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Deep Partial Face Recognition Extracting Features and Age-Gender Prediction using VGG

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Abstract: ***Traditional face recognition systems often struggle when only partial facial information is available due to factors like occlusion, disguise, or low image resolution. To overcome these limitations, this project introduces a deep learning based platform for partial face recognition that eliminates the need for facial alignment and is able to infer gender and age from incomplete facial data. At the heart of the system is a customized VGG Convolutional Neural Network (CNN), specifically adapted for deep feature extraction from partial facial inputs. Designed for real-time operation, the system is well-suited for practical applications such as law enforcement and intelligent surveillance. Unlike conventional methods that depend on precise face alignment, our approach leverages robust spatial feature encoding to recognize individuals even when only segments of the face are visible. In addition to identity recognition, the system simultaneously performs age estimation and gender classification, enriching the recognition process with supplementary demographic information. These tasks are executed concurrently, showcasing the framework's efficiency and adaptability. Comprehensive evaluations on partial face datasets highlight the model's strong accuracy in identity recognition and its consistent performance in predicting gender and age.***

Keywords: Visual Geometry Group, Convolutional Neural Network, Generative Adversarial Network**,** Graphics Processing Unit

1. Introduction

The advent of deep learning has greatly accelerated the progress of face recognition technology, particularly in controlled settings where full facial visibility and precise alignment are possible. However, in real-world scenarios, facial visibility is often limited due to occlusions, non-frontal angles, or environmental challenges—posing serious limitations for traditional systems that depend on accurate alignment and landmark detection. To address these challenges, this study presents a resilient deep learning-based approach for partial face recognition, alignment-free feature extraction, and simultaneous gender and age prediction. At the core of the framework is the VGG Convolutional Neural Network (CNN), employed to extract rich and discriminative features directly from partial facial inputs, thereby removing the need for facial alignment. Renowned for its simplicity and effectiveness, the VGG architecture excels at capturing hierarchical facial representations. Through training on partial face datasets and fine-tuning for multi-task learning, the proposed model not only identifies individuals from incomplete facial regions but also reliably predicts age and gender. This alignment-free, multi-purpose approach significantly improves the system's suitability. Despite its straightforward design, the model delivers strong, real-time performance in predicting both age and gender. Evaluations on publicly available benchmark datasets show that it outperforms several existing methods. Face recognition remains a vital component of biometric technologies, widely used in areas such as surveillance, law enforcement, mobile device authentication, and access control. In controlled environment characterized by frontal face images and ideal lighting conditions modern deep learning models have achieved remarkable accuracy. However, performance often degrades in real-world scenarios involving partial occlusions and suboptimal image capture conditions. To address these challenges, this study introduces a robust, intelligent system for partial face recognition that also predicts age and gender using alignment-free deep features. Our approach eliminates the dependencies, enabling efficient and accurate recognition even when only fragments of the face are visible. This capability proves especially beneficial in practical scenarios such as crowded surveillance settings, identity verification under occlusion, and forensic analysis. The primary contribution of this study lies in the development of a multi-task learning approach that simultaneously performs individual identification, age estimation, and gender classification by leveraging a shared deep feature representation. By utilizing transfer learning with a VGG model using partial face inputs, our system delivers high accuracy across all tasks without requiring face alignment, thus offering a practical and effective solution for complex recognition scenarios.

2. Related Work

This model offers wide-ranging applicability in real-world scenarios where complete facial visibility isn't always possible. In public surveillance, for example, CCTV footage often captures only partial views of individuals. Similarly, in forensic investigations, suspects may deliberately obscure their faces, and during health crises such as pandemics, face masks commonly cover key facial features. Recognizing individuals under these challenging conditions is essential for law enforcement and security operations. Moreover, the system's capability to predict age and determine gender adds valuable demographic insights that extend beyond simple identification. These features can benefit applications in marketing, user analytics, and human-computer interaction. For example, retail environments or smart city infrastructures can tailor services based on demographic information, achieving personalization while respecting privacy by avoiding the use of detailed personal data. The model's alignment-free design further enhances its practicality it is more resilient and simpler to deploy in edge computing contexts, where computational power is limited and real-time performance is vital

a) Face Merging Model

In computer vision, face merging refers to the fusion of multiple facial images into a single composite representation. This technology has diverse applications, including digital identity creation, entertainment, forensics, and data augmentation for machine learning. A reliable face merging model effectively blends facial features, skin tones, and contours from multiple images to generate a realistic and coherent result. Traditionally, the process involves facial detection and landmark extraction, followed by geometric alignment, image warping, and blending. However, with advancements in deep learning, contemporary methods are increasingly employing convolutional neural networks (CNNs) and generative adversarial networks (GANs) (Ijari, 2024) for more natural and context-sensitive synthesis. This approach learn facial structures, feature correlations, and pixel-level details, allowing them to generate highly realistic composite faces, even in varying lighting and pose conditions. In this paper, the face merging model aids in reconstructing partial or occluded facial segments using reference images or auxiliary inputs. This enhances identity verification and enables the restoration of missing regions, particularly in scenarios like surveillance footage or medical imaging where only partial facial data is available.

b) Age Prediction Model

Estimating age based on facial imagery has emerged as a crucial inquiry field in biometrics and human-centered AI, centered on assessing an individual's biological or perceived age which rely on facial characteristics. This prediction is crucial for demographic analysis, targeted services, age-restricted access, health diagnostics, and identity verification. However, facial age prediction is challenging due to the variability in how individuals age, influenced by genetics, lifestyle, ethnicity, and environmental factors, along with the impact of expressions, lighting, and occlusion. While traditional methods emphasized geometric and texture features, deep learning has transformed the field by allowing models to automatically learn age-related features from large datasets. In this study, a Convolutional Neural Network (CNN)-based age prediction model is developed using the VGG architecture, trained on annotated facial datasets with age labels, and fine-tuned to handle partially visible faces. The model, which can treat age prediction as either a regression or classification task, extracts deep facial features and accurately predicts age, even with partial facial visibility.

c) Gender Prediction Model

Gender prediction from facial images presents a complex and multifaceted challenge within the domains of computer vision and biometrics, requiring advanced techniques for accurate analysis and classification, aiming to classify an individual's gender usually male or female based on their facial features. This capability is crucial for improving user experience in applications like facial analytics, personalized advertising, human-computer interaction, and demographic research. While facial gender classification is generally simpler than age prediction, it continues to encounter challenges such as variations in hairstyle, makeup, and occlusions (e.g., masks and sunglasses) and cultural differences in the expression of gender traits. Contemporary gender prediction models leverage deep learning, notably Convolutional Neural Networks (CNNs), to facilitate the automatic extraction of features that effectively distinguish between male and female faces. In this project, a gender prediction model is engineered using the VGG-based deep learning model. This is trained on gender-labelled facial datasets and optimized to perform efficiently, even with partial or occluded faces. By utilizing deep feature representations common to face recognition and age estimation, the model efficiently classifies gender with minimal additional computational overhead. This multi-task approach enhances the robustness and adaptability of the overall facial analysis system.

3. Purpose of the Work

The central aim of this project is to evolve a robust and intelligent facial analysis system that can identify individuals from partial facial images, while also estimating their age and predicting their gender, all using alignment-free deep learning techniques based on the VGG architecture. In real-world applications such as surveillance footage, social media content, and medical imaging, faces are often occluded, partially visible, or captured in uncontrolled environments. Traditional face recognition systems, which rely on full facial visibility and precise alignment, tend to perform poorly under these conditions. This project seeks to overcome these challenges by utilizing deep features that do not require facial alignment, ensuring accurate recognition even from incomplete facial data. In addition to recognition, the system is designed to predict gender and age based upon facial features. The additional biometric attributes enhance user profiling and strengthen the identification process when the face is only partially visible. The consolidation of gender and age estimation makes the model more versatile and applicable in various contexts, such as security, human-computer interaction, demographic analytics, digital forensics, and smart surveillance. By using a unified VGG-based deep learning framework, the system ensures high performance while maintaining computational efficiency. The project also explores how shared deep features extracted from partial faces can be utilized for multiple tasks identification, age outlook, and gender grouping creating a powerful, multitask solution in the fields of computer vision and biometrics.

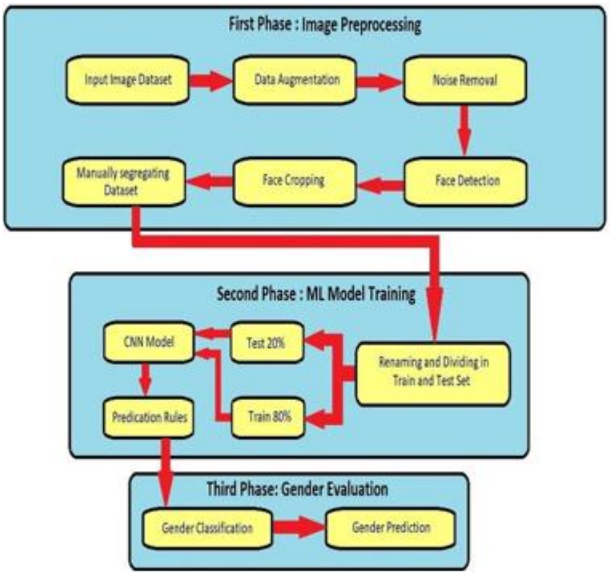

Figure 1: Block diagram for custom CNN

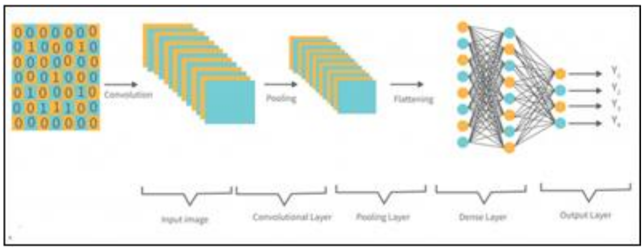

Figure 2: CNN Architectural Diagram

The proposed system seeks to enhance the accuracy and robustness of facial analysis by introducing an integrated framework for deep partial face recognition, as well as gender and age prediction. Designed to overcome the limitations of traditional models that depend on full-face visibility, this system harnesses the capabilities of convolutional neural networks, with a particular focus on the VGG architecture.Unlike earlier approaches, which struggle with occlusions or partial visibility of faces, our model utilizes alignment-free deep features extracted from partial face images, making it resilient to real-world challenges like masks, sunglasses, and side views. At the core of this system is the VGG-16 deep convolutional neural network (S. Smys, 2021), recognized for its consistent architecture and capability to capture hierarchical features from images. Comprising 13 convolutional layers and 3 fully connected layers, VGG-16 employs small 3x3 kernels, allowing for deeper and more refined feature abstraction, making it particularly effective for recognizing facial patterns even from cropped or limited facial regions. In this implementation the model is initially pre-trained on Image Net and subsequently fine-tuned using a combination of facial datasets, including UTK Face Audience and partial-face datasets, to adapt the model for multi-task learning. The system is divided into three primary tasks: partial face recognition, age estimation, and gender classification. During pre-processing, facial images are passed through a face detector, and partial crops are created to simulate real-world scenarios. Unlike alignment-dependent models, this system does not require facial landmarks or geometric normalization, significantly reducing pre-processing complexity. The partial face image is then fed directly into the VGG-based model, which shares convolutional layers among all tasks. The final layers branch into separate outputs: one for identity recognition using a soft max classifier, another for age estimation with a regression or soft-class classification output, and the last for binary gender classification using a sigmoid function. One of the key innovations of this system is its alignment-free approach. By eliminating this dependency and relying on the convolutional layers' ability to learn spatial invariance, the system remains effective even with only partial facial data. This feature makes it especially valuable for applications like surveillance, forensic analysis, and mobile authentication, where full facial visibility cannot be guaranteed. The proposed model is trained using a multi-loss function, optimizing identity, age, and gender predictions simultaneously. This approach enhances shared representations across tasks, improving the performance of each. Additionally, to enhance the model's generalization ability, data augmentation techniques—including random cropping, flipping, brightness adjustment, and occlusion simulation—are employed (Ijari, 2024). Transfer learning with fine-tuning ensures faster convergence and greater accuracy, even with moderately sized, domain-specific datasets. During testing, the system proves to be highly robust in recognizing individuals from partial face images, estimating their age within an acceptable error range, and accurately classifying their gender with minimal error. Utilizing VGG-16 offers an effective balance between model depth and computational efficiency, making the system well-suited for deployment in both cloud-based and edge computing environments.

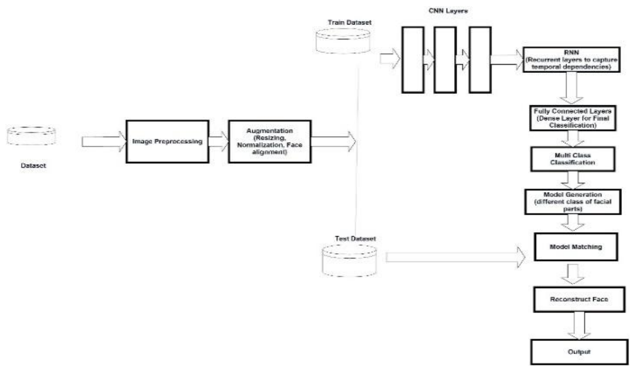

Figure 3: VGG Model

VGG-16 is a deep learning model developed for image sorting and feature extraction, valued for its straightforward and uniform architecture, which enhances its ease of understanding and implementation. The approach starts with an input image of size 224 × 224 × 3 (RGB), which then passes through several layers of small 3×3 convolutional filters which are employed to identify edges, textures, and other fundamental features within an image.with the network applying them multiple times to learn more complex patterns. After each set of convolutional layers, a pooling layer is used to down sample the image, reducing its size while preserving essential information, improving efficiency and helping to prevent over fitting. As the layers go deeper, the filter count increases, allowing the system to acquire more detailed traits. Once all relevant features are extracted, the image is converted into a one-dimensional vector and fed through fully connected layers (Dr. Vijay Kumar Samyal, 2024), which help the model understand the relationships between features and make predictions. The final layer employs a Soft max function to categorize the image into a specific class. At the input stage, the image is resized to a fixed dimension, then passes through multiple convolutional layers, where small filters scan the image to detect basic features such as edges, textures, (Mohanad H. Al-Qadi, 2024) and facial components. These layers help the model interpret various details at increasing levels of complexity. As the image data progresses through the network, pooling layers decrease the spatial dimensions, preserving essential information while reducing redundant computations. Each convolutional block is followed by pooling, ensuring that small changes in lighting or angle don't significantly affect predictions. After several convolutional and pooling layers, the features are flattened into a one-dimensional array and processed by fully connected layers, where the model learns more abstract patterns and relationships. These layers are essential for accurately classifying the input image. The early layers capture basic features like edges and textures, while the deeper layers identify more intricate features such as shapes and objects. This hierarchical feature extraction makes VGG-16 particularly effective for tasks like image classification, age and gender prediction, and face recognition. The final output layer determines the image's category, and while VGG-16 was initially designed to classify images into thousands of categories like animals and objects, it can be adapted for particular tasks like gender and age prediction, the output layer is replaced with custom categories. Although VGG-16 is a powerful model for image classification, it demands considerable computational resources due to its large number of parameters. Despite this, it continues to be a favored approach in deep learning applications, especially in transfer learning, where a pre-trained model is fine-tuned and customized for new tasks without the need for training from the ground up

Table 1: Custom CNN

No of epochs	1	10	20	30	40	50
CNN (accuracy)	50	57	64	74	86	90

Table 2: VGG16 (Fine-Tuned)

No of epochs	1	5	10	15	20
VGG	60	72	81	87	94

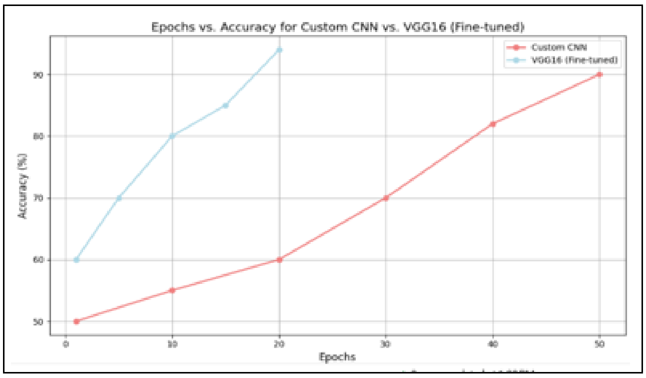

Figure 4: Accuracy for Custom CNN and VGG16

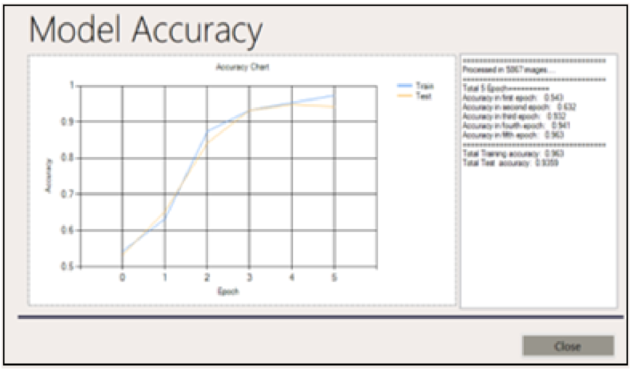

Figure 5: Model Accuracy of VGG

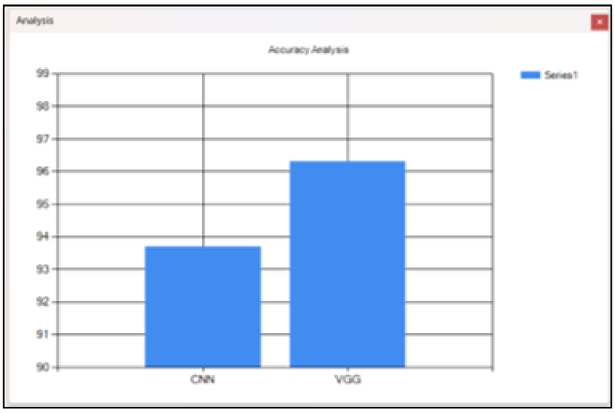

Figure 6: Comparison between Generic CNN and VGG

a) ***Architectural Complexity***

A generic CNN for age estimation and gender prediction can be adapted to suit the specific task by modifying its structure. This may include employing multiple convolutional layers which is succeeded by dense layers to generate predictions. The model's architecture can be fine-tuned by modifying its depth, the number of layers, and the types of filters used, depending on the task's complexity and the nature of the dataset. VGG-16, on the other hand, is a much deeper CNN with 16 layers, specifically designed to capture intricate hierarchical features. For tasks like age estimation and gender prediction, VGG-16 is particularly effective because it can learn detailed representations from images, especially when trained on large-scale datasets.

b) ***Performance***

The performance of a generic CNN is heavily influenced by its design and training quality. For tasks like age and gender prediction, a well-tuned CNN can deliver strong results, particularly when trained on a well-curated dataset. However, VGG-16 tends to outperform shallow CNNs in age estimation and gender prediction tasks. Its deeper layers allow the model to capture complex features, which are essential for differentiating between various ages and genders, particularly when working with large and diverse datasets.

c) ***Computational Efficiency***

A generic CNN can be optimized for improved computational efficiency by using fewer layers or smaller filters, which makes it faster to train and more resource-efficient, especially for age and gender estimation tasks where deep features may not be necessary. In contrast, VGG-16 is computationally demanding due to its deep architecture, with 138 million parameters. This results in high memory and processing power requirements, making it more challenging to deploy in real-time applications or on systems with limited resources.

Table 3: Comparison table for CNN Vs VGG

Feature	Generic CNN	VGG-16
Architecture Complexity	Customizable, simpler, fewer layers	Deep, fixed architecture with 16 layers
Performance (Accuracy)	Good performance with proper tuning	High accuracy due to deep feature learning
Computational Efficiency	Faster to train, less resource-intensive	Requires significant resources for training and inference
Transfer Learning	Custom transfer learning with external models	Strong pre-trained models available for fine-tuning
Real-World Adaptability	Better suited for real-time or resource-constrained environments	Suited for high-performance applications on GPUs or cloud-based systems
Training Time	Faster training, less data required	Longer training time due to deep layers and large parameters

4. Conclusion

In this research, we have introduced a highly sophisticated and intelligent facial analysis system that seamlessly integrates deep partial face recognition with alignment-free feature extraction, coupled with robust gender and age prediction capabilities. The system's core strength stems from its utilization of a fine-tuned deep convolutional neural network based on the VGG architecture, which empowers the system to accurately identify individuals and estimate their demographic attributes even when the facial images are partial or occluded. This represents a notable advancement, especially for real-world scenarios where facial images may be partial or obstructed, like in surveillance applications, security monitoring, healthcare, and smart human-computer interaction environments. One of the key innovations of our system is its alignment-free approach. Traditional face recognition models often rely heavily on full-face visibility and precise alignment, which can be difficult to achieve in real-world settings due to various factors such as pose variations, occlusions (e.g., masks or sunglasses), or inconsistent lighting conditions. Our method overcomes these limitations by using deep features extracted from partial facial images without the need for facial alignment, thus offering a more flexible and adaptive solution. This alignment-free approach enables the system to perform reliably under challenging circumstances, ensuring that it remains functional even when only part of the face is visible. The architecture of the system has been carefully structured into several modular components that each contribute to the overall functionality and accuracy of the system. These components include face merging, feature analysis, age estimation, and gender identification with each element playing a critical role in the seamless operation of the entire system. By segmenting the system into these modules, we ensure that the various tasks ranging from recognizing identities to predicting age and gender are efficiently handled in parallel. Our approach benefits from the incorporation of transfer learning techniques. The VGG model is initially pre trained on large, generic datasets such as Image Net, which allows it to develop a solid foundation of feature extraction. By fine-tuning this pre trained model on specific facial datasets, such as those containing labelled age and gender information, we further enhance its performance for specialized tasks like age regression and gender classification. This process of transfer learning ensures that the system can learn from a broad base of knowledge while adapting to the particular demands of facial analysis. In terms of performance, both generic CNNs and VGG. Both architectures have the potential to perform effectively in age estimation and gender prediction tasks. However, VGG-16 distinguishes itself with its deeper architecture, allowing it to capture more detailed and complex features from facial images.This depth allows VGG-16 to achieve higher accuracy compared to shallower models, especially when working with large and diverse datasets. Nevertheless, it is important to note that VGG-16 comes with a computational trade-off. Due to its 16 layers and large number of parameters (around 138 million), it is computationally expensive, requiring significant memory and processing power. This can pose difficulties when deploying the model in real-time scenarios or on devices with limited computational resources. In conclusion, the proposed facial analysis system integrates advanced deep learning techniques with novel approaches for partial face recognition along with age and gender inference. Leveraging VGG-16 as the model's backbone enables the extraction of deep, discriminative features for precise analysis, while the alignment-free methodology ensures reliable performance under real-world, unconstrained conditions. Additionally, the application of transfer learning boosts the model's adaptability to specific facial analysis tasks, making it a robust and flexible solution suited for diverse applications in surveillance, security, healthcare, and human-computer interaction.

References

[1] S. kumar et al., "Face Spoofing, Age, gender and Facial Expression Recognition Using Advance Neural Network Architecture –Based Biometric System," Sensors, vol.22, no 14, p.5160.2022

[2] T. Grubl and H.S lallie, "Applying Artificial Intelligence for Age Estimation in Digital Forensic Investigations,"arXiv preprint arXiv:03045

[3] K.S Htetand M.M Sein, "Effective Marketing Analysis on Gender and Age Classification with Hyper parameter Tuning," in IEEE 2nd Global Conference on Life Sciences and Technologies (life Tech), pp.247-248, 2020.

[4] S. K Gupta and N.Nain, "Single attribute and multi attribute facial gender and age estimation,"Multimedia Tools Applications, pp.1-23,2022.

[5] D. Kwasny and D.Hemmerling, "Gender and age estimation methods based on speech using deep neural networks" Sensors, vol.21, no.14, p.4785,2021.

[6] T. U Islam, L. K Aswathi, U.Garg, "Gender and age estimation from gait: A review," in International Conference on Innovative Computing and Communications, pp.947-962,2021.

[7] N. Dwivedi and D.K Singh, "Review of deep learning techniques for gender classification in images," in Harmony Search and Nature Inspired Optimization Algorithm: Springer, 2019, pp.1089-1099.

[8] M.G Rhodes, "Age estimation of faces: A review," Applied Cognitive Psychology: The official journal of

the Society for Applied Research in Memory Cognition, vol 23, no.1, pp.1-12, 2009.
[9] Z. Liao, S. Petridis, and M. Pantic, "Local deep neural networks for age and gender classification," arXiv preprint arXiv: 08497, 2017.
[10] Y.Zhang and T.Xu, "Landmark-guided local deep neural networks for age and gender classification" Journal of Sensors, vol.2018.
[11] E. Eidinger, R. Enbar and T. Hassner, "Age and gender estimation of unfiltered faces," IEEE Transactions on information forensics security, vol 9, no 12, pp.2170-2179,2014.
[12] G. Levi and T. Hassner, "Age and gender classification using convolutional neural networks" in Proceedings of the IEEE conference on computer vision and pattern recognition workshops, pp.34-42, 2015.
[13] A.M Abu Nada, E. Alajrami, A. A. Al- Saqqa, and S.S Abu Naser, "Age and gender Prediction and Validation through single user images using CNN," International Journal of Academic Engineering Research, vol 4, no.8, pp.21-24, 2020.
[14] Z. Khan and Y. Fu, "One label, one billion faces: Usage and consistency of racial categories in computer vision" in Proceedings of the 2021 ACM Conference fairness, accountability and transaparency, pp.587-597,2021.
[15] R. Angulu, J.R.Tapamo and A. O, Adewumi, "Age estimation via face images: A survey" EURASIP Journal on Image Video Processing, vol no.1,pp.1-35,2018.
[16] J. I Hayashi, H.Koshimizu and S.Hata, "Age and gender estimation based on facial image analysis" in International Conference on Knowledge based and Intelligent Information and Engineering Systems, pp.863-869,2003.
[17] V. Karimi and A.Tashk "Age and gender estimation by using hybrid facial features" in 20th Telecommunications Forum (TELFOR), pp.1725-1728, 2012.
[18] H. Fukai, H. Takimoto, Y. Mitsukura and M. Fukumi "Age and gender estimation by using facial image," in 11th IEEE International Workshop on Advanced Motion Control (AMC), pp.179-184,2010.
[19] C.Shan, "Learning local features for age estimation on real-life faces" in Proceedings of the 1st ACM International workshop on Multimodal pervasive video analysis, pp.23-28,2010.
[20] J.C Chen, A. Kumar, R. Ranjan, V. M. PATEL, A.Alavi and R. Chellappa "A cascaded convolutional neural network for age estimation of unconstrained faces" in IEEE 8th International Conference on Biometrics Theory, Applications and Systems (BTAS), pp.1-8,2016.
[21] Sebastian Lapuschkin (2017), "Understanding and Comparing Deep Neural Networks for Age and Gender Classification".
[22] Vikas Sheoran, Shreyansh Joshi, and Tanisha R. Bhayani, "Age and Gender Prediction using Deep CNNs and Transfer Learning" Age estimation, Age and gender classification, 2021.
[23] Nathanael L. Baisa, "Joint Person Identity, Gender and Age Estimation from Hand Images using Deep Multi-Task Representation Learning" arxiv.2209.04821, 2023.
[24] Damian Kwasny and Daria Hemmerling, "Joint Gender and Age Estimation Based on Speech Signals Using X-Vectors and Transfer Learning" arxiv. 2012.01551, 2022.
[25] O. Agbo-Ajala, S. Viriri , "Human Age and Gender Prediction from Facial Images Using Deep Learning Methods" published in Procedia Computer Science, Volume 238, 2024, Pages 314-321.
[26] Hai Thanh Nguyen, et al. "Age Prediction from Facial Images Using Deep Learning Architecture" published in Applied Computer Systems, Volume 29, Issue 2, December 2024, Pages 22-29
[27] Deep Convolutional Neural Networks for Age and Gender Estimation Using an Imbalanced Dataset of Human Face Images Published in Neural Computing and Applications, Volume 36, Issue 34, December 2024
[28] Vikas Sheoran, Shreyansh Joshi, Tanisha R. Bhayani , "Age and Gender Prediction Using Deep CNNs and Transfer Learning" published in arXiv preprint arXiv:2110.12633, October 2021.
[29] Amirali Abdolrashidi, Mehdi Minaei, Elham Azimi, Shervin Minaee , "Age and Gender Prediction from Face Images Using Attentional Convolutional Network" published in arXiv preprint arXiv:2010.03791, October 2020.
[30] S. S. R. D. S. Abeykoon, K. S. R. Anuradha, "Prediction of the Age and Gender Based on Human Face Images for Development of a Nutrition Recommendation System" published in Journal of Healthcare Engineering, 2022
[31] Sefik Ilkin Serengil, "DeepFace: A Lightweight Face Recognition and Facial Attribute Analysis Framework" published in GitHub Repository, 2020.
[32] M. A. Khan, M. Sharif, M. Raza, et al., "Gender and Age Estimation from Human Faces Based on Deep Learning Techniques: A Review" Research Gate, 2022.
[33] S. S. R. D. S. Abeykoon, K. S. R. Anuradha, "Face-Based Age and Gender Classification Using Deep Learning Model" Procedia Computer Science, 2024
[34] P. Smith, C. Chen," Age and Gender Prediction Using Deep CNNs and Transfer Learning" arXiv preprint arXiv:2110.12633, 2021
[35] A. S. Khan, M. A. Khan, M. Sharif, et al., "Deep Learning-Based Real Age and Gender Estimation from Unconstrained Face Images" Applied Sciences, 2021
[36] P. Smith, C. Chen , "Transfer Learning with Deep CNNs for Gender Recognition and Age Estimation" arXiv preprint arXiv:1811.07344, 2018
[37] M. A. Khan, M. Sharif, M. Raza, et al., "Deep Faces: Advancing Age and Gender Classification Using Facial Images with Deep Features" International Journal of Information Science and Technology, 2023
[38] M. A. Khan, M. Sharif, M. Raza, et al., "Human Age and Gender Prediction from Facial Images Using Deep Learning Models" DiVA Portal, 2023
[39] A. B. Hassanat, A. Albustanji, A. S. Tarawneh, et al., "Deep Learning for Identification and Face, Gender, Expression Recognition Under Constraints" arXiv preprint arXiv:2111.01930, 2021.