A Hierarchical Estimation System for Human Age using Artificial Neural Networks

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ABSTRACT: Image analysis for human face recorded a wide range of attention by different authors over the last decades. Despite the significant accuracy yielded by Deep Learning Networks (DLN), Artificial Neural Networks (ANN) still has own contribution. This is due to the obstacle detected in DLN classification, where the almost all control on the type of extracted features is by the adopted DLN. On the other side, previous studies on age estimation showed that each period of human life has its own age-progression signs (features), which differ from others in different age periods. As a result controlling the type of extracted features, using DLN, is a challenging task, which can be controlled using the ANN networks. This paper proposes a pyramidal classification system of two stages, within the first on it uses texture features to classify the human age into four age periods child (0- 8) years, teenager (9- 19) years, adult (20- 49) years, and old (50 and above) years. The number and length these periods are determined due to the changes witnessed the period. In the second stage, the system estimates the age within each period by training and testing the features of the specific period. Due to the wide range of periods, the yielded results recorded high accuracy comparing with other works in age estimation and even with the second stage of this work. Determining the exact ages (±1 year) contains more false positive and false negative cases than the first stage, which means less accuracy. As benchmarking with state of art in the field of age estimation, this paper yielded superior results. The experimental results showed considerable performance yielding (97.75%) for the best accuracy of estimation with (96%) as average of yielded accuracy.

Keywords: Age Estimation, Artificial Neural Network, Texture Features, Geometrical age Pyramidal Classification

1. INTRODUCTION

Age estimation is the process of determining a person's age depending on a specific biometric such as face, hand, gait, dental system and others [1,2]. The most public biometric, which was widely studied and analyzed, was the human face since it contains several signs of age progression [3]. Due to significant amount of information contained in it, human face was also adopted for describing human gender [4], face identification [5], face diseases [6] and many other aspects [7]. Previous literatures of age estimation discussed different aspect and biometrics to estimate a person's age. Some of them tended to inspect texture and geometric features [8], human iris [9], human gait [10].

Due to the aforementioned, human ages were estimated using different types of features. On the other side, face changes over age progression were witnessed to be different from age period to another [11]. At childhood and infancy, geometric changes in face outer features and distances between them have the prevailing presence as discriminating features [12,13]. At the older stages of human age, texture features records higher presence than geometric ones [14]. Despite that, the majority of previous works on age estimation didn't pay attention age-related face changes, where most of them depended on a single-type discriminating features. Even the other authors who combined more than one type of features, they used them to enhance each other not to consider age progression signs [15].

Regarding the classifier, different types of classifiers were adopted to build an efficient age estimation system. The new trend in classification procedure is using Deep Learning Networks (DLN), which save resources consumption. They include feature extraction procedures within the learning procedures [16]. In this context, DLN's depend on a

single general type of features in the extraction procedure. In the general concept of the extraction method, feature type in uncontrollable [17], yet some of them are designed to add some control on the extracted type of features [18]. But they still produce a single-type set of features, which is an obstacle regarding for considering different type of changes over age progression stages.

This paper tend to build a pyramidal classification scheme to consider dividing the entire human age into four age classes child, teenager, adult and old. Then, each class is re-classified considering extracted features about the own age-progression signs during it.

The rest of the paper is arranged as the following: Section 2 reviews the most recent published articles within age estimation field.

2. Previous Works

Different works were conducted on age estimation from face image, where most of them handled single type of features for all age stages. The most recent works depended on DLN networks in determining the candidate features as a face descriptor for the classification purposes [1,2] [8]. Some authors depended
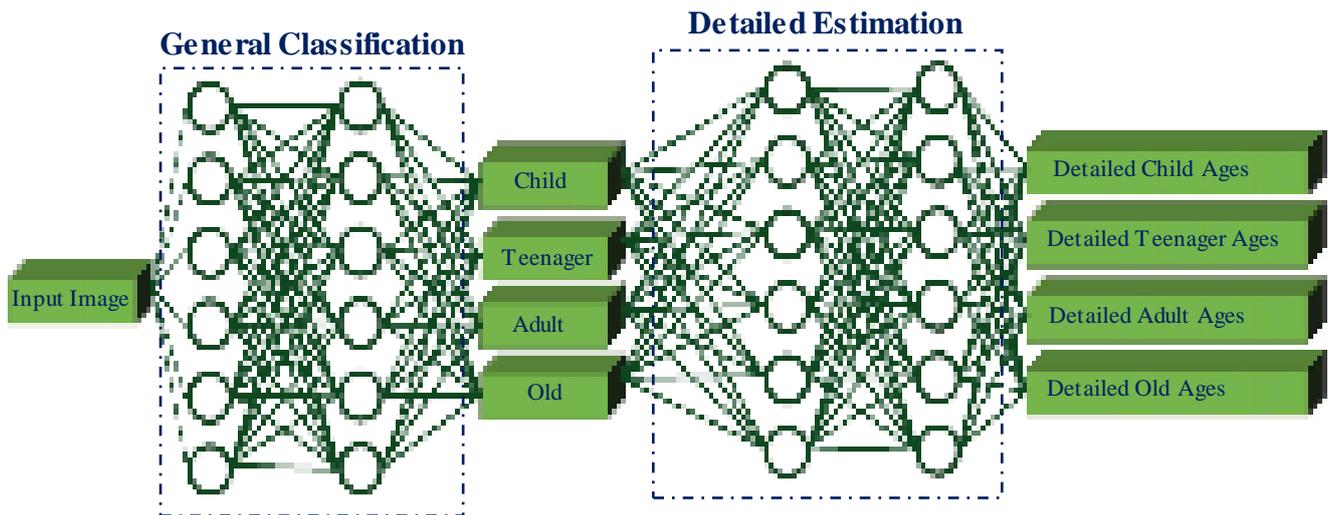

FIGURE 1 Explains the adopted scheme for the pyramidal system containing the general classification and the derailed estimation

on a DLN framework to enhance the estimation performance by merging the FusionNet and AttentionNet DLN's. This means more than one type of extracted feature, where they were merged to enhance each other not to consider age-related changes [18]. Other authors designed a pyramidal classification scheme using DLN's for age estimation. Firstly, they proposed an attention-based approach for image augmentation, and then they combined between ensemble system of regressors and discrete probabilistic age estimation. Obviously, their hierarchy doesn't consider age-related changes but to design a multi-step classification system for butter accuracy [19]. Other set of authors presented a machine-learning system for age estimation, where they applied Distributed Dynamic Kernel Support Vector Machine (DDKSVM) Classifier on texture features describe face image. This obviously means using a single type of feature in a single classification stage [20]. On the other side, the problem that different age stages produce different changes on human face was handled in different ways. Different authors proposed using specific type of features to handle specific period of age, where some authors proposed using single type of features to describe age progression signs over the Senior Adults period of human age [21]. Other sets of authors preferred using geometric features and face head pose to describe face changes over early stages of human age [13] [22].

Due to the previously reviewed literatures and other ones discussed within the context of explaining the methodology, a significant gap can be detected in age-estimation literatures; each period of age produces specific types of changes on human face as age progresses. Yet, previous works proposes single type of features to handle age estimation over all age periods, which makes their features suitable for related periods than other ones. Other authors proposed using the suitable features to handle the related period of age only. This paper proposes a hierarchical scheme for age estimation that consider suitable features for each period of age. Table 1 summarizes the followed methodologies by previous works to be applied on their adopted datasets.

Table 1 A summary discusses followed methodology and adopted datasets of previous works

Article	Methodology	Dataset
Wang, et al, (2022) [18]	CNN	ImageNet
Hiba & Keller (2023) [19]	Probabilistic Regression	MORPH & CACD

Hemasree, & Kumar (2022) [20].	Support Vector Machine	FG-NET
Al-Afare (2023) [22]	Support Vector Machine	FG-NET

3. Methodology

This paper adopts a pyramidal classification scheme for age estimation that considers the related changes over each age period. These changes varied form geometrical features for outer shape features to texture features that describe image-value features. In the early ages, geometric changes in the outer face shape record the significant presence, then texture changes in the skin participate in the witnessed descriptive features within the teenage period. Over the successive age stages, texture features record growing role that surpasses the geometric features, and the texture features record the dominant presence especially in senior adult ages [21]. As in Figure 1, the pyramidal scheme starts with using the texture features that have significant changes over the long age period to classify the human into the main age classes. It's witnessed that such features record weak discrimination performance within the short periods of age. In the second stage, the pyramidal scheme applies the inner classification within each period depending on the related age changes. This work combines two standard dataset for face images, KANFace and MegaAge [23,24], where they contain about 80k face images with age range of (0- 90) year from different races.

3.1 The General Classification (Long-Term Features)

In this type of classification, the major concern is to find such type of features that have discriminative changes over long periods of age. This helps in classifying the age interval into major age classes, which are, in this paper, child, teenager, adult, and old. One of the most important attributes in such features is that they have noticeable changes over all age periods. Geometric features have significant change over the early human ages, while texture features record noticeable change over all ages [25,26]. Regarding texture features, child faces record smooth skin with light color for face hair [3] [13] [26]. In teenage faces, a slight degradation is witnessed in skin smoothness with darker color for face hair [26,27]. Adult and old faces witness significant degradation in skin smoothness with wider areas of face hair in adult face besides noticing face lines, folds, and wrinkles [3] [4] [21]. On the other side, such texture features record insignificant differences between close-age face, as example different-age faces within childhood or adultness have no noticeable changes in skin texture.

This study adopts canny filter [28] for edge detection as a face descriptor that provide detected edges in face image. Using canny filter provides considerable set of features [29] to be fed in the designed network. Smooth faces record consistent transmission between image values in different areas of face image, which decreases the possibility of detecting an image edge [30]. In elder ages, human face image record less smoothness causing more detected ages. The highest presence of edges is witnessed in senior old ages due to the wrinkles, folds and face lines [4] [21]. Figure 2 illustrates the different levels of image edges in human face over the different age periods. For close-age faces, image edges do not record significant differences. One of the biggest challenges against image edges is the face cosmetics, which try to make the human face smoother. Despite that, the experimental results recorded considerable accuracy.
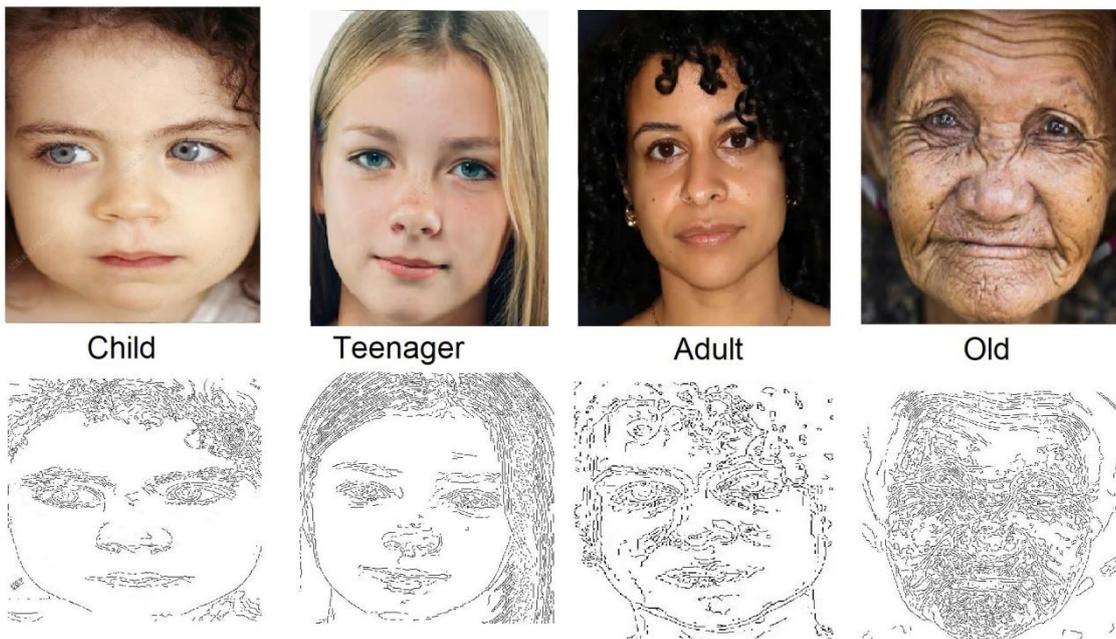
The Detail Estimation (Short-Term Features)

FIGURE 2 Image edges record discriminative changes over different age periods

In this type of classification, each age period is handled as an individual classification case having its own features to describe age-progression changes within the period. The adopted features vary from geometric feature represented by face landmarks and distances between them to the texture features and combinations between them. Each of them is selected due to the aging pattern witnessed in the related age class.

A. Childhood

Child faces witness significant changes over age progression from infancy to the early years of childhood. During the first days of birth, the infant head is exaggerated producing almost round face, which starts longitudinal growth reaching the oval shape [31]. Child age estimation using geometrical features was handled by Al-Afare, et al. (2023) [22], yet the authors depended on selecting two landmarks to build an oval shape represents the face. Despite their considerable results, they ignored other landmarks which cause loosing significant information. This work considers all outer landmarks to consider all available information that represent the face roundness. In the age stage, the inner face landmarks are ignored due to insignificant changes detected in their locations during the infancy [32]. Since human face has longitudinal symmetry, the landmarks are vertically divided into right and left groups, and the adopted features are represented by the distances between the two groups. They have more significance than inner distances since the major concern is to measure the transition from the round to oval face shape. Figure 3-a illustrated the provided landmarks, where the outer (Red) ones are adopted to generate the representative features, and the inner (Blue) ones are ignored. Figures 3-b and 3-c illustrate the human face has round shape in the first few months and converts to the oval shape as age progresses.
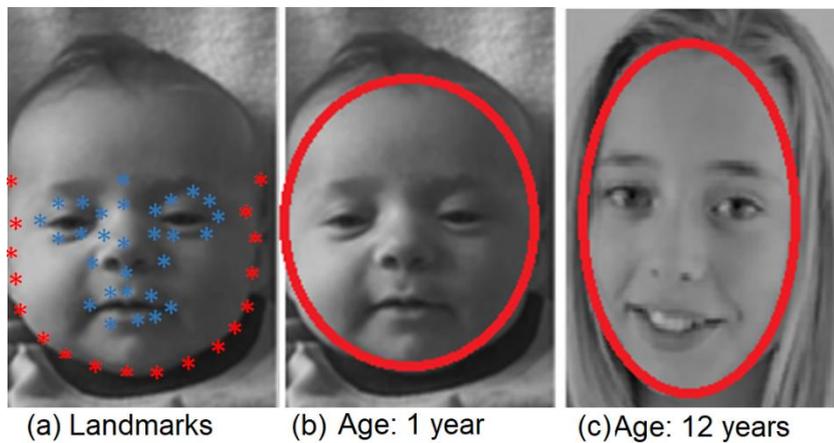

FIGURE 3 explains the face landmarks and the conversion from round to oval shapes

B. Teenage

Converting from childhood to teenage age periods witnesses less effects of head exaggeration and face roundness against more participation of changes in inner face components (chin, mouth, nose and eyes) [4] [12,13]. This involves changes in the locations and shapes of face components, where distances between inner landmarks provide clearer representation than outer ones. Due to the longitudinal growth of human face and in order to avoid different face cases, all inner and outer distances, in Childhood and Teenage, are normalized by face height. This height is represented by the vertical distance between the lower land mark and the horizontal line between the highest two landmarks. Figure 4 illustrates samples of distances between inner and outer landmarks besides the face height. Figure 4- a explains samples of distances between outer landmarks that measure face roundness, and Figure 4-b explains samples of shapes and locations of face components by measuring distances between inner landmarks. Figure 4-c explains the face height by measuring strait distance between lowest and highest landmarks. In addition, other available distances are also considered, where explaining all of them in the figure is confusing and unclear.
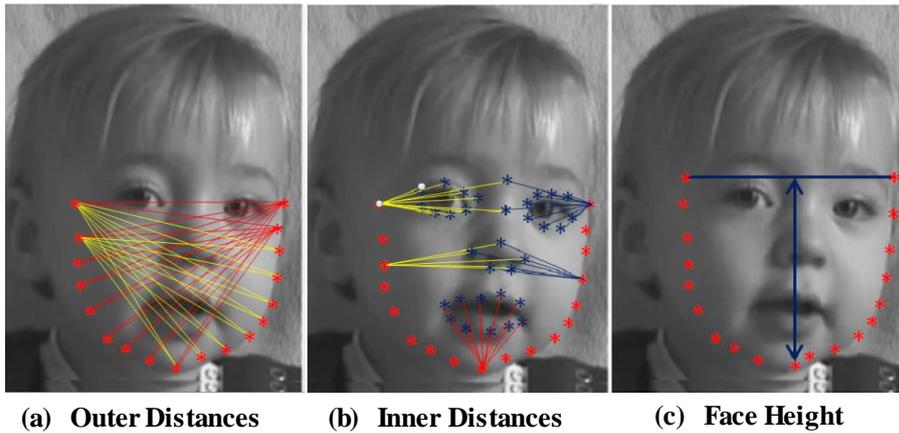
(a) Outer Distances	(b) Inner Distances	(c) Face Height

FIGURE 4 explains extracted relations between face landmarks that describe face changes

C. Adultness

In this age stage, outer changes in human face has trivial effects against weak changes in inner face components [4 & 33], while texture changes start providing considerable set of features [13] [26] [33,34]. Yet, there are set of challenges against providing efficient features to describe human face, where age progression signs records the lowest level of changes during this stage. In addition, eye glasses, face hair, and makeup are common factors that create non-real face features [3] [21] [34]. To overcome such problem, this work proposes feature fusion between geometrical features about changes in distances between inner face landmarks and texture features. In such way, texture and geometrical features supports each other [7] [15]. Texture features for age progression signs are represented in form of skin roughness, face hair, and slight face lines in the latest year of this stage [6] [20]. On the other side, geometrical features are represented in the form of inner distances especially those in nose, mouth and chin area [25] [27] [35].

D. Old ages

Due to the obvious skin sagging in this period of age, it's the richest period of texture features [3] [20,21]. Observable geometrical change in human face are not real, where eyes, nose, mouth and chin boundaries are caused by skin sagging also [11, 12] [36]. Skin sagging produces high levels of skin roughness, face lines, folds and wrinkles. Edge detection is considered as an efficient face descriptor, which produces features all over the human face during this period of age. Yet, such high number of produced features can delay and degrade the network performance. Delay is caused by high number of features and weak ones of them degrade the level of yielded accuracy [37]. To overcome such obstacle, the proposed Feature Selection Method (FSM), in our previous work [21], is adopted in this work to select the best set of features. It follows the concept of Linear Discriminant Analysis (LDA) in evaluating the extracted features, where it selects all features that record significant differences over Interclass sets (different ages) and minimum differences on Intraclass sets (different persons). It was proven to select the highest-performance features and ignore weak ones recording superior performance in age estimation and face recognition [5].

4. Results and Discussion

This paper tends to enhance the classification performance by adopting the concept of pyramidal classification, in which, the entire human age is divided into four main age groups Child, Teenager, Adult and old. In this classification, long-period features are used depending on face smoothness, where human face in the first few years preserves high level of smoothness. As age progresses, face roughness increases providing less levels of smoothness, where face smoothness is gauged using image edges. In smooth faces, color intensity is moving from a color area to another gradually without rigid conversion, which produces low number of edges. On the other side, in old faces, skin sagging produces set of face lines, folds and wrinkles, which provide high contents of image edges. Classification issue of this stage is more general, where all face within (0- 8) years are classified as child, which wide range of classification. Dividing the age into main periods and determining the boundaries of each period was a disagreement point between different literatures regarding different criteria of division. Most of them agreed to determine the upper limit of age for the last period is due to the available ages within dataset images. One of most suitable styles of division is dividing the age into 4 age periods due to the changes in human face over age progression [4] [38]. Table 2 illustrates the four main age periods and their boundaries in years. In machines Learning process and to ensure training all available image samples, this work adopted the k-fold cross validation concept (k=10), where dataset images are categorized into (non-overlapped) equal-size segments. For each ith iteration (i=1, 2 …n), the previous (i-1) segments are represented as a training set, and the testing set utilizes all other segments.

Table 2 Dividing the age into main periods with boundaries specifications for each period

Age Stage	Period Boundaries (years)
Child	0- 8
Teenager	9- 19
Adult	20- 49
Old	50 and above

This work builds an Artificial Neural Network (ANN) to perform the experiment of age estimation into four main age periods and to classify each of them into detailed ages as in Figure 1, and the specifications of the proposed NN are explained in Table 3. In this work, the new methods of Deep Learning were ignored since they propose features without control from the user, ANN allow the user to propose the suitable set of features for each classification problem [39] As it was widely adopted [1-3] [8], dataset images are divided into 70% for training and 30% for testing.

Since that classifying the whole age interval into four wide age periods is simpler than estimating the detailed ages, experimental works yielded better accuracy levels than inner estimation within each period. This indicates that such features record encouraging performance without the need to strength them with additional operations. Table 4 explains the yielded results of age classification into Child, Teenager, Adult and Old age groups. Experimental results that lowest accuracy was yielded within Adult age period, which is justified by the minimum level of changes over age progression during this period. The highest accuracy was noticed within Old age period, which can be justified by the high contents of image edges and lines produced within this period.

Table 3 The descriptions of the NN used to perform the general classification of age interval into four main classes.

Component	Parameter
Input neurons	45
#Hidden-Layer neurons	25
# Hidden Layers	2
Activation Function	Sigmoid
Correlation Coefficient	0.872
Learning Rate	0.3
Training Error	3.95 e-4
Momentum	0.2

Table 4 Yielded accuracy of classifying the age into four main age groups

Age Stage	Yielded Accuracy
Child	95.91%
Teenager	95.81%
Adult	94.78%
Old	97.75%
Overall Performance (Average)	96.06%

Detailed age estimation within each age period was performed to find the exact Age ± 1 year, where Table 5 illustrates the summarized results for estimating the detailed ages within each age group. The detailed results showed that the best results were yielded for the geometric features that estimate ages between few months and 5 years using face roundness. Image edges also yielded better results than other features within their related age groups especially within (age ≥ 57 years) range. Other sets of features varied in their performance, where the minimum accuracy levels were yielded within ($27\leq$ age ≤ 38) where human face witnesses the highest level of stability. To show the differences between Table 5 and Table 4, the ages (1, 3, 3, 5, 7, 7, 8) were estimated as (1, 3, 3, 6, 7, 7) respectively in Table 4, while in Table 5 all of them were classified as childes and so on for the rest age groups. The abovementioned is a summary for the yielded results, where explaining all of them needs higher space than an ordinary paper.

Table 5 **Yielded accuracy for detailed age estimation over age groups**

Age Stage	Yielded Accuracy
Child	97.23%
Teenager	95.58%
Adult	93.94%
Old	97.09%
Average Performance	95.95%
General and Detailed Estimation	96%

For better evaluation of classification performance, this work adopts more evaluation measures like True positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) to be checked between Ground Truth (GT) values and the predicted ones. Considering Child group as an example, TP is represented by child faces predicted truly as child. TN is represented by non-child faces classified truly to be one of the correctly related classes. FP is represented by non-child faces classified as child ones and vice versa for FN. Depending on these measures, Precision and Recall are computed by equations 1 and 2 receptively:

$$Precision = \frac{TP}{TP + FP} \dots \dots \dots 1$$

$$Recall = \frac{TP}{TP + FN} \dots \dots \dots 2$$

Figure 5 explains the behavior of Recall measure against Precision one over the yielded results, where such figure
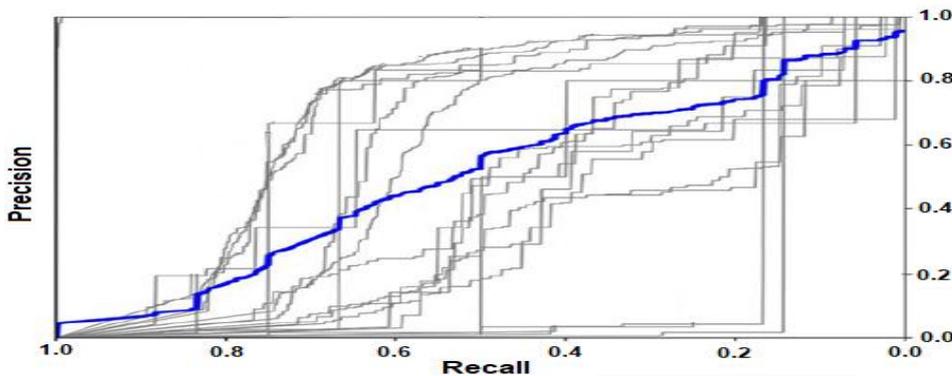

FIGURE 5 **explains the behavior of Recall measure against Precision one for superior performance**

explains the superior performance of the proposed estimation scheme.

As bench marking with previously published works in age estimation, the proposed work overcomes the yielded results in other works. Beichen, and Bao (2022) [40] adopted the cross-dataset learning to utilize image variety in more than one dataset of face images they yielded (95.42%) for classification accuracy. Niloufar, and Boroujeni (2021) [41] combines different types of features to increase the accuracy, yet the authors used the same set of features for all age groups and they yielded (95.53%) as general performance for classification accuracy. Puja, et al,(2024) [42] adopted different standard deep learning networks for face age estimation combined by gender recognition, where they reached almost 59.32% for result accuracy Against that, our proposed work yielded obvious superior results where the general performance was (96%) for accuracy.

5. Conclusions

This paper provided a pyramidal age estimation scheme that depends on general age classification into four age groups, Child, Teenager, Adult and Old. Such classification depends on long-term face changes of age progression, where image edges are adopted as features for face roughness. Over the first years of age, child faces preserve high levels of smoothness, where they decrease as age progresses. ANN network was adopted in this work to control long-term and short-term types of features suitable for the related classification issue. After performing general age classification, detailed age estimation was performed within each age group adopting the related features represent corresponding face changes. Although different age groups with different age boundaries were previously adopted, this work adopted the division that depends on face changes over age progression. The whole age interval is divided into Child (0-8) years, Teenager (9- 19) years, Adult (20- 49) years, and Old (50 and above) years. As inner features, Child

age progression was represented using the changes in outer face roundness and its conversion into ellipse shape. Teenage age group was represented by combining between face roundness and changes in inner face components eyes, nose, mouth, and chin. In Adultness the texture features recorded a significant participation to represent age progression signs. Within Old ages, skin sagging provide considerable set of image edges in form of face lines, folds and wrinkles to represent age progression in this stage. The proposed pyramidal estimation scheme yielded considerable results over the general classification into four major age groups and over detailed age estimation within each group. Besides, the overall yielded results overcome the yielded results in previous work in the field of age estimation. For the future works, a suitable DLN can be designed to control a specific type of extracted feature, or more than one DLN can be combined together for more accuracy.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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