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Computational Intelligence in Automatic Face Age Estimation: A Survey

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Abstract—With the rapid growth of computational intelligence techniques, automatic face age estimation has achieved good accuracy that benefited real-world applications such as access control and monitoring, soft biometrics and information retrieval. Over the past decade, many new algorithms were developed and previous surveys on face age estimation were either outdated or incomplete. Considering the importance of the expanding research in this topic, we aim to provide an up-to-date survey on the face age estimation techniques. First we summarise the state-of-the-art databases and the performance metrics for face age estimation. Then we review the age estimation techniques based on three categories of face features (local, global and hybrid) and discuss different types of age learning algorithms. Finally, we identify the challenges and provide new insights for future research directions of fully automated face age estimation.

Index Terms—Age estimation, face features, feature extraction, age learning, machine learning.

I. INTRODUCTION

IN human communication, face is the first source that provides information to identify a person (such as age, gender and ethnicity), to facilitate communication (mood and emotion) and to explore the skin condition of a person (cosmetic and social habit). Researchers have developed face analysis applications such as face recognition [1], [2], facial expression recognition [3], gender classification [4], face age estimation [5], [6], and facial skin assessment [7], [8]. Amongst these applications, face age estimation has received considerable attention as age can enhance the performance of face recognition, facilitate communication and affect skin quality or appearance.

Face age estimation is defined as the possibility to "label a face image automatically with the exact age (eg. 20 year) or the age group (eg. young, adult) of the individual face" [5]. The goal of automatic age estimation is to judge if age is as close to actual or appearance age as possible. Actual or real age is the number of years that a person has lived while appearance age is the age information revealed by the visual appearance. Perceived and estimated age is the individual age recognized by human and computer respectively from the visual appearance [9]. Age estimation is useful in many real-world applications such as Access Control and

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Monitoring, Soft Biometric, Electronic Customer Relationship Management and Entertainment.

In **Access Control and Surveillance Monitoring**, an accurate age estimation system can prevent children from entering to unauthorized places or websites, when a monitoring camera is used with the system [5], and prevent child and adult seniors from using danger games in a theme park [10]. To control access in a cigarette vending machine, a Japanese company developed vending machine that check a user age by counting wrinkles and skin sags to prevent anyone under the legal age (20 years old) from buying a cigarette[11]. Age estimation system also can be used in health care systems for customized services such as robotic nurse and intelligent intensive care unit [5]. Age estimation as a soft biometrics can be used to improve the recognition accuracies in basic biometric system [12].

The effective marketing strategy which called **Electronic Customer Relationship Management (ECRM)** [5] can benefit from age estimation systems by targeting specific customers in same age group for specific advertisements [13]. It can provide important information for marketing study such as the number of young and adult customers who have visited a mall along with the preferences of each age group [14]. However, it is difficult to access this information while retaining privacy, but using automatic age estimation system can help to perform this task readily without violating the human privacy as the face image of a customer can be captured to identify age and delete the images instantly [5].

Recently, age estimation system is introduced as an application in some smart phones for **Entertainment** purposes such as iPhone Age Detector. When many photos and videos are captured, age information can organize the images to make them easy to access and find the related images when needed (Automatic album management) [14]. This also can be used for age-based image and video retrieval systems (information retrieval), where users could have the ability to restore their images by determining a wanted age-group in e-photo albums.

Age estimation also can be used with age synthesis in **Forensic Art** to find lost people. When the photos of missing children or any other family members are outdated, the system can predict the age and use age synthesis to produce updated face image [15]. In **Human Computer Interaction (HCI)** systems, computer interface can use a face image, classify the age and setup a workspace automatically according to the user's age group [5].

Although there are several techniques that are used in state-of-the-art algorithms to solve age estimation problem, it is yet largely unsolved and remained a challenging issue for the

following reasons:

1) Age estimation is affected mainly by human aging process, including different changes in human face. In addition to these normal changes, there are many external factors such as environmental influence, solar radiation, lifestyle, disease, drug use, and psychological stress that can have effect on face aging process and make it uncontrollable and personalized process [16].

2) The existing input image variations such as different illumination, pose and facial expressions can have a significant impact on age estimation system performance [17].

3) It is difficult to collect a large-scale longitudinal face age dataset for detailed aging progression [5].

Hence, a robust method to represent face image and extract the discriminative features that reduce the negative influence of personalized property is still needed. Although there are several age estimation surveys, e.g. Fu et al. [5] in 2010, Guo and Guodong [14] in 2012 and Dantcheva et al. [12] in 2016, they have not included the new and emerging approaches that significantly increase the accuracy of age estimation. The most recent survey by Dantcheva et al. [12] focused on different soft biometrics attributes, but the age estimation survey is dated as it was mainly based on the 2010 survey by Fu et al. [5]. To bridge the gap, this paper provides a comprehensive survey on automatic face age estimation. It particularly reviews the computational intelligence techniques in the state-of-the-art algorithms and discusses the potential technique, including deep learning, to improve the performance of automatic face age estimation.

This paper is structured as follows: Section 2 discusses different types of face age databases that commonly used in state-of-the-art algorithms and its limitations. Section 3 presents the performance metrics for age estimation. Section 4 surveys the state-of-the-art age estimation algorithms in two phases: feature types and learning algorithms. Finally, conclusions and future directions are summarized in Section 5.

II. FACE AGING DATABASE

There are different types of datasets used in previous work on face age estimation such as CACD [26], FERET [27], FG-NET [28], MORPH [29], [38], PAL [30], YGA [31], [39], WIT [32], HOIP [34], [5], AI &R [5], [33], IAD [37], Iranian Face Database [35] and LHI [36]. However, most of these datasets are not publicly available. The available datasets that provide a large amount of face image with accurate age information are FG-NET [28], FERET [27], MORPH [29], PAL [30], CACD [26] and Iranian face dataset (only male images are available) [35]. The overall comparison of the face aging databases is illustrated in Table I. This section discusses the strength and limitations of the publicly available databases, i.e. FG-NET, MORPH, FERET, PAL and CACD.

FG-NET [28] is a popular baseline database that benchmarks the performance of the existing age estimation algorithms with new algorithms. It contains images for infants and a series of images for individuals during different age
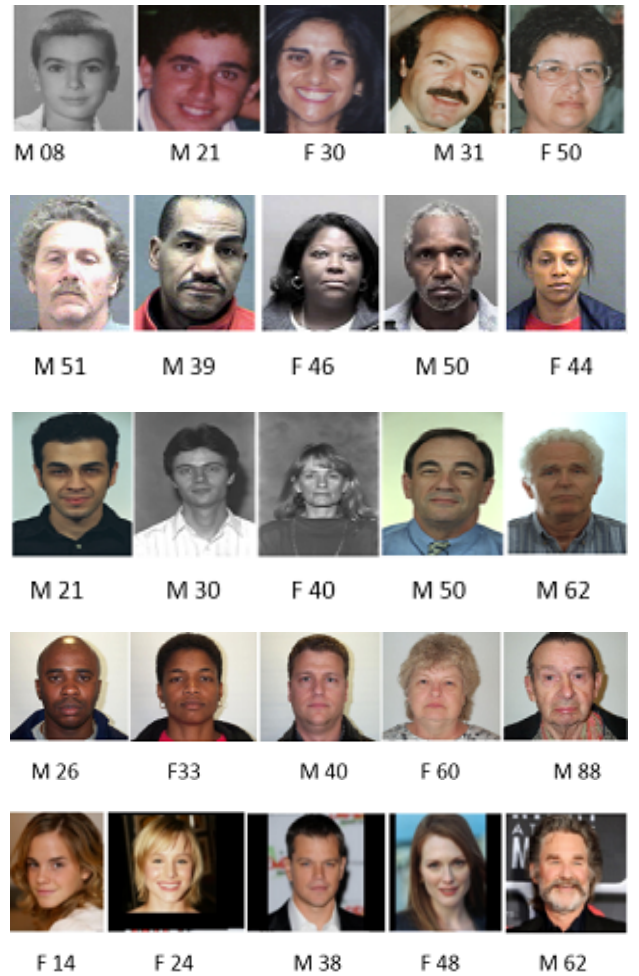
Fig. 1. Sample face images from the publicly available benchmark databases. Row 1: FG-NET [28]; Row 2: MORPH [29]; Row 3: FERET [27]; Row 4: PAL [30]; and Row 5: CACD [26]. These databases are varied in pose, expression, lighting and image resolution.

progression stages. However, FG-NET images were collected by scanning photographs, thus there were very large variations in resolution, background, illumination and noise from scanner. This might complicate the detecting of texture information such as wrinkles.

MORPH [29] is a benchmark database contains 55,134 images, a relatively large-scale database if compared to FG-NET. It was a collection of mugshot images, including information about ethnicity, gender, date of birth and date of acquisition. 42,589 images are African, others are European, Asian and Hispanic.

FERET [27] database were collected in a controlled environment and the image resolution is better if compared to FG-NET and MORPH. It has more representative texture information that works better for local descriptor extraction.

PAL [30] database contains wide age range for adulthood. It contains images for subject with maximum age of 93 years old, which is important for research on aging. The images were captured with good resolution.

CACD [26] is the largest publicly available databases used recently in age estimation, face recognition and retrieval

Name	Total Images	Total Subjects	Age Range	Age Type	Status	Ethnicity	Expression
CACD [26]	163,446	2,000	16-62	Exact age	Public	Yes	Yes
FERET [27]	14,126	1199	10-70	Exact age	Public	Yes	Yes
FG-NET [28]	1,002	82	0-69	Exact age	Public	Yes	Yes
MORPH [29]	55,134	13,000	16-77	Exact age	Public	Yes	Yes
PAL [30]	1,142	576	18-93	Age Range	Public	Yes	No
YGA [31]	8000	1600	0-93	Exact age	Private	Asian	Yes
WIT [32]	26,222	5,500	3-85	Age Range	Private	Japanese	No
AI&R (V2.0) [33]	34	17	22-61	Age Range	Private	Asian	yes
HOIP [34]	306,600	300	15-64	Age Range	Private	Japanese	No
Iranian [35]	3,600	616	1-90	Exact age	Private	Middle-East	Yes
LHI [36]	8,000	8,000	9-89	Exact age	Private	Asian	no
IAD [37]	219,892	-	1-80	Exact age	Private	Yes	Yes

across age research. It contains images for a large number of celebrities collected from internet across ten years. However, this dataset does not include face images with age of 10 or younger. Even though internet is a good platform for data collection, it is very hard to label the ground truth of age or it might not be accurate. In addition, the data collected from the internet could be chaotic.

Although MORPH and CACD databases have large number of images, FERET and PAL with better resolution, they do not contain face images in childhood. Other limitations of the existing databases is the inclusion of certain ethnicities, i.e. YGA, AI&R. Also, the LHI are datasets consist of Asian subjects while WIT contains only Japanese. On the other hand, capturing face images at different ages for the same subject is a big challenge. Besides, we observe that there is lack of consistency and standardisation in data collection, e.g., the age range and the number of images per subject. In some databases such as YGA, MORPH and LHI, only one or a small number of images for each subject is captured, while FG-NET consists of 10 images per subject. WIT captures 1 - 14 image samples from each individual. AI&R database includes limited number of face images. According to Guo et al. [14], databases with a limited number of face images of each subject might not be ideal for the age progression algorithms.

Although there are a number of datasets for age estimation, a large database with balanced distribution of individuals, ethnicity, gender, and age range is still needed. Figure 1 shows the variation in a different conditions such as pose, expression, lighting and makeup in publicly available databases, and Table I provides a summary and a comparison of different face aging databases.

III. PERFORMANCE METRICS FOR AGE ESTIMATION

Two popular metrics are widely used in the literature [40], [41], [42], [43] to measure the performance of age estimation algorithms, i.e. Mean Absolute Error (MAE) and Cumulative Score (CS). MAE is the average of absolute errors between estimated age and the ground truth [44], it is commonly used in previous age estimation research to measure the accuracy

of an algorithm. The mathematical form of MAE is shown in equation (1).

$$MAE = \frac{1}{X} \sum_{n=1}^{X} |a'_n - a_n| \qquad (1)$$

where X is the number of images in the test set, a_n is the n-th ground truth, and a'_n is the estimated age [45]. In addition to general MAE, Guo et al. [46] used "MAE per age" and "MAE per decade" to show the performance of age estimation in more details and allow to compare different approaches to show which method produces better result at each decade or age [41], [46].

The CS measure illustrates the age estimation accuracy by drawing curves in various acceptable error levels and can be defined as:

$$CS(I) = X_{e \leq I}/X \times 100\%. \qquad (2)$$

where $X_{e \leq I}$ is the total number of test images the age estimation produce an absolute error less than I years [41].

IV. FACE AGE ESTIMATION TECHNIQUES

This section contains a survey on face age estimation techniques using computational intelligence algorithms. The state-of-the-art age estimation algorithms predict the exact age or to identify the age range such as teenager or child [47]. Most of these algorithms are composed of two phases: features extraction and age learning [47], [5], [48].

A. Features Extraction

The performance of age estimation system is affected mainly by features extracted from face images. Feature extraction means the face features related to facial appearance changes caused by aging extracted from human face to represent the age [49].

Facial features can be classified as local, global, and hybrid. Local and global features have different roles in face perception. Both of them contains a discriminative data for face analysis. Local information is embedded in the detailed

local variations of the facial appearance, while global information means the overall structural configuration of the facial contour[50]. As such, facial features are responsible for corresponding classification of age estimation algorithms local-based, global-based and hybrid. Table II summarizes the published work in age estimation using different types of features.

1) Local-Based Algorithms: Local features include the geometry of facial components including age spots, depth, wrinkles, and freckles. Local features are usually used in age groups classification. i.e., infant, young and adults, due to the unique characteristics found on local features to differentiate between age groups. For example, the changes in distance ratios between eyes, nose, and mouth are shown clearly in babyhood, while wrinkles are more notable in adulthood. Thus, these features are more suitable to classify age into groups [40].

The first publication on face age estimation was by Kwon and Lobo [51], [52]. They outlined a computational theory for age classification in which they used a combination of distance ratios between facial parts and wrinkle analysis to classify people into children, young adults, and senior adults. They consult studies in cranio-facial research and suggest that the revised cardioidal strain transformation model is the best model to describe human head growth. To differentiate baby faces from the two older groups, a set of distance ratios was computed between the face parts (mouth, nose, forehead, chin, and eyes). Snakelets analysis are used to find wrinkles to differentiate young adults from senior adults. They used only 47 face images in their experiment [52].

Since the methods used by Kwon and Lobo [51], [52] for localization are computationally expensive and database that they used is small [53], Horng et al. [54] proposed age classification algorithm that classify the age into four groups: children, young, middle-aged adults, and senior adults. Firstly, they applied Sobel edge operator to define the positions of eyes, noses, and mouths. To extract the features from the face, two geometric features were used as distances ratios between eyes, noses, and mouths to distinguish babies from other groups. The degree of wrinkles from five areas (forehead, two cheeks, and two eye corners) was found using Sobel edge magnitudes to differentiate between young adults, middle-aged adults, and senior adults. Finally, two back-propagation neural networks were constructed to classify the age. The first one was employed to distinguish the baby face from other classes using geometric features. If it is not a baby, then the second network was used to differentiate between the others three adult groups based on wrinkle features. They achieved 81.58% identification rate using 115 gray-level images [54].

In 2006, Ramanathan and Chellappa [55] proposed a craniofacial growth model to estimate the age during formative years (0 - 18 years). They described the growth of a face using growth parameters that defined over facial landmarks commonly used in anthropometric studies. They detected facial features from eyes, mouth and the outer contour of the face by fitting ellipses of various sizes and orientations.

However, the basic model used by [51], [52], [54], [55], known as anthropometric model, consider the geometry infor-mation only rather than texture information to be appropriate for identifying young age group. It is not useful for the identification of the adults because most changes pertaining to them appear as texture, so that in [51], [54] the authors used wrinkles analysis in addition to anthropometric model to extract aging features. Anthropometric model is sensitive to head pose in that only front face can be used to measure facial geometries. The model also is inappropriate to predict the age in detail [48], [5].

In computer vision, the biologically inspired model [56] have shown superior results in some tasks such as face recognition [1] and object category recognition [57]. The model in [56] consists of simple (S) and complex (C) layers alternately. S units are created using Gabor filters at four orientations and 16 scales. There are 8 bands of units for each orientation created by grouping the adjacent two scales of S units together. Then C units were generated by taking the maximum values within a local spatial neighborhood and across the scales within a band. The MAX operator is used as pooling filter in C units [56].

In 2009 Guo et al. [41] introduced biologically inspired model in age estimation task for the first time and called it Biologically Inspired Feature (BIF). They applied the model in [56] with some improvements in C units generated using non-linear operations including the MAX operation and an standard deviation (STD) operation to obtain a high-performance. Both of these processes were done independently for every orien-tation and scale band. For every face image, a feature vector was constructed by concatenating the outputs of C units. After extracting the biologically inspired features in C, Principal Component Analysis (PCA) was applied for dimensionality reduction while Support Vector Machine (SVM) was applied for age learning. Although the BIF showed a significant improvements in age estimation accuracy, it represent the face images in a high dimension feature vector [14].

Ylioinas et al.[58] proposed an age estimation model us-ing Kernel Local Binary Pattern (KLBP) to represent facial features. Firstly, the face was aligned using similarity trans-formation and the face pose was corrected using an flipping operation to evaluate the pose correction method. For feature extraction the method compared between a histogram and a kernel density estimate for LBP. Finally, a Support Vector Regression (SVR) was applied for age estimation. Ylioinas et al.[58] found that the kernel method was more powerful than the histogram using pose corrected images, which achieved 5.09 and 5.23 respectively for MAE. Using the original im-ages, the MAE is 5.20 for kernel and 5.39 for histogram, which means that the pose correction enhanced the age estimation performance [58].

In 2013 Gunay et al. [59] also extracted local features to estimate the age using Radon transform. After the pre-processing step which included cropping, scaling and resize images to 88 $\times$88, The Radon transform was applied for an image matrix f(x,y) to compute the projections in specified direction. The result from this projection is that a new image R(x,α), which is a sum of the intensities of the pixels in each direction, includes more geometric information than the original image. The concatenation of the Radon projections

taken at $\theta=$ kπ/6 where k = 0,1,2,3,4,5 from local image was used to generate the feature vector. However, the Radon projections produce a high dimension feature vector, so that the PCA was applied to reduce the dimension. Finally, multiple linear regression (MLR) was applied for age learning. Local radon feature achieved a better result on FG-NET (6.18) than MORPH (6.65) and FERET (6.98)[59], which means that the radon feature work better on images with lower resolution [60].

Recently, there are different works that focus on wrinkles in age estimation algorithms [61], [62], [63], [44], [48], [64]. El-Dib and Onsi [42] investigated the ability of wrinkled appearance in eyes, the face parts excluding the forehead and the whole face to estimate the age. They found that the wrinkled appearance in eyes has a significant features related to the age, when it was compared with the other parts. In 2015, Ng et al. [44] investigated the influence of wrinkles on specific age estimation. They localized and presented the wrinkles in a significative way to estimate the age. They proposed a multi-scale aging patterns (MAP) method, which extract the features directly from local patches. MAP was generated by applying a multi-scale filter to different face parts and wrinkles, and thus transformed into meaningful aging patterns. Wrinkles appear in a different sizes. To present this feature, MAP extends a method that used dynamic scale filter called Hybrid Hessian Filter (HHF), which is a wrinkle detection method proposed by Ng et al. [65]. Based on multi-level analysis of Hessian eigenvalues, the local behavior of the face image is emphasized and wrinkles were identified subsequently. Then a multi-scale aging patterns were constructed from extracted wrinkles. Finally, supervised learning algorithm was applied to learn and predict the age. This work demonstrated the ability of wrinkles to estimate the age on high resolution images, where the MAE is 4.87 on FERET [44].

Chang and Chen [43] introduced a framework for age estimation, which applied scattering transform to extract the features from face images and proposed a Cost-Sensitive Ordinal Hyperplanes Ranking (CSOHR) approach for age learning. Scattering Transform (ST) descriptor is a generalization of traditional BIF, where the first-layer of ST and BIF extract the features in a same way, except that the ST employed the Gaussian average in the pooling operators and BIF used standard deviation. ST provides a locally translation invariant representation, which linearizes small deformations, and provides co-occurrence coefficients which characterize textures. This feature is reduced in BIF by pooling operator. After extracting the features using ST, the ranking (or ordinal regression) method CSOHR that focus on pairwise ranking approach was used for age rank estimation. CSOHR with ST achieved 3.82 for MAE in MORPH album2 dataset and 4.70 in FG-NET with slower computation time than BIF for feature extraction and other Multiple Hyperplanes Ranker (MHR) for age learning. However, some features might be lost during dimensionality reduction process using PCA.

2) Global-Based Algorithms: Global features (also known as Holistic) are generally used to predict the age. It contain personal features such as gender, identity, ethnicity, and expression. Personal features are clearer in global features

than aging features. Subspace learning techniques have been used extensively to extract global features. These include Locality Sensitive Discriminant Analysis (LSDA), Marginal Fisher Analysis (MFA) [39], PCA, Neighborhood Preserving Projections (NPP), Locality Preserving Projections (LPP), and Orthogonal LPP (OLPP) [31], [46]. However, Active Appearance Model (AAM) [88] is a most widely used method to extract global features for age estimation and to provide information about the shape and appearance of a face [40], [79].

AAM is a statistical appearance models proposed by Cootes (2001)[88]. It combines shape and texture variation. Building a face model require face images marked with points to determine the main features. The model apply Procrustes analysis to align the sets of points (represented as a vector) and build a statistical shape model. It then warps images by the mean shape, and normalized texture vector by applying a linear transformation. To build a texture model eigen-analysis was applied. Finally, a combined appearance model was generated by learning the correlations between shape and texture [88].

In 2002 AAM was introduced by Lanitis et al. [71] for first time for face age estimation. They generated statistical model from a set of training examples represented by a set of variables. They calculated the mean (X_m) and standard deviation from training set, then applied principal components analysis (PCA) on covariance matrix of the deviation. Their experiment focus on age variation from childhood to adulthood (up to 30 years old). The images were aligned and warped to the mean shape to train shape and intensity model. Then the projection was used to define the aging variations using this formula: (age = f(b)). Three formulation were investigated for aging function (f): linear, quadratic and cubic. Based on their experiment, quadratic function achieved the best result [71].

Geng et al. [73] adopted AAM in their work. They developed an age estimation model known as AGES (AGing pattErn Subspace), which used a series of personal face images to model the aging process. An aging pattern can be defined as a sequence of personal face images sorted in time order, by learning a representative subspace. A projection was used to construct the aging pattern for unseen face image, which define the variation in the data set. While the position in aging pattern defines the specific age, the authors claimed that by using this feature the personalized characteristics were utilized well. An aging pattern can be completed if all positions in aging pattern are filled, otherwise it is called an incomplete aging. There are two stages in AGES: learning stage and age estimation. The aging pattern is highly incomplete, so that an iterative PCA was applied in learning stage to construct a representative subspace. The missing parts in the aging pattern were firstly initialized; and then the first subspace was constructed by applying standard PCA to the initialized data set. By solving a linear system, the subspace is used to reconstruct the missing parts, then the PCA is applied to update the aging pattern. These processes was repeated to minimize the reconstruction error. The age was estimated in two steps determine a suitable aging pattern from aging pattern subspace, and then find the specific age position within aging pattern [73]. However, the process of reconstruction of missing face images produces

TABLE II
A SUMMARY OF FEATURE EXTRACTION METHODS.

Feature Types	Year	Authors
Local	1994	Kwon and Lobo [51]
	2001	Horng et al.[54]
	2006	Ramanathan and Chellappa [55]
	2008	Gunay et al. [66], Yan et al. [67]
	2009	Gao et al. [68], Guo et al. [41]
	2011	Choi et al. [62], El Dib and Onsi [42]
	2012	Lin et al. [69]
	2013	Ylioinas et al. [58], Gunay et al. [59]
	2014	Ng et al. [48]
	2015	Ng et al. [44]. Dibeklioglu et al. [17], Chang et al. [43], Hadchum and Wongthanavasu [63], Khan et al [64]
	2017	Hsu et al. [70]
Global	2002	Lanitis et al. [71]
	2004	Lanitis et al. [72]
	2006	Ueki et al. [32]
	2007	Geng et al. [73], Fu et al. [31]
	2008	Guo et al. [46]
	2009	Geng et al. [74], Geng and Kate [74], Luu et al. [75]
	2010	Chang et al. [76], Zhang et al. [77]
	2011	Chang et al. [78]
	2013	Chao et al. [47]
	2016	Bukar et al. [79]
Hybrid	2008	Suo et al [80]
	2009	Guo et al. [39]
	2010	Luu et al. [81]
	2011	Choi et al. [40], Guo et al. [82]
	2013	Weng et al. [83], Tharwat et al. [19]
	2015	Gunay and Nabiyev [84], Huerta et al. [85]
	2016	Gunay and Nabiyev [86], Bekhouche et al. [49], Qiu [87]
	2017	Ng et al. [60], [6]

a highly redundant face image, and this can increase the prediction error. In addition, the personalized method for age estimation such as AGES and methods in [77], [74], [71] ccan improve the performance of age estimation. However, this method is limited because it is difficult to acquire sequences of facial images for a single person during aging process [43].

Although AAM considers shape and texture features, it produces a high dimensional feature vector; and this may contain an outliers in the age labeling space that may not directly reflect the identical age labels [47]. Some valuable parts of the data (such as wrinkles) that represent discriminatory features might have been lost during dimensionality reduction process [48].

Fu et al. [31] adopted the Manifold Learning Model for first time to estimate the age. Generally, in age manifold, an aging pattern can be learned from many subjects at various ages. Thus, many personal faces are needed to represent ages as each person may have images at specific age or in an age range.

Age manifold use manifold embedding technique like OLPP to learn an aging pattern in low dimension from numerous face images at each age. In this model, each subject may have images only at one age in the database. The authors claimed that this feature makes manifold model more flexible and easier to collect a big aging face database [5]. By using this model to solve age estimation problem, the age manifold is learned to map the original data into a low-dimensional subspace after a pre-processing steps, in training phase. A regression function then was defined to fit the manifold data for further testing. In the testing phase, an input face image is transformed to the learning feature as in training phase. The age is predicted through the learned manifold mapping and regression model fitting. To learn a low-dimensional manifold in the embedded subspace of image space, a projection function which can be linear or nonlinear might use. This model compared between four different algorithms that use linear methods for projection to manifold space: LPP, OLPP, NPP, and PCA. They found

that the OLPP achieved better performance than others. After finding the low dimensional manifold, an age estimation was defined as a multiple linear regression problem in the manifold space.

However, using manifold model required large size of training data to learn the embedded manifold [31], [5]. Another issue in this model is sensitivity to image mis-alignment caused by many factors, such as head rotation, different facial expression, and shape variations in facial growth and aging [14].

Luu et al. [75] introduced an age estimation technique using AAM and Support Vector Machines (SVMs). For each input face image I, 86 landmarks were determined and feature vector x_i with size 30 ×1 was extracted using AAM. SVM was used to train a binary classification module, which consists of two parts: classifier f(x) to differentiate between youths (0 - 20) and adults (21 to 69) and two aging functions: $f_1(x)$ as growth and development function and $f_2(x)$ as adult aging function. Finally, Support Vector Machine for regression (SVR) was used for age prediction. This algorithm outperforms the existing algorithms that used AAM by using the combination of binary classification and then age prediction.

In 2013 Chao et al. [47] adopted AAM for features extraction on their approach. After extracting feature using AAM, this approach added two steps: distance metric adjustment and dimensionality reduction to explore the relation between face features and age labels and mitigate the over-fitting problem in training the age prediction function. For this purpose, the Relevant Component Analysis (RCA) was applied for distance metric adjustment and LPP was used for dimensionality reduction. For age prediction, an age-oriented local regression named K Nearest Neighbors Support Vector Regression (KNN-SVR) was proposed. Although this approach achieved a good result, it used considerably additional functions which might increase the computational complexity.

In 2016 Bukar et al. [79] proposed supervised Appearance Model (sAM) for age and gender estimation that improves the AAM by using the partial least-squares (PLS) as the core of the model rather than PCA. They claimed that their proposed model (sAM) effectively represents the face features than AAM, whereas the PLS preserves worthy parts of the data that represent discriminatory features. PLS creates latent features via a linear combination of the predictor variables and response (class labels). Because sAM considers both shape and texture features, it was used as feature extractor in age estimation model, whereas ordinary least-square (OLS) and quadratic function (QF) regressions were used for age learning with QF showing better results than OLS. The sAM model represents the faces in a convenient way to solve both age and gender classification problems, but it does not outperform the methods that used AAM.

3) Hybrid-Based Algorithms: In various face related applications, the local and global features were combined as hybrid features to offer superior performance. Choi et al. [40] introduced hybrid features representation and hierarchical classifier to increase the age estimation accuracy. For local features extraction, a set of region specific Gabor filters were used to extract wrinkle features. LBP was used for skin features, and

AAM was used for global features extraction. SVM and SVR were used for age classification and age regression. However, the combination of extracted features using this three methods (Gabor, LBP and AAM) produced a high dimension feature vector which can increase the computation time.

Guo et al. [82] also used hybrid features for age estimation. They extracted global features using Active Shape Model (ASM) and both Radon projection and 2D-DCT for local features, where the facial image is converted into Radon space then 2D-DCT is used to obtain the features from this space. Finally, SVM and SVR was used for age estimation. Their results showed that Radon-DCT achieves better results on FG-NET, where the MAE is 4.18 years.

Gunay and Nabiyev [84], [86] conducted several experiments to estimate the age using different local and global methods to produce hybrid-based age estimation algorithms. In 2015 they proposed an age estimation method called "Global and Local feAture based Age estiMation (GLAAM)" that used AAM to extract global features and 2D-DCT for local features. PCA was applied to reduce the dimensionality after concatenating the local and global features. Finally, the age was estimated with multiple linear regression [84]. In 2016 Gunay and Nabiyev [86] repeated the experiment using different methods for local features. They applied Gabor filters to extract wrinkles and LBP for skin features, and applied PCA to reduce the dimensionality. Based on three types of features that were extracted (global, wrinkles and skin), Gunay and Nabiyev [86] modeled three aging functions separately with multiple linear regression, then they got the final decision by performing a decision level fusion to combine the results. They applied Gabor filter and LBP for local features to produce better result than 2D-DCT, where the MAE is 5.39 years for first experiment (AAM and 2D-DCT) and 4.87 years for second one (AAM, Gabor and LBP).

As mentioned above, wrinkle-based features are more effective for face representation. Based on this observation, and the fact that the hybrid based features can offering superior performance for age estimation, Ng et al. [60] proposed Hybrid Ageing Patterns (HAP) feature representation to increase the age estimation accuracy. HAP combines the proposed Multi-scale Wrinkle Patterns (MWP) and Facial Appearance Model (FAM). MWP is a wrinkle-based feature representation method based on the wrinkle statistics, and used a robust wrinkle detection method called Hessian Line Tracking (HLT) [89] to extract wrinkle. The multi-scale wrinkles was extracted from ten regions: forehead, glabella, upper eyelids, crows feet (or eye corners), lower eyelids (or eyebag), cheeks, nasolabial grooves (or nasolabial folds), upper lips, marionette and lower lips. Then the wrinkle intensity and wrinkle density were calculated to represent the pattern. FAM is a generative parametric model that combined shape and texture features. PCA is used in FAM to reduce the dimension. After extracting the features using MWP and FAM the hybrid pattern was constructed. Finally, SVR was used to estimate age from the patterns. HAP outperform the existing method on FERET and MORPH, where the MAE is 3.02 and 3.68 respectively. However, HAP does not achieved a good result on FG-NET, because the texture information is unclear in FG-NET images.

TABLE III
COMPARISON BETWEEN AGE LEARNING TECHNIQUES.

Category	Strength	Weakness
Classification	More appropriate for age range classification.	Not appropriate to predict the age. Class labels are uncorrelated.
Regression	Ability to predict age using a single estimator.	Does not consider the differences of age feature values according to age groups. It is difficult for regressor to learned a non-stationary kernels.
Hierarchical	The performance is improved by considering the differences of age feature values according to age groups.	The errors in the age group estimation step are propagated to the specific age prediction step when using an age group estimator with a hard boundary not including overlapped class.
Ordinal ranking	Preserve the relative order of age labels and provides more stable information than exact age values.	Time consuming.
Deep Learning	Do not require predefined or hand crafted features	Require large-scale data for training process.

Although the hybrid features can improve the performance of age estimation algorithm, it may increase the complexity and computation time for age estimation algorithms.

4) Summary: In general, different methods and algorithms can be effectively applied to estimate the age. Local features contains unique features that differentiate between age groups, so that it is suitable to handle age-group classification problem. On the other hand, individual characteristics might be more notable in global features, so that it is more suitable to predict the exact age. AAM can be recognized as a main model that extract the global feature, due to its ability to extract both shape and texture features. In hybrid features, Guo et al. [39] found that the performance of age estimation can be increased when combining BIF and manifold learning techniques. In addition to hybrid feature, using manifold learning techniques can reduce the dimensionality in BIF, while BIF addresses the problem of sensitivity to image mis-alignment in manifold learning techniques as it has the capability to deal with different changes in scale, translation and rotation.

More recently, researchers investigated the effectiveness of some appearance-based features and found that:

- Wrinkles can increase the age estimation accuracy [44], [60]. There is little research that focuses on age estimation based on wrinkles. However, most of them classified the age into groups rather than predict exact age.
- BIF, introduced by Guo et al. [41], achieved good results in age estimation. In 2017, Hsu et al. [70] proposed the Component Bio-Inspired Feature (CBIF) that achieved MAE of 3.38 on FG-NET.

B. Age Learning Techniques

As mentioned above, the existing facial age estimation methods consist of two phases: features extraction and age learning techniques. Once the features are extracted from the face images, learning technique is needed in order to classify or predict the age. In general, age learning techniques

can be classified into three groups: age groups classification, regression or single-level age estimation and hierarchical age estimation [40]. Other techniques include ordinal ranking and deep learning. For clarification, It is noted that the machine learning techniques for classification, regression, hierarchical and ordinal ranking are referred to as conventional machine learning methods (non deep learning approaches). We summarised the strength and weakness of these five categories in Table III and a detailed review of these five categories.

1) Classification: Classification is an approach used to classify the age into multiple age groups such as babies, young, middle-aged adults, or old adults [51], [52], [54], [55], [53], [32], [72], [106]. This section review the classification methods based on conventional machine learning algorithms such as SVM [107], Linear Discriminant Analysis (LDA) [68], Artificial Neural Networks (ANN) [54], nearest neighbor classifier [72] or distance measure [66] for age group classification. Table IV provides some early popular works based on classification more than a decade ago. The most notable work was by Guo et al. [41] who achieved MAE of 4.77 using BIF features on FG-NET. It is noted that they used both classification and regression approaches to learn age.

Ng et al. [48] developed ANN with three layers: input, hidden and output to classify the age into two groups and applied their proposed method to investigate the effectiveness of wrinkles in age classification, which called Local Wrinkle-based Extractor (LOWEX) that used Canny edge detection to detect the wrinkles from different face regions. Their proposed method with ANN achieved 80% on FG-NET. Im et al. [108] extracted wrinkles feature using Gabor filter and applied SVM for age classification. Their experiment was tested on private data with average accuracy of 76.92%. In 2017, Iqbal et al. [109] proposed local descriptor called Directional Age-Primitive Pattern (DAPP) and applied SVM to classify the age into 7 groups. They achieved accuracy of 73.1% on data collected from flickr.com.

In classification, the class labels are uncorrelated and each

TABLE IV
COMPARISON BETWEEN DIFFERENT FACE AGE ESTIMATION ALGORITHMS ORGANISED BY MACHINE LEARNING TECHNIQUES AND DATABASE (PART I).
TO CLARIFY, THE MACHINE LEARNING TECHNIQUE FOR CLASSIFICATION AND REGRESSION ARE REFERRED TO CONVENTIONAL MACHINE LEARNING
ALGORITHMS.

Machine Learning Technique	Database	Algorithm	Feature Extraction Method	MAE	CS (0-10) (%)	Accuracy (%)
Classification	FG-NET	Mohan et al. 2010 [90]	Topological Texture Features (TTF)	-	-	**94.1**
		Wang et al. 2010 [91]	ASM+BIF	-	-	90
		Liu et al. 2012 [92]	AAM	-	-	79.2
		Zheng et al. 2013[93]	LBP	-	-	74.60
		NG et al. 2014 [48]	LOWEX	-	-	80
	MORPH	Zhou et al. 2011 [94]	Radon transform	-	-	~87
		Mirzaei et al. 2011 [95]	LBP	-	-	67.23
	FERET	Gunay et al. 2008 [66]	LBP	-	-	80
	web data	Gao et al. 2009 [68]	Gabor Filter	-	-	91
		Gao et al. 2009 [68]	LBP	-	-	84.6
Regression	FG-NET	Geng et al. 2007 [73]	AGES	6.77	~ 81	-
		Guo et al. 2009 [41]	BIF	4.77	~ 90	-
		Chao et al. 2013 [47]	AAM	4.38	~ 90	-
		Gunay et al. 2015 [84]	AAM + 2D-DCT	5.39	-	-
		Wang et al. 2015 [96]	deep learned aging pattern (DLA)	4.26	~ 90	-
		Ng et al. 2017 [60]	HAP	5.66	-	-
	FERET	Ng et al. 2015 [44]	multi-scale aging patterns (MAP)	4.87	-	-
		Ng et al. 2017 [60]	HAP	**3.02**	-	-
	MORPH	Lu and Tan. 2010 [97]	cost-sensitive locality preserving projections (CSLPP)	4.24	-	-
		Huerta et al. 2015 [85]	HOG + LBP + SURF	4.25	~ 90	-
		Ng et al. 2017 [60]	HAP	3.68	-	-

label is independent from each others. However, there is strong interrelationships between labels, and the age labels is well-ordered in reality. For example, a person with 12 years old is more likely to be 11 or 13 years old. However, classification approaches do not reflect this property.

2) Regression: Regression approaches consider age label as a set of sequential numbers (e.g., 10, 11, 12,...). This sequence fits the ordinal nature of age label. This is a very popular age learning technique it includes many methods that can be used for regression such as SVR [46], Quadratic Regression [72], Multiple Linear Regression [84], and Multilayer Perceptron (MLP) [110]. Since 2007, Geng et al. [73] has achieved MAE of 6.77 years on FG-NET using facial appearance features. Fu et al. [31] applied multiple linear regression for age estimation after finding the low dimensional aging manifold using manifold embedding technique like OLPP. Later on, Guo et al. [46] used the manifold model to improve their work by using Locally Adjusted Robust Regression (LARR), which applied global and local steps respectively to learn the data. In the global learning, SVR was used for regression over all ages of the training data. Then a local adjustment within a limited range of ages centered at the regression result, where

the linear SVM was used for local age adjustment. LARR produced MAE of 5.07 on FG-NET.

Guo et al. [39], [111] studied the effect of gender and race on age estimation. They applied different classifier and regressor to perform the gender, race and age estimation. However, these tasks were performed separately in different steps, where the gender or race classification was performed first, then the age was estimated within different class. To improve this work, in 2011, Guo et al. [112] proposed a kernel partial least squares (KPLS) regression algorithm for age estimation. KPLS have a flexible output vector that allows to overcome a number of related classification problems such as race, gender and age. It contains multiple labels in a same output vector. In addition, KPLS performs dimensionality reduction and learns the aging function in a single step. In this framework, KPLS was used to classify race, gender and estimate the age in single step. This age estimation method achieved MAE of 4.18 on MORPH.

In 2013, Chao et al. [47] proposed an age estimation algorithm using KNN-SVR. The authors claimed that the local regression function is more likely to overcome the problem of complicated facial aging. The MAE was 4.38 on FG-NET.

TABLE V
COMPARISON BETWEEN DIFFERENT FACE AGE ESTIMATION ALGORITHMS ORGANISED BY MACHINE LEARNING TECHNIQUES AND DATABASE (PART II).
THE MACHINE LEARNING TECHNIQUE FOR HIERARCHICAL AND ORDINAL RANKING ARE REFERRED TO CONVENTIONAL MACHINE LEARNING
ALGORITHMS.

Machine Learning Technique	Database	Algorithm	Feature Extraction Method	MAE	CS (0-10) (%)	Accuracy (%)
Hierarchical	FG-NET	Luu et al. 2010 [81]	AAM + Local Ternary Patterns (LTP)	4.23	∼ 91	-
		Choi et al. 2011 [40]	AAM + LBP + Gabor Filter	4.65	∼ 91	-
		Li et al. 2012 [98]	ASM+LBP	4.32	∼	-
		Han et al. 2013 [25]	BIF	4.6	-	-
		Hsu et al. 2017 [70]	CBIF	3.38	-	-
		Ren et al. 2014 [99]	Scale Invariant Feature Transform (SIFT) + HOG + Gabor	4.49	-	-
	MORPH	Han et al. 2015 [24]	BIF	3.6	-	-
		Liu et al. 2015	BIF + HOG + LBP	2.97	∼ 95	-
		Pontes et al 2016	Local Phase Quantization(LPQ)	5.86	∼ 85	-
		Hsu et al. 2017 [70]	CBIF	**3.21**	-	-
	PAL	Ren et al. 2014 [99]	SIFT + HOG + Gabor	4.29	-	-
Ordinal Ranking	FG-NET	Yan et al. 2007 [100]	AGES	5.33	∼ 85	-
		Chang et al. 2010 [76]	AAM	5.79	∼ 85	-
		Chang et al. 2011 [78]	AAM	4.48	∼ 90	-
		Liu et al. 2016 [101]	AAM	4.14	-	-
	MORPH	Weng et al. 2013 [83]	PCA+LBP+BIF	4.20	∼ 95	-
		Chang et al. 2015 [43]	ST	**3.82**	-	-
Deep Learning	MORPH	Huerta et al. 2015 [85]	Deep Learning	3.88	-	-
		Niu et al. 2016 [102]	Deep Learning	3.27	∼ 95	-
		Liu et al. 2016 [103]	ASM	3.48	-	-
		Niu et al. 2016 [102]	Deep Learning	3.34	∼95	-
		Chen et al. 2017 [104]	Deep Learning	2.96	97	∼ 97
		Liu et al. 2017 [105]	Deep Learning	3.12	∼ 96	-
		Hsu et al. 2017 [70]	CBIF	**2.58**	-	-

Recently, Ng et al. [60] applied SVR with their proposed feature descriptor Hybrid Aging Patterns to estimate the age. They achieved a MAE of 3.02 on FERET. In 2017, Ng et al. [6] proposed a Multi-layer Age Regression (MAR) approach to estimate the age, consisting of two layers. Both layers produced a real number in output rather than class labels. FAM was used to extract the features in the first layer. FAM, BIF, KLBP and MWP were used to extract the features in second layer, then SVR was used for age prediction. Their experiment was validation on four dataset, i.e. FG-NET, MORPH, FERET and PAL. The best result was MAE of 3.00 on FERET. When compared this approach with LARR and Probabilistic Fusion Approach (PFA) [46], [113], PFA and LARR outperformed on FG-NET with the MAE of 4.97 and 5.07 respectively. PFA and LARR applied SVM rather than SVR in the second layer, and treat each age value in the age group as a class label.

Table IV summarises the research and validation mainly on three popular datasets (FG-NET, MORPH and FERET). The strength of regression is its ability to predict age using a single estimator. However, the personalized property in aging process produces non-stationary feature space, which is difficult for regressor to learn non-stationary kernels [78].

3) Hierarchical: Hierarchical age estimation combines the classification and regression methods to predict age. It provides more accurate result and simplifies the computational load, where the data was firstly classified into age groups, then the age was predicted from these pre-defined groups [40]. Choi et al. [40] applied age group classification followed by age regression to predict the age using SVM and SVR respectively. The hybrid features were extracted using AAM, LBP and Gabor. By using this combination of hybrid and hierarchical approach to predict the age, the MAE was 4.6 on FG-NET. Han et al. [25] also applied SVM and SVR, where SVM was used to classify the age into four groups after extracting features using BIF. Within each group, SVR was used to predict the age. In order to reduce the age classification error that produced from strict group boundaries, they used training samples for regression with distance up

to 5 years between age groups. The MAE was 4.6 and 4.2 on FG-NET and MORPH respectively. Later, Han et al [24] improved their work and proposed a generic framework for gender, race and age estimation. In this framework, in order to fix the problem of low-quality images, they applied a quality assessment method to preprocess the images before extracting features. After preprocessing, the same steps and methods used in a previous work [25] were applied for classification and regression. The MAE was reduced by approximately 1 year for both datasets, with MAE of 3.8 on FG-NET and MAE of 3.6 on MORPH.

Li et al. [98] used Sparse Representation-based classification (SRC) algorithm to classify the age into two groups using the shape feature. The texture feature was concatenated with the shape feature and applied the Ordinal Hyperplane Ranker to estimate the age accurately. The MAE was 4.32 on FG-NET. Angulu et al. [114] used ANN to classify the age into 6 groups then applied SVR to predict the age within these groups, after extracting the features using Multi-Frequency Biologically Inspired Features (MF-BIF). They achieved MAE of 4.02 on FG-NET. In 2017, Hsu et al. [70] performed the age classification and regression using traditional SVM and SVR after extracting the features using Component Bio-Inspired Feature (CBIF). To reduce the classification error produced from strict age boundaries, they proposed moving segmentation method to find the age boundaries that can improve the accuracy. After applying the moving segmentation window, they found that the best age boundaries on FG-NET was at 11, 28 and 38 year, and the age boundaries on MORPH were at 29, 44 and 60 year. Based on their experiments, they found that the number of age groups in classification step have notable effect on the overall performance. The MAE was 3.38 on FG-NET and 3.21 on MORPH using 4 groups in classification step.

4) Ordinal ranking: Recently, there has been growing interest in age estimation to **ordinal ranking** (also called ordinal regression) due to the diversity in human aging processes at different age range. Hence, given two labels x_1 and x_2, the "greater than" information ($x_2 > x_1$ or $x_1 > x_2$) is more reliable property for age estimation than the differences between the labels; and provides more stable information than exact age values. Ordinal ranking is built like when we ask a human "Who is the older between two people?". It seems easy to answer this question than asking people to predict the person's age. In ranking approach, the input face is compared with the known age faces from the database. This produces a series of comparisons. Age can then be estimated by integrating the results from these comparison. The age labels l_i is treated as a rank order $l_i \in \{1, ..., x\}$ where x is the labels number. Based on a given x, the dataset D was separated into two subsets $\{D_x^+ \text{ and } D_x^-\}$ as in equation (3).

$$D_x^+ = (d_i, +1)|l_i > x$$
$$D_x^- = (d_i, -1)|l_i < x \qquad (3)$$

These two subsets were used to learn the binary classifier and answer the query "Is the face older than age x?"; then making positive or negative decisions between the two sides (as a binary decision). By using these processes the age estimation task was reduced to a binary classification problem (any classification algorithm can be used as the binary classifier) at each query. Ordinal relationships between the age labels can then be recognized from a series of these query results.

Chang et al. [76] applied the ordinal ranker approach for age estimation in their work. They improved the work in [115], [76] and [116]. In [115] RankBoost algorithm applied cannot reflect the multiple thresholds of different classes properly due to the use of single hyperplane ranker in the feature space. On the other hand, parallel hyperplanes in [76] is more suitable when the database contains small number of classes. The RED-SVM used in [76] constructs $K-1$ parallel hyperplanes that separate the hyperspace into K ranks by using $k-1$ thresholds. However, it is difficult to separate data using parallel hyperplanes when predicting the exact age as the k is always large. The Multiple Hyperplanes Ranker used in [116] overlooks some potentially valuable cues provided by a well ordered set of labels. To overcome the limitations in previous work that used ranking approach, Chang et al. [76] introduced an ordinal hyperplanes ranker (OHRank), which aggregates $K-1$ binary classifiers based on the order of labels, after extracting the features using AAM. OHRank achieved 4.48 MAE on FG-NET.

5) Deep Learning: More recently, convolutional networks and deep learning approach have been successfully applied to several tasks related to facial analysis, including face alignment [117], face detection [118], face verification [119], facial skin analysis [7], and demographic estimation [120] to estimate the age and gender and to address face recognition problem. Later, many researchers implemented deep learning for age estimation [121], [122], [85], [123], [87], [124], [96], [125], [126], due to its superior performance over existing methods.

Generally, the basic methodology in deep learning approach is similar; it consists of alternating convolutional and pooling layers followed by fully-connected layers with the input to successive layers being the feature maps from previous layers. Weights in layers are changed simultaneously for representative features and classification with a specific loss function through back-propagation. The key of success in this approach is the accurate choice of parameters found in different layers [85]. However, deep learning requires a huge amount of data for training process.

Deep learning was introduced by Wang et al. [96] for a first time to solve age estimation problem. Their CNN architecture consists of three convolution layers, two pooling layers and full connection layer. Wang et al. [96] yield good results on FG-NET and Morph. However, this CNN was used to represent the features then traditional linear SVR was applied for age prediction.

In 2016, Rothe et al. [124] proposed CNN called DEX based on VGG-16 architecture CNN [127]. VGG is much deeper CNN with small size for filters. DEX was pre-trained on the ImageNet [128] for image classification and fine-tune on the images from IMDB-WIKI dataset introduced by Rothe et al. [124]. Their experiments on MORPH yield MAE of 3.25. Rothe et al. [124] improves this result by fine-tuning the
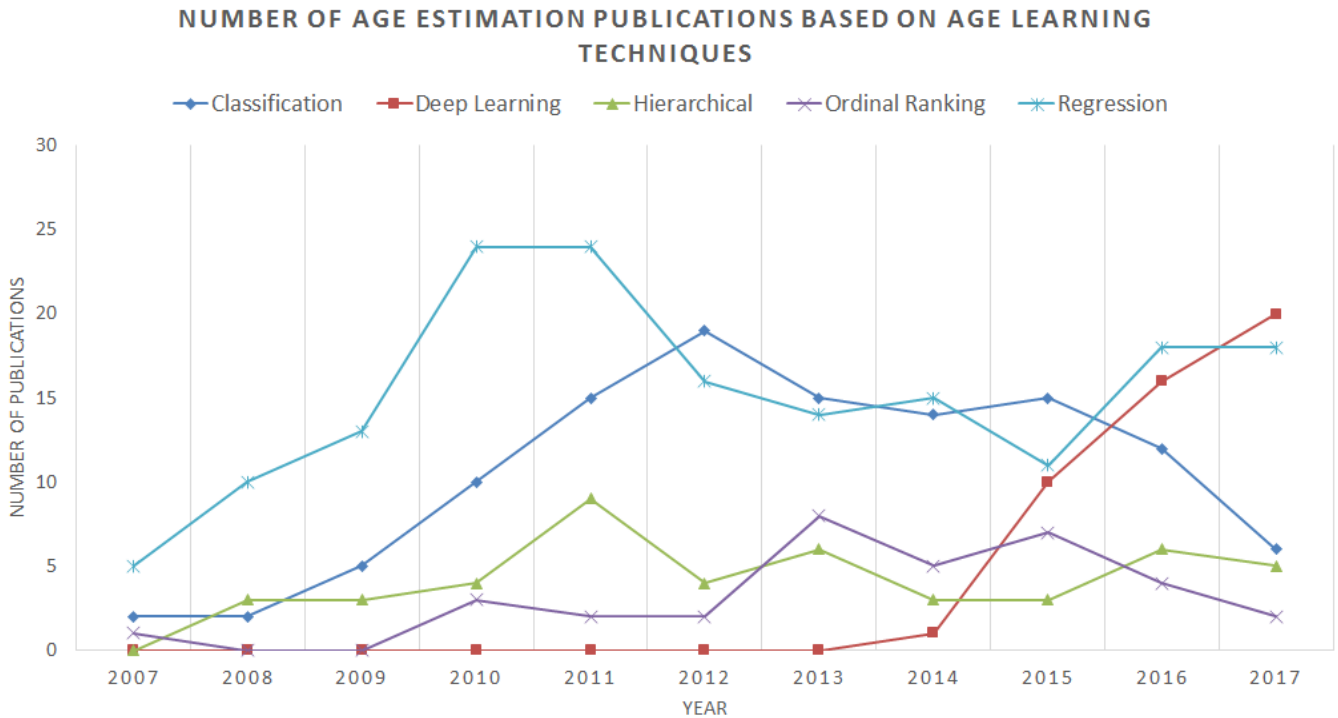
Fig. 2. Illustration of the age estimation publications based on five age learning techniques over the past 10 years. There was an increase of classification and regression methods until 2012. With the growth of deep learning, it is expected that the number of publications using deep learning has a rapid growth from 2014.

CNN on IMDB-WIKI before fine-tuning on the MORPH, this resulted MAE of 2.68 years. DEX achieved 4.63 on FG-NET without fine-tuning on IMDB-WIKI and 3.09 when fine-tuning on IMDB-WIKI before fine-tuning on FG-NET.

Niu et al. [102] proposed CNN called OR-CNN (Ordinal Ranking-CNN) to address age estimation problem consists of 3 convolutional, 3 normalization, and 2 pooling layers followed by a fully connected layer. They used binary ordinal age labels to train a series of basic CNNs, one for each age group. The binary results then are aggregated for the final age prediction. They claimed that the ranking method is preferred for age estimation as it produces smaller prediction error than softmax classifier,because softmax does not consider the ordinal relation between ages. Their experiment on MORPH achieved 3.27 years for MAE and 3.34 years using Asian face age dataset.

In 2017, Chen et al. [104] also proposed a Ranking Convolutional Neural Network (Ranking-CNN) framework. Ranking-CNN consists of three convolutional and sub-sampling layers, and three fully connected layers.. Ranking-CNN outperforms the existing methods for age estimation where the MAE is 2.69 years on MORPH. Table V summarises the deep learning methods on MORPH dataset. It is noted that the researchers preferred MORPH to FG-NET due to the dependency of deep learning on large-scale database.

Figure 2 compares the number of publications over the past decades based on our review. It illustrates the popularity of classification and regression techniques for age learning. However, from 2014, due to the rapid growth of deep learning,

researchers started to explore and invest their time on deep learning technique.

6) Summary: In age learning, ordinal ranking and deep learning algorithms have recently demonstrated great success in handling age estimation problem. Ordinal ranking provides more stable information using a relative order of age labels. Due to the lack of face aging datasets, deep learning was used as features extractor (off the shelf CNN) [122], [96], [125] or fine-tuning the CNN with different datasets [121], [124], [123], [129].

V. CONCLUSION AND FUTURE DIRECTIONS

A comprehensive survey on the state-of-the-art techniques for face age estimation was presented in this paper, including the new age learning technique that significantly improved the age estimation accuracy. In general, there are many factors that affected the overall performance of automatic age estimation, i.e. database, number of face images used for training, pre-processing and face alignment step, feature extraction method and the type of age learning technique.

In order to estimate the age accurately, the design of age estimation system requires careful selection of the face feature. To do so, Gunay et al. [84] stated some issues that need to take into consideration:

- Robust discriminative aging features extraction method is needed, to reduce the negative effect of individual variations.
- Face feature must be extracted from raw face images directly to speed up processing.

- To facilitate the implementation of the classifiers, extracted face feature must lie in a low dimensional space.
- Minimization of the computational costs using suitable image size.

To conclude, we suggest some future directions for face age estimation as follow:

- Web collected images are an efficient way to collect a huge amount of images to establish face aging database, with balance in distribution of age, gender, ethnicity, expression, and pose. Developed web applications to collect images from internet [130] can facilitate the collection process. Large-scale database will have a positive impact on the performance of automatic age estimation system.
- Implementation of general framework that considers most of the factors affecting the performance of age estimation.
- In feature combination, finding a fusion strategy such as feature pooling [85] can produce more accurate results than just concatenating the features in hybrid approach.
- Combination or fusion of methods produces better result, e.g., combining wrinkle features with other local and global features [44], [60]. A similar strategy can be applied for scattering transform [43]. Combining deep learning, ordinal ranking and CBIF will produce superior result for age estimation. By combining these new techniques, the machine may outperforms the ability of human in face age estimation.

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