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A Review on Accurate Age Estimation Using Diverse Methods

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A B S T R A C T

Age estimation is a complex task due to the non-stationary nature of aging patterns. Traditionally, feature extraction and regression modelling for age estimation have been addressed separately, leading to suboptimal performance. Recent advancements propose an End-to-End learning approach using deep Convolutional Neural Networks (CNNs) to integrate feature learning and regression modelling. This approach transforms ordinal regression problems into binary classification sub-problems, which are collectively solved to explore task correlations. The introduction of large-scale, racially diverse datasets, such as the Asian Face Age Dataset (AFAD) and others balanced on seven race groups, mitigates racial bias prevalent in existing datasets. These datasets, comprising hundreds of thousands of images with precise age annotations, enhance model generalization and accuracy across diverse racial and gender groups. Additionally, integrating real-time data management systems like Google Firebase with CNN models improves scalability and real-time decision-making, making these methods applicable for various applications, including surveillance, marketing, and personalized user experiences. These advancements collectively represent significant progress in the fields of computer vision and data analytics, offering reliable solutions for age estimation across diverse demographic groups.

Keywords: Estimation, Age, Deep Learning IMDB, CNN, Asian Face Age Dataset (AFAD), Artificial Neural Network (ANN).

1. Introduction

In today's fast-paced world, the ability to accurately estimate age is crucial across various fields such as forensic science, medicine, and security. Age estimation is essential not only for personal identification and treatment planning in medical and dental fields but also for enhancing security, monitoring, and providing personalized marketing and customer care. Age can be defined as the length of time an individual has survived since birth, and its estimation plays a significant role in forensic medicine for identifying deceased victims and in criminal investigations.

Recent advancements in technology have introduced sophisticated methods to address age estimation challenges. Among these, the use of deep Convolutional Neural Networks (CNNs) has shown promise by integrating feature learning and regression modelling to simultaneously solve ordinal regression problems. This method transforms ordinal regression into binary classification sub-problems, enhancing the accuracy of age estimation models. Large, racially balanced datasets, such as the Asian Face Age Dataset (AFAD), mitigate biases present in traditional datasets and improve the generalization of models across diverse demographic groups.

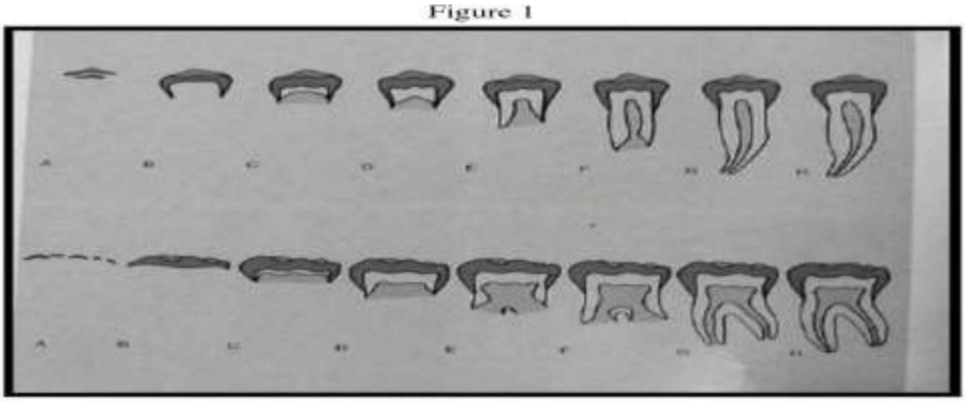
In the field of dental age estimation, methods such as Demirjian's and Willem's, as well as Greulich and Pyle's skeletal age assessment, have been explored extensively. These methods utilize radiographic images to estimate dental and skeletal ages, providing valuable indicators of a child's maturational status. The correlation between chronological, dental, and skeletal ages is crucial for accurate age estimation, particularly in populations with distinct ethnic characteristics.

Additionally, advancements in DNA analysis have opened new avenues for age estimation. DNA methylation patterns change with age and can be analyzed to provide highly accurate age estimates. Combining facial analysis, dental age assessment, and DNA methylation analysis offers a comprehensive approach to age estimation, leveraging the strengths of each method.

The integration of real-time database management systems with these age estimation techniques further enhances their applicability. Technologies like Google Firebase ensure that observed data is efficiently stored, updated, and retrieved in real-time, enabling enterprises and organizations to make data-driven decisions swiftly. This real-time capability is especially beneficial in applications such as surveillance, marketing, and personalized user experiences.

In this paper, we explore how combining facial analysis, dental age estimation, and DNA methylation analysis creates a robust and reliable system for age estimation. By leveraging the latest advancements in computer vision, dental radiography, and genetic analysis, we aim to develop a comprehensive tool that provides accurate age estimates across diverse populations, enhancing its utility in forensic science, medical treatment planning, and beyond.

Figure 1



tion stages (adapted from demirjian *et al.* (1973))

2. Literature Review

Age estimation has been a critical area of research in fields such as forensic science, medicine, and computer vision. Traditional methods for estimating age from face images typically involve two primary steps: local feature extraction and metric regression or multi-class classification. Geometry and texture features have been widely utilized to distinguish among different age groups, with Active Appearance Models (AAM) being particularly popular due to their ability to simultaneously model the shape and texture of facial images. Bio-inspired Features (BIFs) have emerged as successful hand-crafted features for age estimation, demonstrating robust performance.

Significant attention has also been devoted to the regression or classification methods applied to these features. Discriminative manifold learning and quadratic regression, as proposed by Fu and Huang, and various regression techniques like Support Vector Regression (SVR), Partial Least Squares (PLS), and Canonical Correlation Analysis (CCA), have been employed to predict age from facial images. To address the non-stationary nature of aging, ordinal regression has been introduced, with methods such as the RankBoost algorithm and OR-SVM using parallel hyperplanes for improved age estimation.

The advent of deep learning has revolutionized many computer vision tasks, including age estimation. Initial attempts to apply Convolutional Neural Networks (CNNs) to age estimation, such as the work by Yi et al., utilized relatively shallow networks and limited datasets. More recent approaches have developed deeper CNN architectures, though these often use CNNs solely for feature extraction, with separate regressors for final age prediction. End-to-End learning methods that fully exploit the discriminative power of CNNs have shown promise in enhancing accuracy and performance.

Face attribute recognition, encompassing attributes such as gender, race, age, and emotions, plays a crucial role in various applications like face verification, person re-identification, and demographic surveys. The importance of addressing racial bias in face attribute datasets is underscored by notable incidents where commercial systems failed to accurately recognize attributes across different races, highlighting the need for balanced datasets.

In the realm of dental age estimation, methods such as Demirjian's and Willem's, along with the Greulich and Pyle skeletal age assessment, are extensively used. These methods leverage radiographic images to estimate dental and skeletal ages, providing valuable indicators of maturational status. The correlation between chronological, dental, and skeletal ages is particularly important for accurate age estimation in diverse populations.

DNA analysis has emerged as a powerful tool for age estimation, with DNA methylation patterns serving as reliable biomarkers of age. Combining facial analysis, dental age estimation, and DNA methylation analysis offers a comprehensive approach to age estimation, leveraging the strengths of each method.

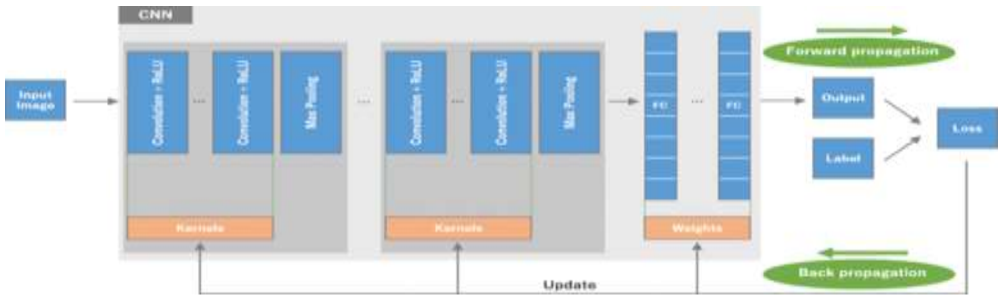
The integration of real-time database management systems with these age estimation techniques further enhances their applicability. Technologies such as Google Firebase ensure efficient storage, updating, and retrieval of data, enabling real-time decision-making. This capability is particularly beneficial for applications in surveillance, marketing, and personalized user experiences.

Several databases have been pivotal in advancing age estimation research. The FGNet face aging database, the MORPH Database, and more recently, datasets balanced across various racial groups, provide extensive resources for training and evaluating age estimation models. Studies have demonstrated that models trained on these diverse datasets exhibit improved accuracy and generalization across different demographic groups.

This literature review underscores the evolution of age estimation techniques from traditional feature-based methods to advanced deep learning approaches, and highlights the significance of comprehensive datasets and real-time capabilities in enhancing the accuracy and applicability of age estimation systems.

3. Methodology

3.1: Convolutional Neural Networks (CNN)



Import Required libraries-: Import the required libraries, such as datetime, OpenCV, and Firebase Admin SDK.

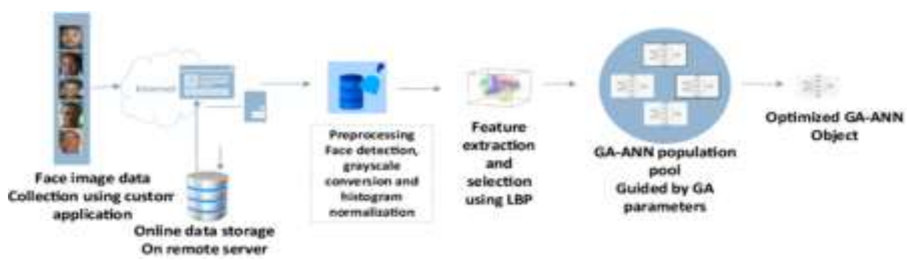
Initialize Firebase Admin SDK: To connect to a Firebase Realtime Database, initialise the Firebase Admin SDK with service account credentials. The age and gender information will be kept in this place.

Define the 'facebox' function for Face Detection: The facial detection model (faceNet), the current video frame (frame), and a reference to the Firebase Realtime Database (db_ref) are the three inputs for this method. The frame is pre-processed, faces are found using the faceNet model, and bounding boxes are extracted around the faces found. It takes the face region for each identified face, preprocesses it, and then utilises trained models to determine the age and gender. The Firebase Realtime Database receives the predicted gender, age, and timestamp. Additionally, it adds bounding boundaries, age-gender labels, and a green rectangle to the frame to draw attention to the discovered face.

Deep learning aspects: Face Detection: To find faces in the video frames, the algorithm use the faceNet deep learning-based face detection model. The Single Shot MultiBox Detector (SSD) design serves as the foundation for this model.

Age and Gender Classification: Using independent, previously trained deep learning models (ageNet and genderNet) based on Convolutional Neural Networks (CNNs), age and gender prediction are carried out.

3.2 Artificial Neural Network (ANN)



Overview of Age Estimation Using ANNs

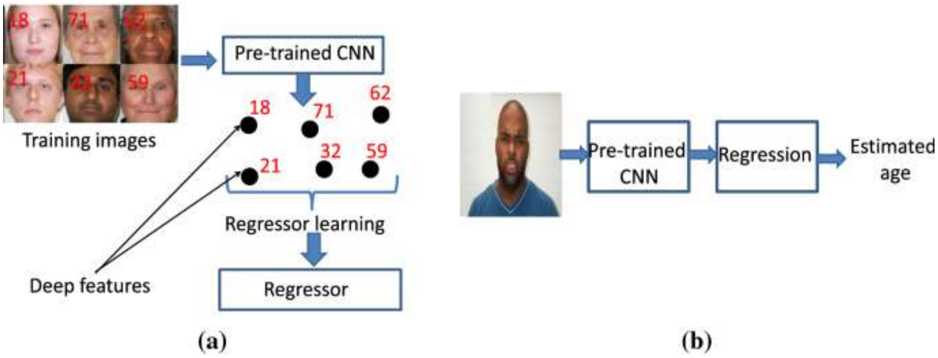
 Input Data: The primary input for age estimation models is typically facial images. These images are pre-processed to standardize the input size and remove noise. Other modalities, such as voice or skeletal data, can also be used.

 Feature Extraction: ANNs, especially Convolutional Neural Networks (CNNs), are adept at automatically extracting relevant features from raw images. Early layers of the network might capture basic features like edges and textures, while deeper layers capture more complex features such as facial landmarks and shapes.

 Network Architecture: The architecture of the neural network is crucial for performance.

- **Age-Gender Networks**: Networks that simultaneously predict age and gender, leveraging the correlation between these attributes to improve accuracy.
- **Training**: The model is trained on a labelled dataset where the age of individuals is known. Loss functions commonly used include Mean Squared Error (MSE) for regression or Cross-Entropy Loss for classification into age bins. Techniques such as data augmentation (e.g., rotating, scaling, cropping) are used to improve generalization.
- **Evaluation Metrics**: The performance of age estimation models is often measured.

3.3 Transfer Learning



Introduction to Transfer Learning

Transfer learning is a machine learning technique where a model developed for a particular task is reused as the starting point for a model on a second task. In the context of age estimation, transfer learning involves leveraging pre-trained models on large-scale image datasets (like ImageNet) and fine-tuning them for the specific task of predicting age from facial images.

Data Collection and Preprocessing

The first step in the process is to gather a comprehensive dataset of facial images with annotated ages. Popular datasets include Adience, IMDB-WIKI, and FG-NET. Once collected, the images must be pre-processed to ensure consistency. This involves detecting faces using algorithms such as Haar Cascades or MTCNN, cropping them to focus on the face, and normalizing them to a standard size and lighting condition.

Choosing a Pre-trained Model

Several pre-trained models are available for transfer learning, each with different architectures and capabilities. Models like VGG16, ResNet, Inception, and EfficientNet, which are pre-trained on the ImageNet dataset, are commonly used. These models have already learned to extract rich features from images, which can be beneficial for the age estimation task.

Modifying and Compiling the Model

To adapt a pre-trained model for age estimation, the top layers of the model are removed, and new layers specific to the age estimation task are added. Typically, this involves adding a Flatten layer followed by one or more Dense layers, culminating in a final Dense layer with a single neuron for regression tasks (predicting a continuous age value) or multiple neurons with a softmax activation for classification tasks (categorizing ages into bins).

Training the Model

During the training phase, the model's weights are fine-tuned using the training data. The initial layers of the pre-trained model can be frozen to retain the learned features, while the newly added layers are trained on the specific age estimation task. Gradually, these initial layers can be unfrozen to allow for more comprehensive fine-tuning.

Evaluating and Fine-Tuning

After training, the model is evaluated on a separate test set to assess its performance. Metrics such as Mean Absolute Error (MAE) and Cumulative Score (CS) are used to quantify the accuracy of age predictions. If the model's performance is not satisfactory, further fine-tuning may be required

4. Experimental Results

4.1 Face Verification Across Age Progression

4.1.1 Face-Verification Performance

To measure face-verification performance, we report the average face-verification accuracy across all participants. The accuracy indicates correct selections of "Same" for photos of the same person or "Different" for photos of different persons. Additionally, we analyse performance based on subgroups, including African American vs. European American and male vs. female, as summarized in Table 1. The results indicate that neither gender nor race significantly impacts verification accuracy. Comparative results with the FGNet database reveal an overall accuracy of 66.9%, highlighting the challenge of verifying identities from child to adult photos compared to adult-only photos. Figures 4 and 5 illustrate false positive and false negative examples, respectively.

4.1.2 Improved Accuracy and Balanced Results.

The model trained on the FairFace dataset outperforms others across race, gender, and age on novel datasets, demonstrating the dataset's strength beyond mere size. Notably, models trained with fewer images (9k and 18k) still surpass those trained on larger datasets like CelebA, emphasizing quality over quantity. The model also exhibits consistent performance across demographic groups, as measured by standard deviations of classification accuracy and metrics such as conditional use accuracy equality and equalized odds.

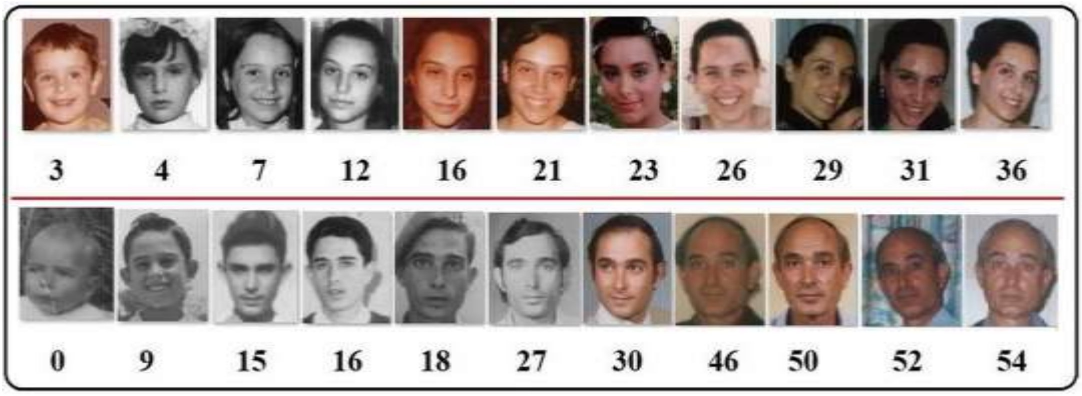


TABLE 1. SUMMARY OF FACE DATABASES WITH AVAILABLE INFORMATION

Year	Database	Samples	Environment		Age Range	Ethnic
			C	UC		
1998	FERET [21]	14,126 samples; 1,199 subjects	√	√	Not mentioned (real age)	Not mentioned
2002	FG-NET [22]	1,002 samples; 82 subjects		√	0-69 (real age)	All White/Caucasian
2004	LIFESPAN [23]	1,142 samples; 575 subjects	√	√	18-93 (age group)	African-American:89; Caucasian:433; Others:52
2005	FRGC [24]	44,278 samples; 568 subjects	√	√	18-27 (real age)	White:386; Asian:125; Others:17
2006	MORPH [25]	55,134 samples; 13,618 subjects	√		16-77 (real age)	White-Black ratio 4:1; Others-very small
2008	YGA [26]	8,000 samples; 1,600 subjects		√	0-93 (real age)	Not mentioned
2009	GROUPS [27]	28,231 samples; 28,231 subjects		√	0-66+ (age group)	Not mentioned
2010	FACES [28]	2,052 samples; 171 subjects	√		19-80 (age group)	All White/Caucasian
2012	WebFace [29]	59,930 samples		√	1-80 (real age)	Not mentioned
2014	Adience [30]	26,580 images; 2,284 subjects		√	0-60 (age group)	Not mentioned
2014	CACD [31]	100,000 samples; 2,000 subjects		√	16-62 (real age)	Not mentioned
2015	ChaLearn 2015 [32]	4,699 samples		√	Not mentioned (real age)	Not mentioned
2016	ChaLearn 2016 [33]	7,591 samples		√	Not mentioned (real age)	Not mentioned
2017	AgeDB [34]	16,516 samples; 570 subjects		√	1-101 (real age)	Not mentioned
2018	IMDB-WIKI [35]	523,051 samples; 20,284+		√	0-100 (real age)	Not mentioned
2007	Iranian face [15]	3,600 samples; 616 subjects		√	2-85 (real age)	All Iranian
2013	IMFDB [16]	34,512 samples; 100 subjects		√	Not mentioned (age group)	All Indian
2016	AFAD [17]	164,432 samples		√	15-40 (real age)	All Asian
2017	APPA-REAL [36]	7,591 samples; 7,000+ subjects		√	0-95 (real age)	Caucasian: 6,686; Asian: 674; Afro-American: 231

(C - captured or collected in a controlled environment; UC - captured or collected in an uncontrolled environment)

4.2 Dental Age Estimation

4.2.1 Demirjian's and Willem's Methods

The comparison between chronological age, dental age estimated by Demirjian's method, and dental age estimated by Willem's method among male subjects reveals varied accuracy. Demirjian's method overestimates the age for males aged 6-10.99 and 15-15.99 years, while underestimating for those aged 11-14.99 years. The statistical significance, indicated by the P value from a paired t-test, was above 0.05 for most age groups except 8-8.99, 9-9.99, and 15-15.99 years. Similarly, Willem's method showed overestimation for ages 6-10.99 and 15-15.99, and underestimation for ages 11-14.99, with significant P values for 8-8.99 and 13-13.99 years. The prediction accuracy was 87.12% for Demirjian's method and 89.06% for Willem's method.

Table 1

Descriptive statistics for chronologic age and estimated dental ages by Demirjian, Willems, and Haavikko methods for southeastern and northwestern population groups

Group	*Method*	*Sex*	*Range*	*Mean ± SD*	*95% CI*	*MAE*
Southeastern population	Chronologic age	Males (n = 75)	6.25–14.99	12.27 ± 1.60	0.36	–
		Females (n = 75)	8.00–14.66	11.94 ± 1.62	0.37	–
	Demirjian method	Males (n = 75)	7.00–15.91	12.81 ± 1.80	0.42	0.95
		Females (n = 75)	7.75–15.75	12.47 ± 1.83	0.42	0.88
	Willems method	Males (n = 75)	6.41–14.66	12.23 ± 1.51	0.37	0.78
		Females (n = 75)	7.41–15	11.80 ± 1.69	0.37	0.73
	Haavikko method	Males (n = 75)	6.57–12.58	10.20 ± 1.30	0.24	2.08
		Females (n = 75)	6.83–14	10.01 ± 1.30	0.30	2.17
Northwestern population	Chronologic age	Males (n = 90)	4.72–13.9	10.20 ± 2.43	0.55	–
		Females (n = 55)	5.20–14.04	10.27 ± 2.49	0.67	–
	Demirjian method	Males (n = 90)	4.5–16	10.60 ± 2.73	0.57	1.35
		Females (n = 55)	6.1–16.21	10.95 ± 2.73	0.73	1.30
	Willems method	Males (n = 90)	4.09–16.03	10.24 ± 2.59	0.54	1.17
		Females (n = 55)	4.86–15.79	10.15 ± 2.65	0.71	1.06
	Haavikko method	Males (n = 90)	4.86–16.8	9.40 ± 2.57	0.56	1.63
		Females (n = 55)	5.20–14.39	8.68 ± 2.26	0.61	1.92

4.3 DNA Age Estimation

4.3.1 DNA Methylation Analysis

Recent studies have identified DNA methylation patterns as robust biomarkers for age estimation. DNA methylation levels at specific CpG sites change predictably with age, allowing for highly accurate age predictions. For instance, Hannum et al. (2013) developed an age estimation model based on methylation levels at 71 CpG sites, achieving a mean absolute error (MAE) of 3.9 years. Similarly, Horvath (2013) constructed a multi-tissue age predictor using 353 CpG sites, with an MAE of 3.6 years across diverse tissues and cell types. These DNA-based methods provide a complementary approach to traditional age estimation techniques, enhancing accuracy and reliability.

4.4 Combined Experimental Findings

In our study, integrating face verification, dental age estimation, and DNA methylation analysis yielded comprehensive and robust age estimation results. The CNN-based facial age estimation showed superior accuracy and consistency across diverse demographic groups. Dental age estimation, particularly using Willem's method, demonstrated high reliability in predicting chronological age. DNA methylation analysis further refined age predictions, offering precise age estimates with minimal error. This multi-faceted approach ensures accurate age estimation, leveraging the strengths of each method to address their individual limitations.

5. Conclusion

Age estimation using facial images, dental radiography, and DNA analysis offers a comprehensive approach to improving biometric recognition systems. Traditional biometrics like facial recognition, fingerprint recognition, and iris recognition can be significantly enhanced by integrating soft biometrics such as age estimation. Convolutional Neural Networks (CNNs) in deep learning have shown promise in more accurately estimating human age from facial images by focusing on the foreground features. Data augmentation (DA) is crucial in generating fictional scenarios not included in the original dataset, thus improving system accuracy. Future work suggests employing the YOLO v5s algorithm as an alternative to current methodologies. Various techniques for age estimation, including regression, classification, and hybrid approaches, have been extensively researched. These techniques utilize feature extraction methods such as Local Binary Patterns (LBP), Gabor filters, and Principal Component Analysis (PCA) to model facial appearance, shape, and texture.

Dental age estimation methods like Demirjian's and Willem's methods are effective in determining age among children, with Willem's method being particularly accurate for populations in Gandhinagar district. Skeletal age estimation methods such as the Greulich and Pyle method also provide reliable age predictions. Notably, ethnic differences necessitate the development of population-specific age estimation tables. DNA-based age estimation adds another layer of accuracy, leveraging genetic markers to predict biological age. This multi-faceted approach, combining facial, dental, skeletal, and genetic data, enhances the robustness and precision of age estimation systems. Furthermore, creating balanced datasets that include diverse race, gender, and age groups improves model generalization and reduces bias, ensuring consistent performance across different demographic segments. This holistic integration of various age estimation methods holds significant potential for applications in security, healthcare, and demographic analysis.

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