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A Systematic Analysis of Two-Dimensional Face Recognition Methods

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Abstract- Face recognition is the most effective and extensively used biometric method. It's cheap, natural, and non-intrusive. Researchers have created hundreds of facial recognition methods in recent years. Based on face data processing, these methods fall into three groups. The suggested recognition system may employ the full face, particular features or parts of the face, or both global and local face characteristics. This article reviews well-known approaches in each category. First, we discuss biometric facial recognition's pros and cons. We then describe each well-known method's concept. Next, the three facial recognition methods are compared. These algorithms are applied to face recognition databases, and some results are shown. Finally, we discuss intriguing new research areas.

Keywords- biometrics; face recognition; person identification

I. INTRODUCTION

The introduction of the computer and its ability to store and display huge amounts of data has led to the development of various forms of biometrics, such as the ability to recognize a person's face or voice, scan their retinas, scan their fingerprints, and so on.

Not only is biometric technology becoming more and more significant, but many scholars are studying it more and more. It comprises both the technology used to measure and those utilized to assess the distinctive qualities of a person due to its unmatched performance. Biometrics come in both behavioral and physical forms. While the latter can be used for either identification or verification, the former is often utilized for verification.

For example, "facial recognition" is an example of a biometric that can be used for identifying purposes. It has been, for a considerable amount of time, a highly interesting field that has caught the interest of a number of academics due to the fact that it is not obtrusive, is quite popular, and does not cost very much. To recognize a face in a 2D image, several different methods have been presented over the course of the previous few decades. These methods' potential applications include video conferencing systems [1,2,3,4,5], facial reconstruction, and security, amongst others.

A face recognition system may be broken down into three distinct steps, which are depicted in Figure 1. These stages are named data gathering, Train the recognizer, and face recognition.

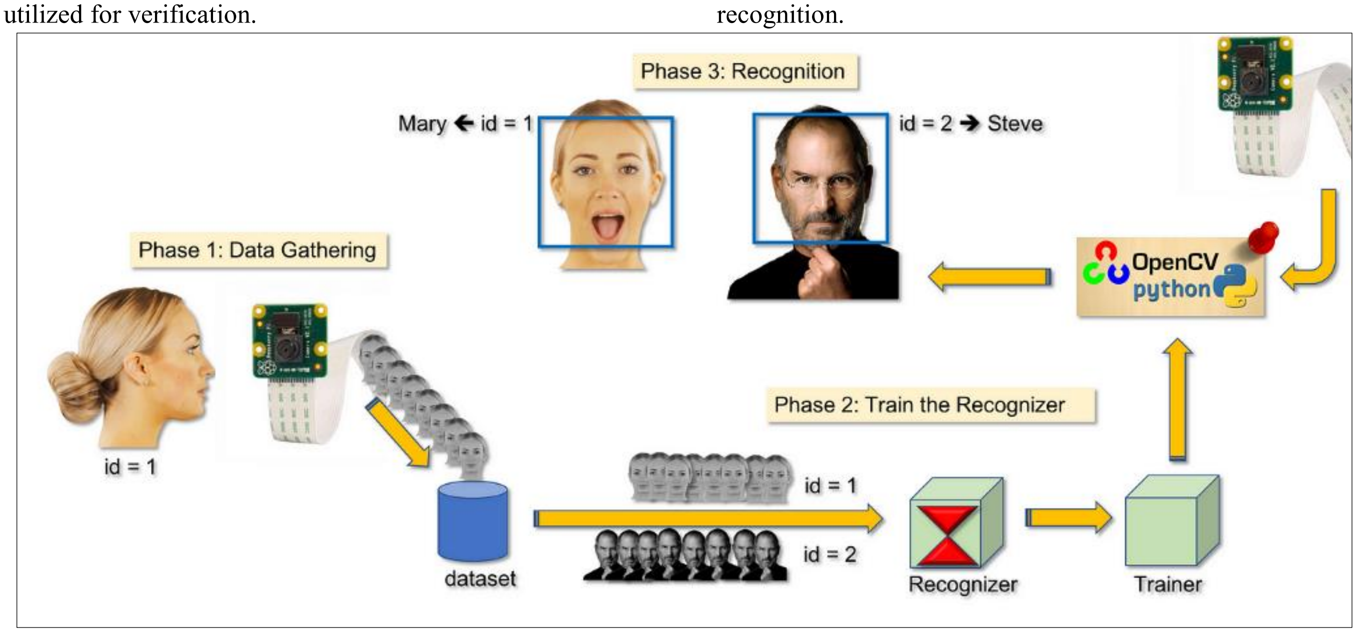

Fig.1 Real-Time Face Recognition

The first step in the process of face recognition is to determine whether or not an image contains a face. In most cases, a face detection system will be able to determine whether or not an image contains a face. In the event that it occurs, the purpose of the system is to pinpoint the location of one or more faces inside the image.

However, if there are any differences in the illumination, location, facial expression (such as smiling, surprise, etc.), orientation, or morphological criteria (such as mustaches, glasses, etc.), then this phase will be more difficult. All of these challenges have the potential to thwart accurate face detection, which will, in turn, bring about a reduction in the rate of face detection.

Following the successful recognition of a face inside an image, we then go on to the process of isolating the facial features [6,7,8]. This stage is critical not only for the recognition of facial expressions but also for the animation of those expressions. In this stage, a feature vector that will be referred to as the signature will be extracted from the recognized face. Therefore, the latter is all that is necessary to represent a face. It is required to validate the individuality of the face in addition to having the ability to differentiate between the appearances of two distinct people. It is important to note that the face detection stage can be combined with this phase to complete the process.

The face recognition process also requires identification and authentication. To validate the requested identification, authentication entails comparing one face to another. However, identification compares a face with a number of other faces to determine the face's identity among various possibilities.

In this paper, I talk about the current state of the art in this area. I do this by focusing on approaches that have changed the world of face recognition, as well as methods that have been developed more recently. Fingerprints are the most popular way to identify someone, even though there are many other ways.

However, numerous studies have shown that the iris texture, which remains constant over the course of a person's life, is the most trustworthy trait. Fingerprint analysis and iris texture analysis both have the significant problem of being intrusive. They also impose limitations on users, which contributes to the severely constrained scope of their applications.

In contrast, the users are not restricted by the facial image recognition technologies. Face recognition does indeed have a number of benefits, some of which include:
Short time: One of the quickest biometric modalities is this one. Real-time applications are possible because the biometric system only needs to be used once.

High security: Let's use the example of a business that verifies visitors' identities at the door. Such a biometric system enables not only staff to confirm visitors' presence at the time, but also allows for the addition of any visitor. As a result, people who are not part of the system are not given access.

Automatic system: This system operates on its own without the need for a person to control or monitor it.
Easy adaptation: It is simple to implement in a business setting. The installation of the capturing system (camera) is all that is required for it to work.

High success rate: This method has reached high recognition rates, particularly after the development of three-dimensional technology, which makes it very difficult to cheat on the system. The end result is that this instills confidence in the people who use the system.
Acceptance in public places: It makes it possible to acquire enormous databases, which ultimately results in improved recognition performance.

This score is displayed in Figure 2 and is one of the six biometric characteristics (facial, voice, eye, hand, signing, and fingers) taken into consideration in [9].

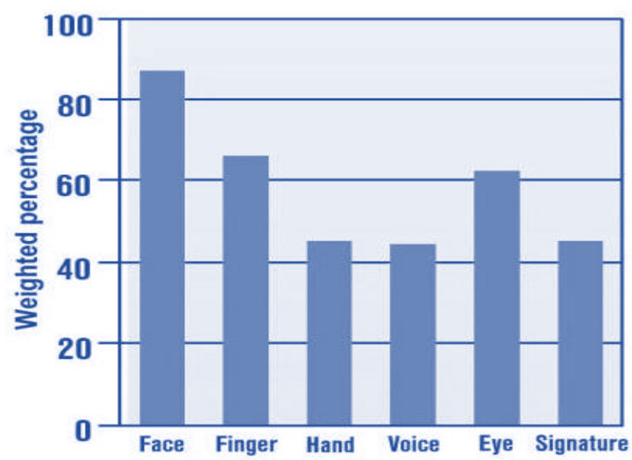

Fig. 2 features scored the highest compatibility

II. 2D FACE RECOGNITION

Since a long time ago, facial recognition has been considered to be a very interesting field that has drawn the attention of a lot of scholars. Recognizing a face in a 2D image has, in fact, been attempted with a variety of different approaches. In order to get an understanding of the fundamentals behind each method, we shall organize these approaches into three distinct groups according to the manner in which they treat the image of the face.

In the first category are the global or holistic techniques, which take the full face into account while gathering the necessary information for the proposed recognition system. After that, these data will be projected into a subspace with a reduced dimensionality.

The second category includes several approaches to the local recognition. They do not take into account the entirety of the face, but rather choose aspects or regions of the face that are categorized in accordance with clearly established statistics.
The third group includes statistical model-based approaches and hybrid strategies. This class comprises hybrid methods that combine global and local characteristics in order to take full advantage of the benefits of the two aforementioned categories and raise the rate of 2D face recognition. It also includes methods based on statistical models that codify interrelationships as mathematical equations that show how one or more random variables relate to one or more other random variables. When the variables are stochastically rather than deterministically connected, the model is deemed statistical.

A. Global Approaches
These techniques, also known as appearance-based methods, treat face images worldwide, eliminating the need to isolate individual facial features like the lips, eyes, or eyebrows. As a result, a facial image is represented by a matrix of pixels. In order to facilitate manipulation, this matrix is frequently translated into pixel vectors. These methods are simple to use, but they are susceptible to changes (in positions, lighting, facial expressions, and orientation). In fact, any modification to the face image alters the pixel values. As was already established, facial input data are later projected in low-dimensional space in global approaches. In fact, a form of the class "face" can be found in an image's sub-space, which frequently contains additional forms (trees, homes, etc.).

Let's look at a 2D picture of a face that is 6060 pixels. A few pixels might be the face, and the rest might be the surroundings, the car, or something else. So, if you only look at the face, you can get rid of a lot of the original picture. This category can be split into linear and non-linear methods based on how the sub-projection areas of the face input data were modeled.

B. Linear Techniques
These methods use a linear projection of the image data from a big space into a face sub-space, which is a smaller space. But there are two big problems with this kind of vision. First, the non-convex face differences that help us tell one person from another cannot be kept. So, the Euclidean distances used to compare the vectors of the pixels in a linear region are not very good at separating face/non-face forms and people. So, the rate at which these methods find and recognize people is usually not good enough. To figure out the feature vectors, a very large number of linear methods were used. We can name a few of these methods:

- Eigenface
- 2D PCA (two-dimensional PCA)
- Multidimensional scaling (MDS)
- Nonnegative matrix factorization (NMF)
- Linear discriminant analysis (LDA)
- Improvements of PCA, LDA and ICA techniques
- Independent high intensity Gabor wavelet
- Gabor features, LDA and ANN classifier
- Regularized discriminant analysis (RDA)
- Regression LDA (RLDA)
- Nullspace LDA (NLDA)
- Dualspace LDA
- Generalized singular value decomposition
- Boosting LDA
- Discriminant local feature analysis
- Block LDA
- Enhanced fisher linear discriminant (FLD) [31].
- Incremental
- Discriminative common vectors (DCV)
- Bilinear discriminant analysis (BDA)

Even though these global linear methods, which are based on how things look globally, avoid the instability of the first geometric methods that were made, they are not detailed enough to describe the subtle geometric differences in the original image's space. This is because they can't handle the fact that face recognition isn't always straightforward. In other words, the deformations of their irregular forms can be smoothed out, and concavities can be filled, which can have bad effects.

C. Non-Linear Techniques
When the data structures that come in are linear, linear methods are a good way to show sparse data. But when the data are not linear, several experts have found that using a function called the "kernel" function to build a large space where the problem becomes linear is the best way to solve it. So, linear methods can be used to reduce the number of dimensions even when the structure of the data itself is not linear. The "kernel trick," which says that any algorithm written with a kernel function can be rewritten with another kernel function, is often used in these methods.

A common way is to use a kernel function to express the method as a scalar product. The "trick" of the kernel makes it possible to work in the transformed space without directly calculating the image of each datum. Several non-linear methods were put forward in this situation:

- Convolutional neural network
- Diffusions maps dans
- Discriminant manifold learning
- Embedded manifold
- Exponential discriminant analysis (EDA)
- Hessian LLE

- Isomap
- KICA (kernel independent component analysis)
- Kohonen cards
- KPCA technique
- Laplacian eigenmaps
- Local linear embedding (LLE) dans
- Local tangent space analysis (LTSA)
- Locality preserving projection (LPP)
- Maximum variance unfolding (MVU)
- Nearest manifold approach
- Neuronal approaches
- Support vector machine (SVM)

These nonlinear projection techniques for the image space onto the feature space enable, to a certain extent, a better image size reduction. However, unlike the linear algorithms, these strategies are too flexible to be resistant to fresh data, despite the fact that they frequently increase recognition rates on particular specific tests

III. GLOBAL, LOCAL, HYBRID APPROACHES

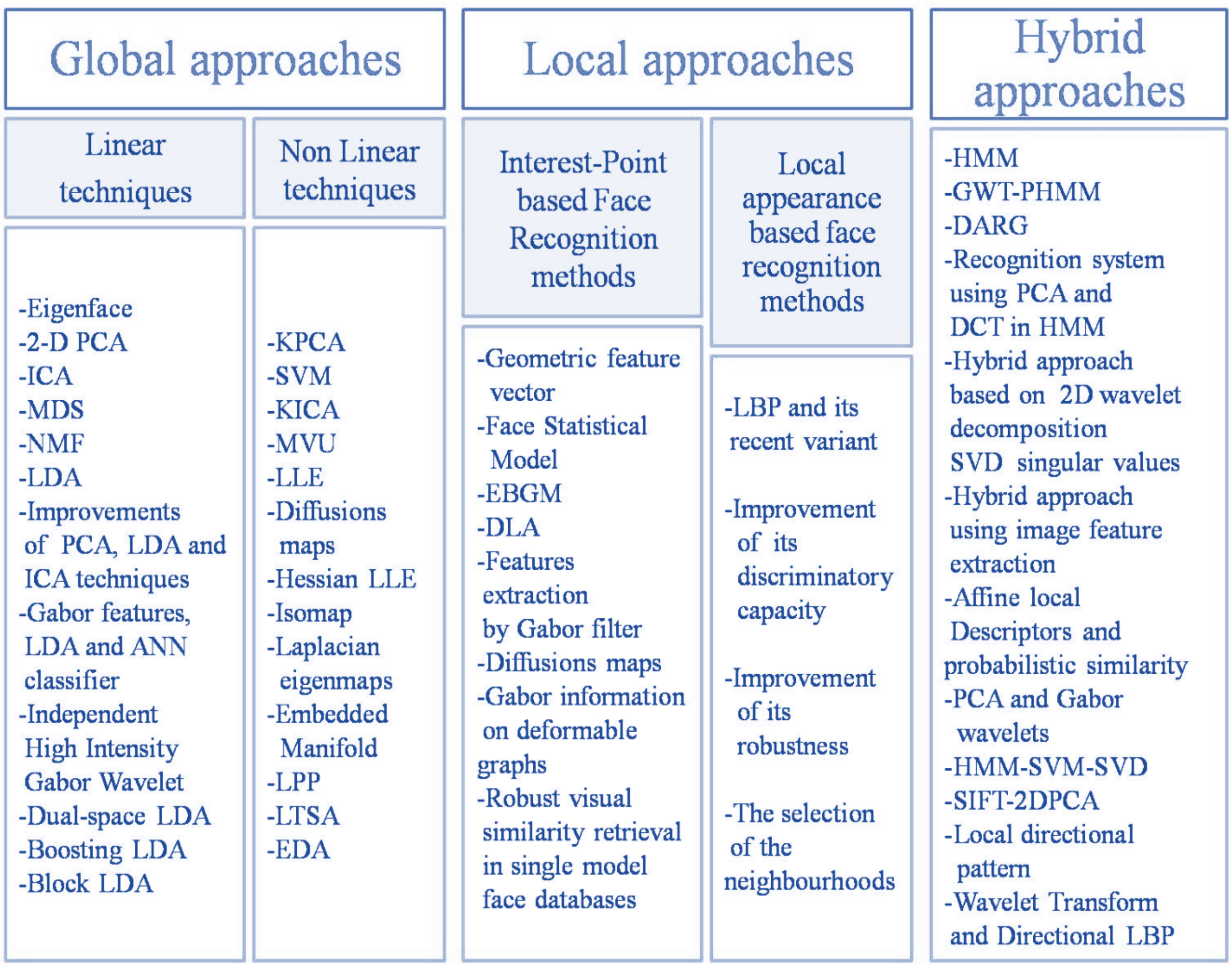

Fig.3 Classification of several face recognition approaches

IV. COMPARISON BETWEEN GLOBAL, LOCAL AND HYBRID APPROACHES

In this section of the article, we will provide a concise assessment of the benefits and drawbacks associated with each category of facial recognition techniques. In addition, we examine each method of facial recognition from the perspective of the advantages and disadvantages that are unique to each sub-class. The conclusion of this comparison is presented in Table 1.

Table 1. Comparative table of 2D face recognition approaches.

	Approach	Advantages	Disadvantages
GLOBAL	Linear	-Reduction of the dimension of the images. -Space of representation faithful to the data when the data structure is linear.	-Euclidean distances used are not very effective either for classification between facial and non-facial shapes or for classification between individuals. -Face detection and recognition rate generally unsatisfying.
	Non linear	-The use of non-linear methods of projection of images space on the feature space remarkably reduces the images size. -The improvement of recognition rates on given tests.	-They are too flexible to be efficient to new data, unlike the linear methods.
LOCAL	Interest-Point-Based Face Recognition methods	-These methods can be useful and effective for face recognition where one reference picture is available.	-Their performance depends greatly on the effectiveness of the algorithms of feature point localization. -The detection and the geometric feature extraction are not easy and have not been reliably resolved, especially when there are occlusions, or variations in pose and facial expressions, or when the shape of the face image can widely vary. -Only geometric characteristics are not sufficient to fully represent a face, and other useful information such as the values of the image to the grayscale are fully spread.
	Local Appearance-Based Face Recognition Methods	-Ability to choose the best way to represent information from each region.	-The step is critical to the system's performance.
HYBRID		-The Combination of both global and local analysis of a face can improve the ability of the classifier. -Allows one to exploit complementarities and provides more efficient systems and faster recognition.	-More difficult to implement than the other two approaches.

V. Two Dimensions (2D) Face Databases

Many face databases (public or private) are available for research purposes. These databases differ from each other according to several criteria. The most interesting ones are the following:

- Pose and orientations of faces
- Sex of the acquired persons.
- The change of illumination
- The number of images contained in each database is the most important criterion
- The number of images per individual class
- The period between shots
- The presence of a uniform background
- The presence of artifacts (glasses, beards, etc.)
- The presence of static images or videos
- The size of image

It is therefore suggested to select the right database when evaluating an algorithm. Some, in fact, have a well-defined technique that allows for direct comparison of the results. Furthermore, the selection should be based on the problem to be tested: illumination, recognition over time, facial emotions, and so on. The availability of numerous different photos per individual can be a decisive argument for an algorithm's proper performance.

The major 2D faces databases are shown in Table 2. These databases provide several variants in terms of: RGB picture or grayscale, size, number of persons, number of images by person, variations of the image.

Table 2. 2D face databases

Database	No of Persons	No of Images	Color	Images Size Pixel
AR database	131	26	RGB	576 × 768
BUF Database	35	10	Gray	-
CVL	119	7	RGB	640 × 480
Extended Yale B	33	576	RGB	640× 480
FEI database	205	14	RGB	-
FERET	30,005	-	RGB	256 × 384
FRAV2D	105	11	RGB to Gray	92 × 112
HUMAN SCAN	25	66	Gray	384 × 286
JAFEE	15	7	Gray	256 × 256
KUFDB	55	5	Gray	24 × 24 36 × 36 64 × 64

LFW	13,238	-	RGB	150 × 150
MIT	21	27	Gray	480 × 512 15 × 16
ORL	45	10	Gray	92 × 112
Oulu Physics	125	16	Gray	42 × 56
PIE	91	608	RGB	640 × 486
UMIST	25	19-36	RGB	220 × 220
USO database	305	1591	Gray	-
XM2VTS	300	-	RGB	576 × 720
Yale	20	11	Gray	320 × 243 100 × 80
Yale B	15	576	Gray	640 × 40 60 × 50

VI. RESULTS

The recent development of face recognition in the analysis of 2D face photographs, as well as the tremendous interest shown in this study area, have resulted in a constant improvement of the findings produced by testing the previously described methodologies on the various 2D face databases reported in the preceding section. Table 3 highlights some of the outcomes reported by the inventories of different methodologies. These findings are classified according to the database used for better organization.

Table 3. Results of the different face recognition methods

Database	Approach	Recognition Rate (%)
AR Database	Eigenface	55.4
	SVM + PCA	92.67
	SVM + ICA	94
	2D-PCA	96.1
	Line edge map (LEM)	96.43
ORL	PCA + MLP	75.2
	PCA	80.5
	SVM for nearest center classification (NCC)	84.6
	ICA	85
	Hidden Markov model (HMMs)	87
	Eigenface	90
	SVM with a binary tree	91.21
	Wavelet transform and improved 2D-PCA	92
	PCA and 2D-PCA]	92.8
	EBGM	94.29
	A pseudo 2DHMM	95
	PCA + DCT	95.122
	Fisherfaces with BCD	95.45
	2D-PCA	96
	PDBNN	96
	SVM + PCA	97
	2D-PCA + SVM	97.3
	2D-PCA principal component uncertainty	97.8
	Several SVM + NN arbitrator	97.9
	Improved 2D-PCA	98.33
	HMM-SVD	99
	Pose estimator	99
	HMM-DCT	99.5
	SHHMM	99.5
	HMM-LBP	99.5
	DCTHMM	99.5
	Fisherfaces + LBP	99.87
	Combination of HMM and SVM	100
	1DHMM + Wavelet	100

	Pseudo 2D HMM + Wavelet	100
	Gabor + ICA	100
	LFA	100
	Boosted parameter based on combined classifier	100
Bern	LEM	100
	Eigenface	100
FRAV2D	GWT	83.25
	PHMM	87.875
YALE	2D-PCA	84.24
	Augmented Local Binary Pattern and Bray Curtis Dissimilarity ALBP-BCD	86.45
	PCA	88.1
	Improved Modular 2D-PCA	90.7
	PCA and 2D-PCA	92.3
	B2D-PCA + FSS	94.44
	Improved 2D-PCA	97.78
	HMM-LBP	99.33
	SVM + PCA	99.39
	SVM + ICA	99.39
	Boosted parameter based combined classifier	99.5
FERET	Gabor wavelet transform (GWT)	81.25
	Pseudo Hidden Markov Model PHMM	84.375
	2D-PCA + SVM	85.2
	PCA	90
	GWT-PHMM	91.6
	HMM-LBP	95
	MLBP	95.1

VII. THE EMERGENCE OF NEW PROMISING RESEARCH DIRECTIONS

As shown in Table 3, the recognition of faces in two dimensions has matured significantly and has a high rate of success. Due to the need for it in other study areas like pattern recognition and image processing, face recognition technology has advanced and now offers more accurate findings after more than three decades of research. It shouldn't be surprising that it is still one of the most active research topics in computer vision. Numerous fascinating new study areas have developed during the last few years.
Despite the high success rate of 2D face recognition, 3D face recognition still faces two significant problems, namely variations in illumination and location. This is so that these issues may be addressed by 3D facial recognition. A new technique known as 3D face recognition has developed to address these two issues and can provide more precise data on the makeup of facial surfaces. As a result, several novel techniques that use three-dimensional data have been created recently [9,10,11,12,13,14]. It has been speculated that 3D face recognition may be able to achieve a greater degree of accuracy than its 2D version by examining the hard feature geometry existing on the face.

Multimodal face recognition, however, claims that the combination of multimodal 2D and 3D face identification is more reliable and accurate than either modality alone [15] and that it performs better than single modal face recognition. [15] Additionally, as compared to single modal face recognition, multimodal face recognition improves face identification performance. They examine potential gains that can result from fusing 2D and 3D features [16,17].
Deep learning strategies: In the area of machine learning, deep learning methods [18] have become the dominating methodology. Deep neural networks, or DNNs, have shown improved performance in a variety of tasks, including the classification of pictures, voice recognition, and face recognition. Recent developments in the area of face recognition, in particular using convolutional neural networks (CNN), have shown encouraging results. These deep learning techniques often utilize the public LFW (Labeled Faces in the Wild) database to train CNNs.

Imagery in the infrared (IR): IR imaging has emerged as a potential study area to get beyond face identification obstacles such position, facial expression, lighting changes, and facial disguises, which may greatly reduce recognition accuracy [19,20]. Attention has been drawn to IR imagery's invariance to changes in light [21]. Comparing IR cameras to visible-spectrum cameras, there are several advantages. There is evidence that the method may be more resistant to changes in facial expression, and infrared images of faces may be obtained in any lighting condition, even the dark [22]. Finally, researchers have taken these new disciplines even farther by combining them, as shown in [23], which benefited from multimodal face recognition and infrared, and [24], who has used both multimodal face recognition and deep learning.

VIII. CONCLUSIONS

Within the scope of this work, we debuted the biometric method of face recognition for the first time. After that, we showed the current state of the art of biometric methods, which we divided into three distinct groups. Following that, we offered face databases that other researchers in this area use to test their methodologies, as well as a table that summarized the conclusions of the experiment. Finally, we discussed a few exciting new possibilities that may be taken in research.

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