Journal of Techniques, ISSN: 2708-8383, Vol. 5, No. 4, 2023, Pages 95-104
DOI: https://doi.org/10.51173/jt.v5i4.1729

JOURNAL OF TECHNIQUES

Journal homepage: http://journal.mtu.edu.iq

REVIEW ARTICLE - ENGINEERING

Facial Recognition Databases: Recent Developments and Review of Methods

Waleed Ayad[1*], Siraj Qays[1], Asanka G. Perera[2], Ali Al-Naji[3]

[1]Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq

[2]School of Engineering and Information Technology, University of New South Wales, Canberra, ACT 2610, Australia

[3]School of Engineering, University of South Australia, Mawson Lakes, SA 5095, Australia

[*] Corresponding author E-mail: bbc0054@mtu.edu.iq

Article Info.

Article history:

Received
25 June 2023

Accepted
10 October 2023

Publishing
31 December 2023

Abstract

Facial recognition is one of the most important biometrics that many researchers are increasingly studying, as it is used in various applications such as surveillance, security, law enforcement, information, person identification, smart cards, access control, etc. There is a fundamental relationship between the development of facial recognition algorithms and the possibility of the existence of databases of different faces that influence the appearance of the face in a constrained manner. Standard datasets of images of appropriate size for a subject should be accessible to the public to compare the performance and assessment of identification or verification of a facial recognition system. This paper aims to present a review of the most popular 2D unmasked and masked face datasets available in the current century that are accessible for free download or can be certified with an acceptable effort, where these databases are suitable for training and testing 2D face recognition approaches. Also, this review discussed the evaluation metrics for face recognition and their two types of tasks (identification and verification).

Publisher: Middle Technical University

Keywords: Face Recognition; 2D Face Datasets; Database.

1. Introduction

The development of the computer and its capability to visualize and store huge quantities of information have produced the evolution of biometrics, such as voice recognition, face recognition, fingerprint, etc.

Biometrics technology is growing in importance and is increasingly studied by many researchers. Because of its excellent and incomparable performance, it includes both techniques used to analyze the unique characteristics of an individual and those utilized for measurement. Biometrics are divided into two types: physical and behavioral. The first is used either for identification or verification, whereas the second can generally be used for verification.

Presently, "face recognition" is considered one of the essential biometrics utilized for identification. Facial recognition is one of the most widely researched subjects in industrial and academic areas because it is inexpensive and very popular and because of its wide applications in surveillance, security, law enforcement, information, Person Identification, smart cards, access control, etc. [1-3].

During the current century, various methods, techniques, and databases have been provided for recognizing faces in 2D images, which are used in diverse fields, such as facial recognition and video surveillance systems [4-8]. The facial recognition system is performed in three steps [9]: facial detection, feature extraction, and facial recognition. An image of the face is entered into the system, and then the facial recognition system (first stage) Begins detecting the presence of one or more faces in the image. Usually, the face detection system can determine whether or not a face(s) has existed in the image. If so, the system's function is to determine the place of a face(s) in the image [10].

Facial feature extraction [11-13] is the second step after detecting a facial(s) in an image. The importance of this step is to recognize facial expressions. The feature extraction stage Includes extracting a feature vector from the detected facial called signature, which is enough to distinguish the face. The characteristic of distinguishing between two different people and the face's uniqueness must be checked. The possibility of performing this step should be mentioned at the stage of facial detection. In other words, the two steps of facial detection and feature extraction can be accomplished simultaneously, as seen in (Fig. 1).

The third step involves facial recognition features extracted from the human face to be compared with all databases of typical faces for human facial identity. There are two various tasks in facial recognition: facial verification and facial identification. In the first mode (verification) [14],

Nomenclature & Symbols			
TA	True Acceptance	IJB-A	IARPA Janus Benchmark-A
FR	False Rejection	CFP	Celebrities in Frontal-Profile
TAR	True Accept Rate	DMFD	Disguise Covariate and/or Make-up Facial Database
FAR	False Accept Rate	VGG	Visual Geometry Group
AUC	Area Under the Curve	MF2	Megaface 2
TPIR	True Positive Identification Rate	DFW	Disguised Faces in the Wild
FPIR	False-Positive Identification Rate	LFR	Left-Front-Right
CMC	Cumulative Matching Characteristic	MFDD	Masked Facial Detection Dataset
FRGC	Great Face Recognition Challenge	RMFRD	Real-World Masked Facial Recognition Dataset
LFW	Labeled Faces in the Wild	SMFRD	Simulated Masked Facial Recognition Dataset
IARPA	Intelligence Advanced Research Projects Activity	MFSR	Masked Facial Segmentation And Recognition

the system performs identity verification based on the input image of the face by comparing the captured face image with the model(s) registered in the database. The system performs a one-to-one comparison to determine the validity of the declared identity or not. In identification [15], a person's photo is matched with a group of pictures of people's faces in the database. A person's face is usually recognized if they have images stored in the database.

There is a close relationship between the development of facial recognition algorithms and the possibility of the existence of databases of different faces that influence the appearance of the face in a constrained (controlled) manner. Standard datasets of images of appropriate size for a subject should be accessible to the public to compare the performance and assessment of identification or verification of a facial recognition system. This review presents the most popular 2D unmasked and masked face datasets available in the current century that are suitable for training and testing approaches to 2D face recognition.

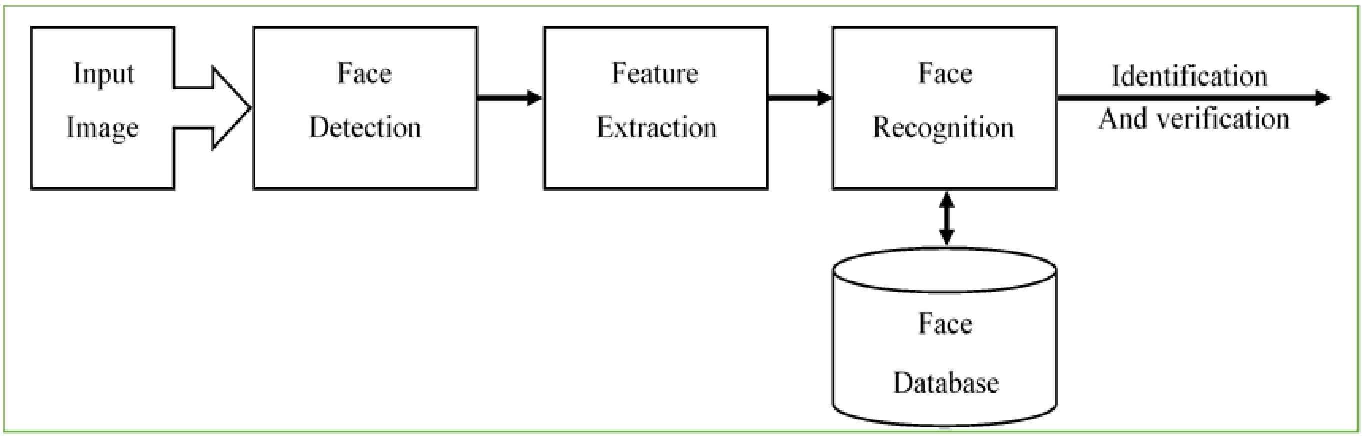

Fig. 1. The overview of the face recognition system [16]

2. Assessment Metrics in Face Recognition

In particular, there are two types of tasks for evaluating facial recognition performance: identification [15] and verification [14], each with corresponding appraisal metrics. There are two sets of samples required for evaluation, the probe and the gallery. While the probe refers to a group of faces required to be recognized in identification or verification. At the same time, the gallery here denotes the set of images of faces stored with identities defined in the facial recognition system. Before discussing the most popular evaluation metrics used, some important terms and concepts will be mentioned [14, 15]. Generally, the facial recognition system specifies whether or not the gallery facial and the probe facial are matched by comparing the similarities between them. The similarity between the two faces is calculated within a certain threshold by some measurement among its features. Especially when there is a symmetric identity for a gallery face and a probe face, In the case that the similarity between them is higher than the threshold, it represents a true acceptance (TA), and if their similarity is less than the threshold, it means that is a false rejection (FR); But if there are asymmetric identities, in case the similarity between them is less than the threshold, it represents a true rejection (TR), and in the case, the similarity between them is higher than the threshold, it represents a false acceptance (FA) [14, 15].

2.1. Verification task

Usually, Verification (validation) calculates the similarity between pairs of faces, as it is applied in identity authentication systems. Where a picture is taken of the face of the person who claims to be the owner of the ID stored in the gallery. Then the system decides whether the person is the same as the identity holder or not by calculating the percentage of similarity between the identity claimant's photo and the face and face registered in the exhibition. Specifically, the task of validating a binary classification process is a one-to-one face match, to detect people using a single identity. Validation performance can be evaluated using the true accept rate (TAR) and false accept rate (FAR). FAR is part of impostor pairs with the similarity exceeding the threshold, which can be found using FA / $(FA + TR)$; TAR represents the part of genuine pairs with the similarity exceeding the threshold, which can be found using $TA/(TA+FR)$. Then, by changing the threshold values, a receiver operating characteristic (ROC) can be plotted using multiple operating points. A pair of TAR versus FAR is used to Determine each point. Broadly, the ROC curve (with the value of TAR when FAR is specified) and its area under the curve (AUC) are used in evaluating the performance of a facial verification task [14].

2.2. Identification task

Identifying the face determines whether the probe face is one of the identities stored in the gallery set or not. This task is done by comparing the face of the person claiming the identity with all the facial models in the gallery set. Thus, the task of identification can be considered as the process of making a one-to-all face comparison. This type of identification is used to prevent an individual from Utilizing more than one identity. Usually, there are two facial identification tasks: 1-open-set Identification and 2-closed-set Identification. Several types of metrics are used to measure the model's accuracy, the most important of which is the true identification rate (TPIR) and the false-positive identification rate (FPIR), in the following two cases. In the first case when the probe facial matches the identity of the person's face stored in the gallery set. In this case, the similarity is greater than the threshold. In this case, the face of the investigation is determined as the person registered in the gallery set. Thus, TPIR is the ratio of successful experiments to find the probe face. The second case is when the probe face does not match any of the identities stored in the gallery set. FPIR refers to the ratio of cases of the probe face that is not registered in the gallery set but was incorrectly identified as a registered identity. By fixation on the rank and changing the threshold value, it is possible to plot a ROC curve using multiple operating points. A pair of TPIR versus FPIR is used to calculate each point. The ROC curve is the most widely used in evaluating the performance of the task of open-set facial identification. For the closed-set Face task, it is assumed that all probe faces have already been registered in the gallery set. Usually, the cumulative matching characteristic (CMC) curve is used to evaluate closed-set facial identification. The CMC curve is plotted through multiple operating points depending on a pair rate of identification versus rank. The rate of identification means the percentage of discovered probe faces matching the identities of the actual persons that their identities stored in the gallery. Hence, the CMC curve uses the correct matching ratio with a certain rank. The CMC is a unique situation for TPIR when its threshold is lowered [15].

3. Available Datasets for 2D Face Recognition

Recognizing and searching for patterns in data sets is a problematic, huge, and complex task. To evaluate, test, and compare the identification or verification performance of pattern recognition systems, particularly face recognition systems, benchmark datasets of video or images of appropriate subject size must be available and obtainable for research and development. This paper mainly summarizes the most popular masked/unmasked faces datasets suitable for testing the performance of 2D face verification methods published this century and which are accessible for free download or can be certified with an acceptable effort.

3.1. Unmasked face datasets

3.1.1. BANCA dataset

In 2003, Bengio et al. [17] introduced a huge, functional, and challenging multi-modal database called BANCA, which is used to train and test multi-modal biometric verification systems. Their data have been obtained in four different European languages (English, Spanish, Italian, and French) by two modalities: face and voice. Low and high-quality cameras and microphones have been utilized for recording. Person's faces and voices have been registered in three various scenarios (controlled, adverse, and degraded) through 12 various times during three months of period. The total number of people obtained was 208, the first half of whom are men and the second half are women. (Fig. 2) contains sample images of these faces. Seven independent experiential configurations have been used for the protocol of evaluation, called: (1) matched degraded (MD), (2) matched controlled (MC), (3) matched adverse (MA), (4) grand test (G), (5) unmatched adverse (UA), (6) unmatched degraded (UD) and (7) pooled test (P). These formations have been created to know which of them can be used for training, and which of them can be used for testing. It is required that the person's data be saved in all configurations from the first session for training.

Fig. 2. An example of a set of images from the BANCA database with various scenarios

3.1.2. Great Face Recognition Challenge (FRGC) dataset

Phillips et al. [18] designed the Great Face Recognition Challenge (FRGC) between 2004 and 2006 to make performance enhancements by tracking algorithm proceed for all proceeds approaches in the literature. FRGC database was collected from images of 200 persons (57% men and 43% women) and a total of 50,000 pictures that were divided into the training and validation parts. A person imaging session in FRGC consisted of two unsupervised images, four controlled still photos, and a 3D picture, as illustrated in (see Fig. 3). FRGC was divided into six experiential protocols:

- In experiential protocol 1, two controlled still pictures for every person are utilized, one for a gallery, and the second for a probe.
- In experimental protocol 2, the four controlled pictures of an individual are distributed between the probe and gallery.
- In experimental protocol 4, single controlled still pictures present the gallery, and single uncontrolled still images present the probe.
- Experimental protocols 3,5 and 6 are created for 3D pictures.

3.1.3. LFW Database

In 2007, Huang et al. [19] created a database of faces named Labeled Faces in the Wild (LFW), which consisted of 13,233 facial pictures collected from the internet from 5,749 unique individuals whose images have been in extreme contrast conditions,1,680 of them have two or more different images and the others have only one distinct image. Each image size is 250 x 250 pixels. LFW was created to help study the unrestricted issue of facial recognition, such as variation of the picture, face expression, background, ethnicity, race, gender, lighting, age, camera quality, clothing, focus, hairstyles, and other parameters (see Fig. 4). In LFW there are three basic performance measurement protocols: 1- unsupervised protocol, 2- restricted protocol, and 3- unrestricted protocol. The first unsupervised protocol is used to evaluate the performance of a facial representation, and the second and third protocols are used to evaluate the metric performance or the whole method. For all protocols, the test set has been fixed, where it contains 6000 face pairs in 10 splits.

Fig. 3. An example from one individual session; (a, b, c) controlled stills, (d, e) uncontrolled stills, and (f) 3D shape

Fig. 4. An example of a set of images from the LFW dataset

3.1.4. CMU Multi-PIE Dataset

From 2004 to 2009, Gross et al. developed a face database called CMU Multi-PIE [20]. Above 750,000 images were collected for 337 individuals captured in four sessions over five months. The pictures were taken from 15 cameras placed with different viewing points (see Fig. 5) and 19 illumination cases (see Fig. 6), as well as a wide range of facial expressions: Neutral, Smile, Surprise, Squint, Disgust, Scream (see Fig. 7). Moreover, it captured High-quality frontal pictures. Globally, the CMU Multi-PIE database contains 305 GB of facial image data.

Fig. 5. An example of a set of images captured in the CMU Multi-PIE database by the 15 cameras located in various locations

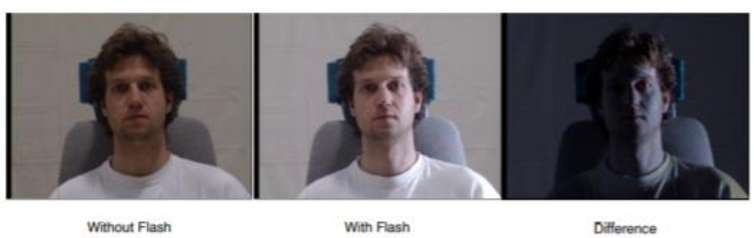

Fig. 6. An example of a set of images from the multi-PIE database at different illumination situations

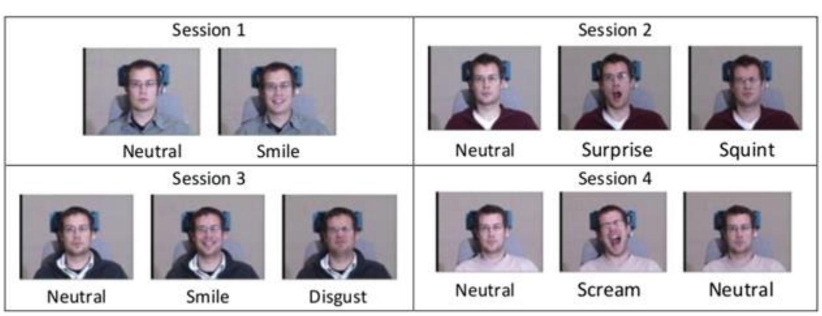

Fig. 7. An example of a set of facial expressions from the CMU Multi PIE database that was captured in four sessions

3.1.5. CASIA-WebFace dataset

In 2014, Yi et al. [21] proposed a large-scale data set for the facial recognition task, named CASIA-WebFace, which was collected semi-automatical from the website of IMDb, where it was gathered 49,414 images of the faces of 10,575 people CASIA-WebFace can be deemed an independent training set for LFW. Combining them can standardize the LFW evaluation protocol and develop a reproducible search for face recognition in the wild. The entire process of constructing a data set and learning a face representation using an 11-layer convolutional network was also described. The high-performance facial recognition engine can also be trained by anyone, using the pipeline proposed.

3.1.6. IARPA Janus benchmark-A

In 2015, Brendan F. Klare et al. [22] developed the Intelligence Advanced Research Projects Activity (IARPA) that contains images and video clips in the wild from 500 subjects from diverse geographies: 5712 images and 2085 clips Video with an average of 11.4 pictures and 4.2 videos for each individual, with each person in the data set having at least one video and five images (Fig. 8). To get a new situation than LFW and full pose variation, face images have been restricted and recognized manually. IJB-A has created two protocols that support both open-set identification (search one-to-many) and validation (comparison one-to-one), and another protocol dedicated to detection. A separate protocol for facial recognition is presented. For the identification and verification protocols, there are 10 subclasses of training and random testing; In every subclass, 333 people are utilized in the training sub-category and 167 people are being used in the training sub-category. The search protocol utilizes probe templates to calculate the accuracy of the closed-set and open-set search on the templates of the gallery. The protocol determines precisely which impostor and genuine comparisons should be done for every subclass.

Fig. 8. An example of a set of images from the IJB-A (Janus Benchmark A) dataset

3.1.7. MegaFace database

In 2016, Kemelmacher-Shlizerman et al. [23] proposed a database called MegaFace, which Contains 1,027,060 images of 690,572 persons. The challenge of MegaFace utilizes a gallery to test the performance of facial identification and verification algorithms with numerous "distractors," i.e., faces that do not exist in the test set, via training them from various probe sets, for instance, FG-NET, [24] (contain 975 pictures of 82 people with a diverse average of ages) and FaceScrub [25] (contain 141,130 facial of 695 famous characters).

3.1.8. CFP (celebrities in frontal-profile) dataset

In 2016, Sengupta et al. [26] collected a public and challenging dataset called CFP (celebrities in frontal-profile) at the University of Maryland. It contains 7000 images of 500 individuals (see Fig. 9). It includes 10 frontal and four profile pictures of every individual. The assessment protocol comprises frontal-profile (FP) and frontal-frontal (FF) facial verification, each with ten parts of 50 subjects and 350 pairs of the various persons and 350 pairs of the same individuals.

Fig. 9. An example of a set of images from the CFP dataset

3.1.9. Ms-Celeb-M1 dataset

Microsoft designed a large-scale training dataset and benchmarked the Ms-Celeb-M1 [27] in 2016, which includes about 10M facial pictures from 100k famous people from various countries most of them female, gathered from the internet to develop face recognition techniques further.

3.1.10. DMFD database

To assess the performance of disguised facial recognition or detection utilizing disguised accessories, in 2016, Tsung Ying Wang et al. [28] presented the Disguise Covariate and/or Make-up Facial Database (DMFD) with ground truth such as (eye-glasses, skin color, goggles, beard) obtained in real environments. DMFD includes 2460 pictures from 410 variant persons; the more significant part of these pictures is from famous people (Fig. 10). Three variant protocols are used: (1) Protocol A computes the corresponding scores on the all-to-all basis; (2) Protocol B computes the corresponding scores for one entered picture; (3) Protocol C utilizes the first pictures with the minimum obstruction such as (disguise, wrong angle, and make-up) to training and the rest of the pictures are used for testing.

Fig. 10. Picture pairs with a variant kind of disguise/ makeup

3.1.11. VGGFACE database

Another large-scale training database for facial recognition tasks is named Visual Geometry Group (VGGFACE). It was collected from the web by combining humans and automation in the loop. It includes 2.6 million pictures, from 2,622 persons (see Fig. 11). It was assembled in 2016 by Parkhi et al. [29] . at the University of Oxford.

Fig. 11. Samples of images for 6 persons from the VGGFACE (visual geometry group) dataset

3.1.12. VGGFACE2 database

In 2018, Cao et al. [30] presented a large-scale facial database named VGGFace2 at the University of Oxford. It was gathered from a Google pictures search with a large difference in ethnicity, pose, illumination, and age. VGGFace2 contains 3.31M images from 9131 persons (Fig. 12) with an average of 362.6 photos per person, they are selected in nearly equal numbers in terms of gender, where 59:3% of them are males and the rest are females. The VGGface2 is partitioned into two subclasses: the first dedicated to the training-set, contains 8631 classes, while the second dedicated to the test (evaluation-set) contains 500 classes. VGGFace2 provides two template annotations to enable evaluation through age and pose: (1) Pose template: with 5 facial for each template acts as a consistent pose (profile, or frontal view) for 9 K face pictures from 1.8 K templates; (2) age template: it includes 400 templates (five images for each template with an apparent age above 34 years, or below 34 years) with 2k face images.

Fig. 12. An example of a set of images from the VGGFACE2 database

3.1.13. IJB-B database

In 2017, Whitelam et al. [31] presented a database called IARPA Janus Benchmark-B (IJB-B) is IJB-A widening. IJB-Bcontains 1845 Identities for 21,798 still pictures (11,754 facial and 10,044 non-facial pictures) In addition to 55,026 frames acquired from 7011 facial videos. IJB-B is created so that detection, recognition, and clustering research in uncontrolled environments. Various IJB-B test protocols are advanced to operational utilize situations, such as access point identification, surveillance video searches, and clustering.

3.1.14. MegaFace 2 (MF2) dataset

In 2017, Nech et al. [32] Presented a dataset for facial recognition called MegaFace 2 (MF2) at the University of Washington. It includes 4,753,320 images and 672,057 Subjects (An average of 7.07 images per subject, with 3 photos per subject at least and 2469 as maximum images per subject). The subject image exists in various expressions, lighting, and camera conditions (see Fig. 13). MF2 was an endeavor to design a benchmark for algorithms training using large-scale datasets and testing at million-scale distractors offered by the MegaFace challenge [23].

Fig. 13. Examples of images for one subject from the MF2 dataset with various conditions

3.1.15. DFW dataset

In 2018, Kushwaha et al. [33] Presented a dataset called Disguised Faces in the Wild (DFW), Containing 1000 persons for 11,157 pictures with both impersonalized and obfuscated faces to enhance the latest techniques for disguises of facial recognition. DFW reports three verification protocols:

- The protocol of impersonation applicable only estimates the performance of impersonation techniques.
- Protocol of obfuscation applicable to various disguise cases.
- Protocol of overall performance helps estimate any algorithm on the whole dataset.

3.1.16. IJB-C database

The IARPA Janus Benchmark-C (IJB-C) facial database is an enlargement of IJB-B; it was introduced in 2018 by Maze et al. [34]. IARPA consists of 3,531 Identities from different geographic areas for 31,334 still pictures (21,294 facial and 10,040 non-facial) (Fig. 14), with a median of 6 pictures for each Identity, 117,542 frames taken from 11,779 videos, with a median of 3 videos and 33 frames for each Identity. To improve the latest techniques of uncontrolled face recognition, one-to-many identifications (supporting open-set and closed-set assessment), one-to-one verification, clustering, and end-to-end system assessment which is a more operationally closed model of face recognition utilize cases.

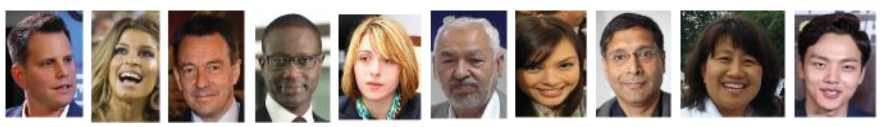

Fig. 14. samples of Identities included in IJB-C from different geographic areas

3.1.17. LFR dataset

In 2020, Elharrouss et al. [35] created a dataset for facial recognition named LFR (Left-Front-Right) at Qatar University to address the challenge of pose-invariant face recognition in the wild. Pose variation defines a challenge face recognition issue in an uncontrolled environment. To address this problem, a CNN model for assessing pose is suggested. The CNN model is trained to utilize a self-collected dataset designed Depending on three popular datasets: CFP, LFW, and CASIA-WebFace, using three groups of face picture capture: right side, Frontal, and Left side. LFR includes 542 subjects that are thus generated, representing every person's facial image from the right, front, and left side. Each left and right folder includes 10 to 100 face pictures, while the front folder includes 50 to 260 facial pictures.

3.1.18. WebFace260M and WebFace42M dataset

In 2021, Zhu et al. [36] proposed two datasets million-scale. The first is WebFace260M which is very huge and includes a wide variety, consisting of noisy 260 million facial images collected from the web from 4 million subjects, with a median of 65 images for each subject. The second dataset is WebFace42M, which contains a clean and extensive training facial recognition dataset, with a median of 21 images for each subject. Consisting of 42 million clean images from 2 million subjects, obtained after purification of the WebFace260M dataset via an automatic cleaning using a self-training (CAST) pipeline. Based on Web-Face42M, the failure rate has been reduced by 40% over the IJB-C dataset. In addition, a protocol of Facial Recognition Under Inference Time constraint (FRUITS) and a test dataset have been created, which helps researchers assess overall facial matches.

3.2. Mask-covered facial recognition datasets

After the spread of the COVID-19 virus, almost all people wear surgical masks to prevent the spread of the disease. This has rendered traditional face-recognition techniques trained on previously available facial-recognition data sets often ineffective, especially in cases of severe obstruction. In this paper, the most famous masked-covered face recognition databases that are currently available will be mentioned.

3.2.1. RMFRD and SMFRD dataset

In 2020, Wang et al. [37] presented three kinds of masked facial datasets, which are: 1. MFDD (Masked Facial Detection Dataset) can be employed to train an accurate masked facial detection model, MFDD mainly collected from previous research, and the internet. 2. RMFRD (Real-world Masked Facial Recognition Dataset) consists of 5000 facial pictures of 525 subjects wearing masks, and 90,000 face images of the same 525 persons without masks crawled from the web (Fig. 15). 3. SMFRD (Simulated Masked Facial Recognition Dataset): Designed to enlarge the size and diversity of the masked facial recognition dataset, the authors used second methods to apply masks to standard large-scale facial datasets, for example, CASIAWebFace [21] and LFW [19] datasets. The collected SMFRD dataset lids 500,000 faces pictures of 10,000 people, which can be utilized practicably in conjunction with their original unmasked counterparts (see Fig. 16).

Fig. 15. An example of a set of images from the RMFRD dataset; (a, b) pictures of faces without masks, (c, d) pictures of faces with a mask

Fig. 16. An example of a set of images from the SMFRD dataset of simulated masked pictures

3.2.2. MFSR dataset

In 2020, Geng et al. [38] designed a masked facial recognition dataset for facial recognition named MFSR (Masked Facial Segmentation and Recognition) dataset at Peking University To tackle two types of issues to train a masked face recognition (MFR) model. The first problem is the lack of real-world testing data as well as large-scale training data. To tackle these problems, the MFSR dataset was presented, which comprises two subsets (Fig. 17). the first subset consists of 9,742 masked facial pictures gathered from the internet, with annotation of mask area segmentation. The second subset includes 11,615 pictures of 1,004 subjects (704 subjects gathered from the real-world and 300 subjects collected from the web); every person has images of the face with or without a mask, with different orientations, mask types, and illumination conditions. However, MFSR subjects are insufficient to train MFR models using deep learning. To address the data not enough issues the GAN Mask (IAMGAN) was introduced Depending on MFSR to create synthetic masked facial pictures from the original full facial pictures. The second problem is that there is a huge intra-class difference between faces with masks and faces without masks. To address this problem, the Domain Constrained Ranking (DCR) loss is presented to improve the strength of MFR models. For each subject, it was proposed two centers, the first corresponding to pictures of the face without a mask and the second corresponding to pictures of the face with a cover. The MFSR dataset showed effective results for the presented approaches during the experiments.

Fig. 17. An example of a set of images with and without masks from the MFSR dataset

3.2.2. CASIA-mask dataset

In 2020, Waleed et al. [39] generated a masked facial recognition dataset for facial recognition called the CASIA-mask dataset from an unmasked facial recognition dataset (CASIA WebFace) by putting a simulated mask on facial exists in the image. the designed CASIA-mask dataset includes 418,978 masked face images of 10,567 people.

Table 1 contains a summary of the unmasked/ masked face databases mentioned in this review in terms of the Number of Subjects, Number of Images, Number of Images per Subject, image dimensions in pixels, the field of use for the database, and the type of images of people in the dataset (masked faces or unmasked faces).

Table 1 Summary of the 2D Unmasked/ Masked Facial Recognition Datasets (Most Famous/Recent) for The Current Century

Reference	Database/ Dataset	Number of Subjects	Number of Images	Images per Subject	image dimensions	field of use	Type
2003 [17]	BANCA	208	-	-	-	training + testing	unmasked
2006 [18]	FRGC	200	50,000	7	1704×2272, 1200×1600	training + testing	unmasked
2007 [19]	LFW	5749	13,233	2.3 nearly	250×250	training + testing	unmasked
2009 [20]	CMU Multi PIE	337	> 750,000 >750K	-	3072×2048	training + testing	unmasked
2014 [21]	CASIA WebFace	10,575	494,414	46.8 nearly	250×250	training only	unmasked
2015 [22]	IJB-A	500	5712	>14	-	training + testing	unmasked
2016 [26]	CFP	500	7000	>14	-	training + testing	unmasked
2016 [23]	MegaFace	690,572	1,027,060	1.4 nearly	Cropped Face size 100×100	training + testing	unmasked
2016 [28]	DMFD	410	2460	6	300×300	training + testing	unmasked

2016 [27]	Ms-Celeb-M1	100,000	10 M	100	-	training only	unmasked
2016 [29]	VGGFACE	2622	2.6 M	1000	224×224	training only	unmasked
2017 [31]	IJB-B	1845	21,798	36.2 nearly		training + testing	unmasked
2018 [30]	VGGFACE2	9131	3.31 M	362.6 nearly	224×224	training only	unmasked
2017 [32]	MF2 (MegaFace 2)	672,057	4.7 M	7 nearly	From 90×90 to 800×800	training + testing	unmasked
2018 [33]	DFW	1000	11,157	5.26 nearly	-	training + testing	unmasked
2018 [34]	IJB-C	3531	31,334	6 nearly	-	training + testing	unmasked
2020 [35]	LFR	542	30,000	10-260	250×250	training + testing	unmasked
2020 [37]	RMFRD	525	95,000	-	-	training + testing	masked
2020 [37]	SMFRD	10,000	500,000	-	-	training + testing	masked
2020 [38]	MFSR	1,004	21,357		256×256	training + testing	masked
2021 [36]	WebFace42M	2 M	42M	21	224×224	training only	unmasked
2021 [36]	WebFace260M	4 M	260M	65	224×224	training only	Unmasked
2023 [39]	CASIA-mask	10,567	418,978	39.6 nearly	-	training + testing	masked

4. Conclusion

There is a close relationship between the development of facial recognition algorithms and the possibility of the existing databases of different faces that influence the appearance of the face in a constrained (controlled) manner. Standard datasets of images of appropriate size for a subject should be accessible to the public to compare the performance and assessment of identification or verification of a facial recognition system. This review presents the most popular 2D unmasked and masked face datasets available in the current century that are suitable for testing approaches to 2D face recognition. In this review, the LFW database was found to be the most important database used by students and researchers as a reference base for comparing their results with previous results. Moreover, it was found that WebFace260M and WebFace42M datasets are the two most enormous datasets used for training. SMFRD dataset is one of the most important face recognition datasets covered with masks. Still, this field needs to be developed more than the rest of the face recognition fields because, since 2020, most people have been wearing surgical masks, and this has rendered traditional facial recognition techniques trained on previously available unmasked facial recognition databases often ineffective. In addition, the evaluation metrics for face recognition and their two types of tasks (identification and verification) have been discussed also in this review in detail.

Acknowledgment

I would like to express my deepest appreciation to Middle Technical University, Electrical Engineering Technical College-Baghdad, Iraq, for the encouragement and support for disseminating the engineering research paper.

Reference

[1] D. N. Parmar and B. B. Mehta, "Face recognition methods & applications," arXiv preprint arXiv:1403.0485, 2014, DOI: https://doi.org/10.48550/arXiv.1403.0485.
[2] Q. Wang, A. Alfalou, and C. Brosseau, "New perspectives in face correlation research: a tutorial," Advances in Optics and Photonics, vol. 9, no. 1, pp. 1-78, 2017, DOI: https://doi.org/10.1364/AOP.9.000001.
[3] F. Keinert, D. Lazzaro, and S. Morigi, "A robust group-sparse representation variational method with applications to face recognition," IEEE Transactions on Image Processing, vol. 28, no. 6, pp. 2785-2798, 2019, DOI: http://dx.doi.org/10.1109/TIP.2018.2890312.
[4] J. Zhang, X. Yan, Z. Cheng, and X. Shen, "A face recognition algorithm based on feature fusion," Concurrency and Computation: Practice and Experience, p. e5748, 2020, DOI: https://doi.org/10.1002/cpe.5748.
[5] Y. Xu, Z. Zhang, G. Lu, and J. Yang, "Approximately symmetrical face images for image preprocessing in face recognition and sparse representation based classification," Pattern Recognition, vol. 54, pp. 68-82, 2016, DOI: https://doi.org/10.1016/j.patcog.2015.12.017.
[6] A. S. Amsalam, A. Al-Naji, A. Y. Daeef, and J. Chahl, "Computer Vision System for Facial Palsy Detection," Journal of Techniques, vol. 5, no. 1, pp. 44-51, 2023, DOI: https://doi.org/10.51173/jt.v5i1.1133.
[7] A. J. Shepley, "Deep learning for face recognition: a critical analysis," arXiv preprint arXiv:1907.12739, 2019, DOI: https://doi.org/10.48550/arXiv.1907.12739.
[8] S. Gupta, K. Thakur, and M. Kumar, "2D-human face recognition using SIFT and SURF descriptors of face's feature regions," The Visual Computer, vol. 37, no. 3, pp. 447-456, 2021, DOI: https://doi.org/10.1007/s00371-020-01814-8.
[9] M. Chihaoui, A. Elkefi, W. Bellil, and C. Ben Amar, "A survey of 2D face recognition techniques," Computers, vol. 5, no. 4, p. 21, 2016, DOI: https://doi.org/10.3390/computers5040021.
[10] E. Varadharajan, R. Dharani, S. Jeevitha, B. Kavinmathi, and S. Hemalatha, "Automatic attendance management system using face detection," in 2016 Online international conference on green engineering and technologies (IC-GET), 2016: IEEE, pp. 1-3, DOI: 10.1109/GET.2016.7916753.
[11] H. Zhang, Z. Qu, L. Yuan, and G. Li, "A face recognition method based on LBP feature for CNN," in 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2017: IEEE, pp. 544-547, DOI: https://doi.org/10.1007/978-981-13-1328-8_29.
[12] S. Adnan, F. Ali, and A. A. Abdulmunem, "Facial feature extraction for face recognition," in Journal of Physics: Conference Series, 2020, vol. 1664, no. 1: IOP Publishing, p. 012050, DOI: 10.1088/1742-6596/1664/1/012050.

[13] S. R. Benedict and J. S. Kumar, "Geometric shaped facial feature extraction for face recognition," in 2016 IEEE International Conference on Advances in Computer Applications (ICACA), 2016: IEEE, pp. 275-278, DOI: 10.1109/ICACA.2016.7887965.
[14] P. Grother, M. Ngan, and K. Hanaoka, "Ongoing face recognition vendor test (frvt) part 1: Verification," National Institute of Standards and Technology, 2018, DOI: https://www.nist.gov/system/files/documents/2018/02/15/frvt_report_2018_02_15.pdf.
[15] P. Grother, P. Grother, M. Ngan, and K. Hanaoka, "Face recognition vendor test (frvt) part 2: Identification," ed: US Department of Commerce, National Institute of Standards and Technology, 2019, DOI: https://doi.org/10.6028/NIST.IR.8271.
[16] Y. Kortli, M. Jridi, A. Al Falou, and M. Atri, "Face recognition systems: A survey," Sensors, vol. 20, no. 2, p. 342, 2020, DOI: https://doi.org/10.3390/s20020342.
[17] E. Bailly-Bailliére et al., "The BANCA database and evaluation protocol," in International conference on Audio-and video-based biometric person authentication, 2003: Springer, pp. 625-638, DOI: https://doi.org/10.1007/3-540-44887-X_74.
[18] P. J. Phillips et al., "Overview of the face recognition grand challenge," in 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05), 2005, vol. 1: IEEE, pp. 947-954, DOI: 10.1109/CVPR.2005.268.
[19] G. B. Huang, M. Mattar, T. Berg, and E. Learned-Miller, "Labeled faces in the wild: A database for studying face recognition in unconstrained environments," in Workshop on faces in'Real-Life'Images: detection, alignment, and recognition, 2008, DOI: https://inria.hal.science/inria-00321923/.
[20] R. Gross, I. Matthews, J. Cohn, T. Kanade, and S. Baker, "Multi-pie," Image and vision computing, vol. 28, no. 5, pp. 807-813, 2010, DOI: https://doi.org/10.1016/j.imavis.2009.08.002.
[21] D. Yi, Z. Lei, S. Liao, and S. Z. Li, "Learning face representation from scratch," arXiv preprint arXiv:1411.7923, 2014, DOI: https://doi.org/10.48550/arXiv.1411.7923.
[22] B. F. Klare 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, 2015, pp. 1931-1939 , DOI: 10.1109/CVPR.2015.7298803.
[23] I. Kemelmacher-Shlizerman, S. M. Seitz, D. Miller, and E. Brossard, "The megaface benchmark: 1 million faces for recognition at scale," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 4873-4882, DOI: 10.1109/CVPR.2016.527.
[24] I. Kemelmacher-Shlizerman, S. Suwajanakorn, and S. M. Seitz, "Illumination-aware age progression," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2014, pp. 3334-3341, DOI: 10.1109/CVPR.2014.426.
[25] H.-W. Ng and S. Winkler, "A data-driven approach to cleaning large face datasets," in 2014 IEEE international conference on image processing (ICIP), 2014: IEEE, pp. 343-347, DOI: 10.1109/ICIP.2014.7025068.
[26] S. Sengupta, J.-C. Chen, C. Castillo, V. M. Patel, R. Chellappa, and D. W. Jacobs, "Frontal to profile face verification in the wild," in 2016 IEEE winter conference on applications of computer vision (WACV), 2016: IEEE, pp. 1-9, DOI: 10.1109/WACV.2016.7477558.
[27] Y. Guo, L. Zhang, Y. Hu, X. He, and J. Gao, "Ms-celeb-1m: A dataset and benchmark for large-scale face recognition," in European conference on computer vision, 2016: Springer, pp. 87-102, DOI: https://doi.org/10.1007/978-3-319-46487-9_6.
[28] T. Y. Wang and A. Kumar, "Recognizing human faces under disguise and makeup," in 2016 IEEE International Conference on Identity, Security and Behavior Analysis (ISBA), 2016: IEEE, pp. 1-7, DOI: 10.1109/ISBA.2016.7477243.
[29] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," 2015, DOI: https://dx.doi.org/10.5244/C.29.41.
[30] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, "Vggface2: A dataset for recognising faces across pose and age," in 2018 13th IEEE international conference on automatic face & gesture recognition (FG 2018), 2018: IEEE, pp. 67-74, DOI: 10.1109/FG.2018.00020.
[31] C. Whitelam et al., "Iarpa janus benchmark-b face dataset," in proceedings of the IEEE conference on computer vision and pattern recognition workshops, 2017, pp. 90-98, DOI: 10.1109/CVPRW.2017.87.
[32] A. Nech and I. Kemelmacher-Shlizerman, "Level playing field for million scale face recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 7044-7053, DOI: https://doi.org/10.48550/arXiv.1705.00393.
[33] V. Kushwaha, M. Singh, R. Singh, M. Vatsa, N. Ratha, and R. Chellappa, "Disguised faces in the wild," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2018, pp. 1-9, DOI: https://doi.org/10.48550/arXiv.1811.08837.
[34] B. Maze et al., "Iarpa janus benchmark-c: Face dataset and protocol," in 2018 international conference on biometrics (ICB), 2018: IEEE, pp. 158-165, DOI: 10.1109/ICB2018.2018.00033.
[35] O. Elharrouss, N. Almaadeed, and S. Al-Maadeed, "LFR face dataset: Left-Front-Right dataset for pose-invariant face recognition in the wild," in 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), 2020: IEEE, pp. 124-130, DOI: 10.1109/ICIoT48696.2020.9089530.
[36] Z. Zhu et al., "Webface260m: A benchmark unveiling the power of million-scale deep face recognition," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 10492-10502, DOI: https://doi.org/10.48550/arXiv.2103.04098.
[37] Z. Wang, B. Huang, G. Wang, P. Yi, and K. Jiang, "Masked face recognition dataset and application," IEEE Transactions on Biometrics, Behavior, and Identity Science, 2023, DOI: https://doi.org/10.48550/arXiv.2003.09093.
[38] M. Geng, P. Peng, Y. Huang, and Y. Tian, "Masked face recognition with generative data augmentation and domain constrained ranking," in Proceedings of the 28th ACM International Conference on Multimedia, 2020, pp. 2246-2254, DOI: https://doi.org/10.1145/3394171.3413723.
[39] W. Ayad, S. Qays, and A. Al-Naji, "Generating and Improving a Dataset of Masked Faces Using Data Augmentation," Journal of Techniques, vol. 5, no. 2, pp. 46-51, 2023, DOI: https://doi.org/10.51173/jt.v5i2.1140.