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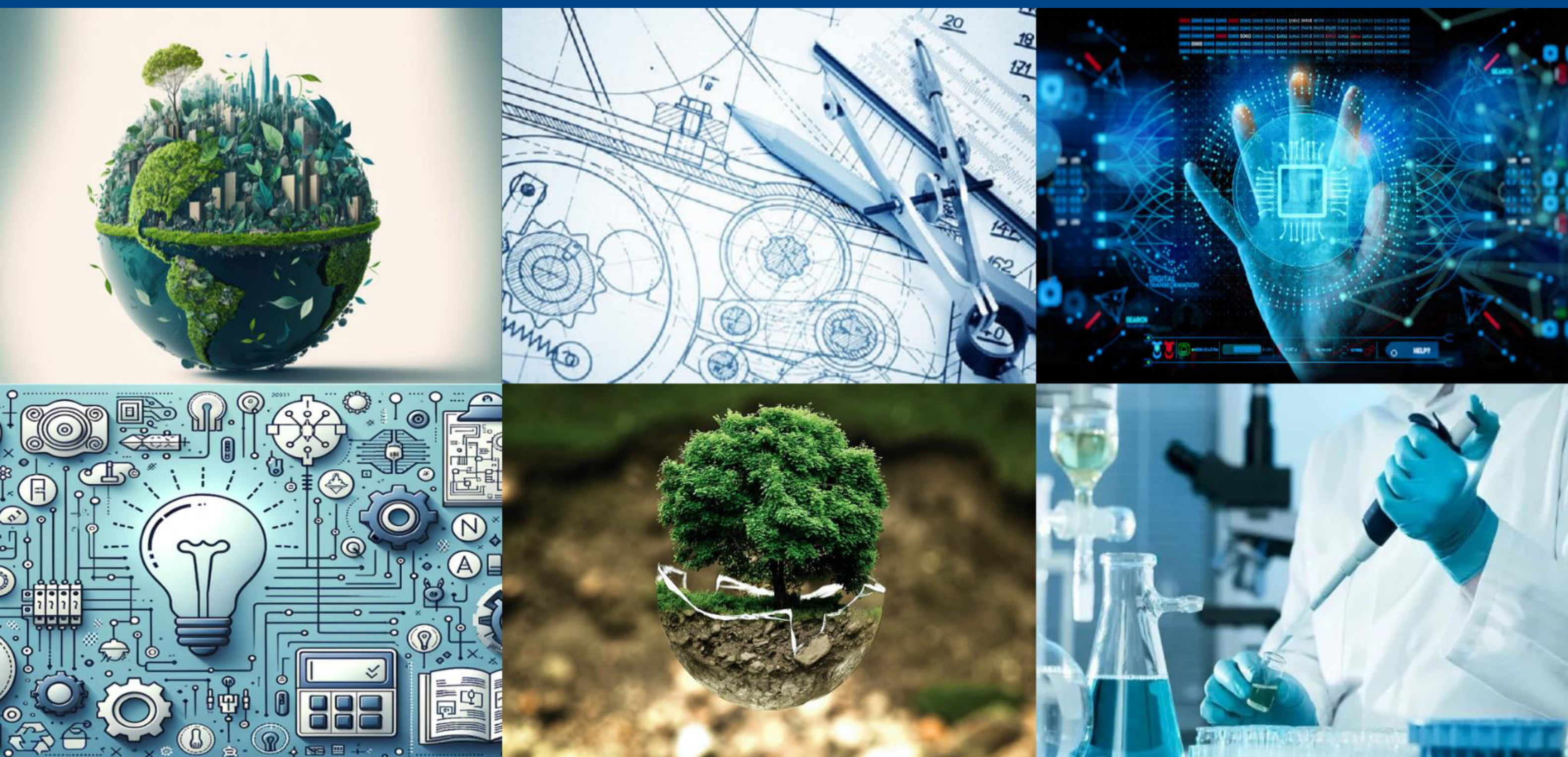

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A Review of Age Estimation Techniques using Image Processing

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ABSTRACT Age estimation using image processing has become an important area of research owed to its varied range of usages in security systems, human-computer interaction, targeted marketing, and biometrics. This review presents a comprehensive overview of the various techniques and methodologies developed for estimating a person's age from facial images. The paper categorizes existing approaches into traditional machine learning methods and deep learning-based models, emphasizing their respective potencies and restrictions. Key factors affecting age estimation accuracy—such as lighting, pose, ethnicity, and facial expressions—are also discussed. Furthermore, commonly used datasets and performance metrics in the field are examined to provide a benchmark for evaluating different techniques. Finally, the paper outlines current challenges and proposes potential directions for future research in building more robust and accurate age estimation systems. This review aims to aid as a foundational reference for academics and experts interested in this evolving domain.

KEYWORDS: Age Prediction, Facial Features, Computer Vision, Facial Landmark Detection

I. INTRODUCTION

Age estimation using image processing has emerged as a pivotal area of research within computer vision, driven by its extensive applications in security, healthcare, digital forensics, and human-computer interaction. The human face, rich in features such as skin texture, bone structure, and facial landmarks, serves as a valuable source for inferring age-related information. However, accurately determining age from facial images presents significant challenges due to factors like individual aging variations, environmental conditions, and diverse facial expressions.

Early methodologies in age estimation primarily relied on handcrafted features and traditional machine learning techniques. For instance, approaches utilizing edge detection combined with regression algorithms have been explored to predict apparent age from facial images. These methods often employed features like the Histogram of Oriented Gradients (HOG) to incarcerate essential facial characteristics. While these techniques provided foundational insights, their performance was often limited by the variability in facial appearances and the complexity of aging patterns. Age estimation has greatly increased with the introduction of deep learning (DL), especially Convolutional Neural Networks (CNNs). Increased precision in age prediction challenges has resulted from deep CNNs' impressive ability to learn feature representations with hierarchy straight from image data. Notably, transfer learning approaches leveraging pre-trained models like VGG-Face have shown promise in enhancing age estimation performance. These models benefit from large-scale face recognition datasets, enabling them to capture intricate facial features pertinent to age estimation.
Furthermore, studies have discovered the integration of DL with other biometric modalities. For example, age estimation using dental images, specifically orthopantomograms, has been investigated using CNN architectures, achieving high accuracy levels in age classification tasks such multimodal approaches underscore the potential of combining various biometric cues to enhance age estimation systems. Even with these developments, several tasks persist in the domain of age estimation. Factors such as lighting conditions, occlusions, and demographic variations can adversely affect the efficiency of age estimation models. Moreover, the virtuous deliberations neighboring privacy and the potential for algorithmic biases necessitate careful scrutiny and responsible deployment of these technologies.

The goal of the article is to present a thorough summary of the most advanced methods for age estimation utilizing image processing at the moment. We delve into traditional methods, DL approaches, and hybrid models, examining their methodologies, datasets, and performance metrics. Additionally, we discuss the prevailing challenges and propose future research directions to address the limitations and ethical concerns associated with age estimation technologies.

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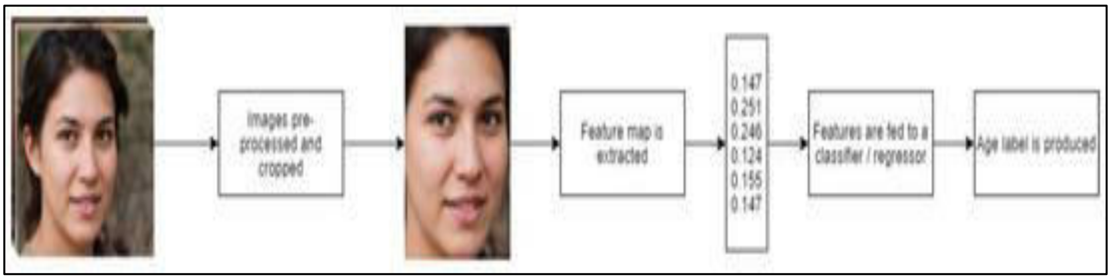

Figure 1: Age estimation Process

II. LITERATURE ANALYSIS

In this part of the article, we examine a number of most recently released works that use a variety of approaches to try and tackle the age estimation challenge. The review starts with a succinct overview of the surveyed work, then moves on to the suggested approach. The review's second section describes the authors' datasets and findings. The evaluation of each method culminates with an assessment of its advantages and disadvantages.

Traditional Machine Learning Approaches

Early age estimation methods relied on handcrafted features and classical machine learning algorithms. Techniques such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Gabor filters were used to extract facial features, which were then fed into classifiers like Support Vector Machines (SVM) or k-Nearest Neighbors (k-NN) for age prediction. While these methods provided foundational insights, their performance was often limited by the variability in facial appearances and the complexity of aging patterns.

Deep Learning Approaches

The advent of DL, particularly CNNs, has suggestively advanced age estimation techniques. Deep CNNs have established amazing competences in learning hierarchical feature depictions directly from raw images, leading to improved accuracy in age prediction tasks. Notably, transfer learning approaches leveraging pre-trained models like VGG-Face have shown promise in enhancing age estimation performance. These models benefit from large-scale face recognition datasets, enabling them to capture intricate facial features pertinent to age estimation. Current studies have also explored the integration of DL with other biometric modalities. For example, age estimation using dental images, specifically orthopantomograms, has been investigated using CNN architectures, achieving high accuracy levels in age classification tasks. Such multimodal approaches underscore the potential of combining various biometric cues to enhance age estimation systems.

Handmade Techniques

An age estimation approach based on an enhanced SVM algorithm [10] was published in a 2015 work by [7]. The suggested technique detects and extracts the subject's face using Viola and Jones [11]. A 68-landmarks facial detector is used to align with the identified face [12].

A local binary pattern (LBP) operator is used for obtaining the face features. The authors utilize the four-patch LBP codes of [14] in conjunction with the LBP of research [13]. According to the scientists, these LBP codes were chosen because they are computationally cheap and robust against a range of face recognition issues.

An updated linear SVM receives the pre-processed images in order to classify them. To lessen overfitting and model complexity, the classifier has a dropout layer. Two distinct dropout rates are tested by the authors. The dropout rate was set at 80% by the authors. The Adience information set, which includes over 20,000 samples collected under unrestricted conditions, was used for both training and testing.

A built-from-scratch network trained on celebrity faces taken in unrestricted settings was presented by the authors of an investigation by [15]. There are four steps in this procedure. To find a subject's face in an image, the authors first use a face detection technique called the deep pyramid deformable components model. Facial alignment is the second phase, and the dlib C++ library is used for this. Feature extraction, the third stage, makes use of a CNN network with ten

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layers. Assessing face age is the last stage, and a specially designed three-layer neural network (NN) trained on Gaussian loss is used for this.

Transfer Learning-enabled Approaches

Pre-trained models such as VGG19 or ResNet50 have solved various machine learning problems. The interest in utilising pre-trained models lies in their ability to produce better accuracy without needing a lot of labelled training samples. The accessibility of sufficient training samples is an ongoing issue in age estimation. To address the issue of inadequate data, a number of research proposed the use of models that have been trained.

A multi-stage age and gender estimation framework utilizing a pre-trained VGG19 model was presented by the researchers of [16]. A saliency detection network that can extract regions of interest—in this case, a subject's face—is the initial element of the suggested approach. The second element is a pre-trained VGG19 network age estimate model. In computer vision tasks that involve segmentation, semantic segmentation, and hole filling, the saliency detection network—a deep encoder–decoder segmentation network—has demonstrated efficacy. The age and gender estimators are integrated into a modified VGG-19 network, which adds two additional segregated layers to estimate age and gender and substitutes average pooling layers for the final fully connected layers.

III. COMPARATIVE ANALYSIS OF PREVIOUS RESEARCH

Paper	Year	Methodology	Dataset Used	Strengths	Limitations
Liu et al., Symmetry [17]	2020	Data augmentation with lightweight CNN	MORPH, FG-NET	Lightweight model; enhanced with data augmentation	Moderate accuracy compared to deeper models
Nam et al., IEEE Access [18]	2020	Super-resolution + GAN-based reconstruction before age estimation	MORPH, Adience	Improves low-res image quality for better estimation; uses adversarial learning	GAN training complexity; computationally intensive
Dagher & Barbara, Multimed. Tools Appl. [19]	2021	Pre-trained CNN (ResNet, VGG) + transfer learning	IMDB-WIKI	Effective use of transfer learning; reduced training time	Heavily dependent on quality of pre-trained models
Angulu et al., EURASIP JIVP [20]	2018	Survey of age estimation techniques	Multiple (review paper)	Comprehensive overview of ML, DL, hybrid methods	No new model proposed; relies on existing literature
Unnikrishnan et al., Procedia Technol. [21]	2016	Texture-based features + SVM classifier	LFW, In-the-wild datasets	Effective for unconstrained ("wild") environments	Lower accuracy in precise age prediction
Eidinger et al., IEEE TIFS [22]	2014	Deep CNN with age and gender classification	Adience	Pioneering work on unfiltered faces; good generalization	Limited age group resolution; earlier deep learning stage

DATASETS

Datasets

Several benchmark datasets have been developed to train and assess age estimation models:

MORPH: Contains over 55,000 images with age labels fluctuating from 16 to 77 years [1].

- **FG-NET**: Comprises 1,002 images of 82 subjects, with ages oscillating from 0 to 69 years [2].
- **Adience**: Includes 26,580 images categorized into eight age groups, collected in uncontrolled conditions [3].
- **IMDB-WIKI**: The largest publicly available dataset with over 500,000 images, though it contains noisy labels [4].

These datasets vary in terms of size, age range, and image conditions, influencing the performance and generalizability of trained models.

COMMON CONTESTS

When developing age estimation theories, researchers face numerous obstacles. Some of these issues are deemed "controllable," meaning that they can be resolved by making more model adjustments or implementing fresh strategies. Head position, image quality, and image resolution are a few instances of these manageable difficulties. On the other hand, "uncontrollable" difficulties are those that scientists are unable to control at this point in (ML) research, which poses serious obstacles to improving age estimation accuracy.

3.1. Head-Pose and Alignment

One of the common controllable challenges is the head pose and alignment, which refers to the position of the face in a given image. Face alignments tends to vary because photos are taken under real-world circumstances. Typically, this problem is fixed when the face is identified and corrected during the pre-processing phase. According to the authors in [5], head postures and alignment were factors in the decline in performance.

3.2. Image Resolution

The precision of an age estimation strategy is greatly influenced by the resolution of training samples in any CV task. Poorer quality images often lose important ageing characteristics like wrinkles or facial shape, which hinders the model's ability to learn all the discriminative information required to distinguish between different ages. Normalizing the resolution of both training and testing samples using various picture upsampling techniques can resolve this problem, which is brought on by the varied resolutions of the image capturing equipment. It has been demonstrated by researchers in [6] that improving image resolution before training increases classification accuracy.

3.3. Healthcare and Leisure

One of the significant uncontrollable factors that hinders the performance of the majority of age estimate models is an individual's lifestyle. A person may appear older or younger than their true age according to their lifestyle and health, which could confuse the model that predicts their age.

3.4. Absence of Information

The absence of varied facial images for training leads to overfitting, a serious problem in age estimation. Despite the existence of extensive facial datasets for a variety of facial analysis issues, the majority of samples are either unlabeled or lack sufficient instances such as participants from diverse genders and ethnicities. According to a number of studies, including [7] and [8], the majority of misclassified samples are caused by a lack of knowledge.

3.5. Genetics

An individual's aging trend is mostly determined by their genetic makeup. Because it relies on the individual's background, gender, and upbringing, this problem is one of the challenges that current ML algorithms are unable to address. The researchers demonstrated a correlation between the subjects' facial ages and sex in [8].

3.6. Changes in Facial Features

Particular characteristics frequently get hazy or vanish completely from an image when facial hair or accessories are present. Although this problem is thought to be uncontrolled, further research could create a model that can normalize all photos by eliminating certain facial embellishments like makeup, piercings, or beards. The results in [9] showed a correlation between face changes and the decreased accuracy.

IV. CONCLUSION

Despite being a popular research topic, facial age estimate is a challenging problem for a number of reasons, including a lack of training data or an algorithm that can account for all the diverse aging processes. The present research looked at the various approaches of estimating age from facial photos, the notion of age estimation from a ML standpoint, and the specifics of multiple benchmark datasets. We also discussed the advantages and disadvantages of each approach, as well as a number of previous research that have tried to address the age estimation problem. We address the typical gaps that still exist and the current research path as we wrap up the study. Traditional ML methods are simpler but less accurate compared to deep learning-based models. GANs and super-resolution help when input images are of poor quality, though at a high computational cost. Transfer learning provides a strong balance between performance and training efficiency.

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