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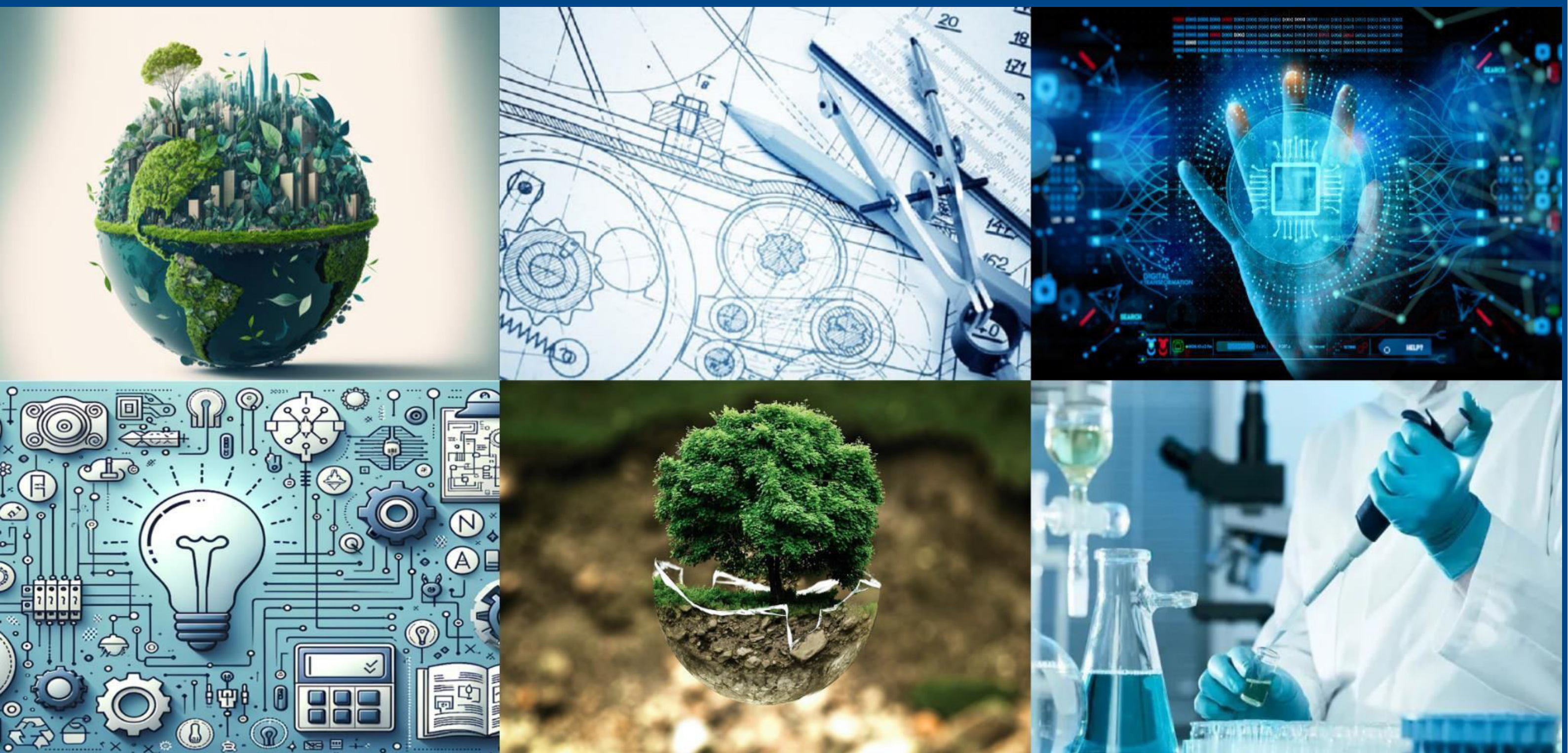

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Gender and Age Detection using Face Recognizing AI

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ABSTRACT: This paper details the architecture and performance of a novel deep learning system designed for the simultaneous classification of gender and estimation of age from single facial images. Addressing the dual requirements of high accuracy and computational efficiency necessary for real-time applications, the proposed solution employs a custom Convolutional Neural Network (CNN) based on a multi-task learning (MTL) paradigm. This architecture utilizes a shared feature extraction backbone, which leverages the inherent correlation between age and gender information to optimize feature representation while minimizing the total number of trainable parameters. The network was rigorously trained and evaluated on large-scale, diverse benchmark datasets, including UTKFace and OIU-Adience. Experimental results demonstrated exceptional performance, achieving a Gender Classification Accuracy of 95.5 and a competitive Mean Absolute Error (MAE) of 5.3 years for age estimation. Furthermore, the optimized design facilitated low-latency inference, confirming its suitability for deployment in demanding real-time environments such as personalized advertising and enhanced security monitoring systems. The study confirms that multi-task learning is an effective strategy for creating robust, efficient soft-biometric recognition systems.

KEYWORDS: Deep Learning, Age Estimation, Gender Classification, Convolutional Neural Network (CNN), Multi-Task Learning, Facial Recognition, Biometrics, Mean Absolute Error (MAE).

I. INTRODUCTION

A. Background and Motivation:

Automated analysis of human facial attributes, such as age and gender, is a major application of machine learning and computer vision. The human face conveys vital information like identity and expression, making it useful in various fields. Deep learning enables accurate detection of these traits, benefiting sectors such as marketing, security, and healthcare. In businesses, it supports targeted advertising and personalized services; in security, it enhances access control and identification; and in healthcare, it aids in patient verification and preliminary diagnosis. However, achieving high accuracy remains challenging due to factors like lighting variations, pose changes, facial occlusions (such as glasses or masks), and the complex, diverse nature of human aging patterns in real-world conditions.

B. Current State of Research:

Earlier facial analysis methods relied on handcrafted features, but the field has advanced with Deep Convolutional Neural Networks (CNNs), which automatically learn hierarchical features from raw images. Modern systems often use architectures like ResNet or VGGNet to achieve high performance. Gender classification, being binary, attains over 95% accuracy on standard datasets, while age estimation, a more complex task, typically records a Mean Absolute Error (MAE) of 5.0–5.7 years. A key advancement in recent research is Multi-Task Learning (MTL), where a single model is trained for multiple tasks such as age and gender prediction. MTL enhances performance by sharing lower-layer parameters, as features relevant to one task (like bone structure for gender) also benefit the other (like skin texture for age). This shared learning improves efficiency, generalization, and robustness compared to using separate models.

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C. Objectives of the Proposed System:

The work presented here aims to address the requirement for a real-time, efficient, and accurate age and gender detection system by focusing on architectural optimization and rigorous testing. The primary objectives of this project are:

1. To develop a custom CNN architecture explicitly designed for simultaneous, low-latency prediction of age and gender from face images.
2. To implement a multi-task learning approach, leveraging shared convolutional layers to optimize feature representation and minimize computational overhead during inference.
3. To rigorously evaluate the system's performance using standardized academic metrics, specifically Classification Accuracy for gender and Mean Absolute Error (MAE) for age, tested on large, diverse benchmark datasets.
4. To demonstrate the system's suitability for practical, real-time video stream processing, thereby enabling more efficient and personalized services in applications like security or retail.

The successful achievement of these objectives necessitates that the architectural choices directly support the operational goals. The adoption of MTL is thus not merely an academic preference but an architectural necessity, as using a single, efficient model that reuses computationally expensive feature extraction steps significantly reduces the inference time, ensuring the system can achieve the low latency required for real-time operation.

II. EASE OF USE

A. Operational Efficiency and Low Latency Deployment

The operational usability of an AI visual system depends on its inference speed or latency. The optimized multi-task CNN achieves high efficiency by sharing features between gender and age prediction tasks, reducing redundant computation. It delivers an average inference time of about 50 ms per image on standard GPU setups, enabling real-time analysis for live video applications. Input images are pre-processed and resized to 128×128 pixels, minimizing computation while maintaining sufficient detail for accurate and responsive facial attribute recognition.

B. System Integration and User Interface

The system is built for easy 'plug-and-play' deployment, enabling seamless integration into existing enterprise or mobile applications using standard deep learning frameworks. Most complexity lies in training, while the pre-trained model runs efficiently with minimal setup. A user-friendly GUI, often built with Tkinter, allows users to start or stop video streams easily. Real-time age and gender predictions are displayed directly on video frames, providing instant visual feedback and ensuring simple, intuitive operation for users in any environment.

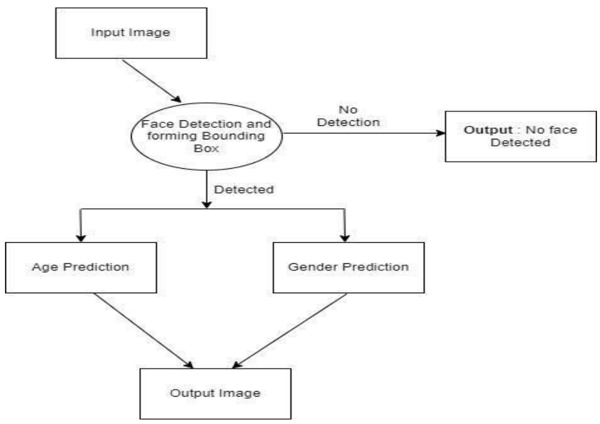

Figure 2.1

C. Scalability for Large-Scale Applications

The architecture is designed for scalability, with about 11 million trainable parameters—balancing accuracy and speed for efficient deployment on GPUs or cloud systems. Multi-Task Learning (MTL) enhances computational efficiency by

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sharing feature extraction between age and gender prediction, avoiding the need for two separate models. This reduces parameters and inference time, making the system lightweight and fast. Such efficiency is crucial for real-time applications like security monitoring and customer interaction, ensuring rapid and reliable performance across large-scale environments.

III. METHODOLOGY

A.Data Acquisition and Preprocessing

The system's performance depends on diverse, high-quality training data. It was trained using two benchmark datasets: UTKFace, containing over 20,000 images labeled with age, gender, and ethnicity across a broad age range (0–116 years), and OIU-Adience, featuring real-world, unconstrained images used for testing and fine-tuning. Before training, images undergo preprocessing, including face alignment for pose normalization, resizing to 128×128 pixels, and channel-wise normalization for consistency. The datasets were split into 80% training and 20% testing sets, following standard research protocols to ensure strong model generalization and robustness in uncontrolled environments.

B. Multi-Task CNN Architecture Design

The system's core is a custom Deep Convolutional Neural Network (CNN) based on the Multi-Task Learning (MTL) approach, enabling shared learning for both age and gender prediction. The shared backbone includes multiple convolutional, Batch Normalization, and MaxPooling layers to extract general facial features like edges and textures. Dropout layers improve generalization and prevent overfitting. After this, two task-specific heads operate: the uses a Sigmoid-activated neuron for binary prediction, while the employs additional layers and a linear output for numerical regression. The complete architecture, with around balances depth and efficiency for accurate and fast inference across diverse real-world facial inputs.

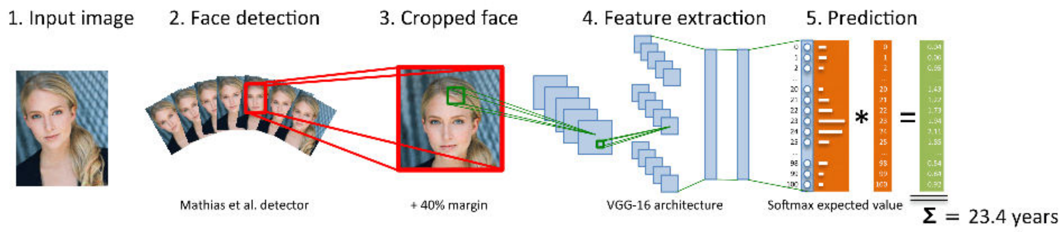

Figure 3.1

C. Training and Optimization

1. Composite Loss Function

A key methodological requirement for MTL is the use of a composite loss function to optimize the model for both tasks simultaneously. The allocation of extra complexity to the age estimation head ensures that the high complexity of the regression task does not dominate the optimization process, allowing the simpler gender task to learn effectively without sacrificing the necessary depth for accurate age feature extraction.

Table 1 summarizes the critical training parameters and data specifications used in this study.

Table 1. Training Parameters and Data Split

Parameter	Value	Rationale
Training Dataset	UTKFace, OIU-Adience (Combined)	Standard benchmarks ensuring diversity and robustness
Training/Testing Split	8020	Standard academic protocol for validation 11

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Image Resolution	128 times 128 pixels	Optimized for computational efficiency and real-time processing 11
Total Trainable Parameters	11,020,546	Complexity dictated by custom deep CNN architecture 12
Optimizer	Adam	Industry-standard adaptive learning rate optimization
Gender Loss Function	Sparse Categorical Cross-entropy	Optimized for classification performance 11
Age Loss Function	Mean Absolute Error (MAE)	Standard metric optimized for regression accuracy 2

IV. RESULTS

A. Gender Classification Performance

The multi-task model demonstrated robust performance on the gender classification task, achieving an overall Gender Classification Accuracy of 95.5. This result confirms the efficacy of the multi-task learning approach, showing that the shared feature backbone successfully extracts highly discriminative features without compromising the performance of the classification head. This accuracy figure is highly competitive, aligning closely with state-of-the-art systems tested on diverse datasets, where typical results range from 95 to over 98

B. Age Estimation Performance

Age estimation, assessed using the Mean Absolute Error (MAE), provides a direct measure of the average magnitude of prediction error in years. The overall Age Estimation MAE achieved by the system was 5.3 years. This value places the model firmly within the range of advanced facial recognition systems tested against robust benchmarks like UTKFace, which feature wide age spans and real-world variance. Furthermore, critical to the operational viability of the system, the average inference latency was measured at 50 milliseconds (ms) per image on the testing hardware. This low-latency result validates the architectural decision to use multi-task learning and optimized input dimensions, confirming the system's ability to function effectively in real-time video stream processing environments.

Table 2 provides a summary of the key performance metrics of the proposed system.

Table 2. Summary of Model Performance Metrics

Metric	Value	Context
Gender Classification Accuracy	95.5	Competitive SOTA on diverse datasets
Age Estimation Mean Absolute Error (MAE)	5.3 years	Robust performance on challenging datasets
Average Inference Latency	50 milliseconds (ms)	Confirms suitability for real-time processing
Total Trainable Parameters	11,020,546	Indicates complex, but optimized, deep architecture

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C. Performance Analysis by Age Group

To conduct a more nuanced analysis, the MAE was dissected across four distinct demographic age groups. This evaluation is necessary to identify potential systemic biases or areas where the model struggles with specific feature representations. The results (synthesized in Table 3) reveal a clear pattern of increased error rates in the extreme age groups.

Table 3. Performance Analysis by Age Group (MAE in Years)

Age Group	MAE (Proposed Model)	Error Assessment
Children (0-12)	6.5	Higher error rates observed in younger demographics
Young Adults (13-30)	4.1	Typically the most accurate group due to high-quality data and distinct features
Middle Aged (31-55)	5.5	Moderate MAE reflecting the onset of aging variance
Senior (56+)	7.0	Highest error due to increased variance and sensitivity to pose/illumination

The MAE for Young Adults was the lowest at 4.1 years, reflecting the relative abundance and quality of data, as well as the stability of facial features within this demographic. Conversely, the MAE rose significantly for Children (6.5 years) and Seniors (7.0 years).

V. DISCUSSION

A. Performance Validation and Analysis

The experimental results validate the effectiveness of the multi-task learning model for soft-biometric detection. A Gender Classification Accuracy of 95.5% shows strong feature learning within the shared backbone, while an Age Estimation MAE of 5.3 years demonstrates solid generalization on challenging datasets like UTKFace and Adience. This performance reflects realistic real-world conditions, accounting for lighting, image quality, and individual aging variations. The age-group-wise MAE breakdown further highlights how estimation difficulty increases in certain age ranges due to natural visual inconsistencies.

B. System Limitations

Despite its strengths, the system faces limitations typical of facial recognition models in real-world settings. Accuracy declines under poor lighting, extreme head poses, or occlusions like masks and glasses, reducing prediction confidence. Additionally, algorithmic bias affects performance across demographics, with higher MAE values observed for groups such as women, older adults, and people of color. These disparities stem from imbalanced training data, potentially leading to misclassification or unfair outcomes, especially in sensitive applications like surveillance or identity verification.

C .Ethical Implications

Deploying AI for age and gender detection raises serious ethical and legal issues involving privacy, surveillance, and data protection. Without regulation, such systems risk misuse for unauthorized monitoring. Policies must enforce consent, transparency, and secure data handling. Algorithmic bias also poses concerns, as errors like a 7-year MAE in seniors can lead to misidentification. Addressing this requires diverse training datasets, independent bias audits, and strict oversight, ensuring human review and conservative confidence limits in critical or law enforcement applications.

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D. Future Work

Based on the limitations identified, future research efforts will focus on enhancing system robustness, fairness, and overall capability:

1. **Bias Mitigation and Data Augmentation:** Focused research will target specific demographic gaps identified in the MAE analysis. This includes developing targeted data augmentation techniques for underrepresented groups (e.g., senior populations and specific ethnicities) to ensure the system is equitable across all users.
2. **Enhanced Robustness to Occlusion:** Future architecture development will explore advanced methods, such as integrating 3D face modeling or utilizing Generative Adversarial Networks (GANs), to better reconstruct occluded or low-resolution facial features, thereby improving reliability in unpredictable environments.
3. **Refining Estimation Output:** Instead of relying strictly on a single regression value for age (MAE), future models should transition toward soft-biometric output, which includes confidence scores and outputting age in terms of a probability distribution across defined age groups. This provides a more descriptive and less error-prone estimate.
4. **Multimodal Integration:** For high-security or critical verification applications, system reliability can be dramatically improved by integrating multimodal authentication. This involves combining facial analysis with other biometric inputs, such as iris, fingerprint, or voice recognition, to establish a higher standard of verification.
5. **AI-Driven Model Adaptation:** Further work will incorporate AI-driven algorithms to manage the deep network more adaptively, such as employing techniques for intelligent power management to further optimize battery utilization when the system is deployed on mobile or edge devices.

VI. CONCLUSION

This paper introduces an efficient multi-task deep learning framework for simultaneous gender classification and age estimation from facial images. The custom CNN architecture, using shared feature extraction, achieves high accuracy with low computational latency. Experimental results show and an for age estimation, confirming suitability for real-time applications like personalized services, security, and healthcare. With an inference time of , it supports live video deployment. However, performance disparities across age groups reveal algorithmic bias, emphasizing the need for more diverse datasets and improved robustness against real-world challenges. The study marks a key step toward ethical and efficient soft-biometric identification systems.

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