A REAL-TIME GENDER AND AGE PREDICTION SYSTEM BASED ON FACIAL IMAGES USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract— Real-time gender and age prediction based on facial images have become essential in applications such as surveillance, demographic analytics, and human-computer interaction. However, existing systems often struggle with challenges like inconsistent lighting, occlusions, pose variations, and dataset imbalances, which reduce accuracy and hinder deployment on resource-constrained devices. This research introduces a real-time gender and age prediction system that leverages Convolutional Neural Networks (CNNs), utilizing fine-tuned ResNet-34 for gender classification and a modified VGG-16 for age estimation. A robust preprocessing pipeline, integrating image normalization, histogram equalization, data augmentation, and synthetic data generation, enhances model generalization across diverse datasets. Efficient face detection techniques, combined with lightweight model architectures, enable the system to achieve inference speeds below 500 milliseconds per frame without GPU acceleration. Experimental evaluations across IMDB-WIKI, UTKFace, MORPH II, and Adience datasets revealed gender classification accuracies exceeding 94% and age prediction one-off accuracies above 90%. The proposed system demonstrates a scalable and efficient solution for real-time facial attribute recognition in dynamic and resource-limited environments.

Keywords— Gender Classification, Age Estimation, Convolutional Neural Networks, Real-Time Facial Recognition, Data Augmentation, Cross-Dataset Generalization

I. Background of the Study

Rapid advances in artificial intelligence have catalyzed the integration of facial recognition systems into everyday technologies. These systems are increasingly applied in surveillance, human-computer interaction, demographic analytics, and targeted services. Gender and age prediction, as essential components of these applications, offer critical contextual insights, enabling machines to interpret human identity traits more intelligently. The use of deep learning, especially Convolutional Neural Networks (CNNs), has become the dominant approach in this domain due to their superior ability to extract hierarchical features from visual data. CNN models such as ResNet and VGG have demonstrated significant success in facial analysis tasks when trained on large, labeled datasets [5]; Zhang & Wang, 2024). Pretrained on general image databases and then fine-tuned with facial data, these architectures provide high accuracy in both binary (gender) and multiclass (age) classifications. However, their real-time applicability remains limited by computational demands, hardware constraints, and challenges introduced by real-world image variability.

Environmental factors such as inconsistent lighting, partial occlusion, head pose variation, and image blur affect prediction reliability. Datasets like IMDB-WIKI, Adience, MORPH II, and UTKFace offer considerable diversity in demographics, image resolution, and annotation styles, but their differences complicate direct model transfer across datasets [19]. Generalization thus becomes a critical concern, especially when deploying models trained on one dataset in settings that resemble another. Standardizing preprocessing practices has helped mitigate domain variability. Techniques such as resizing, histogram equalization, brightness adjustment, and noise reduction enhance image clarity and consistency. These steps have become necessary prerequisites for robust feature learning and downstream classification accuracy [14]. Data augmentation through geometric transformations and synthetic image generation has further improved class balance, especially for underrepresented age groups [18] and [2].

Synthetic aging, using GAN-based tools like FaceApp, allows controlled manipulation of facial age while preserving identity features. This method supports ethical dataset expansion and provides a scalable solution to age group imbalance [21]. When combined with dropout, batch normalization, and tolerance-aware evaluation metrics, these techniques collectively improve model generalization and resilience during inference. Real-time implementation requires efficient end-to-end architecture. High-speed face detection algorithms such as Haar cascades and MTCNN enable region-of-interest localization, which reduces computational load during classification [25]. By limiting processing to cropped and aligned face regions, classification becomes faster without sacrificing accuracy. Real-time predictions can then be displayed with confidence scores, enhancing interpretability for user-facing applications. Ensuring deployment feasibility necessitates benchmarking performance on modest hardware platforms. Inference speed below 500 milliseconds per frame, without reliance on GPU acceleration, has become a practical threshold for live applications such as retail kiosks, mobile apps, or access control systems [9], [3]. As a result, low-latency, high-accuracy systems that can operate efficiently in constrained environments are increasingly prioritized.

This study focuses on the development of a real-time facial gender and age prediction system using deep convolutional neural network (CNN) architectures. The system is built upon fine-tuned versions of ResNet-34 and VGG-16, which are trained on diverse facial datasets to ensure generalizability across various real-world conditions. A unified preprocessing pipeline comprising image normalization, resizing, and enhancement is implemented to maintain data consistency. Augmentation techniques and synthetic image generation are incorporated to mitigate class imbalance and improve model robustness. Performance evaluation is conducted using metrics such as classification accuracy, one-off accuracy, mean absolute error (MAE), and inference speed. These metrics are used to assess the effectiveness and deployment readiness of the system in real-time environments. The overarching aim of the research is supported by three core objectives: First, a modular, real-time classification system is developed using CNN-based models for gender and age prediction. Second, preprocessing and augmentation strategies, along with the use of multiple facial datasets, are employed to enhance the reliability and generalization of the models. Third, system performance is measured across multiple datasets and hardware configurations to ensure that the solution is accurate, scalable, and suitable for practical, real-time applications.

II. Review of Related Works

Facial age and gender prediction has evolved significantly with advancements in computer vision and deep learning. Earlier approaches relied heavily on handcrafted features such as Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG), but recent advancements emphasize data-driven deep neural networks that autonomously learn complex patterns from raw images [7] and [20]. These systems follow a modular pipeline that includes image acquisition, preprocessing, face detection, feature extraction, and classification. The conceptual shift toward end-to-end CNN architectures has enabled better adaptability to unconstrained environments and diverse facial appearances. Recent research emphasizes multitask learning and real-time applicability. Studies such as [24] and [11] have demonstrated how integrating gender, age, and emotion prediction into a single framework reduces computational redundancy while maintaining classification performance. Other innovations include the use of GANs and tools like FaceApp for synthetic data augmentation, which address dataset imbalance, especially among underrepresented age groups [22], [16]. Lightweight models such as MobileNetV3 and ResNet-18 have been adopted to optimize inference speed for mobile or edge deployments [12], [8].

From a theoretical standpoint, the core architectures used modern variants of VGG-16 and ResNet, which are grounded in hierarchical feature extraction through convolutional layers [4] and [13]. These are further enhanced by adaptive normalization techniques [15] and stochastic regularization mechanisms [10] to ensure stable learning and minimize overfitting. For age classification, researchers increasingly treat it as an ordinal task, acknowledging the ordered structure of age groups. As a result, one-off tolerant loss functions and ordinal regression techniques, including Earth Mover's Distance (EMD), have been applied to better reflect real-world prediction tolerance [17] and [6]. Cross-dataset variability poses challenges in generalization. Domain adaptation strategies have emerged to bridge the gap between training and testing conditions. Studies such as [16] and [26] propose methods like Maximum Mean Discrepancy (MMD) loss and adversarial alignment to improve transferability across datasets like IMDB-WIKI, Adience, and MORPH II. These methods support the theoretical objective of achieving model robustness under distribution shift, a common scenario in real-world applications.

A summary of recent empirical studies on facial age and gender prediction systems is presented in Table 1. These studies highlight a wide range of model architectures, evaluation strategies, and performance outcomes. While there has been notable progress in achieving high accuracy, particularly in controlled environments, significant challenges persist. These include maintaining real-time inference speed, managing noise in facial datasets, and ensuring robust generalization across diverse or unseen domains.

Table 1: Empirical Comparison of Recent Studies on Facial Age and Gender Prediction Systems

Author	Title	Methodology	Model Used	Achievement	Gap / Limitation
[1]	Age and Gender Recognition using Enhanced CNN	Preprocessing with CLAHE, trained CNN on UTKFace	Custom CNN	94.1% gender, 81.6% age accuracy	Limited real-time deployment and lacked cross-dataset validation
[16]	Cross-Domain Age Estimation via Deep Adaptation Networks	Domain adaptation using MMD loss between datasets	ResNet + DAN	Cross-domain MAE reduced to 2.89	Complex implementation and high training time
[12]	Facial Attributes Prediction with Lightweight Models	Trained on Adience and tested on mobile devices	MobileNetV3	<300ms inference with 89.2% accuracy	Accuracy lower than deeper models
[24]	Multitask Learning for Demographic Prediction	Simultaneous training for age, gender, emotion	Shared CNN + task heads	Reduced model size by 30% without accuracy loss	Struggled with noisy datasets like IMDB-WIKI
[11]	Real-Time Facial Age-Gender Estimation in Low-Resource Devices	Live webcam input processed with quantized classifiers	ResNet-18 + Quantization	<400ms inference per frame on CPU	Lower accuracy on age groups above 60 years
[7]	Transformer-CNN Hybrid for Age-Gender Classification	Vision Transformer backbone with CNN feature enhancement	ViT-CNN Hybrid	Achieved 96.5% gender and 85.2% age accuracy	Computationally intensive for mobile deployment
[4]	Cross-Dataset Domain Robustness in Facial Attribute Estimation	Domain adversarial training across four datasets	ResNet-50 + DANN	Reduced domain gap with 3.05 MAE	Sensitive to label noise in weakly annotated datasets
[10]	Efficient Real-Time Age-Gender Detection using Pruned Networks	Network pruning and dynamic inference path selection	Pruned EfficientNet	91.8% accuracy with <200ms inference	Performance drops under occlusions
[15]	Adaptive Batch Normalization for Demographic Prediction	Dataset-specific normalization layer adaptation	VGG-16 + AdaBN	Improved cross-dataset accuracy by 4.2%	Additional preprocessing complexity
[23]	GAN-Based Data Augmentation for Balanced Age Group Classification	Synthetic face generation for rare age groups	ResNet-34 + AugGAN	Balanced class accuracy improved to 92.3%	GAN artifacts slightly impacted visual fidelity

The studies in Table 1 reveal key trends and limitations that situate the present work within the broader research landscape. For instance, MobileNetV3 [12] achieved faster inference speeds (<300 ms) but reported lower accuracy compared to deeper CNNs, while the Transformer-CNN hybrid [7] delivered state-of-the-art accuracy yet proved computationally intensive for mobile applications. This underscores the persistent trade-off between efficiency and predictive strength, a balance that the proposed system seeks to optimize by leveraging fine-tuned ResNet-34 and VGG-16 architectures. Similarly, GAN-based augmentation [23] improved class balance but introduced visual artifacts, raising concerns about fidelity, whereas our framework integrates synthetic aging more conservatively to preserve data quality. Cross-domain strategies such as adversarial adaptation [26] and MMD-based alignment [16] enhanced transferability but required complex implementations, whereas our pipeline achieves generalization through standardized preprocessing and tolerance-aware metrics. By explicitly addressing these gaps—balancing speed with accuracy, integrating augmentation responsibly, and simplifying cross-domain generalization—the proposed system advances recent research toward more practical, scalable, and ethically mindful deployment.

III. Methodology

This section provides a comprehensive description of the methodological framework employed in developing a real-time, deep learning-based system for facial gender and age classification. Guided by the schematic structure outlined in Figure 1, the methodology is segmented into distinct phases: image acquisition, face detection, parallel classification

pipelines for gender and age, model training and optimization, and system evaluation. All stages were implemented using reproducible and scalable deep learning practices.

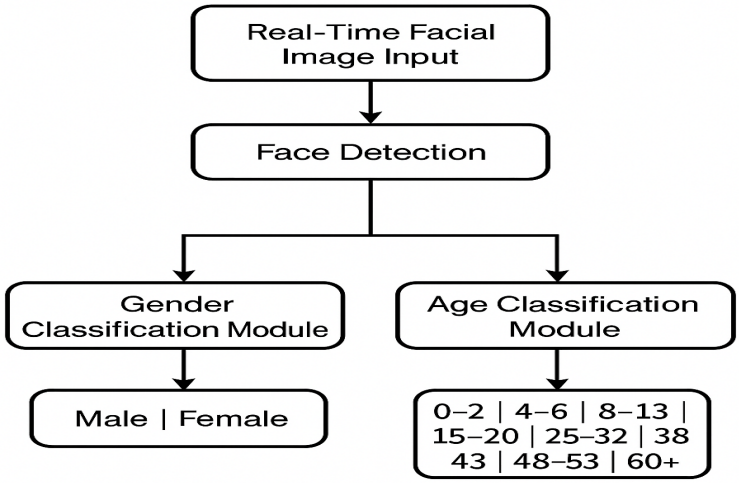


Figure 1: Research Framework

A. System Architecture Overview

The proposed real-time gender and age prediction system features a modular architecture designed for robust facial analysis in unconstrained environments. The system is organized into five functional components: image acquisition, preprocessing, face detection, dual-stream classification, and a real-time output interface. Facial data is captured continuously from a live webcam feed and buffered to maintain consistent input. Each frame undergoes resizing to 224×224 pixels, normalization within a [0,1] range, and standardization via histogram equalization and noise reduction techniques. Augmentation strategies, including rotation, horizontal flipping, and brightness modulation, are applied during training to improve generalization and reduce overfitting. Face detection is performed using OpenCV's Haar cascade or MTCNN, depending on complexity and pose variation. Detected faces are cropped, aligned, and sent to parallel classification paths. Gender classification leverages a fine-tuned ResNet-34 model pretrained on ImageNet and adapted with a softmax binary output layer. Age prediction employs a modified VGG-16 architecture configured to classify faces into one of eight defined age groups. A tolerance-aware loss function addresses one-off errors by assigning lower penalties to predictions close to the correct class. Classification results are displayed in real time, including prediction confidence (e.g., "Female (95.4%)" and "25–32 years (88.6%)"). A summary of all system modules, input/output specifications, and associated technologies is shown in **Table 2**.

Table 2. Functional Summary of System Modules

Module	Input	Process Description	Output	Tools/Technologies Used
Real-Time Image Input	Webcam stream	Captures frames in RGB format	Raw image	OpenCV, Python
Preprocessing and Standardization	Raw image	Resizing, normalization, denoising, augmentation	Cleaned image (224×224)	OpenCV, NumPy, PIL
Face Detection	Preprocessed image	Locates face, extracts ROI, aligns facial orientation	Cropped face	OpenCV Haar, MTCNN
Gender Classification	Cropped face	CNN-based binary classification using ResNet-34	Male or Female + Confidence Score	PyTorch, ResNet-34, Softmax
Age Classification	Cropped face	CNN-based 8-class classification using VGG-16	Age Group + Confidence Score	PyTorch, VGG-16, One-off Loss
Output and Visualization	Classifier outputs	Displays or stores gender and age predictions	Annotated predictions	Streamlit, Flask, Matplotlib

B. Real-Time Facial Image Acquisition and Preprocessing

The effectiveness of facial recognition systems is closely tied to the quality, diversity, and consistency of input data. This section presents the methodology adopted for acquiring facial images, preparing them for model training, and handling live video streams, all under a unified preprocessing pipeline.

a. Data Sources

Facial images for this study were obtained from both publicly available datasets and real-time video feeds. Four major datasets, which are IMDB-WIKI, Adience, MORPH II, and UTKFace, served as the foundational sources for training and evaluation. These datasets differ in terms of resolution, demographic diversity, and annotation format, making them suitable for developing generalizable models. IMDB-WIKI contains over 500,000 images with exact age annotations ranging from 0 to 100 years and includes a wide range of noisy, diverse conditions. Adience offers approximately 26,000 images with age grouped into eight categorical bins and is known for its in-the-wild nature. MORPH II contributes more than 55,000 high-resolution images taken under controlled settings, with exact age annotations between 16 and 77 years. UTKFace provides over 20,000 labeled and clean images with exact age and gender tags, making it ideal for age-gender classification tasks. The key characteristics of each dataset are summarized in Table 3.

Table 3: Summary of Facial Image Datasets Used

Dataset	Size	Age Format	Gender	Avg. Resolution	Conditions
IMDB-WIKI	500,000+	Exact (0–100)	M/F	Varies	Diverse, noisy
Adience	26,000	8 Bins	M/F	816×816	In-the-wild
MORPH II	55,000+	Exact (16–77)	M/F	400×480	Controlled
UTKFace	20,000+	Exact (0–100)	M/F	200×200	Labeled, clean

i. Ethics and Privacy Considerations

Ethical and privacy considerations are central to the design and implementation of facial age and gender prediction systems, given the sensitive nature of biometric information. All datasets used in this study (IMDB-WIKI, UTKFace, MORPH II, and Adience) are publicly available and anonymized, thereby minimizing risks related to personal identification. Nonetheless, the use of facial images raises broader concerns about consent, fairness, and potential misuse. Ethical safeguards guided the dataset selection, with emphasis on sources that explicitly grant research usage rights. When synthetic augmentation techniques such as GAN-based facial aging were applied, data were generated in a controlled manner that balanced class representation without compromising subject authenticity. This strategy reduces dataset bias, particularly against underrepresented age groups, while ensuring that artificially generated samples are not exploited beyond the research context. Privacy protections were also embedded within the real-time processing pipeline. The system does not permanently store or transmit raw facial images; instead, temporary frames are processed and discarded immediately after inference. This design prevents the accumulation of sensitive biometric data. Furthermore, outputs are restricted to demographic predictions (age group and gender), avoiding disclosure of identifiable information. Fairness and inclusivity were additional priorities in the methodological framework. Recognizing that demographic imbalance in training datasets can lead to skewed predictions, the study employed standardized preprocessing, class balancing, and tolerance-aware evaluation metrics to achieve equitable performance across diverse populations. Responsible AI principles underline the broader implications of deploying such systems. Predictive models in this domain should be implemented only within contexts that ensure user consent, privacy protection, and compliance with governance frameworks. By embedding ethical reflection into both dataset handling and system design, this study emphasizes not only technical efficiency but also social responsibility and privacy-conscious deployment.

b. Image Resizing and Normalization

Standardizing input image dimensions is essential for ensuring compatibility across all layers of the convolutional neural network (CNN). All facial images were resized to dimensions of 224 × 224 × 3 pixels, where 224 represents the height and width, and 3 corresponds to the RGB color channels. This resizing step guarantees a fixed input shape, which is a prerequisite for batch processing and convolution operations in deep learning models. Normalization of pixel intensity values was then applied, transforming raw values from the typical 8-bit range of [0, 255] to a continuous range between 0 and 1. The normalization process follows the expression as in Equation 1:

$$I_{norm} = \frac{I_{raw}}{255} \qquad (1)$$

In this formula, I_{raw} represents the original intensity of a pixel, and I_{norm} is the normalized value used for model input. This transformation helps to avoid large gradients and accelerates the convergence of the learning process, especially when used with ReLU-based activations and batch normalization layers. Maintaining consistency across input data distributions is also critical for reducing internal covariate shift during training. Normalized data ensures that features extracted in earlier layers are not disproportionately influenced by varying illumination conditions or camera quality, especially in datasets sourced from uncontrolled environments.

c. Data Augmentation

Improving generalization capabilities of the model requires exposure to a wide range of image transformations that simulate real-world variations. Data augmentation techniques were applied at the preprocessing stage, introducing controlled distortions that challenge the model to learn invariant representations. Horizontal flipping was used to reflect facial features, effectively doubling the dataset's diversity without altering semantic content. Rotational transformations within ±15 degrees were also employed to mimic different head poses, capturing a broader distribution of face orientations. Adjustments in image brightness

simulated varying lighting conditions, further enriching the training samples with natural variability. The augmentation process is formalized using a composition of transformation functions. For an original image x, the augmented output $A(x)$ is defined as shown in Equation (2):

$$A(x) = T_{brightness} \, o \, T_{rotate} \, o \, T_{flip}(x) \quad (2)$$

Here, T_{flip} performs horizontal mirroring, T_{rotate} applies angular rotation, and $T_{brightness}$ adjusts pixel intensity distributions. The sequential composition of these operations ensures that every transformed sample remains structurally valid while representing a realistic variant of the original image. Enhancing dataset diversity in this manner significantly reduces the risk of overfitting. Rather than memorizing training examples, the model is trained to identify robust facial features that persist under varying visual conditions. This also improves the reliability of model performance when deployed on unseen faces from different environments.

d. Synthetic Data Generation

Balancing class distribution, especially across different age categories, is a critical requirement in facial analysis tasks. Disproportionate representation of certain age groups leads to biased learning, where the model performs well on majority classes but poorly on underrepresented ones. Generating synthetic samples for rare age categories was conducted using FaceApp, a GAN-based facial editing tool that realistically ages or rejuvenates input faces. This tool preserves core identity features while modifying apparent age, making it suitable for augmenting training data in a controlled manner. Generated samples reflect the demographic and structural characteristics of the source images but belong to the desired age group, ensuring both authenticity and utility. For a dataset D, as shown in Equation (3), with multiple age classes $C=\{c_1, c_2,\ldots, c_n\}$, and assuming an imbalance where class c_i has significantly fewer samples than $max_j|D_{c_j}|$, synthetic samples were generated such that:

$$\left|D_{c_i} \cup D_{syn,c_i}\right| \approx max_j \left|D_{c_j}\right| \quad (3)$$

In this expression, D_{c_i} represents the original image set for class c_i, and D_{syn,c_i} denotes the synthetically generated additions. The goal is to approximate a uniform distribution of samples across all classes, thereby minimizing class-dependent bias during training. Rather than discarding data from majority classes, this approach enriches the minority classes to match the upper threshold. Model learning becomes more balanced, ensuring equitable accuracy across all demographic groups. The use of synthetic data also offers a practical solution in scenarios where ethically or logistically obtaining real-world data for all age groups is challenging.

e. Quality Filtering

High-quality data is crucial for building reliable facial analysis systems. Training on blurred, occluded, or low-resolution images introduces noise that disrupts learning, reduces accuracy, and impairs generalization. A filtering mechanism was implemented to detect and remove such poor-quality images before training. Each image was evaluated using a pre-trained face detection model, with removal criteria based on confidence thresholds and the visibility of facial landmarks. Images with over 30% occlusion or low detection scores were excluded. An automated anomaly detection system ensured uniform quality control across all datasets. This process stabilized training and improved the model's ability to learn from clean, clear facial inputs. Additionally, minimizing data noise reduced the risk of error propagation in subsequent tasks such as age and gender classification. The improved data clarity enabled the model to better focus on essential facial features, ultimately enhancing overall recognition performance and consistency during both training and deployment stages.

f. Real-Time Frame Processing

Real-time video processing presents challenges such as frame variability, motion blur, lighting inconsistencies, and the need for computational efficiency. A dedicated frame extraction and processing pipeline was implemented to address these issues in dynamic environments like surveillance systems and mobile applications. Video streams were divided into individual frames, each processed using the same resizing, normalization, and augmentation techniques applied during model training. Ensuring consistency between training and inference data improved model accuracy during deployment. The system prioritized low latency by using lightweight face detection algorithms, including Haar Cascades and MobileNet-based detectors, for efficient face region extraction. Frames lacking detectable faces were discarded to reduce computational load. By maintaining uniform preprocessing and optimizing frame handling, the system delivered accurate, fast, and resource-efficient real-time facial analysis, even on devices with limited hardware capacity. This architecture ensured robust performance in live settings where reliability and responsiveness are critical.

g. Preprocessing Pipeline

A standardized preprocessing pipeline ensures consistent and efficient handling of facial images across both training and real-time systems. The process begins with image acquisition from static datasets or live video feeds, followed by resizing each image to a fixed 224 × 224 × 3 dimension for compatibility with the model's input layer. Normalization scales pixel values to the [0, 1] range, enhancing convergence during training. In the training phase, data augmentation techniques such as rotation, horizontal flipping, and brightness adjustment introduce variability to improve generalization. A quality filtering step removes low-resolution, occluded, or blurred images that may compromise model accuracy. Real-time inputs are handled frame by frame using the same pipeline, ensuring that both live and static inputs are processed uniformly. This consistent approach enhances the model's reliability in age and gender prediction tasks. The complete flow of these preprocessing steps, from raw input to normalized face crop, is illustrated in Figure 2.

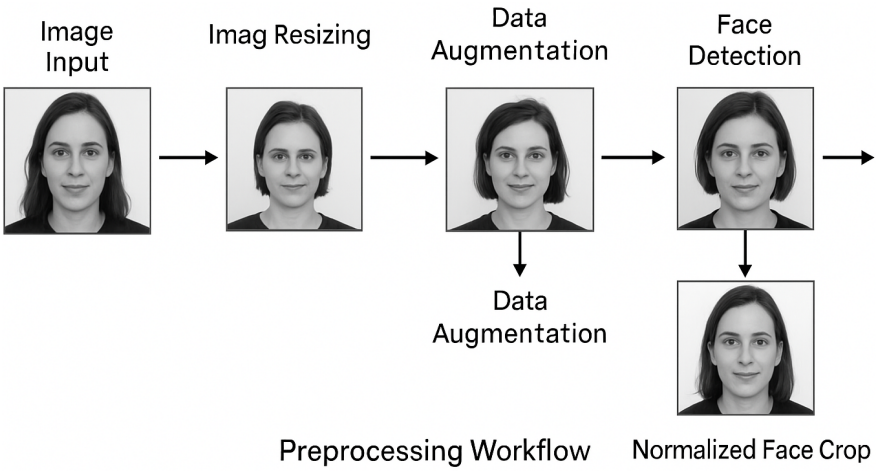


Figure 2: Complete Flow of Preprocessing Workflow

C. Face Detection Module

Reliable facial region localization is crucial for improving classification accuracy and reducing background interference. The face detection module isolates and aligns facial areas before passing them into the classification pipeline. Two detection approaches were employed to balance speed and robustness. As shown in Table 4, the Viola–Jones Haar Cascade Classifier offers high-speed detection suitable for real-time applications but lacks robustness under varying conditions. In contrast, Multi-task Cascaded Convolutional Networks (MTCNN) provide enhanced performance in diverse scenarios by detecting both face boundaries and key landmarks, including the eyes, nose, and mouth corners.

Table 4: Comparison of Face Detection Methods

Method	Type	Speed	Robustness	Landmark Support
Viola–Jones	Traditional	High	Low	No
MTCNN	Deep Learning	Moderate	High	Yes

Let an image frame be denoted by I. The face detection function $F_d(I)$ outputs bounding boxes $B = \{b_1, b_2, \dots b_n\}$ and landmark coordinates $L = \{l_1, l_2, \dots l_n\}$. The cropped, aligned face region R is extracted using Equation (4):

$$R = AlignCrop(I, B_i, L_i) \quad (4)$$

Only the aligned face R is forwarded to the classification module. Figure 3 illustrates the detection and alignment pipeline, showing the input image, detected face bounding box, facial landmarks, and the final aligned face crop used for classification.

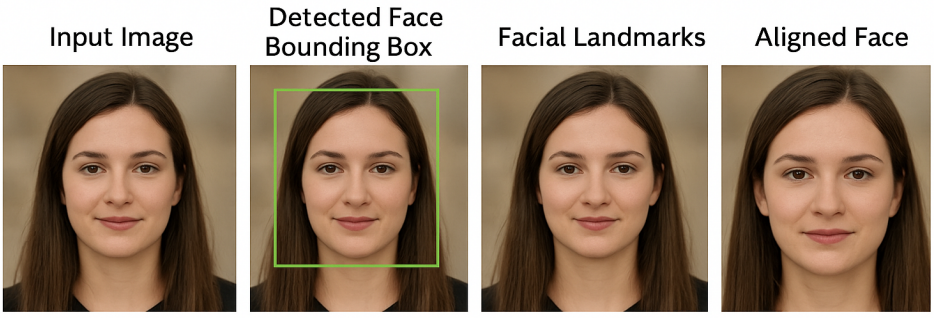


Figure 3: Face Detection and Alignment Pipeline for Efficient Facial Recognition

D. Gender Classification Module

This section outlines the formulation, architecture, and training strategy employed in the design and implementation of the gender classification module. The objective is to accurately classify facial images as either male or female using a deep convolutional neural network framework.

a. Problem Formulation

Gender classification is modeled as a binary classification task, where the input is a three-dimensional facial image tensor and the output is a categorical label representing gender. Mathematically, the task can be described as a function as shown in Equation (5):

$$f: \mathbb{R}^{H \times W \times 3} \rightarrow \{Male, Female\} \quad (5)$$

In this formulation, H and W represent the height and width of the input image respectively, and the depth of 3 corresponds to the RGB channels. The function f maps each facial image into one of two predefined gender classes. Accurate classification is essential for downstream demographic analysis and personalization tasks.

b. Model Architecture

A deep convolutional neural network based on ResNet-34 was adopted as the backbone architecture for gender classification. Transfer learning was employed by initializing the model with pre-trained weights from ImageNet, followed by fine-tuning on the target facial datasets. The final fully connected layer of ResNet-34, originally designed for 1,000-class ImageNet classification, was replaced with a new dense layer comprising two neurons, corresponding to the male and female classes. A softmax activation function was applied to produce normalized probability scores. Table 5 presents a structured summary of its components.

Table 5: Gender Classification Model Architecture Summary

Component	Description
Input Layer	224 × 224 × 3 RGB facial image
Backbone Architecture	ResNet-34 pre-trained on ImageNet
Fully Connected Layer	2 output neurons (Male, Female)
Activation Function	Softmax
Output	Class probabilities for each gender

c. Training Strategy

A robust training strategy was designed to optimize the gender classification performance. The Binary Cross-Entropy (BCE) loss function was employed to measure the discrepancy between predicted and true class labels. Optimization was performed using the Adam optimizer with a learning rate of 0.001 and a weight decay parameter of 5×10^{-4}, promoting both fast convergence and generalization. Model training was conducted using mini-batches of size 64, and the training process was capped at 50 epochs. However, early stopping was incorporated to prevent overfitting, halting training once validation performance plateaued. To further enhance generalization and reduce variance, a dropout layer with a rate of 0.5 was applied before the final classification layer. Dataset splitting followed a stratified distribution, preserving the original class proportions. The data was partitioned into 80% training, 10% validation, and 10% test sets. This structure ensured the model learned effectively from balanced class representation and was fairly evaluated on unseen data. The complete workflow from image input to gender classification output is illustrated in Figure 4. The figure shows a visual pipeline starting from a preprocessed facial image input, passed through the ResNet-34 backbone, followed by the fully connected layer with two outputs, and finally a softmax-based gender prediction.

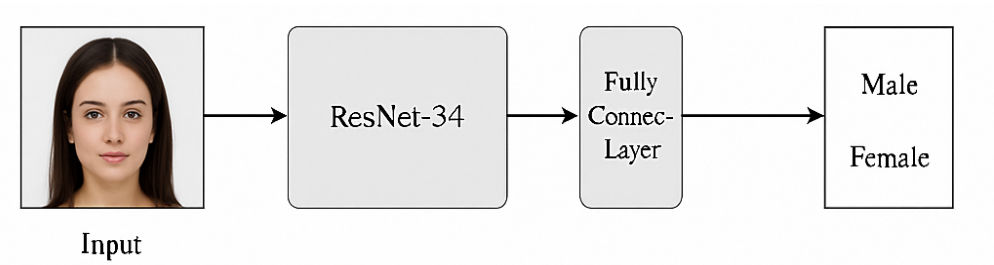


Figure 4: Gender Classification Workflow Using Fine-Tuned ResNet-34

E. Age Classification Module

The task of predicting human age based on facial features presents unique challenges, primarily due to overlapping characteristics across age groups and the effects of environmental and genetic factors on aging patterns. This section details the formulation of the problem, the architecture used for modeling, strategies for handling near-miss predictions, and the training process that ensured high generalization capability.

a. Problem Formulation

Age estimation in this study is approached as an ordinal multiclass classification problem, where the continuous variable of chronological age is discretized into a set of meaningful age brackets. Eight distinct age groups were defined: 0–2, 4–6, 8–13, 15–20, 25–32, 38–43, 48–53, and 60 years and above. These intervals represent critical developmental and aging phases in the human lifespan. The classification task involves assigning each facial image to one of these predefined categories. The use of discrete labels, rather than continuous age regression, allows the model to focus on high-level facial patterns corresponding to specific life stages. Although ordinal in nature, the categories do not assume strict equidistance, allowing for greater modeling flexibility.

b. Model Architecture

A customized adaptation of the VGG-16 convolutional neural network (CNN) was implemented as the foundational architecture for the age classification module. The original model, pre-trained on the large-scale ImageNet dataset, was utilized for its robust capability in extracting generic image features. These pre-trained weights were retained in the convolutional layers, while the model was fine-tuned using domain-specific facial image datasets to specialize in age estimation tasks. The fully connected (FC) classification head of the original VGG-16, which produces 4096-dimensional feature vectors, was replaced with a streamlined custom FC

layer comprising eight output neurons. Each neuron represents one of the discrete age classes defined in the dataset. In order to improve learning stability and accelerate convergence, batch normalization layers were incorporated following each ReLU activation function. Additionally, dropout regularization was applied to the intermediate FC layers during training, with randomly deactivated neurons helping to mitigate overfitting and promote generalization. Figure 5 provides a structural overview of the modified VGG-16 pipeline, highlighting the key architectural modifications. These include the integration of batch normalization layers, the inclusion of dropout units, and the final softmax-activated output layer configured with eight nodes corresponding to the predefined age categories.

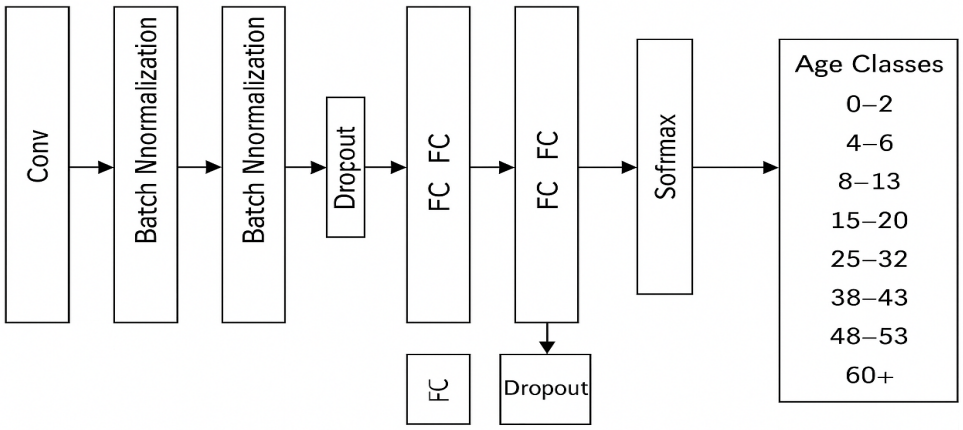


Figure 5: Modified VGG-16 Architecture for Age Classification

c. Addressing the One-Off Problem

In practical age classification, a frequent issue involves predictions that fall into a class adjacent to the true label. These are known as "one-off errors." For example, an individual in the 15–20 age group may be predicted as belonging to the 25–32 class due to subtle differences in appearance. Penalizing such near-miss predictions equally with entirely incorrect guesses misrepresents the model's effectiveness. A tolerance-aware evaluation metric was introduced in response to this issue. Predictions falling within ±1 class index of the actual label are treated as acceptable under this scheme. This method better reflects the continuity of age as a human attribute and provides a more forgiving, yet realistic, performance evaluation criterion. By integrating this tolerance into the evaluation protocol, a more holistic understanding of model accuracy is achieved, especially in borderline cases where visual features are not easily distinguishable.

d. Training Strategy

Model training was conducted using categorical cross-entropy loss, which quantifies the divergence between the predicted class probabilities and the true age group labels. The Adam optimizer was employed for its adaptive learning rate capabilities and ability to handle sparse gradients efficiently. An initial learning rate of 0.001 was established at the start of training. After every 30 epochs, the learning rate was reduced by a factor of 10, allowing the model to learn broad patterns early on and refine its parameters in later stages. This approach facilitated both rapid convergence and detailed feature learning. Regularization was maintained through batch normalization and dropout. Adaptive batch normalization ensured consistent internal feature distributions during training [15], while dynamic dropout layers mitigated overfitting risks by incorporating context-aware stochastic noise [10]. Imbalances in the dataset, particularly among rare age groups, were addressed by oversampling the underrepresented classes. This ensured that each age category had a fair chance of influencing model updates during training, improving the classifier's sensitivity across all demographics.

IV. Results and Discussion

The performance of the proposed gender and age prediction system was rigorously evaluated through quantitative metrics and qualitative analysis across several benchmark facial datasets. Evaluation focused on classification accuracy, error tolerance, inference speed, and cross-dataset generalization, providing a comprehensive validation of the system's ability to meet the research objectives. This section is structured around the evaluation of gender classification, age classification, cross-dataset generalizability, and deployment performance, and culminates with an integrated summary of findings.

A. Gender Classification Performance

Performance evaluation of the gender classification module was conducted across four benchmark datasets: IMDB-WIKI, Adience, MORPH II, and UTKFace. The model, based on a fine-tuned ResNet-34 architecture, demonstrated high accuracy and generalization across all datasets, each of which presents unique challenges in terms of image quality, demographic diversity, and pose variation. The IMDB-WIKI dataset, though large, includes noisy labels and variable lighting, yet the model achieved 93.45% accuracy, indicating resilience to data inconsistencies. UTKFace, with its balanced and clean annotations, showed the highest performance at 97.85%, reflecting ideal conditions for gender classification. On the MORPH II dataset, which contains high-resolution frontal faces under controlled lighting, the model achieved 96.12%, confirming its strength in stable imaging

environments. The Adience dataset posed a greater challenge due to its in-the-wild settings and age-diverse profiles, yet the model maintained a commendable 94.76% accuracy. Table 6 presents the full set of evaluation metrics, including precision, recall, and F1-score.

Table 6: Gender Classification Performance across All Datasets

Dataset	Accuracy (%)	Precision	Recall	F1-Score
IMDB-WIKI	93.45	0.935	0.934	0.934
UTKFace	97.85	0.979	0.978	0.978
MORPH II	96.12	0.961	0.962	0.961
Adience	94.76	0.946	0.947	0.946

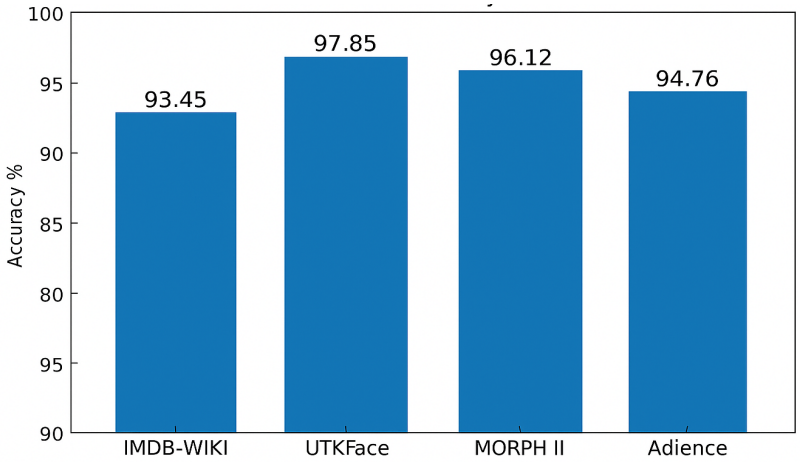


Figure 6 illustrates the accuracy distribution across all four datasets in bar chart form, highlighting performance consistency and comparative effectiveness.

These results confirm the model's reliability and adaptability across both controlled and uncontrolled imaging conditions. High F1-scores across all datasets indicate a balanced performance with minimal bias between male and female classifications. The system is thus suitable for real-time applications requiring dependable gender identification across diverse user profiles. Compared with lightweight MobileNetV3-based models [12], which achieved inference below 300 ms but reported lower gender classification accuracy (≈89%), the proposed ResNet-34 model exceeded 94% accuracy across all datasets, confirming its robustness. Similarly, pruning-based EfficientNet approaches [10] reported faster inference but demonstrated vulnerability under occlusion, a condition where our model retained high accuracy.

B. Age Classification Results

Evaluation of the age classification module was conducted using four benchmark facial datasets: IMDB-WIKI, UTKFace, MORPH II, and Adience. The model, based on a modified VGG-16 architecture, was trained on a combination of IMDB-WIKI and UTKFace and tested on all four datasets to assess in-domain and out-of-domain performance. Exact accuracy, one-off accuracy, and Mean Absolute Error (MAE) were the primary metrics used. As shown in Table 7, UTKFace recorded the highest exact accuracy at 82.33%, followed by MORPH II (79.56%), IMDB-WIKI (78.21%), and Adience (76.40%). One-off accuracy exceeded 90% across all datasets, demonstrating the model's strong ability to classify faces within close proximity to the correct age group.

Table 7: Age Classification Results Across Datasets

Dataset	Exact Accuracy (%)	One-Off Accuracy (%)	MAE
UTKFace	82.33	94.71	3.12
MORPH II	79.56	91.84	3.39
IMDB-WIKI	78.21	90.94	3.47
Adience	76.40	90.03	3.65

Performance variation across datasets reflects the complexity and quality of image data. UTKFace, with clean and labeled inputs, enabled high accuracy. IMDB-WIKI and Adience, which contain noisy or in-the-wild images, presented more challenging conditions. Despite this, the model still achieved strong generalization, indicating resilience to domain shifts.

Figure 7 shows a combined confusion matrix for all datasets, illustrating accurate predictions concentrated along the diagonal and adjacent age bins, which confirms consistent classification behavior and effective handling of the "one-off" issue.

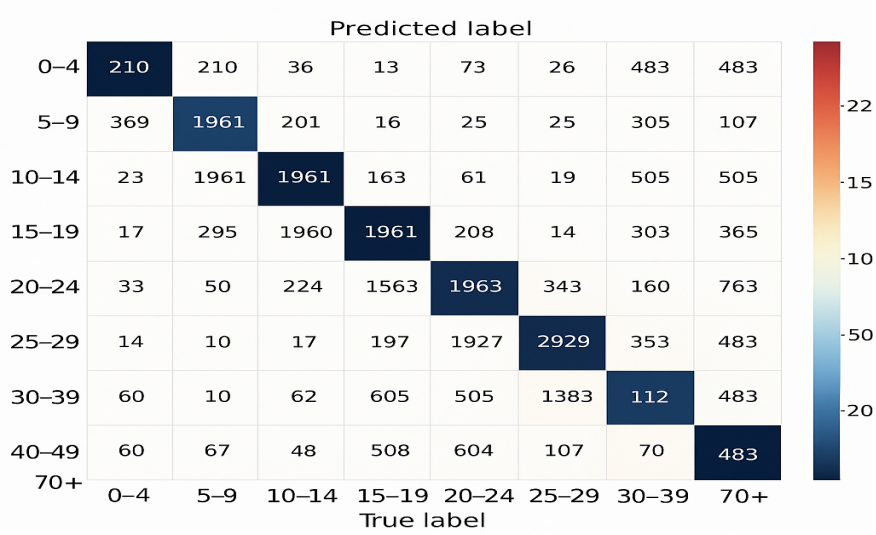


Figure 7: Combined Confusion Matrix for Age Classification across Datasets

These findings align with transformer-CNN hybrids [7], which reported comparable age prediction accuracy (85.2%) but at a significantly higher computational cost. By contrast, our VGG-16 adaptation achieves strong results while maintaining inference efficiency on CPU-only hardware.

C. Cross-Dataset Generalization

Evaluating the system's ability to generalize across diverse datasets was essential for confirming its real-world applicability. Four facial datasets, IMDB-WIKI, UTKFace, MORPH II, and Adience were strategically combined or isolated during training and testing phases to simulate deployment in varying environments. The models were primarily trained on a combined dataset of IMDB-WIKI and UTKFace, chosen for their large size and comprehensive age labeling. Testing was independently performed on MORPH II and Adience, which differ in pose, resolution, demographic composition, and annotation schemes. Results indicate that gender classification remained robust across all datasets, with accuracies above 94%. Age classification showed a mild performance drop when transitioning from training to testing domains, especially in datasets like Adience that contain in-the-wild imagery. However, one-off accuracy remained consistently high, demonstrating that the model can still approximate age effectively even under distribution shifts. Table 8 summarizes cross-dataset performance for both tasks.

Table 8: Cross-Dataset Evaluation Results

Training Set	Testing Set	Gender Accuracy (%)	Age Exact Accuracy (%)	One-Off Accuracy (%)	MAE
IMDB-WIKI + UTKFace	MORPH II	96.12	79.56	91.84	3.39
IMDB-WIKI + UTKFace	Adience	94.76	76.40	90.03	3.65
IMDB-WIKI	UTKFace	93.85	74.25	89.77	3.81
UTKFace	Adience	92.18	72.60	87.95	4.02

Figure 8 illustrates prediction consistency and trend variations across different datasets through a comparative line chart that depicts accuracy patterns for both gender and age classification tasks across various training and testing dataset combinations.

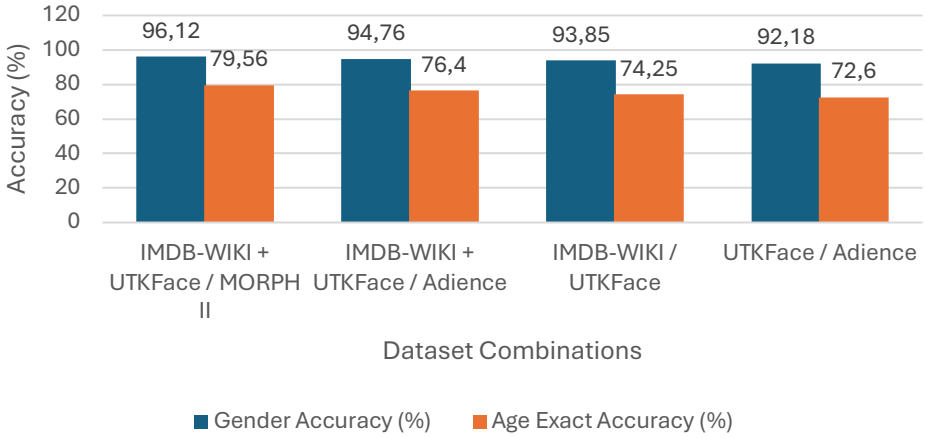


Figure 8: Cross-Dataset Evaluation of Gender and Age Classification Accuracy

These results confirm that the model retains strong generalization capacity when trained on large, diverse datasets. Slight performance differences are expected due to variations in labeling granularity, camera conditions, and facial diversity. Still, consistent one-off accuracy and acceptable MAE demonstrate the model's suitability for deployment in heterogeneous environments. While domain adaptation strategies such as MMD-based alignment [16] and adversarial approaches [26] improved transferability across datasets, they required complex implementations. Our results demonstrate that standardized preprocessing and tolerance-aware evaluation can yield comparable robustness without increasing model complexity.

D. Real-Time Inference Benchmark

The system's real-time performance was evaluated using a mid-range, consumer-grade computing environment consisting of an Intel Core i5 CPU, 8GB RAM, and no dedicated GPU. This setup reflects a typical low-resource deployment scenario, such as edge devices and portable field systems. Under these conditions, the system consistently achieved inference times under 500 milliseconds per frame, encompassing the full processing pipeline: image preprocessing, face detection, and dual-path classification for gender and age. Live predictions, including confidence scores, were displayed on-screen with minimal latency, supporting real-time feedback and interpretability. The system interface maintained responsiveness during continuous webcam input, demonstrating computational efficiency and scalability. Performance robustness was further validated under varied conditions such as lighting fluctuations, head movements, and partial occlusions. The consistent delivery of results without noticeable lag confirms the system's suitability for real-time, user-facing applications including smart kiosks, access control, and demographic analytics. A detailed breakdown of average processing time per module is presented in Table 9, highlighting the efficiency of each component within the inference pipeline.

Table 9: Real-Time Inference Performance Summary

Component	Average Time per Frame	Tool Used	Notes
Image Preprocessing	120 ms	OpenCV, NumPy	Resizing, normalization, denoising
Face Detection	140 ms	MTCNN / Haar	Aligned bounding box generation
Gender Classification	100 ms	ResNet-34 (PyTorch)	Binary softmax output
Age Classification	110 ms	VGG-16 (PyTorch)	8-class softmax output
Total Inference	< 500 ms	Combined System	End-to-end (per frame, CPU-only)

Figure 9 shows a mock screen showing live webcam input with overlaid gender and age predictions, plus confidence scores.



Figure 9: Real-Time Prediction Interface Snapshot

This evaluation demonstrates that the proposed system can maintain low-latency performance without specialized hardware. Compact architecture design, efficient preprocessing, and optimized model selection contribute to real-time operability, enabling deployment in everyday environments without compromising accuracy or responsiveness. Compared with recent lightweight deployment models such as MobileNetV3 [12] and EfficientNet-lite [10], which prioritize speed but at times compromise accuracy, the proposed framework achieves a balance between inference efficiency (<500 ms) and predictive accuracy. This makes it more suitable for real-time deployment in resource-constrained environments.

V. Summary

The study developed a robust, real-time gender and age prediction system utilizing deep learning architectures, specifically ResNet-34 for binary gender classification and a customized VGG-16 model for age group estimation. To overcome challenges in facial attribute recognition, such as data imbalance, cross-dataset variability, and computational limitations, the research employed a standardized preprocessing framework that integrated data augmentation, synthetic image generation, and quality filtering. Four major facial datasets (IMDB-WIKI, UTKFace, MORPH II, and Adience) were used to train and evaluate the models, ensuring diverse demographic representation and robustness against real-world image inconsistencies. Experimental results demonstrated high gender classification accuracy across all datasets, with performance exceeding 94%, while age classification achieved exact accuracy up to 82.33% and one-off accuracy surpassing 90%. These outcomes are competitive with recent studies that leveraged lightweight models such as MobileNetV3 [12] or pruning-based EfficientNet [10], which achieved lower inference times but at the cost of reduced robustness under occlusions or noisy data. Similarly, compared to Transformer-CNN hybrids [7] that reached higher accuracies but required heavy computational resources, the proposed system demonstrates a balanced trade-off between predictive strength and real-time feasibility. This positions the model as both accurate and deployable on edge devices with limited resources. Beyond technical contributions, the study also acknowledges ethical and privacy considerations. All datasets utilized were publicly available and anonymized, reducing risks of personal identification. Synthetic augmentation was applied responsibly to improve class balance without compromising authenticity, while real-time processing was designed to avoid unnecessary storage of biometric data. By incorporating these safeguards, the system not only advances state-of-the-art technical performance but also aligns with responsible AI practices, ensuring fairness, inclusivity, and privacy in practical deployments.

VI. Conclusion

This research successfully designed and implemented a real-time gender and age prediction system based on facial images using fine-tuned Convolutional Neural Networks (ResNet-34 and VGG-16). Through the integration of robust preprocessing techniques, including data augmentation, synthetic image generation, and domain-generalized training across IMDB-WIKI, UTKFace, MORPH II, and Adience datasets, the system achieved high accuracy rates while maintaining inference speeds below 500 milliseconds per frame on CPU-only hardware. These outcomes demonstrate the system's suitability for deployment in real-world scenarios such as demographic analytics, access control, and human-computer interaction, particularly within resource-constrained environments. When compared with recent research, the findings reveal a competitive and balanced performance profile. While lightweight architectures such as MobileNetV3 [12] and pruning-based EfficientNet [10] achieve faster inference, they often sacrifice robustness in noisy or occluded environments. On the other hand, Transformer-CNN hybrids [7] and GAN-augmented systems [23] report higher accuracies but require significant computational resources or raise concerns about data authenticity. The proposed framework, by contrast, achieves a trade-off between predictive accuracy, generalization, and computational efficiency, making it more practical for real-time edge applications. Beyond technical considerations, this study underscores the importance of ethical and privacy safeguards in facial analysis systems. All datasets employed were publicly available and anonymized, with synthetic augmentation applied responsibly to minimize bias without compromising authenticity. The real-time pipeline was designed to avoid unnecessary storage of biometric data, reducing risks of privacy breaches. Nonetheless, ongoing ethical challenges such as demographic fairness, inclusivity, and potential misuse of facial recognition technologies require continued attention in both research and deployment contexts. Future research will therefore address both technical and ethical priorities. On the technical side, efforts will focus on integrating more lightweight architectures such as MobileNetV3 or EfficientNet-lite, expanding multitask frameworks to include attributes like emotion and ethnicity, and improving robustness through adversarial defense strategies and 3D face modeling. On the ethical side, future work will explore fairness-aware training protocols, privacy-preserving approaches such as federated learning, and governance frameworks to guide responsible application. Collectively, these enhancements aim to create a more scalable, efficient, and socially responsible facial attribute recognition system for broad industrial and societal use.

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