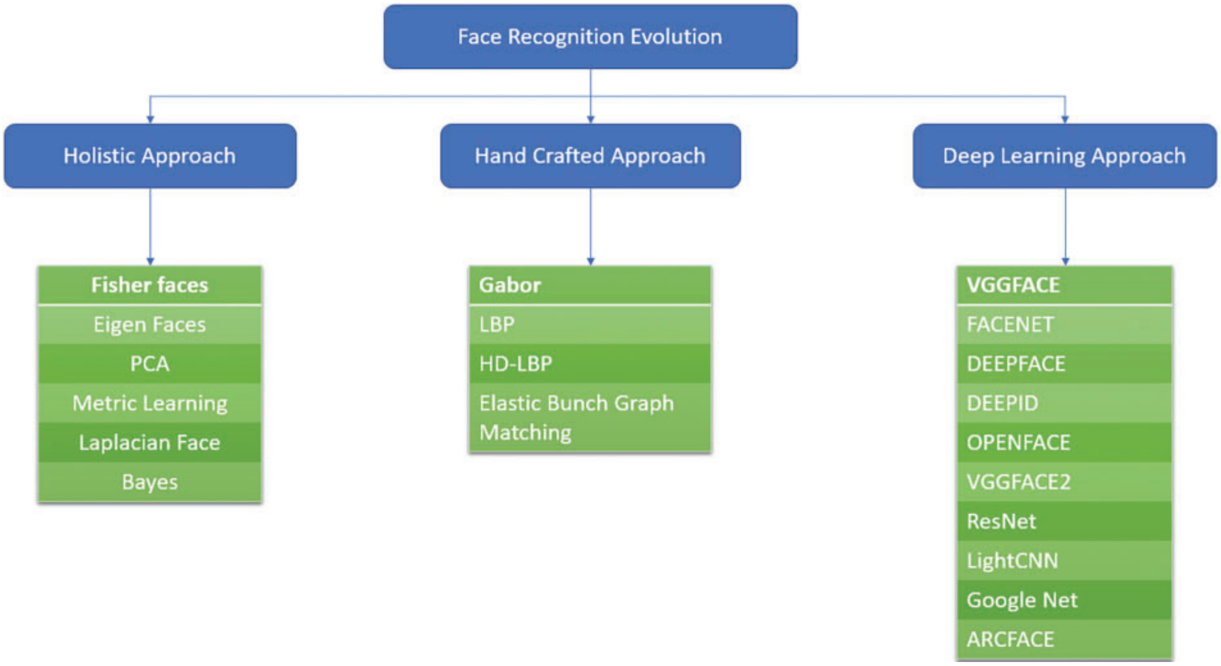

Figure 6: Popular face recognition methods

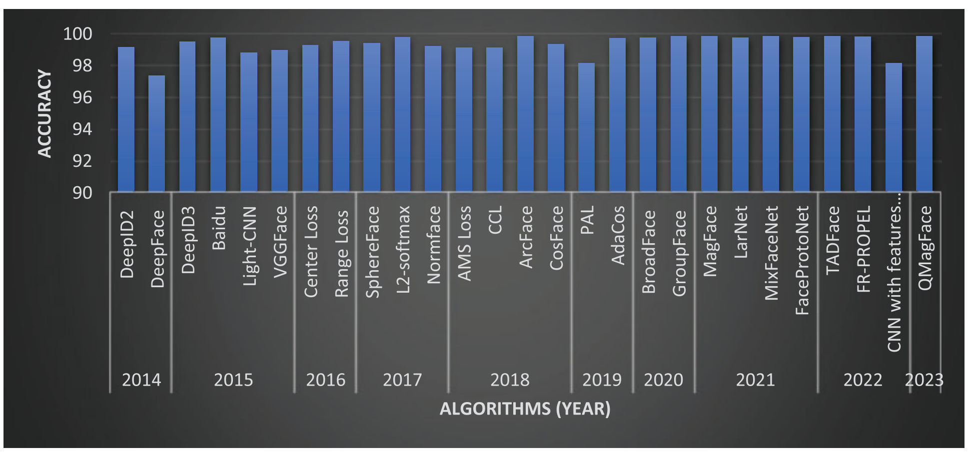

Figure 7: Comparison of published face recognition algorithms based on accuracy (LFW dataset)

The accuracy and speed values are simply estimates and subject to change depending on the exact implementation and testing conditions. It's crucial to evaluate the effectiveness of these algorithms in the context of your particular use case, considering factors such as dataset size, processing power, and the desired level of accuracy and speed. Furthermore, this table is not exhaustive, and there might be other cutting-edge methods of facial recognition that are not included. However, the speed and accuracy statistics are estimates and could vary depending on the specific testing conditions. It is critical to evaluate how well various algorithms perform on a particular dataset and hardware configuration before selecting the optimal approach for a given use case.

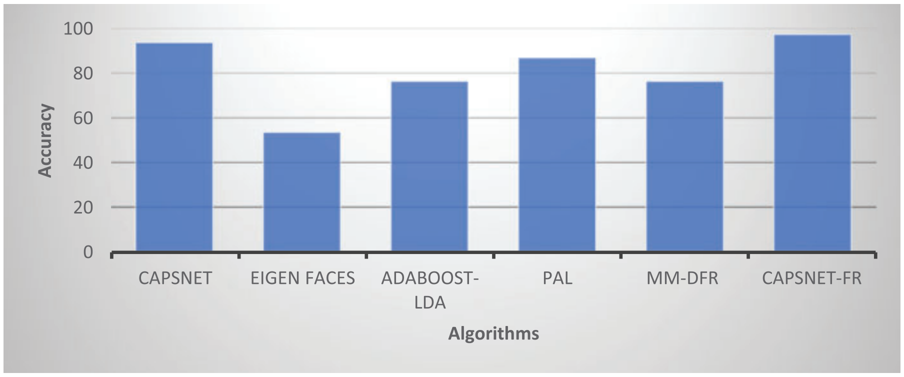

Figure 8: Evaluation accuracy of FR algorithms on the COMSATS face dataset

6 Face Preprocessing

6.1 Facial Data Augmentation

Facial data augmentation/enhancement is an effective method of compensating for a lack of facial training data [77]. It's a method for boosting the amount of training or testing data by modifying real-life or simulated virtual face samples. The actual idea behind data augmentation is to generate additional samples of the class under the given category. Data augmentation can be applied in training, testing, or both. In a sense, a larger volume of data seems to improve deep learning performance [78]. Again, small object detection performance improvement can also be guaranteed by adding the types and the number of small object samples within the dataset. Face transformation creates new face samples by altering the geometry, RGB (Red, Green, Blue) channels, and changing the hairstyles, makeup, and facial expressions [79]. Another method used for face transformation is removing or wearing accessories such as Glasses, hats, earrings, etc. [79].

Memory and computation restrictions are the most important advantages governing the data augmentation algorithms. There are two widely recognized methods of data augmentation: online and offline [80]. Online data augmentation occurs dynamically during training, while offline data augmentation generates the data beforehand and then stores it in memory. The online approach saves space in memory, although it may slow the training down. Offline approaches are faster in training but will take up large amounts of memory [80].

6.2 Face Alignment

Aligning the face is an important part of the facial recognition process. It involves identifying and adjusting the key facial points in a given image to match a standard face template. Face alignment research has advanced in recent years with growing success. A typical face alignment approach seeks to progressively align a standard face shape template to an input facial image by searching the input for predefined facial points. Typically, this begins with a coarse shape refined iteratively through numerous steps and ends when the convergence criteria are met. As the search advances, facial appearance data and the conventional face shape model are combined to discover facial fiducial spots.

Several excellent review studies thoroughly documented the evolution of face alignment algorithms from traditional to modern deep learning-based methods [81]. Heatmap regression is a common method for face localization [82]. Wang et al. [83] presented AdaptiveWingLoss, a Pytorch implementation of a heatmap regression. In 2019, it was posted on GitHub [84]. Based on deep neural network architecture, the Deep

Alignment Network (DAN) is a multi-stage face alignment method that was first presented in [82]. DAN evaluates the face roughly at first, then iteratively improves the findings. Zhang et al. [85] used a cascade classifier featuring a deep learning approach. The researchers built a cascade deep model from their work in which four layers of a convolutional cascade were embedded. Each of the cascade layers was trained to refine the facial landmarks from the prior layer. Another work on the deep convolutional cascade model was proposed by [86]. Their model DeCaFa makes use of an end-to-end CNN with a cascade classifier, thereby keeping the image's spatial resolution intact while passing through the cascade. Between each of the cascade layers, a soft-max-linked multi-chained transfer layer is applied to derive a facial-landmarks-wise output. Authors in [87] proposed a combination of different face alignment techniques, such as a heatmap with coordinate regression network and spatial attention, to increase the stability and accuracy of the model. Their model gives promising results in aligning occluded face images.

6.3 Feature Extraction Techniques

To the success of face detection and recognition, feature extraction methods are fundamental. To enhance the detection/recognition accuracy, raw images are transformed into meaningful information using these techniques. Table 3 summarizes some commonly used feature extraction methods with applications, and advantages in face recognition and detection.

7 Face Detection/Recognition Datasets

The face recognition community has access to a vast array of databases, and the algorithms used for face identification exhibit varying degrees of performance across these datasets. These databases, as presented in Table 4, varied in scope, purpose, and quantity, and were assembled by research teams. Here, we quickly go over the salient characteristics of these publicly accessible face recognition datasets, including occlusion, illumination, image resolution, pose variation, and the number of individuals and images. However, not as much detail is covered on these databases because of the inaccessibility of data.

Table 4: Popular face recognition/detection datasets

Ref.	Dataset	No. of Images	No. of subjects	Illumination	Pose	Occlusion	Expression	Resolution	Year
[95]	AT & T	400	40	Varies	Frontal	Minimal	Varies	High	1992–1994
[96]	JAFFE database	213	10	Controlled	Frontal	Minimal	Seven different expressions	High	1998
[97]	Real-World Masked Face Recognition Dataset	95,000	525	Both indoor and outdoor settings	Varies	5000 masked images and 90,000 unmasked images	Varies	varies	2023
[98]	LFW	13,323	5749	Varies	Varies	Minimal	Neutral	Varies	2007
[99]	YTF	3425 videos	1595	Varies	Varies	Minimal	Neutral	Varies	2013
[100]	IJB-A	5712 images and 2085 videos	500	Varies	Varies	Moderate	Neutral	Varies	2015
[101]	MegaFace	1,027,060	690,572	Varies	Varies	Minimal	Neutral	Varies	2016
[102]	CASIA-WebFace	494,414	10,575	Varies	Frontal	Minimal	Neutral	Varies	2014
[103]	VGGFace2	331,131	8631	Varies	Varies	Minimal	Neutral	Varies	2018
[104]	FG-NET	1002	82	Controlled	Frontal	Minimal	Neutral	High	2004
[105]	BioID	1521	23	Varies	Frontal	Minimal	Neutral	High	2007
[106]	Adience	26,580	2284	Varies	Frontal	Minimal	Neutral	Varies	2014
[107]	Color FERET	14,126	1199	Controlled	Frontal	Moderate	Neutral	High	1996

(Continued)

Table 4 (continued)

Ref.	Dataset	No. of Images	No. of subjects	Illumination	Pose	Occlusion	Expression	Resolution	Year
[108]	SCFace	4160	130	Varies	Frontal	Minimal	Neutral	Varies	2011
[109]	AR Face	4000	126	Four	Frontal	Moderate	Four	High	2005
[110]	FERET	14,126	1199	Two	13 poses	Minimal	Three	High	1996
[111]	MFRD	95,000	525	Varies	Varies	Moderate	Neutral	High	2020
[112]	CELEB-500K	50,000,000	500,000	Varies	Varies	Minimal	Neutral	High	2018
[113]	DigiFace 1M	1,000,000	50,000	Varies	Varies	Moderate	Neutral	High	2023
[114]	YLFW	10,000	3000	Varies	Varies	Minimal	Neutral	High	2023
[115]	Yale face dataset B	5760	10	64 illumination conditions	Nine poses	Minimal	Neutral	High	2001
[116]	Extended yale face database B	2414	38	Varies	Varies	Minimal	Neutral	High	2001
[117]	COMSATS face dataset	850	50	Controlled	Varies	Minimal	Neutral	High	2022
[118]	MS-Celeb-1M	10,000,000	100,000	Varies	Varies	Minimal	Neutral	Varies	2016
[119]	Extended YTF	2425 videos	1595	Varies	Varies	Minimal	Neutral	High	2018
[120]	CMU PIE	40,000	68	43 different illumina-tions	13 poses	Minimal	Four different expressions	High	2002
[121]	CMU Multi-PIE	750,000	337	nineteen	fifteen	Minimal	Varies	High	2010
[53]	VGGFace	26 lacs	2622	Varies	Varies	Minimal	Neutral	Varying	2015
[122]	CelebA	202,599	10,177	Controlled	Frontal	Minimal	Neutral	High	2015
[123]	CALFW	–	4025	Varies	Varies	Minimal	Neutral	Varying	2017
[124]	CPLFW	13,323	5749	Varies	Varies	Minimal	Neutral	Varying	2018
[125]	CACD	163,446	2000	Controlled	Frontal	Minimal	Neutral	High	2014
[126]	RaFD	6000	67	Controlled	Frontal	Maximal	Multiple	High	2008
[127]	BU-3DFE	2500 3D models	101	Controlled	Frontal	Maximal	Six	High	2010
[128]	CelebV-HQ	35,666	15,653	Controlled	varies	Minimal	eight	High	2022
[129]	Celebrities in frontal-profile	7000	500	Minimal	Frontal and profile	Minimal	Neutral	high	2016
[130]	UPM-GTI-Face	4000	11	Varies	Varies	High	Varies	High	2022
[131]	UMD Faces	367,888	8277	Controlled	Varies	Minimal	Neutral	Varies	2017
[97]	Masked face recognition dataset	500,000	10,000	Varies	Varies	High	Varies	–	2023
[132]	Chinese face dataset	7395	130	Varies	Varies	High	Varies	Controlled	2023
[133]	MaskedFace dataset	137,016	–	–	Varies	Masked Images	–	–	2021
[134]	ISL-UFMD dataset	21,816	–	Varies	Varies	High	Varies	Controlled	2023
[135]	USK FEMO dataset	2250	–	–	–	–	Five emotions	–	2023
[136]	Balanced Face dataset	10,000	–	Varies	Varies	Minimal	Varies	–	2023
[137]	Multiface dataset	12,200 (Version 1) and 23,000 (Version 2) frames/subject	13	Varies	Varies	Minimal	Varies	High	2022
[138]	Player face recognition dataset	850	50	Varies	Varies	Varies	Varies	100 × 100 and 50 × 50 pixels	2024

This table provides only a high-level comparison of these datasets and does not account for specific details such as image quality, the diversity of the subjects, etc. The choice of the dataset should be guided by the precise research question/problem and should include diverse images with various characteristics to address the face recognition algorithms' limitations.

8 Addressing the Research Questions

In this study, we tried to address and work on some important aspects of face detection and recognition. We restate each research question and summarize the important findings:

1. *How did face detection and recognition evolve between 2015 and 2024, and what improvements have been made?*

The analysis in Sections 4–6 shows significant improvement, particularly in deep learning approaches, improved feature extraction techniques, and even the increasing accuracy of the systems in regards to changes in illumination, posture, and occlusions.

2. *What are the open-source gaps and challenges do modern face recognition/detection algorithms still face?*

As suggested and explained in detail in Sections 4–6, some challenges remain, for instance, dataset biases, pose variations (50° to 90°), systematic discrimination, privacy issues, loss of efficacy in uncontrolled settings, and many others.

3. *How do different published face detection/recognition datasets compare in terms of size, features, and complexity?*

Section 7 presents an in-depth comparison of several seminal datasets based on parameters such as size, features, complexity, and challenges.

4. *What are the future research directions for researchers in the field of face detection/recognition?*

Key research gaps and potential directions for future research have been addressed in the conclusion and research directions section.

9 Conclusion and Research Directions

The face recognition system holds great theoretical and practical importance, making it a popular study topic in image processing and computer vision. Numerous real-world applications heavily utilize this technology, including human-machine interaction, security, surveillance, homeland security, access control, image search, and entertainment. This study compares several publicly available face detection and recognition algorithms based on the approach, dataset accuracy, limitations, and descriptions. Further, we contrast several publicly available face detection and identification datasets according to several parameters, including size, lighting fluctuation, occlusion, and image resolution. We anticipate that this survey report will motivate scholars working in this area to engage and focus more on facial recognition system methodologies.

Several areas can be investigated in the future to improve face recognition systems' performance and address existing challenges. A critical challenge is to make the algorithm more resilient to handle pose variation, illumination variation, occlusion, and image resolution variation. Although several face recognition algorithms have promising results while dealing with these conditions in a controlled environment, these challenges remain common in uncontrolled scenarios. Another significant area of growth is creating a technique for an accurate face recognition model on limited-resource devices such as mobile phones. One key area that needs improvement in face recognition is enhancing recognition algorithms to increase their accuracy when dealing with face images taken at extreme angles (<50 degrees and having greater than 50% of occlusions). Current models appear to be ineffective in these aspects, which reduces their usefulness in real-time applications like surveillance, biometric authentication, and security systems. Additionally, addressing dataset biases, improving robustness against adversarial attacks, and developing more efficient real-time face recognition models are crucial areas for future exploration. Addressing these concerns would make it possible to develop more accurate face recognition systems that can be deemed trustworthy and reliable. Lastly, continual research and development efforts will be needed to address potential causes of algorithmic bias or data mistakes and improve algorithms.

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References

1. Haq MU, Shahzad A, Mahmood Z, Shah AA, Muhammad N, Akram T. Boosting the face recognition performance of ensemble based LDA for pose, non-uniform illuminations, and low-resolution images. KSII Trans Internet Inf Syst. 2019;13(6):3411–64. doi:10.3837/tiis.2019.06.021.
2. Eltaieb RA, El-Banby GM, El-Shafai W, Abd El-Samie FE, Abbas AM. Efficient implementation of cancelable face recognition based on elliptic curve cryptography. Opt Quantum Electron. 2023;55(9):841. doi:10.1007/s11082-023-04641-y.
3. Farouk AE, Abd-Elnaby M, Ashiba HI, El-Banby GM, El-Shafai W, El-Fishawy AS, et al. Secure cancelable face recognition system based on inverse filter. J Opt. 2024;53(3):1667–88. doi:10.1007/s12596-023-01233-7.
4. Ullah H, Haq MU, Khattak S, Khan GZ, Mahmood Z. A robust face recognition method for occluded and low-resolution images. In: 2019 International Conference on Applied and Engineering Mathematics (ICAEM); 2019 Aug 27–29; Taxila, Pakistan. p. 86–91. doi:10.1109/icaem.2019.8853753.
5. Badr IS, Radwan AG, EL-Rabaie EM, Said LA, El-Shafai W, El-Banby GM, et al. Circuit realization and FPGA-based implementation of a fractional-order chaotic system for cancellable face recognition. Multimed Tools Appl. 2024;83(34):81565–90. doi:10.1007/s11042-023-15867-z.
6. Saleem S, Shiney J, Priestly Shan B, Kumar Mishra V. Face recognition using facial features. Mater Today Proc. 2023;80:3857–62. doi:10.1016/j.matpr.2021.07.402.
7. Munawar F, Khan U, Shahzad A, Haq MU, Mahmood Z, Khattak S, et al. An empirical study of image resolution and pose on automatic face recognition. In: 2019 16th International Bhurban Conference on Applied Sciences and Technology (IBCAST); 2019 Jan 8–12; Islamabad, Pakistan. p. 558–63. doi:10.1109/ibcast.2019.8667233.

8. Rajeshkumar G, Braveen M, Venkatesh R, Josephin Shermila P, Ganesh Prabu B, Veerasamy B, et al. Smart office automation via faster R-CNN based face recognition and Internet of Things. Meas Sens. 2023;27:100719. doi:10.1016/j.measen.2023.100719.
9. Abdulhussain SH, Mahmmod BM, AlGhadhban A, Flusser J. Face recognition algorithm based on fast computation of orthogonal moments. Mathematics. 2022;10(15):2721. doi:10.3390/math10152721.
10. Boutros F, Struc V, Fierrez J, Damer N. Synthetic data for face recognition: current state and future prospects. Image Vis Comput. 2023;135:104688. doi:10.1016/j.imavis.2023.104688.
11. Ahmad S, Haq MU, Sethi MAJ, El Affendi MA, Farid Z, Al Luhaidan AS. Mapping faces from above: exploring face recognition algorithms and datasets for aerial drone images. In: Deep cognitive modelling in remote sensing image processing. Hershey, PA, USA: IGI Global; 2024. p. 55–69. doi:10.4018/979-8-3693-2913-9.ch003.
12. Opanasenko VM, Fazilov SK, Mirzaev ON, Kakharov SSU. An ensemble approach to face recognition in access control systems. J Mob Multimed. 2024:749–68. doi:10.13052/jmm1550-4646.20310.
13. Zhang X, Xuan C, Ma Y, Tang Z, Cui J, Zhang H. High-similarity sheep face recognition method based on a Siamese network with fewer training samples. Comput Electron Agric. 2024;225:109295. doi:10.1016/j.compag.2024.109295.
14. Deng J, Guo J, Zhou Y, Yu J, Kotsia I, Zafeiriou S. RetinaFace: single-stage dense face localisation in the wild. arXiv:1905.00641. 2019.
15. George A, Ecabert C, Shahreza HO, Kotwal K, Marcel S. EdgeFace: efficient face recognition model for edge devices. IEEE Trans Biom Behav Identity Sci. 2024;6(2):158–68. doi:10.1109/TBIOM.2024.3352164.
16. Ahmad S, El-Affendi MA, Anwar MS, Iqbal R. Potential future directions in optimization of students' performance prediction system. Comput Intell Neurosci. 2022;2022:6864955. doi:10.1155/2022/6864955.
17. Hosny KM, AbdElFattah Ibrahim N, Mohamed ER, Hamza HM. Artificial intelligence-based masked face detection: a survey. Intell Syst Appl. 2024;22:200391. doi:10.1016/j.iswa.2024.200391.
18. Yashunin D, Baydasov T, Vlasov R. MaskFace: multi-task face and landmark detector. arXiv:2005.09412. 2020.
19. Li Z, Tang X, Han J, Liu J, He R. PyramidBox++: high performance detector for finding tiny face. arXiv:1904.00386. 2019.
20. Viola P, Jones MJ. Robust real-time face detection. Int J Comput Vis. 2004;57(2):137–54. doi:10.1023/B:VISI.0000013087.49260.fb.
21. Yang S, Luo P, Loy CC, Tang X. Wider Face: a face detection benchmark. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016 Jun 27–30; Las Vegas, NV, USA. p. 5525–33. doi:10.1109/CVPR.2016.596.
22. Li J, Wang Y, Wang C, Tai Y, Qian J, Yang J, et al. DSFD: dual shot face detector. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR); 2019 Jun 15–20; Long Beach, CA, USA. p. 5055–64. doi:10.1109/cvpr.2019.00520.
23. Zhu Y, Cai H, Zhang S, Wang C, Xiong Y. TinaFace: strong but simple baseline for face detection. arXiv:2011.13183. 2020.
24. Hu P, Ramanan D. Finding tiny faces. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2017 Jul 21–26; Honolulu, HI, USA. p. 1522–30. doi:10.1109/CVPR.2017.166.
25. Ren S, He K, Girshick R, Sun J. Faster R-CNN: towards real-time object detection with region proposal networks. Adv Neural Inf Process Syst. 2015;28:1–9.
26. Li H, Lin Z, Shen X, Brandt J, Hua G. A convolutional neural network cascade for face detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2015 Jun 7–12; Boston, MA, USA. p. 5325–34. doi:10.1109/CVPR.2015.7299170.
27. Li X, Xiang Y, Li S. Combining convolutional and vision transformer structures for sheep face recognition. Comput Electron Agric. 2023;205:107651. doi:10.1016/j.compag.2023.107651.
28. Najibi M, Samangouei P, Chellappa R, Davis L. SSH: single stage headless face detector. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018 Sep 8–14; Munich, Germany.
29. Zhang S, Zhu X, Lei Z, Shi H, Wang X, Li SZ. S^3FD: single shot scale-invariant face detector. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2017 Oct 22–29; Venice, Italy. p. 192–201. doi:10.1109/ICCV.2017.30.

30. Yu S, Jiang Y, Lu J, Zhou J. CenterFace: joint face detection and alignment using face as point. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2019 Jun 16–20; Long Beach, CA, USA. doi:10.48550/arXiv.1911.03599.
31. Tan M, Pang R, Le QV. EfficientDet: scalable and efficient object detection. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR); 2020 Jun 13-19; Seattle, WA, USA. p. 10778–87. doi:10.1109/cvpr42600.2020.01079.
32. Thuan D. Evolution of Yolo algorithm and Yolov5: the state-of-the-art object detention algorithm. [cited 2025 Jan 1]. Available from: https://www.theseus.fi/bitstream/handle/10024/452552/Do_Thuan.pdf?sequence=2.
33. Bazarevsky V, Kartynnik Y, Vakunov A, Raveendran K, Grundmann M. BlazeFace: Sub-millisecond neural face detection on mobile GPUs; 2019. doi:10.48550/arXiv.1907.05047.
34. Goyal H, Sidana K, Singh C, Jain A, Jindal S. A real time face mask detection system using convolutional neural network. Multimed Tools Appl. 2022;81(11):14999–5015. doi:10.1007/s11042-022-12166-x.
35. Yu Z, Huang H, Chen W, Su Y, Liu Y, Wang X. YOLO-FaceV2: a scale and occlusion aware face detector. Pattern Recognit. 2024;155:110714. doi:10.1016/j.patcog.2024.110714.
36. Kumar A, Kaur A, Kumar M. Face detection techniques: a review. Artif Intell Rev. 2019;52(2):927–48. doi:10.1007/s10462-018-9650-2.
37. Qin H, Yan J, Li X, Hu X. Joint training of cascaded CNN for face detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016 Jun 27–30; Las Vegas, NV, USA. p. 3456–65. doi:10.1109/CVPR.2016.376.
38. Ranjan R, Patel VM, Chellappa R. HyperFace: a deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition. IEEE Trans Pattern Anal Mach Intell. 2019;41(1):121–35. doi:10.1109/TPAMI.2017.2781233.
39. Yang S, Luo P, Loy CC, Tang X. Faceness-net: face detection through deep facial part responses. IEEE Trans Pattern Anal Mach Intell. 2017;40(8):1845–59. doi:10.48550/arXiv.1701.08393.
40. Yu J, Jiang Y, Wang Z, Cao Z, Huang T. UnitBox: an advanced object detection network. In: Proceedings of the 24th ACM International Conference on Multimedia; 2016 Oct 15–19; Amsterdam, The Netherlands. p. 516–20. doi:10.1145/2964284.2967274.
41. Ranjan R, Bansal A, Zheng J, Xu H, Gleason J, Lu B, et al. A fast and accurate system for face detection, identification, and verification. IEEE Trans Biom Behav Identity Sci. 2019;1(2):82–96. doi:10.1109/TBIOM.2019.2908436.
42. Chi C, Zhang S, Xing J, Lei Z, Li SZ, Zou X. Selective refinement network for high performance face detection. Proc AAAI Conf Artif Intell. 2019;33(1):8231–8. doi:10.1609/aaai.v33i01.33018231.
43. Chaudhuri B, Vesdapunt N, Wang B. Joint face detection and facial motion retargeting for multiple faces. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR); 2019 Jun 15–20; Long Beach, CA, USA. p. 9711–20. doi:10.1109/cvpr.2019.00995.
44. Moghaddam B, Wahid W, Pentland A. Beyond eigenfaces: probabilistic matching for face recognition. In: Proceedings Third IEEE International Conference on Automatic Face and Gesture Recognition; 1998 Apr 14–16; Nara, Japan. p. 30–5. doi:10.1109/AFGR.1998.670921.
45. He X, Yan S, Hu Y, Niyogi P, Zhang HJ. Face recognition using laplacianfaces. IEEE Trans Pattern Anal Mach Intell. 2005;27(3):328–40. doi:10.1109/TPAMI.2005.55.
46. Wiskott L, Fellous JM, Krüger N, von der Malsburg C. Face recognition by elastic bunch graph matching. In: Intelligent biometric techniques in fingerprint and face recognition. Boca Raton, FL, USA: Routledge; 2022. p. 355–96. doi:10.1201/9780203750520-11.
47. Belhumeur PN, Hespanha JP, Kriegman DJ. Eigenfaces vs. Fisherfaces: recognition using class specific linear projection. IEEE Trans Pattern Anal Mach Intell. 1997;19(7):711–20. doi:10.1109/34.598228.
48. Liu C, Wechsler H. A Gabor feature classifier for face recognition. In: Proceedings Eighth IEEE International Conference on Computer Vision, ICCV 2001; 2001 Jul 7–14; Vancouver, BC, Canada. p. 270–5. doi:10.1109/ICCV.2001.937635.

49. Ahonen T, Hadid A, Pietikainen M. Face description with local binary patterns: application to face recognition. IEEE Trans Pattern Anal Mach Intell. 2006;28(12):2037–41. doi:10.1109/TPAMI.2006.244.
50. Chen D, Cao X, Wen F, Sun J. Blessing of dimensionality: high-dimensional feature and its efficient compression for face verification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2013 Jun 23–28; Portland, OR, USA. p. 3025–32. doi:10.1109/CVPR.2013.389.
51. Lei Z, Pietikäinen M, Li SZ. Learning discriminant face descriptor. IEEE Trans Pattern Anal Mach Intell. 2014;36(2):289–302. doi:10.1109/TPAMI.2013.112.
52. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Adv Neural Inf Process Syst. 2012;25:1–9. doi:10.1145/3065386.
53. Parkhi OM, Vedaldi A, Zisserman A. Deep face recognition. In: Proceedings of the British Machine Vision Conference 2015; 2015 Sep 7–10; Swansea, UK. Durham, UK: British Machine Vision Association; 2015. doi:10.5244/c.29.41.
54. Schroff F, Kalenichenko D, Philbin J. FaceNet: a unified embedding for face recognition and clustering. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2015 Jun 7–12; Boston, MA, USA. p. 815–23. doi:10.1109/CVPR.2015.7298682.
55. Taigman Y, Yang M, Ranzato M, Wolf L. DeepFace: closing the gap to human-level performance in face verification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2014 Jun 23–28; Columbus, OH, USA. p. 1701–8. doi:10.1109/CVPR.2014.220.
56. Deng J, Guo J, Xue N, Zafeiriou S. ArcFace: additive angular margin loss for deep face recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2019 Jun 15–20; Long Beach, CA, USA. p. 4685–94. doi:10.1109/cvpr.2019.00482.
57. Chen Y, Wen Y, Sun J, Li Z. MobileFaceNets: efficient CNNs for accurate real-time face verification on mobile devices. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2018 Jun 18–22; Salt Lake City, UT, USA. p. 3693–701. doi:10.48550/arXiv.1804.07573.
58. Tan W, Guo Y, Wu Z, Zhang Z, Huang R, Li J. TResNet: high-performance GPU-dedicated architecture for deep learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops; 2021 Jun 19–25; Virtual. p. 567–76. doi:10.48550/arXiv.2003.13630.
59. Mukhometzianov R, Carrillo J. CapsNet comparative performance evaluation for image classification. arXiv:1805.11195. 2018.
60. Sreekala K, Cyril CPD, Neelakandan S, Chandrasekaran S, Walia R, Martinson EO. Capsule network-based deep transfer learning model for face recognition. Wirel Commun Mob Comput. 2022;2022:2086613. doi:10.1155/2022/2086613.
61. Wen Y, Zhang K, Li Z, Qiao Y. A discriminative feature learning approach for deep face recognition. In: Proceedings of the European Conference on Computer Vision; 2016 Oct 11–14; Amsterdam, The Netherlands. p. 499–515. doi:10.1007/978-3-319-46478-7_31.
62. Wang H, Wang Y, Zhou Z, Ji X, Gong D, Zhou J, et al. CosFace: large margin cosine loss for deep face recognition. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2018 Jun 18–22; Salt Lake City, UT, USA. p. 5265–74. doi:10.48550/arXiv.1801.09414.
63. Liu W, Wen Y, Yu Z, Li M, Raj B, Song L. SphereFace: deep hypersphere embedding for face recognition. In: Proceedings of the IEEE International Conference on Computer Vision; 2017 Jul 22–29; Venice, Italy. p. 6738–46. doi:10.1109/CVPR.2017.713.
64. Zhu X, Zhen L, Yan J, Dong Y, Li SZ. High-fidelity Pose and Expression Normalization for face recognition in the wild. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2015 Jun 7-12; Boston, MA, USA. p. 787–96. doi:10.1109/CVPR.2015.7298679.
65. Eldifrawi I, Abo-Zahhad M, Abdelwahab M, El-Malek AHA. New face recognition algorithm adopting wide fast embedded capsule networks with reduced complexity and preserved accuracy. In: 2021 9th International Japan-Africa Conference on Electronics, Communications, and Computations (JAC-ECC); 2021 Dec 13–14; Alexandria, Egypt. p. 20–5. doi:10.1109/JAC-ECC54461.2021.9691419.

66. Sun S, Zhuang S, Zhou Z, Huang Q, Liu Y, Zhang Z. High-resolution representations for labeling pixels and regions. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2020 Jun 14–19; Seattle, WA, USA. p. 7132–41. doi:10.48550/arXiv.1904.04514.
67. Zhang P, Zhao F, Liu P, Li M. Efficient lightweight attention network for face recognition. IEEE Access. 2022;10:31740–50. doi:10.1109/ACCESS.2022.3150862.
68. Chui A, Patnaik A, Ramesh K, Wang L. Capsule networks and face recognition. [cited 2025 Jan 1]. Available from: https://lindawangg.github.io.
69. Hariri W. Efficient masked face recognition method during the COVID-19 pandemic. Signal Image Video Process. 2022;16(3):605–12. doi:10.1007/s11760-021-02050-w.
70. Terhörst P, Ihlefeld M, Huber M, Damer N, Kirchbuchner F, Raja K, et al. QMagFace: simple and accurate quality-aware face recognition. In: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV); 2023 Jan 2–7; Waikoloa, HI, USA. p. 3473–83. doi:10.1109/WACV56688.2023.00348.
71. Tsai TH, Lu JX, Chou XY, Wang CY. Joint masked face recognition and temperature measurement system using convolutional neural networks. Sensors. 2023;23(6):2901. doi:10.3390/s23062901.
72. Xiao J, Jiang G, Liu H. A lightweight face recognition model based on MobileFaceNet for limited computation environment. EAI Endorsed Trans IoT. 2022;7(27):1–9. doi:10.4108/eai.28-2-2022.173547.
73. Xu X, Deng H, Wang Y, Zhang S, Song H. Boosting cattle face recognition under uncontrolled scenes by embedding enhancement and optimization. Appl Soft Comput. 2024;164:111951. doi:10.1016/j.asoc.2024.111951.
74. Haq MU, Sethi MAJ, Ben Aoun N, Alluhaidan AS, Ahmad S, Farid Z. CapsNet-FR: capsule networks for improved recognition of facial features. Comput Mater Contin. 2024;79(2):2169–86. doi:10.32604/cmc.2024.049645.
75. Bergman N, Yitzhaky Y, Halachmi I. Biometric identification of dairy cows via real-time facial recognition. Animal. 2024;18(3):101079. doi:10.1016/j.animal.2024.101079.
76. Haq MU, Sethi MAJ, Ahmad S, ELAffendi MA, Asim M. Automatic player face detection and recognition for players in cricket games. IEEE Access. 2024;12:41219–33. doi:10.1109/ACCESS.2024.3377564.
77. Lv JJ, Shao XH, Huang JS, Zhou XD, Zhou X. Data augmentation for face recognition. Neurocomputing. 2017;230:184–96. doi:10.1016/j.neucom.2016.12.025.
78. Masi I, Trân AT, Hassner T, Sahin G, Medioni G. Face-specific data augmentation for unconstrained face recognition. Int J Comput Vis. 2019;127(6):642–67. doi:10.1007/s11263-019-01178-0.
79. Dalvi J, Bafna S, Bagaria D, Virnodkar S. A survey on face recognition systems. arXiv:2201.02991. 2022.
80. Nanni L, Paci M, Brahnam S, Lumini A. Comparison of different image data augmentation approaches. J Imaging. 2021;7(12):254. doi:10.3390/jimaging7120254.
81. Wang N, Gao X, Tao D, Yang H, Li X. Facial feature point detection: a comprehensive survey. Neurocomputing. 2018;275:50–65. doi:10.1016/j.neucom.2017.05.013.
82. Bulat A, Tzimiropoulos G. Two-stage convolutional part heatmap regression for the 1st 3D face alignment in the wild (3DFAW) challenge. In: Computer Vision—ECCV 2016 Workshops; 2016 Oct 11–14; Amsterdam, The Netherlands. Cham, Switzerland: Springer International Publishing. p. 616–24. doi:10.1007/978-3-319-48881-3_43.
83. Wang X, Bo L, Li F. Adaptive wing loss for robust face alignment via heatmap regression. In: Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV); 2019 Oct 27–Nov 2; Seoul, Republic of Korea. p. 6970–80. doi:10.1109/iccv.2019.00707.
84. Hou A. Adaptive wing loss for face alignment [GitHub repository]. San Francisco, CA, USA: GitHub. [cited 2025 Jan 15]. Available from: https://github.com/andrewhou1/Adaptive-Wing-Loss-for-Face-Alignment.
85. Zhang Z, Luo P, Loy CC, Tang X. Facial landmark detection by deep multi-task learning. In: Computer Vision—ECCV 2014: 13th European Conference; 2014 Sep 6–12; Zurich, Switzerland. Cham, Switzerland: Springer International Publishing. p. 94–108. doi:10.1007/978-3-319-10599-4_7.
86. Dapogny A, Cord M, Bailly K. DeCaFA: deep convolutional cascade for face alignment in the wild. In: Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV); 2019 Oct 27–Nov 2; Seoul, Republic of Korea. p. 6892–900. doi:10.1109/iccv.2019.00699.
87. Park H, Kim D. ACN: occlusion-tolerant face alignment by attentional combination of heterogeneous regression networks. Pattern Recognit. 2021;114:107761. doi:10.1016/j.patcog.2020.107761.

88. Besnassi M, Neggaz N, Benyettou A. Face detection based on evolutionary haar filter. Pattern Anal Appl. 2020;23(1):309–30. doi:10.1007/s10044-019-00784-5.
89. Rahmad C, Asmara RA, Putra DH, Dharma I, Darmono H, Muhiqqin I. Comparison of Viola-Jones haar cascade classifier and histogram of oriented gradients (HOG) for face detection. IOP Conf Ser Mater Sci Eng. 2020;732(1):012038. doi:10.1088/1757-899x/732/1/012038.
90. Karanwal S. Robust local binary pattern for face recognition in different challenges. Multimed Tools Appl. 2022;81(20):29405–21. doi:10.1007/s11042-022-13006-8.
91. Alamri J, Harrabi R, Ben S. Face recognition based on convolution neural network and scale invariant feature transform. Int J Adv Comput Sci Appl. 2021;12(2):644–54. doi:10.14569/ijacsa.2021.0120281.
92. Setta S, Sinha S, Mishra M, Choudhury P. Real-time facial recognition using SURF-FAST. In: Sharma N, Chakrabarti A, Balas VE, Bruckstein AM, editors. Data management, analytics and innovation. Vol. 2. Singapore: Springer; 2021. p. 505–22. doi:10.1007/978-981-16-2937-2_32.
93. Prasad PS, Pathak R, Gunjan VK, Ramana Rao HV. Deep learning based representation for face recognition. In: ICCCE 2019: Proceedings of the 2nd International Conference on Communications and Cyber Physical Engineering. Singapore: Springer; 2020. p. 419–24. doi:10.1007/978-981-13-8715-9_50.
94. Li HA, Fan J, Zhang J, Li Z, He D, Si M, et al. Facial image segmentation based on Gabor filter. Math Probl Eng. 2021;2021:6620742. doi:10.1155/2021/6620742.
95. Kasikrit. ATT database of faces [Internet]. San Francisco, CA, USA; Kaggle. [cited 2024 Apr 16]. Available from: https://www.kaggle.com/datasets/kasikrit/att-database-of-faces.
96. Kamachi M, Ullah TM, Akamatsu S. Japanese female facial expression (JAFFE) database. In: Proceedings of the International Conference on Automatic Face and Gesture Recognition; 2023 Jan 5–8; Waikoloa Beach, HI, USA. doi:10.5281/zenodo.3451524.
97. Wang Z, Huang B, Wang G, Yi P, Jiang K. Masked face recognition dataset and application. IEEE Trans Biom Behav Identity Sci. 2023;5(2):298–304. doi:10.1109/TBIOM.2023.3242085.
98. Huang GB, Ramesh M, Berg T, Learned-Miller E. Labeled faces in the wild: a database for studying face recognition in unconstrained environments [Internet]. [cited 2024 Apr 16]. Available from: http://vis-www.cs.umass.edu/lfw/.
99. Wolf L, Hassner T, Maoz I. Face recognition in unconstrained videos with matched background similarity. In: CVPR 2011; 2011 Jun 20–25; Colorado Springs, CO, USA. p. 529–34. doi: 10.1109/CVPR.2011.5995566.
100. Klare BF, Klein B, Taborsky E, Blanton A, Cheney J, Allen K, et al. Pushing the frontiers of unconstrained face detection and recognition: iarpa Janus Benchmark A. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2015 Jun 7–12; Boston, MA, USA. p. 1931–9. doi:10.1109/CVPR.2015.7298803.
101. Kemelmacher-Shlizerman I, Seitz SM, Miller D, Brossard E. The MegaFace benchmark: 1 million faces for recognition at scale. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016 Jun 27–30; Las Vegas, NV, USA. p. 4873–82. doi:10.1109/CVPR.2016.527.
102. Zhang J, Shan S, Kan M, Chen X. WebFace: a scalable face image dataset with varying pose and age; 2014 [Internet]. [cited 2025 Apr 24]. Available from: https://paperswithcode.com/dataset/casia-webface.
103. Cao Q, Shen L, Xie W, Parkhi OM, Zisserman A. VGGFace2: a dataset for recognising faces across pose and age. In: 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018); 2018 May 15–19; Xi'an, China. p. 67–74. doi:10.1109/FG.2018.00020.
104. Panis G, Lanitis A, Tsapatsoulis N, Cootes TF. Overview of research on facial ageing using the FG-NET ageing database. IET Biom. 2016;5(2):37–46. doi:10.1049/iet-bmt.2014.0053.
105. BioID facial recognition (Version 2.2.2). [Mobile app, 2022] retrieved from Google Play Store [Internet]. [cited 2025 Apr 24]. Available from: https://play.google.com/store/apps/details?id=com.bioid.authenticator.
106. Levi G, Hassncer T. Age and gender classification using convolutional neural networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW); 2015 Jun 7–12; Boston, MA, USA. p. 34–42. doi:10.1109/CVPRW.2015.7301352.
107. Color FERET database [Internet]. [cited 2022 May 20]. Available from: https://www.nist.gov/itl/products-and-services/color-feret-database.

108. Grgic M, Delac K, Grgic S. SCface-surveillance cameras face database. Multimed Tools Appl. 2011;51(3):863–79. doi:10.1007/s11042-009-0417-2.
109. Martinez A, Benavente R. The AR face database. Barcelona, Spain: CVC; 1998. Report No.: 24.
110. Phillips PJ, Wechsler H, Huang J, Rauss PJ. The FERET database and evaluation procedure for face-recognition algorithms. Image Vis Comput. 1998;16(5):295–306. doi:10.1016/S0262-8856(97)00070-X.
111. Wang Z, Wang G, Huang B, Xiong Z, Hong Q, Wu H, et al. Masked face recognition dataset and application. arXiv:2003.09093. 2020.
112. Cao J, Li Y, Zhang Z. Celeb-500K: a large training dataset for face recognition. In: 25th IEEE International Conference on Image Processing (ICIP); 2018 Oct 7–10; Athens, Greece. p. 2406–10. doi:10.1109/ICIP.2018.8451704.
113. Bae G, de la Gorce M, Baltrušaitis T, Hewitt C, Chen D, Valentin J, et al. DigiFace-1M: 1 million digital face images for face recognition. In: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV); 2023 Jan 2–7; Waikoloa, HI, USA. p. 3515–24. doi:10.1109/WACV56688.2023.00352.
114. Medvedev I, Shadmand F, Gonçalves N. Young labeled faces in the wild (YLFW): a dataset for children faces recognition. arXiv:2301.05776. 2023.
115. Center for computational vision and control. Yale face database B [Internet]. New Haven, CT, USA: Yale University. 2001. [cited 2025 Apr 17]. Available from: https://www.cs.yale.edu/cvc/projects/yalefacesB/yalefacesB.html.
116. Georghiades AS, Belhumeur PN, Kriegman DJ. From few to many: illumination cone models for face recognition under variable lighting and pose. IEEE Trans Pattern Anal Mach Intell. 2001;23(6):643–60. doi:10.1109/34.927464.
117. Haq MU, Sethi MAJ, Ullah R, Shazhad A, Hasan L, Karami GM. COMSATS face: a dataset of face images with pose variations, its design, and aspects. Math Probl Eng. 2022;2022:4589057. doi:10.1155/2022/4589057.
118. Guo Y, Zhang L, Hu Y, He X, Gao J. MS-celeb-1M: a dataset and benchmark for large-scale face recognition. In: Computer Vision—ECCV 2016: 14th European Conference; 2016 Oct 11–14; Amsterdam, The Netherlands. Cham, Switzerland: Springer International Publishing; 2016. p. 87–102. doi:10.1007/978-3-319-46487-9_6.
119. Ferrari C, Berretti S, Del Bimbo A. Extended YouTube faces: a dataset for heterogeneous open-set face identification. In: 2018 24th International Conference on Pattern Recognition (ICPR); 2018 Aug 20–24; Beijing, China. p. 3408–13. doi:10.1109/ICPR.2018.8545642.
120. Sim T, Baker S, Bsat M. The CMU pose, illumination, and expression (PIE) database. In: Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition; 2002 May 21; Washington, DC, USA. p. 53–8. doi:10.1109/AFGR.2002.1004130.
121. Gross R, Matthews I, Cohn J, Kanade T, Baker S. Multi-PIE. Image Vis Comput. 2010;28(5):807–13. doi:10.1016/j.imavis.2009.08.002.
122. Liu Z, Luo P, Wang X, Tang X. Deep learning face attributes in the wild. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2015 Dec 7–13; Santiago, Chile. p. 3730–8. doi:10.1109/ICCV.2015.425.
123. Zheng T, Deng W, Hu J. Cross-age LFW: a database for studying cross-age face recognition in unconstrained environments. arXiv:1708.08197. 2017.
124. Zheng T, Deng W. Cross-pose LFW: a database for studying cross-pose face recognition in unconstrained environments [Internet]. Beijing, China: Beijing University of Posts and Telecommunications. 2018 [cited 2025 Apr 24]. Available from: https://pan.baidu.com/s/1i6iHztN.
125. Papers with code. CACD dataset [Internet]. [cited 2025 Apr 17]. Available from: http://paperswithcode.com/dataset/cacd.
126. Langner O, Dotsch R, Bijlstra G, Wigboldus DHJ, Hawk ST, van Knippenberg A. Presentation and validation of the radboud faces database. Cogn Emot. 2010;24(8):1377–88. doi:10.1080/02699930903485076.
127. Yin L, Chen X, Sun Y, Worm T, Reale M. A high-resolution 3D dynamic facial expression database. In: Proceedings of the IEEE International Conference on Automatic Face & Gesture Recognition; 2008 Sep 17–19; Amsterdam, The Netherlands. p. 1–6. doi:10.1109/AFGR.2008.4813324.
128. Zhu H, Wu W, Zhu W, Jiang L, Tang S, Zhang L, et al. CelebV-HQ: a large-scale video facial attributes dataset. In: European Conference on Computer Vision; 2022; Cham, Switzerland: Springer Nature Switzerland; p. 650–67. doi:10.1007/978-3-031-20071-7_38.

129. Sengupta S, Chen JC, Castillo C, Patel VM, Chellappa R, Jacobs DW. Frontal to profile face verification in the wild. In: 2016 IEEE Winter Conference on Applications of Computer Vision (WACV); 2016 Mar 7–10; Lake Placid, NY, USA. p. 1–9. doi:10.1109/WACV.2016.7477558.
130. Rodrigo M, González-Sosa E, Cuevas C, García N. UPM-GTI-face: a dataset for the evaluation of the impact of distance and masks in face detection and recognition systems. In: 2022 18th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS); 2022 Nov 29–Dec 2; Madrid, Spain. p. 1–8. doi:10.1109/AVSS56176.2022.9959558.
131. Bansal A, Nanduri A, Castillo CD, Ranjan R, Chellappa R. UMDFaces: an annotated face dataset for training deep networks. In: 2017 IEEE International Joint Conference on Biometrics (IJCB); 2017 Oct 1–4; Denver, CO, USA. p. 464–73. doi:10.1109/BTAS.2017.8272731.
132. Li N, Shen X, Sun L, Xiao Z, Ding T, Li T, et al. Chinese face dataset for face recognition in an uncontrolled classroom environment. IEEE Access. 2023;11:86963–76. doi:10.1109/ACCESS.2023.3302919.
133. Cabani A, Hammoudi K, Benhabiles H, Melkemi M. MaskedFace-Net—a dataset of correctly/incorrectly masked face images in the context of COVID-19. Smart Health. 2021;19:100144. doi:10.1016/j.smhl.2020.100144.
134. Eyiokur FI, Ekenel HK, Waibel A. Unconstrained face mask and face-hand interaction datasets: building a computer vision system to help prevent the transmission of COVID-19. Signal Image Video Process. 2023;17(4):1027–34. doi:10.1007/s11760-022-02308-x.
135. Muhajir M, Oktiana M, Muchtar K, Fitria M, Akhyar A, Pratama MD, et al. USK-FEMO: a face emotion dataset using deep learning for effective learning. In: 2023 2nd International Conference on Computer System, Information Technology, and Electrical Engineering (COSITE); 2023 Aug 2–3; Banda Aceh, Indonesia. p. 199–203. doi:10.1109/COSITE60233.2023.10249834.
136. Mekonnen KA. Balanced face dataset: guiding StyleGAN to generate labeled synthetic face image dataset for underrepresented group. arXiv:2308.03495. 2023.
137. Wuu CH, Zheng N, Ardisson S, Bali R, Belko D, Brockmeyer E, et al. Multiface: a dataset for neural face rendering. arXiv:2207.11243. 2022.
138. Haq MU, Sethi MAJ, Ullah S, Ullah A. The development, applications, challenges, and analysis of a cricket player face recognition dataset. In: Deep cognitive modelling in remote sensing image processing. Hershey, PA, USA: IGI Global; 2024. p. 173–97. doi:10.4018/979-8-3693-2913-9.ch008.