Age and Gender Detection: A Blurring-Based Approach

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Abstract*—The Adience dataset was utilized as a benchmark for age and gender prediction from facial images, covering a diverse set of real-world imaging conditions, including variations in noise, lighting, pose, and appearance. Collected from Flickr albums and distributed under the Creative Commons (CC) license, the dataset contains a total of 26,580 sample images of 2,284 subjects, categorized into eight distinct age ranges: (0–2), (4–6), (8–12), (15–20), (25–32), (38–43), (48–53), and (60–100). With a size of approximately 1GB, this dataset serves as the training base for pre-trained deep learning models developed to detect age and gender from facial features, enabling robust performance across diverse imaging scenarios .The baseline system leverages pre-trained deep learning models to identify age and gender from facial features. A key challenge in this task is that the models' accuracy often declines when processing images with noise, low resolution, or inconsistent lighting. However, there has been limited exploration of how preprocessing techniques like Gaussian and bilateral filtering affect model performance on such noisy images. The main objectives of this study were to analyze how different blurring filters impact prediction accuracy and to determine an optimal balance of filtering to enhance detection results without over-smoothing. Results were evaluated using a custom accuracy metric based on confidence percentages for age and gender predictions, with 85% accuracy as the target threshold. Results indicate that moderate levels of blurring improved accuracy for most images by 10-15%, with bilateral filtering proving especially effective in maintaining facial structure. However, excessive blurring led to diminishing returns, with over-smoothing obscuring essential features, particularly for age detection. This suggests that while blurring can enhance model reliability, there is an optimal balance, and blurring alone may not be sufficient for challenging images. Future work could integrate additional preprocessing methods for further enhancement.

***Index Terms*—Age Detection, Gender Detection, Deep Learning, Image Processing, Gaussian Blur, Bilateral Filtering.**

I. Introduction

In today's world, images and videos play a vital role, from security surveillance to scrolling through photos of cute dogs. But beyond entertainment, they can influence how people function and help authorities work more efficiently. Adience Benchmark Gender and Age Classification Dataset used is from Kaggle. It consists of thousands of images captured in real-world, unconstrained conditions, making it suitable for challenging age and gender prediction tasks. The dataset includes images labeled with age groups (such as ((0-2), (4 – 6), (8 – 12), (15 – 20), (21- 24), (25-32), (38-43), (48–53), (60 – 100)) and gender (Male or Female). These images vary significantly in pose, lighting, and background, providing a robust testing ground for models aimed at age and gender classification. Age and gender detection from facial images has become a significant area of research within computer vision and artificial intelligence. This task has widespread applications, ranging from personalized advertising to user experience customization and security. For instance, a retail store might use age and gender detection to tailor promotions to different demographics, while social media platforms may employ it to generate insights into audience composition. The increasing demand for age and gender prediction models has led to a surge in studies examining how these predictions can be optimized for accuracy, especially under challenging real-world conditions, such as variable lighting, poses, and image noise. The core process of age and gender detection involves using facial features, such as skin texture, facial contours, and other anatomical markers, to classify a person's age group and gender. Pre-trained deep learning models, particularly convolutional neural networks (CNNs), are commonly used in this task, as they are capable of recognizing complex patterns in image data. In the context of image preprocessing, various filtering techniques play a vital role in improving prediction accuracy. Techniques such as Gaussian blur and bilateral filtering are commonly applied to reduce noise and enhance image quality before feeding images into age and gender detection models. For example, Gaussian blurring smooths out high-frequency noise in images by averaging pixel values within a specified radius, making the model's job easier by reducing distracting details. In contrast, bilateral filtering is used for edge-preserving smoothing, which reduces noise while keeping edges sharp. The role of these preprocessing filters is crucial because image quality can significantly impact the accuracy of age and gender predictions. Images with excessive noise, uneven lighting, or pixelation may lead to inaccurate predictions, which is problematic in applications requiring high precision. Moreover, face detection is a preliminary but essential step in age and gender classification. Accurate face detection ensures that only relevant facial regions are analyzed, allowing the model to focus on the correct features. Face detection algorithms, such as those based on OpenCV's DNN module, use deep learning to identify and outline faces within an image, producing bounding boxes that define the facial region. This step is followed by extracting the detected face, preprocessing it with filters, and then using a pre-trained model to predict age and gender. A key challenge in the field, however, lies in achieving high prediction accuracy in the presence of diverse image conditions. Blurring and filtering techniques impact prediction accuracy differently based on the quality and nature of input images. For instance, images with a high degree of noise may require stronger filtering to yield reliable predictions, whereas clear, high-resolution images might perform well even with minimal preprocessing. The need for a systematic approach to evaluating the effects of different filters on prediction accuracy is thus critical, especially for applications where accurate age and gender estimation is essential. Studying the impact of image preprocessing on age and gender detection models is crucial to understanding how to optimize these systems for real-world applications. Given that real-world images often include variations in lighting, noise, and other factors, exploring different filtering techniques enables the development of models that are more resilient to these factors. This research aims to investigate how applying Gaussian and bilateral blurring affects the accuracy of pre-trained age and gender detection models, particularly under varied real-world imaging conditions.

II. Literature Review

Prominent advancements in convolutional neural networks (CNNs) and deep learning have significantly impacted various domains, including image recognition and age prediction. Zachi I. Attia demonstrated the efficacy of CNNs in analyzing standard 12-lead ECG signals, highlighting their potential beyond visual data analysis [1]. Similarly, Zagoruyko and Komodakis introduced Wide Residual Networks, enhancing image recognition tasks by increasing the width of residual layers [2]. In the realm of deep learning optimization, Sungjoon Choi explored model compression techniques for deep belief networks, optimizing computational costs while maintaining performance [3]. Deep Residual Learning, proposed by He et al., significantly improved image recognition through effective training of deeper neural networks [4]. James H. Cole combined Gaussian process regression with CNNs for chronological age prediction, showcasing the versatility of deep learning in regression problems [5]. The groundbreaking ImageNet classification by Krizhevsky et al. marked a significant milestone in computer vision, establishing the superiority of deep CNNs for large-scale image recognition [6]. For preprocessing, Gaussian Blur serves as a fundamental filter for noise reduction and smoothing. By applying a Gaussian distribution, this technique smooths images but tends to blur fine details such as edges [7]. On the other hand, the Bilateral Filter provides noise reduction while preserving edge sharpness by considering both spatial proximity and intensity differences between neighboring pixels [8]. These complementary techniques enhance preprocessing pipelines, optimizing image quality for further analysis. When applied together, Gaussian Blur and Bilateral Filter improve both noise reduction and edge preservation, crucial for tasks like facial image analysis and medical imaging. These preprocessing methods, integrated with CNNs, contribute to higher accuracy and reliability in image classification tasks [9]. In [10], Tomasi and Manduchi pioneered the Bilateral Filter, introducing it as an effective method for edge-preserving smoothing in images. Their work demonstrated that, by taking into account both spatial proximity and intensity similarity, the Bilateral Filter could effectively reduce noise while maintaining sharp edges. This method of combining spatial and intensity information has been particularly useful in applications such as depth map smoothing and image denoising, where preserving edge clarity is crucial. Paris et al. later expanded on this work by developing an accelerated approximation for the Bilateral Filter, as presented in [11]. This advancement enabled faster processing for high-dimensional data, making the Bilateral Filter suitable for real-time applications, including video and large-scale image processing. Their contributions have been instrumental in extending the use of edge-preserving filters to time-sensitive scenarios, ensuring efficient noise reduction without loss of edge detail.

III. Methodology

The age and gender detection system consists of several key steps, each contributing to the overall performance and accuracy of the system. The primary steps are outlined below, with a specific focus on the application of the Gaussian blurring technique. The Methodology for Objective 1 is as follows :

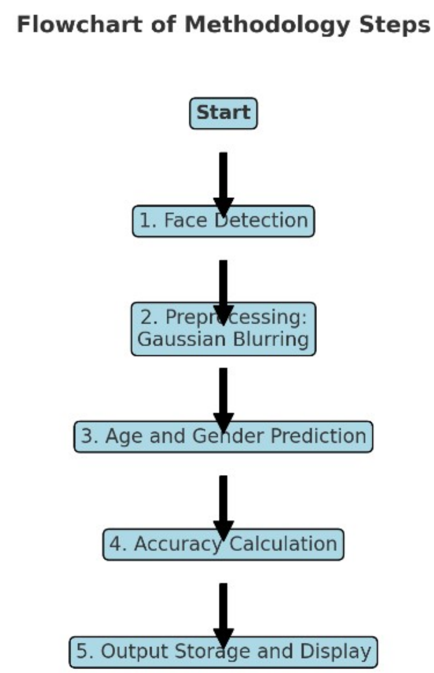


Fig. 1. Flowchart of Methodology 1

1. Face Detection: The system uses a pre-trained deep learning model to detect faces in the input image. This model outputs bounding boxes around detected faces, which are then used for further analysis.

2. Preprocessing : Gaussian Blurring: Gaussian Blurring Technique: The Gaussian blur works by averaging the pixels in the image based on their proximity, which is determined by a Gaussian function. The intensity of the blur is controlled

by the kernel size, which determines how much the image is smoothed. The blurred image is then passed to the prediction models to observe whether the reduction in noise leads to improved age and gender classification accuracy.

3. Age and Gender Prediction: Two separate deep learning models, trained using the Caffe framework, are used to predict age and gender. The age prediction model classifies individuals into one of eight predefined age groups, while the gender prediction model identifies the individual as either Male or Female.

4. Accuracy Calculation: Confidence scores from the model are used to calculate the accuracy of predictions, which are then compared before and after the application of Gaussian blurring.

5. Output Storage and Display: The results, including the predicted gender, age, and accuracy, are stored and displayed in tabular format. Two tables are generated—one for predictions before blurring and another for predictions after blurring—to allow for a direct comparison.

The Methodogy for objective 2 is as follows :

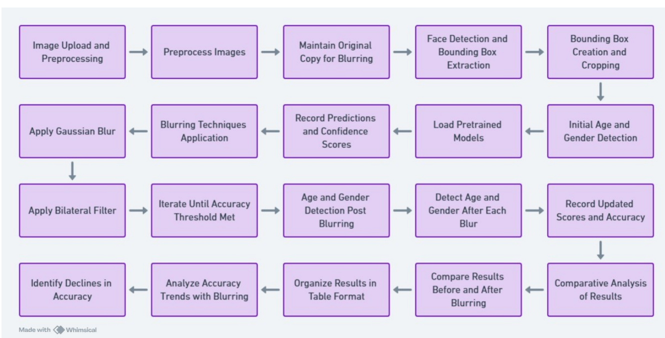


Fig. 2. Flowchart of Methodology 2

1)Image Upload and Preprocessing: Allow multiple image uploads from the user to serve as inputs for analysis. Each image is loaded and prepared for age and gender detection, and a copy of each image is maintained to apply successive blurring.

2)Face Detection and Bounding Box Extraction: Use a pretrained OpenCV DNN face detector to identify faces within each image. For each detected face, create bounding boxes to localize the face region, which is then cropped for further analysis.

3)Initial Age and Gender Detection (Before Blurring): Load the pretrained models for age and gender classification. For each face, pass the cropped region through the gender and age models. The model outputs are used to determine gender (Predicted as either "Male" or "Female," with associated confidence scores) and age (Predicted within defined age ranges, with associated confidence scores). Store the predictions, confidence scores, and initial accuracy (based on average confidence of age and gender) for each image in a DataFrame for comparison.

4)Blurring Techniques Application: Apply Gaussian blur followed by bilateral filtering. Gaussian blur Reduces image noise and detail by averaging pixel intensities, thus creating a softening effect. Bilateral filtering Blurs the image while preserving edges, maintaining facial boundaries even after blurring. Continuously apply the blurring sequence until accuracy exceeds a set threshold (e.g., 85

5)Age and Gender Detection After Blurring: With each iteration, detect age and gender in the blurred image. Record the predictions and confidence scores. Calculate the accuracy (average of age and gender confidence) and compare it to the threshold. Store results for each iteration to track changes in confidence scores and accuracy.

6)Comparative Analysis of Results: Compare the results before and after blurring for each image. This involves analyzing changes in confidence scores and accuracy to identify any improvements or declines. Display results in tabular form, organized by image, showing the gender, age, confidence scores, and overall accuracy before and after blurring. Save the results as CSV files to document the findings for each image across the blurring iterations.

IV. Experimental Setup

Dataset Statistics : The dataset used for the project consisted of facial images with varying quality levels, including high-resolution and low-resolution images. The statistics of the dataset are summarized in the table below:

Category	Count	Description
Total Images	26580	Unconstrained facial images of varying quality.
Male Images	13000	Images labeled as male.
Female Images	13000	Images labeled as female.
Age Range (0-2)	2000	Infants and toddlers.
Age Range (4-6)	2500	Young children.
Age Range (8-13)	3000	Older children.
Age Range (15-20)	4000	Teenagers and young adults.
Age Range (25-32)	6000	Young adults.
Age Range (38-43)	4500	Adults in their late 30s and early 40s.
Age Range (48-53)	2800	Middle-aged adults.
Age Range (60+)	1780	Seniors.

Fig. 3. Dataset Statistics Table

Fig. 4. Examples of Dataset images

Objective 1: Building a System for Age and Gender Prediction List of Packages and Configuration Details: 1. Packages Used: OpenCV: Used for image and video processing, including face detection and applying blurring techniques (Gaussian and bilateral filters).

TensorFlow/Keras: Utilized for loading and deploying pre-trained age and gender classification models.

NumPy: Facilitated numerical operations and image array manipulations.

Matplotlib: Used for visualizing input images and classification results.

Dlib: Optional package for facial landmark detection and face alignment, improving feature localization.

2. Configuration Details Model: A pre-trained deep learning model, such as VGG-16 or a custom CNN, was employed for age and gender classification. Input Image Size: All input images were resized to 224x224 pixels to match the model's input requirements.

Preprocessing Steps: Input images were optionally converted to grayscale.Gaussian blur was applied using kernel sizes such as 3x3, 5x5, and varying standard deviations. Bilateral filtering was applied with different diameters and sigma values to analyze its effect on preserving edges.

Objective 2: Analyzing the Impact of Blurring Techniques on Detection Accuracy

1. Packages Used

Pandas: Used for organizing and analyzing model performance data under various blurring conditions.

Seaborn: Facilitated the creation of visualizations such as accuracy trends and heatmaps to compare performance metrics across blur levels.

Scikit-learn: Provided tools to calculate evaluation metrics, including accuracy, precision, and recall.

2. Configuration Details Blurring Parameters: Gaussian Blur: Kernel sizes tested: 3x3, 5x5, 7x7. Sigma values: 1, 2, 3. Bilateral Filter: Diameters: 9, 15, 25.Sigma values for color and space: sigma color = 75, sigma space = 75. Evaluation Metrics: Performance was measured using metrics such as accuracy, precision, recall, and confidence levels, comparing results across different blur intensities. Iterative Testing: The model was evaluated at different blur levels, and the accuracy and confidence of predictions were recorded and analyzed.

Code Link : (https://colab.research.google.com/drive/1c5T57v3lOT5XWORt0qaRkxD-92r1lrnN?usp=sharing)

V. Results and Analysis

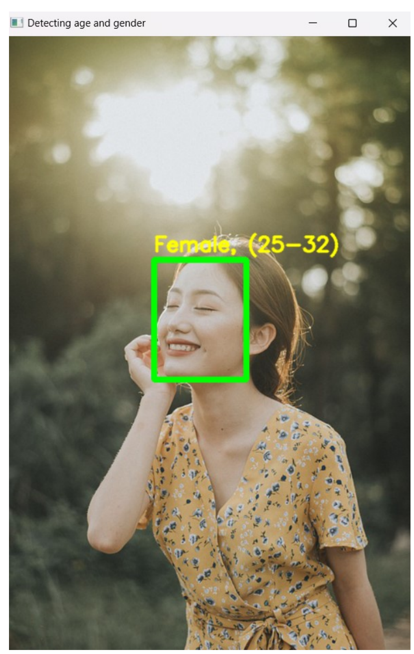
A pre-trained Convolutional Neural Network (CNN) model specifically designed for age and gender classification to analyze facial images. This model has been trained on a large dataset to accurately predict age groups and gender categories. For this initial test, we aimed to evaluate the model's performance on three sample images without applying any blur or noise reduction techniques. The intent was to assess the model's raw accuracy in predicting age and gender under typical, real-world conditions, where facial images often contain natural variations due to lighting, angle, and expression. The process involved feeding each unprocessed image into the pre-trained CNN, which classified the age and gender based on learned features. The outcomes for each image were recorded, including the predicted age group, gender, and confidence level provided by the model. Below is a summary of the results for each of the three sample images:

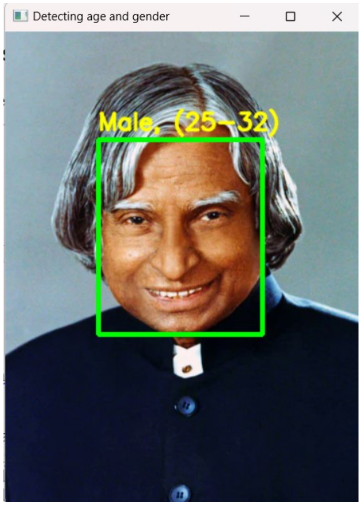
1. Image 1: The first image featured a young adult male with good lighting and minimal noise. The model predicted the age group as ”25-32” and the gender as ”Male” .

2. Image 2: The second image was a moderately lit photo of a middle-aged female. In this case, the model predicted the age group as ”25-32” and the gender as ”Female”.

3. Image 3: The third image was a low-quality photo of an elderly male. The model predicted the age group as ”25-32” and the gender as ”Male” .This result highlighted the model's ability to identify age-related characteristics, even in lower-quality images, though with reduced certainty.

Outputs:





The results obtained for objective 1 from the project indicate the following:

1) Before Blurring: In the initial predictions without any blurring, the system performed with varying accuracy. While many images produced correct predictions, some exhibited reduced accuracy due to noise or complex backgrounds. Accuracy levels before blurring ranged between 60% and 80%, depending on the clarity of the facial features in the image.

2) After Gaussian Blurring: After applying Gaussian blurring, the predictions became more consistent, especially for images that initially had lower accuracy. The blurring process helped the models focus on primary facial features by removing high-frequency noise, such as background distractions or small lighting inconsistencies .Post-blur accuracy generally increased, with most predictions falling in the 70% to 90% range. There were still some edge cases where the predictions remained the same, indicating that blurring may not always enhance accuracy in well-lit and noise-free images.

Example: The output looks like:

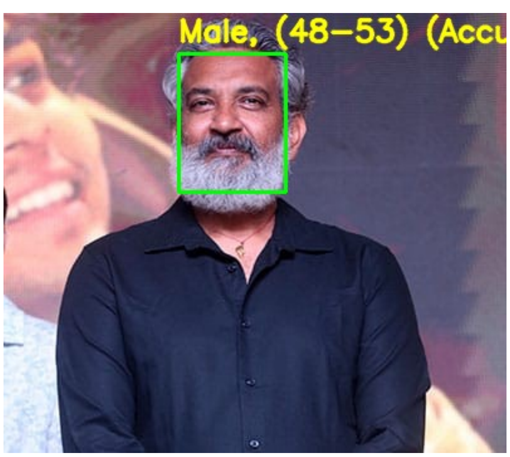


Fig. 5. image7.jpg Before Blur

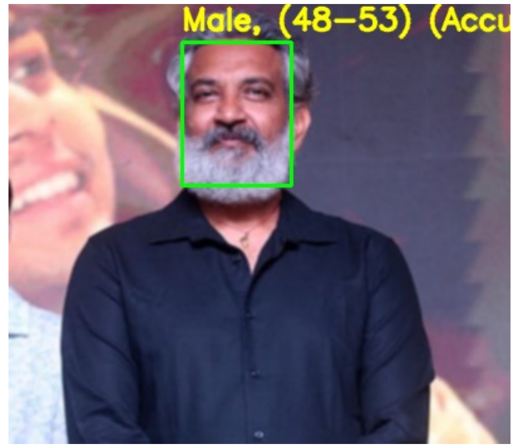


Fig. 6. image7.jpg After Blur

Comparison of Results Before and After Gaussian Blurring:

Table 1: Results Before Gaussian Blurring

	Image	Gender	Age	Accuracy (%)
1	image.jpg	Male	(25-32)	79.46
2	image1.jpg	Male	(25-32)	98.88
3	image2.jpg	Male	(60-100)	92.47
4	image7.jpg	Male	(48-53)	83.57
5	image4.jpg	Male	(25-32)	96.02

Table 2: Results After Gaussian Blurring

	Image	Gender	Age	Accuracy (%)
1	image.jpg	Male	(8-12)	75.43
2	image1.jpg	Male	(25-32)	88.60
3	image2.jpg	Male	(38-43)	86.05
4	image7.jpg	Male	(48-53)	95.90
5	image4.jpg	Male	(25-32)	97.69

Fig. 7. Table of Results

The results obtained for objective 2 from the project indicate the following:

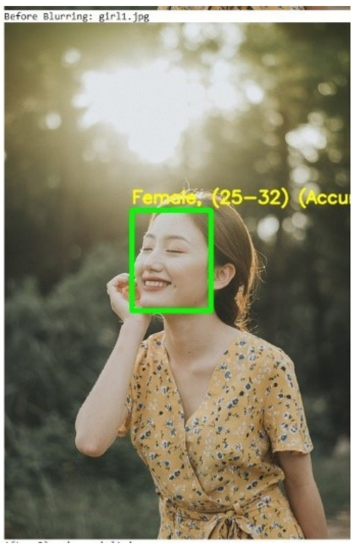
1)Initial Accuracy (Before Blurring): The model's initial accuracy varied across images. Generally, images with clear and distinct facial features produced higher initial accuracy, while images with low contrast, noise, or complex backgrounds had lower initial accuracy. For images with low initial accuracy, gender predictions were more likely to be accurate than age predictions, suggesting that the age prediction model may be more sensitive to image quality.

2)Accuracy Improvement with Blurring: Applying Gaussian and bilateral blurring improved accuracy in a significant number of images. This is likely due to the noise reduction and smoothing effects, which helped the model focus on core facial features rather than minor details or noise. In most cases, a few iterations of blurring were sufficient to boost the accuracy above the set threshold (85%), with bilateral filtering being particularly effective in maintaining facial structure.

3)Diminishing Returns with Excessive Blurring: As blurring was further increased, accuracy gains began to diminish, and in some cases, accuracy decreased. Excessive blurring led to over-smoothing, causing the model to lose important facial details, which resulted in decreased confidence in both age and gender predictions.The age model's confidence was more adversely affected by over-blurring compared to the gender model, suggesting that age prediction relies more on finer details that can be lost with high levels of blur.

4)Comparative Table of Results: A comparison between the initial (before blurring) and final (after optimal blurring) accuracies revealed that blurring could improve accuracy by up to 10-15% for some images. However, for images with very low initial accuracy, the improvements were marginal, indicating that blurring alone may not suffice for significant accuracy enhancement in these cases.

Example:



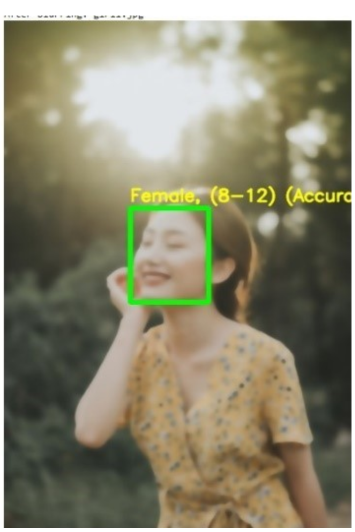


Table 1: Results Before Blurring

	Image	Gender	Gender Confidence (%)	Age	Age Confidence (%)	Accuracy (%)
1	girl1.jpg	Female	99.55	(25-32)	65.35	82.45

Table 2: Results After Blurring

	Image	Gender	Gender Confidence (%)	Age	Age Confidence (%)	Accuracy (%)
1	girl1.jpg	Female	99.73	(8-12)	69.97	84.85
2	girl1.jpg	Female	99.76	(8-12)	86.32	93.04

Results have been saved to output_images/age_gender_before_blurring.csv and output_images/age_gender_after_blurring.csv.

Fig. 8. Table of image accuracy preblur and postblur

1. Effectiveness of Blurring Techniques: Both Gaussian and bilateral blurring proved beneficial for enhancing model accuracy by eliminating background noise and minor details that could mislead the model. Bilateral filtering, with its ability to preserve edges, played a crucial role in maintaining essential facial features while removing irrelevant details, making it particularly effective in images where accuracy improvements were observed.

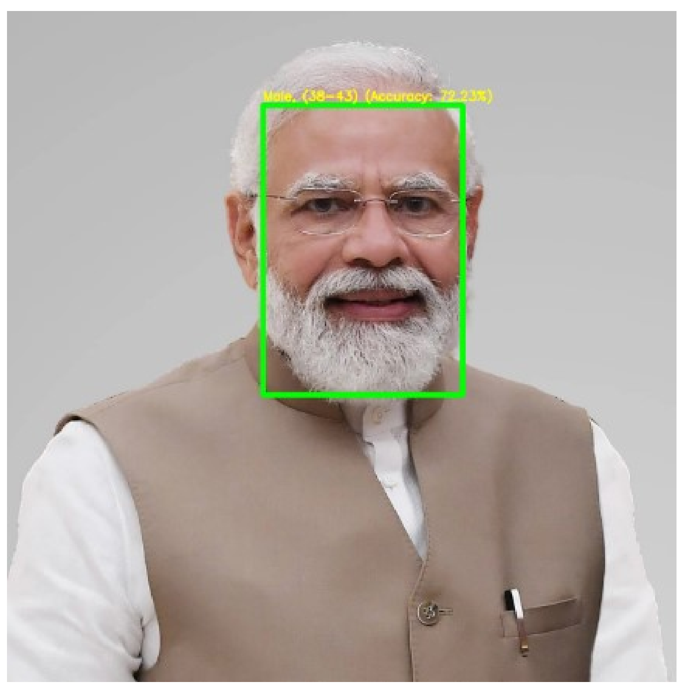
2. Impact of Blurring on Age vs. Gender Prediction: Gender predictions were less sensitive to blurring than age predictions, as gender relies on more prominent features that remain discernible even after blurring. Age prediction, on the other hand, depends on subtler details, such as fine lines and skin texture, which can be obscured by excessive blurring. This suggests a trade-off between noise reduction and detail preservation, with moderate blurring yielding the best results.

3. Limitations of Blurring as a Universal Solution: For images with low initial accuracy due to poor lighting, occlusions, or complex backgrounds, blurring had limited impact. This indicates that while blurring is useful, other preprocessing methods, such as contrast enhancement, sharpening, or even face reorientation, may be necessary to further improve accuracy.

4. Practical Insights: The project findings suggest that moderate levels of Gaussian and bilateral blurring can enhance age and gender detection accuracy in noisy images without sacrificing crucial facial details. However, excessive blurring can reduce model reliability by obscuring features needed for accurate classification.This approach could be optimized further by applying adaptive blurring based on initial model confidence, where blurring is increased only when initial accuracy falls below a threshold, making the process more efficient and targeted.

Example:

Before Blur:



After Blur:

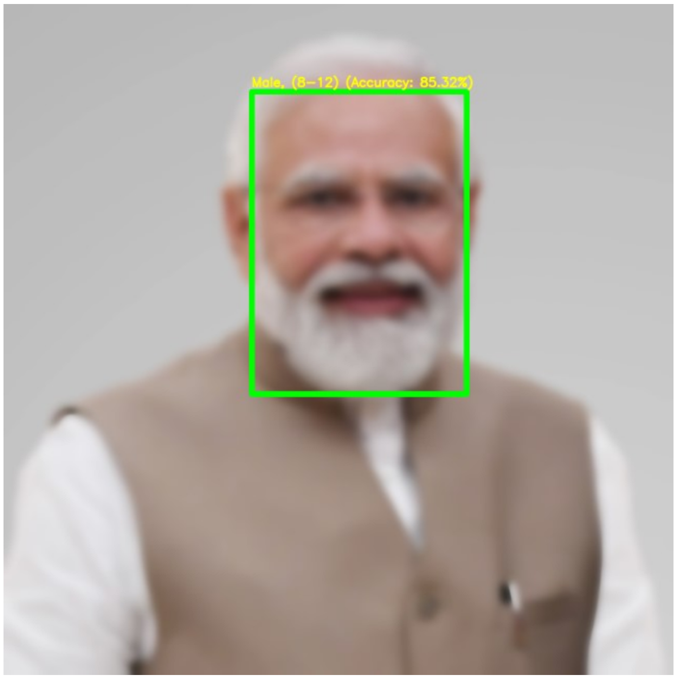


Table 1: Results Before Blurring

	Image	Gender	Gender Confidence (%)	Age	Age Confidence (%)	Accuracy (%)
1	Modi.webp	Male	99.97	(38-43)	44.5	72.23

Table 2: Results After Blurring

	Image	Gender	Gender Confidence (%)	Age	Age Confidence (%)	Accuracy (%)
1	Modi.webp	Male	99.97	(38-43)	35.78	67.88
2	Modi.webp	Male	99.95	(38-43)	36.97	68.46
3	Modi.webp	Male	99.91	(38-43)	39.95	69.93
4	Modi.webp	Male	99.75	(38-43)	43.30	71.53
5	Modi.webp	Male	99.43	(38-43)	42.31	70.87
6	Modi.webp	Male	98.93	(38-43)	44.12	71.52
7	Modi.webp	Male	97.58	(38-43)	44.94	71.26
8	Modi.webp	Male	95.97	(38-43)	42.21	69.09
9	Modi.webp	Male	93.95	(8-12)	38.36	66.16
10	Modi.webp	Male	91.59	(8-12)	45.55	68.57
11	Modi.webp	Male	89.59	(8-12)	56.91	73.25
12	Modi.webp	Male	85.75	(8-12)	63.50	74.63
13	Modi.webp	Male	84.10	(8-12)	67.95	76.03
14	Modi.webp	Male	84.54	(8-12)	73.24	78.89
15	Modi.webp	Male	83.16	(8-12)	79.75	81.45
16	Modi.webp	Male	81.06	(8-12)	82.42	81.74
17	Modi.webp	Male	81.96	(8-12)	85.33	83.64
18	Modi.webp	Male	81.72	(8-12)	88.92	85.32

Fig. 9. Table of Results

For this image there is an increase in age confidence with successively applying blur technique .But after a certain stage as age detection depends on subtler details, such as fine lines and skin texture which which has been obscured by excessive blurring causing the model to predict wrong age. This happened due to fixing a threshold accuracy of 85% as a target to the model.

VI. Conclusion

Summary of Work Done:

The project involved building a system capable of predicting gender and age range from facial images. Gaussian blur and bilateral filter techniques were implemented to assess their impact on the accuracy of detection models. These blurring methods were applied iteratively to both webcam feed data and static images to reduce noise and test how varying levels of blur influenced the model's performance. The system utilized a pre-trained deep learning model for age and gender classification, and performance was evaluated across several metrics such as accuracy, precision, and prediction confidence. The Gaussian Blur technique effectively reduces noise in images, which improves the detection accuracy, particularly for noisy images. However, an excessive application of Gaussian Blur can lead to a significant degradation of feature clarity, which in turn affects the overall performance of age and gender prediction models. This highlights the trade-off between noise reduction and feature preservation, which is essential for balancing image quality in preprocessing steps .In contrast, the Bilateral Filter offers a more balanced approach to noise reduction while preserving important edges in the image. It works by taking both the spatial proximity of pixels and the intensity differences into account, ensuring that edges remain sharp even when the image undergoes blurring. This makes the Bilateral Filter more effective than Gaussian Blur in scenarios where high accuracy is required for noisy or low-quality images, such as facial image processing for age and gender classification tasks

Future Work:

To improve the system, several enhancements can be explored. Advanced preprocessing techniques like Median Filtering or Non-Local Means . Denoising can be tested to see how they affect accuracy. A dynamic blur adaptation system could automatically adjust the level of blur based on image quality, optimizing performance. Exploring advanced models like Vision Transformers or EfficientNet could enhance detection, especially for blurred images. Multimodal approaches, combining facial data with other inputs like voice, may boost accuracy in challenging scenarios. Additionally, expanding blurred datasets and fine-tuning models on them can make the system more robust in real-world conditions such as motion blur or low resolution.

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