A Literature Review on Facial Age Estimation Researches

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Abstract—**Face is the unique characteristic of humans that distinguishes between individuals. Every feature on the face can be analyzed to produce demographic information such as gender, age, race, etc. Any such information can be estimated through an automated process, including age. Age estimation through facial images is one of the areas that is still being pursued to deliver accurate values. To better understand facial age estimation, this paper will discuss several things regarding age estimation. First, the factors that can affect the accuracy of predictions, second, the methods used to estimate the age, and then various databases of facial images and information of age at which the picture was taken, and also the parameters that commonly used to measure the accuracy of the estimation results. This review also provides a summary regarding some researches already conducted in age estimation. In the conclusion section, there is a brief about future work that could be done, along with the reason why such research needs to do**

Keywords—age estimation, facial feature, deep learning, CNN

I. INTRODUCTION

Human age is one of the demographic information that uses in many fields. So, in the information technology field, many studies are being conducted so that the age estimation process can be carried out automatically and results in a higher level of accuracy. There are various examples of the use of age estimation applications: (1) controlling a person's access to a specific product or content, (2) age synthesis, which is commonly used for finding missing people, (3) electronic customer relationship management (ECRM) needed to improve customer experience, etc. [1].

Age estimation can be done through some aspects of the human body, e.g., face. The human face is part of the human body that contains many demographic identities [2]. Besides, the face is a unique part of a human that can distinguish each individual. The facial feature depends on ethnicity, gender, expression, etc. Because of these aspects, age estimation still something with significant challenges and continues to be studied to get better performance. The research in this field has even been conducted in 1994 by Kwon and Lobo [3] until these days.

To understand the facial age estimation system generally, so this paper provides a literature review from previous relevant researches. This paper will explain the factors that influence the age estimation process, the methods used, the database, and the performance evaluation indicators of the age estimation system.

This paper consists of six sections. Section II will explain regarding affecting factors/challenges in the human age estimation process. Section III shows the general process and method of age estimation. Several databases that can be utilized to develop an age estimation system will be explained in section IV. Section V defines the parameters to measure age estimation accuracy. Section VI gives the conclusion.

II. AFFECTING FACTORS ON AGE ESTIMATION SYSTEMS

In general, the age estimation process steps are divided into two parts, namely feature extraction and estimate the age. Without feature information, the estimation process cannot occur. The types of features on the human face can be divided into two types, namely global features and local features [1]. Local features include aging spots, depth, and amount of wrinkles, and geometry features. Local features are generally used to predict age groups, such as childhood or adulthood, where the adult phase typically owns wrinkles. Based on Aznar-Casanova *et al.* [4], the higher the intensity of lines on the face, the older the person is. Figure 1 shows eleven wrinkle regions on the human face defined in Lemperle *et al.* [5] research. While global features are more suitable for use in research with exact age targets. Besides aging information, the face can describe other characteristics such as gender, ethnicity, and expression [6].

Here are some challenging aspects of the facial age estimation system:

1. The distribution of the number of samples for each age is not balanced [1] [7]

2. Large variations of image conditions [7] [8] [9] [10] such as noise, various resolution, head pose, lighting, expressions

3. Inadequate dataset related to image availability per subject in wide age range [9]

4. The aging process of human face depends on many factors such as pollution, lifestyle, disease, etc. [11]

5. The human face is also affected by gender, race, and other attributes [12]

Based on previous researches, the age estimation process using deep learning models can produce lower error values than other techniques [1]. Several factors contribute to the accuracy of the resulting model:

1. The model generated from a constrained database can produce smaller errors than an unconstrained database

2. Modeling that is made with additional attributes such as gender and race is generally more accurate than single input such as image only

3. The choice of CNN architecture also determines the accuracy of the model, where the more in-depth the CNN, the higher the accuracy obtained

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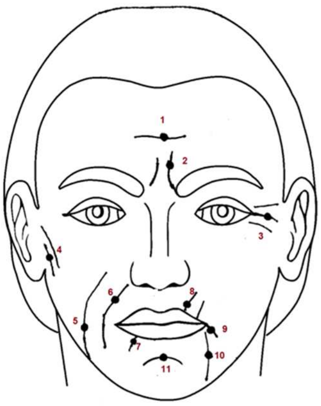
4. The wider the age range and the more balanced the sample image for each age in the training set, the better the model obtained

5. Variation of training sets, one technique to increase training variation is data augmentation

6. Preprocessing steps, such as face detection and face alignment, can improve the accuracy of the model



1. Horizontal forehead lines
2. Glabellar frown
3. Periorbital lines
4. Preauricular lines
5. Cheek lines
6. Nasolabial folds
7. Lower radial lip lines
8. Upper radial lip lines
9. Mouth corner lines
10. Marionette lines
11. Labiomental crease

Fig. 1. Eleven wrinkles region [5]

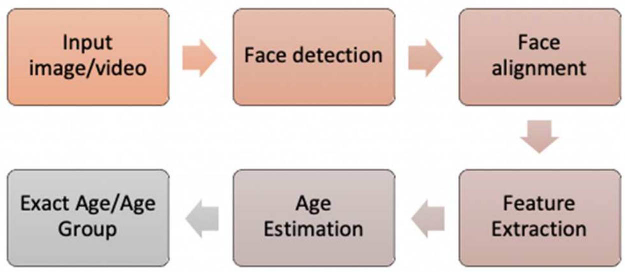


Fig. 2. Age Estimation System

III. Age Estimation Method

Broadly speaking, the age estimation system process sequence can be described, as shown in Figure 2. As written in [6] and explained in the previous section, the main processes in an age estimation system are grouped into two steps, namely feature extraction and estimate the age. Face detection steps are carried out to ensure that the image that will be used as input is the focus of any face object. Meanwhile, face alignment is a technique to improve the accuracy of the estimation results. Results of face detection and face alignment are shown in Figure 3. Face image used in figure 3 is one of image in AgeDB database. However, not all face images can be aligned because not all face detection results have the complete face landmarks required for alignment, such as the center point of the eyes.

Feature extraction is intended to get features that exist from each input image while estimate the age aims to calculate or classify age as the final result of the estimate. Estimation results can be either the exact age or age group. Figure 4 summarizes the method that can be applied in the age estimation system.

(a) (b) (c)

Fig. 3. Input image (a), face detection (b), and face alignment (c)

A. Feature Extraction

Feature extraction can be done either by manual rule and algorithm [3] [13] [14] [15] or using deep learning [16] [17] [18] [19] [20]. Based on previous relevant researches, feature extraction that uses deep learning gives better performance. And recently, research on age estimation has focused mostly on this method.

The first research about facial age estimation was conducted by Kwon and Lobo [3]. This research presented age group classification (baby, young adult, senior adult) by combining facial feature ratios and wrinkles. Ali *et al.* [13] aimed to classify age into three groups: 10-30, 30-50, and 50+. Their research uses biometric ratios and wrinkles analysis in three areas: forehead, eye corners, and cheeks. To detect wrinkles, they used Canny Edge Detection. Hayashi *et al.* [14] also estimated age based on lines and color of facial images. They used DHTH (Digital Template Hough Transform) to get all wrinkles (shorter and longer) on the faces. In 2020, Hasan and Mahdi [15] adopted Local Binary Pattern (LBP) for features production and Feature Selection Method (FSM) for feature selection.

Yang *et al.* [17] used a Convolutional Neural Network (CNN) to training the dataset to get the estimated age. Before training, face alignment is carried out on each input image. Wan *et al.* [16] proposed a framework for age estimation system by utilizing other demographic information (i.e., gender and race). This research also uses CNN to create a model for estimating the exact age. Dong *et al.* [18] developed a new algorithm for automatic age-group estimation. They use pre-trained and fine-tuned Deep Covnets to extract high-level features from all images in the training dataset. In 2019, Xie and Pun [19] created the framework to estimate human age using age-related facial attributes. In their experiments, they used pre-trained CNN (i.e., VGG-16 and AlexNet). Research on facial age estimation based on facial expressions is scarce. Therefore Pei *et al.* [20] developed the Spatially-Indexed Attention Model (SIAM) with the CNN method to build a model for age prediction using dynamic facial expressions from a video as input.

B. Estimating the Age

After obtaining the feature from each image input, the next step is to classify the element to produce an estimated value, in this case, age. In general, the techniques used in age estimation process are divided into four, namely classification, regression, ranking, and hybrid.

TABLE I. STRENGTH AND WEAKNESS OF AGE ESTIMATION METHOD [1][3][10][12]

Process		Strength	Weakness
Feature extraction	Manual rule/algorithm	Can be used to estimate age even though the sample of image is only a few	The features to be analyzed must be defined first
	Deep learning	- The facial feature for age estimation can be extracted automatically without having to be defined first - Generally, resulting in a lower age estimation error	Requires a large number of sample images
Age Estimation	Classification	Suitable for cases with a small number of classes, so this method can be used to estimate age with the target age group	- Each age group must have a large number of samples so that they can be easily divided into training sets and validation sets - Not suitable for cases with target exact age
	Regression	This technique is more suitable for age estimation cases with target exact age rather than classification. Because age is a continuous variable in nature.	More sensitive than other techniques to imbalance sample images of each age in the training set
	Ranking	- Less sensitivity than classification and regression regarding the imbalance of training set in each age - Utilize the gap between age to improve the performance of age estimation	Less accurate than other techniques
	Hybrid	- Combining classification and regression, so it provided more accurate performance than classification - Because the last step using regression, so it can be used to estimate exact/real age - Can be used to enhance the estimation by using fusion input such as race and gender as additional variables	It is more complicated than regression or classification as it is a combination of two approaches

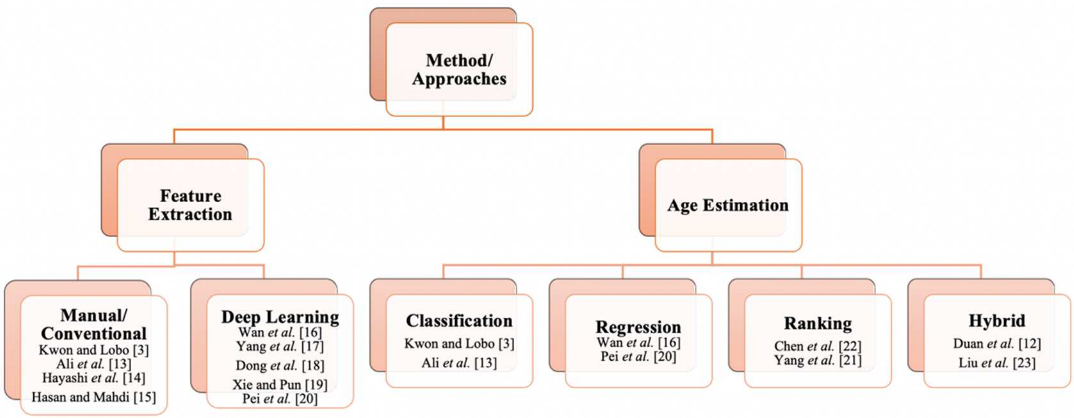


Fig. 4. Choice of methods or approaches in age estimation

The classification approach is a technique in which the age or age group is considered a class. To use this approach, it must be determined in advance how many classes you want. Kwon and Lobo [3] classified facial images into three classes (e.i. baby, young adult, and senior adult). Ali et al. [13] also used the classification approach. In their research, they used three classifiers (i.e., Naïve Bayesian, Decision Trees, and k-NN)

In the regression approach, age is considered a numerical value [1]. Wan et al. [16] and Pei et al. [20] treated age estimation as a regression problem. They used linear regression to obtain the exact age.

The ranking approach is suitable for answering questions such as "Who is the older between A or B?" or "Is A younger than x years old?" [10]. This approach was first introduced in the study by Yang et al. [21], which is intended to overcome the shortcomings of the classification and regression method to better reflect the human aging process. Chen et al. [22] proposed a novel deep-ranking framework named ranking-CNN for age estimation.

A hybrid is an approach that combines classification and regression. Liu et al. [23] and Duan et al. [12] used hybrid approach to estimate age value. They used classification as an additional process that can strengthen predictions using regression.

IV. FACIAL AGE DATABASES

A database is needed as a supporting instrument to research facial age estimation. The database used at least has information in the form of facial images and age. The larger the sample size, the more attributes available, and the more diverse databases used, it can produce a more accurate estimate value. In general, databases can be grouped into two types, namely constrained and unconstrained databases [1]. The database constraint is a database consisting of frontal and upright facial images. On the other hand, the unconstrained database includes facial images with various conditions, non-frontal faces, or tilted head poses. Table II is a summary of several databases that can be used in research on age estimation.

AgeDB [24] is an unconstrained dataset consisting of 568 subjects with a total of 16488 images (6700 females and 9788 males). Each photo is equipped with a description in the form of gender, names of subjects, and age. The available age attribute is the exact age with a range of values from 1 to 101, so this database can be used for research with an estimated target of a single age.

Morph II [25] is the second album of Morph database compiled from 2003 to 2007. This database contains more than 55 000 images (46,645 males and 8,489 females) of about 13,000 subjects. Apart from information regarding age (from 16 years to 77 years), this database also has additional information such as gender, race, date of birth, and date of the photo was taken.

The FG-NET [26] database provides 1,002 unconstrained facial images from 82 subjects. This dataset contains images with ages range from 0 to 69 years. Because of that, it can be used for developing an exact age estimation system.

UTKFace [27] is a database that provides face images with age range from 0 to 116 years old, where each image only has a single face. It consists of more than 20,000 images that are equipped with gender, ethnicity, age, and the date and time labels of each image were collected.

IMDB-WIKI [28] is a database of 523,051 images of celebrities that were crawled from IMDb and Wikipedia. The range of ages for this database is from 0 to 100 years old. Additional information that can be obtained from this database is gender, age, and name of celebrity.

ChaLearn 2015 [29] database consists of 4,699 unconstrained images where each image contains a single face. The database is divided into three parts: 2,476 training dataset, 1,136 validation, and 1,087 testing images. This database has a 3 to 85 years old age range.

The Cross-Age Celebrity Dataset (CACD) [30] provides 163,446 images of celebrities with different ages. Each image contains information such as the name of fame, date of birth, age, and estimated year of which the photo was taken. The age range of this database is from 16 to 62 years.

The Asian Face Database (AFAD) [31] consists of more than 160,000 facial images of Asians with age labels. AFAD has 63,680 female photos and 100,752 male photos with age range from 15 to 40.

The availability of databases that can be used for age estimation is very diverse. However, each database has its drawbacks. Although there are some databases with a wide range of ages, the distribution of the samples for each age is not balanced, causing bias in the estimation results. To overcome each database's shortcomings, researchers can combine existing databases by preprocessing each image from the database that will be used. Preprocessing can be done by cropping each image so that training can focus more on facial features, then ensuring that the image file name structure is uniform.

V. FACIAL AGE ESTIMATION PERFORMANCE EVALUATION

For measuring the performance of the age estimation system that has been built, a quantitative evaluation parameter is needed that can provide a value for the accuracy of the prediction results. In general, two parameters can be used, namely, Mean Absolute Error (MAE) and Cumulative Score (CS) [1]. Among these two parameters, MAE is the parameter most commonly used in previous studies.

A. MAE

MAE is the absolute mean value of the difference between the actual age and the estimated age. The smaller the MAE value indicates that, the better the system that has been developed [22].

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|e_n| \tag{1}$$

where N is the sample size of testing set, $e_n = \hat{y}_n - y_n$ is the difference between ground truth age of the n-th sample (y_n) and estimated age value of n-th sample ($\hat{y}_n$)

B. CS

CS is an evaluation parameter that applies a tolerance value (±d years), so if the estimated age (y̑) ranges between y+d years and y-d years, where y is ground truth age, so the estimation results can be accepted [36]. CS can be defined as in (2):

$$CS(d) = \frac{N_d}{N} x100\% \tag{2}$$

where N is the sample size of testing set, N_d is total samples that have value of $\hat{y}$ between $y \pm d$ years.

In a system that has a target in the form of age group/classification, the CS formula can be defined in (3):

$$CS(a) = \frac{n_a}{N_a} x100\% \tag{3}$$

where N_a is a total of testing samples that belong to age group a and n_a is total of testing samples that has estimated value in range of age group a.

TABLE II. SUMMARY OF DATABASES

Name	Total of Images	Total of Subjects	Age Range	Database Type	Additional Information
AgeDB [24]	16,488	568	1-101	unconstrained	6,700 females, 9,788 males
Morph II [25]	55,134	> 13,000	16 - 77	constrained	46,645 males and 8,489 females
FG-NET [26]	1,002	82	0 - 69	constrained	
UTKFace [27]	> 20000	N/A	0 - 116	unconstrained	gender, ethnicity, and datetime of each image was collected
IMDB-WIKI [28]	523,051	> 20,000	0 - 100	unconstrained	
ChaLearn 2015 [29]	4,699	N/A	3 - 85	unconstrained	
CACD [30]	163,446	2,000	16 - 62	unconstrained	name of the celebrity, date of birth, and estimated year of which the photo was taken
AFAD [31]	> 160,000	N/A	15 - 40	unconstrained	63,680 females and 100,752 males

TABLE III. SUMMARY OF AGE ESTIMATION RESEARCHES

Research	Database Type	Database	Algorithm	Input	Target	MAE (tahun)	Accuracy (%)
Kwon and Lobo 1994 [3]	constrained	Private dataset (with 47 images)	Snakelets + classification	Face image	Age group	-	100
Geng et al. 2007 [36]	constrained	FG-Net	AGES (Aging pattern Subspace) + classification	Face image	Age group	8.83	70
Choi et al. 2011 [6]	constrained	BERC, PAL, FG-Net	AMM, Gabor, LBP + hybrid	Face image	Age group	4.7, 4.3, 4.7	65, 70, 73
Ali et al. 2015 [13]	constrained	Private dataset (with 885 images	Canny edge detection + classification	Face image	Age group	-	62.86 - 72.48
Dong et al. 2015 [18]	unconstrained	IoG	Deep ConvNets + classification	Face image	Age group		56
Niu et al. 2016 [31]	constrained	Morph II, AFAD	Ordinal regression CNN	Face image	Real age	3.27, 3.34	-
Li et al. 2017 [7]	constrained	Morph II	D2C learning + regression	Face image	Real age	3.06	-
	unconstrained	WebFace				6.04	
Liu et al. 2017 [9]	constrained	FG-Net, Morph II	Group-aware deep learning (GA-DFL) + ranking	Face image	Real age	3.93, 3.25	-
Duan et al. 2018 [12]	constrained	Morph II	CNN2ELM + hybrid	Face image, gender, race	Real age	2.61	-
	unconstrained	Adience				-	66.49
Rothe et al. 2018 [28]	constrained	Morph II, FG-Net	Deep-Expectation (DEX), VGG16 + classification	Face image	Real age	2.68, 3.09	-
	unconstrained	CACD				6.521	
Wan et al. 2018 [16]	constrained	Morph II	5 cascaded CNNs + regression	Face image, gender, race	Real age	2.93	-
	unconstrained	CACD				5.22	
Chen et al. 2018 [20]	constrained	Morph II, FG-Net	Ranking CNN	Face image, gender, race	Real age	2.96, 4.13	-
	unconstrained	Adience				-	53.7
Xie et al. 2019 [24]	constrained	Morph II	Alexnet, VGG-16 + classification	Face image, gender, race	Real age	2.69	-
	unconstrained	AgeDB				5.74	
Liu et al. 2020 [32]	constrained	Morph II, FG-Net	Similarity-aware and variational adversarial learning + ranking	Face image	Real age	2.57, 2.98	-
Xia et al. 2020 [34]	constrained	Morph II, FG-Net	Multi-Stage feature constraints learning (MSFCL) + classification	Face image	Real age	2.73, 2.71	-
Zeng et al. 2020 [35]	constrained	Morph II	CNN + Soft-Ranking	Face image	Real age	1.74	-
	unconstrained	AgeDB				5.58	
Xie et al. 2020 [19]	constrained	Morph II	Deep and Ordinal Ensemble Learning with 2 Groups Classification	Face image	Real age	2.81	-
	unconstrained	AgeDB				5.8	
Liu et al. 2020 [23]	constrained	Morph II	Multi-task learning + hybrid	Face image	Real age	2.30-3.02	-
	unconstrained	WebFace				5.67	

C. Gaussian Error

Gaussian error was introduced in the study by Liu et al. [32]. This metric was also used by Zeng et al. [35]. The smaller the Gaussian error, the higher the performance. Gaussian error can be defined as in (3):

$$Gaussian\ Error = 1 - \sum_{n=1}^{N} \exp(-\frac{(\hat{y}_n - y_n)^2}{2\sigma_n^2}) \quad (4)$$

where N is sample size of testing set, $\hat{y}_n$ estimated age value of the n-th sample, σ_n is a standard deviation, y_n is ground truth

Various protocols can be used to conduct evaluations. In [24], the evaluation process applies the "80% -20%" protocol, where 80% of the total dataset is taken randomly for training sets and another 20% is treated as a testing set. In [16], the evaluation step works with the S1-S2-S3 protocol, where the dataset is divided into three parts (S1, S2, and S3). Table III is a summary of the evaluation results of several existing facial age estimation studies.

VI. CONCLUSION

Since it was first carried out more than two decades ago, research on age estimation is still being carried out intensively today. This happens with the hope that it can produce a more accurate estimate value and also a higher speed than before. However, the many factors that influence the aging process both from within the individual and in the environment make the estimation process difficult. Therefore, to achieve these two targets, the researchers focused on various things, namely determining the features to be used, building the architecture, the framework, determining the method in the feature classification process, selecting the most representative database of the main research objectives, and so on. In general, research that uses deep learning methods such as CNN can produce more accurate estimated values than conventional methods. However, that does not mean that the conventional method is abandoned because the use of deep learning methods is very dependent on the availability of information from the dataset used where this information is needed for the modeling process. From various existing databases, the commonly available features are age, race, and gender. The rest, feature extraction, depends on the ability of researchers to produce new and more precise algorithms.

The facial age estimation model generated using a constrained database gives a smaller error than the unconstrained database. However, for real-life applications such as video analytics, the facial image will be dominated by unconstrained conditions. For this reason, so that the resulting model can be more applicable, further development is needed to produce a model using an unconstrained database with smaller errors. Also, the more additional information is available (gender and race), the higher the model's accuracy can be obtained than if the input is only an image. Based on these two conditions, for future work, it is necessary to carry out further research to produce a model with higher accuracy using an unconstrained dataset and a minimum of input variables.

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