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Comprehensive Survey on Real-Time Face Recognition: Methods, Datasets, and Applications

[1]Mr. Jagadish Kumar G M, [2]Dr. K Ramesh

[1]Research Scholar, Dept. of ECE, Dr. Ambedkar Institute of Technology, Bangalore

[2]Professor and HOD Dept. of VLSI Design and Technology, Dr. Ambedkar Institute of Technology

Abstract: The non-intrusive nature of face recognition and its broad range of applications in security, surveillance, access control, and identity verification systems have made it one of the most popular biometric technologies. The need for precise and effective real-time face recognition systems has grown dramatically with the quick development of digital imaging equipment, artificial intelligence, and embedded computing platforms. However, differences in lighting, position, facial expression, occlusion, and computing restrictions make it difficult to achieve high identification accuracy while meeting real-time requirements. A thorough analysis of real-time face recognition systems is given in this study, which covers both conventional and modern methods, publicly accessible datasets, performance assessment measures, and deployment issues. In addition to local feature-based approaches like LBP, HOG, SIFT, and their variations, the study methodically examines traditional appearance-based and statistical techniques like PCA, LDA, and ICA. The contributions and limits of key-point descriptors and correlation filter-based techniques in real-time settings are also examined. The study also addresses the shift to deep-learning-based facial recognition models, with a focus on resource-constrained and real-time systems that are light weight. The size, annotation kinds, and appropriateness for real-time assessment of publicly accessible datasets that are often used for benchmarking face recognition systems are summarized. Along with the trade-offs between accuracy, speed, memory usage, and energy efficiency, this study also looks at the role of hardware acceleration employing CPUs, GPUs, and FPGAs. There is also discussion of important issues including scalability, privacy, security, and ethical issues. This study seeks to provide academics and practitioners a comprehensive knowledge of the present status of real-time face recognition and to suggest attractive avenues for future research by compiling recent developments and highlighting outstanding research concerns.

Keywords: Real-Time Face Recognition; Face Detection; Computer Vision; Feature Extraction; Face Recognition Datasets; Performance Evaluation; Hardware Acceleration; Security and Surveillance

1 Introduction

Face recognition is the process of finding and naming human faces in one or more photos or videos. Even though people can easily recognize faces in a wide range of situations, it is still hard for computers to do the same thing. Face recognition is now a major area of study in computer vision and pattern recognition because digital cameras, surveillance systems, and portable devices are becoming more common very quickly. It is widely used in security and access control systems, law enforcement, video surveillance, gender recognition [1], generic identity verification [2], finding missing people, and many other real-world situations. Face detection is an important first step in most practical systems because the accuracy of locating facial regions directly affects how well the recognition process works.

There are two main types of face recognition systems: face verification and face identification. Face verification is the process of figuring out if two pictures of faces are of the same person. Face identification, on the other hand, is the process of giving a name to a target face by comparing it to a database or training set. There are three main types of face recognition methods: holistic, structural, and hybrid [3]. These types are based on how the face is represented. Eigen faces, Principal Component Analysis (PCA) [4],[5], and Linear Discriminant Analysis (LDA) [6] are all examples of holistic methods that look at the whole face to recognize it. On the other hand, structural approaches focus on the eyes, nose, mouth, and other facial features, as well as their spatial relationships and statistical properties. Hybrid methods use both holistic and structural information to make recognition work better. A typical face recognition system processes an input image of a face and compares it to stored representations in a training database to figure out who it is.

Physiological biometric systems have gotten a lot of attention because they are easy to use, reliable, and convenient. Facial features are one of the most interesting biometric modalities because they can be captured without having to interact with the user directly. The human face has unique features and structures that make it useful for identifying people in many situations, including surveillance, home security, and border control [7],[8]. Facial recognition as a way to prove identity has already been used in real life, not just on mobile devices, but also at airports, sports stadiums, and public events. Face recognition systems can also work on their own by using pictures taken by cameras, so there is no need for people to get involved. Existing biometric systems do a good job of identifying people, but they still have a long way to go before they can work in real time. This is why more efficient face recognition solutions are being developed.

The growing amount of visual data and the fast progress of AI have shown that traditional computing models have their limits, especially when it comes to tasks that require a lot of processing power, like feature extraction and classification. To solve these problems, high-performance computing platforms like central processing units (CPUs)[9], graphics processing units (GPUs) [10], and field-programmable gate arrays (FPGAs) [11] have been used. GPUs have a lot more computing cores than CPUs, which lets them run deep-learning models faster. FPGAs, on the other hand, have more flexible hardware configurations and use less energy. However, they are harder to program and take longer to develop than CPUs and GPUs.

Many computer vision methods have been suggested for reliable and accurate face detection and recognition, such as local, subspace, and hybrid techniques [12],[13],[14],[15]. Even though they work well, there are still some problems because of differences in head pose, lighting, facial expressions, and occlusions. There are now more advanced ways to deal with these problems, but they usually require a lot of processing power, memory, and complicated system design. As a result, it is still an open research problem to find a way to meet real-time performance requirements while still getting high accuracy. Real-time face recognition is still one of the most popular and actively researched biometric technologies. This is because there is a growing need for security-focused applications and imaging and computing technologies are changing quickly.

2 Essential Steps of Face Recognition Systems

Before describing the techniques, the challenges that must be overcome to conduct face recognition successfully must be briefly described. As described in[16],[17], a face recognition system is useful for several security applications if it can process videos and images in real time, be robust in different lighting conditions, be independent of the person (regardless of hair, ethnicity, or gender), and work with faces from different angles. Data is collected using RGB, depth, EEG, temperature, and wearable inertial sensors.

These sensors may assist face recognition systems detect static and video facial pictures. In pure image/video processing, illumination variation, head attitude, and facial expression sensors may enhance face recognition system dependability and accuracy by addressing obstacles. Audio, depth, and EEG sensors give additional information to the visual dimension and increase identification reliability in light fluctuation and location change situations. Second, detailed-facial sensors like eye-trackers can distinguish background noise from face pictures by detecting minute dynamic changes in face components. Finally, target-focused sensors like infrared heat sensors may assist face recognition algorithms filter irrelevant visual material and withstand lighting change.

A strong face recognition system is created using three fundamental steps: (1) face detection,

(2) feature extraction, and (3) face recognition (shown in Figure 1) [18]. Finding and identifying the human face picture that the system has acquired is done via the face detection process. Any human face found in the first step may have its feature vectors extracted using the feature extraction step. In order to determine the identification of the human face, the characteristics retrieved from the human face are finally compared with all template face databases in the face recognition process.

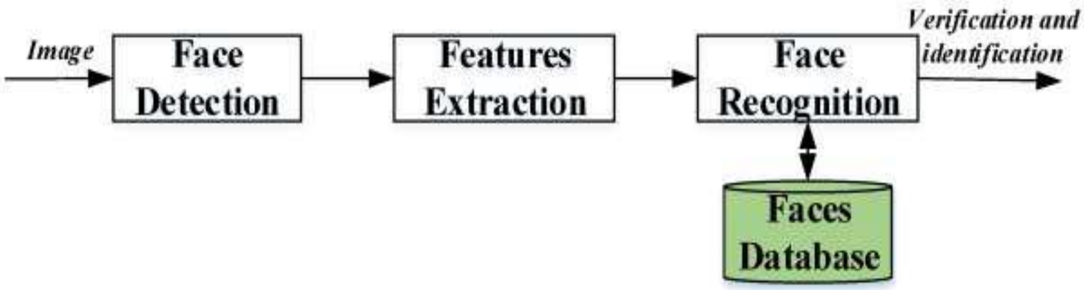

Figure1: Face recognition structure [3,23].

Face Detection:

The localization of human faces in a given picture is the initial step in the face recognition process. This step's objective is to as certain whether or not human faces are present in the input picture. Proper face identification may be impeded by fluctuations in light and facial expression. Pre-processing activities are carried out to enable the creation of an additional facial recognition system easier and more reliable. The human face picture is detected and located using a variety of methods, such as principal component analysis (PCA)[19], histogram of oriented gradient (HOG) [20], and the Viola–Jones detector [21]. Additionally, the face detection stage may be used to object identification [22], region-of-interest detection, video and image classification, and other applications.

Feature Extraction:

This step's primary purpose is to extract the features from the face photos that were found throughout the detection process. In this stage, a face is represented by a vector of characteristics known as a "signature," which specifies the faces' main features, including the eyes, nose, and mouth, along with their distribution of geometry [23]. Each face may be recognized thanks to its unique size, shape, and structure. In order to identify the face based on size and distance, a number of methods extract the form of the mouth, eyes, or nose. The face features are extracted using a variety of methods, including HOG [24], Eigen face, independent component analysis (ICA), linear discriminant analysis (LDA) [25], scale-invariant feature transform (SIFT), gabor filter, local phase quantization (LPQ) [26], Haar wavelets, Fourier transforms, and local binary pattern (LBP).

Face Recognition:

In this stage, the features that were taken out of the back drop in the feature extraction step are compared to known faces that are kept in a particular database. Identification and verification are the two broad uses of facial recognition technology. In order to determine the most probable match, a test face is compared with a collection of faces during the identification stage. To decide whether to accept or reject a test face, the identification step compares it with a known face in the database [27],[28]. This job is known to be successfully addressed by correlation filters (CFs)[29],[30], convolutional neural networks(CNN)[31],and k-nearest neighbor (K-NN) [32].

Figure2: Face recognition challenges due to variations in pose, lighting, and facial expression.

3 Real-Time Face Recognition Pipeline

Many advanced biometric authentication technologies are based on traditional face recognition methods. These methods can be grouped into three main types: appearance-based, statistical, and local feature-based. These methods use hand-crafted features and traditional machine learning algorithms. They are easier to understand and less computationally complex than deep learning methods. But changes in lighting, pose, facial expression, and image quality can often affect how well they work. Most of the time, early face recognition methods that look at the whole face use the global intensity information of facial images. Eigen faces [33] and Linear Discriminant Analysis (LDA) [34] are two methods that try to project high-dimensional facial data into a lower-dimensional subspace that keeps information that can be used to tell the difference between faces. These methods are easy to use and don't take up lot of processing power, but they don't work well when the lighting changes, things get in the way, or the pose changes. Independent Component Analysis (ICA) is an extension of these statistical methods that tries to find higher-order statistical relationships between facial features. Even though they are simple, these methods are still useful in controlled environments and systems with few resources.

Local feature-based methods have gotten a lot of attention because they are strong against changes in the area. Local Binary Pattern (LBP) is one of the most popular descriptors because it is not affected by changes in light or rotation. Khoi et al. [17] came up with a fast face recognition system that uses LBP, Pyramid LBP (PLBP), and Rotation-Invariant LBP (RI-LBP). It works well on databases like TDF, CF1999, and LFW. Xi et al. [15] came up with LBPNet, an unsupervised deep learning-inspired architecture that keeps the shape of convolutional neural networks but uses LBP operators instead. The experimental results on the FERET and LFW datasets showed that LBP Net can recognize things at rates similar to other unsupervised methods.

To make LBP more stable, several versions of it have been made. Bonnen et al. [35] came up with the Multi scale Local Binary Pattern (MLBP) to deal with changes in facial expressions. Ren et al. [36] came up with the Local Ternary Pattern (LTP), which is less sensitive to noise because it uses a three-level thresholding scheme. Hussain et al. [37] made Local Quantized Patterns (LQP/LPQ) to make the system more stable when the lighting changes.

Laure et.al 32] used the K-Nearest Neighbor (KNN) classifier with LBP to deal with big changes in expression and pose. They got very high accuracy on the CMU-PIE and LFW datasets. There have also been studies on other local descriptors, like Histogram of Oriented Gradients (HOG) and Pyramid HOG (PHOG). Arigbabu et al. [38] suggested a face recognition system based on PHO Gand Support Vector Machines (SVM). This system showed that it could handle changes in head pose even though it was more complicated to compute.

Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) are two key-point-based methods that have also been used for face recognition. Lenc et al.[39] showed that SIFT works well on the FERET, AR, and LFW datasets, getting high recognition accuracy even when there are no restrictions.

Another important group of traditional methods for recognizing faces are those that use correlation filters. These methods have shown good results in terms of robustness, accuracy of location, and built-in parallelism. A lot of optoelectronics hybrid solutions have been made since the first use of optical correlators. Some examples are the Vander Lugt Correlator (VLC) [47] and the Joint Transform Correlator (JTC). Leonard et al. [40], Heflin et al. [41], and Ghorbel et al. [42] showed that correlation filters work well with descriptors like LBP, Difference of Gaussian (DoG), and PCA to deal with changes in light and obstructions. To match target and reference images, these methods use similarity measures like Peak-to-Correlation Energy (PCE) and Peak-to-Side lobe Ratio (PSR).

Even though they have some benefits, traditional face recognition methods have a lot of problems when used in real time. Many methods need a lot of preprocessing, exact facial alignment, and hand-crafted feature extraction, which makes them more expensive to run and use more memory. Techniques like SIFT, SURF, and PHOG are strong, but they take a long time to process, so they aren't good for real-time use. PCA and LDA are statistical methods that are sensitive to changes in the environment. Correlation-based methods, on the other hand, often need careful parameter tuning and high-quality reference images. These problems show the trade-off between accuracy, robustness, and computational efficiency, which is why we are moving toward real-time face recognition systems that use deep learning and hardware acceleration.

TABLE1: SUMMARY OF TECHNIQUES USED IN FACE RECOGNITION

Author / Technique Used	Database	Matching	Limitation	Advantage
Xietal.[15]– LBPNet	FERET/ LFW	Cosine similarity	CNN complexity	High recognition accuracy
Khoietal.[17]– PLBP	TDF/CF/ LFW	MAP	Skewness	Robust frontal features
Laureetal.[32]– LBP + KNN	LFW / CMU-PIE	KNN	Illumination sensitivity	Robust
Renetal.[36]– LTP	CMU-PIE/ YaleB	Chi-square	Noise level	Superior to LBP/LTP
Hussainetal.[37] – LPQ	FERET/ LFW	Cosine similarity	Information redundancy	Illumination robustness
Arigbabuetal. [38]–PHOG+ SVM	LFW	SVM	Computational complexity	Pose variation handling
Lencetal.[39]– SIFT	FERET/A R / LFW	Posterior probability	Not fully invariant	Robust to low-quality data
Duetal.[43]– SURF	LFW	FLANN distance	Processing time	Robust &distinctive

4 DEEP LEARNING–BASED FACE RECOGNITION METHODS

Several scholars have suggested machine learning techniques in their literature reviews. They have discovered a number of methods and solutions for recognizing and detecting faces. According to the combined ResNet-50 proposed by Lee, Won, and Hong [44], top-1 accuracy increased from 76.3% to 82.78%, mCE from 76.0% to 48.9%, and mFR from 57.7% to 32.3% of the ILSVRC2012 validation collection. Bau, Zhu, Strobelt, Lapedriza, Zhou, and Torralba [45] examined a convolution neural network (CNN) that specializes in scene categorization and finding units that match a wide variety of intricate object notions. A FinRL DRL library was introduced by Liu et al. [46] to let novices invest in quantitative finance and create their own stock trading methods. Carion, Massa, Kirillov, & Zagoruyko,[47] suggested that the new system, known as Detection Transformer or DETR, consist of a transforming encoder-decoder architecture and a set-based global loss that uses bipartite matching to compel certain predictions. DETR explanations for object relations, global image meaning for direct creation, and a fixed restricted number of taught object queries.

A garap, [48] stated that in this instance, CNN-SVM attained test accuracy of 90.72%, while CNN-Softmax attained test accuracy of 91.86%. Chopade, Edwards, Khan, & Pu, [49] suggested that there be a clear interest in how collaboration abilities and interactions are shown via both spoken and non verbal behaviors, as well as how these behaviors may be documented and assessed by passive data collection of Trabelsi, Chaabane, & Ben-Hur, [50] worked on deep RAM, an end-to-end deep learning platform that enables the implementation of both previously proposed and novel architectures; its fully automated model selection process enables a fair and logical assessment of deep learning architectures. A study [51] suggested a deep learning approach for wind speed forecasting. In order to give a solution for wind speed weather forecasting, they use several methodologies. Howard et al., [52] developed a model that was expanded and adapted to challenges including semantic segmentation and object recognition. Lite Reduced Atrous Spatial Pyramid Pooling (LR-ASPP), a novel and efficient segmentation decoder, is proposed for the purpose of semantic segmentation or any dense pixel prediction. A collaborative random faces (RFs) and Sparse many to one encoder (SMF) were suggested by Shao, Zhang, & Fu, [53]. In order to recognize faces, they have worked on pose-invariant face representation. Using real-world datasets, YouTube datasets (YTF), and Multi PIE posture datasets, the author is working on a separate article. They have increased their face detection and recognition performance from 7 to 14%. 2018 saw the proposal of a hybrid optimization framework and an unsupervised learning framework by Tsai et al.,[54]. This method improves the co-segmentation mask to enhance the co-saliency characteristics. A combined optimization framework and unsupervised learning are investigating the idea of objectness and saliency in various kinds of multiple pictures or datasets. Results on co-saliency and co-segmentation from the Cosal2015, iCoseg, Image Pair, and MSRC datasets are of excellent quality.

Huetal. [55] developed an on-blind de-convolution approach to eliminate light-induced ringing artifacts in face detection and identification. A non-blind de-convolution algorithm detects light stretches in damaged pictures and embeds it in an optimal framework for face identification. The author works with low-light png and jpeg photos. Anwar [56] presented class-specific de-blurring and genetic blind de-convolution. This strategy overcomes limitations of previous methods. In cases of hazy images with low frequency. This approach focuses on blurred pictures with a single object and class-specific training utilizing CMUPIE, CAR, FTHZ, and INRIA datasets. Wang et al.[57] suggested Region NET or RexNet and Salient Object detection methods for face recognition. RexNet offers end-to-end saliency mapping for VGG, Image Net, Contex Net, ECSSD, DOTOMRON, and RGBD1000 datasets inside form object borders. In face detection and identification, RexNet has developed a multi-scale conceptual robustness approach. A study by Deng et al. [58] suggested using image filtering binarization and spatial histogram for face identification and recognition. The author created the SCBP description to enhance facial image effectiveness. SCB utilizes hand crafted 6RF Eigen filters for precise and reliable performance. To enhance the strength of LBP, CBP is used. This study employs DFD and CBFD to provide noise-sensitive filtering for face detection and identification using FERET, LPW, and PaSC databases with fine-grained structures.

5 Publicly Available Face Recognition Datasets

The publicly accessible datasets used in the field of facial recognition systems are described in detail in this section. Numerous datasets have been used to assess the effectiveness of facial recognition systems, according to the literature. Below is a discussion of several dataset descriptions:

CASIA Web Face: CASIA Web Face is a dataset containing approximately 500,000 images of 10,000 subjects. Initially gathered by the CASIA group and later refined manually. This dataset follows a common pattern seen in collections based on celebrities or well known individuals. It exhibits a long tail distribution which indicates a few popular subjects have the majority of images while others are represented by only a few pictures.

VGG Face: The Oxford group introduced VGG Face, a tool for deep learning model training. About 2.6 million faces from 2,622 people are included. In contrast to CASIA, VGG Face has a balanced distribution, with hundreds of samples of high-quality frontal faces taken from search engines for each topic. Nevertheless, this dataset has certain noise-related problems, such as outliers, which cause intra-class variation, even after cleaning attempts.

UMD Faces: UMD Faces, first presented by Bansal et al. [61], combined pre-trained deep-based facial analysis techniques with human annotators using Amazon Mechanical Turk (AMT). The goal of this novel method was to produce medium-sized sets that were more difficult than those that already existed, such as VGGFace [62] and CASIA [63]. The UMD Faces dataset is prone to motion blur even though it includes both high-quality still photos and video frames. Gender information, face posture angles, and facial important points are annotated in this dataset. In particular, it contains 3.7 million annotated video frames taken from around 22,000 films with 3,100 subjects and 367, 888 face annotations in still photos with 8,277 individuals.

MS-Celeb-1M: MS-Celeb-1M was first made available to the multimedia community before being embraced by the computer vision community [64]. Approximately 10 million photos with 100,000 celebrities were included. Using the celebrity's name as the search query, 100 photos from the Bing search engine are used to represent each star in the collection. No filters were applied to the search results before the photographs were obtained. However, MS-Celeb-1M has a lot of problems in spite of its enormous size. MSCeleb-1M was published with the express purpose of learning from noisy labels; it was never modified or arranged for quality.

VGGFace2: A better version of VGG Face, called VGGFace2, was created to address the shortcomings of the original [65]. This collection includes 3.31 million photos with 9,131 topics, including famous people and celebrities. The average number of photos per person has somewhat dropped to 362.6 images when compared to the original VGG Face. None the less, VGGFace2 aims to reduce label noise while purposefully including a broad spectrum of positions, ages, and races [66], [67]. Using both automated and human procedures, this label noise reduction was accomplished.

Labeled Faces in the Wild (LFW): In order to solve the difficulties presented by unconstrained FR, Labeled Faces in the Wild (LFW) is a comprehensive collection of face photos [63]. This dataset is a huge collection of more than 13,000 photos of faces taken from the internet, each of which has been carefully labeled with the individual's name.A total of 1,680 people are represented in this collection via many different images. It's crucial to remember that the Viola Jones face detector was first used to identify these facial photos[9] , [68]. Four sets of LFW photos make up the dataset: three sets of aligned images and one original set. Notably, as compared to the original and funneled photos, LFW and the deep funneled images perform better over a broad spectrum of face verification techniques. For testing and research, this feature makes them indispensable.

The following table lists popular publicly available datasets used in face recognition research and real-time system evaluation.

TABLE 2: FACE RECOGNITION DATASETS

Task	Dataset	Images/ Videos	Image Format and Example	Labels	Performance Metrics
Face recognition	Labeled Faces in the Wild (LFW)[69]	13,233 Images	RGB face images (unconstrained)	Bounding box with identity	Accuracy = 99.83% [59]
Face recognition	CelebA [70]	200,000 images	RGB face images	Bounding box with identity and attributes	Accuracy =82% [61]
Face recognition	YouTube Faces Database(YTF) (Kaggle. Segmentation Full Body MADS Dataset. Available online: https://www.kaggle.com/datasets/tapakah68/segmentation-full-body-mads-dataset)	3,425 videos	Video frames (RGB)	Bounding box with identity	Accuracy = 98.02% [59]
Face recognition	VGG Face[65]	2.6 million images	Cropped RGB face images	Identity labels	Accuracy = 98% [64]

The YouTube Face Database (YTF): Face films made especially for unrestrained FR maybe found in the YouTube Face Data base (YTF). The clips in this data base have an average duration of 181.3 frames and range in length from 48 to 6,070 frames [68],[65]. Every video was taken from YouTube, and on average, 2.15 videos covering various topics are accessible. YTF is a useful tool for researching FR algorithms in uncontrolled real-world environments. Applications of Real-Time Face Recognition

5.1 Access control

Many automated access control methods for human-machine interaction have embraced facial recognition technologies due to their growing popularity. Other authentication control techniques, such fingerprints, iris recognition, password protection, etc., have also taken its place. Additionally, with the ubiquitous usage of smart phones and CCTV cameras, face-based

5.2 ENTERTAINMENT

The entertainment industry has also seen a rise in the use of facial recognition technology. Virtual reality, mobile gaming, human-robot interaction, human-computer interface, training, and theme park gaming zones are among the most intriguing fields. Additionally, T. Felt well et al.[76] just released an intriguing game in which players are tasked with capturing the image of popular figures. They suggested an alternative experience where users may search and catch members virtually in the real world, but they were inspired by free-to-play models and the enormous popularity of the well-known game "Pokemon GO."

5.3 LAW ENFORCEMENT

Law enforcement agencies have found that face recognition software is a very useful tool for identifying offenders and tracking down missing people. It is quite time-consuming for law enforcement officers to manually examine hours of video footage in order to look for a certain identify. For instance, it was recently claimed that Chinese law enforcement, using its robust CCTV camera network of over 170 million cameras and facial recognition technology, was able to find BBC correspondent John Sudworth in only seven minutes. Research on face recognition gives law enforcement agencies a new generation of sophisticated and effective investigation tools [77]. Another difficult issue for densely inhabited cities worldwide is overstay and illicit citizenship. Face recognition technology advancements make it easier to apprehend overstaying tourists and illegal immigrants. Additionally, facial recognition technology is used for immigration, banking [78], voter identification [79], criminal investigation [75], and counterterrorism [80].

5.4 OTHER COMMON APPLICATIONS

Kwon and Lee [81] have shown a wide range of methods for facial recognition in software applications. Similarly, face recognition applications for the forensic investigation department are shown by Salici and Ciampini [82]. Experts in forensics have proven the efficacy of identification experiments conducted on130 actual instances. Calo et al. [83] provide another new application for controlling privacy while reading, modifying, and deleting digital data.

6 CHALLENGES AND OPEN RESEARCH ISSUES

While face recognition research in controlled settings has shown great success in achieving the necessary goals for social applications, there are still significant obstacles in an uncontrolled setting where subjects are dynamic and variations are hard to detect from a machine perspective because of certain factors. This section outlines the many difficulties that facial recognition technology faces.

6.1 POSE VARIATION

In 2D or 3D perspectives, It mostly refers to the rotation or alteration of the subject picture out of the plane in various positions [84]. Posing is the most challenging identification task, particularly when the subject is in an uncooperative setting, such also locating a spy in a crowded public area, protecting terrorists at an airport, or seeing criminals in large stores, etc. Although gathering many gallery photos of the topic would be the best way to do this work, it seems to be unfeasible for the majority of real-world applications. For instance, how can we spot a Terrorist amid a throng of people at a foot ball stadium if the picture data base just contains each person's passport photo? In terms of numbers, two photographs of the same subject in a different stance vary more than two images of different subjects. As a result, local methods like Elastic Bunch Graph Matching (EBGM) and Local Binary Pattern (LBP) are thought to be more effective than holistic methods. The Point-and-Shoot Face Recognition Challenge (PaSC), which was introduced by Beveridge et al. [85], evaluated five distinct approaches on the PaSC database, which comprises un constrained face images and videos of both indoor and outdoor scenarios. The top-performing algorithm in this competition [86] asserts that their strategy is almost flawless on pose variation; yet, the same set of techniques eventually turned out to be ineffective on other face datasets.

6.2 ILLUMINATI ON VARIATION

Another significant issue for facial recognition systems is the lightning effect or variable lighting. Lighting is completely uncontrollable for machine intelligence because of skin reflectance characteristics, various camera sensors, resolution impacts, and ambient factors. Conventional methods offer different lighting effects and their own drawbacks. The effects of variable lighting have been shown to be more substantial than the difference between two distinct pictures, both logically and practically. Variations in illumination cannot be handled by traditional techniques such as eigenface, fisher face, probabilistic and Bayesian matching [175], and SVM [181]. However, a wealth of recent research [87], [88], [89], [90], [91], [92], [93] attests to the importance of addressing light variations for face recognition system performance tuning. A example from the CMU-PIE dataset is shown in Fig.3, which demonstrates the substantial influence of changing lighting conditions:

Figure3: Different lightning conditions for same face as presented in CMUPIE data bas e

6.3 Occlusion

Face occlusion occurs when significant facial characteristics are obscured by the presence of other things, such as a mask, scarf, hand, helmet, sunglasses, hatred, etc. Another crucial element that significantly impairs the effectiveness of the face recognition method is occlusion.

Certain facial characteristics are often obscured in real life by hands, hair, scarves, etc., as seen in Fig. 4. This is particularly typical when the individual is in an unsupervised setting.

Figure4 Faces with occlusion effect as presented in Hand 2 Face [180]

Occlusion in face pictures has been the subject of significant study efforts [94], [95], [96], [97]. Although it is not always applicable, a straight forward method is used in many models: treat the obscured portion as noise, remove it from the provided facial picture, and compare the remaining data with the stored image. A model to handle handover occlusions using a collection of non-occluded faces was recently introduced by Nojavanasghari et al. [98]. In a similar vein, Iliadis et al. [99] provide an iterative approach to the face recognition occlusion issue. The suggested method effectively models occlusion by using robust representation based on two characteristics. The occluded portion is first stated by a particular structure and then fitted as a distribution that is characterized by a customized loss function. Finally, to make it resilient and computationally economical, the Alternating Direction Method of Multipliers (ADMM) model is used.

6.4 Aging

The human face undergoes nonlinear and irregular changes throughout time. This is essential for identifying faces with different age effects in both human and machine intelligence. There are just a few attempts in the literature to handle age variation since this issue is sufficiently difficult to tackle in comparison to other face recognition difficulties. A person's face's texture, shape, and look all change as they age. The majority of traditional approaches [100] that address the issue of age variation consist of two stages: feature extraction and distance metric computation. The algorithm's performance may be impacted by a predetermined distance threshold when these stages disregard the touch of these components. Additionally, the majority of real-world applications, such as picture data bases for ID cards or passports, cannot update gallery photos on a regular basis. To address age invariance, Chen et al. [101] suggest the Cross-Age Reference Coding (CARC) paradigm. The model uses an age variation reference space to represent a face image's low-level properties. Its highly scalable characteristics can be extracted with only a linear projection. Using a self-created dataset of over 160,000 photos of 2000 celebrities in the 16–62 age range, the authors test the algorithm and find that it performs well. Wen et al. present an additional age-invariant facial recognition model based on deep convolutional neural networks [102].The model's two main parts are the latent factor fully connected layer, which handles age variation feature learning, and the convolution unit, which handles feature learning. The CNN architecture has shown to be effective since it is meticulously crafted to capture micro-level fluctuations.

7 Conclusion

As security requirements rise and image and computer technology become more widely available, real-time face recognition has emerged as a crucial part of contemporary biometric systems. A thorough review of facial recognition systems with an emphasis on real-time applications has been provided by this survey. A thorough analysis of conventional face recognition techniques, such as appearance-based, statistical, and local feature-based methods, was conducted in order to highlight their advantages, disadvantages, and applicability in modern systems. When used in real-time applications, environmental fluctuations and processing inefficiencies often limit the performance of these traditional approaches, notwithstanding their simplicity and interpretability.

The report also stressed how crucial publicly accessible face recognition datasets are for assessing and comparing algorithms. Robust recognition models have benefited greatly from the emergence of large-scale, unconstrained datasets; nonetheless, problems including dataset bias and a lack of real-time annotations still pose difficulties. It was mentioned that hardware acceleration platforms, such as FPGAs and GPUs, are essential for fulfilling real-time performance demands. Each platform has unique benefits in terms of energy economy, speed, and adaptability.

Handling severe posture fluctuations, lighting changes, occlusions, and scalability to huge populations under stringent latency limitations are among the outstanding difficulties that remain despite significant advancements. Furthermore, in real-world deployments, privacy

protection, ethical issues, an defense against spoofing and adversarial assaults have grown in significance. It is recommended that future research concentrate on models that are light weight and energy-efficient, hybrid techniques that combine learnt and handmade characteristics, and edge-based intelligent systems that can function with limited resources. Furthermore, including explainable AI and privacy-aware learning processes will be essential to developing reliable face recognition systems.

Therefore, real-time facial recognition research is still ongoing and developing. Researchers looking to create precise, effective, and dependable real-time face recognition systems will benefit from this survey's insightful analysis of current approaches, datasets, and difficulties.

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