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Comparative analysis of image processing-based age estimation algorithms

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Abstract— The human body grows and develops with age. Age-Specific Human-Computer Interaction (ASHCI) has vast potential applications in daily life. One of the main reasons is that the aging effects on human faces exhibit several unique characteristics, making age estimation a challenging task that requires non-standard classification approaches. Age estimation is further complicated by uncontrollable environmental conditions, insufficient and incomplete training data, strong person-specific variations, and a wide range of age spans. In real-life scenarios, computer vision applications that require automatic age estimation from facial images have attracted increasing attention. In this paper, we discuss the main perspectives used to improve the performance of age estimation systems, present various techniques employed in age estimation, and highlight where experimental studies are being conducted. Additionally, we briefly describe several aging databases containing age-related information. Finally, we present a comparative analysis of the most commonly used methods based on the techniques they employ.

Keywords: age estimation, human computer interaction, computor vision, facial images, neural networks.

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I. INTRODUCTION

Human faces convey a notable amount of nonverbal information, facilitating human-to-human communication in the real world. Because of this, intelligent systems must be capable of recognizing and interpreting human faces in real time. Accuracy in age estimation is particularly important in regulated settings such as access to products like alcohol, tobacco, and cigarettes. The growing need for automation in real-world applications, including Human-Computer Interaction (HCI), multimedia communication, law enforcement, and security, has encouraged the development of various facial identification systems.

Facial features such as identity, age, gender, expression, and ethnic origin play a vital role in facial image analysis. Due to the significant dissimilarities in facial appearance, Automatic Age Estimation (AAE) from facial images is a compelling research topic. This complexity arises from both extrinsic and intrinsic factors. Extrinsic factors include lifestyle, health conditions, and living circumstances, while intrinsic factors are physiological, such as genetics [1].

Facial features, particularly wrinkles, have received growing attention in recent research due to their significance in applications like age estimation, skin texture classification, expression recognition, and facial simulation [2].

Despite ongoing interest in age estimation systems, challenges remain in accurately predicting a person's age, especially when high-resolution images are unavailable in real-world environments. The novelty of the proposed age estimation method lies in its integration of Active Appearance Models (AAMs) for feature extraction, Support Vector Machines (SVMs) for binary classification (distinguishing between youths and adults), and Support Vector Regression (SVR) for constructing regression functions to estimate age. This comprehensive approach not only outperforms previous methods in terms of Mean Absolute Error (MAE) but also demonstrates potential for improved accuracy in age estimation tasks [3].

Age synthesis involves generating realistic aging or rejuvenating effects on a face image and is useful in applications like finding missing persons and suspect identification. Age estimation predicts a person's age from their face and supports tasks such as age-based access control and targeted advertising. Age-invariant face recognition aims to recognize individuals accurately despite age-related changes in appearance [4].

Human face image analysis is a critical area in pattern recognition and computer vision, encompassing tasks such as face recognition, age classification, and gender recognition. A single face image provides valuable information, including identity, emotion, gender, race, and age, which is essential for applications like parental controls, personalized recommendations, and video services. While convolutional neural networks (CNNs) have recently been employed for age and gender classification, their performance still requires improvement, particularly under unconstrained, real-world conditions, especially for age estimation tasks [5].

This paper reviews the age estimation methods developed so far. Specifically, we aim to address the following aspects:

- Distinct techniques used in age estimation algorithms.
- Various facial aging databases.
- Parameters used for experimental evaluation.
- Quantitative metrics for performance comparison.

The paper is organized as follows: Section II provides a brief overview of age estimation methods categorized by algorithm type.

Section III describes the datasets used in different age estimation studies. Section IV outlines the experimental parameters. Section V presents a comparative analysis of various algorithms. Section VI summarizes existing age estimation techniques, and Section VII concludes the study.

II. LITERATURE REVIEW

Facial aging is a complex process that affects both the structure and texture of the face. In recent years, age estimation has been extensively studied to understand aging patterns and variations in order to achieve accurate predictions. The aging process can be divided into two main subprocesses: extracting aging features and predicting age based on those extracted features.

To extract aging feature vectors from facial images, various methods have been employed, including the Active Appearance Model (AAM) [2], Convolutional Neural Networks (CNN) [6], Local Binary Patterns (LBP) [7], Scattering Transform [8] and so on.

Based on the techniques used for feature extraction and age group classification, the existing literature can be categorized into four main approaches:

- Transformation-based techniques
- Spatial domain techniques
- Neural network-based techniques
- Composite techniques
- Each of these categories is discussed in the following sections.

a. *Transformation-based Techniques*

Transformation-based techniques primarily rely on the Active Appearance Model (AAM) or Principal Component Analysis (PCA) for feature extraction. AAM is a computer vision algorithm that matches an analytical model of shape and appearance to a new facial image. PCA, an analytical dimensionality reduction technique, is employed to reduce the dimensions of facial image data by identifying principal components—thereby compressing data while minimizing information loss.

A novel method was proposed for detecting nasolabial wrinkle lines using an improved Active Appearance Model (AAM) and Hessian filter. Unlike many existing methods that focus on simpler, linear forehead wrinkles, this approach effectively handles the curved and structurally complex nature of nasolabial wrinkles. Experimental results demonstrate the model's ability to accurately track and localize wrinkle lines with varying shapes. However, the method still faces challenges due to variability in wrinkle patterns, facial alignment, lighting, and skin texture, which can affect detection accuracy.

The proposed model shows strong potential for enhancing age estimation, facial expression recognition, and dermatological analysis. Future research should incorporate skin texture information and address the influence of colour variation, face alignment, and illumination to improve robustness. Developing a comprehensive wrinkle mapping model could further extend the application of this work in fields such as cosmetic analysis, medical diagnostics, and human-computer interaction [2].

An effective approach for face age estimation using scattering transform was presented as a feature descriptor combined with Support Vector Regression (SVR) for prediction. The scattering transform, which processes Gabor coefficients with Gaussian smoothing across layers, captures discriminative aging features effectively. The method achieves promising results on benchmark datasets FERET (Facial Recognition Technology) and PAL (People's Age Lab), with low Mean Absolute Error (MAE) values of 2.12 and 2.22 years, respectively. However, the evaluation is limited to controlled datasets, and the model's performance under unconstrained or real-world conditions remains unexplored.

This approach demonstrates strong potential for applications requiring high-precision age estimation, such as biometric security, customer profiling, and surveillance. Future work could explore the integration of scattering transform with deep learning frameworks to enhance robustness in varying lighting, pose, and background conditions. Additionally, testing on more diverse and unconstrained datasets would help validate the method's generalization and real-world applicability [8].

An approach proposed as Crow Deep Belief Network (CDBN) which effectively combines Deep Belief Networks with the Crow Search Algorithm to optimize weight learning for age estimation. By using features extracted from the Scattering Transform and the Active Appearance Model (AAM), the model captures both texture and shape characteristics of facial images. Experimental results across four benchmark datasets, including IMDB and FG-NET, show promising performance, with a minimum MAE of 2.186 and high AEO and AEM values of 0.972 and 0.971, respectively.

However, the reliance on handcrafted features limits adaptability and scalability compared to end-to-end deep learning approaches. Additionally, the model's complexity may hinder its application in real-time scenarios. Despite its strong accuracy, it lacks comparative evaluation against more recent CNN or transformer-based architectures [9].

A novel deep learning framework for age estimation using facial images, leveraging a dual image augmentation strategy and Transformer-based embedding aggregation to enhance feature representation. A probabilistic hierarchical regression model refines age prediction by combining discrete classification with specialized regressors for age subranges. The proposed method achieves state-of-the-art results on the MORPH II dataset and uniquely contributes a bias analysis of age estimation models.

While the method is robust and accurate, its complexity—due to multi-augmentation processing and multiple regressors—may pose computational challenges for real-time applications. Moreover, while the bias analysis is a valuable step toward fairness, further exploration across diverse demographic datasets is needed.

Future directions could include simplifying the model for deployment on edge devices, extending bias mitigation techniques, and exploring self-supervised pretraining for improved generalization across unseen age distributions and ethnicities [10].

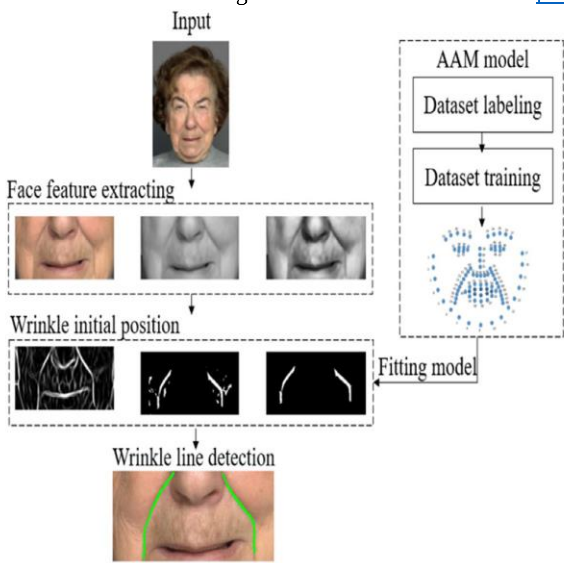

Figure 1: Detecting nasolabial wrinkle lines using an improved Active Appearance Model (AAM) and Hessian filter [2].
Source: Own elaboration.

Additionally, introduced a robust framework for multi-view age estimation by integrating both local and global facial features. Key innovations include the Median Gradient Ternary Pattern (MGTP) for texture extraction, Pseudo Zernike Moment (PZM) for shape representation, and View-based Active Appearance Model (VAAM) for capturing appearance variation. The use of Multi-class Support Vector Machine (SVM) to categorize poses, followed by Support Vector Regression (SVR) with Radial Basis Function (RBF) kernels for age estimation, allows for effective handling of pose variability. While the method performs well on benchmark datasets FG-NET and CACD (Cross-Age Celebrity Dataset), its reliance on controlled conditions and offline processing may limit real-time application.

The proposed model has strong potential for improving age estimation across non-frontal views, which is valuable in surveillance and multimedia applications. Future enhancements could include adaptation for real-time processing, expanding the framework to consider other variables such as race and facial expressions, and testing on more diverse, in-the-wild datasets. Additionally, extending this framework to jointly estimate age and gender could further enrich its utility in demographic analysis systems [11].

Table 1 presents a comparative analysis of the transformation-based techniques mentioned above, highlighting the methods employed and their respective performance outcomes.

Table 1: Comparative analysis between Transformation-based techniques.

References	Method	The database used with MAE
U. Sabina et. al. [2]	Active Appearance Model (AAM) and Hessian filter	FACES:--
O. Osman [8]	Scattering Transform	FERET :2.12; PAL :2.22
A. Shejul et. al. [9]	Crow Deep Belief Network (CDBN)	FGNET: 2.186; IMDB: 4.278
S. Hiba et. al. [10]	Probabilistic hierarchical age estimation	MORPH II:2.53
A. Micheal et. al. [11]	Median Gradient Ternary Pattern	FG-NET: 2.98; CACD: 4.04

Source: Own elaboration.

b. *Spatial Domain Techniques*

Spatial domain techniques operate directly on image pixels to enhance facial images, either by referencing nearest neighbour pixel values or by applying regression methods to adjust gray-level intensities. These techniques aim to uniformly enhance the entire image, thereby improving the accuracy of age estimation. This section provides an overview of methods that utilize spatial domain techniques for automatic age estimation.

The proposed hierarchical age estimation model using Gaussian Processes (GPs) effectively segments age groups and applies Warped Gaussian Process (WGP) regression for refined prediction. By tuning hyperparameters separately for each group, the model improves accuracy and computational efficiency, showing superior results on FG-NET and MORPH-II datasets. While promising, the scalability of GPs to large datasets remains a concern due to their inherent complexity.

This approach offers potential for more adaptive and accurate age estimation. Future work could combine deep learning for feature extraction with the GP model to handle diverse real-world data. Expanding the model to include factors like gender or ethnicity, and using non-parametric transformations, could further enhance its robustness and applicability [3].

The proposed age estimation method combines Local Binary Pattern (LBP) for feature extraction, a Feature Selection Method (FSM) for optimizing the extracted features, and Support Vector Machine (SVM) for classification. This combination significantly improves accuracy on the FG-NET dataset, increasing from 81.61% to 93.81%, and even up to 94.57% when low-quality images are excluded. However, the approach is sensitive to image quality and performs poorly on smaller, private datasets, indicating limited robustness and generalization capability in real-world conditions.

This method shows promise for practical use in systems requiring age-based classification, such as access control and surveillance. Future research should focus on increasing robustness by integrating deep learning models, enhancing performance on diverse datasets, and using automated feature selection techniques. Addressing image quality issues and expanding the training dataset would also help improve its effectiveness across real-world applications [7].

Table 2 provides a comparative analysis of the spatial domain techniques discussed above, highlighting the methodologies employed and their respective performance outcomes.

Table 2: Comparative analysis between spatial domain techniques.

References	Method	The database used with MAE
M. Sawant et.al. [3]	Multi-Class Gaussian Process Classifier and Warped Gaussian Process Regression	FG-NET:4.41 MORPH II: 3.7
N. Hasan et.al. [7]	Local Binary Pattern Algorithm	FG-NET: 4.51

Source: Own elaboration.

c. *Neural Network-based Techniques*

Neural network-based techniques utilize convolution operations for feature extraction from facial images. These methods primarily employ Convolutional Neural Networks (CNNs), which replace general matrix multiplications with convolutions in at least one layer. CNNs typically consist of input, hidden, and output layers, where the hidden layers perform convolution operations. These networks often incorporate both local and global pooling layers to reduce the dimensionality of facial features while retaining essential information.

This section surveys various neural network-based approaches developed for automatic age estimation.

A comprehensive comparative analysis of multiple CNN-based frameworks for Automatic Age Estimation (AAE) was presented, highlighting the superior performance of deep features over traditional hand-crafted ones. Among the tested architectures, the Xception network achieved state-of-the-art accuracy, with Mean Absolute Errors of 2.35 (ImageNet pretraining) and 2.01 (CASIA-WebFace pretraining). The paper also explores layer-wise transfer learning, showing that optimal fine-tuning depth varies by architecture and dataset size, and evaluates model robustness under varying facial expressions, gender, and ethnicity.

While the CNN-based models show strong generalization across gender, they suffer from reduced accuracy under expression variations and when tested on ethnicities not represented in training data—especially Black faces, suggesting unique aging patterns. The study makes its models publicly available to encourage reproducibility and further research.

Future work could address age estimation under challenging conditions such as occlusion and varied lighting, and explore more equitable training strategies using balanced, demographically diverse datasets to reduce ethnic bias in AAE systems [1].

A deep learning-based facial age estimation approach was introduced that combines robust feature extraction with a novel divide-and-rule learning strategy. Leveraging convolutional neural networks for facial representation and replacing traditional PCA with Factor Analysis Model (FAM) for dimensionality reduction, the model captures more discriminative features than conventional methods like Gabor, LBP, and BIF.

On the learning side, age estimation is treated as an ordinal regression task, decomposed into binary classification subproblems via the divide-and-rule framework, which outperforms standard SVM and SVR models. Experimental validation on FG-NET, MORPH Album 2, and IMDB-WIKI datasets demonstrates improved robustness and accuracy, benefiting from the ordinal nature of age.

Future directions could include enhancing generalizability across diverse demographics and environments, integrating attention mechanisms, and exploring real-time implementation scenarios. Additionally, combining the divide-and-rule approach with ensemble learning or transformer-based architectures may further enhance performance [6].

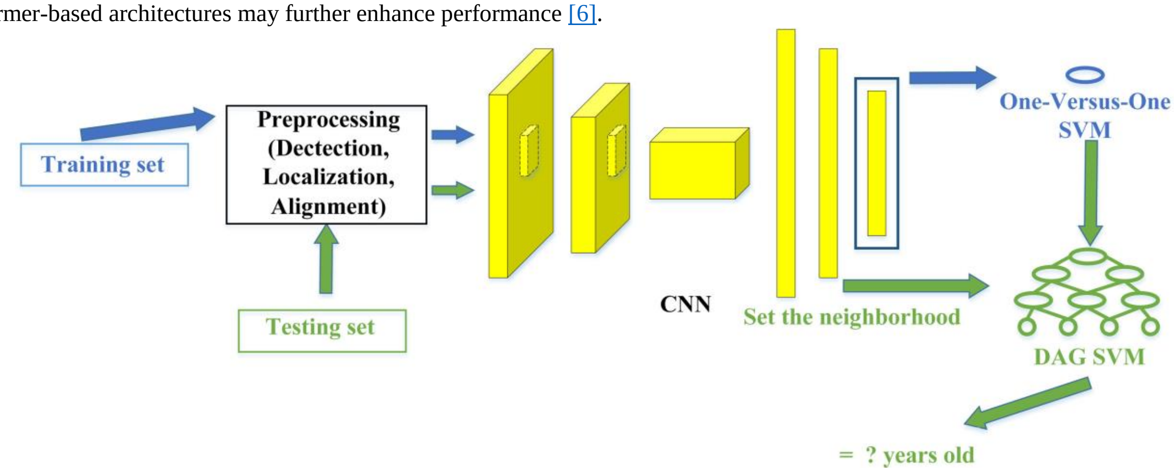

Figure 2: Local Adjustment of Age Estimation (LAAE) method integrates a fine-tuned SE-ResNet-50 [12].
Source: Own elaboration.

The proposed Local Adjustment of Age Estimation (LAAE) method integrates a fine-tuned SE-ResNet-50 with a Directed Acyclic Graph SVM to improve age estimation accuracy. The model first generates a rough global estimate using deep learning, then refines it through locally adjusted SVM predictions based on a manually defined neighbourhood. Experimental results on MORPH and AFAD datasets confirm its effectiveness across different racial groups.

Despite its strong performance, the method has several limitations. It relies heavily on pre-training with large-scale datasets like VGGFace2, which may limit its applicability in data-scarce domains. The manual definition of the neighbourhood introduces rigidity and may not adapt well to datasets with different age distributions. Additionally, the use of multiple One-Versus-One SVMs within a DAG structure increases computational complexity. While the method is claimed to be generalizable, it has only been tested on age estimation, leaving its broader applicability unproven.

The LAAE framework has strong potential for other pattern recognition tasks that benefit from coarse-to-fine refinement. Future work could focus on developing adaptive, data-driven methods to define the local neighbourhood dynamically, improving flexibility and performance. Given its effective use of shallow networks, the method is also well-suited for deployment in resource-constrained environments such as mobile or edge devices. Additionally, integrating LAAE with modern architectures like Vision Transformers could further enhance its capability. Finally, applying the approach to other domains, such as medical diagnosis or emotion recognition, would help validate its generalizability and real-world utility [12].

A novel uncertainty-aware gait-based age estimation approach employed using a label distribution learning framework. By predicting a distribution over possible age labels rather than a single value, the model effectively captures the natural uncertainty associated with different age groups-especially useful given the typically lower variance in age prediction for children and higher for adults.

Experimental results on the large-scale OULP-Age gait database confirm the method's effectiveness in both representing estimation uncertainty and achieving competitive or superior accuracy compared to existing approaches. Unlike prior Gaussian Process Regression-based methods, this framework naturally handles similar gait patterns across varying ages.

Looking forward, the method aims to enhance performance by adopting more powerful backbone architectures and replacing the fixed uncertainty hyperparameter with a sample-dependent version. Future work could also explore multimodal integration (e.g., combining gait and face cues) and real-time deployment in surveillance or healthcare settings [13].

A novel, interpretable deep learning approach introduced for automatic age estimation from lateral cephalometric (LC) radiographs, leveraging saliency maps to highlight age-relevant regions. Unlike traditional manual methods that rely on subjective feature measurement, this technique reduces labor and enhances consistency. Experimental results on 3014 LC images demonstrate strong performance, especially in underrepresented age groups and samples above 25 years, achieving a lower MAE than state-of-the-art benchmarks.

The use of Grad-CAM-based saliency maps not only improved accuracy by guiding model attention but also allowed for visualization and analysis of region-specific contributions. Interestingly, findings revealed that even partial image regions carry sufficient age-related information, suggesting redundancy in full-image analysis. Additionally, incorporating gender prediction significantly enhanced stability and accuracy—particularly reducing error in older age ranges by 18.8%.

Looking forward, this interpretable and data-efficient framework has potential applications in pediatric and forensic radiology, especially where data is limited. Future work could explore domain adaptation across different radiograph types or integrate multimodal clinical features for broader applicability [14].

The long-standing challenge of age progression for young children was addressed particularly difficult due to drastic facial shape changes during early development-by introducing a heritability-aware, two-stage cGAN framework. Unlike existing cGAN-based methods that struggle with early childhood faces, this approach innovatively incorporates visual features from both parents and the child to predict future facial characteristics more reliably.

In the first stage, the model estimates a matured facial feature representation of the child based on parent-child facial feature correlations. In the second, a cGAN synthesizes realistic, age-progressed face images conditioned on age and gender. Experiments confirm improved visual similarity between the generated images and real adult faces, with controllable heritability parameters allowing for adjustable resemblance to parent features.

Critically, the method leverages biological insights into facial structure inheritance, enhancing realism and plausibility in synthesized results. However, its performance may vary across diverse populations where parent-child resemblance is less visually distinct or affected by environmental factors.

Prospectively, increasing the resolution of generated images and exploring age regression from parent to child could enrich model capabilities. Moreover, integrating this method with missing person search systems could offer meaningful real-world impact, especially for long-term child disappearance cases [15].

A compact multi-attention deep network effectively addresses the challenge of fine-grained age estimation by combining both global and local age-related features using spatial and channel attention mechanisms. It performs competitively against state-of-the-art bulky models while maintaining efficiency. However, its performance may be sensitive to image quality issues such as occlusion, poor lighting, or low resolution, and it heavily depends on the quality and diversity of the training data.

Future improvements could focus on enhancing the model's robustness in real-world conditions with occlusions and varying illumination. Incorporating interpretability tools to better understand attention mechanisms could increase its trustworthiness. Additionally, integrating multimodal data like speech or motion could further refine age estimation, and adapting the model for deployment on mobile or edge devices could broaden its practical applications [16].

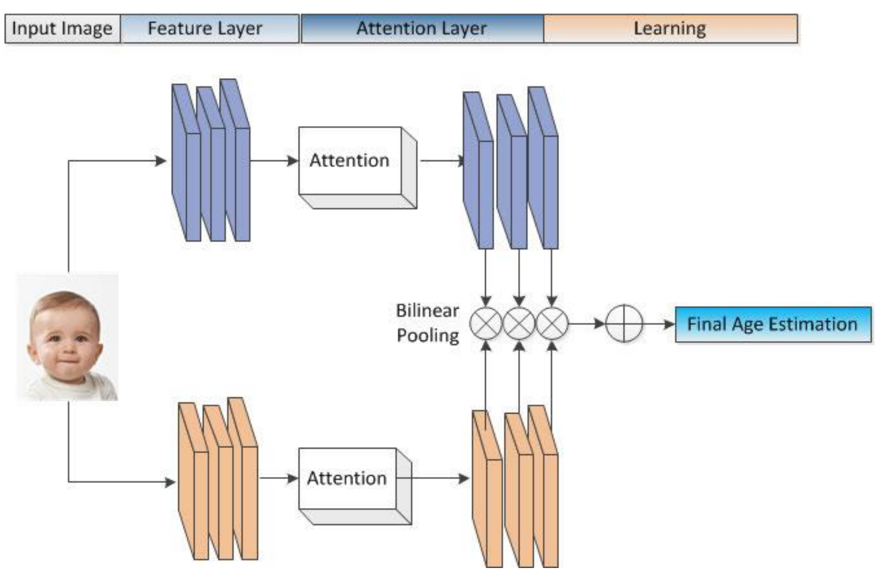

Figure 3: Model for Multi-attention deep network for Age Estimation [16].
Source: Own elaboration.

The proposed DOEL2groups and DOEL3groups models effectively address the inconsistencies often found in ordinal age estimation tasks by leveraging ensemble-based group classification with implicit ordinal structure. The two-stage aggregation strategy enables robust age prediction, even in the presence of contradictory outputs from binary classifiers. Moreover, the models perform competitively across both controlled and in-the-wild datasets without relying on demographic attributes like gender or race, which enhances generalizability. However, the three-group version (DOEL3groups) shows sensitivity to noisy labels during pretraining, which can degrade its performance, especially in datasets like IMDB-WIKI with uncertain age annotations. Additionally, factors such as misalignment, occlusion, and poor lighting in facial images still contribute to performance degradation.

Future improvements can focus on enhancing the robustness of the DOEL3groups model to label noise, possibly through noise-aware training strategies or label smoothing techniques. Incorporating advanced image pre-processing methods—such as pose normalization, illumination correction, and occlusion detection—may help mitigate issues from poor input quality. Furthermore, integrating demographic priors (e.g., gender or ethnicity) as auxiliary tasks, while maintaining model fairness, could further boost accuracy. Lastly, adaptive ensemble strategies that dynamically adjust group boundaries based on data distribution may enhance flexibility and performance across diverse datasets [17].

The proposed Divergence-driven Consistency Training (DCT) framework presents an effective semi-supervised approach for facial age estimation by intelligently leveraging unlabelled data. Through innovations like Efficient Sample Selection (ESS) and identity-based consistency regularization (IC), it addresses the limitations of conventional pseudo-labelling methods, reducing training time while enhancing performance. However, the approach may still be sensitive to errors in pseudo-labels, particularly in datasets with high intra-class variance or noisy samples, and its reliance on a pre-trained teacher model can propagate bias or inaccuracies.

Future research could focus on dynamically refining pseudo-labels using uncertainty estimation or ensemble teacher models to enhance robustness. Extending this framework to accommodate cross-domain generalization or domain adaptation could make it more applicable to real-world scenarios. Moreover, integrating facial attribute disentanglement or generative data augmentation might further boost performance in data-scarce environments, especially for underrepresented age groups [18].

A valuable enhancement to age estimation models proposed by replacing the traditional Mean Square Error (MSE) loss with more robust alternatives, such as the L1 norm and an adaptive loss function. These alternatives demonstrate improved resilience to outliers, which are often present in real-world datasets, thereby enhancing both the accuracy and reliability of age estimation. Additionally, the adaptive loss significantly accelerates training convergence, achieving comparable or better results in fewer epochs compared to MSE and MAE. This not only reduces computational cost but also implies better optimization dynamics. However, the approach is still limited by the quality and diversity of training datasets, and it does not address domain adaptation or demographic biases explicitly, which may affect performance across populations.

To build on the strengths of robust loss functions, future research could explore dynamic loss adaptation mechanisms that adjust the loss function during training based on error distribution or learning progress. Furthermore, integrating robust loss frameworks with attention-based or transformer models might yield superior age estimation performance. It would also be beneficial to investigate the robustness of these losses under cross-dataset evaluations and in the presence of occlusions, varied expressions, and ethnicity-induced aging patterns. Finally, combining robust loss functions with fairness-aware training techniques could lead to more equitable and generalizable age estimation systems [19].

The proposed Cross-Dataset Training Convolutional Neural Network (CDCNN) presents an effective solution to the challenges posed by limited and low-quality age-labeled datasets. By jointly training on multiple datasets such as MORPH, CACD, and AFAD, the model leverages diverse facial data, improving its generalization ability across demographics and imaging conditions. The re-framing of age estimation as a classification task, along with the use of softmax for output refinement, helps address issues commonly associated with regression-based approaches, especially in the presence of data scarcity. The method achieves state-of-the-art accuracy on benchmark datasets, validating the advantage of cross-dataset training. However, reliance on the heavy VGG-16 backbone limits model efficiency and scalability, particularly for real-time or resource-constrained applications. Moreover, although the method demonstrates robustness, it doesn't explore adaptation strategies for unseen domains or demographic imbalance.

To further enhance CDCNN's effectiveness, future research could explore integrating lightweight architectures like MobileNet or transformer-based models to balance accuracy and efficiency. Additionally, adopting domain adaptation techniques could help the model better generalize to entirely new datasets or demographics not seen during training. Incorporating semi-supervised learning or self-supervised pretraining might also address the limitation of labelled data scarcity more effectively. Lastly, extending the framework to multitask learning setups—predicting attributes like gender, emotion, or health alongside age—could enrich the shared representations and further boost performance in holistic facial analysis tasks [20].

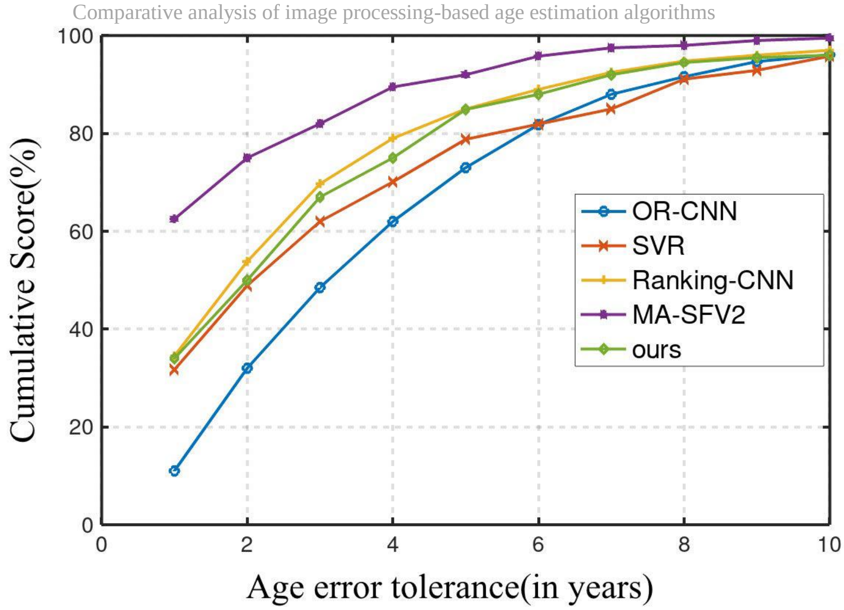

Figure 4: CS curve on MORPH [20].
Source: Own elaboration.

This study addresses the increasing demand for real-time age estimation systems by proposing a lightweight CNN architecture optimized for mobile deployment. Unlike conventional deep CNNs that are computationally intensive, the proposed model maintains competitive accuracy on benchmark datasets such as FG-NET, MORPH-II, and APPA-REAL while significantly reducing model complexity and training time. This balance between efficiency and performance makes it particularly suitable for applications with hardware limitations, such as mobile health apps or portable age-verification systems. The incorporation of robust image pre-processing and adaptive augmentation also contributes to the model's resilience across various imaging conditions. However, despite promising results, the system's dependence on relatively well-curated datasets may still limit its effectiveness on real-world, low-quality, or non-frontal face inputs. Furthermore, the use of static architectures without leveraging recent advances in attention mechanisms or transformers may constrain its full potential.

Future improvements should aim at integrating lightweight attention modules or neural architecture search (NAS) techniques to further enhance the accuracy of compact models without increasing computational load. Developing pre-processing pipelines that can quickly detect and align non-frontal or occluded faces would also boost the model's usability in real-world scenarios. Additionally, expanding the model's capability to handle diverse demographics, lighting conditions, and spontaneous expressions could make it more robust across varied user environments. Finally, incorporating cross-task learning to predict related facial attributes (e.g., gender, emotion, or ethnicity) alongside age could lead to richer, context-aware age predictions and further expand the application scope of mobile-friendly facial analysis systems [21].

Table 3 provides a comparative analysis of the neural network-based techniques discussed above, detailing the employed methodologies and resulting performance metrics.

Table 3: Comparative analysis between neural network techniques.

References	Method	The database used with MAE
A. Othmani et. al. [1]**¡Error! No se encuentra el origen de la referencia.**	AAE based on different Convolutional Neural Network	MORPH II: 2.01
H. Liao et.al. [6]**¡Error! No se encuentra el origen de la referencia.**	CNN and Deep Learning Method, Divide-and-Rule Face Age Estimator	FG-NET: 4.02; MORPH II: 3.48 IMDB-WIKI: 3.29
C. Xiao et. al. [12]	LAAE	MORPH:--; AFAD:--
A. Sakata et.al. [13]**¡Error! No se encuentra el origen de la referencia.**	Uncertainty-Aware Gait-based Age Estimation	Largest Gait database-OULPAge : 5.43
N. Liu [14]	Saliency map enhanced age estimation method with Deep Learning	NA
P. Siritanawan et. al. [15]	Conditional generative Adversarial Network	CACD: NA
C. Hu et. al. [16]	MAN	MORPH II:2.72; IMDB WIKI:2.86
J. Xie et. al. [17]	Deep and Ordinal Ensemble Learning	MORPH II:2.81; FGNET:3.44 AGEDB:5.80; CHALEARN LAP 2015:2.9
Z. Bao et. al. [18]**¡Error! No se encuentra el origen de la referencia.**	Divergence-Driven Consistency Training	MORPH:2.17; CACD:4.09 CHALEARN:2.87
F. Dornaika et. al.**¡Error! No se encuentra el origen de la referencia.** [19]	Robust regression with deep CNNs	FG-NET:3.05; PAL:2.74 MORPH:2.75
B. Zhang et. al. [20]	Cross-Dataset Learning	MORPH:2.76; CACD:4.58 AFAD:3.30
O. Agbo-Ajala et. al. [21]	Lightweight CNN	FGNET: 3.05; MORPH II:2.31

Source: Own elaboration.

d. Composite Techniques

Composite techniques in age estimation combine multiple modelling strategies to leverage the strengths of individual methods and enhance overall accuracy.

A novel exploration into the use of facial image sensing technology for estimating the age of cadavers was envented. One of its main strengths lies in the dual evaluation of the software's performance on both living individuals and deceased subjects, which offers practical insights for forensic applications. The use of statistical analysis, such as correlation coefficients and accuracy within ±10 years, supports the reliability of the findings.

However, the study has notable limitations. The sample size is relatively small, with only 28 living subjects and 61 cadavers, which restricts the generalizability of the results. Additionally, the reliance on a single commercial software, FieldAnalyst Ver. 6.0, limits the scope of the findings, especially since no comparison was made with other age estimation tools or modern deep learning approaches. The software also exhibited a consistent tendency to underestimate the ages of cadavers, likely due to postmortem changes in facial features such as muscle relaxation and skin tone variation. Despite these issues, the study's conclusion—that current facial image sensing tools developed for living subjects are not yet reliable for cadaveric age estimation-is well supported by the results.

Looking ahead, there is significant potential for improving age estimation for deceased individuals. One promising direction is the creation of a specialized dataset containing facial images of cadavers, which would allow for the training of deep learning models specifically tailored to postmortem conditions. Domain adaptation techniques, such as transfer learning, could help adapt models trained on living individuals to work better with postmortem data.

Furthermore, integrating additional forensic data-such as dental records, bone analysis, or 3D facial morphology—could enhance the accuracy of age predictions. Developing preprocessing algorithms that correct for postmortem facial changes, such as skin discoloration or sagging, would also be beneficial. Lightweight AI models that can be deployed on mobile devices could support forensic teams during field investigations, especially in disaster scenarios involving mass casualties.

In the long term, collaboration between forensic experts, medical institutions, and AI researchers will be essential to build robust, ethical, and effective age estimation tools. While current systems fall short, the field holds great promise if supported by targeted data collection, algorithmic innovation, and thoughtful integration into forensic workflows [22].

The paper introduces a novel application of Hidden Factor Analysis (HFA) for age estimation, highlighting the often-overlooked age component in age-invariant face recognition systems. By decomposing facial features into age and identity components, the authors leverage the age-specific subspace to perform discriminative manifold learning, followed by regression-based age prediction. This approach effectively isolates and utilizes age-relevant information, which traditionally remained underused in prior HFA-based systems. The use of a low-dimensional representation enhances feature robustness and computational efficiency. Results on the MORPH II dataset show superior performance over existing methods, underscoring the strength of the proposed aging manifold in capturing age-discriminative patterns. However, the model's reliance on well-controlled datasets like MORPH II may limit its generalization to more diverse or unconstrained face images. Furthermore, the paper does not address the computational overhead of HFA modelling or the sensitivity of subspace learning to noise and demographic variation.

Future work could explore integrating HFA with deep learning architectures to automatically learn more expressive and generalized age-related features across varied datasets. Additionally, introducing domain adaptation techniques could improve the model's robustness to cross-dataset performance, especially for applications in the wild. There is also potential to fuse the identity and age subspaces to develop multi-task learning frameworks that simultaneously estimate age and verify identity, enhancing system efficiency and contextual understanding. Finally, incorporating temporal progression modelling (e.g., with sequence data or longitudinal face datasets) could further refine age estimation by capturing how aging manifests dynamically across different individuals [23].

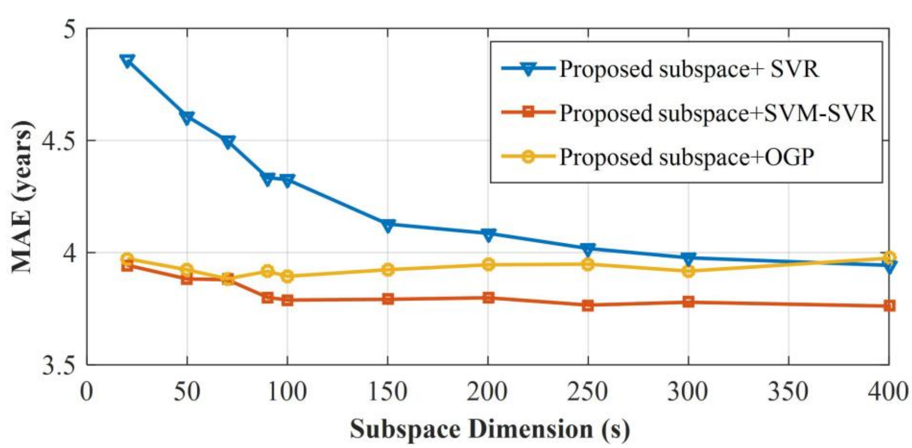

Figure 5: MAE versus dimensionality of proposed aging subspace [23].
Source: Own elaboration.

Table 4 provides a comparative analysis of the composite techniques mentioned above, summarizing the methodologies used and their respective performance outcomes.

Table 4: Comparative analysis between composite techniques.

References	Method	The database used with MAE
A. Takeda et.al. [22]	Face image sensing technology with Software Field Analyst for Signage Ver. 6.0 AW32	NA
M. Sawant et.al. [23]	HFA+SVM+SVR	MORPH II: 3.75

Source: Own elaboration.

III. AGE DATABASE

Public databases play a critical role in advancing research by providing readily accessible and standardized resources for experimental analysis and comparative evaluation. In the domain of facial aging and age estimation, numerous datasets have been developed and shared over the years. These databases vary in terms of subject diversity, age coverage, image resolution, and availability, thus catering to different research needs.

Early and foundational datasets include FG-NET [24] and MORPH II [25], which have been widely adopted in aging pattern analysis. More recently, datasets such as SCAF and LCAF [18] have been introduced to address age imbalance and provide richer subject diversity.

Adience Dataset [11]: Contains 26,580 images of 2,284 subjects, labeled with gender and age groups, captured in uncontrolled conditions.

LC Image Database [14]: Contains 20,174 lateral cephalometric images of individuals aged 4-40, organized in 5-year age intervals.

FG-NET Aging Database [24]: Contains 1,002 images from 82 individuals, primarily covering ages up to 40 years. Each image includes 68 annotated facial landmarks. The dataset is publicly available.

MORPH II Age Database [25]: One of the most widely used databases, it includes 55,314 face images of subjects aged 16–77, with an average of four images per individual.

IMDB-WIKI Database [26]: The largest publicly available dataset, featuring 523,051 images compiled from IMDB and Wikipedia profiles of 100,000 celebrities.

FERET Database [27]: Sponsored by DARPA, contains 14,126 face images from 1,199 subjects aged 10–70, supporting facial recognition under varying conditions.

Cross-Age Celebrity Dataset (CACD) [28]: Includes 163,446 images of 2,000 individuals. While publicly available, the dataset suffers from labeling noise and duplicate entries.

ChaLearn LAP 2015 Dataset [29]: Contains 7,591 labeled images for training, validation, and testing in apparent age estimation challenges.

OU-ISIR Gait Database [30]: The world's largest gait database with 63,846 samples, used for age estimation based on walking patterns.

Productive Aging Lab (PAL) Database [31]: Comprises 1,142 neutral-expression face images from 575 subjects aged 18–93.

LCAF and SCAF Databases [32]: LCAF contains 1.7 million images drawn from a 5-million-face collection, emphasizing subjects under 20 years old. The SCAF subset includes 0.5 million images from 12,000 individuals.

AgeDB [33]: A wild dataset with 16,488 face images of 568 subjects, capturing real-world variation.

Cross-Age Labeled Faces in the Wild (CALFW) [34]: Comprises 12,176 images of 4,025 individuals, created to test face recognition with large age differences.

Asian Face Age Dataset (AFAD) [35]: Includes over 160,000 facial images with consistent age and gender labels, representing a broad age spectrum.

Table 5 provides a comparative summary of these databases, including parameters such as age range, number of subjects, total images, and public accessibility.

Table 5: Summary of different database.

Database name	Total Images	Total subjects	Age Range	Year
FERET image database [27]	14,126	1,199	10-70	1998
FG-NET Age Database [24]	1,002	82	0-69	2002
PAL Age image database [31]	1,142	575	18-93	2004
MORPH II Age Database [25]	55,134	13,618	16-77	2009
OULP-Age image database [30]	63,846	31,923	2-90	2012
Cross-age celebrity database (CACD) [28]	163,446	2,000	16-62	2014
Audience image database [11]	26,580	2284	0-60	2014
IMDB-WIKI image database [26]	523,051	20,284	0-100	2015
Chalearn LAP 2015 Databases [29]	4691	3,125	0-100	2015
Asian Face Age Dataset (AFAD) image database [35]	164,432	164,432	15-40	2016

LC image database [14]	20,174	20,174	4-40	2017
AgeDB image database [33]	16,488	568	1-101	2017
Cross-age labeled faces in the wild (CALFW) database [34]	12,176	4,025	0-60	2017
LCAF and SCAF image database [32]	2.2 million	1.5 million	0-20	2021

Source: Own elaboration.

IV. AGE ESTIMATION EXPERIMENTAL PARAMETER

To evaluate the performance of age estimation methods, two primary metrics are commonly employed: Mean Absolute Error (MAE) and Cumulative Score (CS). These evaluation parameters are frequently used in age estimation research [3].

MAE is defined as the average of the absolute differences between the estimated ages and the ground truth ages, as expressed in Equation (1).

$$\mathrm{MAE} = \sum_{k=1}^{N} \frac{|\hat{l}_k - l_k|}{N} \quad (1)$$

where l_k is the ground truth age for the test is image k and $\hat{l}_k$ is the estimated age and N is the total number of test images.

The cumulative score is defined from (2) as:

$$CS_{(j)} = \frac{N_{e\leq j}}{N} * 100 \quad (2)$$

where $N_{e\leq j}$ is the number of test images on which the age estimation makes an absolute error no higher than j years.

Also, to measure the performance of age classification and estimation, classification accuracy is calculated that gives exact age group and gender results. It is given as the ratio of the accurate predictions to the total number of the ground-truth labels [7]. Mathematically, the metric is described from (3) as:

$$\mathrm{Accuracy} = \frac{\text{Number of Accurate prediction}}{\text{ground} - \text{truth class}} \quad (3)$$

These evaluation metrics collectively enable researchers to comprehensively assess the effectiveness and reliability of age classification and estimation algorithms, facilitating informed comparisons and advancements in the field.

V. GIST OF VARIOUS AGE ESTIMATION TECHNIQUES

Age estimation research involves various methodologies and datasets aimed at accurately predicting human age from facial images. Transformation-based techniques, which convert images into feature representations, are commonly employed. However, these methods often require a substantial number of samples for each age group, limiting their applicability in scenarios with fewer classes.

Spatial-domain techniques provide precise age estimation by directly analysing spatial features. However, they can be sensitive to feature variance and are prone to inaccuracies when trained on imbalanced datasets. Composite techniques, which integrate both transformation-based and spatial-domain approaches, seek to mitigate classification errors. However, they introduce challenges such as parameter tuning and the need to balance trade-offs between the different methodologies.

Neural network-based techniques, particularly those leveraging deep learning architectures, have gained prominence due to their ability to learn complex patterns and representations directly from data. Combining various convolutional neural network (CNN) structures can further enhance the performance of age estimation algorithms.

To ensure the robustness of age estimation algorithms, validation with diverse datasets is essential. Datasets like FG-NET, MORPH II, and IMDB-WIKI provide comprehensive benchmarks for evaluating the performance of different techniques. These datasets offer a wide range of facial images spanning various age groups, allowing researchers to compare and benchmark the accuracy of their algorithms effectively.

VI. FUTURE TRENDS AND RESEARCH GAPS IN AUTOMATIC AGE ESTIMATION

As the field of automatic age estimation evolves, several future trends and emerging methodologies hold the potential to significantly enhance the accuracy and robustness of age prediction systems. These include the use of advanced techniques such as generative networks, pre-trained models like Vision Transformers (ViTs), and innovative hybrid approaches that combine multiple methodologies.

- Generative Networks for Age Estimation: The use of generative adversarial networks (GANs) and conditional GANs (cGANs) has shown promising results in synthesizing age-progressed or age-regressed facial images. These methods, such as the heritability-aware cGAN framework, have made strides in predicting age-related transformations by considering the biological inheritance of facial features. However, despite their success in simulating realistic facial aging processes, generative networks still face challenges with early childhood face predictions and their performance across diverse populations. Future advancements may focus on improving the realism of age progression in children and enhancing cross-population applicability through improved training datasets and domain adaptation techniques. Moreover, coupling generative networks with emotion recognition or health diagnostics could extend their applications beyond age estimation, offering a more holistic approach to facial analysis.

- Pre-Trained Models and Transfer Learning with Vision Transformers: Pre-trained models, particularly Vision Transformers (ViTs), have emerged as strong contenders in the deep learning landscape, surpassing traditional CNN architectures in some domains. Vision Transformers leverage self-attention mechanisms to capture both global and local features, which can improve age estimation accuracy, especially in the presence of challenging factors like occlusion, poor lighting, or variable expressions. However, the challenge remains in fine-tuning these models effectively for age estimation tasks without introducing demographic biases or performance degradation on underrepresented age groups. Future research could focus on exploring ViT-based models specifically fine-tuned for age-related features, possibly combining them with lightweight architectures for real-time deployment in mobile applications. Additionally, applying Vision Transformers to cross-dataset training frameworks could enhance the model's ability to generalize across diverse imaging conditions and demographic distributions.
- Hybrid Approaches and Multi-Modal Integration: The trend of combining multiple techniques into hybrid models is gaining traction. For instance, models that combine convolutional networks with uncertainty-aware methods or hierarchical refinement approaches could provide more robust age predictions under real-world conditions. Composite models could also benefit from integrating multimodal data, such as combining facial images with gait analysis, speech patterns, or medical records, to create more holistic age estimation systems. This would be especially useful in resource-constrained environments, such as mobile devices or remote healthcare applications. Additionally, by merging generative networks with classical CNNs, hybrid architectures could refine age estimation predictions by synthesizing facial images under different conditions, enhancing the model's robustness to varied lighting, occlusions, and ethnicity-induced aging patterns.
- Attention Mechanisms and Robustness to Data Quality Issues: The growing use of attention mechanisms, both spatial and channel-based, in age estimation models has shown promise in improving performance while reducing the need for large computational resources. These models highlight critical regions of the face that contribute most significantly to age-related features, allowing for fine-grained age estimation. However, current attention-based models remain sensitive to data quality issues, including image occlusion, non-frontal faces, and low-resolution inputs. Future research could focus on enhancing the robustness of attention mechanisms through adaptive training techniques or by incorporating pre-processing methods that correct for poor-quality images before they are input into the model. Additionally, the exploration of uncertainty-aware attention modules could help improve the model's reliability in uncertain conditions, such as when facial features are partially obscured.

VII. RESEARCH GAPS AND OPPORTUNITIES

Despite the significant progress made in the field of automatic age estimation, several research gaps and challenges remain:

- **Cross-Dataset Generalization and Data Scarcity:** Many current models rely on well-curated datasets like MORPH or CASIA-WebFace, which may not capture the full spectrum of demographic diversity. There is a need for larger, more diverse datasets that represent a wide range of ethnicities, genders, and age distributions to improve the generalization of age estimation systems. Moreover, in data-scarce domains, semi-supervised learning and domain adaptation techniques could play a crucial role in enabling more robust model training without requiring large labelled datasets.
- **Ethnic and Gender Biases:** Ethnic and gender biases remain prevalent in many age estimation models. For example, models that perform well on datasets dominated by certain ethnic groups may struggle when applied to faces not represented in the training data, especially with respect to unique aging patterns across races. To address these issues, future research should focus on creating more balanced training datasets and explore techniques like fairness-aware learning to ensure equitable performance across all demographic groups.
- **Real-Time Deployment and Efficiency:** Although many models achieve high accuracy, they are often computationally intensive and not suitable for real-time deployment, especially on mobile or edge devices. The challenge lies in developing lightweight models that balance high performance with low computational overhead. Research into model compression techniques, efficient architectures like MobileNet or EfficientNet, and neural architecture search (NAS) could pave the way for practical real-time age estimation systems.
- **Interpretability and Explainability:** As age estimation models become more complex, there is an increasing demand for interpretability and explainability in AI systems. Understanding which facial regions contribute most to age estimation or how different age groups are represented in the model could improve trust and transparency, especially in sensitive applications like healthcare or forensic investigations. Future work should focus on developing tools for visualizing and understanding the decision-making process of these models, making them more interpretable and accessible to non-technical users.
- In summary, the future of age estimation lies in integrating cutting-edge technologies like generative models, pre-trained Vision Transformers, and hybrid architectures that leverage multimodal data and attention mechanisms. By addressing current research gaps related to dataset diversity, bias mitigation, real-time efficiency, and model interpretability, the field can continue to improve and expand its applications across various industries, from healthcare to forensic science and beyond.

VIII. CONCLUSIONS

Research in age estimation from facial images is driven by the need to efficiently interpret nonverbal cues, ensuring seamless human-computer interaction. With applications ranging from access control to personalized services, accurate age estimation is critical. This review paper describes the aging process as stochastic, uncontrollable, inevitable, and irreversible, resulting in variations in facial shape and texture. Recent trends in information technology aim to enhance human-computer interaction, and this paper extensively covers various age estimation algorithms. The interplay of intrinsic and extrinsic factors in facial aging presents challenges, which have been addressed through several methodologies:

- Transformation-based techniques leverage models such as Active Appearance Models (AAMs) and Principal Component Analysis (PCA) to extract age-related features. While effective, these methods require substantial samples for each age group. However, they can also work with smaller datasets and simpler models, delivering good results.

- Spatial-domain techniques directly manipulate pixel values for precise age estimation. These techniques often outperform classifiers in accurately estimating age as continuous values. However, they are sensitive to feature variance and imbalanced datasets.
- Composite techniques combine transformation-based and spatial-domain approaches to mitigate classification inaccuracies. By integrating features from different models, they create more robust systems. Additionally, deep learning-based algorithms, particularly those employing CNN architectures, have gained significant attention for age estimation. Despite their potential, they face challenges in parameter tuning and balancing trade-offs.
- Neural network-based techniques, particularly deep learning, offer promising results by learning complex patterns. Combining various CNN structures can enhance algorithm performance. Challenges in estimating real age arise due to the inherent aging process and skin variations, which affect the accuracy of models. Unstable configurations and limited datasets also pose obstacles for realizing robust age estimation methods.
- Validation with datasets like FG-NET, MORPH II, and IMDB-WIKI is crucial for developing robust age estimation algorithms. These datasets provide benchmarks for evaluating performance across different methodologies.

In summary, the integration of diverse techniques, combined with rigorous validation using comprehensive datasets, drives the advancement of age estimation algorithms. This progress contributes to more seamless human-computer interaction and personalized services across various domains.

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