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Comprehensive Analysis of the Literature for Age Estimation From Facial Images

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ABSTRACT Recently, vast attention has grown in the field of computer vision, especially in face recognition, detection, and facial landmarks localization. Many significant features can be directly derived from the human face, such as age, gender, and race. Estimating the age can be defined as the automatic process of classifying the facial image into the exact age or to a specific age range. Practically, age estimation from the face is still a challenging problem due to the effects from many internal factors, such as gender and race, and external factors, such as environments and lifestyle. Huge efforts have been addressed to reach an accepted and satisfied accuracy of age estimation task. In this paper, we try to analyze the main aspects that can increase the performance of the age estimation system, present the handcrafted-based models and deep learning-based models, and show how the evaluations are being conducted, discuss the proposed algorithms and models in the age estimation, and show the main limitations and challenges facing the age estimation process. Also, different aging databases that contain age annotations are discussed. Finally, few guidelines and the future prospect related to the age estimation are investigated.

INDEX TERMS Age estimation, deep learning, handcrafted, CNN, age estimation algorithms.

I. INTRODUCTION

Human age is considered as a significant personal feature that directly can be derived from the emerging of different patterns of the facial appearance [1]. The problem of estimating the facial age has the same challenges as other facial image recognition tasks. While they need firstly to detect the face then to locate the main facial features related to the task, later the feature vector should be formulated and finally the image will be classified [2]. Age Estimation (AE) via facial image is defined as the process of " Label a face image automatically with the exact age (year) or the age group (year range) of the individual face'' [1], [3].

AE is also classified as one of the secondary soft biometrics [4] which offers an extra information about users' identity. This kind of data could be used to improve the performance and to supplement the main biometric features, such as face, fingerprint, and iris.

Practically, age determination could be found and used in many real applications. One of these applications is called age-based access control. For example, different restrictions related to the age are needed to be applied on a physical access or virtual entrée to a website or mobile application. Another important application for AE which can be useful in age specific human computer interaction. Where different requirements are needed from persons who belong to different age groups. Automatic AE is very beneficial for determining individual user needs based on his/her facial age group i.e., AE can help in tuning specific interface's settings that are age-related [2].

Generally, age estimation models can be based on handcrafted algorithms or deep learning technology. The main difference between these two models, is the process of features extraction and selection which is accomplished manually for handcrafted models. While in case of deep learning this process is performed automatically without human interference.

On the other side, age estimation models can be categorized based on the algorithm that is used as a final stage to estimate the age. Thus, if we consider the AE problem as multi-classification task [5], [6], the ages are treated as separated class labels and the real age is inferred by learning the classifiers such as Support Vector Machine (SVM) on the

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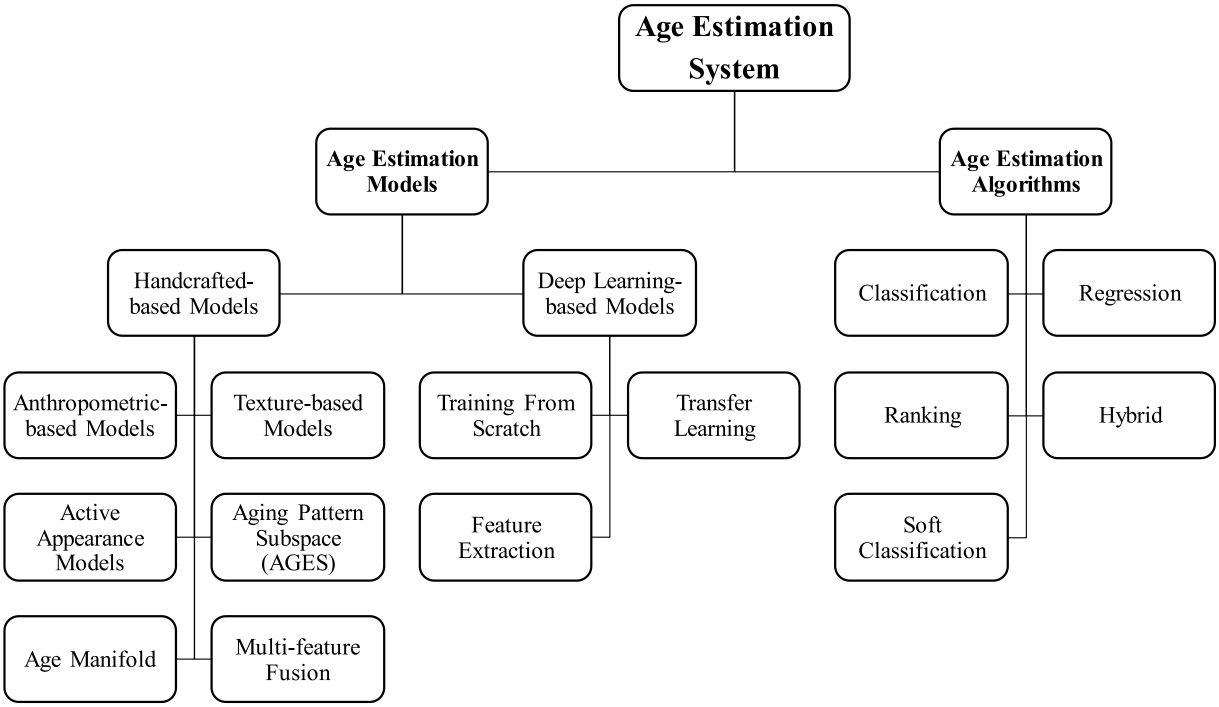

FIGURE 1. An overview of age estimation system.

labeled data [7]. Instead of dealing with AE as a multiclass problem, the labels could be considered as numerical values, this approach is called a regression [8], [9].

More robust system can be designed by combining the classification with regression methods, this approach is known as the hybrid [10], [11]. Recently, the interest on the ranking-based [12] models has significantly increased for AE, since the process of human aging demonstrates a diversity among different ranges of age [13]. As well, an intermediate case between regression and classification is called soft classification [14] which based on the gaussian distribution centered at the target age, was used to estimate the age from facial image.

Two kinds of datasets could be used in AE system: the constrained and unconstrained datasets. The constrained datasets can be described as the perfect image that captured under perfect conditions. While the unconstrained datasets can be defined as their images are captured in uncontrolled conditions, and contains a diversity of occlusion, facial expression, and head's poses, etc. Recently, a rising awareness exists in face recognition from unconstrained images and videos that comprise problems such as the detection of face, localization of facial landmarks, and AE [15]. So, testing the system on unconstrained datasets, will make AE more robust to real application.

An overview of AE system is shown in Fig. 1.

This review aims to:

1- Outline all the issues related to AE system.
2- Compare between the traditional methods with the most recent technologies which used deep learning.
3- Analyze the recent powerful techniques in the field of AE.
4- Investigate the main factors which affect the accuracy of AE system.
5- Show how each model overcomes the main challenges of AE to improve the performance.
6- Conduct an evaluation between the different models to summarize the overall work.

The remainder sections are organized as follows: Section II gives a brief description of facial aging patterns. Section III illustrates generally the main stages of age estimation process. Section IV shows the main challenges on age estimation process. In section V, several real applications are described where age estimation can be used. Section VI displays the available aging databases. Section VII shows the common evaluation metrics. The handcrafted-based models are explained in section VIII. Section IX explains the deep learning-based models. Section X shows the common algorithms that were used to estimate the age. Section XI presents the conclusion.

II. CHARACTERISTICS OF FACIAL AGING PATTERNS

Even though the aging process shows different patterns among different people and ages, general variations and similarities can be always described [16], [17]. From the biological side, the human life could be roughly divided into two stages that show a different growth and change in face and aging forms [18]. In the early stage of human life from birth to adulthood, the main change is in the face shape and geometry (craniofacial growth). It has been shown by craniofacial studies that there is a modification from circular to oval in the shape of human faces as one ages [19]. Because of these shape changes, the fiducial landmarks positions will be different [20]. During the second stage from adulthood to old age, (texture change) is the most noticeable modification in skin aging, while there are still slight changes in shape. Biologically, while human becomes older, the skin becomes thinner, darker, less elastic, and tougher due to the deficiency of collagen and gravity effects [1]. Progressively, the wrinkles and spots will start to appear on the skin. Those differences in shape and texture during aging process should be extracted to be suitable for using in age estimation system [21].

III. AGE ESTIMATION PROCESS

Generally AE system includes two major stages: image representation and age estimation [22]. In the image representation step, many descriptors such as Active Appearance Model (AAM) [23], Biologically Inspired Features(BIF) [24], Local Binary Patterns (LBP) [25] and Convolutional Neural Network (CNN) [26] have been used to extract and represent the features vector from facial images. In case of handcrafted methods, many steps should be accomplished before getting the appropriate feature vector. To characterize great details of the face, the images should be processed as a first step. Then a good descriptor is chosen to extract local and global features that are related to aging. As a last step of this stage, a reduction algorithm is used such as Principle Components Analysis (PCA) to reduce the feature vector for faster AE process. On the other hand, to extract the features from facial images while using deep learning, the system will automatically make the process and select the appropriate features related to age. In the second stage, the available datasets are used for training the classifier or regressor to estimate the final age value [27].

IV. CHALLENGES IN AGE ESTIMATION PROCESS

AE based on facial images is still a challenging problem and further from real acceptance and practical satisfactory [28]. So far, an extensive attention has been paid by researchers on AE and many approaches have been proposed to solve this problem. Mainly, many aspects which make AE as a challenging problem:

1. Many factors have a direct influences on the aging process, consisting of internal factors such as identity, gender, race, and health status etc., also external factors such as non-frontal face, wearing glasses, makeup, moustache, lifestyle, environment, body pose, and facial expression [22], 29].
2. Controlling the aging process is difficult [30]
3. Lack on training data especially the images at the older ages [31].
4. Dealing with multi-class characteristic as each age could be represented as one class.
5. The process of collecting and labeling datasets that contain appropriate and enough samples for all possible ages is difficult and hard to obtain 31], [32].
6. Most benchmark datasets have imbalanced age distributions [32].
7. Some wild conditions that usually affect the AE process such as lighting, occlusion and disorderly background of face images [33].
8. Any changes in the current time at any spot or area in the skin affects the facial appearance in the future [21].

V. REAL APPLICATIONS FOR AGE ESTIMATION

AE could be used in many real time applications. It is considered as a facial feature that supports many other main features used for identity verification or authentication. The following applications are examples of the different areas where AE may be used as a useful system.

A. AGE SIMULATION

Age simulation needs to know the facial appearance for the same person at different ages. It uses this information to model the face at a specific time. So, the AE helps this system to learn the different patterns of aging for a person. More information found in [34].

B. ELECTRONIC CUSTOMER RELATIONSHIP MANAGEMENT (ECRM)

In online commercial systems, the contact with the customers is virtual. So, to manage the relationships and know the expectations for each customer, AE may be used to know the age of customer. In such system, the services will be modified and personalized related to the customer's age [1].

C. ACCESS CONTROL AND SURVEILLANCE

Access control and surveillance tracking problems are increasingly more essential in our normal lifestyles, once the data is becoming easy to access. AE system may help in controlling the access to some products such as preventing child from purchasing cigars or refusing from entering to some bars [35]. As well as, AE can be used to control the virtual access to some unwanted websites or films which are not suitable for underage. A futuristic used in health care system, AE can be posed in the nurse robotic or the intelligent care unit. These intelligent systems can offer many services which are adapted with the patient's age [1].

D. AGE SPECIFIC HUMAN COMPUTER INTERACTION (ASHCI)

Different requirements are needed from persons with different age groups. Automatic AE is very beneficial for determining individual user needs based on his/her facial age group i.e., AE can help in tuning some specific age-related interface settings [2].

TABLE 1. Summary of DLBMs on different databases.

Database Name	#images	#subject	Age range	Age type	In the wild (unconstrained)	year
FERET [38]	14,126	1,199	N/A	Real Age	Partially	1998
FG-net [36]	1,002	82	0 – 69	Real Age	No	2002
PAL [39]	575	575	18 – 93	4 Age groups	No	2004
Iranian Face Database IFDB [40]	3600	616	2–85	Real Age	No	2007
YGA [41][9]	8,000	1,600	0 – 93	Real Age	No	2008
MORPH-II [37]	55,134	13,618	16 – 77	Real Age	No	2009
Images of Group IoG [42]	5080	28,231	0 – 66+	7 Age group	Yes	2009
WebFace [43]	77,021	219,892	1 – 80	Real Age	Yes	2011
HOIP [44]	306,600	300	15 – 64	10 Age groups	No	2014
Adience [45][46]	26,580	2,284	0 – 60+	8 Age groups	Yes	2014
CACD [47]	163,446	2,000	16 – 62	Real age	Yes	2014
MSU LFW+ [48] [49]	15,699	8,000	N/A	Real Age	Yes	2014
IMDB-WIKI [51]	523,051	20,284	0 – 100	Real age	Yes	2015
AFAD [52]	164,432	N/A	15 – 40	Real age	No	2016
MegaAge	41,941	N/A	0 – 70	Real age	Yes	2017
SoF [54]	42,592	112	N/A	Real age	Yes	2017
AgeDB [55]	16,488	568	1 – 101	Real age	Yes	2017

E. BIOMETRICS

AE is classified as one of the secondary soft biometrics [4] which offers an extra information about users' identity. This kind of data could be used to improve the performance and to supplement the main biometric features, such as face, fingerprint, and iris.

F. MISSING PERSONS

In identification system, AE with age simulation can help in identifying a person that is missing for a time. By estimating the age of the person using his current pictures and comparing them with previous ones [21].

VI. AGING DATABASES

In this section, a large survey is presented of the most common and available datasets that have age annotations. Accurate age estimation requires large, balanced and labeled database. In practice, collecting such aging databases is extremely hard, moreover, it is more difficult to collect a series of images for one individual at different ages. Table 1 summarizes the existing benchmark of aging datasets for different age ranges since 1998. The arrangement of the datasets is based on year. A number of these datasets have annotations with real age while the other have age group labels. The most common datasets that were used to conduct the evaluation between different AE models are FG-NET [36] and MORPH-II [37].

FERET [38] database consists of 14,126 images belong to 1199 subjects. A duplicate set of 365 images contains of other images of some individuals that exist in the database, but those images are taken on different time. For other set of persons, a number of images are taken after two years. This diversity on the dataset can enable the researcher to learn features of aging appearance across these groups of people. It is widely used for face recognition purpose.

FG-NET [36] database contains a total of 1002 images belong to 82 subjects and was developed to study real age. These images are both in color and grayscale resolution. The range of the ages are from 0 to 69 years. For each individual there are 12 images in average. The database provides also annotation for different human races. There exists a diversity of head poses and some facial expression as well as some illumination on the images. Moreover, the database provides 68 landmark points that are useful for facial shape modeling. The dataset is available online.[1]

PAL [39] database contains a total of 575 images and has 4 age groups for adults and older that represent the age across the lifespan. The ages range from 18-70+. The first group of ages contains 218 images and ranging from 18-29, the second group contains 76 images and ranging from 30-49, the third group contains 123 images and ranging from 50-69, and the fourth group contains 158 images and ranging from 70 and older. The dataset is available online.[2]

Iranian Face Database IFDB [40] contains a total of 3600 color images belong to 616 subjects. This dataset can be used to study different tasks related to face such as age classification and race detection. The images are divided as 787 for males and 129 for female. The age labels ranging from 2 to 85. The images include variations of head pose, expression, without glasses. The resolution of the images is 640 X 480 and with color depth of 24 bits. The dataset is available online.[3]

YGA [41], [9] database has 1600 subjects from Asia with a total of 8,000 outdoor images. The images are high-resolution and colored. 800 of the images are belong to females and 800 belong to males. The ages are ranging from 0 (newborn) to 93 years. On average each subject has 5 images with a label of the approximate age. There is a huge diversity of

[1] http://www-prima.inrialpes.fr/FGnet/html/benchmarks.html
[2] http://agingmind.utdallas.edu/download-stimuli/face-database/
[3] http://www.iranprc.org/en/ifdb.php

illumination and facial expression. A face detector was used to crop the faces. The images then resized to 60x60 patches on gray-level.

MORPH [37] is a public face database. It has two albums. Album1 contains 1724 images belong to 515 individuals. Album 2 (MORPH-II) database contains 55,134 images belong to 13,618 subjects collected over 4 years. The ages ranging from 16 to 77. This dataset is particularly used for evaluating different deep learning methods on the age estimation task. This dataset contains labels for race, gender, birth date, and acquisition date. Another important data that can be requested is eye coordinates. There is a larger set that is commercially available collected over a longer time span. This version has some extra information of the individual such as the height and weight. The dataset is available online.[4]

Images of Group IoG [42] is a special database where each image contains more than one face and each face is labeled with one of the seven age groups and gender. This database was collected from Flickr.com image search engine and developed to study the relation between people's social behavior with computer vision especially in group's photos. The total number of images is 5080 which contains 28,231 faces. There are seven age groups, these groups are ranging from 0–2, 3–7, 8–12, 13–19, 20–36, 37–65, and 66+.This dataset is suitable for age-group estimation. In older age the age group becomes wider. The dataset is available online.[5]

WebFace [43] contains 77,021 images belong to 219,892 faces. The ages are ranging from 1 to 80 years. The dataset was collected from Flickr and Google Image. After detecting and aligning the face, the images were cropped and normalized to 240×240 image size.

Human and Object Interaction Processing (HOIP) [44] database contains 300 individuals with total number of images about 306,600. The range of the ages is between 15 and 64 years. The ages are divided into 10 age groups. The subjects are distributed equally between the age groups. So that, there are 30 subjects in each group, 15 images for females and 15 images for males.

Adience [45], [46] database was developed to make a classification based on the age group and gender and collected from Fliker.com albums. It contains 26,580 images belong to 2,284 subjects. The set is divided into 8 age groups from 0 to 60 years and older. This database embodies big challenges, while the images have low resolution with extreme blurring, occlusions, different head poses and expressions. The dataset is available online.[6]

CACD [47] is a large-scale database which was developed for face recognition and age retrieval tasks and collected from Internet. This database has 163,446 images belong to 2,000 celebrities. The range of the age are ranging from 16 to 62. The dataset is available online.[7]

MSU LFW+ [48], [49] is an extended database of LFW [50] and was developed to learn the and estimate different facial attributes such as age, gender, and race from unconstrained images. The dataset contains 15,699 images belongs to 8000 individuals. The dataset is available online[8].

IMDB-WIKI [51] is considered as the largest dataset that is publicly available and was developed to tackle the age estimation task. This dataset has facial images labeled with gender and age annotations. It contains 523,051 images of 20,284 subjects. The ages are ranging from 0 to 100 years. The dataset was collected from IMDB and Wikipedia websites. The set does not have any image without metadata about the date when it was taken. The dataset is available online.[9]

AFAD [52] is a new dataset which contains about 160K facial images. The dataset was developed to evaluate the age estimation performance and collected from selfies taken by Asian students on a social network. The images contain only Asian faces. The ages cover a range from 15 to 40 years. 63,680 photos belong to female and 100,752 belong to male faces. The dataset is available online.[10]

MegaAge [53] is a large in the wild dataset which contains 41,941 images. Each image is labeled with a posterior age distribution. The dataset was developed to make a posterior distribution learning. An effective and novel way was developed using a deep learning method to make the annotations on a large quantity of images. The dataset is available online.[11]

SoF [54] database contains a set of 42,592 images belong to 112 individuals distributed into 66 males and 46 females. The images have different illumination situations and can be used in face recognition and detection tasks. For academic research, the dataset can be freely use. Each image is associated with many metadata such as facial landmarks, gender and labels for age and more. The dataset is available online.[12]

AgeDB [55] database contains 16,488 images belong to 568 subjects. Each image is labeled with identity, age and gender annotations. Each subject has on average 29 images. The ages are ranging from 1 to 101. This dataset can be used for age estimation and age progression.

Table 1 summarizes the different datasets which have age annotations. For each dataset, we determine whether the images are captured under controlled conditions (constrained) or uncontrolled conditions (unconstrained).

Figure 2 shows some samples from four popular datasets that are used in AE.

[4] http://www.faceaginggroup.com/morph/
[5] http://chenlab.ece.cornell.edu/people/Andy/ImagesOfGroups.html
[6] https://talhassner.github.io/home/projects/Adience/Adience-data.html#agegender
[7] http://bcsiriuschen.github.io/CARC/
[8] http://biometrics.cse.msu.edu/Publications/Databases/MSU_LFW+/
[9] https://data.vision.ee.ethz.ch/cvl/rrothe/imdb-wiki/
[10] http://afad-dataset.github.io/
[11] http://mmlab.ie.cuhk.edu.hk/projects/MegaAge/
[12] https://sites.google.com/view/sof-dataset

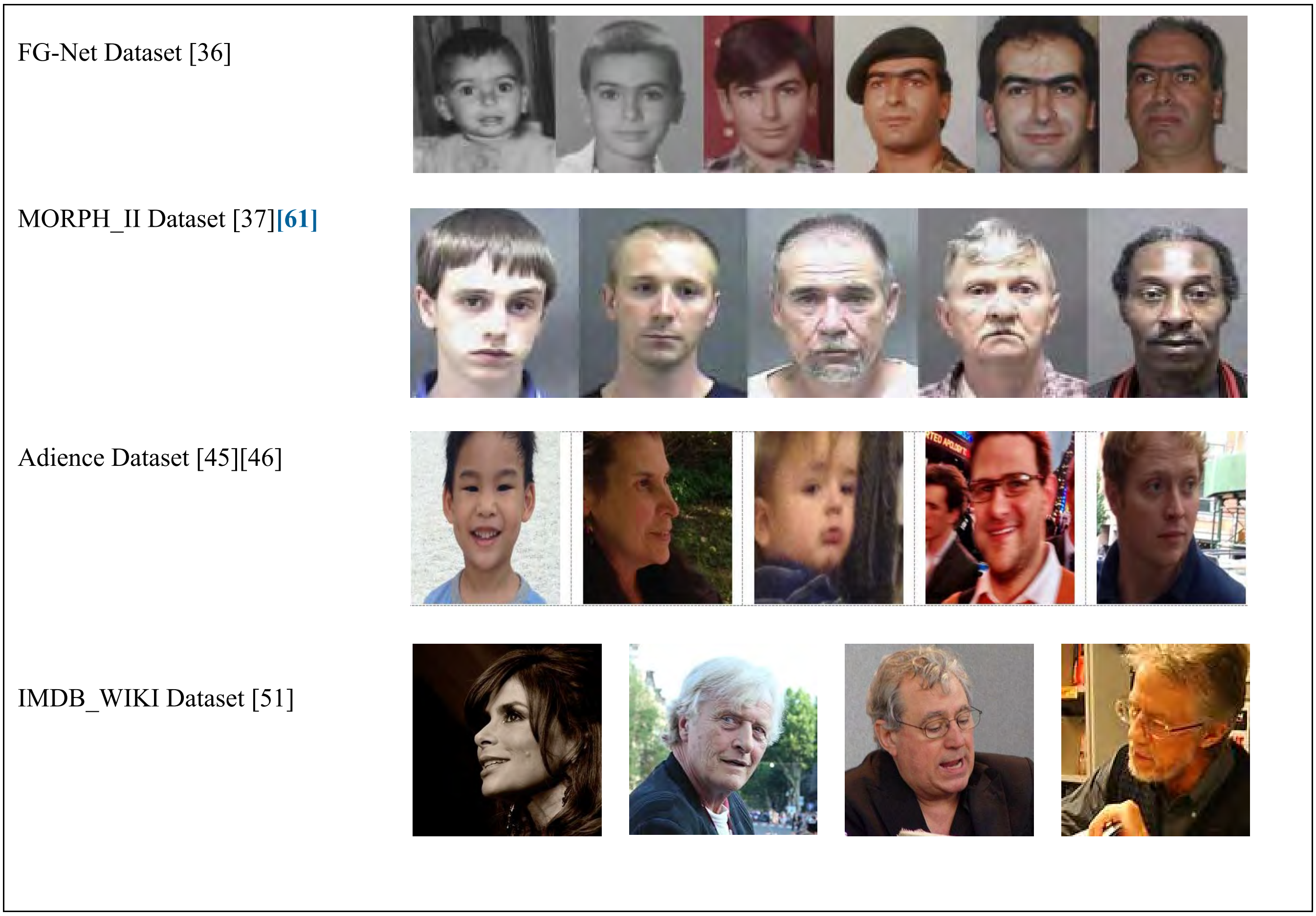

FIGURE 2. Samples from four common datasets in age estimation.

VII. AGE ESTIMATION EVALUATION PARAMETERS

To evaluate the performance of AE system, two main metrics were developed for this purpose. **Mean Absolute Error (*MAE*)** is considered as the common evaluation metric in the literature for AE. Refer to (1), *MAE* is defined as:

$$MAE = \sum_{i=1}^{n} \frac{|\widehat{x_i} - x_i|}{N_i} \tag{1}$$

where $\widehat{x_i}$ represents the estimated age, the actual age is represented by x_i and N is the number of testing samples. Minimum value of *MAE* indicates good performance which means that the difference between estimated and actual age is minimum. If the training data has many missing ages or data, the useful evaluation parameter could be *MAE* [1]. **Cumulative Score (CS)** [56], [9].

is another metric in AE, which can be defined as in (2):

$$CS(j) = \frac{N_{e\leq j}}{N} 100\% \tag{2}$$

where $N_{e\leq j}$ determines the number of images for testing on which an absolute error is made not greater than j years. A classification accuracy can be represented by $CS\,(j)$ that reflects the performance in case of having a dense distribution in large data for different ages.

In case of age group classification, the range of the ages are represented by labels which are related to the age groups. So, the CS becomes as in (3):

$$CS\,(x) = \frac{n_x}{N_x} * 100\% \tag{3}$$

where n_x determines the test images which are classified correctly to age group x and N_x represents the overall number of test images that are belonging to age group x [31], this metric is also called the accuracy of exact age.

Another metric is called the 1-off accuracy which is related to the adjacent prediction of the age group as described in [45]. This metric can be also used to evaluate age group classification models. This accuracy can be defined as the error of one age category (AEO) [57] as follows:

$$AEO\,(x) = \frac{n_o}{N_x} * 100\% \tag{4}$$

where n_o determines the correct prediction with one class error and N_x represents the number of test images.

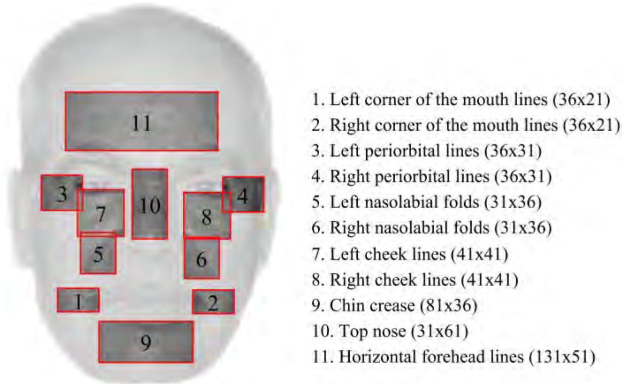

FIGURE 3. Eleven skin areas for aging process [62].

To avoid overfitting and improve the capability for generalization, it is necessary for AE system to be validated using data that are unseen before. One of the common strategies which is used for evaluation is cross-validation [58]. By using cross-validation, data is divided into two subsets; one set is used for training or learning AE model and then the model is validated and evaluated using the other part. The basic form of cross-validation is k-fold [59], where the other types are special cases from the basic form. A special type of cross-validation is called Leave-One-Person-Out (LOPO), at which the dataset is divided based on the classes C. So, for training process the system used data from C-1, and the left part from one class is used for validation.

One of the strategies that has been considered in the literature while testing AE system on Morph-II [37] dataset is explained as follows: The dataset is divided into three sets S1-S2-S3 All experiments will be repeated twice: a) S1 will be the training set, and S2+S3 are the testing sets. b) then S2 is training set and S1+S3 are the testing sets [60].

VIII. HANDCRAFTED-BASED MODELS

Generally, handcrafted-based models depend on extracting the features from images manually using set of rules and algorithms. Indeed, this process requires extra knowledge by hand. Two types of features can describe the facial components, these features are the local features and the global features [61]. The facial wrinkles and the different landmarks such as eyes, cheeks, and nose can be represented using the local features. Lemperle [62] selected eleven areas from the face that are extremely related to aging process. These features are listed in Figure 3 such as corners of the eyes, mouth and nose.

After selecting the different areas of skin, the next step is to crop them. This is an important step to eliminate the irrelevant skin areas and keep the most significant parts for the AE process [61].

The global features can be represented using the facial texture and shape. These features are changing while the human becomes older. To extract texture and shape features, a statistical model AAM [23] is widely used for this purpose. In this model, the training set is used to capture the changeability of shape and texture. A parametric face model is produced using the PCA that applies on shape and texture. The face model is then used to describe both learned and new faces. While the extracted landmark points could be represented as a vector that describes the shape. This step is followed with the alignment of the shape into common frame to conduct the shape variations analysis using PCA.

Similarly, the alignment process to a reference frame is needed for the texture samples while modeling the texture. To build the texture model, PCA is also used. Finally, a combination of both representations of the shape and the texture constitutes the final single statistical model of the features. This final model represents a face by using a single vector of appearance parameters in a compact way [61]. The general AE process for handcrafted-based models follows the steps outlined in Figure 4.

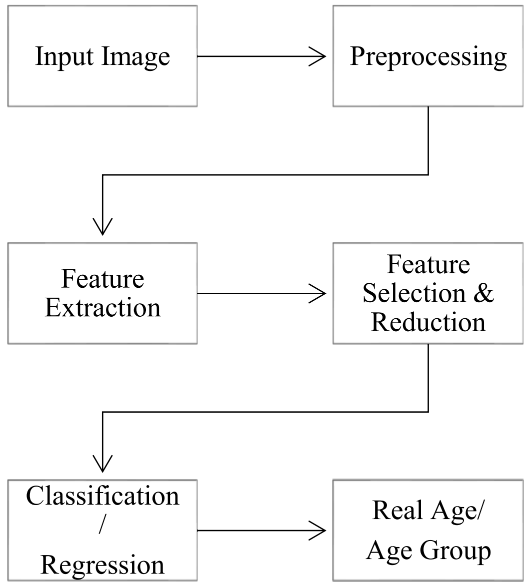

FIGURE 4. General framework for handcrafted-based model.

Principally, the traditional methods for feature extraction can be divided into six main groups:

A. ANTHROPOMETRIC-BASED MODELS

The first work on age estimation has been presented by Kwon and Lobo [63]. Their model was based on the wrinkle patterns and their geometrics to classify the images into three age groups. Six distance ratios were computed to discriminate children from adults. They used snakelets to detect curves and extract the wrinkle patterns from skin areas. A small private dataset with 47 images was used in the experiments. 2-Dimensional Linear Discriminant Analysis (2DLDA) model was proposed by Ueki *et al.* [6] to discover the most discriminant vectors that related to age-group classification. Their experiments were carried on WIT-DB (Waseda human-computer Interaction Technology- DataBase).

Later, Dehshibi and Bastanfard [20] computed the geometric ratios from the facial images to extract the related features of facial components and texture and used these features for image classification into four age groups. Practically, to measure the facial geometric from facial images, images should be in frontal view, because of the sensitivity of computing these ratios. While this approach is considering only the geometric features, it might be inappropriate for adults and old people since the appearance of the skin is the noticeable feature that represents the aging information [64].

B. TEXTURE-BASED MODELS

Facial features that are related to aging can be concentrated by the appearance model. A combined model of texture and shape features can be used to describe facial image, Hayashi *et al.* [65], [66] worked on these features using an algorithm to model the wrinkles and finally estimate the age.

The texture information can be directly extracted from images using the intensities of pixels. One of the most primary and effective texture descriptors is LBP [25]. It was widely used for AE [67]–[69]. Different skin areas such as spots, lines, and edges can be detected using LBP [70]. Another important descriptor was investigated by Guo *et al.* [24] called the BIF. One advantage of this model is that, the new set of aging patterns can effectively handle small transformation including translations, rotations, and scale changes. Several studies [22], [24], [71]–[73] have used the BIF which was proved to be particularly effective for AE. Later, Active Shape Models (ASM) was used by Dib and El-Saban [74] to enhance the performance of AE. They tried to extend BIF by integrating facial features with automatic initialization. In their model, extra forehead details have been added from the facial area.

A few other hand-crafted features rather than LBP and BIF were also experimented for AE. A boosting model by Zhou *et al.* [75] for AE was trained using Haar-like for feature extraction. An age classification system was designed by Hajizadeh and Ebrahimnezhad [76] based on Histograms of Oriented Gradients (HOG) for feature extraction and classified the images into four groups using probabilistic neural network. Another feature descriptor is called Spatially Flexible Patch (SFP) was utilized by Belver *et al.* [64] and Hayashi *et al.* [65] to extract the local variations from the appearance of the face. In addition to the extracted information of local patches and their corresponding positions, extra conditions can be effectively handled such as occlusion, and the pose of head.

Recently, Chang and Chen [79] evaluated scattering transform descriptor [80] to extract the features, this efficient descriptor is used to scatter the Gabor coefficients. The remarkable results on their study is that scattering transform is more general than conventional BIF and effective for inferencing face-based age.

C. ACTIVE APPEARANCE MODELS

A statistical model called AAM is initially proposed by Cootes *et al.* [23] and commonly used to represent the facial image. The learning step for the shape and texture models is performed through the training process on some images. Then a parametric face model is produced using PCA. An extended AAM model was produced by Lanitis *et al.* [5], [8] to represent age using a function age = f(b), a correlation is found between the actual age with the model parameters. It is hard to extract the exact information of the age as ordinal labels, comparatively, the age ranges could be represented as intervals. Based on solving the age problem as a ranking model, Yan *et al.* [81] represented the age features from a low-level to high-level of ranks with uncertain labels. To overcome the problem of imbalanced and sparse data, Chen *et al.* [82] utilized cumulative attribute space for learning aging features regression model. They used AAM to extract the related features. Recently, a new approach using AAM to model the features, was designed by Feng *et al.* [12] based on making the ranks of each age label by predicting their relevance to the facial image.

Significantly, AAM technique shows a clear advantage over anthropometric model that it can deal with any age and consider both texture and geometric models. Nevertheless, a serious weakness with this model is the loss of some skin areas and wrinkles information because of using dimensionality reduction [7]. Another crucial issue of this techniques is the intensive computations and the need of large number of images to learn the features that are related to the shape and appearance. Moreover, the performance of AAM model depends on the image quality, so dealing with image intensities in the gray-level, may lead to a vulnerable model [21].

D. AGING PATTERN SUBSPACE (AGES)

A new algorithm AGES was explored by Geng *et al.* [83], [31] that used AAM to encode the faces. The main concept of this algorithm is to use the images which are belonging to one person and define the related aging pattern for that subject. Figure 5 shows an example on how to vectorize the aging pattern while the ages are ranges from 0 to 8. The feature vectors are represented by b2, b5 and b8 at the ages 2, 5 and 8, respectively. The process of learning the subspace

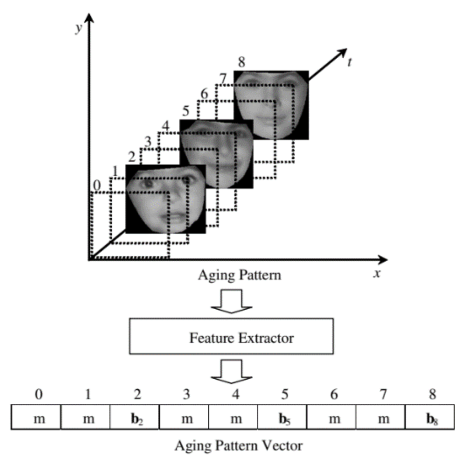

FIGURE 5. Vectorization of aging pattern, the corresponding numbers represents the ages (0-8), m represents missing parts [83].

from the different images can help to compensate the missing ages denoted by m, while modeling the related series of aging face. This approach is not well suited to encode the wrinkles for senior people duo to the using of AAM, so the features should be concentrated by using texture patterns for local areas. Another serious weakness is the difficulty of collecting a large database consisting of different images that are belonging to the same person with different ages.

E. AGE MANIFOLD

The aging pattern can be commonly learned as a trend for several subjects at different ages rather than the process of finding a specific pattern for each person, like the AGES approach [83], [31]. The nature of the aging pattern for a specific age indicates that many faces could be considered to represent the age. Moreover, many images may be found for one person at a single age or related to a range of ages. So, representing the face aging using this type of learning is more flexible than the AGES approach [83], [31]. Later, a method was proposed to learn the common pattern across different ages belonging to many faces is called age manifold [9].

The idea of age manifold has been utilized on age estimation system by Fu and Huang [41]. The formulation of manifold was defined using Conformal Embedding Analysis (CEA) to represent a low-dimensional subspace. The final statistical age was estimated using multiple linear regression.

Raw pixels include redundant information which can be eliminated using dimensionality reduction approaches. Because of the complexity of the AE process, Guo *et al.* [56] observed that using unsupervised methods to reduce the dimensionality like PCA, or locally linear embedding are not appropriate to discriminative subspaces. As an alternative, the authors effectively utilized a supervised manifold learning algorithm called Orthogonal Locality Preserving Projections (OLPP) on their model. Firstly, they predicted ages by a regression function. Later, ages are locally adjusted so that they matched the correct values within a bound. This helpful idea of using manifold learning was later utilized in different works in the field of AE [71], [72]. Depending on 3-D head pose, Yan *et al.* [84] presented a framework by looking for submanifold embedding using subject identity information. Later, an effective age estimation model was proposed by Cai *et al*. [13]. The method is based on discovering the low-dimensional manifold. Opposing with the AGES method, the age manifold learns the low-dimensional manifold depending on the images of several subjects at different ages without necessity of images at different ages of the same subject.

F. MULTI-FEATURE FUSION

The recent trend in biometrics is to fuse the data from different models. This technology is known as data fusion approach [85]. Many researchers have applied this approach to enhance the performance of their systems. So, the technique is based on merging a few feature representations in one model.

LBP and Gabor wavelets (GW) [23] have been utilized for extraction the appearance feature in the work of [11] and [86]. Fusing of local texture and appearance descriptors such as HOG, AAM, and SURF were used by Huerta *et al.* [87]. In study [88], the authors tried to fuse the ordinal information with the geometrical information that can guarantee the discriminative ability of the selected features and their smoothness on the manifold. Recently, Dibeklioğlu *et al.* [89] developed a framework that combined dynamic with appearance features and used this model to train the classifiers. They derived the dynamic features from the different expressions of the face. To deal with the problem of the adjacent ages on the boundaries, they depended on the smile dynamics to improve the performance of the system.

The work introduced by Eidinger *et al.* [45] which prescribes the use of the feature descriptors combination. They used LBP with Four Patch LBP codes (FPLBP) for feature extraction and tested the model using their own unfiltered and extensive data set. Similarly, a hierarchical AE model by Liu *et al.* [85] that combined LBP, HOG and BIF features achieving the state-of-the-art performances. In the interest on age group classification, Jagtap and Kokare [90] classified the facial images into four groups using Artificial Neural Network (ANN). Local Gabor Binary Pattern Histogram (LGBPH) and wrinkle analysis were used to extract the aging features. Their model was tested using PAL database and the results showed a good accuracy.

Recently, a combination of the AAM and the texture-based models were used by Pontes *et al.* [61] to propose a novel approach of age estimation with flexible hierarchical structure. They considered the hybrid model of classification and regression. The system classified the age into age groups using a multi-class SVM. A support vector regression was used to estimate final real age. Their framework integrated the AAM to extract the global features, with LBP, GW and Local Phase Quantization (LPQ) to extract the local features.

G. SUMMARY OF HANDCRAFTED-BASED MODELS

Using hand-crafted methods to represent the face and extract the features, has the advantage of molding less complexity systems, but it may lead to loss critical data as well as extra knowledge are required by hand. Recently, a trend to replace the hand-crafted features with more powerful feature learning techniques. Whereas the traditional methods may not be compatible with the process of aging because of losing many important data during the process of feature extraction and selection. In the ideal case, age image representation should consists the sufficient information about the age [91]. Table 2 summarizes different models that were evaluated on different databases. These models used the traditional techniques to extract the relevant features to aging. Massive efforts were made by researchers to improve the performance of age estimation system either for age group classification or estimating the real age. we observed that, using fusion approach or hybrid approach can improve the performance comparing with other approaches. Table 3 summarizes the

TABLE 2. Summary of handcrafted-based models on different databases.

Feature Model	Ref	Database & Testing protocol	Descriptor	AE Algorithm	Performance MAE	CS	Accuracy
Anthropometric	Kwon and Lobo 1999 [63]	Private dataset :15 images for test	Snakelets	Group classification	N/A	N/A	100%
	Ueki et al. 2006 [6]	WIT-DB: 2-fold cross-validation	(2DLDA)	Group classification	N/A	50%(M), 43%(F)	N/A
	Dehshibi and Bastanfard 2010 [20]	IFDB: 298 for training 200 for testing	Combined Projection Function (CPF)	Group classification	N/A	N/A	86.64%
Texture	Zhou et al. 2005 [75]	FG-NET: 5-fold cross-validation	Haar-like	Regression	5.81	N/A	N/A
	Yang and Ai 2007 [67]	FERET: 20% for testing PIE	LBP histogram	Group classification	N/A	N/A	92.12% FERET 87.5% PIE
	Yan et al. 2008 [78]	YGA:1000 for training 3000 for testing	Spatially Flexible Patch (SFP)	Regression	7.82 (M), 8.53 (F);	75%(M) 70% (F)	N/A
	Yan et al. 2008 [77]	YGA: 1000 for training 3000 for testing FG-NET:LOPO	Coordinate Patch	Regression	4.38 (M), 4.94 (F); 4.95 FG-NET	88%(M) 85% (F)	N/A
	Gunay and Nabiyev 2008 [68]	FERET	Spatial and global LBP histogram	Group classification	N/A	80%	N/A
	Guo et al. 2009 [24]	FG-NET: LOPO	BIF	Regression	4.77	89%	N/A
	Dib and El-saban 2010 [74]	FG-NET, MORPH: Train on FG-NET, Test on MORPH	ASM	Hybrid	3.17 FG-NET, 4.11 Morph	N/A	N/A
	Yang et al. 2010 [120]	FG-NET: 4-fold cross validation	Haar-like	Regression	5.67	N/A	N/A
	Guo and Mu 2011 [71]	MORPH-II: 50% for training, 50% for testing	BIF	Regression	4.2	N/A	N/A
	Hajizadeh and Ebrahimnezhad 2011 [76]	IFDB: 246 for training, 131 for testing	HOG	Group classification	N/A	N/A	87.025%
	Guo and Mu 2014 [72]	MORPH-II: Divided into 3 sets:2 for training, 1 for testing	BIF	Classification	3.92	N/A	N/A
	Han and Jain 2014 [48]	LFW, FG-NET: 98.8% for training 1.2% for testing	BIF	Classification	4.5 FG-NET	66.7% LFW, 68.1% FG-NET	N/A
	Chang and Chen 2015 [79]	FG-NET, MORPH-II: 80% for training 20% for testing	Scattering Transform	Ranking	4.7 FG-NET 3.82 Morph2	N/A	N/A
	Onifade and Akinyemi 2015 [69]	FG-NET: LOPO	LBP	Ranking	2.34	N/A	N/A
Active appearance	Lanitis et al. 2002 [8]	Private: 500 for training, 65 for testing	AAM	Regression	4.3	N/A	N/A
	Lanitis et al. 2004 [5]	Private: 50% for training, 50% for testing	AAM	Classification	3.82–5.58	N/A	N/A
	Yan et al. 2007 [81]	FG-NET: LOPO YGA: 4-fold cross validation	AAM	Ranking	5.33 FG-NET 6.95(M),YGA 6.95(F)	79%(M), 78%(F) YGA	N/A
	Chen et al. 2013 [82]	FG-NET: LOPO MORPH: 80% for training, 20% for testing	AAM	Regression	4.67 FG_NET 5.88 MORPH	74.5% FG_NET 57.9% MORPH	N/A
	Feng et al. 2016 [12]	FG-NET: LOPO MORPH: 10-fold cross validation WebFace: 4/5 for training and 1/5 for testing over 10 trails	AAM	Ranking	4.35 FG-NET 4.59 MORPH 6.03 WebFace	N/A	N/A
AGES	Geng et al. 2006 [83]	FG-NET: LOPO	AAM	Regression	6.77	N/A	81%
	Geng et al. 2007 [31]	FG-NET:LOPO Tested on MORPH	AAM	Classification	8.83	N/A	70%
Age Manifold	Fu and Huang 2008 [41]	YGA: 50% for training, 50% for testing	CEA	Quadratic Regression	5-6 year	N/A	N/A
	Guo et al. 2008 [56]	YGA: 4-fold cross-validation, FG-NET: LOPO	OLPP	Regression	5.30(M) 5.25 (F) YGA 5.07 FG-NET	83%(M) 81%(F)	N/A
	Yan et al. 2009 [84]	FG-NET: LOPO	SSE	Regression	5.21	N/A	N/A
	Cai et al. 2016 [13]	FG-NET: LOPO MORPH: 80% for training, 20% for testing	Dual Histogram LBP	Gaussian Process Regression	4.64FG-NET 4.66 MORPH	72.1% FG-NET 62.2% MORPH	N/A
Multi-Feature Fusion	Guo et al. 2008 [118]	YGA: 4-fold cross-validation, FG-NET: LOPO	AAM, Manifold	Hybrid	5.12(M) 5.11(F) 4.97 FG-NET	83%(M) 82%(F)	N/A
	Choi et al. 2011 [11]	FG-NET: LOPO PAL,BERC: 5-folds cross validations	AAM, Gabor, LBP	Hybrid	4.7(FG-NET), 4.3(PAL), 4.7(BERC);	N/A	73%, 70%, 65%
	Eidinger et al. 2014 [45]	Adience, Gallagher: testing on Adience test set training on a Gallagher training set	LBP, FPLBP	Group classification	N/A	N/A	45.1 , 80.7% Adience 95.3% Gallagher
	Li et al. 2014 [88]	FG-NET, FACES: 5-fold cross validation	2D age manifold, BIF	Classification	1.3 FG-NET 8.2 FACES	N/A	N/A
	Huerta et al. 2015 [87]	MORPH, FRGC: 4-fold cross validation	HOG, LBP, SURF	Classification	4.25 MORPH 4.17 FRGC	N/A	71.17% MORPH 76.24% FRGC
	Liu et al. 2015 [85]	FG-NET: LOPO MORPH-II: Divided into 3 sets:2 for training, 1 for testing	LBP, HOG and BIF	Hybrid	2.81 FG-NET 2.97 MORPH-II	N/A	N/A
	Pontes et al. 2016 [61]	FG-NET: LOPO MORPH-II : 75% training 25% testing	AAM, LBP, LPQ, GW	Hybrid	4.50 FG-NET 5.86 MORPH-II	N/A	N/A
				Group classification	N/A	N/A	68.8% FG-NET 50.06% MORPH-II
	Jagtap and Kokare 2016 [90]	PAL: 10-fold cross validation	Gabor, Histogram LBP	Group Classification	N/A	N/A	94.17%M 93.75% F

TABLE 3. Comparison of different feature models.

Feature Model	Strength(s)	Weakness(es)
Anthropometric	-Appropriate to the age from child to adult.	-While this approach is considering only the geometric features, it might be inappropriate for adults and old people. -To measure the facial geometric, images should be in frontal view, because of the sensitivity of computing the ratios of distances from 2D facial images. -This model has been experimented only on small private datasets.
Texture	-Can effectively handle small transformation including translations, rotations and scale changes.	-Some descriptors are less accurate such as LBP. -Some descriptors are complex and slow such as HOG and Haar-like. -Some descriptors are less robust to occlusion such as Haar-like. -Different illumination conditions may change the surface texture.
AAM	-Can deal with any age and consider the both texture and geometric models.	-The loss of some skin areas and wrinkles information. -The intensive computations and the need of large number of images to learn the features that are related to the shape and appearance. -Dealing with image intensities in the gray-level, may lead to vulnerable model
AGES	-Learning a subspace representation helps to compensate the missing ages while modeling the related series of aging face.	- Many images are needed at several ages to represent the same person. -Is not suitable to encode the wrinkles for senior people.
Age Manifold	-Many images are not needed at several ages to represent the same person. -Flexible means of face representation	-Large datasets are needed for manifold subspace learning.
Multi-Feature Fusion	-Combines the features from different model, so the features will complement each other, to get more robust system. -Enhancing the performance of AE system.	-More complex model

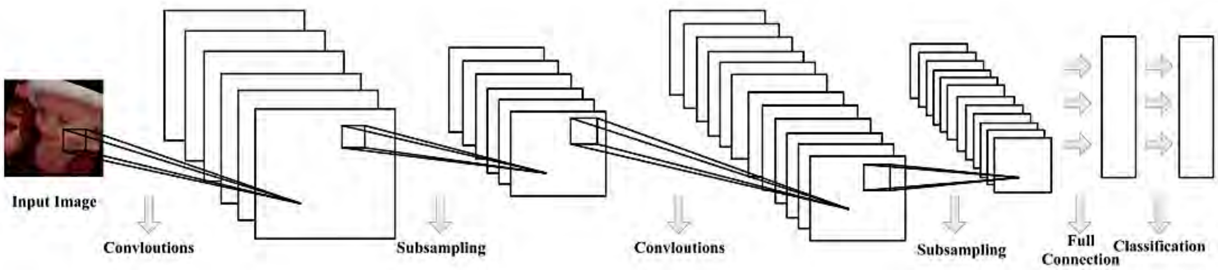

FIGURE 6. The structure of CNN for visual recognition [94].

main variances between different kind of feature extraction approaches. The most effective technique is to fuse the multiple feature approaches in one model to get more robust and accurate system while a more complex system could be generated.

IX. DEEP LEARNING-BASED MODELS

Learning a series of nonlinear features using deep learning enhancing the performance of many tasks in computer vision. In AE system, deep learning have been effectively utilized to make a transformation of face images to output the age label space [92].

A different approach is taken by Deep Learning-Based Models (DLBMs) and especially CNN comparing with hand-crafted based methods. The features are automatically extracted during the training process instead of defining a set of algorithms. The basic idea of using deep learning is based on trying to solve the problem in a hierarchical manner of concepts. The basic representation is encoded in the lower layers, while the more abstract concepts are formed in the higher layers using the basic concepts received from the low layers. Thus, this way of learning gives us the power to replace the hand-crafted methods with DLBMs. Given an image, inputs to the CNN are the values of pixel intensity. The features are being extracted from the image using a series of hidden layers [93].

A. DEEP LEARNING ARCHITECTURE

As shown in Figure 6, the basic structure of CNNs primarily consists of three parts: the first part contains the convolution layers, the second part is the subsampling layers and the classification layer represents the final stage of the network. The local patterns are extracted in the convolutional layers. The original signal can be enhanced by the convolutional operations while the noise will be reduced.

Then the features are re-extracted from the convolutional layers in the subsampling part. One of the main purposes of subsampling operations are to neglect non-maximal values. The second objective of this layer is to decrease the computations for previous layer and control overfitting. Finally, some improvements may be happened in this layer to the distortion tolerance while providing robustness to position. In the full connection layer the received features from the previous layers will be encoded into a 1-D vectors, then a trainable classifier will categorize these vectors into classes [94].

The recent published articles on the field of AE were using the CNN in one of their model parts either in the feature extraction stage or in the classification / regression stage. Several factors should be taken into consideration while building AE system and choosing an optimum architecture of CNNs [14]. These factors are:

1) The target age encoding algorithm (classification, regression, ranking or soft classification).
2) The related loss function of the encoding algorithm that measures the inaccuracy of predictions.
3) The depth of CNNs architecture (Shallow < two layers or Deep > two layers or very Deep >10 layers) [93].
4) The pre-training strategy: (training the network from scratch on specific task or already pre-trained on general task). The main goal of training process is to fine-tune the network's parameters such as the weights and biases. Hence, the trained CNN will be capable to predict the classes from the datasets [94].

B. CREATE AND TRAIN DEEP LEARNING

To perform deep learning, three main common ways are used:

1) TRAINING FROM SCRATCH

In case of having new application or large number of classes as output, it can be useful to train the network from scratch on large labeled data to allow learning the features. This approach is less common due to the need of long time for training and requires huge amount of data. The first use of CNN was by Yang *et al.* [95] to estimate the age. They created the deep network and trained it from scratch. In their model, a recognition system was built to recognize the face from videos and images then extract the corresponding human profile. Many outputs were obtained from the model related to gender, age and race, while the performance of age estimation is inferior than that obtained by BIF. Later, Levi and Hassner [46] used a shallow CNN architecture to classify the Adience dataset into eight age groups. They compromised between the complexity of the network with the performance to reduce the chance for overfitting.

A multi-task deep model was built by Xing *et al.* [96] to estimate the age depending on race and gender classification. The model was trained from scratch on AE task. Wan *et al.* [97] also trained from scratch five cascaded deep networks to extract features related to gender and race and used these features to enhance the aging related features.

Based on ranking approach, Chen *et al.* [98] built their ranking CNNs network which was trained using the ordinal information of the age as labels.

2) TRANSFER LEARNING

The procedure of fine-tuning the already trained model is known as transfer learning. The idea is to transfer the knowledge from a pretrained network such as AlexNet [99], VGG-NET [100] or GoogLeNet [101] and train the network on different or related task. It requires less amount of data as well as less computation time. This approach was commonly used in AE models.

By using transfer learning, Dong *et al.* [57] overcame the problem of lacking labeled images. In their model, a Deep Convolutional Neural Networks (Deep ConvNets) was used for age groups classification task by extracting high-level age features. Seven age range of input face image were predicted using (Deep ConvNets). Additionally, to describe the relations between labels, a new loss function was defined. They found that age ranges from 0–2 and 66+ are easier to be predicted than other ranges, and it was also concluded that regions surrounding eyes provide more identification information. However, the model cannot be generalized while it was evaluated using a small dataset with unbalanced age group intervals.

It is necessary to have a large and labeled facial dataset for the process of estimating the accurate age or classifying the images into age groups. Some datasets may have unlabeled images, but the age difference between two images which belongs to the same person can be easily derived. Another learning scheme that depends on the age difference was proposed by Hu *et al.* [91]. They used CNNs to benefit from the weakly labeled data. To find the age difference information between image pair, Kullback-Leibler divergence was used.

We observed that, most of the mentioned literature assume a constrained environment of the face images. Such that, the face in the input image should be normalized (frontal) view. While other models employed a face pre-processing step to make face localization and alignment which is essential for the next processing steps.

In general, to minimize the error of AE on validation data, the age estimators should work on three aspects which includes the feature representation along with the extracted features. And it is important to learn models from training data. Consequently, the entire process of AE assumes that, the data which are being used for training, validation, and testing have the same characteristic according to the distribution and the conditions where the images are captured. To obtain more reliable model, AE system should be trained, fine-tuned or validated under unconstrained environment. Rothe *et al.* [51] increased the performance of their system by fine-tuning the CNNs over unconstrained IMDB-WIKI database.

A novel method was proposed by Li *et al.* [32] that using AlexNet for feature extraction with cumulative hidden layer. The main advantage of using cumulative hidden layer, is to learn indirectly using faces with neighboring ages and thus overcoming the problem of sample imbalance. To make more enhancement on the AE process, an extra layer was added to make a comparative ranking. The aim of adding this layer was to make a facilitating for the learning of aging feature and thus enhancing the overall performance.

Another model that consists of a validation step using unconstrained dataset, was proposed by

Rodríguez *et al.* [102]. Their model was based on a feedforward CNNs pipeline which combined with attention mechanism. To get more details for specific regions on the face, attention mechanism was used to extract more detailed features from face. Moreover, the aim of using this mechanism, was to reduce the complexity of the task and discard the irrelevant information. Particularly, discriminative patches were extracted from a down-sampled images which are belonging to a high-resolution image. Significant improvements can be obtained when fine-tuning pre-trained models using limited aging data.

However, different datasets have various scale of data, this strong invariance of the model may have a negative impact on a single face input. To overcome this issue, a multi-path CNN model is proposed by Liu *et al.* [33] to extract the features at different scales. To obtain the joint fine-tuning for the networks, the objective loss function was deployed on the top of the multi-path CNNs. Their model combined a VGG-16 Face Net which was pretrained on face recognition task with two shallower CNNs to extract the fine-grain features. The final feature vector from multi-CNNs was normalized to single vector and fed to the age estimator. The ordinal ages were splitting into discrete groups, to deeply learn the feature transformations across these groups.

Antipov *et al.* [14] utilized the idea of transfer learning on special task of face recognition to enhance the performance of AE system. A pre-trained GoogleNet has been used by Shang and Ai [103] to extract the related features to aging. They used a clustering algorithm k-means++ to separate the features into different groups then trained the network again for each group. Zhang *et al.* [104] combined the Residual networks of Residual networks (RoR) models. They used RoR model, which was already pre-trained on ImageNet, then used another dataset IMDB-WIKI-101 to do the fine-tuning to extract more features. Later, Zhang *et al.* [105] used the DEX method [51] to estimate the real age. They enhanced the AE system by extracting the fine-grained features using the attention mechanism.

3) FEATURE EXTRACTION

A least common approach in AE is to use the deep network to extract the features. The output feature vector can then be used to feed machine learning algorithms to perform the classification or regression step. Based on this approach, a new framework was built by Wang *et al.* [28] for extracting facial age-related feature. In their work, feature maps were obtained in different layers instead of obtaining the feature at the top layer. As well, they adopted a manifold learning algorithm with the proposed model which enhanced the performance significantly. For AE, several SVM for classification and SVR for regression schemes were also evaluated using the Deep Learned Aging pattern (DLA). Another model proposed by Duan *et al.* [29] used the deep network as feature extractor and then fed the output to Extreme Machine Learning (ELM) to classify the image into age groups then to regress the final value of the age using ELM regressor.

C. SUMMARY OF DEEP LEARNING-BASED MODELS

Table 4 summarizes the different models of AE that are based on deep learning either as a feature extractor or as end-to-end network. These models were evaluated using different datasets and using different architecture of CNNs. Some of these models made an age classification task, while other models concentrated on estimating the real age. According to the AE algorithms, many approaches used the regression to estimate the real age and achieved good results. While three recent models used the soft classification to estimate the final age and improved the performance of the AE system [14], [103], [91]. It can be seen, the good impact of combining the regression with classification in one hybrid model such as in [29], [96]. So, the improvement of the performance does not depend on one factor, it is a combination between many factors to obtain a good and robust model.

X. AGE ESTIMATION ALGORITHMS

After representing the aging feature vector, a classifier or regressor is used in training stage on the available datasets for AE. Using classification-based methods, the subjects can be classified into a real age label or an age group. Otherwise, the age of a person could be estimated as a numerical value using regression-based methods. Recently, ranking-based methods have attracted the researchers on the field of computer vision and have been utilized in AE related task. The hybrid-based methods can be used to combine the benefits of the classification approach with regression. Finally, a soft classification algorithm which can be considered as a middle case between classification and regression, is being used by different models to enhance the performance of AE task.

A. CLASSIFICATION-BASED METHODS

This approach is based on treating the ages or age groups as separated class labels. The person age is inferred by learning the classifiers [12]. In 2004, Lanitis *et al.* [5] made a comparative study between three classifiers related to AE task, their results indicated that machines can estimate the age reliably like humans. A new method called AGES has been produced by Geng *et al.* [31] that was dealing with the AE process as a conventional classification problem.

Based on furthest nearest-neighbor (FNN), Wang *et al.* [106] classified the images into age groups. Guo and Mu [72] built a framework that joint the features of gender and ethnicity to estimate the age for each resulted group. Han and Jain [48] used three different SVMs to expect the age group and the exact age, gender, and race of a subject. Many studies have been published that dealing with AE as a multiclass problem [87], [88], [107], [108].

Age grouping classification are common for age estimation and many approaches have been proposed. Age grouping is based on splitting the whole age range into several aging groups that have common characteristics and then a classification algorithm is used to classify faces image to one of these groups. The first work on age group classification was

TABLE 4. Summary of DLBMs on different databases.

Creation of Deep learning	Ref	Model	Database & Testing Protocol	AE Algorithm	MAE	Performance Accuracy Exact Age	Accuracy 1-off
Training from Scratch	Yang et al. 2011 [95]	CNNs with correspondence driven adaptation	**FG-NET**: LOPO	Regression	4.88	N/A	N/A
	Levi and Hassner 2015 [46]	Shallow CNNs	**Adience:** 5-fold cross validation	Group classification	N/A	50.7	84.7
	Xing et al. 2017 [96]	Multi-task and fusion using VGG-16 CNNs	**MORPH-II**: divided into 3 sets, 2 for training and 1 for testing. **WebFace**	Hybrid	2.96 Morph-II 5.75 WebFace	N/A	N/A
	Wan et al. 2018 [97]	Data Fusion using Five cascaded VGG-16 CNNs	**MORPH-II**: divided into 3 sets, 2 for training and 1 for testing. **CACD**	Regression	2.93, 3.30 MORPH-II, 5.22 CACD	N/A	N/A
	Chen et al. 2018 [98]	Basic CNNs for each age group using Ranking-CNNs	**MORPH-II, FG-NET**: 80% for training, 20% for testing	Ranking	2.96 MORPH_II 4.13 FG-NET	N/A	N/A
			Adience: 80% for training, 20% for testing	Group classification	N/A	53.7	N/A
Transfer Learning	Dong et al. 2015 [57]	20 Deep ConvNets + Patches	**IoG:** 3500 images for training, 1050 images for testing	Group classification	N/A	56	92
	Liu et al. 2016 [33]	Group-Aware + OHranker using VGG-16 CNN + two shallow CNNs	**FG-NET**: LOPO **MORPH-II**: divided into 3 sets, 2 for training and 1 for testing.	Ranking	3.93 FG-NET 3.25 MORPH-II	N/A	N/A
	Hu et al. 2016 [91]	AgeDifference using GoogLeNet CNN	**FG-NET**: LOPO **MORPH-II**: divided into 3 sets, 2 for training and 1 for testing.	Soft classification	2.78 MORPH-II 2.8 FG-NET	N/A	N/A
	Rothe et al. 2016 [51]	VGG-16 CNNs with DEX method	**MORPH-II**: 80% for training, 20% for testing **FG-NET**: LOPO **CACD**: 145,275 images for training, 7600 for testing.	Regression	2.68 MORPH-II 3.09 FG-NET 6.521 CACD	N/A	N/A
			Adience: 5-fold cross validation	Group classification	N/A	64.0	96.6
	Li et al. 2017 [32]	AlexNet CNNs with D2C	**MORPH-II**: divided into 3 sets, 2 for training and 1 for testing. **WebFace**	Regression	3.06 MORPH-II 6.04 WebFace	N/A	N/A
			MORPH II: 80% for training, 20% for testing	Classification	2.56	N/A	N/A
	Rodríguez et al. 2017 [102]	VGG-16 CNNs with Attention mechanism	**Adience, IoG:** 5-fold cross validation	Group classification	N/A	61.8 Adience 60.0 IoG	95.1 Adience 94.5 IoG
	Antipov et al. 2017 [14]	LDAE using VGG-16 CNNs	**MORPH-II**:80% for training, 20% for testing **FG-NET**: LOPO	Soft classification	2.99, 2.35 MORPH-II 2.84 FG-NET	N/A	N/A
	Shang and Ai 2017 [103]	GoogleNet CNNs with Feature clustering using k-means++	**MORPH-II**:80% for training, 20% for testing **FG-NET**: LOPO	Soft classification	2.71 MORPH-II 3.85 FG-NET	N/A	N/A
	Zhang et al. 2017 [104]	ROR	**Adience:** 5-fold cross validation	Group classification	N/A	67.34	97.51
	Zhang et al. 2018 [105]	Fine-Grained with attention mechanism using ResNets + RoR model	**MORPH-II**:80% for training, 20% for testing **FG-NET**: LOPO	Regression	2.36 MORPH-II 2.39 FG-NET	N/A	N/A
			Adience: 5-fold cross validation	Group classification	N/A	67.83	97.53
Feature Extraction	Wang et al. 2015 [28]	DLA using Single-layer CNN + RNN	**FG-NET**: LOPO **MORPH-II:** 80% for training, 20% for testing	Regression	4.77 MORPH-II 4.26 FG-NET	N/A	N/A
	Duan et al. 2018 [29]	Data Fusion + ELM using Three CNNs (Age-Net, Gender-Net, Race-Net)	**MORPH-II**: 35,440 images for training, 8,860 for validation, and 8,860 for testing	Hybrid	2.61	N/A	N/A
			Adience: 4,113 images for training, 1,500 for validation, and 1978 for testing	Group classification	N/A	66.49	N/A

proposed by Kwon and Lobo [63], they evaluated the model on a small private dataset. After that, Ueki *et al*. [6] reduced the dimensionality of the feature vector and classified the age into groups using a combination of gaussian models. Another model proposed by Dehshibi and Bastanfard [20] that classified the images into four groups based on the anthropometric features.

Later, Hajizadeh and Ebrahimnezhad [76] used Probabilistic Neural Network (PNN) as a classifier and achieved better results on IFDB by extracting HOG features. Using projections of pose specific, Tokola *et al.* [109] tried to decrease the influence of the variations in the image. The image features were mapped into a latent space which is insensitive to pose. Finally, they used a multi-class SVM to classify the images into age groups. With the increasing interest on deep learning, many researchers tried to increase the performance of age group classification task such as in [29], [46], [51], [57], [102], [104], [105].

B. REGRESSION-BASED METHODS

Instead of dealing with the ages as a multiclass problem, the labels could be considered as numerical values. In the literature there are several studies used this approach on AE. Three regressors were constructed to estimate the age by Lanitis *et al.* [8]. Their model can be also used for face recognition task. To reduce the dimension of the feature space, Fu *et al.* [9] and Fu and Huang [41] used the manifold learning and the aging patterns were effectively extracted. Their models were based on the quadratic function which is a multiple linear regression.

Another study used the age manifold learning to extract the aging features from faces proposed by Guo *et al.* [110]. They designed a robust regressor to learn and estimate the ages. Later, Zhang and Yeung [111] built a multi-task framework that based on wrapped Gaussian to represent customized aging patterns. To enhance the performance of AE, Su *et al.* [112] utilized the transfer learning to transmit the gained information from the training dataset to the target dataset. A good age regressor was obtained by Kernel Partial Least Squares (KPLS) model that was designed by Guo and Mu [71]. Recently, to deal with the problem of unbalanced and sparse dataset, [82] utilized the cumulative attribute to build a framework for learning the regression.

Another regression model was adopted by Cai *et al.* [13] based on the Gaussian process. The low-dimensional representations were discovered using the manifold learning which represent the ages patterns. A method called Deep EXpectation (DEX) by Rothe *et al.* [51] used CNNs that pre-trained as a multi-class classification of age on ImageNet dataset and fine-tuned over unconstrained IMDB-WIKI dataset [51]. The classification step was followed by a SoftMax regression to estimate the real age. SoftMax regression was designed in case of multiple classes which are independent. However, the IMDB-WIKI dataset suffers from many wrong age annotations. So, to use this dataset, it should be cleaned to have only the correct annotations.

Age estimation is still a challenging problem due to the variations in intrinsic and extrinsic factors. Wan *et al.* [97] proposed a framework for age estimation based on CNNs that includes five cascaded structure frameworks. They supposed a relationship between age and another demographic information (i.e., gender and race). So, the five frameworks were learned and guided using this information. Each framework was designed to have a parent network and several subnetworks. Furthermore, they used the Gaussian process regression for features extraction from the cascaded structure frameworks. Using deep learning, many studies [28], [32], [95], [105] estimated the real age depend on regression.

C. RANKING-BASED METHODS

Recently, the interest on the ordinal ranking concept has significantly increased for AE, since the process of human aging shows a variety among different ranges of age. AE can be solved as a multi-class problem, in this case the labels that are associated with each class are uncorrelated and independent. Nevertheless, age labels perform some ordinality as an ordered set with strong correlations. For example, age of a person can be classified to one of the adjacent ages rather than ages which are far from the neighboring. This property cannot be reflected using multi-class approaches. The same concept is considering while dealing the AE as a regression problem, which looks to the ages labels as numerical values [79].

Ordinal regression is considered as a type of regression which is appropriate for AE [33], due to its ability to design many two-class classifiers to represent the age [13]. Moreover, a relative sorting for the information is appropriately employed through the age labels. On the other hand, a limited improvement in the performance can be achieved because of using of the parallel hyperplanes in a single kernel in case of dense data [79]. AE task can be transformed into many binary classification subproblems. Chang *et al.* [113], [114] solved those transformed cost-sensitive subproblems using Ordinal Hyperplane Ranking (OH Rank) algorithm.

In order to learn the ordinal features from facial images, the aging characteristics were temporally considered by Li *et al.* [115], [88]. Chen and Hsu [116] joint the aging manifold with implicit age ranks of unlabeled data and used the proposed feature subspace to train SVR. The age ranks on their method can be incorporated from unlabeled images.

Later, they measured the ordinal distance to keep the local data about geometry and the ordinal relationships between the facial images. More robust model to illumination and expression variations that utilized a cost-sensitive learning method for local binary features was proposed by Lu *et al.* [117]. Raw pixel values that were extracted from facial patches, are associated with multiple groups of hashing functions to exploit corresponding information. Later, Chang and Chen [79] made an adoption to the scattering transform idea and scattered the Gabor coefficients for features extraction. In their model, the age rank can be obtained by combining the results of series of binary classification. Feng *et al.* [12] combined the strategy of cost-sensitive with the theories of low-rank matrix. Based on predicted importance of the image, the age labels are ranked in a descending order. This proposed approach of ranking made the problem simpler hence there was no need of huge amount of training data.

Based on ordinal regression and deep learning, Niu *et al.* [52] proposed a method to estimate the real age. A series of sub-problems were transformed into binary classification from the ordinal regression then solved by CNNs as each output layer matching one sub-problem. Recently, Chen *et al.* [98] proposed a ranking-CNNs model that depended on multiple basic CNNs which learned the aging features from each age group independently. To predict the final age, the binary outputs for CNNs were aggregated.

D. HYBRID-BASED METHODS

AE model can be built by combining the classification and regression algorithms to improve the performance and obtain more robust system. Early study was proposed by Guo *et al.* [56], [110] and Dib and El-Saban [74]. They approved that by combining a classifier with a regressor, a better performance can be achieved. Firstly, the regression was performed using all available age data, then the classifiers were constrained using the regression results with a minor local search range. The parameters of the local search range can be determined automatically in a data-driven manner using a probabilistic approach that proposed in [118]. Another approach as in [11] combined SVM with SVR to classify the image into age group using SVM and then estimate the exact age using SVR.

Pontes *et al.* [61] also built a hybrid system by making group age estimation using SVM then for each group, the real age was estimated using multiple SVRs. A robust and less sensitive model to heterogeneous data at different age group was proposed by Kumar and Haider [10]. The appearance features were extracted used the hybrid PCA. An inter-age group classifier was combined with regressor to estimate the age of a person.

The performance of the AE system that are based on deep learning can be boosted by learning the networks using multi-task techniques. Each network can be learned on a special task then the final feature vector is the fusion of these different features. Xing *et al.* [96] built their hybrid multi-task architecture based on deep learning. From the same spirit, Duan *et al.* [29] introduced a hybrid structure, which combined CNNs with ELM. Their system consists of three level where the features are extracted and fused. The age grouping was done using the ELM classifier and the estimation of the age was done using ELM regressor. Three CNNs were trained for different goals. These three networks are Age-Net, Gender-Net, and Race-Net. The features were extracted from these three networks related to age, gender, and race. The main idea is to enhance the age estimation process by making the fusion of the race and gender features. The next stage was to reach a narrow range of the age. So, the ELM classifier was used to classify the fusion results to age groups. Then the estimated age was made using ELM regressor. The model presented the relation between the age and the other human identities such as gender and race.

E. SOFT CLASSIFICATION-BASED METHODS

A middle case between classification and regression is known as soft classification. This approach shares a property with pure classification where ages are encoded by vectors which have a relation with the classes. The facial image can be regarded with a label distribution rather than associating each image with a separated label [3]. The label distribution for a face image x, is represented by a set of the description degrees as a vector of the neighboring ages. For age y, the description degree is defined as real number $d_{y,x} \in [0, 1]$ denotes the degree to which y describes the image x. The label distribution for image x should satisfy two conditions: the description degree of x should have the highest value and description degree of the neighboring ages should decreases while going far from x. So, the proper representation for this distribution is the Gaussian distribution [3]. Figure 7 shows the difference between classification, regression and soft classification as an algorithm used to encode the age.

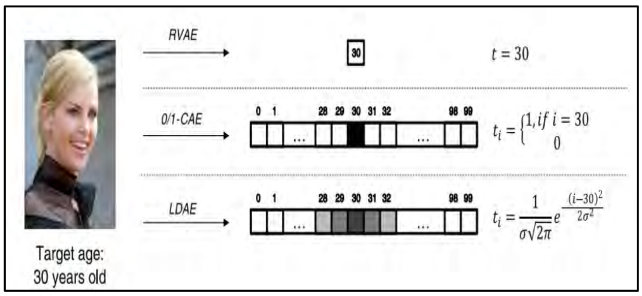

FIGURE 7. The difference between classification, regression and soft classification age encoding [14].

To overcome the problem of lack training data, the label distribution was introduced by Geng *et al.* [3] for each facial image. The chronological age and adjacent ages for each image can be learned by contributing the image itself. However, the aging distribution was assumed to be consistent with the entropy condition, which may be not real.

The label distribution can be also represented by probability distribution because of sharing the same properties. Hu *et al.* [91] used a group of three loss functions to force the probability distribution of age classes. Antipov *et al.* [14] found that using label distribution to encode the age (LDAE) is more effective than classification and regression encodings. He *et al.* [119] combined the distribution learning of age-label with the learning of age prediction. Their approach learned the context relationship using different faces samples to find the correlation of the cross-age.

Shang and Ai [103] used CNNs to extract the related features to aging from facial images, followed by clustering algorithm k-means++ to divide the features into different groups and train again for each group. The clusters were sampled according the probability distribution.

TABLE 5. Comparison between different AE algorithms.

Age Estimation Algorithm	Ref	Strength(s)	Weakness(es)
Classification (real age/age group)	Lanitis et al. 2004 [5] Ueki et al. 2006 [6] Geng et al. 2007 [31] Wang et al. 2011 [106] Geng et al. 2011 [107] Zhan et al. 2011 [108] Li et al. 2014 [88] Tokola et al. 2014 [109] Huerta et al. 2015 [87] Levi and Hassner 2015 [46] Dong et al. 2015 [57] Rothe et al. 2016 [51] Zhang et al. 2017 [104] Rodríguez et al. 2017 [102] Zhang et al. 2018 [105] Zhang et al. 2018 [105] Duan et al. 2018 [29].	-Works well for small number of classes such as the case of age group classification.	-Requires enough samples for each class to train the classifier -Ignores inter-relationships and ordinal information between age labels. -In case of real age estimation, the multi-classification can be heavy because of big number of classes that represents the ages.
Regression	Lanitis et al. 2002 [8] Fu et al. 2007 [9] Fu and Huang 2008 [41] Guo et al. 2008 [110] Zhang and Yeung 2010 [111] Su et al. 2010 [112] Guo and Mu 2011 [71] Yang et al. 2011 [95] Chen et al. 2013 [82] Wang et al. 2015 [28] Cai et al. 2016 [13] Rothe et al. 2016 [51] Li et al. 2017 [32] Wan et al. 2018 [97] Zhang et al. 2018 [105]	-Obtains more accurate performance for the estimated age than using classifier. -Seems to be more reasonable, because the ages are being represented as continuous values which suitable to the nature of age that is continues.	-In certain circumstances, the regression function may overfit the training data, thus decreases the performance. -More sensitive to the inconsistency and incompleteness of the features. -More sensitive to the sparse and imbalanced training data.
Ranking	Chang et al. 2010 [113] Chang et al. 2011 [114] Li et al. 2012 [115] Chen and Hsu 2013 [116] Li et al. 2014 [88] Lu et al. 2015 [117] Chang and Chen 2015 [79] Feng et al. 2016 [12] Niu et al. 2016 [52] Chen et al. 2018 [98]	-Simplifies the problem by ranking the age labels in descending order that are relevant to a given image using a series of quires, thus avoiding the binary decision for each label. -The sensitivity to the number of training samples is less than classification or regression approaches.	-Obtains less accurate performance for the estimated age than hybrid and soft classification.
Soft classification	Geng et al. 2013 [3] Hu et al. 2016 [91] Antipov et al. 2017 [14] He et al. 2017 [119] Shang and Ai 2017 [103]	-Allows a notion of neighborhood to be encoded between different age. -Is more robust than hard classification.	-Requires the generation of the label distribution of the training data for each face under certain assumptions. -Requires an adaptive algorithm that is capable to learn the label distributions on different ages.
Hybrid	Guo et al. 2008 [56] Guo et al. 2008 [110] Dib and El-saban 2010 [74] Choi et al. 2011[11] Pontes et al. 2016 [61] Kumar and Haider 2017 [10] Xing et al. 2017 [96] Duan et al. 2018 [29]	-Compensates the generated errors from the classifiers in the regression step.	-May inherit the weaknesses of the classification and regression.

F. SUMMARY OF AGE ESTIMATION ALGORITHMS

In this section, we summarize the main strengths and weaknesses of the different AE algorithms. As shown in Table 5, the common algorithms that were used by the majority are classification and regression. Recently, researchers start looking to simplify and get more reliable models to adapt the problem of AE. The hybrid system that combines the classification with regression gives more robust model while the weak points in classification stage can be compensated in the regression stage. On the other hand, ranking-based model can simplify the whole system by converting the multi-classification into multiple binary classification problems with considering the ordinal information of different ages. Using soft classification can obtain more robust model by generating a label distribution for each age with its adjacent ages.

XI. CONCLUSION

In this review paper, a general view is presented for different AE models and all their related issues. Moreover, the most common and available datasets that have age annotations have been also offered in this review. Mainly, we have listed handcrafted-based models and deep learning-based models. Using handcrafted-based model has the advantage of requiring small dataset and less complex model to achieve good results. Nonetheless, many important features and data may be lost because of lack knowledge in extracting the most relevant features of aging. The recent technology that based on deep learning has acquired much attention by researchers in the field of computer vision. The different performances that exhibited by deep-based models are related to the different CNN architectures. Another factor that have a direct influence on the deep network performance is related to whether the model is training from scratch or using a pre-trained model for classification task on huge datasets. A noticeable practice which adds a good improvement to the AE system, when using a model that pre-trained on a specific-domain and related to age's task such as training on face recognition.

Although using deep learning in AE from facial image improves the performance of the model. Nevertheless, this technology needs massive data and high system quality to obtain promising results. On the other side, AE models can be classified based on the algorithm that is used to estimate the final real age. The highest performance was obtained by the models that used the regression, hybrid and soft classification to estimate the age. In case of classification the facial image into age groups, using deeper CNNs increases the accuracy of AE.

Some practices can be joint while using deep learning in order to have more accurate and robust system. We observed from the review, the advantage of using transfer learning on specific task that is related to AE over training the CNNs model from scratch to extract more features. Moreover, attention mechanism showed a good impact that concentrating on specific regions of the face to extract more relevant features. To get more robust system, the model should be validated and tested on unconstrained datasets such as Adience and IMDB_WIKI.

The main limitations in estimating the real age from facial images are related to the aging process of human which is uncontrollable and any changes in the skin may affect in the future pattern. The unbalanced distribution and limited datasets of age may also have a negative influence on the performance of AE system. Thus, a good data augmentation could be a practical solution. Moreover, AE can be further enhanced by applying the data fusion of different biometrics with age to obtain more useful and robust system or making a fusion from different CNNs architectures as one model.

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