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Advanced Techniques in Age-Invariant Face Recognition: A Survey

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Abstract

Age-Invariant Face Recognition (AIFR) addresses the critical challenge of identifying individuals despite age induced facial changes over time. This paper presents a structured survey of recent advancements in AIFR, emphasizing deep learning-based solutions, particularly Generative Adversarial Networks (GANs). Through a comparative analysis of benchmark datasets MORPH-II, FG-NET, and CACD we highlight the performance trends and limitations of current models. GANs have shown exceptional promise in synthesizing realistic age-progressed or age-regressed facial images, thereby improving recognition accuracy across age gaps. Furthermore, we analyze key factors affecting model performance, including dataset diversity, illumination, and pose variations. Despite significant progress, challenges remain in generalizing across ethnicities, age ranges, and real-world conditions.

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AIFR, Face Recognition, Face Aging, Contrastive Learning, GANs, Deep Learning.

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1. INTRODUCTION

Biometric systems distinguish individuals based on physical traits, such as facial features, iris patterns, and fingerprints, as well as behavioral traits, such as walking style, voice characteristics, and typing patterns. Face is the most widely used biometric trait because of its accessibility and minimal need for subject cooperation. Among *soft biometrics*, age stands out for its versatile applications: *Age Estimation*: Used in security and surveillance to prevent minors from accessing age-inappropriate content or products [1]. Facial aging synthesis involves creating visual representations that depict the progression of facial appearance across various age stages. [2]. This field has attracted considerable interest because of its diverse applications, such as enhancing face recognition across different age groups and supporting entertainment technologies. [3]. *Face recognition* is a specialized subset of visual pattern recognition. While humans process visual information through their eyes and recognize it as a meaningful concepts via the brain, computers interpret images or videos as pixel matrices, requiring algorithms to identify and classify patterns. To perform face recognition, systems need to identify unique individuals from facial data, which requires a series of steps, such as detecting faces, aligning their positions, recognizing identities, and preprocessing the images. Facial detection identifies facial coordinates in an image by scanning candidate areas, producing outputs such a square or rectangular coordinate systems. Face- positioning pinpoints facial features within these coordinates, typically leveraging deep learning frameworks for efficiency. Compared with detection, positioning requires significantly less computation time [4]. Face-recognition performance is often constrained by substantial intraclass variations arising from factors such as pose, lighting conditions, facial expressions, and aging. As a result, most current research on face recognition focuses on compensating for variations that degrade performance. However, facial aging has not received adequate attention compared with other sources of variation, such as pose, lighting, and expression [5], [6]. Age-invariant face *Recognition (AIFR)* focuses on identifying individuals over time, regardless of changes in facial features caused by aging. It plays a critical role in applications such as criminal identification,

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locating missing persons, and verifying identities from photos taken at different ages [7]. Age-invariant facial recognition presents several challenges. As people age, natural changes in the skin, bones, and muscles can significantly alter facial features, making it difficult to match faces across different age groups. The availability of diverse datasets that cover all age ranges is often limited, which complicates the training of accurate models [8]. Many existing datasets tend to be biased toward certain age groups or demographics, further affecting the performance of the model. Moreover, environmental factors, such as variations in lighting, camera angles, and facial poses, add another layer of complexity, reducing the accuracy of face recognition across age groups [9], [10]. Exploring the challenges of using these techniques in real applications. This survey aimed to explore advancements in Age-Invariant Face Recognition techniques, particularly addressing the challenges associated with age progression, limited dataset diversity, and environmental variations. The focus is on the most promising methodologies that aim to improve the accuracy and robustness of AIFR systems, with a detailed review of the solutions proposed in the literature, including the integration of deep learning techniques, age-invariant feature extraction, and data augmentation strategies. By investigating these advancements , thise research seeks to thoroughly examine the present landscape of the AIFR and its potential to address these challenges in practical applications. Despite significant progress and a growing number of studies on age-invariant face recognition (AIFR), previous surveys have several limitations. They often overlook recent deep learning advances, such as GANs and contrastive learning, lack a unified taxonomy of techniques, provide insufficient analysis of real-world challenges and dataset biases, and pay limited attention to practical applications. This survey aimed to address these gaps by offering a comprehensive and up-to-date review that covers both theoretical and practical aspects.

2. SCOPE AND MOTIVATION

The growing demand for reliable identity verification across age spans has intensified interest in Age-Invariant Face Recognition (AIFR). Unlike general face recognition tasks, AIFR systems must contend with age-induced changes in facial structure and texture, which significantly increase intra-class variance [3]. This survey was driven by the need to comprehensively examine the evolution, strengths, and limitations of AIFR methodologies, particularly in light of recent advances in deep learning. A comprehensive review of the scholarly literature was conducted, covering a broad range of publication periods and methodological approaches. From these, six highly influential studies were selected for a detailed analysis based on their strong experimental design, diversity of techniques, and evaluation of benchmark datasets. These key papers serve as representative examples of the recent progress and ongoing challenges in the field.

- The scope of this survey includes:
- Benchmark datasets used in AIFR research (e.g., MORPH-II, FG-NET, CACD).

- Evaluation of performance metrics and dataset-specific results.
- Comparative analysis of model architectures and training strategies.
- Identification of open challenges and underexplored research directions.

By synthesizing findings across a wide range of studies, this study aims to guide researchers in understanding the landscape of AIFR, identifying promising methodologies, and highlighting areas in need of further innovation, such as real-world deployment, dataset diversity, and fairness in cross-demographic scenarios.

3. HISTORICAL BACKGROUND

1960s, Woodrow Wilson Bledsoe pioneered a manual facial recognition system in which facial feature coordinates are manually recorded and compared in a database. By the 1970s, advances in pattern recognition and computing had led to further developments. Goldstein, Lesk, and Harmon proposed 21 unique facial features, including hair color and lip thickness, for automated facial recognition; however, their advancement was constrained by limited technology and a lack of large-scale datasets [11].

Early Approaches (Before 2000): Traditional facial recognition methods primarily rely on geometric facial feature analysis and classification algorithms such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). However, these methods do not consider age-related variations, which limits their effectiveness in long-term identity verification [11], [12].

The Transitional Phase (2000–2010): During this period , facial recognition accuracy began to improve with the introduction of machine learning approaches and the initial development of deep neural networks. Despite these advancements, age-related facial variations remain a significant challenge [13]. Before the rise of deep learning, facial recognition relied on handcrafted feature extraction methods. **Eigenface** utilized **PCA** to project facial images into a lower-dimensional subspace, while **Fisherface** improved this approach using **LDA**, which optimized class separability. Additionally, "To boost classification accuracy,**Support Vector Machines (SVM)** were integrated with advanced feature extraction methods, including **Independent Component Analysis (ICA)** and **Kernel Principal Component Analysis (KPCA)**. Texture-based approaches such as Local Binary Patterns (LBP) and Local Ternary Patterns (LTP)

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have, also been employed to capture fine-grained facial details. Despite these improvements, the capacity to manage age-related variations in facial characteristics remains a major limitation [14].

The Modern Era (2010–Present): The introduction of CNNs and GANs has significantly improved the accuracy of facial recognition across age differences. These techniques have demonstrated remarkable success in generating aged facial images and mitigating the effects of age progression on recognition accuracy [15], [16].

Future Trends and Challenges: Future research on Age-Invariant Face Recognition (AIFR) should focus on integrating Contrastive Learning with GANs to enhance model robustness against age-related variations. These advancements aim to improve recognition accuracy in high-security applications, such as national identity verification and law enforcement [17].

4. FACE RECOGNITION

4.1. Face Recognition Overview

Facial recognition is a form of biometric identification that relies on the analysis of unique facial characteristics to recognize individuals. Over the years, its development has undergone three major stages. Initially, face recognition relied on manual feature analysis. This was followed by the use of geometric parameters and multidimensional vectors combined with human-computer interaction. Since the 1990s, artificial intelligence (AI) has played a crucial role in automating the recognition process, improving the performance even for occluded and 3D faces [18]. Facial recognition is widely applied in banking, healthcare, identity verification, and surveillance. Unlike other biometric methods such as fingerprint or iris scanning, it does not require active user cooperation, making it more convenient and user-friendly [19]. Conventional two-dimensional (2D) facial recognition methods have shown reliable accuracy when tested in well-controlled environments. However, applying these systems to real-world scenarios presents challenges, including inconsistent lighting, variations in head pose, and dynamic facial expressions. Deep learning significantly enhances the robustness of these methods [20]. Despite these advancements, 2D face recognition still struggles with occlusions and extreme pose variations [21]. In contrast, **3D face recognition** offers greater accuracy because it is more robust to illumination changes and pose variations. The availability of rich geometric information in 3D facial data enhances the recognition performance. Recent advancements have integrated 2D and 3D face recognition models to improve accuracy and reliability [22], [23]. Initially, 3D face recognition techniques relied on Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), and Gabor wavelets. Over time, these approaches have evolved with the combination of deep convolutional neural networks (DCNN) and GANs, enabling better handling of pose variations [24].

4.2. Challenges of Face Recognition

Despite significant advancements, face recognition systems have several challenges that affect their accuracy and robustness in real-world applications.

Impact of Lighting Variations :Lighting conditions significantly influence the recognition accuracy. Variations in illumination can distort facial appearances, affecting shadow distribution and contrast. Poor lighting may obscure key facial features, which makes it difficult to extract fine details for accurate identification. Advanced normalization techniques and deep learning models help mitigate these effects and enhance the system robustness [25].

Variations in Facial Expressions :Facial expressions introduce a different level of complexity. Changes such as smiling, frowning, or raising eyebrows alter the spatial distribution of facial features, making it difficult for recognition systems to distinguish between identity and emotional states. Addressing this challenge requires sophisticated deep-learning models to extract expression-invariant features. Techniques such as data augmentation and expression normalization improve the system performance under dynamic conditions [25].

Occlusions and Aging Effects :Facial occlusions, such as glasses, masks, and facial hair, can obstruct key identity-related features, leading to recognition errors [26]. Similarly, the natural aging process alters facial structure over time, making it difficult for traditional recognition models to maintain consistent identification [27].

5. AGE-INVARIANT FACE RECOGNITION (AIFR)

5.1. Age-Invariant Face Recognition Overview

Age-Invariant Face Recognition (AIFR) is an area of study that focuses on minimizing the impact of age-related variations on facial recognition systems . The main challenge is that facial features change significantly with aging, leading to an increase in intra-class variance, which makes it more difficult to recognize individuals across different age stages [28].

5.2. Challenges of Age-Invariant Face Recognition

Regardless of age, face recognition systems faces several challenges that affect their accuracy and effectiveness. The most prominent of these challenges are: •**Lack of Longitudinal Data for Individuals Over Time:** The lack of longitudinal data, which refers to datasets containing images of the same individuals captured over

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extended periods, is a major challenge in Age-Invariant Face Recognition (AIFR) [29]. This limitation limits the ability of models to learn and adapt to age-related changes. For example, longitudinal datasets such as **MORPH II**, which include 55,134 facial images of over 13,000 individuals, are rare and limited [30], [31]Additionally, collecting images from a single person across different age phases is expensive and difficult, resulting in a lack of reliable data for training the models [32] . This scarcity of data negatively affects the functionality of facial recognition systems across ages, as studies have shown a significant decline in recognition accuracy as the time gap between images increases [33].

• **Age-related transformations:** Facial aging, also referred to as facial aging synthesis, involves generating images that depict how a person's face might appear at different stages of life [34]. Aging presents a considerable challenge for face recognition systems because of the biological changes that accompany age. These changes can lead to significant discrepancies in the facial features between images of the same individual taken at different ages. Because faces undergo the most noticeable changes over time, there is an increasing demand for the extraction of robust facial features for age-invariant face recognition, particularly when addressing large age gaps between images of the same person [35]. As people age, natural changes in the skin, bones, and muscles can significantly alter their facial features, making it more challenging to match faces across different age groups [36].

6. AGING DATASET

Table1: summarizes the most widely used aging datasets for face- recognition research. Each dataset varied in size, subject diversity, and age range, making it suitable for different experimental settings. The table includes brief descriptions, key limitations, and relevant references to help understand the strengths and constraints of each dataset in age-invariant face recognition (AIFR) studies

7. RECENT ADVANCEMENTS IN AIFR TECHNIQUES

With rapid advancements in artificial intelligence techniques, new and advanced methods have emerged in the field of AIFR, aimed at addressing the morphological changes that accompany aging. These developments rely on deep neural networks, generative models, and contrastive learning techniques, leading to improved identity- verification accuracy over long periods [38].

7.1. Deep Neural Networks (DNN) in AIFR

7.1.1. Convolutional Neural Networks (CNNs)

Deep learning, particularly convolutional neural networks (CNNs, is one of the most advanced techniques used for image analysis and facial recognition, achieving accuracy rates exceeding 90%. These networks rely on sequential layers for feature extraction, where the output of each layer is fed into the subsequent layer, enabling the construction of more complex image representations. Despite their high efficiency, CNNs require significant computational resources and longer training times than traditional algorithms. Models such as **DeepFace** and other CNN-based approaches have demonstrated remarkable improvements in facial recognition, particularly in Age-Invariant Face Recognition (AIFR). However, this field still requires further research and development to enhance accuracy and performance under various conditions and challenges [39], [40], [41].

7.1.2. ResNet

The ResNet architecture integrates residual learning techniques, that support stable and accurate training of deep neural networks. proposed a deep coupled ResNet model for low-resolution faciale recognition. It extracts shared facial features from images of different resolutions using a ResNet-like trunk network, and then maps these features through branch networks. The model achieved 93.6% - 98.7% accuracy on LFW and 73.0% - 98.0% on SCface [42]. ResNet (Residual Network) won ILSVRC-2015 and is known for using skip connections, which helps in incremental learning. ResNet-50 is a variant with 50 layers [43].

7.1.3. AlexNet

AlexNet, the winner of LSVRC2012, consists of eight trainable layers, five convolutional layers, and three fully connected layers. All trainable layers used the ReLU activation function, except for the last fully connected layer, which applieds softmax. The architecture also includes non-trainable layers, such as pooling layers [43].

7.1.4. Inception V3

is a deep CNN with 48 layers, designed to improve GoogleNet Inception. Factorization methods are employed to decrease both the parameter count and network connections while preserving computational efficiency [43].

7.1.5. GoogleNet

GoogleNet, developed by researchers at Google and the winner of the ImageNet 2014 challenge, adopts a split-transform-merge architecture, rather than a purely sequential architecture. This enables each layer to incor-

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Table 1. Summary of Commonly Used Aging Datasets in Age-Invariant Face Recognition Research

Dataset	Details	Limitations
FERET [37]	14,126 images of 1,199 subjects, minimal age variation.	Limited age differences, not ideal for age-invariant face recognition (AIFR).
FG-NET [31]	1,002 images from 82 subjects, used for facial aging research.	Few subjects, limits its generalization for large-scale age-based recognition.
MORPH [37]	Large dataset with 79,897 images of 21,194 subjects.	Still lacks enough age diversity for certain age groups.
CACD [37]	163,446 images from 2,000 celebrities.	Celebrity-focused, introduces bias for non-celebrity recognition tasks.
PCSO-LS [37]	1.5 million images of 18,007 criminals, with images taken over 5 years.	Excludes ages 0-15 and focuses on criminal profiles.
WIT [37]	1,109 images from 110 subjects, sourced from the internet.	Small size, potential variability due to internet-sourced images.
FACES [31]	1,026 images of 171 subjects with 6 facial expressions.	Fixed lighting and frontal views limit natural pose and lighting variations.
ADIENCE [37]	26,580 images from 2,284 subjects with variation in posture, lighting, and noise.	Wild images limit controlled condition testing, affecting recognition accuracy.
In-house Dataset [37]	200 images from various subjects with limited environmental diversity.	Small sample size and limited age variation affect generalizability.

porate multiple feature- extraction paths. Compared to VGG-Net, GoogleNet offers faster training and a more compact pre-trained model. However, it requires customization for almost every module, which can be a challenge when used for tasks such as face age estimation [44].

7.1.6. SqueezeNet

SqueezeNet is a neural network architecture that matches AlexNet's accuracy on the ImageNet dataset while utilizing nearly 50% fewer parameters, thanks to the application of model compression strategies , the model size can be compressed to under 0.5MB, making its size is roughly 510 times smaller than that of AlexNet . Its advantages include reduced communication overhead in distributed training, lower bandwidth requirements for cloud model exports, and easier deployment on hardware, such as FPGAs, with minimal available memory . The model relies on a growth phase using 1 $\times$ 1 and 3 $\times$ 3 convolutions through its fire modules, which reduce the spatial volume size [45].

7.1.7. VGGNet

The VGG model was created by the Visual Geometry Group at the University of Oxford, and is an extension of conventional CNNs with significantly increased depth. The architecture consists of 16 convolutional layers (VGG-16), with some variants extending to 19 layers (VGG-19). It incorporated five max-pooling layers by applying the ReLU activation function to introduce nonlinearity and perform spatial pooling. Additionally, 1$\times$1 convolution filters enhance the nonlinearity of the model in the decision function. To maintain spatial consistency, padding was applied after convolution in some of the layers. VGG-16 features three fully connected layers with a similar arrangement, including a softmax output layer for classification. Despite its 138 million parameters, VGG-16 remains a popular research model because of its structured and uniform architecture. It demonstrated impressive performance in the ILSVRC (ImageNet) 2014 competition, achieving a top-5 error rate of 7.32%, significantly improving over AlexNet [45].

7.2. Generative Models in AIFR

Generative Adversarial Networks (GANs) are widely used models for simulating face aging, because they enable the generation of high-quality images while preserving individual identity. Leading approaches include models such as CAAE, Age-cGAN, and IPC-GAN, which focus on maintaining essential facial features while applying the aging effects. In addition, networks such as StyleGAN and PFA-GAN leverage advancements in neural network architectures, allowing for the realistic generation of faces across a broader time span. Moreover, other generative models, such as Variational Autoencoders (VAEs) and deep Convolutional Neural Networks (CNNs), have emerged to facilitate the gradual synthesis of faces across different age groups. These models rely on techniques that learn shared features among age categories, enhancing the accuracy of identity verification systems over long periods [32].

7.3. Contrastive Learning and Metric Learning

Contrastive Learning and Metric Learning play a crucial roles in deep-learning-based face recognition by optimizing feature representations for identity verification. Contrastive Loss is a distance-based loss function that minimizes the gap between similar samples, while maximizing the difference between dissimilar samples. It operates by mapping images into a lower-dimensional space, where intra-class distances are small, and inter-

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Table 2. Taxonomy of AIFR Methods Based on Model Architecture and Objective

Category	Key Techniques / Models	Objective
CNN-Based	ResNet, VGGNet, GoogleNet	Feature extraction and classification
Generative Models	CAAE, CycleGAN, StyleGAN	Age progression and synthetic face generation
Contrastive Learning	FaceNet, Triplet Loss, CA-Con	Embedding learning and identity preservation
Hybrid Architectures	GAN + CNN, Multi-task Learning	Joint training for age and identity modeling

class distances are large. Triplet Loss further refines this concept by forming triplets of images: an anchor, a positive sample (same identity), and a negative sample (different identity). The objective was to ensure that the anchor was closer to the positive than to the negative by a predefined margin. This approach is extensively used in face verification systems, as seen in FaceNet and other deep metric learning techniques, to enhance the feature discriminability [24]. **Table 2**: A taxonomy of AIFR methods, categorized by architecture and learning objective. This classification highlights representative models and their specific roles in addressing age-invariance in face recognition systems. Figure 1 presents a comprehensive taxonomy of Age-Invariant Face Recognition (AIFR) methods, which reflects the structural organization of this study. The proposed classification divides AIFR research into four primary categories, each of which represents a major direction in the literature. **Table 3:** presents a

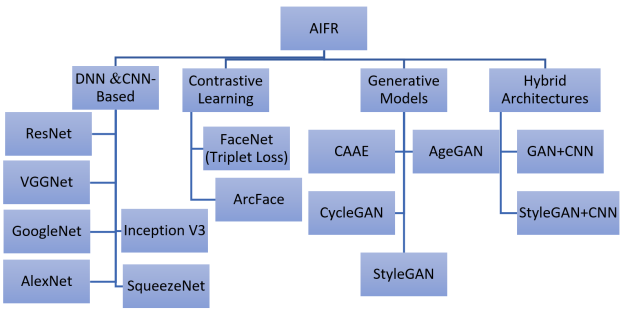


Figure 1. Taxonomy of Age-Invariant Face Recognition (AIFR) Technique

comparative analysis of the latest techniques in **AIFR**, including deep-learning techniques, **GANs**, contrastive learning, and **CNNs**. The table is based on data from various sources, such as **CACD, MORPH-II, FG-NET, and CelebA-HQ**, highlighting accuracy rates and performance across these datasets. Wang, Sanchez, and Li [1] presented a contrastive learning across age variations approach for AIFR. Their method leveraged contrastive learning to learn robust representations of faces across different ages, effectively addressing the challenge of age-related variations in facial features. By using a contrastive loss function, the model encourages the learning of features that remain consistent across age groups, thus enhancing facial recognition performance under age variation conditions. However, this study does not fully address the challenges related to data scarcity for certain age groups, particularly for younger and older populations. Further improvements could involve the use of synthetic data generation techniques, such as GANs, to enrich the training data diversity and optimize the recognition performance across different age groups. Syuhada and Sa'adati [46] improved cross-age face verification using GANs by generating facial images that reflected age progression. They integrated facial landmark features to enhance accuracy and addressed challenges such as the difficulty in verifying identity due to facial changes over time. To overcome these issues, GANs and deep learning techniques have been used to generate precise age-progressed images and to minimize the gap between the generated and original images. However, the study did not fully address the challenge of balancing the image accuracy with the generation time, especially in real-time applications. Integrating techniques, such as multi-task learning, could further improve the verification accuracy. Russel and Selvaraj [47] introduced a method for AIFR that utilizes transfer learning. They leveraged pre-trained models to overcome the lack of data tailored for age-related verification. This method improves the accuracy of identity verification across different age groups and enhances performance by using limited data. However, the study did not fully address challenges, such as the impact of lighting, angles, and image quality in practical scenarios. The accuracy of the model can be improved by employing domain adaptation techniques or integrating additional data for better identity verification. Liu and Wang [48] proposed a face aging synthesis method using a deep CycleGAN combined with a bias loss function. The authors proposed a model that can generate realistic aging effects on facial images, thus addressing the challenge of simulating natural age progression. By incorporating bias loss, the model effectively reduced artifacts and enhanced the quality of the generated aging images. However, this study did not fully explore the effects of diverse environmental factors, such as lighting and facial expressions, on the quality of the generated images. Future improvements could focus on integrating these factors for more robust and accurate aging synthesis. Yao, Farooq, Lemley, and Corcoran [49]

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Table 3. Overview of Recent Advancements in Age-Invariant Face Recognition

Authors	Year	Method/Algorithm	Dataset Used	Accuracy
[46]	2025	Face Matching Across Ages Using GANs and Facial Landmark Features	In-house collected face dataset (200 images)	ArcFace: 88.02% VGG-Face: 80.57% Facenet: 74.48%
[47]	2024	• Local Binary Pattern (LBP) • Histogram of Oriented Gradients (HOG) • MobileNetV2 • VGG-16 (Transfer Learning)	CACD	98.32%
[48]	2024	• Deep Cycle Generative Adversarial Networks (CycleGAN) • bias loss • VGG16	CACD2000 MORPH-II	**Aging Accuracy:** Best results for age **31–40** in MORPH-II **Identity Preservation: Ranked 1st** for age **50**+ in CACD2000 & MORPH-II **Subjective Evaluation: 56%** of **15 participants** preferred the proposed model over Lifespan, A^3GAN, and SAM
[1]	2024	Cross-Age Contrastive Learning (CA-Con)	FG-NET MORPH II CACD-VS	**LIOI:** 94.61% **MFI:** 64.37% **MF2:** 64.94% **MORPH-II:** 99.57% **Cross-Dataset Accuracy (CA Con):** MORPH-II → FG-NET: 82.03% MORPH-II → CACD-VS: 86.77% FG-NET → MORPH-II: 64.53% FG-NET → CACD-VS: 62.85% CACD-VS → MORPH-II: 75.38% CACD-VS → FG-NET: 58.37%
[49]	2023	• SAM (Style-based Age Manipulation) • CUSP (Custom Structure Preservation) • AgeTransGAN • ArcFace	CelebA-HQ B3FD	The recognition rate improved by 3.33% with synthetic aging images, with **CelebA-Syn-55** achieving the best performance for large age gaps.
[50]	2022	ResNet50 ResNet50-SE ResNet101 ResNet101-SE ResNet50 ResNet50-SE ResNet101 ResNet101-SE	FG-Net FG-Net CACD CACD	88.17% 89.55% <80% <80% 86.67% 88.21% <80% <80%
[51]	2021	Improved ASM + 7-layer CNN	FG-NET LAG CACD FG-NET MORPH-II	95.02% 91.76% 99.4% 89.55% (Rank-1 Accuracy) 96.0%
[52]	2020	GoogLeNet + HOG + LBP + Enhanced Convolution Neural Network (Majority Voting)	MORPH FG-NET	99.8% (Testing Accuracy) 100% (Testing Accuracy)

conducted a thorough evaluation of synthetic face aging techniques to improve age-invariant face recognition systems. Their study assessed several generative models, including Style-based Age Manipulation (SAM), Custom Structure Preservation (CUSP), AgeTransGAN, and ArcFace, using datasets such as CelebA-HQ and B3FD. The results demonstrated a 3.33% improvement in the recognition accuracy when synthetic aging images were incorporated, with the CelebA-Syn-55 subset delivering the best performance for large age gaps. The authors emphasized the value of synthetic data in compensating for the scarcity of real age-diverse datasets. However, they also noted challenges concerning the realism and preservation of facial structures in generated images, recommending further refinement of generative models to enhance identity consistency during aging transformations. Pi [50] introduced an approach for AIFR based on Convolutional Neural Networks (CNNs). This approach leverages the powerful feature extraction capabilities of CNNs to extract deep, age-invariant features from facial images. By training the network on a large dataset, the model learns to capture both the age-related and invariant features of faces, allowing it to perform face recognition across different ages with improved accuracy. This method addresses the challenges of aging-induced facial changes by focusing on features that remain con-

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sistent over time, thereby contributing to more reliable face recognition in age-diverse scenarios. However, this study does not fully address challenges such as variability in lighting, image quality, and pose, which can affect the performance in real-world applications. Integrating data augmentation or multi-task learning could potentially improve robustness and accuracy in more complex, uncontrolled environments. Dhamija and Dubey [51] proposed an innovative model based on deep neural networks and an Active Shape Model (ASM) for AIFR. This model utilizes deep- learning techniques to analyze facial shapes and effectively identify landmarks across different ages. By integrating the Active Shape Model, the model improves its ability to adapt to changes in facial features due to aging, thereby enhancing the accuracy of the cross-age identity verification. However, the study faced challenges when applying the model in complex scenarios, such as environmental changes, lighting conditions, and varying image qualities, which could affect the accuracy of verification. The model can be further improved by incorporating additional techniques, such as data augmentation or the use of GANs to generate supplementary data. In [52], Osman and Viriri proposed a deep learning method for face verification across age progression, addressing the texture and shape variations that occur owing to aging. Their approach integrates a pre-trained GoogLeNet convolutional neural network with hand-crafted features, specifically the Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP), to enhance feature extraction. Classification is performed using similarity measurements based on Euclidean distance. The method was evaluated on the MORPH and FG-NET datasets and, achieved 99.8% accuracy on MORPH and 100% accuracy on FG-NET, outperforming several state-of-the-art approaches. Despite its high performance, the study did not adequately consider the effects of data imbalance across age groups, which could affect generalizability. Incorporating generative models, such as GANs to synthetically expand age-specific data could further improve the model's robustness against age-related variations.

The results presented in the table indicate that the performance of age-invariant facial recognition techniques is influenced by several key factors. First, the model type plays a significant role, with deep neural networks and GAN-based methods generally achieving better results because of their ability to extract more stable features and handle age variations by generating synthetic images. Second, the quality, size, and diversity of the datasets directly affected the model's generalization capability across different age groups. Additionally, environmental conditions such as lighting and face angles pose considerable challenges, and models that account for these factors tend to deliver more accurate results. Therefore, no single method consistently outperforms the others in all scenarios, highlighting the need to develop flexible, multifaceted models to enhance the accuracy and reliability of face recognition systems across different ages.

8. APPLICATIONS OF AIFR

AIFR is a critical technology for identity verification across various domains. The key applications of AIFR:

• **Identity Verification in Official Documents** Official documents, such as passports, driver's licenses, and national IDs, require reliable identity verification over long durations. AIFR systems integrate deep feature extraction and GAN-based face synthesis to predict future facial appearances, thereby enhancing the verification process during document renewal or security checks. This approach ensures the accuracy of identity verification, even as individuals age, reducing false rejections caused by age-related facial changes [5], [17].

• **Finding Missing Children** Identifying missing individuals, especially children who age significantly over time, is a major challenge for law enforcement and humanitarian organizations. Traditional face recognition systems struggle because of drastic facial changes during growth. To address this, **Age-Invariant Face Recognition (AIFR)** helps identify missing children as they grow older, aiding law enforcement and families in reunification efforts [53]. AIFR systems leverage contrastive learning and deep convolutional neural networks (CNNs) to extract age-invariant features and improve matching accuracy despite age gaps [54]. Furthermore, Generative Adversarial Networks (GANs) are employed to simulate age progression or regression, generating synthetic images that assist in matching aged faces with existing records [55]

• **Smart Cities and Public Safety** Smart cities encounter various challenges such as traffic congestion, public safety threats, and the demand for efficient law enforcement. Age-Invariant Face Recognition (AIFR) is a powerful solution that enables the accurate and consistent identification of individuals over time. Face recognition is considered a reliable biometric tool for smart city and environment applications. Key technologies, such as low-complexity Convolutional Neural Networks (CNNs), optimized cost functions, and carefully selected training data, contribute to building effective AIFR systems. Additionally, the integration of face anti-spoofing techniques and the push for standardization further enhances system reliability in real-world scenarios [56], [57].

9. FUTURE DIRECTIONS IN AGE-INVARIANT FACE RECOGNITION (AIFR)

Although significant progress has been made in the field of Age-Invariant Face Recognition (AIFR), several critical areas remain underexplored. The following research directions outline the emerging challenges and opportu-

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nities for advancing this field.:

• **Multimodal AIFR Systems Research Question:** How can integrating multiple biometric modalities (e.g., 3D face recognition, voice, gait, and thermal imaging) enhance the robustness and accuracy of Age-Invariant Face Recognition (AIFR) systems in unconstrained environments? The fusion of multimodal biometric data leverages the complementary strengths of each modality, helping overcome challenges such as aging, expression changes, occlusion, and varying illumination, thereby improving.

• **Real-Time and Lightweight Models for Edge Devices Research Question:** How can AIFR models be optimized for deployment on mobile and embedded systems without compromising accuracy? Exploring lightweight architectures such as MobileNet and SqueezeNet enables real-time Age-Invariant Face Recognition applications in smart surveillance, wearable devices, and IoT systems by reducing the computational complexity while maintaining competitive accuracy [58].

• **Synthetic Data Generation and Domain Adaptation Research Question:** How can GANs and domain adaptation techniques be utilized to compensate for the scarcity of longitudinal and age-diverse facial datasets? Enhancing the quality and diversity of synthetic aging data can support the training of more robust and generalizable AIFR models [2].

10. CONCLUSION

This survey provides an in-depth analysis of age-invariant facial recognition (AIFR) techniques, focusing on deep learning and generative models designed to handle age-related facial variations. It highlights the significant progress achieved through CNNs, GANs, and contrastive learning models, while also addressing critical challenges, such as dataset bias, large age gaps, and real-world deployment limitations. This study shows that although datasets such as MORPH-II and CACD are widely used, they suffer from demographic imbalances that affect model generalization. Future research should explore the integration of multimodal biometrics (e.g., voice and 3D facial data), lightweight architectures for edge devices, and improved synthetic data generation using GANs. By addressing these open problems, AIFR systems can achieve higher accuracy, fairness, and scalability in real-world identity-verification scenarios.

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