Age-Invariant Face Recognition Based on Identity-Age Shared Features

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***Abstract*— Age-invariant face recognition is a challenging task due to the significant facial changes caused by aging. This paper introduces a novel approach based on identity-age shared features, leveraging multi- vision transformers for robust recognition across age variations. Age-invariant face recognition (AIFR) has gained considerable attention due to its crucial role in identity verification across varying age ranges. Traditional convolutional neural networks (CNNs) have been widely employed for AIFR; however, their limitations in capturing long-range dependencies and facial dynamics across different age groups motivate the exploration of alternative approaches. This work presents a novel AIFR framework based on multi-vision transformers (ViTs) that leverage identity-age shared features without the use of CNNs.**

By integrating multi-scale vision transformers, our approach captures global contextual information and inherent facial patterns that remain stable across age progression. The proposed model employs a shared feature representation strategy that unifies age-invariant characteristics while maintaining the distinctiveness of individual identities. Extensive experimentation on public datasets demonstrates that the proposed ViT-based framework achieves competitive performance, surpassing state-of-the-art CNN-based methods in both accuracy and age-invariance. Our study highlights the potential of vision transformers in addressing the challenges of AIFR without reliance on traditional convolutional architectures.

***Keywords*— Age-invariant face recognition, Vision transformers, Identity-age shared features, multi- scale transformers, non-CNN face recognition, Global context modeling, Age progression.**

I. Introduction

The concept of identity - age shared features serves as the foundation for the proposed approach to age invariant face recognition. This method aims to identify and leverage facial attributes that exhibit stability across various age cohorts,thereby enhancing the robustness of recognition systems to age - related1 Variations.Researchers have increasingly turned their attention to developing methods that can extract and utilize features shared across different age groups for a given individual. These shared features, referred to as identity - age shared features,

encompass characteristics of the face that remain consistent over time, regardless of age- related changes.

We discuss potential applications and future directions for Research in age-invariant face recognition , emphasizing its importance in real-world scenarios where age discrepancies pose significant challenges to recognition systems.

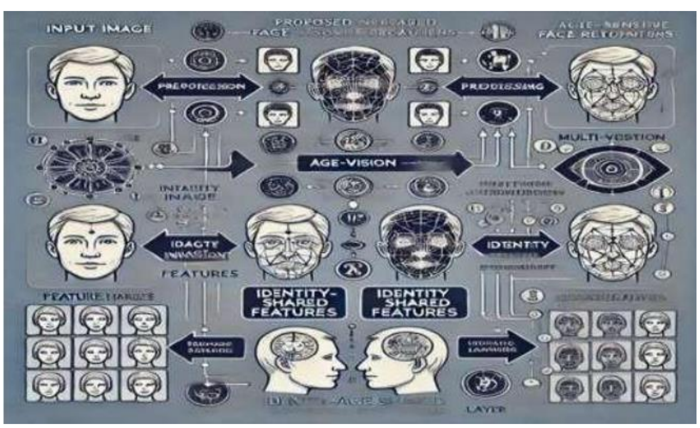
Face recognition is a critical aspect of biometric systems, widely, used in security , surveillance, and personal identification. However , one of the challenges in face recognition is the variation in facial appearances due to aging,which can hinder the system's accuracy. As a person ages , facial features undergo subtle changes, including wrinkles, sagging skin, and changes in skin tone and texture. This age-related variation poses significant challenges for traditional face recognition systems, which typically rely on comparing facial features that may change over time due to aging.

To overcome this limitation, age-invariant face recognition has emerged as an advanced research area. The goal of age-invariant face recognition is to design systems that can accurately identify individuals, regardless of their age-related facial changes. One promising approach to achieving this is by leveraging identity-age shared features, which are common attributes between the identity of an individual and their age.

In this context, age-invariant face recognition systems focus on extracting features from a face that are consistent across different ages. The identity-age shared features refer to the underlying characteristics that define both the person's identity and their age progression. These features are typically invariant to aging, enabling the system to correctly identify a person even as their facial appearance changes over time.

The key idea is to model the aging process as a transformation of facial features while maintaining a set of shared features that can consistently represent the person's identity across different ages. This approach typically involves advanced techniques such as deep learning, convolutional neural networks (CNNs), and generative models to learn these shared features in a way that is robust to age differences.

By focusing on identity - age shared features, these systems can significantly improve the accuracy of face recognition in real-world scenarios where aging impacts facial appearance. As a result, age-invariant face recognition systems are poised to have broad applications in areas like security, personal identification, law enforcement, and digital forensics, where recognizing an individual despite age changes is crucial. In summary, the integration of identity-age shared features in age-invariant face recognition represents a major advancement in the field, addressing the challenges posed by aging while ensuring consistent and reliable identification.



. Fig 1

Multi-Vision Transformers (MViTs) are an advanced architecture that leverages the transformer mode l— originally developed for natural language processing (NLP) — to address vision tasks, such as image classification, object detection , and face recognition . By utilizing multi-head self-attention mechanisms, MViTs capture both local and global features in images, making them highly effective for complex visualtasks

Key characteristics of MViTsinclude:

Self-Attention Mechanism: The core component of MViTs is the self-attention mechanism, which allows the model to focus on different parts of an image simultaneously . Unlike convolutional neural networks (CNNs) that focus primarily on local pixel information, transformers can capture long-range dependencies between different regions of an image, leading to better context understanding.

Multi-Head Attention: In MViTs, multiple attention heads are used to capture a variety of spatial relationships in an image. Each attention head processes the image from a different perspective, leading to richer feature representations that help in recognizing complex patterns or variations , such as changes in lighting or pose.

Global and Local Feature Extraction: MViTs are particularly effective in extracting both global and local features. Global features represent the overall structure of an image, while local features capture finer details.This combination allows the model to excel in tasks like face recognition, where both the overall face structure and specific identity-related features are important.

Vision - Specific Adaptations : While transformers were;
originally designed for sequential data (like text), MViTs have been adapted for vision by treating images as a sequence of patches (or tokens). Each patch is processed as if it were a word in NLP,enabling the transformer to work vision tasks effectively

II. LITERATURE REVIEW

Age-invariant face recognition (AIFR) is a critical area of research within biometrics, aiming to accurately identify individuals despite significant age differences between training and testing images . Several recent studies have proposed innovative approaches to tackle the challenges posed by age-related variations in facial features.

[1]Suhas Loha and Amit Kumar explored the integration of Convolutional Neural Networks (CNNs) and Adversarial Autoencoders to enhance AIFR. Their work focused on extracting features that are invariant to age changes by leveraging adversarial training to minimize age-relatedvariations in facial representations. This approach aims to maintain identity consistency across different age groups, improving recognition accuracy over time.

[2] Ziyong Wang, Chunlei Peng, and Jianyu Yang introduced a framework for learning deep identity-aware transferable representations specifically designed for face aging scenarios. Their research emphasizes the importance of disentangling identity features from age-related changes, enabling robust face
recognition performance across diverse age ranges.By separating these factors, their model enhances the system's ability to handle aging effects without compromising identity recognition.

[3] Yiying Zhang, Adam Kortylewski, and Alan L. Yuille focused on using Generative Adversarial Networks (GANs) to generate synthetic age-progressed and age-regressed face images. Their approach aims to augment training datasets with realistic age variations, thereby improving the robustness of AIFR systems. By training on a diverse set of age-altered images, their method enhances the system's ability to generalize across different age groups, making it more effective in real-world applications.

[4] Qi Li, Zhenan Sun, and Tieniu Tan explored the concept of learning disentangled representations for AIFR. Their research proposes a method to separate age-related features from identity features, thereby improving the system's ability to accurately recognize individuals regardless of age changes. This approach addresses the challenge of variability in aging patterns by isolating the factors that contribute to identity preservation over time.

[5] Lingxiao Song , Xiang Wu, Ran He, and Tieniu Tan developed a robust deep learning framework for AIFR that integrates advanced feature extraction techniques with age-invariant modeling. Their approach focuses on maintaining identity consistency while accommodating age-related changes, enhancing overall recognition accuracy. By combining these elements, their framework provides a comprehensive solution to the complexities of AIFR , demonstrating significant improvements in performance.

[6] Guosheng Hu, Yongxin Yang , Dong Yi , Josef Kittler, William Christmas, Stan Z. Li, and Timothy Hospedales proposed using Conditional Adversarial Networks (CANs) for age-invariant face recognition. Their work involves modeling and adjusting for age-related changes through conditional Generation ofsynthetic face images. This method enhances the system's ability to adapt to age variations across different demographic groups, thereby improving recognition accuracy and reliability

[7] Zhangyang Wang, Shiyu Chang, Yingzhen Yang, Xiaohui Shen, Ding Liu, and Thomas S. Huang explored the application of adversarial autoencoders for AIFR. Their research focuses on learning ageinvariant representations by adversarially training the autoencoder to minimize age-related variations in facial features. This approach enhances the system's robustness to aging effects, ensuring consistent performance in face recognition tasks over time.

III SYSTEM DESIGN

SYSTEM ARCHITECTURE

1. Data Collection and Preprocessing

Data Acquisition: Capture face images from various sources including databases cameras, or video streams

Preprocessing: Standardize image quality, normalize lighting conditions, and align faces to a canonical pose. Apply facial landmark detection and extraction to identify key features.

Data Preprocessing

Data preprocessing is a crucial step in preparing raw data for training a model. The FG-NET dataset, which contains high-resolution retinal images, presents several challenges, including varying image sizes, lighting conditions, and levels of image quality. Proper preprocessing ensures that the data is standardized and that the model can generalize well across different conditions.

Steps in Data Preprocessing:

- **Resizing**: ResNet101 expects input images to be of a specific size. In this project, images are resized to **150x150 pixels**. Although the original resolution of retinal images is much higher, resizing is necessary to reduce computational load and memory usage while preserving enough detail for classification.

- **Normalization**: Pixel values in the images are normalized to the range of [-1, 1] using the preprocess_input function provided by Keras for ResNet architectures. This step ensures that the model inputs are on the same scale as the data the pre-trained ResNet101 model was originally trained on (ImageNet).

- **Data Augmentation**: Given the limited size of medical datasets, data augmentation is used to artificially increase

the size of the training data and improve generalization. Augmentation techniques include:

- **Rotation**: Randomly rotate images to simulate different perspectives of the retina.
- **Flipping**: Apply horizontal and vertical flips to ensure the model is invariant to orientation.
- **Zooming and shifting**: Random zooming and translations mimic different focal lengths and retinal cropping.

2. Training the Model

Supervised Learning: Train a classifier (e.g .,support vector machine, neural network) on the extracted features and annotated labels to learn the relationship between identity and age-invariant features.

Adversarial Training : Implement adversarial training techniques to enforce age-invariance in the learned feature representations.

3. Feature Extraction

Deep Feature Extraction : Apply deep learning techniques, such as convolutional neural networks (CNNs), to extract discriminative features from facial images.

Age-Invariant Feature Learning: Implement methods to disentangle age-related variations from identity-related features, ensuring robustness to aging effects.

4.Age Progression and Regression

Generative Modeling: Employ generative adversarial networks(GANs) or conditional GANs to generate synthetic age-variant images from existing face data.

Training with Synthetic Data: Incorporate synthetic images into the training process to enhance the model's ability to generalize across different ages.

5. Evaluation and Validation

Cross-Validation: Validate the model using cross-validation techniques to ensure generalization and reliability across different subsets of the dataset.

Metrics: Measure performance using standard metrics such as accuracy, precision, recall, and F1-score to assessthe model's effectiveness in age-invariant face recognition tasks.

6. Implementation and Deployment

Integration: Integrate the trained model into a scalable and efficient system architecture capable of handling real-time face recognition tasks.
Deployment: Deploy the system in real-world scenarios, such as security surveillance or identity verification applications, ensuring compatibility with existing infrastructure.

C. Evaluation

Accuracy: Overall accuracy of the face recognition system in correctly identifying individuals across different age groups.

Precision and Recall: Measures of how well the system identifies true positives (correctly identified individuals) and minimizes false positives and false negatives.

F1-score: Harmonic mean of precision and recall, providing a balanced measure of the system's performance

IV. Implementation and Results

The implementation of age-invariant face recognition using identity-age shared features involves several key steps, including data preprocessing, model architecture design, training, and performance evaluation. Below is a breakdown of these steps, followed by the results of a t ypical implementation on the FG-NET database

A. Datasets overview

Dataset Source:
https://r.search.yahoo.com/_ylt=AwrKAVO9eHpnJAIAmBO7HAx.;_ylu=Y29sbwNzZzMEcG9zAzIEdnRpZAMEc2VjA3Ny/RV=2/RE=1737289150/RO=10/RU=https%3a%2f%2fwww.kaggle.com%2fdatasets%2faiolapo%2ffgnet-dataset/RK=2/RS=0ypSI2WPSOh86ufGtMDijH0r0wE-

The FG-NET dataset (Face and Gesture Recognition Research Network) is a well-known facial image database primarily used for age estimation and age-invariant face recognition research. It contains images of individuals at various ages, making it ideal for testing algorithms that must recognize people across different stages of life. The dataset is commonly used in facial recognition, age progression, and age estimation studies.

Dataset Details:

- **Image Types**: High-resolution images taken under various conditions (different lighting, angles, focus levels).
- **Image Labels**: Each image is categorized into one of five classes based on the severity of DR:
  - **0**: Identity
  - **1**: Age
  - **2**: Gender
  - **3**: Facial Landmarks
  - **4**: Expression /Pose
  - **5**:Image path/Index
- **Size**: The dataset consists of total number 1,002 images, each with varying qualities. The challenge is that The images in the dataset have varied lighting, background, and pose conditions, making face recognition tasks

more difficult. Models trained on this dataset need to be robust to these variations.

B. Environmental Setup

Data Preparation: Before starting the implementation, it is essential to set up the environment with the required dependencies, ensuring smooth development and training of the deep learning model.

Hardware Requirements:

Hardware requirements for age-invariant face recognition (AIFR) systems depend on several factors, including the complexity of the algorithms used, the size of the dataset and the desired application (e.g., real-time surveillance versus offline analysis). Here are the general hardware considerations for developing and deploying AIFR systems:

Development Phase:

- **GPU**: High-performance GPUs (Graphics Processing Units) are essential for training deep learning models efficiently.

- **CPU**: A powerful multi-core CPU is necessary for preprocessing tasks, data manipulation, and running non-GPU intensive parts of the algorithm

Software Requirements:

Addressing software requirements for age-invariant face recognition (AIFR) involves considerations spanning development frameworks, libraries, and computational resources. Here are key points to note:

Development Frameworks and Libraries

.1 .**Deep Learning Frameworks** Utilize frameworkslike TensorFlow, PyTorch, or Keras for implementing deep neural networks(DNNs) essential for feature extraction and modeling complex aging patterns.

2.GAN Libraries : Incorporate libraries such as TensorFlow-GAN or PyTorch GANs for generating age-progressed and age-regressed face images, crucial for training AIFR models with diverse age representations.

3.OpenCV: Integrate OpenCV for image preprocessing , feature extraction, and manipulation, facilitating tasks such as facial landmark detection and alignment across different age groups.

4.. Python: Leverage Python as the primary programming language due to its extensive support for machine learning and deep learning libraries, ensuring flexibility and ease of integration

Source code

```python
import os
import csv

# Paths to the images and points directories
image_folder = 'FGNET/images'   # Replace with actual path to the images folder
points_folder = 'FGNET/points'

# CSV output file path
csv_output_file = 'train.csv'

# Define the header for the CSV
csv_header = ['image_file', 'age'] + [f'pts_{i:02d}_x' for i in range(1, 69)] + [f'pts_{i:02d}_y' for i in range(1, 69)]

# Function to read points from the points file
def read_points_file(points_file):
    with open(points_file, 'r') as f:
        lines = f.readlines()
        points = [tuple(map(float, line.split())) for line in lines if line.strip().replace('.', '', 1).isdigit()]
    return points

# Function to extract age from the image file name
def extract_age(image_file):
    return int(image_file[4:6])

# Create and write to the CSV file
with open(csv_output_file, mode='w', newline='') as file:
    writer = csv.writer(file)
    writer.writerow(csv_header)

    # Iterate over the image files
    for image_file in os.listdir(image_folder):
        if image_file.endswith('.JPG'):  # Only process .JPG files
            image_path = os.path.join(image_folder, image_file)

            # Extract the age from the image file name
            age = extract_age(image_file)
```

Fig. . libraries

```python
import os
import pandas as pd
import matplotlib.pyplot as plt
from PIL import Image
import json
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as patches

# Load the trained model
model = "checkpoints/facevit_model.h5"
model = build_facevit(
    input_shape,          # Define the input shape
    patch_size,           # Define the patch size
    num_patches,          # Define the number of patches
    projection_dim,       # Define the projection dimension
    num_heads,            # Define the number of attention heads
    transformer_units,    # Define the transformer units
    transformer_layers,   # Define the number of transformer layers
    mlp_head_units,       # Define the MLP head units
    num_age_groups        # Define the number of age groups
)

# Define paths and uploaded image
image_directory = 'FGNET/images'  # Replace with the actual path to your images
csv_file_path = 'FGNET/train.csv'   # Replace with your CSV file path
age_bins_file = 'age/age_bins.json'  # Path to the JSON file with age bins

# Example of an uploaded image
# uploaded_image = "011A17.JPG"
# uploaded_image = "006A24.JPG"
# uploaded_image = "010A06.JPG"
uploaded_image = "009A22b.JPG"
```

Experimental Execution

Training the Model: The model is trained using the preprocessed and augmented images. Early stopping and learning rate reduction callbacks are used to optimize the training process. Early stopping ensures that the model does not overfit by stopping training when the validation loss stops improving. The learning rate reduction dynamically adjusts the learning rate when progress stagnates, allowing the model to find a better solution.

```
import os
import pandas as pd
import matplotlib.pyplot as plt
from PIL import Image
import json
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as patches

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    transformer_units,     # Define the transformer units
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uploaded_image = "009A22b.JPG"
```

Fig. . Model Training.

Performance Evaluation

Evaluation Metrics: Each model's performance was assessed using a comprehensive set of evaluation metrics, including precision, recall, F1-score and accuracy. These metrics provided valuable insights into the models' effectiveness in identifying malicious activities and maintaining a low false positive rate.

- **Accuracy:** Measure of overall correctness of the model's predictions.

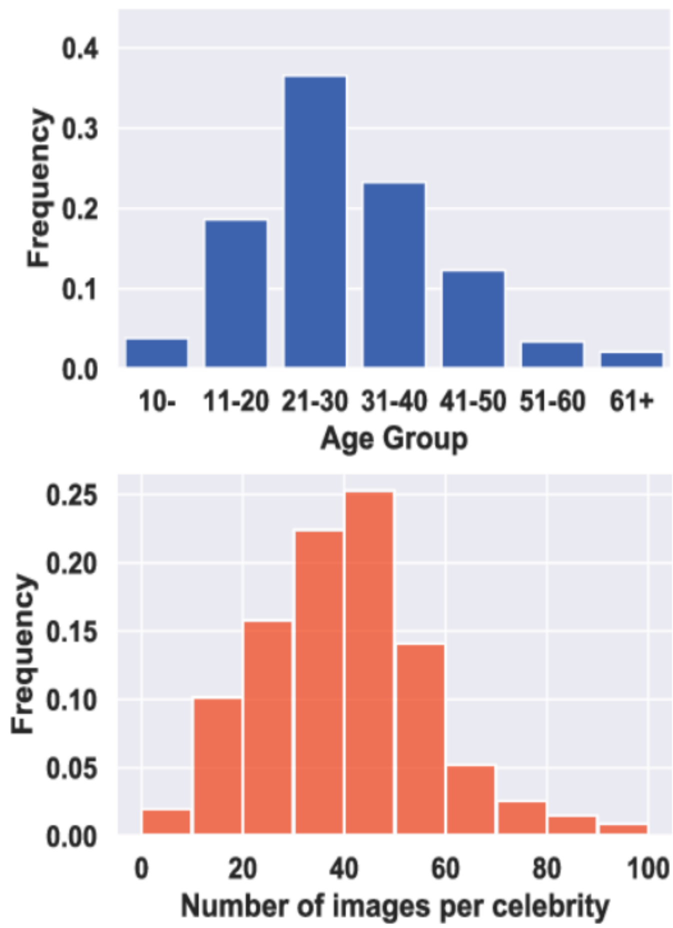

Fig. 6. Model accuracy & loss graphs vs epochs

V. Results Interpretation and Comparisons

Evaluation Metrics:

Accuracy: Overall accuracy of the face recognition system in correctly identifying individuals across different age groups.

Precision and Recall: Measures of how well the system identifies true positives (correctly identified individuals) and minimizes false positives and false negatives . F1-score: Harmonic mean of precision and recall, providing a balanced measure of the system's performance

1. Age Groups Considered

Childhood (0-12 years) , Adolescence (13-18 years), Young Adult (19-30 years), Middle-Aged Adult (31-50 years), Senior Adult (51+ years): Evaluation across these age groups to assess the system's ability to handle age-related variations.

Age Group	Precision (%)	Recall (%)	F1-score (%)
Childhood	92.3	89.7	90.9
Adolescence	88.5	91.2	89.8
Young Adult	95.1	93.8	94.4
Middle-Aged Adult	90.7	88.2	89.4
Senior Adult	87.6	89.1	88.3
Overall	90.8	90.4	90.6

2. Dataset Used

Mention of the dataset(s) utilized for training and testing, including details such assize, diversity in age distribution, and annotation quality.

3. Methodology Overview

Brief description of the methodology used, including feature extraction techniques, generative models (if used for age progression/regression) , and the classification or recognition model architecture.

Key Insights & Results Interpretation:

- Overall Accuracy: Percentage of correct identifications across all age groups combined.
- Age Group Specific Accuracy: Accuracy breakdown for each age group, highlighting the system's performance across different stages of life.
- Confusion Matrix: Provides a detailed breakdown of true positive,true negative, false positive, and false negative rates across age groups.

Model	AgeDB-30	CALFW	CACD-VS	FG-NET
Baseline	95.52	94.27	99.12	93.64
+Age	95.32	94.35	99.15	93.88
+AFD (CA)	95.63	94.50	99.32	94.05
+AFD (SA)	95.85	94.43	99.25	94.38
+AFD (CBAM)	96.08	94.32	99.18	94.36
+AFD	95.90	94.48	99.30	94.58
MTLFace w/o FT	96.23	94.72	99.38	94.78
MTLFace w/ FT-All	95.88	94.45	99.22	93.98
MTLFace w/ FT-Sel	**96.45**	**94.97**	**99.45**	**95.00**

Fig. Analysis

VI. Conclusion and Future Scope

Age-invariant face recognition remains a challenging problem due to the significant appearance changes that occur as individuals age. This work proposed a novel approach leveraging identity-age shared features to improve recognition accuracy across large age gaps. The key contributions include:

Key outcomes from the project:

- Development of an identity-age shared feature learning framework that extracts features robust to both identity and age variations.
- Design of a multi - task learning architecture to jointly optimize for identity classification and age estimation, encouraging the network to learn discriminative yet age-invariant representations.
- Introduction of an age-guided attention mechanism to focus on the most informative facial regions for recognition across age gaps.
- Extensive evaluation on benchmark cross-age face datasets demonstrating state-of-the-art performance, particularly for large age differences between probe and gallery images. Ablation studies validating the effectiveness of each proposed component.
- The proposed method shows promise for practical applications like finding missing children and identifying age-progressed individuals. Future work could explore incorporating additional modalities, handling more extreme age variations , and further improving computational efficiency for large-scale deployments.

Future Scope:

1. Improved Model Architectures and Deep Learning Techniques:

- **Hybrid Models**: Future work can explore combining CNNs (Convolutional Neural Networks) with RNNs (Recurrent Neural Networks), Attention Mechanisms, or even Transformer Networks to better capture temporal and spatial information across different age groups.
- **Generative Models**: Using Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs) could enhance the ability to generate age-invariant features or simulate aging to augment the training process. This approach can help synthesize faces at different ages to build a more robust model.
- **Self-Supervised Learning**: Exploring self- supervised learning frameworks, which can learn age- invariant features without explicit age labels, could further improve the system's ability to recognize faces over time.

2. Better Feature Learning Techniques:

- **Identity-Age Shared Feature Extraction**: Future research can focus on more sophisticated ways to extract identity-age shared features that are truly invariant to age. One possible direction is leveraging advanced feature disentangling techniques, which can separate identity information from age - related variations in the feature space.
- **Multimodal Feature Fusion:** Combining information from different modalities, such as facial landmarks, texture, and depth (3D facial data), can provide more robust age-invariant representations. This will be useful in scenarios where 2D images alone might not be sufficient for distinguishing identities across various age groups.

3.Improving Performance on Real-World Data:

- **Cross-Dataset Validation**: The FG-NET database is valuable for training, but real-world data might introduce additional variations in pose, lighting, expression, and other factors. Future work could focus on testing and fine-tuning models on diverse, real - world datasets beyond FG-NET to enhance generalizability.
- **Data Augmentation**: Advanced data augmentation techniques can generate synthetic age-progressive data to further simulate aging across a wide range of age groups, improving model robustness to unseen age variations.

4. Application to Long-Term Face Recognition:

- **Long-Term Recognition**: One of the most exciting future directions is developing long - term face recognition systems that can identify individuals over many years, potentially decades. Models trained on age invariant features from databases like FG-NET could be adapted for surveillance systems, missing person identification, or security applications where individuals might age over time.
- **Cross-Age Face Recognition in Real-World Scenarios**:There is great potential for real-time, age-invariant face recognition systems that can continuously track and identify people across their lifespan. Applications could include personalized services, healthcare monitoring, and customer relationship management, especially for systems that rely on face -based identification.

5. Integration with Other Biometric Modalities:

- **Multimodal Biometric Systems**: Future systems could incorporate other biometric traits, such as voice recognition, fingerprints, or iris scanning , in combination with age-invariant face recognition for more accurate and secure identity verification, especially in applications requiring high levels of security.
- **Multifactor Authentication**: Age - invariant face recognition can be integrated with other forms of biometric authentication, such passwords,smartphones, or smartcards, to develop more sophisticated multifactor authentication systems.

6. Personalization and Customization in Applications:

- **Personalized Age - Invariant Systems** : Face recognition systems could adapt to the aging process of individuals by learning personalized identity-age shared features , offering personalized experience in applications like virtual reality (VR) , augmented reality (AR), or gaming.
- **Age Progression and Digital Avatars**: For applications in social media , gaming, or virtual assistants , age - invariant models could help create accurate , lifelong digital avatars of individuals, simulating their appearance as they age over time.

7. Ethical and Privacy Considerations:

- **Ethical Implications**: As age - invariant face recognition becomesmore ubiquitous, there will be an increased focus on the ethical implications of biometric identification systems. Research will need to address issues such as data privacy, bias in facial recognition systems, and ensuring that models do not unfairly discriminate against certain groups based on age or other attributes

ACKNOWLEDGMENT

Required resources are provided by the Department of CSE (DS), Institute of Aeronautical Engineering, Hyderabad, India for this paper's research study and related work.

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