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Face Recognition and Age Estimation Implications of Changes in Facial Features: A Critical Review Study

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ABSTRACT Facial features are considered as one of the important personal characteristics. This can be used in many applications, such as face recognition and age estimation. The value of these applications depends in several areas, such as security applications, law enforcement applications, and attendance systems. In addition, facial features are particularly the key usage in the finding of lost child. Present applications have achieved a high level of accuracy. This paper provides a survey of face recognition, including the age estimation, which was discussed. Moreover, the research outlines several challenges faced in face recognition area that had been explored. The research also provides a landscape mapping based on integrating into a critical and coherent taxonomy. In the methodology sections, the exploration the accomplished via a deep focused in every single article in ''Face Recognition'', then ''Age Estimation'', and later in ''Facial Features''. The ''Articles extraction'' is mining from diverse sources, such as Web of Science, ACM, IEEE, Science Direct, and Springer databases. The research covers overall 72 articles; 32/72 articles were face recognition. Moreover, 39/72 of the articles were for age estimation. A comparison based on the objectives of the approaches is presented to underline the taxonomy. Ending by research conclusion on face techniques contributes to the understanding of the recognition approaches, which can be used in future researches. The research concluded that face techniques' performance is distinct from one data set to another. This paper contributes to display gaps for other researchers to join this line of research.

INDEX TERMS Face recognition, age estimation, and aging.

I. INTRODUCTION

This One of the most active areas used in face technology are the facial features. This includes the nose, eyes, mouth, and wrinkles, along with advanced properties such as gender and emotion. Facial features are regarded as a rich source of information, and it consists of three levels of features. The first level is a high level which can be extracted from images with low resolutions. This features are the nature of the face, using identifiers such as gender, race, and general age [3]. The micro level features give more details. These include scars, facial marks, moles, freckles, and birth marks. These features require high spatial frequency images to extract them [4]. Facial features are used in a wide range of applications, such as face recognition and age estimation, which is considered as important process in face techniques' models. However, a person's facial appearance changes over time as they age. These lead to age-related inclusions, with wrinkles, which constitutes one of the most crucial challenges in face applications. Detecting facial expression is one of the challenges in the future of computer science applications, particularly in areas such as identification systems, verifying applications, and security. Face expression changes can be either minor changes like wrinkles or major changes like those affecting the eyes and nose [5]. This is where age estimation comes in, building an automatic model to determine the exact age or age range. There are some concepts, which need to be elucidated in order to differentiate between them. The actual age is a person's real age, which can be calculated by years from birth. The appearance age is estimated by facial appearance, and the age estimation means the recognition of age by the software based on the person's visual appearance [6]. Aging is a normal process through the life of a person. It is an uncontrollable process and it differs from person to person, depending on how time affects them individually [7]. Aging as a process, which has an effect on face recognition, can be used to find missing children through law enforcement and forensic investigation systems. A comprehensive and critical survey for different face techniques were carried out in this study as there are many pre-existing challenges in the field of face recognition. The survey in this paper provides more details on the rules, methods, architecture, advantages, and limitations of these techniques. Many related face technologies are applied to help the world in areas such as forensic, security, and cosmetology. Human forensics use the technology to reconstruct the facial tissues in order to identify a dead person [8]. Moreover, face recognition is one of the most important components for security, particularly when dealing with biometric identification and verification [9]. Face techniques involve many problems. One of these problems is the lack of the collection of labeled data used with real age estimation. This is more challenging compared to age classification or face detection problems [10], [11]. The challenging aspect lies in the high human error in estimating the real age of a person as it is higher than when estimated by computer software. It is also difficult to depend on human annotators to label faces in databases with their corresponding real ages. This study is organized into five sections. Section 1 introduces the topic of the study, which tackles changes in facial features. Section 2 discusses the methodology or research design of the study, the different databases' sources, which were used to obtain the findings of the study, as well as the eligibility criteria for the selection of the papers used. Section 3 provides the results of the study and surveys the methods of face recognition and age estimation. It also describes the performance comparison of the existing systems with different results obtained from various databases. Section 4 discusses the motivation, open issues, and the existing challenges. It also proposes a number of useful solutions. The last section concludes the study and provides promising future directions. In summary, this study reviews different face recognition and detection techniques. This study particularly reviews the problems of face recognition, and discusses its challenges in detail. Furthermore, it also discusses the methods, architecture, advantages, and limitations of face recognition techniques.

II. METHODOLOGY

The most important keywords in the scope of this paper are face recognition and age estimation. This excludes any system, which does not use the facial face in its processes. This study also limits its scope to the relevant English papers. However, the study considers all extract features and aging areas.

A. INFORMATION SOURCES

Five digital databases were chosen to conduct the search for review articles. They are: 1) Springer database, which provides access to computer science, biomedical, and mathematical journal articles, 2) Science Direct database, which provides access to computer science and mathematical articles, 3) IEEE Xplore library of technical literature in engineering and technology, 4) Web of Science (WoS) service, which provides indexing of cross-disciplinary research in computer science, mathematics, and social sciences, and 5) ACM Digital Library (DL), which provides access to computer science and different topics.

B. SELECT PAPER

The selection process was based on searching the five mentioned databases for relevant scholarly papers. The process involved two phases: iteration to extract papers and filtering. During the extraction process, irrelevant and duplicated papers were removed. The filtering phase took place after reading the entire text. (Past tense??)

C. ELIGIBILITY CRITERIA

Every scholarly article that met the criteria illustrated in Figure 1 below was selected. The criterion for selection and filtering was based on the period from 2010 to 2017. The selected articles must be in English, and the key terms are facial features, face recognition, and age estimation.

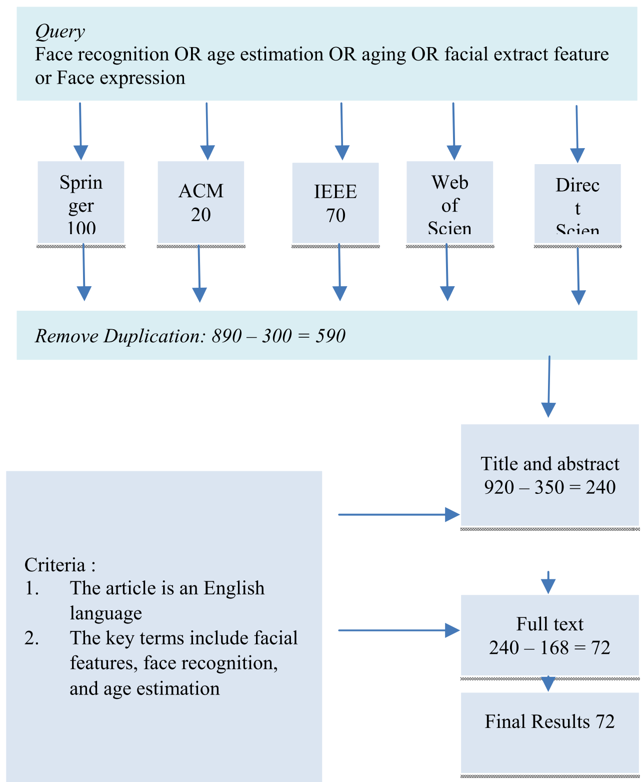

FIGURE 1. Flowchart of the study selection.

III. RESULTS

A. DATABASES

Through the evaluation process for different algorithms and methods in the selected review papers, as shown in Table 2,

TABLE 1. Different databases used for face recognition.

Name of Database	Number of Images	Approach	Accuracy Rate
ORL (Olivetti Research Laboratory)	400	Eigenvalues [12]	99.40
		Quantum Neural networks (QNN) [13]	97.8
		Vector Projection Length [14]	96.88
		Sparse Boosting Representation Based Classification [15]	89.50
		Genetic Algorithm (GA) [16]	95.895
		SVM [17]	98.4
Yale database B	5760	Eigenvalues [12]	97.50
		Vector Projection Length [14]	73.16
		Sparse Boosting Representation Based Classification [15]	79.785
FERET	14,126	Eigenvalues [12]	98.00
		Vector Projection Length [14]	67.35
		Kernel collaborative representation (KCR) [18]	88.3
		Sparse Boosting Representation Based Classification [15]	65.40
		SVM [17]	97.945
		Principal Local Binary Patterns [19]	94
		Partial Least Squares (PLS) [20]	88.825
AR	4000	L2-Norm Regularization[21]	95.3
		Kernel Collaborative Representation (KCR) [18]	99.3
		Sparse Representation Based Classifier (SRC) [22]	98.5
		Sparse Boosting Representation Based Classification [15]	87.3
		Linear Discriminant Approach [23]	69.88
		Principle Component Analysis (PCA) & Locality Preserving Projections (LPPs) - [24]	86.23
CMU PIE	41,368	l2-norm regularization[21]	94.4
Sheffield(previously UMIST))	564	L2-Norm Regularization[21]	89.3
CAS-PEAL- R1	30,900	l2-norm regularization[21]	76.0
Yale	165	Vector Projection Length [14]	96.67
		Linear discriminant approach [23]	100
UMIST	757	Vector Projection Length [14]	100
		Genetic Algorithm (GA) [16]	96.386
		Linear discriminant approach [23]	89

TABLE 1. *(Continued.)* Different databases used for face recognition.

Extended Yale B	2414	Kernel collaborative representation (KCR) [18]	99.8
		Nearest-farthest subspace (NFS) [25]	82.47
		Grayscale Arranging Pairs (GAP) [26]	99.85
		Principle component analysis (PCA) & Locality preserving projections (LPPs) - [24]	91.66
		Kernel Discriminant Transformation (KDT) [27]	97.9
CMU Multi-PIE		Sparse Representation based classifier (SRC) [22]	85.75
		Linear discriminant approach [23]	88.85
		Principle component analysis (PCA) & Locality preserving projections (LPPs) - [24]	86.46
LFW		Sparse Representation based classifier (SRC) [22]	76.75
		Sparse boosting representation based classification [15]	51.46
		Kernel Discriminant Transformation (KDT) [27]	65.3
		Deep neural network [28]	97.35
Libor Spacek's	7240	k-class [29]	97
IRIS Thermal/Visible Face	4228	Dictionary construction & sparse representation [30]	91.5%
Indase	150	Genetic Algorithm (GA) [16]	97.44
JAFFFE	230	SVM [17]	97.145
		Principle component analysis (PCA) & Locality preserving projections (LPPs) - [24]	86.42
Georgiatech(GT)	750	Nearest-farthest subspace (NFS) [25]	92.29
AT&T	400	Nearest-farthest subspace (NFS) [25]	97.125
Database of University of Essex	395	Artificial Neural Networks (ANN) [31]	95
XM2VTS	200	Principle component analysis (PCA) & Locality preserving projections (LPPs) - [24]	32.63
BANCA	52	Principle component analysis (PCA) & Locality preserving projections (LPPs) - [24]	41.98
FRGC	86, 634	Partial Least Squares (PLS) [20]	91.7
IIT(BHU)	2100	Deep Convolutional Neural Network(CNN) [32]	89.58

there are 23 databases that are used for the evaluation of face recognition methods. The various databases differed in various ways. CAS-PEAL- R1 is the largest dataset, which

TABLE 2. Summary of the scholarly papers from 2010 to 2017.

Citation	Dataset	No. of Images	Method	Result
[42]	4 million images was collected	4 million	Deep convolutional neural networks	96
[40]	Public Database LFW (Labeled Faces in theWild)	13,233	Convolutional Neural Network CNN	88.70
[20]	FERET and FRGC Datasets.	2345	Partial Least Squares (PLS)	92.75
[32]	IIT(BHU)	2100	Deep Convolutional Neural Network(CNN)	89.58
[39]	Passport I, Passport II	1,800 image pairs , With different years for each person pair.	Support vector machine	81.27
[34]	Passport databases and the FGnet dataset	12745	Support vector machine (SVM)	ERROR RATES= 15.1
[35]	Yale, Extended Yale Group B , Yale Group B.	6015	Support vector machines (SVMs)	99.80
[28]	Faces in the Wild (LFW) dataset	5 million	Deep neural network	Accuracy 97.35
[43]	FG-NET dataset	1002	Bayesian framework	0.41
[36]	Extended Yale-B, FRGC-204 , CAS-PEAL-R1 , FRGC-204	70095	Local Binary Patterns (LBP)	98.7
[37]	FERET, MPIE-2 ,AR ,Yale	9450	Histograms of Oriented Gradients (HOGs)	95.5
[38]	ORL, FRGC and FERET databases	5444	Kernel Discriminant Embedding (KDE)	Error rate :10.601
[27]	Self-compiled database , Yale Face Database B	615	kernel discriminant transformation (KDT)	81.6
[13]	ORL	400	quantum neural networks (QNN)	97.8
[24]	CMU , ORL AR , PIE , BANCA , Yale face database B , XM2VTS	106110	Principle component analysis (PCA) , Locality preserving projections (LPPs)	90
[19]	FERET	11338	Principal Local Binary Patterns	94%
[31]	Database of University of Essex	395	Artificial Neural Networks (ANN)	95
[26]	Extended Yale B	43800	Grayscale	99.85
	face		Arranging Pairs (GAP)	recognition accuracies

TABLE 2. *(Continued.)* Summary of the scholarly papers from 2010 to 2017.

[25]	Extended Yale B , AT&T , Georgia Tech and AR.	7564	Nearest-farthest subspace (NFS)	90.24
[25]	PIE, YALE , CAS-PEAL-R1 database	72433	Enhanced local directional patterns (ELDP)	78.69 Average recognition rate
[23]	PIE , UMIST, AR , Yale	46097 images	Two-Dimensional Neighborhood Margin and Variation Embedding (2DNMVE)	82.43
[17]	JAFFE, ORL , FERET	11968	SVM	96.9766
[16]	ORL, UMIST , Indbase.	180	Genetic Algorithm (GA)	96.507
[30]	IRIS Thermal/Visible Face Database	4228 pairs	Dictionary construction & sparse representation	91.5%
[41]	AR ORL,, Extended Yale B	6814	K-NN algorithm	92.7
[15]	AR, Extended Yale B, ORL, FERET and LFW	11587	Sparse boosting representation based classification	76.296
[29]	Libor Spacek's	7240	k-class approach	97%
[22]	Extended Yale B , CMU Multi-PIE , LFW, CAS-Peal , AR database , LFW	12678	Sparse representation based classifier (SRC)	76.75
[18]	Yale B, AR, face databases	6414	Kernel collaborative representation (KCR)	99.5
[14]	Yale , FERET , ORL , UMIST , Yale B and AR	24951	Vector projection length	89.48
[21]	AR, CMU PIE, CAS-PEAL-R1, and the Sheffield	76832	l2-norm regularization	93.2
[12]	ORL, FERET, Yale database B.	20286	Eigenvalues	98.3

includes 30,900 images. BANCA is the smallest dataset, which includes 52 images.

B. TAXONOMY BASED ON FACE RECOGNITION

The face recognition system can be divided into two categories: identification and verification [9]. Face identification compares the inputted face image with all the images in the database. Face verification, on the other hand, compares the inputted face image with a template face image, whose identity is being claimed [33]. As shown in Figure 2, the basic process of the face recognition model is a three-phase process: face detection, features extraction, and face recognition.

1) METHODS USED FOR FACE RECOGNITION FROM 2011 TO 2017

It is worth mentioning that the term "face detection" is widely used in many published works. However, the results

TABLE 3. Summary of the scholarly papers from 2011 to 2017.

Citation	Dataset	No. Images	Method	Result Of MAE
[42]	The dataset was collected from more than 40,000 people , over 4 million images was collected	4 million	Consists of several deep convolutional neural networks that	5.78
[52]	Private , Adience Age Database		SVM & CNN	An error of 0.294835
[80]	MORPH	55000	Kernel partial least squares (KPLS) regression for age estimation	Average Mean 4.18
[54]	MORPH database And FG-NET	MORPH :5475 images FG-NET :1002images	Convolutional neural network (CNN)	Error rates :4.515
[55]	Adience benchmark	19487	Deep-convolutional neural networks (DCNN)	86.35
[62]	IMDB-WIKI dataset	4699	Convolutional neural network use the google net architecture, add batch normalization Layer after each relu operation	Don't mention
[63]	Chalearn Looking at People 2016	7,591	The model based on Deep Convolutional network to face detector, and features ,also used Kernel extreme learning machines for classification	MAE 3.85
[56]	MORPH Google image search Bing image search Baidu image search FG-NET Adience Competition	123,154	Deep CNN (Convolutional Neural Network)	0.3057
[57]	Chalearn LAP	4691	Deep Convolutional Neural Networks (CNN).	Performance of 0.287

TABLE 3. (Continued.) Summary of the scholarly papers from 2011 to 2017.

[58]	IMDB and Wikipedia	524,230	Convolutional neural Networks (CNNS) use the VGG-16 architecture	Error 0.264975 MAE : 3.221
[59]	Iccv2015 looking at people challenge	4,699	Convolution Neural Network with google net	MAE: 3.3345
[64]	IMDB-WIKI dataset ICCV 2015 chalearn Looking at People workshop Dataset CVPR 2016 chalearn Looking at People workshop Dataset	249264	Deep Convolutional Neural Network(CNN)	E-error : 0.3214
[65]	IMDB-Wiki	523, 051 images	Deep Convolutional Neural Networks (DCNNS).	E-error:0.2411
[66]	Adience dataset FG-Net aging dataset Images of groups Chalearn Workshop Challenge dataset	60512	Deep Convolutional Neural Networks (DCNNs)	88.45 ± 2.2
[67]	FERET and the Adience	2,413	Compact Deep Convolutional Neural Network (DCNN) architecture	85.34% for age in 10 years intervals on the FERET database
[68]	Asian Face Age Dataset (AFAD)	55, 608 Face Images	Deep Convolutional Neural Network	MAE3.305
[69]	Adience	17393	Deep Convolutional Neural Networks	Accuracy: 90.5%.
[70]	MORPH	55, 132	CNN : Convolutional Neural Network	

TABLE 3. *(Continued.)* Summary of the scholarly papers from 2011 to 2017.

[71]	Own dataset , we generate a dataset that contains 8025 persons and each person owns 20 face images Images of Groups (IOG)	16050 0	Deep Convolutional Neural Networks (Deep convents)	92
[72]	IMDB-WIKI	7591	Convolutional Neural Networks (CNNS) that Are based on VGG-16	Error 0.3668
[73]	FG-NET MORPH Images of Groups (IOG)	61214	Region Convolutional Neural Network (CRCNN)	Standar d deviatio ns=3.93 5
[74]	Public PAL and MORPH	55,0 0 0	Wmlbp, Gabor filtering, and the SVR method.	MAES= 5 .822
[60]	FG-NET Aging and MORPH	56610	Support Vector Machine (SVM)	MAE of 5.20
[76]	Morph II Webface	11493 0	Convolutional Neural Network	MAE 5
[77]	Morph ii Webface	11493 0	Deep learning	Mae of 4.355
[78]	FG-NET , MORPH , Chalearn Challenge Dataset	60722	Deep Convolutional Neural Networks	MAE: 3.833
[75]	BERC database, the PAL aging database, and the FG-Net aging database	1420	Active Appearance Models (AAM)	7.016±6 .37
[43]	FG-net and morph	56610	Bayesian framework	.49
[48]	MORPH Album 2	55000	Sub Network Convolutional Neural Network (CNN	MAE= 3:63
[79]	MORPH II, PAL, iog, LFW ,FERET, Apparent age; Smile and Gender	93464	SVM SVR	MORP HII and PAL MAE =4.25 Chalear n2016 Error: 0 .2874
[51]	MORPH , Lifespan and FACES	56388	Wavelet Scattering Network (SCATNET)	3.49
[76]	FG-NET, MORPH,	10000 00	Deep Convolutional Neural Networks	MAE:2. 78
[49]	FG-NET	1002	HC-SVR algorithm	MAE ; 5.28+0. 05

TABLE 3. *(Continued.)* Summary of the scholarly papers from 2011 to 2017.

[50]	MORPH	55,00 0	CCA	MAE 3.98
[46]	FG-NET database	1001	Active Appearance Models (AAMS)	3.85
[2]	BERC, PAL and FG-Net aging databases.	1822	Active Appearance Models (AAMS)	4.6577
[44]	FG-NET, MORPH	2692	Bio-inspired features (BIF)	3.17
[47]	S, MORPH-II and MEDS-II,	22367	Bisection Search Tree (BST)	4.715
[45]	Images of Groups Dataset and the FG-NET dataset	1002	Ordinal Discriminative Feature Learning	4.82

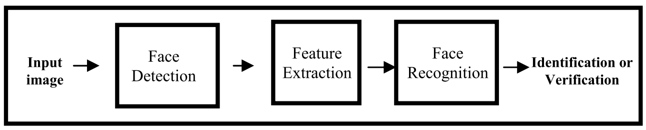

FIGURE 2. Flow of recognition.

and examples in these works show only the passport-like input image (i.e., face localization). An early attempt to detect the face from images were made through the implementation of many algorithms and methods, which were used and resulted in different performances and limitations.

Partial Least Squares (PLS) were used to build a face identification system, by using a set of low level features. The experiment was applied in two datasets: FERET and FRGC, with 2345 and the result was 92.75 [20]. Another model for face verification was based on gradient orientation pyramid, (GOP) combined with the support vector machine (SVM). The model was evaluated by three datasets: passport databases I, passport databases II and FGnet dataset. The error rates = 15.1 [34].

In addition, the integrated face recognition model aimed to enhance local features by using contrast, select adaptive features and variable dimensions of feature vectors by the supporting vector machines (SVM). The system was evaluated by three databases: Yale Group B, Extended Yale Group B and namely, Yale. Results revealed that the performance was 99.80 [35]. Another method, which can deal with uncontrolled lighting for face recognition, was based on pre-processing and improvement in the local texture descriptor (LBP). The method was evaluated by three databases: FRGC-204, Extended Yale-B and CAS-PEAL-R1, and the result of 98.7 % was obtained [36].

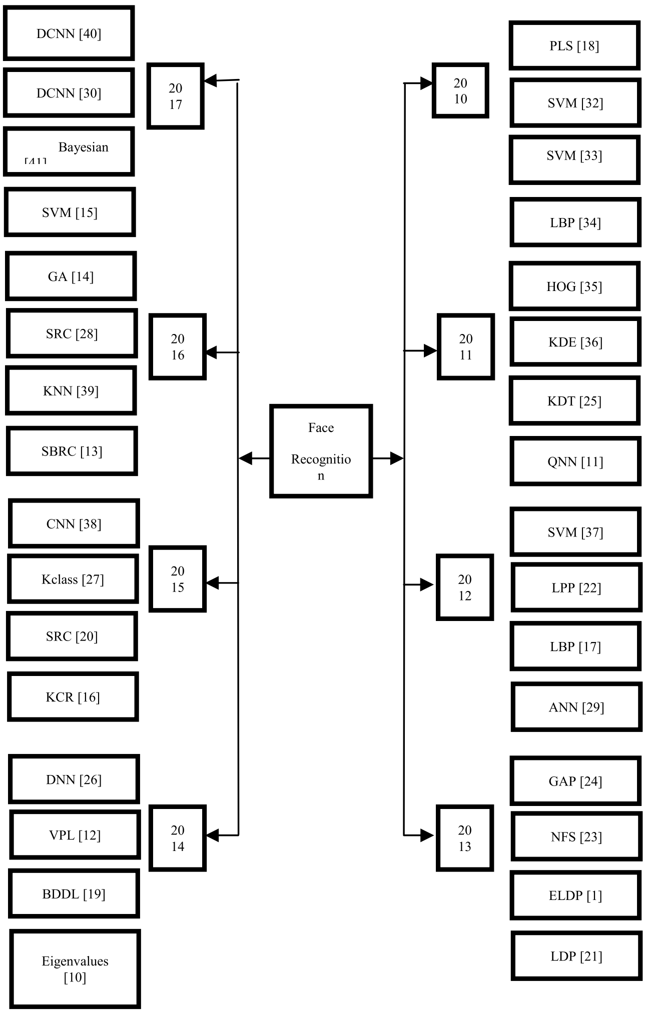

FIGURE 3. Methods used for face recognition from 2011 to 2017.

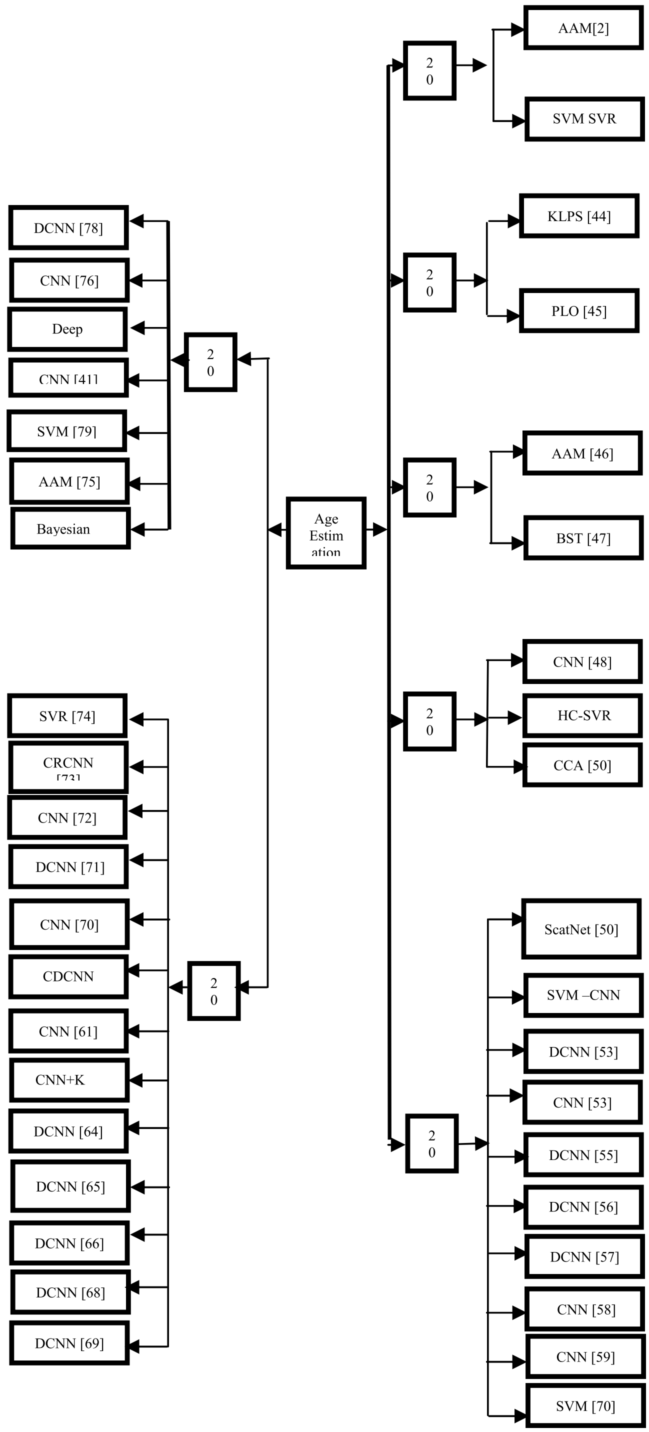

FIGURE 4. Methods used for age estimation from 2011 to 2017.

After that, Histograms of Oriented Gradients (HOGs) was used for face recognition. The model was evaluated by four datasets: FERET, MPIE-2, AR, and Yale [37]. Then, a feature extraction model was used for face recognition, based on Kernel Discriminant Embedding (KDE). The model was validated by three datasets: ORL, FRGC, and FERET databases, with an error rate of 10.601% [38]. Kernel Discriminant Transformation (KDT) was used in a model to recognize the face. The model was evaluated by database B, self-compiled database, and Yale Face with 615 images. The obtained result was 81.6% [27]. Another model was built for face recognition, based on the Quantum Neural Network (QNN). The model was evaluated by ORL database with 400 images. The results showed a recognition rate of 97.8% [13].

In 2012, an algorithm based on reducing dimensionality named the Elastic Preserving Projections (EPPs), was used. It merges between local geometrical structures and global information of the face space. It was validated by different databases such as ORL, AR, CMU PIE, Yale face database B, BANCA, XM2VTS. The results showed that the average recognition rate=26.44%, and the classification accuracy rate=2.133% [24]. Furthermore, Principal Local Binary Patterns were used to recognize the face. It was tested by the FERET database which includes 11338 images. The recognition rate was between 90% and 94% [19]. The hybrid system was used to recognize the face based on 2D-CWT, for face feature extraction and also used the 3 Artificial Neural Networks (ANN) as classifier. The system was evaluated by the University of Essex's database, which includes 395 images. The result was 95 % [31].

The Problems in verification systems include face recognition and age variation. Therefore, a model was built using a Support Vector Machine (SVM) as a classifier with a Gradient Orientation Pyramid. The model was applied in two passport datasets, which included 1800 image pairs for every person, but with different ages. The accuracy rate was 81.27%. However, the error rate was higher when the age gap was more than four to ten years [39].

In 2013, Grayscale Arranging Pairs (GAP) was used for the recognition of face feature. The built system was evaluated by PIE and Extended Yale B databases with 43800 images. The accuracy rate was 99.85% [26]. Another technique was used based on linear regression to solve the face recognition. The model was evaluated by four databases: Extended Yale B, AT&T, Georgia Tech, and AR. The average result for all the databases was 90.24% [25]. A model was built based on Enhanced Local Directional Patterns (ELDP). PIE had 41368 images and it was evaluated by three databases: YALE had 165 images, and CAS-PEAL-R1 had 30900 images with an average recognition rate of 78.69% [1]. Another model was founded based on Two-Dimensional Neighborhood Margin and Variation Embedding (2DNMVE) based on linear discriminant approach. It was evaluated by four databases: AR, Yale, PIE, and UMIST. This databases have 46097 images. The average recognition rate of results was 82.43 [23].

In 2014, a model for face verification, which utilized a nine-layer deep neural network, was tested. It resulted in 97.35% accuracy. It was trained in three databases: Labeled Faces in the Wild (LFW), YouTube Faces (YTF), and Social Face Classification (SFC) [28]. Another algorithm, named Local Vector Projection Classification (LVPC), was used for pattern recognition extraction. The model was evaluated using six face databases: ORL, Yale, UMIST, FERET, AR, and Yale B. The average recognition rate was 89.48. The algorithm deals with faces wearing sunglasses. The recognition rate was 70% and scarfs brought the recognition rate to 83.33% [14]. A model based on the dictionary learning method was also tested. This used Bilinear Discriminative Dictionary Learning (BDDL) to learn features and the Collaborative Representation Based Classification (CRC) had become a classifier. The model was evaluated by four databases: AR, CMU PIE, CAS-PEAL-R1, and the Sheffield. The recognition accuracy rate was 93.2% [21]. Moreover, a model, which was founded based on the polynomial coefficients, was used for face recognition. The model used covariance matrix and algorithm on common eigenvalues. It calculated a symmetric matrix by the polynomial coefficients-based companion matrices of two compared images. It was evaluated by 3 databases: Yale B, ORL and FERET. The average recognition rate for all databases was 98.3 % [12].

In 2015, the performance of the CNN model was improved to 0.8763 when adding Joint Bayesian with a fusion network. However, the layers of CNN depend on the size of data and, therefore, they have 2 models, one for small size and median size and another one for large size. The model was operated by GPU to reduce the time of training. The used dataset was the public database LFW (Labeled Faces in the Wild), with 13,233 images [40]. Another model for face recognition, named kCAFRe, was based on the k-class approach. The model was evaluated by Libor Spacek's with 7240 images. It gave a 97 % recognition rate [29]. Joint Representation and Pattern Learning (JRPL) algorithm was used to recognize faces. The model collected pattern dictionary and estimated if there were sunglasses, a hat or a scarf. The experiment was carried out by five databases: CMU Multi-PIE, AR, CAS-Peal, Extended Yale B, and LFW. For the result of recognizing the face without occlusion, the recognition rate was 97.3 %. As for recognizing the face that has blocked occlusions, when the level of the block was 40, the average recognition rate was 98.8%. When the level block was 50, the average recognition rate was 94.55%, and when the level block was 60, the average recognition rate was 87%. For face recognition with sunglasses, the average recognition rate was 96.25%, with scarves 91.1%, and with a hat 76% [22]. Kernel Collaborative Representation (KCR) with squared $\ell 2$-regularization was used for face recognition. The model was evaluated by two databases: Yale B and AR. The recognition rate was 99.55% [18].

In 2016, Genetic Algorithm (GA) was used to improve the recognition rate. The model was evaluated by three databases: ORL, UMIST and Indbase, with a recognition rate of 96.507% [16]. A multi-feature fusion technique was also used to enhance thermal face recognition. The model included four components: 1) extracting the features, 2) local classification, 3) feature weight vector computation, and 4) residual computation, dictionary construction, and sparse representation as a classifier for each single feature. The result derived was 91.5% [30]. Another method was proposed to extract features through high rank classes in the images by using dynamic low rank representations and choosing K-NN as a classifier. The model was evaluated by three databases: AR, Extended Yale B and ORL, with 6814 images. The average recognition rate was 92.7% [41]. Moreover, Sparse Boosting Representation Classification (SBRC) was another model used for face recognition. The model was evaluated by five databases AR, Extended Yale B, ORL, FERET, and LFW. The average recognition face rate was 76.296% for all databases [15].

In 2017, the existing commercial systems had problems when they dealt with real world scenarios. Many types of software have tried to solve these problems, for example, Convolutional Neural Networks (CNN), to estimate gender, age and emotion. The dataset was collected from more than 40,000 people and over 4 million images were collected. However, these images are labeled with gender labels and parts of emotions by human annotators. The mean absolute error became 5.76. And the age classification accuracy was 96.2 %, when the images were annotated and 61.3% when the data were not annotated [42]. The deep convolution neural networks' model for the recognition of new born faces is another model. It was applied in the IIT (BHU) dataset with 220 faces, and for every face; there were 10 images in different poses. CNN architecture with 2 convolutional layers and 1 hidden layer gave the best performance. However, there were a few limitations. No separate pre-processing has been done for the database. Although all the parameters have been changed and tested multiple times, there can be a case where a certain combination of parameters was not tested. Alongside this, and the model was tested separately for pose or illumination challenges [32]. Another algorithm called age-variational was used for face recognition based on Bayesian framework (FRAB) to improve the performance of face recognition by automatic age estimation. The experimental results on FG-NET with 0.41 performance were obtained [43]. Another technique was used to extract features was called 'contourlet transform' (CNT) and 'curvelet transform' (CLT). Support Vector Machine (SVM) was used as a classifier. The model was applied on three Databases: JAFFE, ORL and FERET, with 11968 images. The recognition rate of 96.9766% was obtained [17].

C. TAXONOMY BASED ON FACIAL AGE ESTIMATION TECHNIQUES

Age estimation means the ability to determine the exact age by year or determine the year range for every face individually [6]. However, it is hard to estimate an exact age due to a diversity on the aging process across different ages [44]. To estimate the exact age based on images is thus one of the most challenging problems. Furthermore, to estimate the age accurately, the model need a huge amount of labeled face data.

In 2011, many techniques were used for age estimation. Some of these techniques are mentioned here. A model was built based on bio-inspired features (BIF) to extract the aging features. It was used to analyze and estimate human ages, based on eye wrinkles and the entirety of the face. The internal face and eye wrinkles are detected using Active Shape Model (ASM). Through this model, the SVR and SVM methods were used to estimate the age on FG-NET and MORPH databases. The MAE for the whole face was 3.17 [44]. Another age estimation method used a hierarchical classifier method based on both global and local facial features with MAE 4.6577 [2].

In 2012, studies showed that learning about the ordinal discriminative aging features was a helpful technique for age estimation. The model was evaluated by two databases FG-NET and Images of Groups. It gave MAE 4.82 for the estimation of the exact age [45]. Linear PLS regression or Kernel Partial Least Squares (KPLS) were used for age estimation. The evaluation was applied in the MORPH database, with 55000 images, and the MAE was 4.18 [44].

In 2013, Active Appearance Models (AAMs) were used as age estimation classifiers. The model was evaluated by the FG-NET database, which had 1001 images. It gave MAE 3.85 [46]. Plus Bisection Search Tree (BST) algorithm was used for age estimation. It extracted the face features by using Gabor wavelet face representation, followed by PCA and LDA to reduce dimensionality. The algorithm was evaluated by two databases: MEDS-II and MORPH-II. The average MAE was 4.715 [47].

In 2014, convolutional Neural Network (CNN) was applied to reduce the error rate in age estimation. It can use the pixels of an image to estimate age. The input image was divided into smaller pieces. These pieces were fed to sub convolution neural network, then all the results were combined in fully connected layers with age, ethnicity and gender estimation. The experiment was carried out in the MORPH Album 2 dataset. It gave MAE = 3:63. However, the result was the same whether it is a single task network or multi task network [48]. Hybrid Constraint Support Vector Regression (HC-SVR) algorithm was used for age estimation, and combined with Support Vector Regression (SVR). It was evaluated by FG-NET database, which includes 1002 images. The MAE was 5.28+0.05 [49]. Canonical Correlation Analysis (CCA) was used for age estimation and it was extended to linear CCA. Regularized CCA gave MEA 4.42, but Kernel CCA gave MAE 4.06. The biologically-inspired features' model (BIFs) was used to feature extraction. The model was evaluated by the MORPH database, which includes 55,000 images [50].

In 2015, deep ranking techniques were used for Automatic Age Estimation (AAE). First, scattering network (ScatNet) with three layers (L1-3) was used to features extraction. Second, Principal Component Analysis (PCA) was used to decrease the dimensionality of the features. Finally, category-wise rankers were used for age prediction. The MAE was 3.5 for MORPH-II dataset [51]. Deep neural networks also helped in solving the unavailability of the labeled images. The model was proposed to apply age grouping and local age estimators by choosing GoogLeNet, which included a 22-layer deep neural network, to train the deep models. However, using Support Vector Machine (SVM) to make age groupings by extracting the features improved the performance. It achieved an error of 0.294835, but increased the load on the cpu [52].

In addition, Deep Convolutional Neural Networks (DCNN) were used to build a model to extract features, and train the model for face-identification and age estimation. However, DCNN, which was supported by Gaussian loss, performed better than the traditional one for estimation [53]. Another model was used Convolutional Neural Network (CNN) algorithm to estimate age. The model used different layers to get the map of the features. The evaluation was applied by two databases: MORPH and FG-NET, with error rates of 4.515 [54]. Enhancing an automatic classifier for age and gender was based on Deep Convolutional Neural Networks (DCNN), by adding 2 dropouts layers to limit the risk of overfitting. The model was applied by the Adience dataset, which is collected from Flickr, but with a fewer number of images. The results demonstrated a performance of 86.35%.

However, more training data may improve the results [55]. Deep Label Distribution Learning was used to estimate the apparent age. The result was 0.3057 [56].

Another proposed model utilizing the deep CNN model was first introduced to learn age-related representation. The regressor from deep representation to age discussed datasets was used to estimate age from unconstrained face images at the ChaLearn Looking At People (LAP) challenge 2015. The model obtained the performance of 0.287 [57]. A model, which is based on the Convolutional Neural Networks (CNNs), with the VGG-16 architecture to estimate age, was evaluated by using IMDB, Wikipedia dataset, and MAE 3.221 [58]. The two auxiliary loss layers in GoogLeNet were removed, which improved the model and added batch normalization. The model was tested on the ICCV2015 Looking at People Challenge dataset, which included 4,699 images. It achieved improvements in the result of MAE: 3.3345 [59]. Based on this model, a multi class Support Vector Machine (SVM) was founded to classify age groups and estimate the exact age by Support Vector Regression (SVR). The model was evaluated by FG-NET Aging and MORPH dataset with MAE of 5.20 [60].

In 2016, Recurrent Neural Network (RNN) was able to identify the ages of people from 0 to 80, especially when Long Short Term Memory (LSTM) networks were used. The framework gave the best performance of all the previous models. However, the method failed in learning the wrinkles in the training phase [61]. Also, Convolutional Neural Network used the GoogLeNet architecture to estimate the apparent age by adding batch normalization layer after each ReLU operation. The model was applied by the IMDB-WIKI dataset. The result showed robustness with color, ethnicity, occlusion, lighting and variations in pose, but the performance was not particularly good with facial blur [62]. In addition, Deep Convolutional Network was used as a face detector and features extraction and Kernel extreme learning machines were used for classification to Apparent Age Estimation. The model was evaluated by ChaLearn Looking at People 2016, which consists of 7,591 images with MAE 3.85 [63].

A model named DADL was based on the deep Convolutional Neural Network (CNN), supported by VGGFace model. The model used three databases, ICCV 2015 ChaLearn Looking at People workshop, CVPR 2016 ChaLearn Looking at People workshop, and IMDB-WIKI. The model gave an E-error of 0.3214 [64]. Another model called OrangeLabs used VGG-16 convolutional neural network to recognize the face, and IMDB-Wiki database for biological was used to train the system. The model gave an E-error of 0.2411 [65]. Deep Convolution Neural Network (DCNNs) was used to estimate age from unconstrained images with different expressions, poses and illumination. The performance was 88.45 $\pm$ 2.2 [66]. Then, a model compact Deep Convolutional Neural Network (DCNN) architecture for age estimation was used. The architecture involved three layers (two hidden and an output). The result was 85.34% for age in 10 years intervals on the FERET database [67]. A Multiple Deep Convolutional Neural Network output learning model was used for features' extraction, learn regression models, and to ordinal regression problem in age estimation changing. The model's evaluation was MAE 3.305 in the Asian Face Age Dataset (AFAD) [68]. Deep Convolutional Neural Network (CNN) was used to classify age and gender with AlexNet. It has become the VGG-Face CNN model to classify age and gender in uncontrolled environments. The MODEL accuracy was 90.5% [69]. Another model based on the Convolutional Neural Network (CNN) with GoogLeNet was built. It was evaluated by MORPH database [70] . A framework based on multiple Deep Convolutional Neural Networks (Deep ConvNets) was used for age classification and age prediction range. The framework collected the results of 20 images from the same person to solve the lack of labeled images to train the network. The result was 92% [71]. After that, three Convolutional Neural Networks (CNNs) with VGG-16 were used to build a model for age estimation. The model was evaluated by the IMDB-WIKI dataset and the error obtained on the test set was 0.3668 [72].

Region Convolutional Neural Network (CRCNN) was used to estimate age. The model was evaluated by three datasets: FG-NET, MORPH, and Images of Groups (IoG). The obtained results were the average standard deviations of 3.935. Based on the model, there are baseline samples to compare the input images with the group. However, the problem is that the effect of aging is different from person to person [73]. Age can also be estimated using Support Vector Regression (SVR) method based on a combination of weighted multi-level local binary patterned (wMLBP) features and Gabor wavelet features. The experimental results obtained using the public PAL and MORPH age databases with MAEs 5 were .822 [74].

In 2017, a new method was found, which relates to the residual image. The method was used for age simulation based on the aging function of the synergetic combination of global features, local features and the residual image. The residual image represents the personal characteristics of the input image in relation to the aged facial appearance, whereas local features represent the local aging characteristics that have not yet appeared at the current age. However, they typically appear as aging proceeds. Aging function patterns were used for training data. Therefore, it was hard to model person-specific aging processes by using them [75]. The existing commercial systems, however, are still problematic in dealing with real world scenarios. Many novel kinds of software have tried to solve this issue by using Convolutional Neural Networks (CNN) to estimate emotions, gender and age. The dataset was collected from more than 40,000 people and over 4 million images were collected. However, these images were labeled with gender label and part of emotion by human annotators. The mean absolute error was 5.76. Age classification accuracy was 96.2 % when the images were annotated, and 61.3% when the data were not annotated [42].

In addition, a model to estimate age was based on the convolutional neural network with deep cumulatively and comparatively (D2C) with cumulative hidden layer. The model was evaluated by Morph II and WebFace with MAE 5 [76]. Another model is the age estimation model, which is based on the AlexNet architecture. It is one of the most famous modern deep learning architectures and it obtained an average MAE of 4.355 on the Morph II and WebFace datasets [77]. A group-aware deep feature learning (GA-DFL) model was used. It is for facial age estimation under deep convolutional neural networks. Based on this model, a design for a multi-path CNN approach was used to enhance the discriminative capacity of face representation. The result was MAE: 3.833 [78].

An automatic age simulation method was based on a synergetic combination of the residual image, local features, global features, and Active Appearance Models (AAM) global features. The result was MAE 7.016±6.37 [75].A combination of automatic age estimation and age-variational face recognition algorithm were based on Bayesian framework (FRAB) were used to improve the performance of face recognition. The experimental results were conducted by FG-NET and Morph datasets to evaluate the performance of 0.49 [43].

PML (BSIF + LPQ) + SVM / SVR) is another model. It is composed of three parts: Viola–Jones algorithm for face alignment, Pyramid Multi-Level (PML) representation to extract the feature, which has components of Local Phase Quantization (LPQ) for texture classifications, and Binarized Statistical Image Features for the binary code for each pixel. The selection features a linear discriminant approach, and demographic attributes estimation, which uses Support Vector Machine (SVM) and Support Vector Regression (SVR). One of the model's objectives is to estimate age. The experiment was carried out by three databases for age estimation and gave MAE 4.23, with MORPHII and PAL datasets. With ChaLearn 2016, it gave an error of 0.2874 [79]. One of the age estimation problems is the aforementioned lack of a dataset with age labels. Therefore, deep Convolutional Neural Networks (CNNs) was used to extract information from different age images. The system was evaluated by FG-NET and MORPH databases, and the MAE was 2.78 [76].

D. DEEP CONVOLUTION NEURAL NETWORKS (CNN) MODELS

Overfitting happens when the machine is trained by small dataset. Deep Convolution Neural Networks (CNN) was thus used to solve overfitting problems in age estimation. CNN consists of three convolution layers and two fully connected layers with a small number of neurons. The model affects the CPU and the computer resources according to the 2 fully connected layers, and the pre-process of regenerating the image from the real images by taking parts of the image from the fourth corner and from the center. This will also affect the CPU performance. The model improved the accuracy to 84.6 [55].

A hybrid system was built for age and gender classification using unconstrained images. The Convolution Neural Network (CNN) was used to extract the features from the input images, while ELM classified the intermediate results. The system was evaluated by two databases: MORPHII and Adience Benchmark. It gave an accuracy of 52.3% for age classification and 88.2% for gender classification. However, the system misclassified some faces, particularly when dealing with younger faces. Additionally, higher requirements were needed in order to operate the system [81].

E. FACE RECOGNITION WITH DISGUISE

Vector projection classification (VPC) was used for face recognition. The system was evaluated by the AR database. Sunglasses and scarfs are commonly used to obstruct facial features. The model gave 62.67% accuracy in sunglasses' images. However, the accuracy increased to 70.00 % when the images were divided into four pieces. In the scarfs' images, accuracy was 6.67 % and it increased to 83.33 % with four partitions [14]. The accuracy in the KSR (LBP+HK) and KCR-$\ell2$ (LBP+HK) methods was 100% in images of sunglasses or scarfs. Therefore, accuracy was improved, but the model was evaluated in twelve images from AR databases [18]. In the SBRC model, the accuracy of sunglasses' images was 96.00 %. AR databases were used to evaluate the model. Six images were used for training and two images just for testing. The scarf image resulted in an 84.00%, but it was tested in two images [15].

IV. DISCUSSION

A. MOTIVATION

Research on facial age simulation has become important, because it is used in many real-world applications, including public and commercial systems. Facial age simulation is utilized as a core technology in many public systems. For example, it is used in forensic montages of long-term unsolved cases, searching for missing children or separated families, and also face aging recognition. Automatic face recognition systems are currently deployed in many important applications around the globe. Face recognition plays a key role in identifying card re-duplications, to prevent a person from obtaining multiple ID cards, such as driving licenses and passports, under different names. Nowadays, commercial applications of automatic face recognition are abundant. These include "tag" suggestions on Facebook, the organization of personal photos collections, and the mobile phones unlock function. Thus, to briefly summarize the contributions of this paper, its objectives are as follows:

1. To review different approaches used to recognize faces and to estimate ages.
2. To map critical and coherent taxonomy of the methods and databases so that researchers can identify relevant techniques with respect to face techniques.
3. To identify research challenges and forward recommendations for future research in the field of face detection and age estimation techniques.

B. OPEN ISSUES AND CHALLENGES WITH POSSIBLE SOLUTIONS

Face techniques have many problems and face many challenges, especially in a real situational context.

1) AVAILABILITY OF IMAGES

In order to increase the accuracy of face recognition or to increase the accuracy of age estimation and face aging, for example more posed images are required for the same face in databases,. However, it is difficult to collect multiple images of the same person or to take images of the same person at different ages. Therefore, high performance methods are required; methods that are more sophisticated to adapt to such challenges.

In fact, the insufficient collection of the labeled data, which are used with real age estimation, is more challenging compared to age classification data collection [10] or the detection of face problems [11]. This difficulty arises due to the high rate in human errors in relation to the real age estimation. The human error is greater than an estimation performed by computer software. It is also difficult to depend on human annotators to label faces in the databases with their identical real age. Although there are many techniques, which have proven their efficiency and accuracy, they still have some limitations and problems.

To solve this shortage, different algorithms can be applied in the same image, such as crop, scale, and rotation. Accordingly, different poses for the same person can be obtained. Moreover, the image illumination can be changed, which makes a difference in the images. This trick leads to an increase of the number of images. Hence, it can be one method of solving the aforementioned problem. It is not possible to rely on human annotators as there is a high rate of human error in the labeling process and, therefore, there is a need to review the image label.

2) TIME

Multiple Convolution Neural Network (CNN) network architecture is a technique for face recognition. In spite of its high performance, it takes time for processing, it is slow in speed and it is need a large amount of a dataset. The multiple CNNs need a minimum of 88 forward passes for each image in their pipeline, which makes it impossible to use the system in a real-time or even close-to real-time, application. All the runner up approaches suffer from the same limitations [65]. To decrease time, Graphics Processing Units (GPUs) can be used. GPU are very efficient in manipulating images, where the processing of large blocks of data is done in parallel. The GPU can operate the training more quickly

3) AGING PROCESS

There are multiple reasons why automatic age estimation is a very challenging task. The most principle amongst them is the uncontrolled nature of the aging process, which leads to a significant variance among faces in the same age range, and a high dependency of aging traits on a person [65]. However, progress in unconstrained facial age estimation is much slower due to the difficulty of collecting and labeling large datasets, which is essential for training deep networks [65]. The vast majority of the existing age estimation studies deal with the problem of estimation of a person's biological age (i.e., the objective age is defined as the elapsed time since a person's birth date) [65].

Based on the related literature, there is a lack of quantitative measurements for the evaluation of the aging result. Furthermore, it is very difficult to collect face images of the same person over an extended period of time. The age-related variations are often mixed among all factors; variations are often mixed with other variations (i.e., illumination, expression, etc.) [82]. Therefore, aging is the main cause of the facial appearance changes [51]. Generative Adversarial Networks (GANs) are used to generate more realistic images. These images cannot be differentiated from the real images. Moreover, GANs can make different changes in the human face, like hair color and aging. Through using GANs, faces may look older or younger without particular age categories (Larsen, 2015) (Perarnau, 2016). Consequently, many researchers have started to deploy GANs to take care of the details of the personality of aging.

4) AGE

Nowadays, there are lots of commercial applications for face age estimations. However they only operate effectively for photos of adults or older children (the minimum age is 18), whereas the new iPhone gets to the minimum age of 15 [6]. In addition, a considerable number of papers indicated that the identification accuracy rate is strongly dependent on subject age. Many researchers have applied different methods to deal with children. In particular, the deep Convolutional Neural Network (CNN) method was used to detect new-born babies with the IIT (BHU) new-born database. The result of the accuracy rate was 91.03% [83]. There is another technique, which was used, It was known as the Local Binary Pattern (LBP), It was used for feature extraction and semi-supervised learning with the obtained accuracy rate result of 92% [14].

V. CONCLUSION

Based on this study, a complete survey of the state-of-the art techniques for age estimation and face recognition have been reviewed and discussed via face images. Face images have become important in recent decades, primarily due to their promising real-world applications in several emerging fields. In this paper, variant solutions to technical difficulties have been proposed by the researchers, with different databases which used for evaluation the methods. There are 23 databases that were used for the evaluation of face recognition methods. Also, a summary of the published scholarly papers in this field of study was done, including the used methods, their performance and limitations. The results of this study indicated that the SVM (99.80%) and the LBP (98.7%) had the highest detection accuracy rates, along with GAP (99.85 %). In general, different age estimation and face recognition techniques and algorithms can be effectively applied to particular scenarios or applications. In addition, new issues were found regarding the techniques of age estimation and face recognition. Therefore, the study has provided new trends and prospects for future researchers. With regard to the effect of aging, it is difficult to predict the aging effect. It varies significantly between individuals and the robustness of the systems needs to account for new-born babies' faces.

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