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Automated Gender and Facial Identification Using a Novel Evolutionary Algorithm

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Abstract: Systems for facial identification concentrate on comparing a person's face to a recognized identity or figuring out whether a face is unfamiliar. In order to assess distinctive facial traits like eye distance, nose shape, and face contours, these systems use advanced algorithms. Numerous uses for facial recognition exist, from access control and law enforcement to tailored services. It provides improved security safeguards, effective identity verification, and frictionless user interactions. However, examining several facial features and the way they work together might assist in determining a person's gender from face images. In this paper, we propose an approach particle swarm-optimized improved genetic algorithm (PSO-IGA). This approach is used for automated gender and facial identification. There are 840 men and 917 women in the audience dataset. For feature extraction, Principal Component Analysis (PCA) approaches are employed. The experiment parameters have been performed accuracy (98.2%), precision (95.1%), specificity (93.3%), recall (92.7%), and sensitivity (96.4%). When compared to the existing approach, the suggested methods are highly accurate. In summary, automated facial and gender recognition technologies have proven they have the power to change a number of sectors. They provide improved security, individualized service, and quick identity verification.

Keywords*: Automated, gender, facial identification, particle swarm-optimized improved genetic algorithm (PSO-IGA)*

1. Introduction

Clinical A number of ethical and security considerations, the technique of automatically detecting sex has lately gained a lot of attention. The number of photos uploaded to the Internet over the last ten years has grown almost exponentially. Technologists have been able to resolve computer vision issues that were previously insurmountable or unsolvable because of the fresh information they have acquired. Used to construct frameworks for facial recognition that are incredibly precise and powerful [1]. New digital technologies are increasingly incorporating the idea that the body and face are clear indicators of gender and sex. This change is particularly noticeable in computer vision studies and applications, more especially in automated body analysis and face analysis technologies, which use a wide range of machine learning techniques to identify and categorize features of the person's face and body [2]. In the fields of computer vision and artificial intelligence, facial recognition and gender discrimination have grown to be important research and development topics. Security, marketing, and human-computer interaction are just a few of the areas where gender may be automatically recognized and classified, as well as properly identified based on visual features [3].The process of recognizing and confirming an individual's identity based on their visual traits, on the other hand, goes beyond gender classification. Because of the possible uses in security, law enforcement, and tailored services, this topic has attracted a lot of interest.In many different industries, including healthcare and e-commerce, facial identification technologies may be used to detect criminals, monitor people in surveillance footage, or offer tailored experiences [4].To accurately define a person's gender, facial areas can be examined independently, and the results combined. The facial areas could be more forgiving of expression fluctuations than the entire face picture. For determining gender, this is useful. The many face features that have been employed in this study to classify people's genders are depicted in Fig.1.

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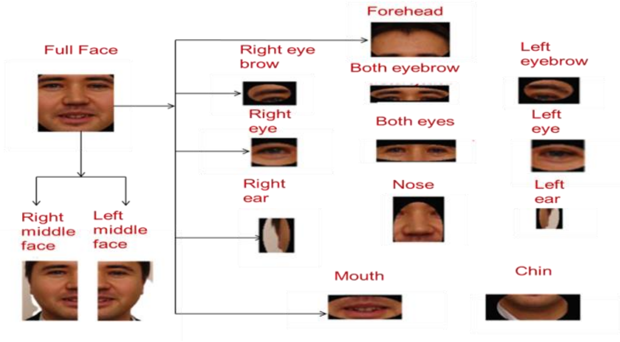

Fig.1. Facial regions that is likely to contribute to predicting the gender of a person

Given Faces are captured in facial photos or video data from a variety of sources, including databases, security cameras, and live video feeds. Finding and identifying faces within the frames of the photos or videos is the first stage. Face detection algorithms are employed to find and extract important face parts [5]. The capacity to automatically determine gender has applications in a variety of fields. Automated gender recognition in safety devices can help with access control by identifying men and women in real time. Giving demographic details regarding the gender distribution in a certain area can help improve surveillance activities. Additionally, automated gender recognition in marketing and advertising enables companies to customize their campaigns and product offers to particular gender demographics, resulting in more precise targeting [6]. Face recognition technology has the ability to completely transform many different sectors and businesses. It provides improved security measures and makes access management easier in business, governmental, and airport settings. It has also been used in law enforcement to help identify suspects and stop crimes from happening. Additionally, consumer gadgets have included face identification, allowing consumers to unlock their devices or verify payments using facial recognition [7]. Technology for gender identification has many real-world uses. It enables focused efforts that are catered to particular gender groups in marketing and advertising. It gives researchers in the social sciences and demography understanding of population dynamics and gender-related problems. User authentication systems may also employ gender identity, which may be used as an extra verification element [8].

The study [9] raised issues of discrimination and the escalation of pre-existing prejudices that online platforms keep reproducing and that literature is beginning to emphasize. Through a multidisciplinary approach that incorporates legal, computer science, and critical feminist media-studies viewpoints, the implications of misgendering on Twitter are investigated to illustrate the impact of algorithmic bias on unintentional privacy violations and reinforcement of social preconceptions of gender. This research [10] also explains the possible negative impacts that this might have on society. However, the paper largely focuses on voice-based conversational agents, and chatbots were not included in the analysis. As sensitive data is included in biometric systems like face recognition and the technology is frequently applied in unethical ways, this worry becomes even more relevant. They present a set of five ethical issues in the context of auditing commercial face processing technology, indicating extra design considerations and ethical tensions the auditor should be aware of in order to avoid aggravating or aggravating the harms caused by the reviewed system [11]. Based on digital scans of teeth, a completely computerized system has been created that can determine a person's gender and age. The process of identifying gender and age-related information from people is routinely carried out by analyzing orthopantomogram(OPG) images because teeth are a strong and distinctive component of the human body that exhibits the least subject to risk in natural structure and remains unchanged for a longer period of time [12].

The article [13] determined a person's gender based on appearance, conduct, and other characteristics. Raw face photos are not used in the proposed convolutional neural network (CNN) based strategy to learn the characteristics. First, highlighted pictures are created from raw photographs to represent a collection of significant qualities. The major goal of this experiment [14] is to evaluate an automated computer system built on deep learning's capacity to recognize not only people but also gender, age, and facial emotions like a grin in the eyes. The study [15] investigated if automation technology installation affects the career prospects of female seafarers and operators in the commercial marine sector. Through a qualitative investigation, a group of subject matter experts, including ship owners, maritime education and training providers, and shipboard officers, were asked to expound on the perceived impediments to female employment and the possibilities for it in the age of autonomous shipping. The study [16] examined forth a computer vision technology to help with the precise management of animals and enhance cattle wellbeing. This study integrates Additive Angular Margin Loss with RetinaFace-Mobilenet to create a unique face detection system called CattleFaceNet. The study [17] is crucial in determining each community fellow's interests in order to accomplish this aim. In reality, eliminating the gender gap across several disciplines depends critically on demographic characteristics like gender. This study examines the accuracy of various cutting-edge transformer-based models on the job of gender detection among CQA fellows.

2. Methodology

This section discusses automatic face and gender identification using the suggested approach. The method of automatically determining a person's gender based on their visual features is known as gender identification. Due to its potential uses in a number of fields, including security systems, marketing research, and human-computer interaction, this topic has attracted a lot of attention. Advanced algorithms can determine a person's gender with a high degree of accuracy by examining visual traits, including the jawline, brows, and lip shape. Technology for gender identification has the potential to lead to more individualized and inclusive experiences in a variety of sectors. The process of identifying and verifying people based on their facial traits is known as facial identification. Fig.2 depicts the method's flow. It seeks to identify if a face is known or unknown by comparing it to a person's face that matches a known identity in a database. Personalized services, access control, and law enforcement are just a few of the many uses for facial identification.

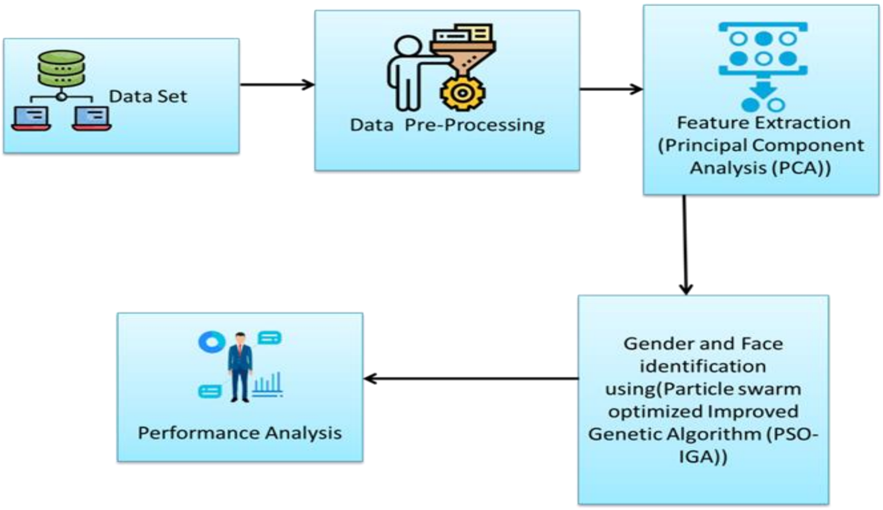

Fig.2. Flow diagram of the proposed method

2.1. Dataset

The adience dataset includes frontal and non-frontal face photographs of individuals from various nations, ethnicities, and age ranges. The dataset is provided with details. We overlooked the non-frontal photos in our study and only took into account frontal face photographs. Some kid facial photos, where the gender could not be determined by eye inspection, were left out of the study. Different lighting, backgrounds, occlusions, and expressions may be seen in the photographs. This study employed a collection of 1757 photos in accordance with the aforementioned procedure. There are 840 men and 917 women in total.

2.2Data pre-processing

The study, the Chehra model, was built to assist in the recognition of face landmark points. A fascinating challenge in computer vision is the creation and alignment of universal deformable models that can capture the changes of a non-rigid object, like the human face. Techniques are divided into two categories: generating techniques and discriminative methods, depending on how deformable models are built and how they are aligned. The challenge of modeling on the face is the deformable model's biggest concern. In order to represent the forms of entirely distinct facial photos acquired in unrestricted situations, the sparse face shape's generative model maybe trained using faces captured in confined environments.

2.3 Feature extraction using PCA

A crucial statistical method known as PCA is also referred to as an orthogonal linear transformation. In a dataset, this technique highlights variance and draws attention to prominent patterns. It is employed to condense a huge dataset into a smaller dataset that still retains almost all of the data from the larger dataset. Data mean and primary components are discovered using PCA. It is a common approach for dimension reduction. The method is typically applied to increase variation and identify prominent feature patterns in a dataset. PCA is a powerful statistical technique.

PCA is effective for correlated data. Another type of strongly connected data is a picture. PCA performs better when extracting features from images. The image matrix is subjected to several processes before being translated into a lower dimensions Eigen subspace. Then, using the matrix with the smaller dimension, get the covariance matrix. The covariance matrix is used to depict the relative variation among pixels in a picture. Afterward, this covariance matrix is used to create Eigenvectors. Principal components are those Eigenvectors with the greatest Eigenvalues. The following lists the steps in the PCA algorithm:

Algorithm 1: PCA algorithm

Step1: *Input data*

Step2: *Calculate the data's mean value*

Step3: *Take the mean value out of each input value*

Step4: *Create a matrix of covariance*

Step5: *Calculate the Eigenvalues and the Eigenvectors*

Step6: *Determining the highest eigenvalue*

Step7: *Calculate Weight*

2.4 Particle swarm optimized improved genetic algorithm (PSO-IGA)

2.4.1 Improved genetic algorithm

A type of evolutionary algorithm known as a genetic algorithm is frequently employed in machine learning to address both limited and unconstrained optimization issues. It is a soft computing method that mimics biological evolution by basing decisions on the results of natural selection. The solution to the issue is essentially a simulation of Darwin's theory of the survival of the fittest among people through many generations. Although genetic algorithms are randomized, they are not completely random; rather, they focus the search on areas of the search space where they perform best.

A population of people makes up each generation. Every member of the population serves as both a point in the search space and a potential answer to the issue. Each individual is represented by a finite-length vector of components or variables, often expressed in terms of an alphabet.

In order to retain the comparison to Darwin's theory, a solution is compared to a chromosome and the elements that make it up are compared to genes. Chromosome populations with corresponding fitness values make up the algorithm. The algorithm chooses people to have children to create the next generation's kids based on the fitness values of their chromosomes. An objective function establishes the value of fitness. This illustrates how natural selection works. After the selection process, the next stage is the two additional children produced by this generation are added to the population. To address the issue of local minima, mutation can be performed by randomly altering a few components of offspring. We have given an improved genetic algorithm-based solution for scoring various face areas in this research. The population has been randomly initialized. Where the weights are given to various faceareas$b_1, b_2, \dots . b_Q$. As the goal function is to reduce, the classification error has been taken into account. The linear weighted combination of identification scores has been used to determine the final class for each test sample. This is the equation we want to optimize in this issue, and it can be written as

$$\widehat{D} = \sum_{j=1}^{Q} b_j d_j \tag{1}$$

Where $b_j$is the weight given to the j^{th} classification block $d_j (j = 1,2 \dots . Q)$. The likelihood ratings for the j^{th} face area make upd_j. GA seeks to iteratively determine the ideal weights to increase classification accuracy.

2.4.2 Particle Swarm Optimization

A typical type of intelligent algorithm is PSO. Fish schooling or bird flocking social behavior has an impact on it. PSO uses a swarm of particles to scour the alternative spaces in pursuit of the ideal result. Considering the magnitude of the swarm N is represented as $= [w_1, w_2, \dots w_n]^s$, where S stands for the operator for transposing, the location of the j^{th} particle is defined as $w_j = \{w_{j1}, w_{j2}, \dots w_{jC}\}$, where C signifies a spatial dimension. The velocity of j^{th} a particle is described as $U_j = \{U_{j1}, U_{j2}, \dots U_{jC}\}$. At l^{th}iteration, the value of the function fitness $e\left(w_j^l\right)$ of each particle w_j^l is computed and put up against its own function fitness value $\{f\left(w_j^1\right), f\left(w_j^2\right), \dots f\left(w_j^{l-1}\right)\}$at the earlier iterations. Finding the best local candidates is the aim of this approachk_{best}. At the same time, $f\left(w_j^l\right)$is compared to the swarm members with the best fitness to find H_{best}. After identifying the top two answers (k_{best}) and (H_{best}), the particles will adjust their velocities and locations to move to the new places. To keep a remote movement away from l^{th} to (l + 1)th iteration of each particle w_j , secured is a restriction requirement for velocity updating. The velocity is therefore restricted to the range [U_{min}, U_{max}]. If the speeds are outside of this range, they will be required to accept either [U_{min} or U_{max}. Moreover, in case w_j breaks the rules of the boundaries ($w_j < w_{min}\ or\ w_j > w_{max}$) using the restricted velocities, a forced solution is obtained $w_j \epsilon [w_{min}, w_{max}]$must be designed to prevent a wasteful method for updating positions. The position update procedure is described in Eqs. (2) and (3).

$$\begin{cases} U_j^{l+1=xU_j^l+d_1q_1\left(K_{bwst,j}^l-W_j^l\right)+d_2q_2\left(H_{bwst,j}^l-W_j^l\right)} \\ U_{min} \leq U_j^{l+1} \leq U_{max} \end{cases}, \quad (2)$$

$$\begin{cases} w_j^{l+1} = w_j^l + U_j^l \\ W_{min} \leq W_j^{l+1} \leq W_{max} \end{cases} \quad (3)$$

Whereq_1 and q_2 represent two random vectors with values in the following range [0, 1]. d_1, d_2 are learning factors, the term $d_1q_1\left(k_{best,j}^l - W_j^l\right)$is the word for individual thought, which results in W_j moving closer to thek_{best}. The additional term $d_2q_2\left(H_{best,j}^l - W_j^l\right)$ is the concept of social cognition, and this indicates the exchange of knowledge and expertise on the swarm's optimum particle movement. The term wU_j^l is referred to as a vector introduced for widening the search space. $W$is a weight of inertia, take the impact of the preceding velocity into account U_j^l . If w is large, The particle is capable of veering considerably from the equilibrium position between$k_{best}$and H_{best}. In difference, if w is small, It implies that only the area surrounding the balancing position is taken into account. Usually, w is presented as shown in Eq. (4).

$$X = x_{min} + \frac{l^{Iter}}{max^{Iter}}(x_{max} - x_{min}) \quad (4)$$

$$x_{max} = 0.9, x_{min} = 0.4 \quad (5)$$

3. Result and Discussion

The results of the automated face and gender identification are presented in this section. In this study, we evaluate the suggested approach in comparison to existing methods such as Convolutional Neural Networks (CNN) [17], Multi-task Cascade Convolution Neural Networks (MTCNN) [18], and Long Short Term Memory (LSTM) [19]. The parameters include sensitivity, recall, F1-score, accuracy, and precision.

There have been notable improvements in the accuracy of facial recognition systems. Modern face recognition may reach accuracy rates of over 98.3% in controlled scenarios with images of excellent quality and favorable circumstances. However, real-world situations bring difficulties, such as fluctuations in lighting, position, attitude, and image quality, which might affect the effectiveness of these systems. It can be difficult to estimate gender correctly using face features in gender recognition systems.

$$Accuracy = \frac{(TP+TN)}{TP+TN+FP+FN} \quad (6)$$

The accuracy of the suggested and current methods is shown in Fig.3. Table 1 presents the results of the accuracy test. Despite the great accuracy rates that these systems may attain, the precise accuracy might vary depending on the algorithm and dataset used. To guarantee accurate and impartial results while resolving any potential biases or ethical issues, responsible creation and continuing enhancement of these systems are vital.

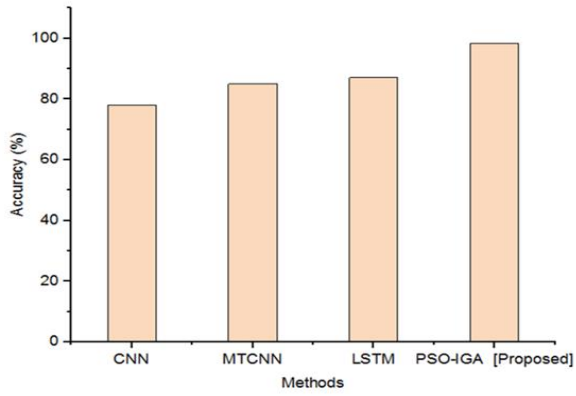

Fig.3. Accuracy of the proposed and existing method

Table 1: Outcomes of the accuracy

Methods	Accuracy (%)
CNN	78
MTCNN	85
LSTM	87
PSO-IGA [Proposed]	98.2

Effectiveness varies across gender identification systems as well, which try to identify a person's gender based on their visual traits. The robustness of the algorithms, the variety of the training data, and the precise visual traits are taken into account for gender categorizations are all variables that might affect how accurately gender identification systems work. Since gender identification relies on more subtle facial traits and can be impacted by things like haircuts, accessories, or cosmetics, it is often harder to achieve high accuracy in gender identification than in face recognition.

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

The precision of the proposed and existing methods is shown in Fig.4. Table 2 displays the precision test results.

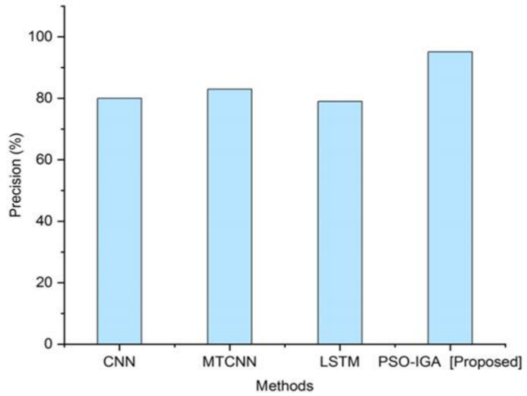

Fig.4. Precision of the proposed and existing method

Table 2: Results of the precision

Methods	Precision (%)
CNN	80
MTCNN	83
LSTM	79
PSO-IGA [Proposed]	95.1

The proportion of faces that were properly recognized out of all the faces that were expected to be recognized is represented by the recall value that results. A system that can identify faces more accurately and sensitively has a greater recall value, which also suggests a reduced percentage of false negative identifications. When evaluating the effectiveness of face identification systems, recall is frequently taken into account along with precision.

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

A collection of images of people with gender labels that is accurate in the actual world. Male or female should be indicated in each photograph. Fig.5 presents the recall of the proposed and existing method. Table 3 depicts the result of the recall.

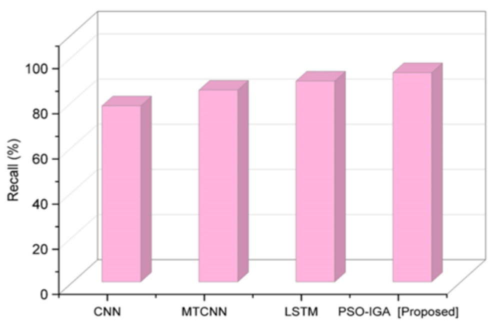

Fig.5. Recall of the proposed and existing method

Table 3: Results of the Recall

Methods	Recall (%)
CNN	78
MTCNN	85
LSTM	89
PSO-IGA [Proposed]	92.7

Sensitivity evaluates a system's capacity to accurately recognize faces as belonging to certain people in the context of face identification. Sensitivity in gender identification indicates how well a system can distinguish between male and female faces. In situations where accurately detecting positive instances is essential, including in security applications or medical diagnostics, sensitivity is particularly significant. However, in order to conduct a thorough analysis of the face and gender recognition systems, sensitivity must be taken into account in addition to other performance measures. Fig.6 denotes the sensitivity of the proposed and existing method. Table 4 denotes the comparison of the sensitivity.

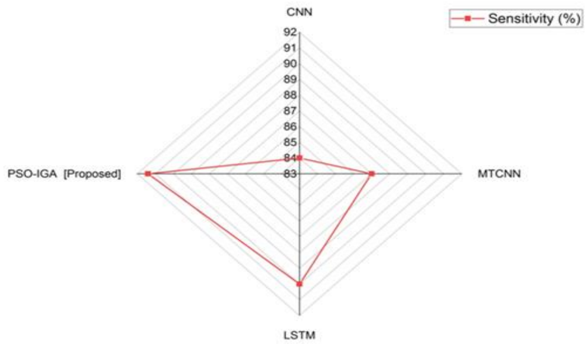

Fig.6. Sensitivity of the proposed and existing method

Table 4: Comparison of the sensitivity

Methods	Sensitivity (%)
CNN	84
MTCNN	87
LSTM	90
PSO-IGA [Proposed]	91.4

Specificity assesses the system's capacity to accurately reject faces that don't belong to certain people in the context of face identification. Specificity indicates how well a system can identify non-male or non-female faces in gender identification. In applications where accurately detecting negative instances is essential, such as lowering false positive identifications or preventing misclassifications, specificity is particularly significant. Figure 7 denotes the specificity of the proposed and existing method. However, in order to conduct a thorough analysis of the face and gender recognition systems, it is crucial to take specificity into account with other performance measures like precision, recall, accuracy, and F1 score. Table 5 denotes the outcomes of the specificity.

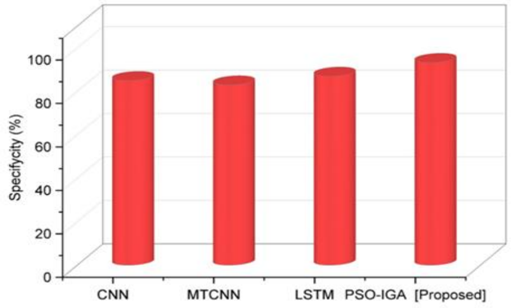

Fig.7. Specificity of the proposed and existing method

Table 5: Outcomes of the specificity

Methods	Specificity (%)
CNN	85
MTCNN	83
LSTM	87
PSO-IGA [Proposed]	93.3

4. Conclusion

Finally, automated face and gender identification systems have significantly improved in performance and accuracy, providing useful tools for a variety of applications. One of the difficult aspectsof image analysis and computer vision is face recognition. The algorithms for face recognition are carefully investigated using a variety of test photos and altering the settings and factors. When compared to current approaches, the suggested method provides a higher recognition rate. The suggested PSO-IGA based technique has reportedly attained a greater accuracy of 98.2% for face recognition. Future studies can concentrate on creating methods for gender and facial identification that protect privacy. This involves looking at ways to reduce the amount of sensitive face data that is stored and sent, such as by employing federated learning, secure multi-party computing, or differential privacy.

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