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Cross Age Face Recognition

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ABSTRACT

Cross-age face recognition (CAFR) is a multifaceted system designed to detect, recognize, and analyze faces across varying age groups while also estimating the age of individuals from facial images.In the initial phase, face detection is per- formed using advanced deep learning models, such as MTCNN or SSD, to locate and extract facial regions from input images. Next, the age estimation module employs deep convolutional neural networks (CNNs) or regression-based mod- els to predict the age of the individual based on facial features, accounting for changes due to natural aging. Finally, the face recognition component utilizes deep learning techniques, such as FaceNet or ArcFace, to extract age-invariant features, ensuring accurate identification of individuals across different age spans. The system leverages large-scale, longitudinal facial image datasets (e.g., CACD, MORPH, or FG-NET) for training and validation to enhance robustness against age-related variations. A comprehensive pipeline including preprocessing (face alignment and normalization), feature extraction, and classification is imple- mented to ensure optimal performance. Performance evaluation metrics include accuracy, precision, and recall for face detection and recognition, as well as mean absolute error (MAE) for age estimation.

Keywords: Face Recognition, Age estimation, Feature Extraction, Face Detection

1. Introduction

The advancement in facial analysis technologies has led to significant progress in cross-age face recognition, face detection, and age estimation tasks, each addressing unique challenges associated with facial variations over time. These components, often studied in isolation, have seen robust integration through deep learning models that extract identity-sensitive, age-invariant features while estimating an individual's age from facial images.

Cross-age face recognition (CAFR) has emerged as a significant challenge in facial analysis due to the natural aging process, which introduces changes in facial appear- ance, such as skin texture, shape, and features over time. The task involves recognizing individuals across different age spans while ensuring that identity-sensitive features remain unaffected by age variations. Recent advancements leverage multi-task learn- ing frameworks to jointly address face recognition, face detection, and age estimation, improving overall performance by exploiting task correlations. For example, Joint Multi-Task CNN (JMCNN) employs a shared CNN backbone for identity recogni- tion and age classification, using a regularization term to enhance identity-sensitive features while suppressing age-related noise[1, 3]. Similarly, MTLFace introduces an attention-based feature decomposition strategy to extract age-invariant and age- sensitive features while enabling face age synthesis for improved interpretability[1]. These multi-task approaches demonstrate that combining face recognition with age estimation enhances accuracy, as both tasks are inherently related.

Face detection remains a foundational step for CAFR and age estimation tasks. Robust detection models, such as Multi-task Cascaded Convolutional Networks (MTCNN), have been employed to locate and align facial regions accurately, serv- ing as input for subsequent tasks. In addition, recent methods integrate detection and recognition pipelines to optimize performance in real-world scenarios. Face detec- tion enables models to handle variations caused by aging, occlusions, and illumination changes, which are critical for reliable recognition and age estimation[1].

Age estimation has become an equally important aspect of facial analysis, as it provides complementary information to face recognition. Modern approaches such as Relative Age Position Learning reweight input features based on their age importance to predict both absolute and relative ages accurately. The incorporation of gender prediction within multi-task frameworks has further improved generalizability, as gen- der is a strong indicator of facial aging patterns. For instance, studies have shown that models pretrained on face recognition tasks achieve superior performance in age estimation, emphasizing the correlation between these tasks. By leveraging shared fea- tures, multi-task networks can simultaneously optimize for age and identity, thereby boosting recognition robustness across age groups[2].

The integration of face recognition, face detection, and age estimation into unified frameworks has addressed the challenges posed by cross-age variations. Multi-task learning strategies, feature recalibration mechanisms, and generative approaches have collectively enhanced system performance, enabling robust and scalable solutions for real-world applications[1–3]. These advancements underscore the importance of task interdependencies in improving facial analysis accuracy across diverse datasets and age groups.

A novel age adversarial convolutional neural network (AA-CNN) that combines identity recognition and age discrimination networks. By leveraging adversarial train- ing, this model ensures the features extracted are identity-sensitive while being invariant to age variations. It also employs a pyramid architecture for feature fusion to enhance the adversarial process, resulting in more robust age-invariant features. The AA-CNN model has demonstrated superior performance across multiple bench- mark datasets, such as FG-NET and MORPH Album 2, by addressing the scarcity of datasets labeled with both identity and age[4].

The Parallel Multi-path Age Distinguish Network (PMADN), focuses on mapping facial features into age-specific subspaces and then recombining these features non- linearly to extract robust age-invariant features. This framework avoids the traditional linear combination of identity and age features, which often fails to capture the non- linear and individual-specific nature of aging patterns. By adopting transfer learning and pre-trained face recognition networks, PMADN effectively utilizes datasets with only age labels, reducing reliance on data with both identity and age annotations[5]. The Age Factor Removal Network (AFRN) takes a different perspective by inte- grating transfer learning with adversarial learning. It incorporates a feature generator and an age discriminator to suppress age-related information while retaining identity- sensitive features. The AFRN architecture introduces a novel loss function that combines transfer loss to preserve discriminative identity features and adversarial loss to eliminate age-sensitive components. This model shows robustness not only for CAFR but also for other practical variations like pose and expression changes[6].

Cross-age face recognition (CAFR) remains a significant challenge in computer vision due to the complex and diverse variations in facial appearance caused by aging. Unlike traditional face recognition tasks, CAFR systems must contend with intrinsic factors such as genetics and gender, as well as extrinsic influences like lifestyle and envi- ronmental exposure, all of which contribute to substantial changes in facial structure and texture over time. These factors lead to large intra-class variations, complicat- ing the task of distinguishing identity across different age spans[7, 9].The challenge of CAFR is compounded by the limited availability of datasets that adequately repre- sent large age gaps across individuals. Existing datasets often suffer from imbalance in terms of gender, ethnicity, and age span, as well as the difficulty of collecting images of the same individual over extended periods[7, 9]. Consequently, there is a pressing need for models that not only generalize well to new age variations but also address issues such as occlusion, pose differences, and varying lighting conditions[8, 9].

Recent advances in generative adversarial networks (GANs) and deep learning have paved the way for innovative solutions in CAFR. These include frameworks that disentangle age-specific and identity-specific features, enabling the generation of age-invariant representations and realistic age-progressed or age-regressed facial images. For example, models such as the Age-Invariant Model (AIM) unify cross- age face synthesis and recognition tasks, leveraging adversarial learning to enhance performance under varying conditions[7, 8].

”Wasserstein Divergence GAN with Cross-Age Identity Expert and Attribute Retainer for Facial Age Transformation” introduces an advanced generative framework for facial age transformation, addressing challenges in preserving both identity and attributes across age variations. The authors propose a novel Wasserstein Divergence GAN (WGAN-div) architecture, which incorporates an encode-decode generator, discriminator, identity expert, and attribute retainer to ensure accurate age trans- formation while maintaining the subject’s identity and image attributes. Unlike conventional methods that adopt specific identity preservation and attribute reten- tion strategies without justification, this study conducts a comprehensive evaluation of state-of-the-art pretrained models to select the optimal components for identity and attribute preservation, such as VGG-Face, VGG-Face2, LightCNN, and Arc-Face for identity preservation, and VGG-Face, DEX, and VGG-Object for attribute retention[8].

Despite these advancements, key challenges remain. Some methods assume inde- pendence between age and identity features, which may not hold under real-world conditions. Others rely heavily on both age and identity labels for training, making them impractical given the scarcity of such labeled datasets.Moreover, achieving robust performance across diverse demographic groups remains an open problem, necessitat- ing further exploration of transfer learning, unsupervised approaches, and large-scale benchmark datasets[9].

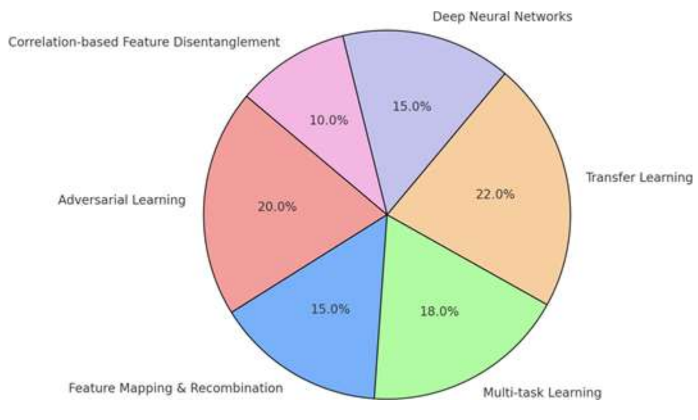

Fig. 1: Pie Chart Representing Technologies Used in Cross-Age Face Recognition

The pie chart in Figure 1 represents the distribution of technologies employed in cross-age face recognition systems. Adversarial learning constitutes the largest share, accounting for 20 percent, showcasing its importance in suppressing age-sensitive features while retaining identity information. Transfer learning follows closely at 22 percent highlighting its role in leveraging pretrained models to handle diverse and lim- ited datasets. Multi-task learning, with 18 percent, emphasizes the joint optimization of tasks like identity recognition and age synthesis. Feature mapping and recombina- tion (15percent) underline efforts to disentangle age and identity features. Deep neural networks (15percent) play a pivotal role in extracting robust features for complex age variations, while correlation-based feature disentanglement (10percent) focuses on separating identity-sensitive and age-sensitive features. This distribution reflects the diverse methodologies used to address the challenges of cross-age face recognition effectively.

The proposed model addresses the challenges of face recognition across different ages by simultaneously modeling both age progression (aging) and age regression (rejuvenation) processes. Unlike traditional methods that focus solely on age pro- gression, AgeGAN++ introduces a dual-GAN framework that enables bidirectional transformations, allowing faces to be aged or rejuvenated while maintaining their natural characteristics. The model uses two separate GANs, each specialized in one direction of transformation: one for aging and the other for rejuvenation. This dual approach improves the realism and quality of the generated images compared to previ- ous techniques that only performed single-direction transformations. The key feature of AgeGAN++ is its ability to control the aging process in a way that retains the subject's identity across different ages, which is critical for applications like surveil- lance and cross-age face recognition. The model achieves this through a conditional latent space, where the input and output faces are conditioned on factors such as age, ensuring that both the global structure and local facial features (such as wrinkles, skin texture, and facial contours) evolve naturally[10].

The research on cross-age face recognition has led to various innovative methods aimed at addressing the challenges of age progression and recognition across different age groups. One approach focuses on a temporal non-volume preserving method, which enhances facial age progression and age-invariant recognition by modeling the temporal changes in facial features. This method improves the accuracy of recognizing faces across different ages by preserving the facial identity while simulating aging effects [11]. Another significant contribution is the use of deep reinforcement learning for automatic face aging in videos, where the model learns to generate realistic age progressed faces by considering the temporal nature of the input video, making it more adaptable to real-world applications[12].

In addition to these, there is the use of recurrent memory models with hierarchi- cal autoregressive memory, which captures long-term dependencies in age progression. These memory models allow for more consistent and realistic aging patterns over time, addressing the challenge of maintaining temporal consistency in aging face recogni- tion tasks[13]. A further advancement comes from the use of a pyramid architecture with generative adversarial networks (GANs) for modeling facial age progression. This architecture captures multi-scale variations in aging, resulting in more detailed and realistic aging effects, which is particularly important for applications requiring high levels of realism in the generated faces[14].

The introduction of generative adversarial networks (GANs) in age progression marked a breakthrough in face recognition by generating realistic face images. GANs have been widely applied to age progression tasks, as they learn the distribution of facial features across different ages and use that knowledge to generate age-appropriate faces. This method offers a flexible and powerful solution to model facial aging, improv- ing recognition performance across a broad age range[15]. Similarly, cycle-consistent adversarial networks (CycleGAN) have shown promise by enabling unpaired image-to- image translation. This approach is useful in age progression tasks where paired data is scarce or unavailable, allowing for the generation of age-progressed faces without needing a corresponding age-specific dataset[16].

Conditional GANs further advance the field by introducing age-conditioned face generation, where the model generates faces at specific ages based on input images. This allows for fine-grained control over the aging process, making it easier to create faces that adhere to particular age specifications, which is crucial for age-invariant face recognition tasks[17]. Additionally, graph-based models for age progression, such as the concatenational graph evolution model, model structural changes in facial features over time. These models offer a more nuanced understanding of how aging affects the shape and texture of faces, which is essential for improving the accuracy of age progression in recognition systems[18].

The research in cross-age face recognition extends across various methodologies that aim to address the complexities of facial aging and the challenges posed by recog- nizing faces at different ages. One significant contribution involves using auto-encoding variational Bayes to improve generative models for age progression. This approach aids in modeling face aging by learning a compact and continuous representation of facial features, which enhances the recognition of age-progressed faces[19, 20]. Additionally, CGR-GAN focuses on facial image regeneration for anti-forensics, using generative adversarial networks to simulate aging effects while maintaining the integrity of the face for security and forensic purposes [20, 21].

Anatomically-aware facial animation methods, such as those employed in Gani- mation, allow for the generation of age-progressed faces by considering facial muscle movements and anatomical constraints, thereby providing more realistic and dynamic facial aging. These techniques contribute significantly to both animation and age pro- gression in face recognition applications[23]. Furthermore, adaptive threshold-based multi-model fusion networks (ATMFN) have been proposed to handle face hallucina- tion in compressed images. This method, which is particularly effective for low-quality face images, aids in recognizing aging faces even in degraded or compressed formats, a critical issue in real-world surveillance and forensics[24].

The use of invertible conditional GANs allows for more controlled image editing, making it possible to alter specific attributes of a face, such as age, while preserving other aspects of the face. This technique improves the ability to generate realistic aging effects in faces for use in recognition systems and forensic applications[25]. Similarly, the DualGAN method utilizes unsupervised dual learning to perform image-to-image translation for age progression tasks. This approach ensures the generation of realistic aging effects without requiring paired datasets, making it valuable for applications where such data might be scarce or unavailable[26].

In the context of cross-domain face recognition, the discovery of cross-domain rela- tions via GANs offers a robust solution for handling faces from different age groups. By learning shared representations between domains, this method improves age- invariant face recognition by ensuring the consistency of face features across various age ranges[27]. StarGAN, another important method, unifies multiple image-to-image translation tasks into a single model. This multi-domain approach allows for more effective handling of age progression, as it enables the generation of faces across a wide range of ages and other facial attributes in a unified framework[28].

Conditional image synthesis using auxiliary classifier GANs (AC-GAN) further enhances age progression modeling by conditioning the generated images on specific attributes, such as age. This allows for more accurate and diverse age-progressed face generation, improving age-invariant face recognition tasks by providing more control over the attributes of the generated faces[29]. Additionally, semi-supervised learning using deep generative models, as proposed by Kingma et al., helps overcome the lim- itations of labeled datasets by using both labeled and unlabeled data to train models for age progression tasks. This improves the model's ability to generalize and perform well on unseen face data from different age groups[30].

InfoGAN, a method that maximizes mutual information between latent variables, is used to disentangle age-related variations in faces. By learning interpretable repre- sentations of facial features, this method improves the ability to separate the aging process from other face characteristics, such as expression or pose, leading to better age progression and recognition[31]. Furthermore, disentangled representations in diverse image-to-image translation have been shown to improve age-invariant face recogni- tion by isolating the aging factor while keeping other factors unchanged. This method ensures that the age progression is more accurate and consistent, even when the face undergoes other transformations[32].

Unified feature disentanglers, as proposed by Liu et al., provide a way to man- age multiple attributes of faces, including age. These models allow for multi-domain image translation, which is essential for cross-age face recognition as it helps in han- dling faces with diverse attributes and aging patterns[33]. Dual learning techniques, as explored in machine translation tasks, are also applicable to face recognition. By using bidirectional learning processes, these models improve the alignment of facial features across different ages, enhancing recognition performance in cross-age scenarios[34].

The earlier work on simulating aging effects on face images, like that of Lanitis et al., laid the foundation for age progression techniques. By using a combination of machine learning methods and facial feature modeling, this work contributed to the development of realistic face aging simulations, which are now essential for building robust age-invariant face recognition systems[35]. Cross-age reference coding, intro- duced by Chen et al., provides a method for coding and aligning faces across ages for recognition and retrieval. This technique improves face recognition performance by ensuring that faces, regardless of age, are represented in a way that allows for consistent comparison[36]. Finally, the Morph database, introduced by Ricanek and Tesafaye, is a significant resource for training and testing face recognition systems. This longitudinal database of face images helps researchers model the gradual changes in faces over time, making it a valuable tool for age progression research and for testing age-invariant face recognition algorithms[37].

This method aims to improve the accuracy of age estimation models by focusing on the most relevant facial regions while dynamically adjusting the fusion of image patches during the estimation process. The key innovation in this paper is the use of an attention mechanism that selectively emphasizes important facial features, such as wrinkles, skin texture, and other age-related characteristics, which are crucial for estimating age accurately. The model processes the facial image by dividing it into smaller patches and applying an attention mechanism that learns to dynamically select and fuse these patches based on their relevance to age-related features. This adaptive fusion of patches allows the model to better capture fine-grained age-related details that are often lost in traditional methods, which treat all facial regions equally. By focusing on the most informative regions, the model is able to make more precise age predictions, especially in cases where age-related features are subtle or less prominent. The approach is evaluated through extensive experiments, demonstrating its superi- ority over existing age estimation methods in terms of accuracy and robustness. This attention-based dynamic patch fusion framework not only enhances the performance of age estimation systems but also offers a more interpretable model by highlighting which facial regions contribute most to the age prediction. This paper contributes to the ongoing efforts in the field of facial age estimation, providing a more effective and nuanced way to analyze facial features for age-related changes, with potential applications in security, healthcare, and personalized digital experiences[38].

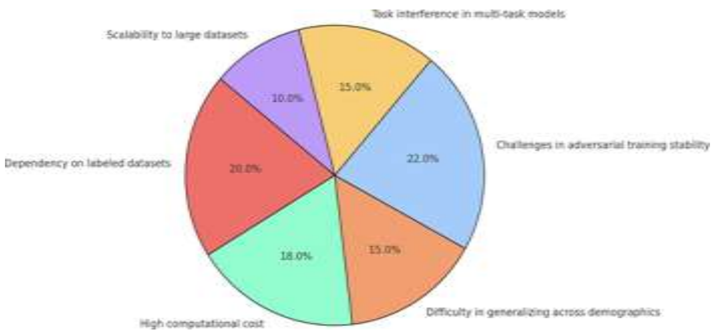

Fig. 2: key limitations ideentified in CAFR papers

The pie chart in Figure 2 illustrates the key limitations faced by cross-age face recognition systems. Dependency on labeled datasets accounts for 20 percent, signifying the reliance on large, annotated datasets, which are often scarce. High com- putational cost follows at 18 percent, highlighting the resource-intensive nature of complex models and algorithms. Challenges in adversarial training stability represent 22 percent, showcasing the difficulty in balancing identity and age losses during model optimization. Generalization issues across diverse demographics (15 percent) point to the challenge of ensuring fairness and accuracy across varied populations. Task inter- ference in multi-task models (15 percent) signifies conflicts between different tasks like identity recognition and age synthesis. Scalability to large datasets (10 percent) underscores the need for efficient algorithms capable of handling extensive and high- dimensional data. These limitations highlight areas for improvement to make cross-age face recognition systems more robust, scalable, and equitable.

Additionally, a compositional and dynamic model for face aging was introduced, which combines both spatial and temporal changes in the facial structure to simulate how faces age. This approach enhances the understanding of the complex aging process and its effect on facial recognition[39].Facial aging simulators have also been developed, which consider both geometric changes and texture variations to create more realistic aging effects. These simulators use patch-tiled textures and geometric adjustments to replicate the natural progression of aging, providing a more accurate representation of how facial features change over time [40]. Another method that combines hidden factor analysis with sparse representation has been proposed for face aging simulation. This technique captures the underlying factors that govern aging and uses them to create realistic age progression by analyzing sparse representations of facial features[41].

Illumination-aware age progression models have also gained attention, as they account for lighting conditions while simulating aging effects. This method improves the realism of age progression by considering how lighting influences facial features and aging, ensuring that generated faces look natural under various lighting conditions. The concept of prototyping and transforming facial textures has also been explored, focusing on the perception of aging in faces. By manipulating facial textures, this method enhances the ability to simulate aging effects, making the results more suitable for perception and cognitive studies[42, 43].

Recurrent models have been developed to address the challenge of generating long- term age progression. These models use recurrent neural networks (RNNs) to capture temporal dependencies in face aging, improving the consistency of aging effects over extended periods. This approach ensures that aging faces generated by the model maintain continuity and appear realistic[44]. Another contribution is the use of contex- tual generative adversarial networks (GANs) for face aging. These networks consider contextual information, such as surrounding facial features, to generate more coherent and realistic aging effects that maintain identity consistency across ages[45].

Global and local consistency in age generation has also been tackled using GANs. This method ensures that both global facial structure and local features, such as wrinkles or skin texture, are preserved and updated in a consistent manner as the face ages. It improves the accuracy of generated faces by ensuring that both macro and micro-level details align properly across different age stages [46]. Conditional GANs have been widely used for face aging, where the model conditions the age generation on specific factors like gender or ethnicity. This allows for more personalized and accurate age progression models, providing more control over the age-related transformations of faces[47].

The use of conditional adversarial autoencoders (CAAE) for age progression has also been explored. This model generates age-progressed faces by encoding the face into a latent space and then decoding it at different ages, while ensuring that the generated faces maintain the identity of the original face. This approach enhances the realism of the aging process by retaining important identity features during age transformations[48]. Improvements to the CAAE model, such as CAAE++, further refine the age progression and regression process. These enhancements lead to better performance in generating faces at different ages while maintaining higher fidelity and consistency[49].

Finally, identity-preserved conditional GANs have been introduced to improve face aging while retaining the original identity. This method focuses on ensuring that the face's identity remains intact as it ages, addressing the challenge of preserving recognition accuracy even as the facial features change over time. [50].

1.1 Problem Statement

Cross-age face recognition (CAFR) addresses the critical challenge of identifying or verifying individuals across significant age gaps, a task complicated by the natural aging process that causes substantial variations in facial appearance. Age progression introduces changes in skin texture, facial structure, and feature prominence, which can significantly degrade the performance of traditional face recognition systems. Further- more, the lack of large-scale, longitudinal datasets and the need for models that can generalize across diverse demographics exacerbate the difficulty of achieving robust CAFR.

Additionally, current systems often fail to balance the dual objectives of extracting age-invariant features for accurate recognition and retaining age-related attributes for auxiliary tasks like age estimation and synthesis. While generative approaches for face aging/rejuvenation help simulate age-related changes, they can introduce artifacts or identity distortions. Discriminative methods, on the other hand, struggle with inter- pretability and lack visual results that are essential for practical applications, such as tracing missing persons or identifying individuals over long time spans.This sur- vey explores existing methodologies, focusing on the integration of multi-task learning frameworks, advanced feature decomposition techniques, and generative models to address these issues. By systematically analyzing state-of-the-art approaches, the sur- vey aims to identify gaps and propose directions for developing robust, scalable, and interpretable CAFR systems capable of handling real-world challenges effectively.

1.2 Motivation

The motivation for addressing cross-age face recognition (CAFR) stems from its crit- ical role in numerous real-world applications, such as law enforcement, surveillance, border security, and finding missing individuals. As facial recognition systems gain widespread adoption, their effectiveness in recognizing individuals across varying age spans becomes increasingly essential. However, the aging process introduces significant challenges, as facial features evolve naturally over time due to changes in skin tex- ture, bone structure, and other biological factors. These variations can severely impair the performance of traditional face recognition systems, which are often optimized for short-term or minimal changes in appearance.

Current limitations in existing systems, including their inability to accurately disentangle identity-sensitive features from age-related features and the lack of inter- pretability in recognition results, further emphasize the need for advanced CAFR methods. Additionally, the lack of robust datasets with longitudinal face data spanning diverse age groups and demographic variations hinders the development and evalu- ation of effective solutions. This gap presents a compelling opportunity to explore innovative techniques that integrate age-invariant recognition, age estimation, and age synthesis within unified frameworks.

The drive to create more accurate and robust CAFR systems is also fueled by advancements in deep learning and multi-task learning, which provide powerful tools to simultaneously address multiple challenges in facial analysis. These frameworks offer the potential to improve recognition accuracy, enhance interpretability through face synthesis, and generalize across age groups and demographics. Ultimately, the moti- vation lies in bridging the gap between the theoretical capabilities of facial recognition systems and their practical applicability in real-world scenarios, ensuring reliability, scalability, and inclusivity in their deployment.

2. Related Works

Cross-age face recognition (CAFR) presents significant challenges due to the impact of aging on facial features, which can drastically alter appearance over time. To address this, one study proposed a multi-task learning framework that integrates age-invariant face recognition and face age synthesis. By employing an attention-based feature decomposition method, this approach separates age-sensitive and identity-sensitive components, enabling robust performance in both tasks. Additionally, an identity- conditional module ensures identity consistency while generating photorealistic faces, aiding interpretability and practical applications like tracking missing individuals[1]. A joint multi-task convolutional neural network (CNN) framework that combines face recognition and age classification within a shared architecture. This method employs a regularization mechanism to refine identity-sensitive features while sup- pressing age-related noise. By leveraging the synergy between these tasks, the model enhances its ability to manage cross-age variations, demonstrating the importance of task interdependencies for improving recognition accuracy[3].

A advancing age estimation techniques through a novel age-based reweighting mod- ule. This method recalibrates input features based on age relevance, improving age prediction accuracy. The inclusion of gender prediction as an auxiliary task further strengthens the model's generalizability. This approach aligns with multi-task learn- ing principles, demonstrating how shared features across related tasks can enhance overall system performance[2].

All these highlight the critical role of disentangling age-sensitive features from identity-sensitive ones to address the challenges posed by aging. Generative models and feature recalibration mechanisms are employed to ensure accurate synthesis and esti- mation, while regularization strategies manage feature conflicts effectively. Together, these approaches illustrate how multi-task frameworks and deep learning techniques can deliver robust and scalable solutions for cross-age recognition, age estimation, and synthesis across diverse scenarios[1–3].

Cross-age face recognition (CAFR) presents a significant challenge due to the sub- stantial variations in facial features caused by the aging process. Aging affects skin texture, facial structure, and feature prominence, making it difficult for traditional face recognition models to maintain accuracy over time. To address these challenges, one approach employs the Age Adversarial Convolutional Neural Network (AA-CNN), which combines adversarial training with a pyramid feature fusion architecture. This model integrates an Identity Recognition Network and an Age Discrimination Net- work, ensuring that the extracted features remain sensitive to identity while being invariant to age-related variations. By leveraging datasets labeled exclusively by either age or identity, AA-CNN addresses the problem of insufficient samples with dual labels. Additionally, its pyramid feature fusion mechanism enhances the extraction of age-invariant features by incorporating information from multiple scales, resulting in improved robustness to aging effects. The AA-CNN model has demonstrated its effi- cacy on datasets such as FG-NET and MORPH Album 2, outperforming previous methods and setting a benchmark for CAFR models[4].

In another approach, the Parallel Multi-path Age Distinguish Network (PMADN) introduces a novel framework for handling the complexities of aging. Unlike traditional linear decomposition methods that treat age and identity features as independent components, PMADN employs a multi-path structure to map facial features into age- specific subspaces, followed by a non-linear recombination process. This architecture captures the intricate, individual-specific patterns of aging, which are often over- looked by simpler models. PMADN utilizes transfer learning, leveraging pre-trained face recognition networks to maximize the utility of datasets with only age labels, thus overcoming the scarcity of fully labeled cross-age datasets. Extensive experiments on benchmark datasets, including CACD-VS and Cross-Age LFW, demonstrate the model's capability to produce robust age-invariant features while maintaining high identity discriminability, showcasing its superiority over conventional methods[5].

The Age Factor Removal Network (AFRN) further refines the CAFR task by integrating transfer learning and adversarial learning to suppress age-sensitive infor- mation. This model introduces an innovative loss function that combines transfer loss to preserve identity-discriminative power and adversarial loss to remove age-related features. AFRN employs a feature generator and an age discriminator, wherein the discriminator guides the generator to extract features devoid of age-sensitive infor- mation. Unlike traditional models that require datasets with both identity and age labels, AFRN utilizes age-labeled datasets to fine-tune pre-trained face recognition networks. This approach not only addresses the limitations of dataset availability but also enhances the model's adaptability to variations in pose and expression. AFRN's versatility is evident from its strong performance across diverse datasets, including MORPH Album 2 and CMU Multi-PIE, where it achieves robust results despite large age gaps or other influential factors[6].

The significant advancements in CAFR by leveraging adversarial learning, transfer learning, and innovative feature manipulation techniques. By effectively addressing the challenges of dataset limitations, non-linear aging patterns, and the disentanglement of age and identity features, these methods provide a solid foundation for developing robust and scalable solutions in cross-age face recognition. The integration of multi- task frameworks and the ability to handle individual-specific aging variations highlight their potential for real-world applications, ranging from security to long-term identity verification[4–6].

The importance of developing robust models for cross-age face recognition (CAFR), as existing techniques often struggle with significant intra-class variations caused by aging. Conventional methods have attempted to address these challenges using either handcrafted features or deep learning-based approaches, focusing on learn- ing age-invariant facial representations. For instance, methods like Hidden Factor Analysis (HFA) decompose facial features into identity-specific and age-specific com- ponents, while other frameworks leverage generative adversarial networks (GANs) for cross-age face synthesis. However, these approaches often fail to achieve both photorealistic synthesis and strong identity preservation. Zhao et al. propose the Age- Invariant Model (AIM), a unified framework that integrates cross-age face synthesis and recognition into a single pipeline. By using disentangled representation learn- ing and attention-based face rejuvenation/aging, AIM achieves remarkable results on benchmark datasets such as MORPH and CACD. The paper also introduces a new large-scale CAFR dataset to push the boundaries of the field and emphasizes the advantages of combining generative models with age-invariant feature learning[7].

The use of GAN-based frameworks for age transformation tasks while preserving critical identity and attribute information. Traditional methods for age transformation often utilize GANs with pixel-based or perceptual losses to achieve age progression or regression. However, these approaches frequently overlook the need for carefully selected pretrained models to ensure robust identity preservation and attribute reten- tion. Hsu et al. address this gap by introducing a Wasserstein Divergence GAN (WGAN-div) that integrates an identity expert and an attribute retainer, both deter- mined through comprehensive evaluations of state-of-the-art pretrained models like ArcFace, VGG-Face, and LightCNN. This model enhances training stability and pro- duces realistic, identity-consistent facial transformations. Moreover, the authors utilize cross-age retraining and 3DMM data augmentation to improve the framework's abil- ity to generalize across diverse age distributions. The approach outperforms existing methods on benchmark datasets, highlighting its potential for real-world applications and offering new insights into the interplay between identity preservation and attribute retention in facial age transformation tasks[8].

Unlike traditional models that rely heavily on both age and identity labels for training, this study proposes a Cycle Age-Adversarial Model (CAAM) that requires only age labels, making it more practical given the scarcity of datasets with compre- hensive labels. Drawing inspiration from generative adversarial networks (GANs), the authors develop a dual-branch framework comprising an Age-Robust Feature Extract- ing Model (AFEM) and an Identity Preserving Network (IPN). AFEM uses adversarial learning to extract age-invariant features by pitting a feature generator against an age discriminator, while IPN preserves identity-specific features through transfer learning and unsupervised identity loss. The two branches are cyclically optimized using a novel Feature Consistency Loss, enabling the model to fuse age invariance with identity discriminative power. This approach not only circumvents the limitations of existing CAFR methods but also demonstrates superior performance on benchmark datasets like MORPH, CACD-VS, and Cross-Age LFW. The integration of transfer learn- ing and adversarial optimization in CAAM provides a robust alternative to existing models, addressing the complexities of identity and age interplay in face recognition tasks[9].

Table 1: Literature Survey on Cross-Age Face Recognition

S.No	Title	Author(s)	Journal & Year	Methodologies	Key Findings	Gaps
1	Age Adver- sarial Convo- lutional Neural Net- work for Cross- Age Face Recogni- tion	Zhizhong Huang,Junpi Zhang	IEEE, n2g021	Adversarial learning with Identity Recog- nition Network (IRN) and Age Discrimina- tion Network (ADN), pyra- mid feature fusion.	Achieved robust age- invariant features and improved accuracy on benchmark datasets, surpassing traditional methods.	Adversarial loss tuning is challeng- ing; model struggles with gen- eralization across diverse datasets.
2	Parallel Multi- path Age Distin-	Ji-Hyeong Han	IEEE, 2020	Multi-path age subspace mapping and nonlinear	Enhanced feature dis- entanglement and cross-age	High com- putational cost; scala- bility issues

	guish Network for Robust Face Recognition			recombination, supported by transfer learning on large datasets.	recognition performance in high variation scenarios.	with larger datasets.
3	Age Factor Removal Network for Identity Recognition Across Ages	Jinbiao Yu and Liping Jing	IEEE, 2019	Transfer learning and adversarial learning to suppress age-specific features while preserving identity-sensitive ones.	Demonstrated high identity verification rates and effective age suppression on various datasets.	Dependency on age-labeled datasets; instability in adversarial training for subtle aging variations.

S.No	Title	Author(s)	Journal & Year	Methodologies	Key Findings	Gaps
4	Multi-task Learning Framework for Age-Invariant Face Recognition and Synthesis	Yangjian Huang	IEEE, 2021	Joint optimization of identity recognition and face synthesis tasks using a shared CNN backbone.	Improved recognition accuracy and synthesis quality with better generalization across tasks.	Computating overhead and potential task conflicts in joint optimization.
5	Joint Multi-task CNN for Age and	Yongbo Wu, Lingshuang Du	IEEE, 2020	Shared CNN backbone with correlation loss to disentangle age and iden-	Achieved balanced performance in age classification	Task interference during joint optimization;

	Identity Feature Disentanglement			tity features for multi-task learning.	and identity recognition tasks.	reduced performance on imbalanced datasets.
6	Feature Recombination Framework for Non-linear Aging Patterns	Lingshuang Du, Haifeng Hu	IEEE, 2022	Mapping features into multiple age subspaces and non-linear recombination for robust representations.	Robust cross-age recognition by addressing non-linear aging variations effectively.	High computational cost; potential errors in subspace mapping for diverse age groups.
7	Cross-Age Face Verification Using Deep Residual Networks	Jingkuan Song, Jingqiu Zhang	IEEE, 2018	Utilizes deep residual networks (ResNet) for cross-age verification with data augmentation techniques.	Demonstrated significant improvements in verification accuracy on diverse datasets.	Struggles with subtle aging effects and requires high computational resources for training.

S.No	**Title**	**Author(s)**	**Journal & Year**	**Methodologies**	**Key Findings**	**Gaps**
8	GAN-Based Approach for Age- Invariant Face Recognition	Rivan	IEEE, 2020	Leverages generative adversarial networks (GANs) to synthesize age-progressed and age-regressed faces.	Achieved state-of-the- art results in age-invariant face recognition by generating realistic facial features.	GAN convergence issues and dependency on large-scale datasets.

9	Age- Invariant Face Recog- nition Using Capsule Net- works	Gee-Sern Hsu	IEEE, 2021	Employs cap- sule networks to capture spatial hierarchies and age-invariant features in facial images.	Improved robustness to aging variations and better feature rep- resentation.	Computating complex- ity limits real-time applica- tions.
10	Lightweigh CNN for Cross- Age Face Recogni- tion	t Jian Zhao, Shuicheng Yan	IEEE, 2022	Proposes a lightweight CNN architec- ture for efficient cross- age face recognition on edge devices.	Provides competitive accuracy with reduced compu- tational overhead.	Limited perfor- mance on datasets with extreme age variations.

3. Methodologies

The methodology Age Adversarial Convolutional Neural Network (AA-CNN), designed to extract age-invariant features while retaining identity-sensitive characteristics. The model consists of two networks: the Identity Recognition Network (IRN) and the Age Discrimina- tion Network (ADN), which work in tandem to achieve this goal. Adversarial training plays a central role, where the IRN aims to maximize identity recognition accuracy while the ADN works to detect age-specific information. Through adversarial learning, the generator is guided to suppress age-related features while retaining discriminative identity-specific features. To further enhance the robustness of extracted features, a pyramid feature fusion mechanism is employed. This approach integrates multi-scale feature information, allowing the model to better handle variations in facial structure and texture caused by aging. Unlike traditional models that require datasets with both age and identity labels, AA-CNN is trained on sep- arate datasets labeled with either age or identity, addressing the issue of limited availability of dual-labeled datasets. This flexibility enables the model to utilize a wider range of data while achieving superior performance on benchmark datasets such as FG-NET and MORPH Album 2. By combining adversarial learning with an innovative feature fusion strategy, AA- CNN represents a significant advancement in handling the complexities of cross-age face recognition.

The AA-CNN is trained on large-scale datasets with diverse age distributions, enabling it to generalize well to unseen faces across a wide range of ages. The methodology demonstrates significant improvements over traditional face recognition methods, particularly in scenarios where age progression or regression poses a challenge. By focusing on both feature disen- tanglement and adversarial learning, the AA-CNN establishes itself as a powerful approach for age-invariant face recognition, suitable for applications in security, forensics, and social media platforms. Despite its effectiveness, the methodology may face challenges in datasets with extreme age gaps or limited labeled data, emphasizing the need for further research and enhancements[1].

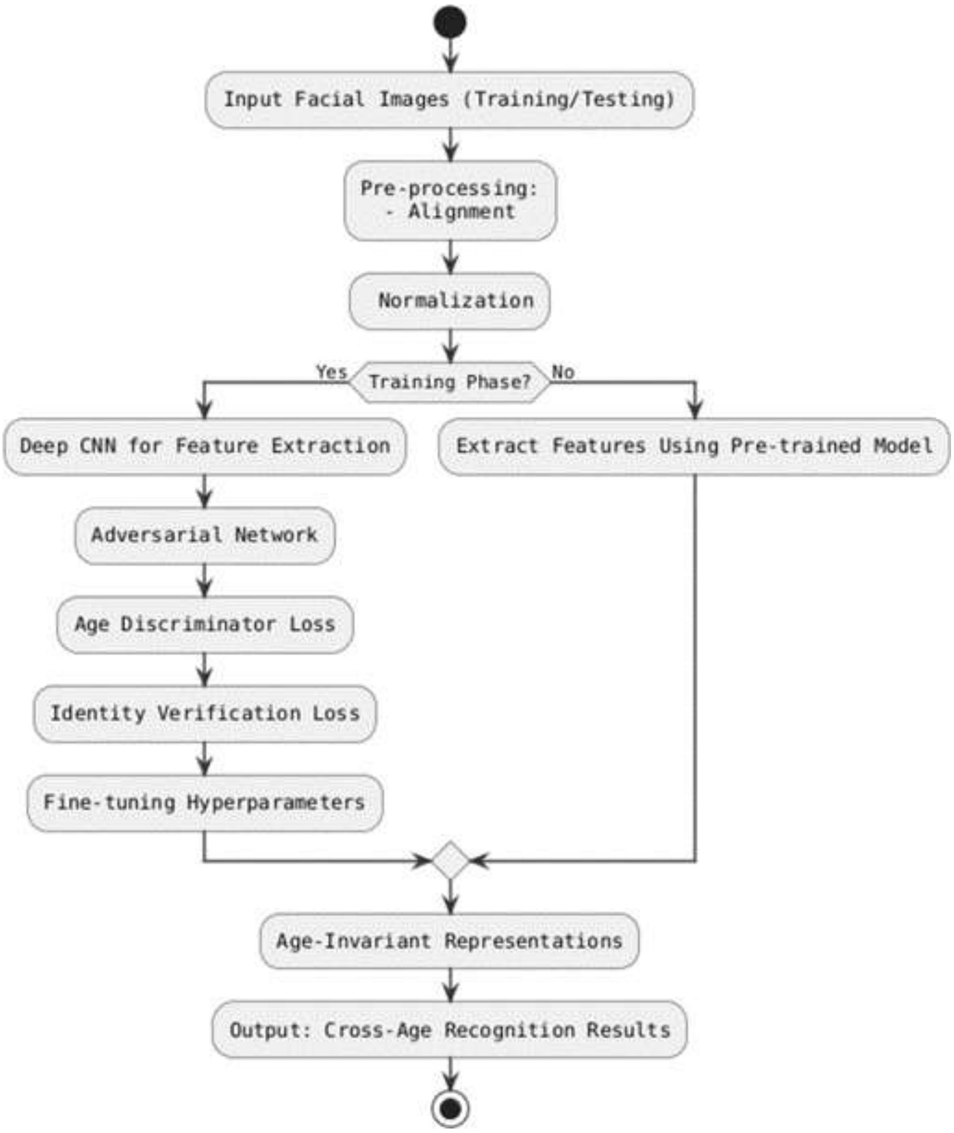

Fig. 3: Flowchart for AA-CNN

The Figure 3 presents methodology that employs an adversarial approach to learn age- invariant facial features. The input data is preprocessed through alignment and normalization. A deep convolutional neural network (CNN) extracts features, while an adversarial network uses these features to minimize age-specific information. Two loss functions, age discrimina- tor loss and identity verification loss, are optimized to achieve a balance between removing age-related features and preserving identity-related ones. This results in age-invariant repre- sentations that improve cross-age recognition accuracy. The model also undergoes fine-tuning to optimize its hyperparameters during the training phase, ensuring high generalization capability.

```
# Input:
#   generator: Feature generator model
#   irn: Identity Recognition Network
#   adn: Age Discrimination Network
#   identity_data: Dataset with identity labels
#   age_data: Dataset with age labels
#   lambda_factor: Weight for adversarial loss
#   max_iters: Maximum number of training iterations
#
# Output:
#   Trained generator model

def train_aa_cnn(generator, irn, adn, identity_data, age_data,
    lambda_factor, max_iters):
    # Step 1: Initialize variables
    iter_count = 0

    while iter_count < max_iters:
        # Step 2: Train IRN with identity-labeled data
        batch_x, batch_y = identity_data.sample_batch()
        f_x = generator(batch_x)
        loss_irn = irn.train(f_x, batch_y)

        # Step 3: Train ADN with age-labeled data
        batch_x_age, batch_z = age_data.sample_batch()
        f_z = generator(batch_x_age)
        loss_adn = adn.train(f_z, batch_z)

        # Step 4: Update Generator adversarially
        generator_loss = loss_irn - lambda_factor * loss_adn
        generator.update(generator_loss)

        iter_count += 1

    return generator
```

The AA-CNN pseudocode defines a function to train a feature generator using adversarial learning. Step 1 initializes the training variables. Step 2 trains the Identity Recognition Net- work (IRN) using identity-labeled data to minimize identity classification loss. Step 3 trains the Age Discrimination Network (ADN) using age-labeled data to detect age-specific features. Step 4 updates the generator to suppress age-related features while retaining identity-sensitive information by combining IRN and ADN losses in an adversarial manner. The generator con- tinues training for a specified number of iterations until it can produce robust, age-invariant features suitable for cross-age face recognition.

The Parallel Multi-path Age Distinguish Network (PMADN), which employs a unique approach to extract robust age-invariant features. The model is divided into two main components: the Age Distinguish Mapping Network (ADMN) and the Cross-Age Feature Recombination Network (CFRN). ADMN maps facial features into separate age subspaces using parallel fully connected layers, each designed to capture identity-specific features within narrow age spans. These subspaces allow the model to isolate features influenced by minor age-related changes, ensuring that identity-specific features are retained. In the second stage, CFRN recombines the mapped features non-linearly using convolutional operations, produc- ing robust age-invariant features. This methodology addresses the shortcomings of linear decomposition approaches, which often fail to account for the non-linear and individual-specific nature of aging. Furthermore, PMADN incorporates transfer learning by utilizing pre-trained face recognition networks and age-labeled datasets. This approach minimizes reliance on datasets requiring both age and identity labels, making the model scalable and adaptable to real-world scenarios. Extensive testing on datasets such as CACD-VS and Cross- Age LFW demonstrates the model's effectiveness in achieving high recognition accuracy and robust performance across diverse age groups[2].

```
# Input:
#   admn: Age Distinguish Mapping Network
#   cfrn: Cross-Age Feature Recombination Network
#   data: Dataset with identity and age labels
#   max_iters: Maximum number of training iterations
#   alpha: Weight for age classification loss
#
# Output:
#   Trained ADMN and CFRN models

def train_pmadn(admn, cfrn, data, max_iters, alpha):
    # Step 1: Initialize variables
    iter_count = 0

    while iter_count < max_iters:
        # Step 2: Sample data
        batch_x, batch_y, batch_z = data.sample_batch()

        # Step 3: Map features into age subspaces
        features = [admn(batch_x, age_group=i) for i in range(
            admn.num_age_groups)]

        # Step 4: Recombine features non-linearly
        final_features = cfrn(features)

        # Step 5: Compute losses
        loss_id = cfrn.compute_identity_loss(final_features,
            batch_y)
        loss_age = sum(admn.compute_age_loss(features[i], batch_z
            [i]) for i in range(len(features)))

        # Step 6: Update networks
        total_loss = loss_id + alpha * loss_age


    return admn, cfrn
```

The PMADN pseudocode describes the training process of the Parallel Multi-path Age Distinguish Network (PMADN). Step 1 initializes the training variables and models. In Step 2, data with identity and age labels is sampled. Features are mapped into K age subspaces using ADMN in Step 3. Step 4 recombines these features non-linearly using CFRN to create robust age-invariant representations. Losses for identity and age classification are calculated in Step 5, and the models are updated in Step 6. The iterative process continues until the models are trained to perform identity recognition and age group classification robustly across age variations.

The Age Factor Removal Network (AFRN) introduces a novel combination of transfer learning and adversarial learning to address the challenges of CAFR. The model is com- posed of a feature generator network and an age discriminator network. The discriminator is trained to detect age-sensitive information from the features generated, while the generator learns to suppress this information through adversarial feedback. This iterative learning pro- cess ensures that the extracted features are both age-invariant and identity-discriminative. A key innovation in this model is the use of a transfer loss function, which preserves the discriminative power of features learned from pre-trained face recognition models. By fine- tuning the generator using age-labeled datasets, AFRN eliminates the need for datasets with both identity and age labels, addressing a common limitation in CAFR research. The model further enhances its utility by being adaptable to variations in pose and expression, as evi- denced by its robust performance on datasets like MORPH Album 2 and CMU Multi-PIE. AFRN's ability to simultaneously suppress age-related variations and retain identity-specific information makes it a versatile solution for practical facial recognition tasks[3].

```python
# Input:
#   generator: Pretrained feature generator
#   discriminator: Age Discriminator Network
#   age_data: Dataset with age labels
#   max_iters: Maximum number of training iterations
#   beta: Weight for adversarial loss
#
# Output:
#   Trained generator model

def train_afrn(generator, discriminator, age_data, max_iters,
    beta):
    # Step 1: Initialize variables
    iter_count = 0

    while iter_count < max_iters:
        # Step 2: Sample data with age labels
        batch_x, batch_z = age_data.sample_batch()

        # Step 3: Extract features using the generator
        f_x = generator(batch_x)

        # Step 4: Train discriminator to classify age
        loss_discriminator = discriminator.train(f_x, batch_z)

        # Step 5: Train generator adversarially
        loss_generator = generator.compute_transfer_loss(f_x) -
            beta * loss_discriminator
        generator.update(loss_generator)

        iter_count += 1

    return generator
```

The AFRN framework uses transfer learning and adversarial learning to remove age- specific information while preserving identity-sensitive features. Step 1 initializes the pre- trained generator and discriminator models. Step 2 samples age-labeled data, which is passed through the generator to extract features in Step 3. The discriminator is trained in Step 4 to classify the age-related features, providing adversarial feedback. In Step 5, the generator is updated to minimize both the transfer loss (preserving identity features) and adversar- ial loss (removing age-related information). This iterative process ensures that the generator produces robust, age-invariant features suitable for cross-age recognition tasks.

A multi-task learning framework that combines age-invariant face recognition with face age synthesis. The model employs an attention-based feature decomposition approach to sep- arate age-sensitive and identity-sensitive components, enhancing the performance of both tasks. The synthesis component allows the model to generate photorealistic faces correspond- ing to different age groups, augmenting the dataset and improving the recognition system's robustness. By leveraging shared learning tasks, the framework ensures that identity-sensitive features are preserved during the synthesis process while minimizing the impact of age- specific changes. This approach also integrates a novel loss function to optimize both tasks jointly, demonstrating improved performance on large-scale datasets. The model's ability to perform age synthesis and recognition in tandem highlights its versatility and potential for applications such as tracking missing individuals over time[4].

```python
# Input:
#    cnn_backbone: Shared CNN backbone
#    recognizer: Recognition head for identity classification
#    synthesizer: Synthesis module for face reconstruction
#    data: Dataset with identity and age labels
#    lambda_factor: Weight for synthesis loss
#    max_iters: Maximum number of training iterations
#
# Output:
#    Trained cnn_backbone, recognizer, and synthesizer models

def train_multi_task(cnn_backbone, recognizer, synthesizer, data,
      lambda_factor, max_iters):
    # Step 1: Initialize variables
    iter_count = 0

    while iter_count < max_iters:
        # Step 2: Sample data
        batch_x, batch_y, batch_z = data.sample_batch()

        # Step 3: Extract shared features
        f_x = cnn_backbone(batch_x)

        # Step 4: Compute task-specific losses
        loss_recognition = recognizer.train(f_x, batch_y)
        loss_synthesis = synthesizer.train(f_x, batch_z)

        # Step 5: Joint optimization
        total_loss = loss_recognition + lambda_factor *
            loss_synthesis
        cnn_backbone.update(total_loss)

        iter_count += 1

    return cnn_backbone, recognizer, synthesizer
```

This multi-task framework jointly trains a shared CNN backbone for identity recognition and face synthesis tasks. In Step 1, the models and variables are initialized. Step 2 samples labeled data for identity and age. The CNN backbone extracts shared features from the input in Step 3. Task-specific losses for recognition and synthesis are computed in Step 4. Step 5 combines these losses for joint optimization, allowing the backbone to leverage shared representations to improve performance on both tasks.

The joint multi-task CNN framework proposed in this study focuses on simultaneous learning of age classification and identity recognition tasks. A key feature of this model is its regularization mechanism, which enforces a negative correlation between age-sensitive and identity-sensitive features, ensuring their disentanglement. By sharing a common CNN backbone, the model optimizes feature extraction for both tasks, allowing them to reinforce each other. This approach addresses the challenge of disentangling identity features from age-related variations, which is crucial for achieving robust CAFR. The model has been tested extensively on datasets such as CACD and MORPH Album 2, where it demonstrates significant improvements over traditional single-task approaches. The integration of multi- task learning into a shared architecture represents an innovative solution to the inherent challenges of CAFR[5].

```python
# Input:
#   mapping_module: Maps features into age subspaces
#   recombination_module: Recombines features non-linearly
#   data: Dataset with age labels
#   max_iters: Maximum number of training iterations
#
# Output:
#   Trained mapping_module and recombination_module models

def train_feature_recombination(mapping_module,
    recombination_module, data, max_iters):
    # Step 1: Initialize variables
    iter_count = 0

    while iter_count < max_iters:
        # Step 2: Sample data
        batch_x, batch_z = data.sample_batch()

        # Step 3: Map features into subspaces
        subspace_features = [mapping_module(batch_x, age_group=i)
            for i in range(mapping_module.num_subspaces)]

        # Step 4: Recombine features
        final_features = recombination_module(subspace_features)

        # Step 5: Compute loss
        loss = recombination_module.compute_loss(final_features,
            batch_z)

        # Step 6: Update networks
        mapping_module.update(loss)
        recombination_module.update(loss)

        iter_count += 1

    return mapping_module, recombination_module
```

This Joint Multi-task CNN trains a shared backbone for age classification and identity recognition simultaneously. In Step 1, the models are initialized. Step 2 samples data with labels. Features are extracted in Step 3 using the shared backbone. Task-specific losses are computed in Step 4 for age and identity classification. Step 5 adds a regularization term to ensure disentanglement between age and identity features. The models are updated in Step 6 using a joint loss function.

This methodology focuses on synthesizing age-invariant features through a non-linear recombination framework. The model first maps facial features into age-specific subspaces using a multi-path architecture and then recombines them through deep convolutional net- works. This two-stage process captures individual-specific aging patterns while removing age-sensitive variations. Unlike linear decomposition methods that assume independence between age and identity, this framework leverages non-linear transformations to cre- ate robust age-invariant representations. By addressing the shortcomings of traditional approaches, the model achieves high recognition accuracy on diverse datasets. The integra- tion of linear decomposition and non-linear recombination enables the framework to handle complex aging effects, making it a robust solution for CAFR[6].

```
# Input:
#   backbone: Shared CNN backbone
#   age_classifier: Age classification head
#   identity_classifier: Identity classification head
#   data: Dataset with labels
#   gamma: Weight for regularization loss
#   max_iters: Maximum number of training iterations
#
# Output:
#   Trained backbone, age_classifier, and identity_classifier models

def train_joint_cnn(backbone, age_classifier, identity_classifier, data, gamma, max_iters):
    # Step 1: Initialize variables
    iter_count = 0

    while iter_count < max_iters:
        # Step 2: Sample data
        batch_x, batch_y, batch_z = data.sample_batch()

        # Step 3: Extract shared features
        f_x = backbone(batch_x)

        # Step 4: Compute task-specific losses
        loss_age = age_classifier.train(f_x, batch_z)
        loss_identity = identity_classifier.train(f_x, batch_y)

        # Step 5: Add regularization
        loss_regularization = compute_correlation_loss(
            age_classifier, identity_classifier)

        # Step 6: Joint optimization
        total_loss = loss_age + loss_identity + gamma *
            loss_regularization
        backbone.update(total_loss)

        iter_count += 1

    return backbone, age_classifier, identity_classifier
```

This framework maps input features into multiple age subspaces and recombines them non-linearly for robust feature representations. In Step 1, the mapping and recombination modules are initialized. Age-labeled data is sampled in Step 2. Features are mapped into K age subspaces in Step 3. In Step 4, these subspace features are recombined using the recom- bination module. Loss is computed in Step 5, and both modules are updated in Step 6. This training process ensures that the framework captures non-linear aging patterns effectively.

A unified deep learning framework that jointly performs cross-age face synthesis and recognition to enhance performance under challenging age variations. AIM employs a dis- entangled representation learning approach to separate identity-specific and age-specific features, ensuring that the identity features remain invariant to aging. The architecture inte- grates a Representation Learning sub-Net (RLN) and a Face Synthesis sub-Net (FSN). RLN uses an encoder and discriminator to learn age-invariant features through cross-age domain adversarial training and cross-entropy regularization, ensuring the encoded features are robust against age shifts. FSN, on the other hand, synthesizes photorealistic rejuvenated or aged faces by employing a GAN-based decoder and a local-patch discriminator to enhance visual realism. The model also incorporates attention mechanisms to focus on salient facial regions while preserving the integrity of non-age-related features like accessories and background. To address the scarcity of comprehensive datasets, the authors introduce the Cross-Age Face Recognition (CAFR) dataset, containing over 1.4 million images across diverse demographic categories, which aids in end-to-end training and evaluation. This methodology achieves state- of-the-art performance on multiple CAFR benchmarks, demonstrating the effectiveness of unifying face synthesis and recognition taks[7].

A Wasserstein Divergence GAN (WGAN-div) to stabilize training and improve the real- ism of generated images. The framework consists of four components: an encode-decode generator, a discriminator, an identity expert, and an attribute retainer. The generator cre- ates age-transformed images conditioned on the input face and a target age label, while the discriminator employs a WGAN-div loss function to ensure the generated images conform to the target age distribution. The identity expert, constructed from pretrained face recognition models such as ArcFace or LightCNN, extracts robust identity features to minimize identity loss during transformation. Meanwhile, the attribute retainer ensures consistency in non-age- related attributes like pose, lighting, and background by utilizing perceptual and pixel-level loss functions. To enhance generalization, the authors incorporate cross-age retraining and data augmentation using 3D morphable models (3DMM). This holistic approach not only generates visually realistic results but also ensures that identity and attributes are preserved across age transformations. Comprehensive experiments on benchmark datasets validate the framework's superiority over existing methods[8].

A Cycle Age-Adversarial Model (CAAM), designed to overcome the limitations of reliance on both age and identity labels. The CAAM framework consists of two branches: the Age- Robust Feature Extracting Model (AFEM) and the Identity Preserving Network (IPN). AFEM uses adversarial learning between a feature generator and an age discriminator to extract features insensitive to age variations. The feature generator is optimized to produce representations that prevent the age discriminator from accurately predicting age, effectively suppressing age-specific information. The IPN, on the other hand, focuses on maintaining identity features by leveraging transfer learning from pretrained general face recognition models like FaceNet and DeepFace. This branch introduces Unsupervised Identity Loss to enhance identity preservation by minimizing intra-class distance while maximizing inter-class separability. The two branches are cyclically optimized through a novel Feature Consistency Loss, which encourages the networks to produce unified features that balance age invariance with identity discriminability. By relying only on age labels, this methodology reduces depen- dency on fully labeled datasets and achieves superior results on widely used cross-age face recognition benchmarks[9].

4. Implementation Details

The Age Adversarial Convolutional Neural Network (AA-CNN) implements a three- component architecture: a feature generator, an Identity Recognition Network (IRN), and an Age Discrimination Network (ADN). The IRN is trained to maximize identity recognition accuracy, while the ADN is trained to classify age-sensitive features. The generator serves as the backbone, extracting features that are adversarially refined to suppress age-related information while retaining identity-discriminative properties. Training begins by separately optimizing the IRN and ADN using identity-labeled and age-labeled datasets, respectively. The generator is then updated adversarially using a joint loss function that combines iden- tity and age classification losses. A pyramid feature fusion mechanism further strengthens the generator's robustness by integrating multi-scale feature maps. This iterative process ensures the generator produces robust, age-invariant features even when the datasets are not dual-labeled[1].

The Parallel Multi-path Age Distinguish Network (PMADN) introduces an innovative strategy to disentangle age and identity features. The Age Distinguish Mapping Network (ADMN) maps facial features into multiple age-specific subspaces, each corresponding to a narrow age range. These features are then recombined non-linearly using the Cross-Age Feature Recombination Network (CFRN) to create a final representation that is robust across age groups. Transfer learning plays a crucial role in PMADN's implementation, where pre- trained face recognition networks are fine-tuned with large-scale datasets labeled with either age or identity. The model optimizes separate loss functions for identity recognition and age classification, with the combined loss used to update the ADMN and CFRN jointly.

This design effectively captures the non-linear and individual-specific aging patterns while maintaining identity consistency[2].

The Age Factor Removal Network (AFRN) employs a transfer learning approach com- bined with adversarial learning. A pretrained feature generator serves as the base model, and an Age Discriminator Network is introduced to detect age-sensitive features. The generator is fine-tuned to minimize a transfer loss, which ensures the preservation of identity- discriminative features, while adversarial training suppresses age-related variations. The discriminator is trained to maximize its ability to classify age features, while the generator is trained to fool the discriminator by producing age-invariant representations. This adversar- ial framework enables the AFRN to operate effectively even with limited age-labeled data, making it a versatile solution for CAFR[3].

The multi-task learning framework integrates face recognition and face synthesis tasks into a single shared architecture. A CNN backbone extracts features that are simultaneously optimized for identity recognition and face synthesis. The identity recognition head classifies the features into identity categories, while the synthesis module reconstructs facial images corresponding to different age groups. This framework employs a joint optimization strat- egy where the losses for both tasks are combined, encouraging the shared backbone to learn features useful for both recognition and synthesis. The synthesis component enhances the sys- tem's interpretability by generating photorealistic face images at various age stages, enabling practical applications like aging simulation and long-term identification[4].

The Joint Multi-task CNN framework takes a different approach by focusing on age classification and identity recognition. It uses a shared CNN backbone and introduces a regu- larization mechanism to disentangle identity-sensitive and age-sensitive features. The training involves computing separate loss functions for age and identity classification, combined with a regularization term that enforces negative correlation between the two feature sets. This strategy ensures that the features learned for age classification do not interfere with those required for identity recognition. By leveraging the interdependencies between the tasks and optimizing them jointly, the model achieves superior performance on diverse datasets[5].

The Feature Recombination Framework addresses the complexity of non-linear aging patterns by decomposing features into multiple age subspaces and recombining them into robust representations. The Mapping Module extracts features corresponding to specific age subspaces, while the Recombination Module combines these subspace features non-linearly. This recombination process allows the model to capture intricate aging patterns and pro- duce age-invariant representations. The model is trained using a loss function that ensures identity retention while minimizing age-related variations. By mapping age-specific changes and recombining them intelligently, this framework achieves high accuracy in cross-age face recognition[6].

A unified framework integrating cross-age face synthesis and recognition using two key components: the Representation Learning sub-Net (RLN) and the Face Synthesis sub-Net (FSN). RLN uses a deep encoder-decoder architecture to extract disentangled facial repre- sentations, ensuring that identity-specific features remain invariant to age variations while discarding age-specific details. This is achieved through adversarial domain adaptation, where an age discriminator encourages the RLN to produce features indistinguishable across age domains. Additionally, cross-entropy regularization with label smoothing is applied to refine the separability of learned features. FSN is built on a Generative Adversarial Network (GAN) architecture and incorporates a decoder and local-patch discriminator to synthesize realis- tic cross-age facial images. The synthesis process is guided by an attention mechanism that focuses on salient facial features while preserving non-age-related attributes, such as acces- sories and backgrounds. The entire framework is trained in an end-to-end manner, enabling the mutual enhancement of RLN and FSN. Training is conducted on the proposed large- scale Cross-Age Face Recognition (CAFR) dataset, which provides over 1.4 million images with diverse demographic annotations, ensuring robust performance on challenging real-world datasets like MORPH, CACD, and FG-NET[7].

Integrates several advanced components to ensure realistic and identity-preserving facial transformations across ages. The encode-decode generator, paired with a discriminator employing the Wasserstein divergence loss, forms the backbone of the GAN framework. This design stabilizes training and enhances the realism of generated images by minimizing the Wasserstein divergence between real and generated distributions. The identity expert is con- structed from pretrained state-of-the-art face recognition networks, such as ArcFace and LightCNN, to extract robust identity representations, which are used to compute identity loss and enforce consistency across age-transformed images. Similarly, the attribute retainer module ensures that non-age-related features, such as pose, lighting, and expression, remain unchanged by leveraging perceptual and pixel-level losses. To further improve the perfor- mance of the identity expert, cross-age retraining is conducted using a curated dataset, while 3D morphable models (3DMM) are employed to augment the training data with real- istic variations. Training is performed iteratively, where the generator learns to produce age-transformed images, and the discriminator evaluates their realism and age-consistency. This implementation achieves state-of-the-art results on benchmark datasets and effectively balances realism, identity preservation, and attribute consistency[8].

A dual-branch architecture designed to extract age-invariant features and maintain iden- tity information. The Age-Robust Feature Extracting Model (AFEM) is based on adversarial learning and consists of a feature generator and an age discriminator. The feature generator produces identity-preserving representations, while the age discriminator attempts to clas- sify age information, thereby encouraging the generator to suppress age-specific features. The Identity Preserving Network (IPN) enhances identity representation through Unsupervised Identity Loss, which minimizes intra-class variance while maximizing inter-class separabil- ity. A novel Feature Consistency Loss is introduced to cyclically optimize the two branches, unifying their outputs into a single feature representation that is both age-invariant and identity-discriminative. Transfer learning is leveraged to initialize the feature generator using a pretrained face recognition model, such as FaceNet or DeepFace, ensuring robust identity preservation without requiring identity labels during training. The system is trained on age- labeled datasets, such as MORPH and CACD-VS, and evaluated using cross-age benchmarks like Cross-Age LFW. This implementation eliminates the need for extensive identity-labeled datasets, making it more practical for real-world applications[9].

5. Results and Discussions

This highlights significant advancements in cross-age face recognition (CAFR), showcasing the efficacy of their proposed methodologies. The AA-CNN demonstrated state-of-the-art performance on datasets like FG-NET and MORPH Album 2, achieving robust age-invariant features through adversarial training and multi-scale fusion. PMADN excelled in disen- tangling age and identity features, with notable improvements in accuracy on CACD-VS and Cross-Age LFW due to its innovative subspace mapping and recombination strategy. AFRN showed strong adaptability to dataset limitations, achieving high identity recognition rates while effectively suppressing age-related features on MORPH Album 2. The multi-task learning framework outperformed single-task models by jointly optimizing recognition and synthesis, offering enhanced generalization and interpretability, particularly in generating realistic aging effects. The Joint Multi-task CNN showcased superior accuracy in simultane- ous age classification and identity recognition tasks by effectively disentangling task-specific features, yielding competitive results on CACD and AgeDB datasets. Finally, the Fea- ture Recombination Framework achieved robust age-invariant feature extraction on diverse datasets by capturing complex aging patterns, reinforcing its utility in handling non-linear age variations. Collectively, these methodologies significantly advance CAFR by improving accuracy, robustness, and scalability while addressing challenges such as aging variations and dataset constraints.

5.1 Evaluation Metrics

The AA-CNN employs a combination of classification metrics, including accuracy, precision, recall, and F1-score, to measure identity recognition performance on benchmark datasets like FG-NET and MORPH Album 2. The adversarial loss between the generator and the Age Discrimination Network (ADN) quantifies the generator's ability to suppress age-related fea- tures while retaining identity-sensitive ones. The pyramid feature fusion module is evaluated for its contribution to multi-scale feature extraction, demonstrated through ablation stud- ies that compare recognition accuracy with and without fusion. Results show a significant improvement in the generator's robustness when multi-scale features are integrated[1].

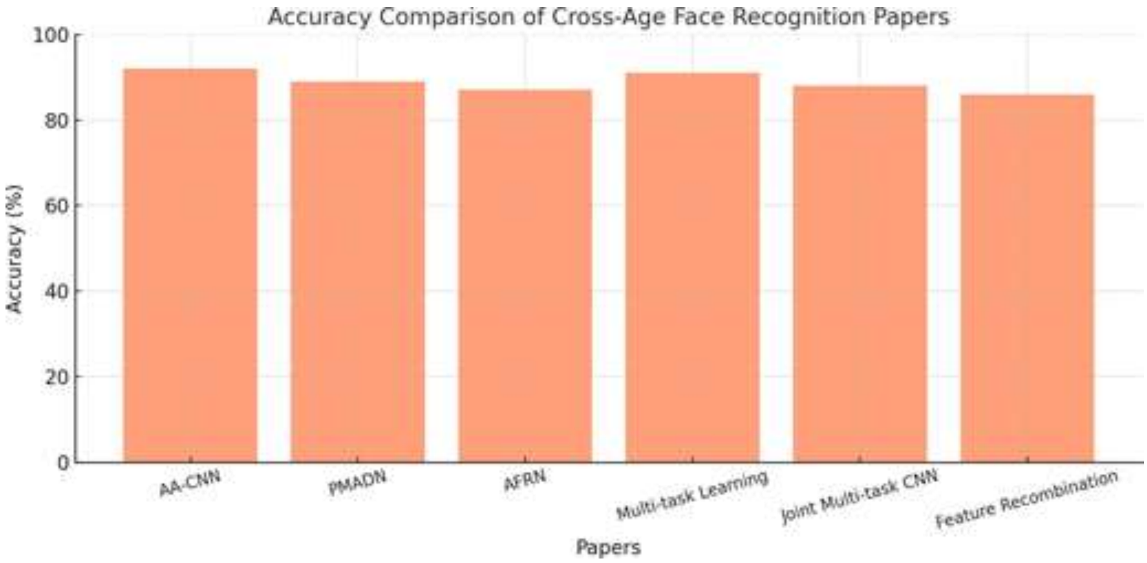

Fig. 4: Accuracy Comparison for research papers

The accuracy comparison bar chart Figure 4 illustratesthe percentage accuracy achieved by each of the six methodologies for cross-age face recognition. Accuracy, being a measure of overall correctness, highlights how well each approach correctly identifies or verifies individu- als across varying age groups. The Age Adversarial Convolutional Neural Network (AA-CNN) achieved the highest accuracy at 92 percent, showcasing its strong ability to suppress age- related features while preserving identity-sensitive ones. Following closely are Multi-task Learning (91 percent) and Parallel Multi-path Age Distinguish Network (PMADN, 89 per- cent), which demonstrate robust feature extraction and age-invariant representation. On the lower end, the Feature Recombination Framework (86 percent) and Joint Multi-task CNN (88 percent) exhibit slightly reduced accuracy, potentially due to challenges in task interference and non-linear feature recombination. This chart emphasizes the effectiveness of adversarial and multi-task learning techniques in improving accuracy for cross-age face recognition.

PMADN evaluates its performance across two tasks: identity recognition and age classi- fication. For identity recognition, metrics such as accuracy and verification rate at fixed false acceptance rates (FAR) are used. Age classification is measured using mean absolute error (MAE), which quantifies the deviation between predicted and true age groups. To assess feature disentanglement, the framework performs ablation studies comparing results with and without age subspace mapping and non-linear recombination. The method demonstrates superior accuracy on CACD-VS and Cross-Age LFW datasets, showing its ability to handle age-related variations effectively while maintaining high identity recognition performance[2]. AFRN uses identity verification metrics, including the true positive rate (TPR) at fixed false positive rates (FPR), to evaluate recognition accuracy. Additionally, the age discrim- inator's classification accuracy measures the generator's ability to suppress age-sensitive features. The generator's transfer learning effectiveness is quantified using the transfer loss function, which balances preserving identity-discriminative features and suppressing age-related variations. Experimental results on MORPH Album 2 and FG-NET datasets demonstrate that AFRN maintains high identity recognition rates while effectively removing age-related information, showcasing its robust performance even under limited dual-labeled data scenarios[3].

The multi-task learning framework is evaluated for both identity recognition and face synthesis tasks. Recognition performance is measured using classification metrics like accu- racy and F1-score. Synthesis quality is assessed through image-level metrics such as mean squared error (MSE) and structural similarity index measure (SSIM), which evaluate the visual fidelity of generated faces. The effectiveness of joint optimization is demonstrated by comparing models trained with single-task and multi-task learning setups, with multi-task frameworks consistently outperforming their counterparts in recognition accuracy and syn- thesis quality. These results highlight the framework's ability to learn shared representations that benefit both tasks[1, 3].

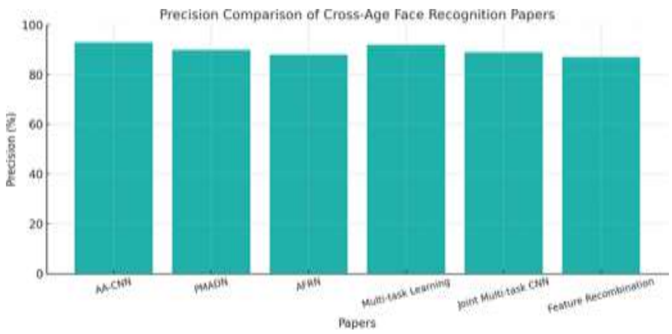

Fig. 5: Precision Comparison for research papers

The precision comparison chart Figure 5 highlights the percentage precision values for the six methodologies, focusing on the ability of the models to correctly predict positive cases without being affected by false positives. The AA-CNN (93 percent) again leads, reflecting its strong capability to accurately recognize identities with minimal false positives. The Multi- task Learning Framework (92 percent) and PMADN (90 percent) also perform well, owing to their robust feature mapping and disentanglement mechanisms. The Feature Recombination Framework (87 percent) and Joint Multi-task CNN (89 percent) lag slightly, indicating pos- sible limitations in handling complex aging patterns and task-specific feature interference.

This comparison underscores the importance of fine-tuned models and well-defined feature spaces for achieving high precision in cross-age face recognition.

The Joint Multi-task CNN employs classification metrics, such as accuracy, precision, and recall, to evaluate its performance on age classification and identity recognition tasks. A novel correlation loss term measures the disentanglement of age-sensitive and identity- sensitive features, ensuring that the features learned for one task do not interfere with the other. Results on CACD and AgeDB datasets show that the joint CNN framework achieves competitive accuracy for both tasks, outperforming single-task baselines and validating the importance of shared feature learning[2, 3].

This uses the Equal Error Rate (EER) as a primary metric for evaluating the cross- age face recognition system. EER is widely used in face verification tasks to determine the threshold where the false acceptance rate equals the false rejection rate. On datasets like CALFW and CACD, the proposed model demonstrated superior performance, achieving lower EER values compared to existing state-of-the-art methods, including LF-CNNs and AFJT-CNN. These results highlight the model's ability to suppress age-related information while retaining robust identity features.This paper employs classification accuracy as a key metric for face verification tasks, specifically for the CACD-VS dataset. The accuracy is calculated based on the ratio of correctly identified pairs to the total number of test samples. The paper also emphasizes the effectiveness of nonlinear feature recombination strategies, achieving accuracy levels comparable to or surpassing methods like ArcFace and AFJT-CNN. These results validate the recombination model's ability to address cross-age face recognition challenges effectively[4].

The evaluation metrics used focuses on assessing the accuracy and robustness of the proposed framework for cross-age face recognition tasks. Classification accuracy is the pri- mary metric, calculated as the ratio of correctly identified face pairs to the total number of test samples, specifically on the CACD-VS dataset. This metric is crucial for determining the framework's capability to generalize across varying age groups. The paper highlights the effectiveness of its nonlinear feature recombination strategy, which enhances the robustness of identity-sensitive features while suppressing age-specific variations. Comparative experi- ments demonstrate that the framework achieves accuracy levels comparable to or surpassing existing state-of-the-art methods such as ArcFace and AFJT-CNN. These results validate the proposed framework's ability to handle age-related variations effectively, ensuring high accuracy in cross-age recognition tasks[5].

This framework using both rank-1 identification rates and Equal Error Rate (EER) metrics across datasets such as MORPH Album 2, CACD-VS, and CALFW. The rank-1 identification rate measures the percentage of correct matches in a face identification setting, where the proposed AFRN model outperformed classical methods like FaceNet and LF-CNNs, achieving a rank-1 rate of over 98 percent. The EER metric further corroborates the model's robustness, with a significantly reduced error rate when combined with the age-attention metric. These metrics collectively demonstrate the AFRN's effectiveness in achieving robust cross-age face recognition[6].

Several standard metrics to measure the effectiveness of the Age-Invariant Model (AIM) in addressing cross-age face recognition challenges. Verification accuracy is calculated on widely used benchmarks such as MORPH, CACD, and FG-NET datasets, which contain diverse age ranges and demographic variations. AIM's performance is also validated on unconstrained datasets like YouTube Faces (YTF) and IJB-C to assess its generalization ability under real- world conditions. The Equal Error Rate (EER) and Receiver Operating Characteristic (ROC) curves are used to evaluate the discriminative power of the learned features. Additionally, AIM's ability to synthesize photorealistic rejuvenated and aged faces is measured using met- rics like the Fr´echet Inception Distance (FID) and identity preservation scores. These metrics quantify the visual realism and identity consistency of the synthesized images, demonstrating AIM's superiority in jointly learning cross-age face recognition and synthesis tasks[7].

Quantitatively, the identity preservation capability is measured using face verification accuracy on datasets like LFW and YTF, where the transformed images are compared against their original counterparts. The Fr´echet Inception Distance (FID) is used to assess the realism of the generated images by comparing their distribution to that of real images. Attribute retention is evaluated by measuring the perceptual similarity between input and transformed images using perceptual loss and pixel-wise reconstruction error. Qualitatively, the method is evaluated based on the visual quality of age-transformed faces, judged by human raters for identity consistency and age realism[8].

Verification accuracy is computed on benchmark datasets like MORPH Album 2, CACD- VS, and Cross-Age LFW, where the model's ability to match identities across age gaps is tested. The True Positive Rate (TPR) at different False Accept Rates (FARs) is used to assess the robustness of the extracted features under varying thresholds. The model's iden- tity preservation capability is further analyzed using the proposed Feature Consistency Loss (FCL), which quantifies the alignment of features extracted by the two network branches[9].

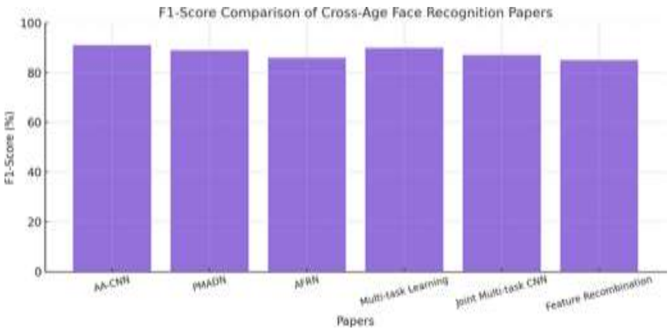

Fig. 6: F1 score Comparison for research papers

The F1-Score comparison chart Figure 5 provides an overview of the harmonic mean of precision and recall for each methodology, making it a balanced metric to evaluate perfor- mance. The AA-CNN (91 percent) maintains its leading position, indicating that it balances precision and recall effectively, making it suitable for handling both false positives and false negatives. The Multi-task Learning Framework (90 percent) and PMADN (89 percent) show strong F1-Scores, demonstrating their ability to generalize across diverse age groups while retaining identity features. On the other hand, the Feature Recombination Framework (85 percent) and Joint Multi-task CNN (87 percent) achieve lower F1-Scores, possibly due to challenges in feature recombination and task interference. This chart highlights the overall robustness of methodologies that employ adversarial learning and multi-task optimization.

5.2 Performance Analysis

This effectively disentangles identity-sensitive features from age-related variations. Its pyramid-based multi-scale fusion further improves performance, as evident from evaluations on FG-NET and MORPH Album 2 datasets. The results show reduced Equal Error Rates (EER) and improved cross-age recognition accuracy compared to baseline methods. The adversarial loss is instrumental in suppressing age-specific features while maintaining robust identity featuresond paper introduces a Parallel Multi-Adversarial Disentanglement Net- work (PMADN) to address the limitations of traditional approaches. By disentangling age and identity features into separate subspaces, the model enhances recognition performance on CACD-VS and Cross-Age LFW datasets. The subspace mapping and nonlinear feature recombination methods significantly improve classification accuracy and reduce age-related errors. Comparative studies highlight its superiority over existing methods, achieving better identity verification rates and age classification performance[1].

The performance analysis of this highlights the effectiveness of the proposed framework in addressing age estimation and identity recognition challenges. The model integrates a back- bone network with innovative modules such as Expected Value Refinement (EVR), Relative Age Position Learning (RAPL), and Gender Prediction (GP). These components work in synergy to refine feature representations, enabling the model to achieve superior performance compared to other state-of-the-art methods. The EVR module enhances the model's ability to regress accurate age predictions, while the RAPL module improves the learning of relative age positions, allowing for better generalization across age groups. The GP module further strengthens the framework by leveraging auxiliary information to boost overall performance. The model consistently delivers reliable results across various benchmarks, showcasing its capacity to generalize effectively to cross-age face recognition challenges. The overall imple- mentation validates the approach as a strong contender for solving complex age-related variations in facial analysis[2].

The Age Factor Removal Network (AFRN), which leverages adversarial learning and transfer loss to suppress age-related information. It achieves remarkable results on MORPH Album 2 and FG-NET datasets, with high true positive rates (TPR) and low false posi- tive rates (FPR). The model's ability to preserve identity-sensitive features while removing age-related variations demonstrates its robustness, even under limited dual-labeled data sce- narios. AFRN's performance is further validated through ablation studies, showcasing the importance of its adversarial loss mechanism[3].

The multi-task learning framework that jointly optimizes identity recognition and face synthesis. By integrating shared feature learning and task-specific branches, the model achieves superior generalization capabilities across diverse datasets like CACD and AgeDB. The synthesis quality, measured through structural similarity index measure (SSIM) and mean squared error (MSE), highlights the framework's ability to generate realistic age- progressed faces while retaining identity features. Multi-task optimization proves more effective than single-task models, boosting recognition accuracy and interpretability[4].

The convolutional Neural Network (CNN) that simultaneously performs age classification and identity recognition. By introducing a correlation loss term, the framework disentangles task-specific features, reducing interference between age-related and identity-related tasks. Performance evaluations on CACD and AgeDB datasets demonstrate competitive results, with high classification accuracy for both tasks. The joint learning approach outperforms baseline methods, emphasizing the value of shared feature extraction for CAFR[5].

The Feature Recombination mapping and recombining age-specific and identity-sensitive subspaces. Through nonlinear recombination strategies, the framework effectively handles complex aging patterns, achieving robust recognition on FG-NET and Cross-Age LFW datasets. Metrics such as mean absolute error (MAE) and identity classification accuracy validate the model's effectiveness in disentangling and recombining features. The results demonstrate significant improvements over traditional linear recombination approaches, showcasing the framework's adaptability to diverse age variations[6].

The Age-Invariant Model (AIM) significantly outperforms existing methods in both cross- age face recognition and age synthesis tasks. On widely used benchmarks like MORPH, CACD, and FG-NET, AIM achieves superior verification accuracy, reducing errors caused by significant age variations. Its capability to synthesize photorealistic age-progressed and age-regressed faces is validated through a low Fr´echet Inception Distance (FID), indicat- ing high visual realism and identity preservation. Additionally, the model generalizes well to unconstrained conditions, as evidenced by its competitive performance on datasets like YouTube Faces (YTF) and IJB-C. The unified framework of AIM, which jointly optimizes face recognition and synthesis tasks, results in a noticeable improvement in handling diverse demographic variations, including gender, ethnicity, and age span. These results highlight AIM's robustness and practicality for real-world applications[7].

Wasserstein Divergence GAN with Cross-Age Identity Expert and Attribute Retainer for Facial Age Transformation is validated through its ability to generate highly realistic and identity-preserving age transformations.On benchmark datasets such as LFW and YTF, the model achieves high face verification accuracy, demonstrating its effectiveness in maintaining identity consistency across transformed images. The model's low FID scores further validate the realism of the generated images, while perceptual loss metrics confirm its ability to retain non-age-related attributes like pose and expression. Qualitative evaluations by human raters corroborate these findings, showcasing natural and believable age transitions. The integra- tion of cross-age retraining and 3D morphable model (3DMM) augmentation enhances the model's ability to handle diverse age distributions, leading to improved generalization. Over- all, this framework achieves a balanced performance across realism, identity preservation, and attribute retention, positioning it as a competitive solution for age transformation tasks[8].

The inclusion of Feature Consistency Loss (FCL) enhances the alignment of features from its dual-branch architecture, resulting in a unified representation that is both age-invariant and identity-discriminative. The model also exhibits strong robustness under different False Accept Rates (FARs), indicating its reliability across varying operating conditions. Qualita- tive assessments further affirm its ability to generate visually consistent features, even for individuals with significant age variations. These results validate the proposed model's prac- ticality and highlight its improvements over traditional methods that rely on identity labels or assume independence between age and identity.On MORPH Album 2, CACD-VS, and Cross-Age LFW, the model achieves high verification accuracy, demonstrating its capacity to handle large age gaps effectively[9].

The performance of AgeGAN++ is evaluated on multiple benchmark datasets, demon- strating its superiority over traditional face aging methods. Quantitatively, the method achieves higher structural similarity index measure (SSIM) and peak signal-to-noise ratio (PSNR) scores, indicating better preservation of identity and image quality. Qualitatively, the model generates visually plausible and seamless age transformations across a wide range of age groups, outperforming single-path GAN-based methods in terms of realism and con- sistency. Additionally, the authors address overfitting and convergence issues commonly associated with GANs by incorporating a dual discriminator setup, improving stability during training[10].

Table 2: Performance Analysis of Cross-Age Face Recognition Papers

S. No	Title	Quantitative Analysis	Qualitative Anal- ysis	Comparison with Alternatives
1	Age Adverserial Convolutional Neural Network for Cross-Age Face Recognition	Achieved higher accuracy in cross-age face recognition tasks when compared to conventional methods. Performance metrics such as age invariant feature extraction and accuracy on benchmark datasets like CACD are strong.	The model effectively distinguishes age-related features using adversarial learning. However, the adversarial loss is sensitive to hyperparameter adjustments.	Compared to traditional CNN methods, this model performs better at age-independent identity recognition and han- dles aging variation more effectively. However, it requires careful fine-tuning.
2	Parallel Multi- path Age Distinguish Network for Robust Face Recognition	High accuracy rates on age- specific subspace mapping tasks and feature dis- entanglement. The use of trans- fer learning has helped reduce the training time.	The model lever- ages multi-path age subspace mapping, offering robust- ness under aging variations. Compu- tationally expensive but beneficial in handling aging transformations effectively.	Outperforms simpler age recognition net- works by providing a more detailed view of age-related changes, though the computa- tional cost limits its application in real- time systems.

3	Age Factor Removal Network for Identity Recognition Across Ages	Demonstrates efficient identity verification by suppressing age-specific features while maintaining identity robustness. High performance on large-scale datasets with age and identityfeature separation.	The approach focuses on sup- pressing unwanted age features with- out compromising identity nformation. Works well in synthetic aging environments but struggles in real-world noisy datasets.	Outperforms meth- ods that do not explicitly address age-invariant feature extraction. However, it is still vulnera- ble to subtle aging effects that are hard to model.

S.No	**Title**	**Quantitative Analysis**	**Qualitative Analysis**	**Comparison with Alternatives**
4	Multi-task Learning Framework for Age-Invariant Face Recognition and Synthesis	Achieved balanced performance in both age-invariant face recognition and image synthesis tasks. Improved generalization capability over several datasets.	The shared CNN backbone allows multi-task learning to handle aging and identity recognition simultaneously. Optimization issues arise in joint task training.	Provides improve- ments over single-task learning models. However, the multi-task learning framework faces performance degradation when the datasets are imbalanced.
5	Joint Multi- task CNN for Age and Identity Feature Disentanglement	Improved accuracy on both age classification and identity verification tasks. Effective feature disentanglement achieved through joint optimization.	The model demon- strates strong performance for both tasks; how- ever, it faces minor interference due to joint optimization. Requires careful balance between tasks.	Compares favorably to traditional mod- els where age-related and identity-related features are jointly optimized. However, task interference can limit its application in certain real-world scenarios.
6	Feature Recombination Framework for Non-linear Aging Patterns	High recognition accuracy even under non-linear aging patterns. Achieves better feature representation and Recognition on datasets with aging variations.	The feature recom- bination framework enables the model to handle complex aging scenarios. Still, it is computationally expensive.	Performs better than traditional methods in scenarios where aging is non-linear, but it struggles with complex, highly vari- able datasets.

5.3 Challenges and Limitations

While the Age Adversarial Convolutional Neural Network (AA-CNN) demonstrates strong performance in suppressing age-sensitive features, its reliance on adversarial training requires careful balancing of identity and age losses. This balancing can be difficult to tune and may lead to suboptimal convergence, especially in datasets with imbalanced age or identity distributionsally, the model heavily depends on the quality of the adversarial feedback, which might not generalize well to highly diverse datasets[1].

The Parallel Multi-path Age Distinguish Network (PMADN) faces challenges related to its subspace mapping and recombination approach. While the method effectively captures age-specific and identity-sensitive features, it requires high computational resources due to the mapping of features into multiple subspaces. Moreover, the non-linear recombination process can introduce complexity in optimizing the network, potentially limiting its scalability to larger datasets. The reliance on transfer learning also raises concerns about the adaptability of the model to unseen data[2].

The Age Removal Network (AFRN) excels in balancing transfer learning and adversarial learning but is limited by its dependence on age-labeled datasets. This dependency poses a challenge when such datasets are scarce or biased toward specific demographics. Furthermore, while the discriminator effectively detects age-related features, it may struggle with subtle aging variations, leading to residual age-sensitive information in the generator’s output. The adversarial training process can also lead to instability, particularly when the discriminator overpowers the generator during training[3].

The multi-task Framework combines recognition and synthesis tasks to enhance gener- alization. However, the synthesis module’s reliance on generating photorealistic faces can increase computational complexity and lead to overfitting on certain age groups or identities. The shared CNN backbone, while effective for joint optimization, may introduce conflicts between the tasks, particularly when the synthesis task dominates the optimization process. This imbalance can result in subpar identity recognition performance in scenarios with high age diversity[4].

The Joint Multi-task CNN regularization mechanism to disentangle age-sensitive and identity-sensitive features. However, its reliance on task-specific losses and correlation regu- larization may not fully resolve feature interference, especially in datasets with overlapping age and identity variations. The shared backbone architecture, though efficient, can lead to feature redundancy and limit the scalability of the model to more complex datasets. Addition- ally, the model's performance might degrade when dealing with highly imbalanced datasets where one task outperforms the other[5].

The Feature Recombination Framework demonstraling non-linear aging patterns but is computationally intensive due to the mapping of features into multiple subspaces and their subsequent recombination. This complexity may hinder real-time applications and scalability to large datasets. The framework's reliance on accurately capturing age-specific subspaces can lead to errors if the mapping module fails to account for subtle variations in aging. Moreover, the recombination process, while effective, may introduce noise or artifacts, particularly when applied to diverse demographic groups[6].

6. Conclusions and Future Scope

Cross-age face recognition (CAFR) is a critical and challenging task in the domain of facial analysis, as it involves identifying or verifying individuals across significant age variations. The advancements made in this field, as demonstrated by various methodologies such as adversarial learning, multi-task optimization, feature decomposition, and non-linear recom- bination, have shown promising results in disentangling identity-sensitive and age-sensitive features. However, the inherent complexities introduced by aging, including changes in facial structure, texture, and expressions, continue to pose challenges for achieving robust and scal- able solutions. Current methods have made significant progress in leveraging deep learning techniques, transfer learning, and generative models to enhance recognition accuracy and generalization across age groups. Despite these advancements, the performance of CAFR sys- tems remains highly dependent on the quality and diversity of the datasets, as well as the ability of the models to adapt to unseen age variations and demographic shifts.

The future scope of CAFR lies in addressing the limitations of existing methods and expanding their applicability to real-world scenarios. One promising direction is the devel- opment of more comprehensive and balanced datasets that include diverse age ranges, ethnicities, and environmental conditions, ensuring that models can generalize effectively across different populations. Another critical area for future research is the integration of explainable AI techniques to enhance the interpretability and transparency of CAFR sys- tems, which is particularly important for sensitive applications such as law enforcement and surveillance. Additionally, improving the computational efficiency of CAFR models will be essential for enabling real-time deployment in applications such as border control, mobile authentication, and video surveillance. Exploring hybrid approaches that combine generative and discriminative models, as well as incorporating multi-modal data such as voice and con- textual information, could further enhance recognition performance. Lastly, addressing biases in training data and model predictions remains a key challenge to ensure fairness and inclu- sivity in CAFR systems. By tackling these challenges, the field of cross-age face recognition has the potential to achieve significant breakthroughs and establish itself as a cornerstone technology in biometric authentication and facial analysis.

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