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Analysis of challenges and methods for face detection systems: A survey

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Abstract

Face recognition has come to the top of the list of the most frequently used image processing applications, owing in large part to the availability of practical technology in this area. Despite significant progress in this sector, several issues such as ageing, partial blockage, and facial emotions impede the system's efficacy. Face identification from real-world data, recorded photographs, sensor images, and dataset images is difficult to solve because of the huge range of facial appearances, lighting effects, and complexity of the image background. Face recognition is a very successful and practical use of image processing and biometric systems. In this paper, we analyze the most significant challenges confronting the subject of face recognition; we discuss the challenges, how they were addressed using scientific methods, which databases are the most useful, and we summarize the most significant previous studies on age and gender that have been widely cited by researchers in the last year, along with a concise definition.

Keywords: Face Recognition, Image Processing, Applications, Face Identification, Challenges, Methods, Age, Gender.
2010 MSC: 68U10, 94A08

1. Introduction

Face recognition has been the most commonly used application of image analysis. The breadth of its commercial and law enforcement applications, as well as the availability of cutting-edge methodology, have all contributed to its popularity. Additionally, it may be utilized for image retrieval based

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on content, video coding, video conference, crowd monitoring, and intelligent human-computer interactions [35]. Face detection is computer technology for detecting human faces in digital photographs. It is utilized in a variety of applications [28]. Face detection and recognition have developed into a very active and significant area of image processing research. The bulk of current face detection algorithms focused on frontal human face identification and face recognition being a well-studied issue in computer vision [57].

Face recognition is a challenging vision issue with several practical applications, including identity verification, intelligent visual surveillance, and automated immigration screening systems [34]. According to numerous application scenarios, recognizing aces in real-world applications remains a challenging process [42]. The underlying reason is that the face is a non-rigid entity that exhibits a broad range of looks owing to its variety of facial expressions, ages, angles, and, most importantly, light intensities. Detection and identification of human faces in digital photographs is an area of computer science that uses computer technology. It may be used in a variety of ways [39].

Face detection and recognition have developed into a very active and significant area of image processing research. The bulk of current face detection algorithms focused on frontal human face identification and face recognition being a well-studied issue in computer vision [61]. Face recognition is a difficult visual problem that impacts many practical applications, such as identity verification, intelligent visual surveillance, and automated immigration processing systems. Face recognition is still a difficult problem [29]. The underlying reason is that the face is a non-rigid object that exhibits a broad diversity of looks owing to the variety of facial expressions, ages, angles, and, most importantly, light intensities. Additionally, various factors, like occlusions and locations, continue to impact the capacity to recognize faces [**?**].

Face detection algorithms may be classified into two basic and significant types: deep learning and machine learning [56]. Each kind comprises a variety of algorithms that can identify and recognize the face, but deep learning is the most extensively used idea [51]. An artificial intelligence (AI) technique called deep learning is used to mimic the way humans learn. Data science's subject of deep learning includes statistics and predictive modeling [55]. The process of collecting, analyzing, and interpreting large amounts of data is made much more efficient and straightforward for data scientists thanks to this tool [57].

They detect and find people's faces in a photo or sequence of photographs. Faces aren't required in photos; however, they may come with intricate backdrops. Humans can instantly discern facial features and other elements in an image, but computers have difficulty doing so [47]. Face detection is primarily concerned with distinguishing between actual faces and objects that do not have faces on them. It may be used for teleconferencing, tagging, Face Recognition, facial feature identification, gender recognition, automation of cameras, video surveillance systems, and gesture recognition. Face detection is a must for all of these applications, especially face recognition [37].

2. Face System Modes

Face technology is supposed to recognize faces in photos and videos automatically. It has two modes of operation [45, 53]:

- Face Verification (Or Authentication)
- Face Identification (Or Recognition).

A query face image is compared to a template face image that accurately portrays the individual whose identity is being confirmed. Face recognition compares a query face to all of the database's templates using one-to-many matches. Checking watch lists is a type of one-to-few match (figure 1), in which the query face is compared to a list of suspects.

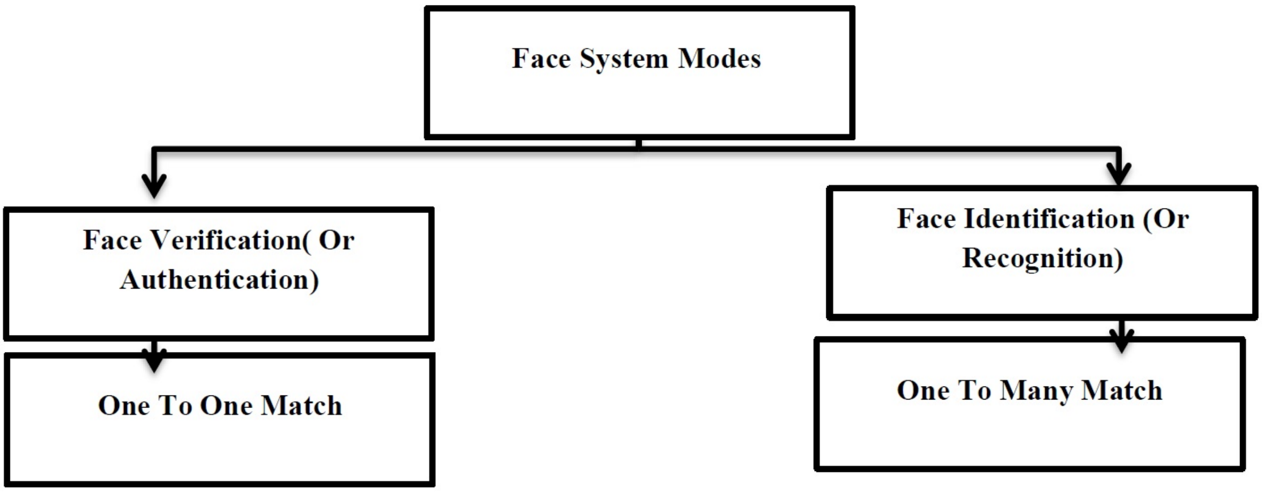


Figure 1: Face System Modes [26].

Biometric techniques and algorithms are not novel verification approaches. Several years ago, Babylonian monarchs utilized clay fingerprints to verify legitimacy. Egyptians employed physical traits such as hand length or half arm [50]. Holistic, feature-based, and hybrid face-recognition algorithms exist. When using holistic face recognition algorithms, they consider the correlations between images and the overall structure of the images [46]. As shown in figure 2.

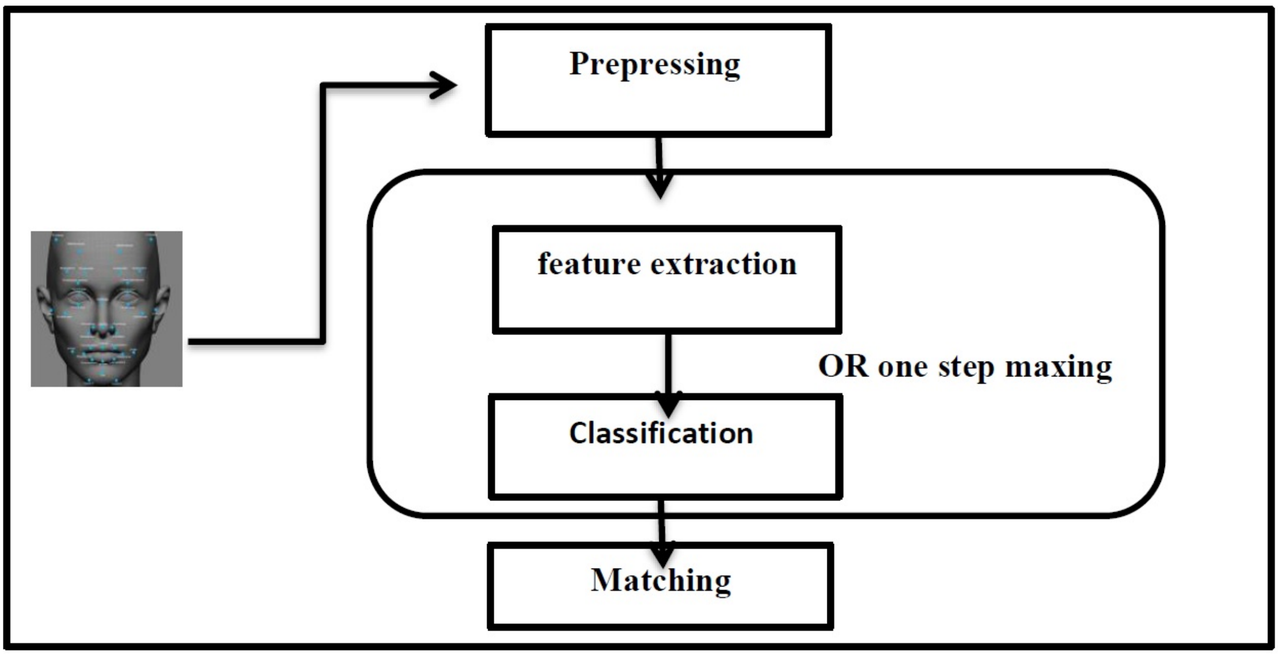


Figure 2: Face Recognition System General [18].

In terms of the general structure of the facet system, there are two major groups of techniques: deep learning (DL) and machine learning (ML). DL incorporates feature extraction and classification, whereas ML includes just feature extraction [52].

Table 1 illustrates the differences between the two kinds of systems:

Table 1: Different Between Deep And Machine Learning System **??**.

NO	Supervisor	Un-Supervisor	clustering	Classification	Complexity	Traditional	Developer	advanced
DL	⊠	✓	⊠	✓	⊠	⊠	✓	✓
ML	✓	⊠	✓	⊠	✓	✓	⊠	⊠

Table 2 summarizes the most notable distinctions between machine learning and deep learning:

Table 2: Fames Key Differences Between Machine Learning And Deep.

RF	**Key Name**	**Description**
[27]	Human Involvement	Machine learning requires a higher level of ongoing human participation to deliver results. While deep learning requires more effort to set up, it requires relatively little interaction once it is running.
[40]	Hardware	Deep learning systems demand significantly more powerful hardware and resources than machine learning systems operated on ordinary computers. A rise in the utilization of graphics processing units can be attributed to the rising demand for power. As a result of GPU thread parallelism, high bandwidth memory and the ability to disguise memory transfer latency (delays) are both advantages (the ability of many operations to run efficiently at the same time).
[59]	Time	Automated machine learning systems are simple to implement, but their results may be less than satisfactory. Deep learning systems require a long time to get up and running, but they may deliver benefits practically immediately (although the quality is likely to improve over time as more data becomes available).
[31]	Approach	Linear regression and other well-known algorithms are used in machine learning, which often needs organized data. There are many different types of neural networks that are used in deep learning. It can handle a lot of unstructured information.
[5]	Applications	Machine learning is already being used in places like the bank and doctor's office, so don't worry. Deep learning technology makes it possible to create more complicated and autonomous programs, like self-driving cars and surgical robots.
[58]	General Structure	Steps In ML (load dataset, Feature extraction, Classification, output) Steps In DL (load dataset, [Feature extraction and Classification], output)

3. Background Problem Domain

The following is a table 3 showing the range of problems that face recognition systems suffer from, and they are the most famous problems that researchers have worked on:

Table 3: Famous Problems With Facial Recognition Systems

RF	Problem	Domain Description
[12]	Dimensional image	Faces are difficult to distinguish from patterns in the visual field. When it comes to identifying a three-dimensional item like a face, though, a two-dimensional picture is the best way to go (three-dimensional images, e.g., obtained from a laser, may also be used).
[63]	Configuration	The face is a non-rigid object, and its appearance is frequently modified due to diverse facial expressions, varying ages, variable perspectives, and, most significantly, varying light intensities.
[56]	Factors	Face identification and recognition in real-world surveillance films are difficult because faces can be impacted in video streams by fluctuations in lighting and posture. Additionally, some input photos may have interference elements such as noise, significantly hindering the face identification process.
[32]	COVID-19	The coronavirus disease (COVID-19) is a catastrophe on a scale never seen before, resulting in a large number of fatalities and security concerns. To help prevent the transmission of coronavirus, individuals frequently wear masks. This makes facial identification extremely difficult, as some features of the face are obscured.
[19]	Touching	Inadequate security is becoming a problem for traditional biometric systems that rely on passwords or fingerprints to transmit COVID-19 (Face recognition is safer without the need to touch any device).
[15]	Mask	A masked face has the following side effects: Masks are used by criminals and robbers to hide their identities. Masking a substantial section of a person's face increases the difficulty of community access control and face authentication.

4. Challenges

There are many challenges that researchers have faced in the subject of Face systems, and the following is a table 4 that shows the most important challenges:

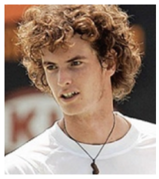
5. Applications Domains

Previously used techniques nowadays, industry incorporates face recognition research into cutting-edge technology development for commercial use, as seen in table 5 below the application domain.

Research has shown that facial recognition technology is already being used in various applications, including border crossings and access to scarce resources that are considered high-risk. On the other hand, other application domains have yet to see the utilization of facial recognition. Face recognition technology's possible application areas can be summarized as follows:

1. The goal of automated surveillance is to recognize and track people [24].
2. Closed-circuit television (CCTV) networks might use face recognition technology to assist in finding missing children and others and track down offenders who are already on the loose [36].
3. A search of image databases of licensed drivers is one example of a picture database study [44].

Table 4: Important Challenges

RF	Challenges	Description	Image
[42]	Pose variations	Head motions, such as egocentric rotation angles or camera point of view changes, can result in significant changes in facial look and/or form, as well as intra-subject face differences.	
[61]	Structured elements/ occlusions (presence/absence)	It's possible that intra-subject variability in facial pictures is caused by a lack of anatomical traits or the presence of occlusions such as beards or mustache caps, or sunglasses.	
[7]	Facial expression changes	Changes in facial expressions caused by changing emotional states may result in even more variation in facial expressions.	
[28]	Ageing of the face	Another reason for changes in the human face's appearance could be age.	
[4]	Varying illumination conditions	Large changes in light can have a detrimental effect on the performance of systems. Face identification and recognition become far more difficult when the backdrop or foreground illumination is weak.	
[30]	Modality and image resolution	The clarity and resolution of the face image and the setup and mode of the digital hardware used to record the face are other often utilized performance parameters.	

4. Human-computer interfaces can adapt to different multimedia settings (as a component of omnipresent or context-aware systems, monitoring children's or senior citizens' behavior, identifying and analyzing consumers' requirements) [11].
5. Face recognition may be used in airport boarding gates to filter passengers for further investigation [15].
6. Sketch-based face reconstruction is a method used by law enforcement agencies worldwide to help crime witnesses figure out how to make likenesses of faces [20].
7. Forensic artists are frequently utilized in conjunction with eyewitnesses to create a drawing of the individual who committed the crime based on the information provided by the witness [23].
8. Face spoofing and ant spoofing are ways to get into facilities or services by using a picture or

Table 5: Application Domain Of Face System

RF	APP	Description
[4]	Security	According to organizations like Aurora, facial recognition is one of the most powerful biometric techniques for security objectives, including airport passenger management, passport recreation, border control, and highly secure access control. And the Fames app is a master card facial recognition software.
[61]	Multimedia	On social media platforms such as Facebook, Google, and Yahoo!, various collaborative programs are accessible. Snapchat, for example, requires the usage of a mobile device. Daily, 200 million people use Snapchat, making it the world's most popular image messaging and multimedia app. Text, drawing, and filters may customize Snap camera photographs and movies. With Snapchat's Lens and Memories features, users can apply real-time effects to their images and search for material by date or by utilizing location recognition algorithms.
[32]	Medical	Face recognition is the best security available for preserving patient information and authenticating identification in healthcare.

video of an authorized person's face. As a result, spoofing attacks use fake biometric features to get into resources that are protected by a biometric authentication system [17].

The majority of devices now use a basic user interface entirely controlled by the user's active instructions. Certain gadgets can detect their surroundings and collect data about the physical environment and the people in their vicinity. Recognizing people's identities in close proximity to a device is a vital function of smart gadgets that increase human awareness. It is being implemented in a range of smartphones with varying outcomes. When used with other biometrics, it is necessary to account for face recognition's passive nature [4].

6. Common Methods

There are several components to the face recognition system, and the algorithms may be classified into two broad categories, as seen in the accompanying diagram (figure 3):

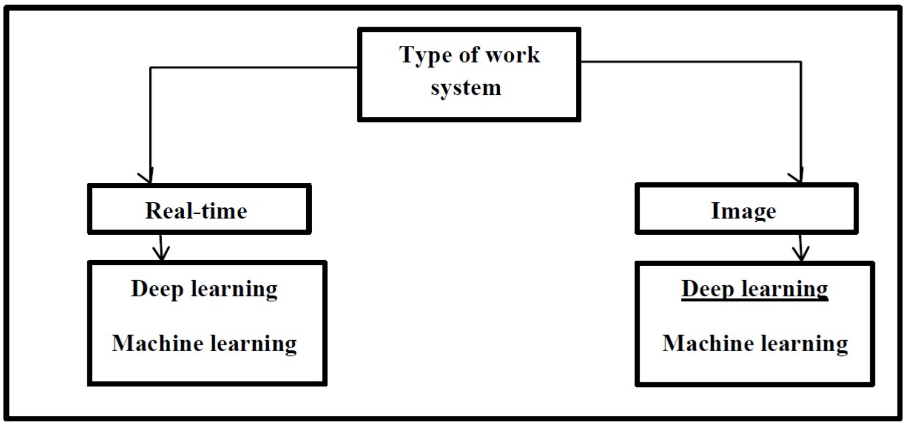


Figure 3: Face Recognition System Subdivisions

Face recognition is a difficult but fascinating topic that has drawn researchers from various fields, such as psychology, pattern recognition, artificial neural networks, machine learning, and computer graphics. It's possible to recognize a person's face using these methods. Table 6 shows the following information:

Table 6: Type And Description Methods

RF	**Type**	**Description**
[4]	Holistic Matching Methods	The face capture system analyzes the complete face as a source of information. There are a number of holistic techniques, such as eigen faces, principal component analysis, linear discriminant analysis, and independent component analysis.
[7]	Feature-based (structural) Methods	Their technique treats the recognition of faces as a two-dimensional issue. And they differ in their phases (a well-known example of an eigenface-based method is the core concept of employing censored data, such as (PCA).
[58]	Hybrid Methods	Hybrid face recognition systems combine holistic, and feature extraction approaches. The majority of hybrid techniques make use of three-dimensional imagery. A person's eye sockets, chin, and forehead contours may all be detected by the system since it collects a 3D snapshot of their face. Even a profile face would work because of the technique's reliance on depth and an axis of measurement, which provides enough information to reconstruct a whole face. Detection, location, measurement, representation, and matching are typical phases in a 3D system. When a person's face is captured by scanning or taking a live photo, it is detection. The term "position" is used to describe the process of determining the head's location, size, and angle of incidence.

The following table 7 summarizes the most widely used Artificial Neural Networks in face recognition.

7. Gender And Age Recognition

Human facial characteristics may be categorized into three categories for face recognition. To begin, the process of facial recognition is based on geometric characteristics such as the jaw, mouth, nose, eyes, and brows. Each face on the planet is unique due to facial traits that vary. This indicates that the geometric representation of facial characteristics (such as relative position and angle) will be recognized as a critical property for identifying faces [62].

It is possible for a covariate to have an impact on both the intra-class and inter-class variance. Pose, lighting, emotion, and the quality of the image all impact how well a system can recognize faces [1]. The constraints of the face recognition system are controlled variables during picture capture. The constraints imposed by these elements have been thoroughly examined in the literature, and several techniques for overcoming them have been proposed [48]. Face recognition algorithms' performance is also impacted by uncontrollable elements associated with an individual (e.g., race, gender, age groups, and aging) [16]. Aging has been thoroughly investigated, and pertinent statistics have been created to assist researchers in their efforts to tackle the aging problem [3].

Table 7: Type And Description Methods

Algorithm	**Description**
Retinal Connected Neural Network (RCNN)	To detect objects, a region-based CNN (RCNN) was utilized. Two portions comprise the pipeline. The first phase includes employing selective search to generate a list of category-independent item suggestions. The second stage of refinement involves deforming the image region included inside each proposal to a set size. The R-CNN must do a forward pass over the network for each item proposal to extract features from the convolutional network, incurring a significant computational cost.
Principal Component Analysis with ANN (PCA & ANN)	Artificial neural networks (ANNs) and principal component analysis (PCA) are used in a hybrid approach (ANNs). While PCA is a statistical technique for identifying the underlying linear patterns in a data set in such a way that it can be expressed in terms of a lower-dimensional data set with the least amount of information loss, Artificial Neural Networks (ANNs) are algorithms inspired by brain function that may be used to model and anticipate complex patterns and issues.
Polynomial Neural Network (PNN)	The International Method of Group Methods of Data Handling is another name for the Polynomial Neural Network (PNN) algorithm (GMDH). Prof. A.G. Ivakhnenko was the first to suggest GMDH. A PNN uses (non) linear regression to connect input and target variables, and a feed-forward neural network is a type of neural network that is commonly used to solve classification and pattern recognition challenges. A Bayesian network and a statistical method are known as Kernel Fisher discriminant analysis developed this form of ANN.
Convolutional Neural Network (CNN)	Many artificial neurons are used in the construction of convolutional neural networks. Like biological neurons, artificial neurons are mathematical functions that compute the weighted sum of several inputs and produce an activation value. Numerous activation functions are generated by each layer of a ConvNet when a photo is supplied.

Men's faces differ from women's in terms of regional characteristics and forms. Males have broader chins than females, whereas females have smoother cheeks. Typically, women's noses are smaller than men's. Men and women are also differentiated by their hairstyles and cosmetics. Males, anthropological studies indicate, have a distinct skeletal structure from females. On the other hand, boys and girls have comparable bone characteristics, complicating gender categorization in children's items [1, 14].

Since the study's inception in 2002, researchers have concentrated on age groups and their effect on facial recognition abilities, with test results heavily weighted toward demographic data [38]. This conclusion is consistent with prior studies indicating that older individuals are simpler to recognize than younger individuals. Since the study's inception in 2002, researchers have concentrated on age groups and their effect on facial recognition abilities, with test results heavily weighted toward

Figure 4: Sample Of Gender [3].

Figure 5: Sample Of Age [1].

demographic data [10]. Almost every prior study has demonstrated that older people are more easily identifiable than younger people. They used the facial recognition technology database (FERET) [1]. They were trying to determine which faces were more youthful and more mature. They believe that the characteristics of children and adolescents lack personality.

8. Data

Many types of data are used in evaluating the algorithms of facial recognition systems, and the following is table 8 showing the most important and most popular types:

Table 8: The Most Important And Most Popular Types Of Data

RF	Name	Year	Description
[13]	APPA-REAL	2016	There are 7,591 photos in the APPA-REAL collection that show real people and appear to be old. More than 250,000 votes are thought to have been cast. In each picture, there are an average of 38 votes. The perceived average age is quite consistent (0.3 standard error of the mean). The train, valid, and test folders include 4113 train photos, 1500 valid images, and 1978 test images. X.jpg face.jpg is the picture corresponding to each X. picture in jpg format. It features a cropped and rotated face with a 40% margin of error, as determined by the Mathias et al. face detector (http://markusmathias.bitbucket.org/2014/eccv face detection/). Additionally, an X.jpeg.mat file with metadata about the discovered fac is transmitted.
[64]	CASIA	2005	From 2001, ten images of twenty people a human possesses 12 picture sequences, four for each of the three axes. Each has its four-part sequence.

[60]	RMFD Dataset	2020	This is because the COVID-19 virus has been spreading around the world, and as a result, many people are wearing masks, and there are many masked faces. We then created the world's largest collection of masked faces to amass data resources for future wiser monitoring and control of public safety situations. If the community is closed, masked face datasets are utilized to assist residents in entering and exiting. This is accomplished through the employment of masked face detection and recognition techniques. Face recognition gates, facial attendance devices, and security checks at railway stations have all been created due to the rising usage of pedestrian masks. Additionally, the NERCMS is primarily sponsored by Wuhan University's School of Computer Science. Furthermore, the dataset is freely accessible to the public, and the following image represents a sample.
[9]	Yale Face Database		There are 165 grayscale GIF images of 15 people in the Yale Face Database. To capture a wide range of facial expressions and expressions, each subject includes 11 images, one for each of the 11 various emotions and expressions that the human face may evoke. These 11 photos include joyful, sad, confused, sleepy, surprised, and even a wink. The collection contains 5760 single-light-source photographs of ten individuals, each viewed under 576 different viewing conditions, totaling around 6.4MB.
[33]	Large-Scale CelebFaces Attributes (CelebA) Dataset	2016-2020	For each image in CelebFaces Attributes (CelebA), there are around 200K photos of celebrities with 40 attribute annotations. This collection has a broad variety of positions and settings. 10,177 unique individuals, 202,599 face photographs, and five landmark places are included in the 200K bytes collection. Each image comprises 40 binary characteristics annotations.
[?]	YouTube Faces Dataset with Facial Keypoints	2020	We took the publicly available and freely downloadable YouTube Faces Dataset and analyzed it to create this dataset. There are several videos of each star online (up to six per celebrity). About 1293 recordings with up to 240 continuous frames per original video are included in the 10GB dataset. All in all, 155,560 individual photo frames may be found.
[?]	UTKFace Large Scale Face Dataset	2018	There are 116 years of age represented in the UTKFace dataset, which is an enormous collection of faces. Pose, facial expression, lighting, occlusion, and resolution are all shown in these images. Approximately 20K pictures are included in the collection, each with age, gender, and ethnicity label.

[22]	Labelled Faces In The Wild Home (LFW) Dataset	2007	Labeled Faces in the Wild (LFW) is an unconstrained collection of face photos intended to investigate the topic of face identification. In the wild, facial labeling is held to the standard of face verification, more commonly referred to as pair matching. This 173MB collection contains almost 13,000 images of people's faces gathered from the internet.
[?]	Face Images With Marked Landmark Points	2020	Researchers were able to explore the topic of face recognition without any limits by utilizing the LFW dataset (labeled faces in the wild). In the wild, facial identification is subjected to face verification, which is sometimes referred to as pair matching. The collection, 173MB in size, has over 13,000 photos of people's faces gathered from the internet.
[?]	Google Facial Expression Comparison Dataset	2018	Google has created a massive collection of human-annotated facial expression triplets, each of which has two faces with very identical facial expressions. In addition, 500K triplets and 156K facial images are included in the 200MB collection.
[?]	Real And Fake Face Detection	2019	Professionals developed these photoshopped photographs of people's faces and are of the highest quality. They are composites of many people's faces, divided by the eyes, nose, mouth, or entire face. The file size is 215MB.
[43]	Tufts-Face-Database	2018	This database, dubbed the Tufts Face Database, is the world's largest and most comprehensive face database. LYTRO, video, and three-dimensional pictures are among the seven image kinds that the gadget may capture: infrared, thermographic, computerized sketch, LYTRO, and video. It has several photographs of people from over 15 different nations, ranging from four to seventy. The dataset contains 74 women and 38 males from over 15 nations.
[?]	Flickr-Faces-HQ Dataset (FFHQ)	2019	FFHQ has a larger age, ethnicity, and picture background variation range than CELEBA-HQ, as well as a higher coverage of accessories such as eyeglasses, sunglasses, and hats on people's faces than CELEBA-HQ. All of the photographs were automatically aligned and cropped after browsing Flickr. All of the PNG photos in the collection are high-quality, and they range in age, ethnicity, and background color.
[49]	IMDB-WIKI	2015	This is the largest free dataset for training with gender and age labels. We provide pre-trained age and gender prediction algorithms. One example of this image style is a still from a long-running film. For a total of 523,051, we gathered 460,723 images of famous faces from 20,284 IMDb bios and 62,328 from Wikipedia.

9. Previous Studies

In this section, we will focus on studies related to gender and age:

Table 9: Previous Studies On Age and Gender-Based On Face System

RF	Year	Description	Contribution	Dataset	Main results
[54]	2016	To determine if gender, age differences, empathy, and the Big Five personality qualities can predict facial emotion identification, researchers are examining the relationship between face recognition and the Big Five. In line with what we thought, females were better at recognizing emotions than males. A negative relationship was found between how well you could recognize emotions and how neurotic you were.	Introducing a method for differentiating feelings based on gender and face image	Productive Aging Laboratory (PAL)	Angry=62.8 Surprised = 64.6 Happy= 96.1 Disgusted= 66.1 Scared=65.5 Sad=77.2 Other= from 1.8-3.9 Mean differences in predictor variables between men and women Meal is better for a woman than for a man.
[48]	2017	The suggested model is made up of three key components: 1) a "Where" CNN to determine the ideal attention grid for conducting glances, 2) "What" and "How" CNNs, and 3) a "Multi-Layer Perceptron" (MLP) to aggregate the input from both CNNs and do the categorization.	The most significant and reliable features of a face may be identified using a feed-forward attention approach, which we provide here as a means of improving age and gender classification. The proposed model uses a novel end-to-end learning architecture to train a down-sampled face picture to extract the most discriminative patches from the original high-resolution image.	Benchmark Datasets (Adience benchmark) IoG dataset	Accuracy =98.7 In Adience dataset And Accuracy = 98.0 in IoG dataset
[16]	2018	It is advised that the model be broken down into the following three fundamental components: Patch CNN (what) examines the higher resolution patches based on their expected relevance predicted by the attention grid, and Multi-Layer Perceptron (MLP) combines the information gathered from both CNNs and executes the final classification.	Deep Convolutional Neural Network Architecture (D-CNN). Before 2018, no one had ever used VGGNet to predict gender from a celebrity face dataset with such high accuracy.	Celebrity face dataset LFW	Accuracy=0.95

[62]	2019	The influence of age and gender on identity verification findings and the use of the deep learning technique to categorize facial traits and investigate the impact of age and gender on classification outcomes are examined in this study. Compared to younger males and the elderly, middle-aged men had a smaller influence on male participants' perceptions of social status. When it comes to women's recognition effects, age does not seem to influence. Males outperformed females in recognition rates using Multi-task Cascaded Convolutional Networks (MTCNN).	A face recognition algorithm model is built utilizing a deep neural network-based learning mechanism, which is used to explore the effects of gender and age on recognition outcomes.	Cas-peal face	Accuracy=87.63
[3]	2020	This article provides an in-depth examination of how and why men and women differ in their ability to recognize faces. We demonstrate that women have worse accuracy due to a combination of (1) an imposter distribution skewing toward greater similarity scores and (2) a true distribution skewing toward lower similarity scores. We demonstrate that this trend toward convergence of the imposter and real distributions for women is widespread across datasets of African-American, Caucasian, and Asian faces.	While ROC curves for women and men may seem comparable in limited datasets, they have considerably varied facial recognition accuracy. Women and men get the same FMR at significantly different rates. Females have a shifted imposter distribution, which results in higher impostor thresholds. Additionally, the true distribution of females has changed, although to lower values. As a result, women are disadvantageous compared to males on both the FMR and FNMR.	MORPH A-A Female MORPH C Notre Dame AFD	MORPH A-A Female in Neutral Expression 9.083 (4.39%) And Head Pose M= 10.682 (3.55%) and Visible Forehead= -1.486 MORPH C Neutral Expression= 8.874 (7.36%) And Visible Forehead= 9.939 (3.09%) Notre Dame Neutral Expression= 11.531 (9.41%) 10.722 AFD Neutral Expression= 3.866 (10.55%)

[6]	2021	They devised a method for calculating an individual's age and gender-based on selfie ocular images taken with a smartphone. Partial facial occlusion has become a concern due to the mandatory use of face masks. As a result of the tremendous rise in mobile device usage, digital services are being adopted faster. On the other hand, convolutional neural networks are state-of-the-art solutions for applications such as facial recognition and identification that need large amounts of processing power and software size. This problem was solved by modifying two lightweight CNN's proposed for the ImageNet Challenge.	It utilizes smartphone ocular pictures to estimate age and gender. Partial faces may be predicted in uncontrolled and regulated circumstances since masks are used, and just the ocular area is exposed. There are no photos of people wearing masks or photographs that have been hidden; instead, we utilized self-portraits with the ocular region removed. With the same input data, you may examine if the ocular region is used more frequently than the rest of the face. It was decided to deliver the paper's draft at the conference.	Adience	Accuracy = 76.6/78.9%
[21]	2021	The article discusses a way for enhancing data. The proposed approach improves the quality of the input data by modeling probable barriers that may arise in real-world circumstances. The suggested method begins by randomly picking a fixed-size region from an input image and then using one of the occlusion approaches. When utilizing blackout, random brightness, or blur occlusion techniques, faces are obscured, lightning is powerful, and resolution is restricted. a convolutional neural network and a VGG16 deep neural network.	Even if the original shots are the same, create additional training images that are changed with various occlusion techniques in a variety of locations throughout each training pass. As a consequence, the resilience and generality of the network are enhanced. Additionally, it mitigates the problem of overfitting, which is typical in settings with inadequate data. AdienceNet's age categorization accuracy was raised by 1.0 and 0.8%, thanks to our enhancement approach.	Adience	Accuracy= 86.2% in (Black) 85.5% In (Grey) 85.4% In (White)

[41]	2021	Automated facial recognition systems identify individuals by comparing a photograph of their face to a database of previously collected photos. Recognition system reaction times decrease as the quantity of the training database increases. By utilizing the gender of the probing image, the number of candidate gallery photographs utilized for comparison may be decreased. When comparing the probing image to just gallery images of the same gender, the gender classification model's output is utilized for the age-invariant face recognition model. PCA may be used to analyze meals and females.	One way to identify a person using automated facial recognition is to compare the image used with previously saved images. Adding more data to the training database speeds up the recognition system's response time. The candidate gallery photographs used for comparison can be limited by using the gender of the probing image.	ORL Indian FG-NET	Accuracy(%) ORL =83.01 Indian =66.92 DG-NET= 57.44

Relying on the previous table, we will analyze and classify previous studies in a summarized way in table 10:

Table 10: Investigation of alignment between research variables

RF	**Year**	**Methods**	**Dataset**	**Learning**	**Factor**
[49]	2016	Big Five personality and Toronto Empathy Questionnaire (TEQ)	Productive Aging Laboratory (PAL)	ML	Categorize feelings
[48]	2017	CNN	Benchmark Datasets(Adience benchmark) IoG dataset	DL	Accuracy
[16]	2018	CNN	Celebrity face data-set LFW	DL	Accuracy
[62]	2019	Multi-task Cascaded Convolutional Networks (MTCNN)	Cas-peal face	DL	Accuracy
[3]	2020	CNN	MORPH A-AFemale MORPH C NotreDame AFD	DL	Accuracy
[54]	2021	CNN	Adience	DL	Accuracy
[6]	2021	VGG16 and CNN	Adience	DL	Accuracy
[21]	2021	PCA	ORL Indian DG-NET	ML	Accuracy Time

10. Conclusion

In the field of computer vision, face recognition is a challenging topic. It has grown in popularity in recent years due to its numerous uses in a number of sectors. Despite considerable research being undertaken on this subject, this article presented an overview of the problems, methodology, and applications of face recognition. Prior studies explored the words "age" and "gender." There is still an effort to design systems that correctly reflect how humans see faces and use the face's temporal development best. Recently, and more precisely during the last three years, the issue of identifying or exposing faces has taken on new relevance in terms of health and security, owing to the coronavirus and the widespread usage of masks. As a result, the area of facial recognition has grown rapidly. Numerous types of databases on face systems have evolved due to technological breakthroughs.

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