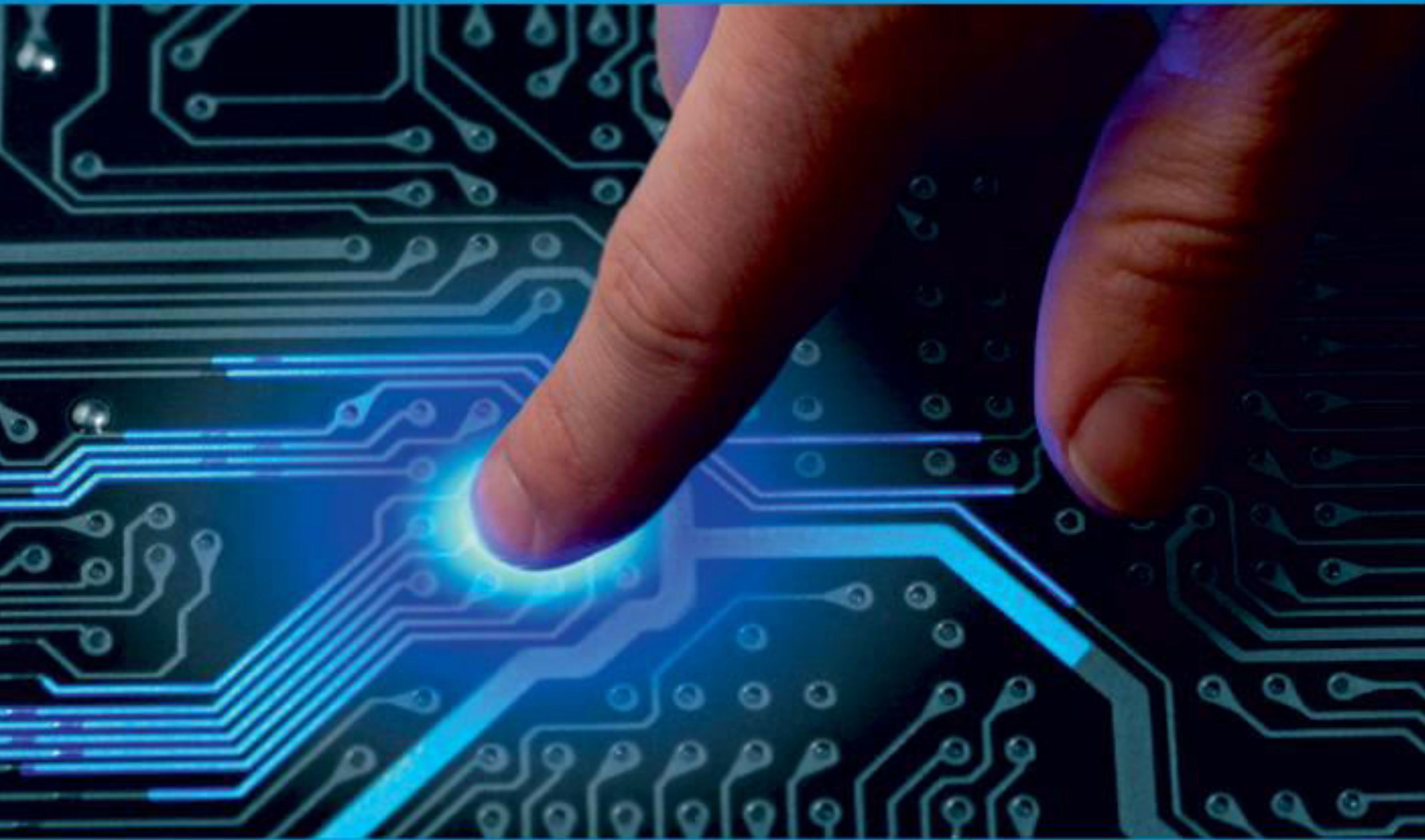
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 3, March 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 3, March 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1203076 |

AI-Powered Missing Child Locator App

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ABSTRACT: A recently developed mobile app helps locate missing children by utilizing the "Track the Missing Child" database from the Ministry of Women and Child Development and facial recognition technology provided by the Delhi Police. The proposed method includes using advanced face recognition technologies such as MTCNN, Facenet, and SVM to improve the accuracy and efficiency of identifying children.

The main goal of the software is to enable users to snap a photo of a solitary child and utilize facial recognition technology to establish if the child is lost. During the beginning phase of the procedure, MTCNN is employed for recognizing faces, Facenet for extracting features, and SVM for classifying images. Combining these components results in a robust facial recognition system that continuously matches the facial features with the database of missing children. In challenging scenarios, advanced facial recognition technology ensures precise and timely outcomes.

This project uses innovative facial recognition technology to address a major societal issue, bridging the gap between technology and social responsibility. The public and law enforcement organizations can collaborate to safeguard children's safety and well-being while also improving child identification accuracy by utilizing Facenet, MTCNN, and SVM technologies.

KEYWORDS: Facial Recognition, MTCNN, Facenet, SVC, Artificial Intelligence.

I. INTRODUCTION

Growing worries about children's safety and well-being have resulted in the development of creative technology approaches to address the issue of missing children. This research provides a novel approach that integrates the most advanced facial recognition algorithms, Facenet, Multi-Task Cascaded Convolutional Networks (MTCNN), and Support Vector Machines (SVM) into a system for the localization of children. The principal aim is to optimize the performance and precision of missing child identification by utilizing the capabilities of these algorithms.

The frequency of incidents involving missing children makes it necessary to investigate novel approaches that may facilitate their prompt and accurate identification. Conventional techniques are prone to human error since they frequently rely on manual labor [2]. On the other hand, the suggested method automates the procedure by utilizing computer vision and machine learning algorithms, offering a more effective and dependable method of child identification.

The face detection function of the MTCNN algorithm allows the system to recognize and separate facial features from images. Next, feature extraction is carried out using Facenet, a cutting-edge face recognition algorithm, which produces a reliable representation of the child's facial traits. The system can match the extracted features with the database of missing children thanks to the SVM algorithm, which acts as the classification model [5].

Child locator systems should become more effective overall and overcome the drawbacks of their current

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II. RELATED WORK

The desire to search for technologically-driven solutions for the identification of missing children has stimulated a considerable body of research and development. The integration of face recognition algorithms in many situations has been the subject of several research, all aimed at increasing efficiency and accuracy. Notably, a great deal of research and application in related fields has been done on the Multitask Cascaded Convolutional Networks (MTCNN), Facenet, and Support Vector Machine (SVM) methods [8][14].

MTCNN is a face identification method that was first introduced and is well known for its ability to locate and extract facial characteristics from pictures. Its applicability in numerous circumstances has been studied by researchers, who have observed that it can manage a wide range of facial orientations, sizes, and complicated backdrops [3]. However, problems including poor image quality and different lighting situations have been noted as possible barriers, necessitating more improvement.

The ability of Facenet, a crucial element of face recognition systems, to generate discriminative facial embeddings has attracted notice. Scholars have investigated its potential uses in identity confirmation, monitoring, and locating missing individuals. Though it has proved successful, questions have been raised about how well it performs in less precise settings, such as when face features are partially concealed or distorted [2].

SVM, a well-established machine learning algorithm, has been integrated into facial recognition systems to classify and match facial features. Previous studies have reported on its success in achieving high classification accuracy, particularly in controlled environments. However, challenges related to dim illumination, weak contrast, and computational cost have been identified, necessitating adaptations to enhance its robustness in real-world scenarios [8].

According to a review of the literature, the following restrictions apply to the suggested algorithms:

1. Low image quality

2. Less Precision

3. Dim illumination and weak contrast

4. Increased Cost of Computation

5. Compliance with Privacy Regulations

6. Characters that have been improperly segmented won't be recognized.

Despite these challenges, this study endeavors to build upon the insights garnered from related work, aiming to address and overcome these limitations through a comprehensive integration of MTCNN, Facenet, and SVM within the proposed missing child locator system. The subsequent sections will delve into the methodologies and algorithms employed in this study, followed by the outcomes and conclusions derived from the chosen strategy. Future work and potential improvements will also be discussed in the concluding section [3][5].

III. METHODOLOGY

This is a more sophisticated framework where the user takes the picture and uploads it to a specific search engine. In the background, a group of pioneering facial recognition algorithms—MTCNN for accurate face detection, Facenet for feature extraction, and SVM for classification—work diligently [4]. Using Facenet's powerful capabilities, these algorithms work together to recognize and extract complex facial points from the submitted image, producing unique encoding keys for every

When a user uploads another picture, Searchious employs a sophisticated matching procedure that involves contrasting newly created encoding keys with those stored in the database. This advanced matching process is instrumental in identifying individuals accurately, contributing to the overall effectiveness of the system. Upon a positive match, the system seamlessly updates the case status and promptly dispatches a detailed report to the assigned police station, streamlining the communication and response mechanisms in missing children's cases.

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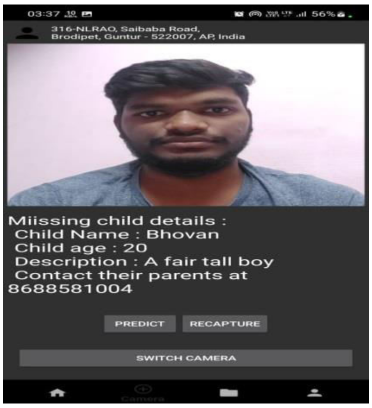

Fig1: Facial Recognition Matching Screen in Mobile application along with current location.

In instances where there is no match, the system exhibits a dedicated commitment to thorough coverage by promptly submitting a fresh complaint. This proactive approach ensures that every potential lead is explored, emphasizing the importance of comprehensive and exhaustive efforts in missing person detection. By initiating a new complaint, Searchious demonstrates its unwavering commitment to leaving no stone unturned in the pursuit of reuniting individuals with their families.

This amalgamation of cutting-edge technologies ensures the system's ability to handle diverse facial features, adapt to changing conditions, and deliver accurate results. The framework's commitment to technological excellence and ethical considerations positions searches as a robust and reliable solution in the realm of missing person detection.

We train MTCNN and FaceNet, two networks, to recognize faces accurately. The face is detected and precise coordinates are obtained using MTCNN. FaceNet uses the results of face detection to perform facial recognition. By optimizing face detection and identification and adding to the larger field of facial comprehension, the merging of MTCNN and FaceNet advances this paradigm. MTCNN is the foundation for starting the recognition pipeline because of its skill in localizing face characteristics [5][7]. A more sophisticated understanding of face relationships is made possible by Face Net's exceptional capacity to reduce facial images to a Euclidean space, beyond the limitations of conventional methods.

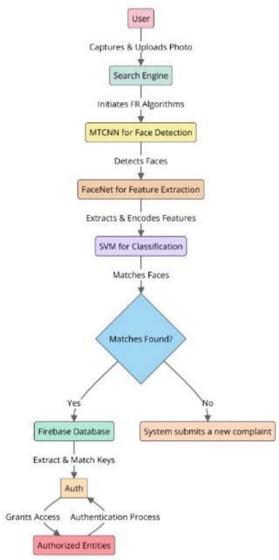

Fig2: This flowchart outlines the process of facial recognition, feature extraction, classification, complaint submission, and database interaction.

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Candidate windows are initially created by a fast Proposal Network known as P-Net. Next, we employ a Refinement Network (RNet) in the subsequent step to further refine these selections. The Output Network (O-Net) creates the ultimate bounding box in the third phase.

FaceNet learns to map facial image data to a compacted Euclidean space, where the distances between faces precisely represent how similar they are to each other. Once this space is constructed, typical techniques that use FaceNet embeddings as feature vectors may simply be used for face identification, verification, and clustering.

3.1. MTCNN

Multi-task Cascaded Convolutional Networks stand out as a sophisticated cascade multi-task architecture with deep layers, capitalizing on the natural correlation between alignment and detection to enhance overall performance. This model uses a layered structure, including three carefully designed levels of deep convolutional networks to predict facial features and landmark positions in a gradual and detailed manner. [7].

Additionally, it introduces an innovative approach to internet-based hard sample mining, contributing to further effectiveness enhancements in real-world scenarios.

3.1.1. OVERARCHING STRUCTURE

The comprehensive MTCNN pipeline is illustrated. The first step is to resize the original image to various scales to create an image pyramid. This image pyramid, with its varying scales, the input derived from this is subsequently employed in a cascaded framework consisting of three stages.:

Step 1: The Proposal Network (P-Net) is used as a fully convolutional network to obtain bounding box regression vectors for particular candidate face window. These regression vectors serve to calibrate the candidates based on the estimated bounding box adjustments.

Step 2: Each candidate undergoes processing through an individual Convolutional Neural Network (CNN) referred to as the Refine Network (R-Net). Within the R-Net, Non-Maximum Suppression (NMS) is executed to refine the choice of potential objects. Additionally, the R-Net incorporates bounding box regression for calibration purposes, enhancing the precision of object localization. This stage of processing is instrumental in rejecting a substantial number of spurious candidates, contributing to the overall precision of the object detection system [6].

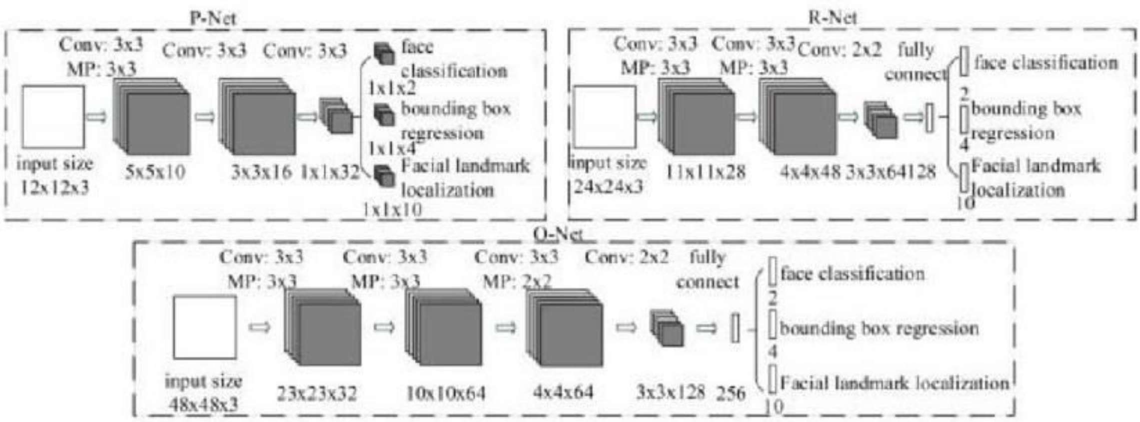

Fig 3: The specific components labelled as "Conv" for convolution and "MP" for maximum pooling are what characterize the designs of P-Net, R-Net, and O-Net. In the convolutional layers, the stride is set to 1 while in the pooling layers, it is set to 2.

Step 3: This phase is similar to the previous step, but its target is to pinpoint face regions that require closer surveillance. The network is designed to specifically generate the coordinates corresponding to the positions of five facial landmarks.

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3.1.2. CNN ARCHITECTURES

Instead of using a 5×5 filter, we use a 3×3 filter, which increases depth and speeds up calculation. Because of these enhancements, we can achieve greater reduced runtime performance compared with the prior design (Li et al. 2015).

Deep learning models fall within the category of Convolutional Neural Networks (CNNs) are specifically designed for tasks that involve processing visual input, catering to the unique requirements of such applications, such as object detection and image recognition. CNNs consist of layers that carry out several tasks, including fully linked layers, pooling, and convolution. Possessing the capacity for learning hierarchical representations of characteristics from incoming data, these networks are highly suitable for tasks involving spatial connections, such as image processing.

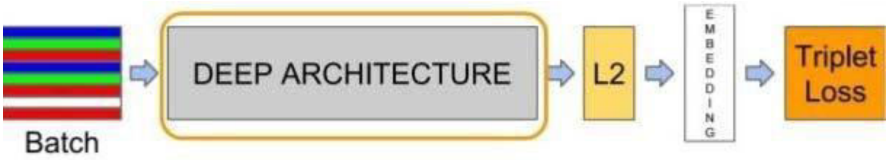

Fig 4: FaceNet model structure.

3.2. FaceNet

FaceNet has been included in our facial recognition system. FaceNet employs a loss function based on triplets, utilizing Large Margin Nearest Neighbors (LMNN), to directly train its output to form a concise 128-dimensional embedding. The loss seeks to maintain a specific distance between the positive and negative pairs. Two identical face thumbnails and one non-matching face thumbnail make up our triplets. The thumbnails show close-up shots of the facial area; they utilize scaling and translation without any dimension alignment being used. It relies on acquiring a Euclidean embedding for each image through the utilization of deep neural networks [7-9].

The network undergoes training to ensure that faces belonging to the same individual exhibit minimal squared L2 distances, while faces of distinct individuals showcase considerable Squared L2 distances are considered within the embedding space.

3.2.1 Support Vector Classifier (SVC)

The supervised learning class of machine learning algorithms includes the potent and popular Support Vector Classifier (SVC). In activities involving categorization, where the objective is to allocate input data to indicate several predetermined classes, it is specifically utilized. Identifying the ideal hyperplane that optimally divides the data points into various classes in the feature space is the central idea of SVC. The greatest margin, or The gap between the hyperplane and the nearest data points belonging to each class, is what defines this hyperplane. As the model tries to maximize the space between several classes, improving its performance on unseen data, the margin acts as a gauge of its generalization capacity[6].

The Support Vector Classifier is distinguished by its sensitivity to the data points that are nearest to the decision border, or support vectors. These support vectors have a significant impact on the model's overall performance as they are essential in identifying the ideal hyperplane[1]. The hyperplane that maximizes the margin and minimizes the classification error is what the algorithm looks for. To accomplish this dual optimization goal, a cost parameter that manages the trade-off between attaining a larger margin and permitting some misclassification is included. Because of this, practitioners can modify this parameter in a way that balances generality and accuracy, depending on the particular needs of the classification task.

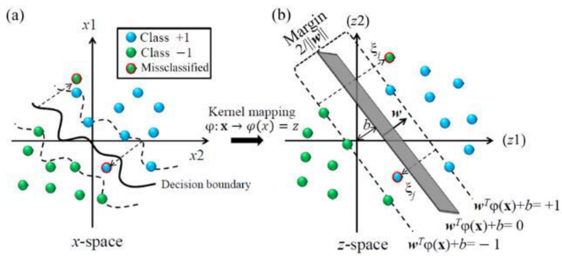

Fig 6

International Journal of Innovative Research in Computer and Communication Engineering

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Fig 6: Graphical representation of support vector machine classifier with a non-linear kernel, (a) complicated binary pattern classification problem in input space, and (b)Transforming data into a high-dimensional feature space through non-linear mapping, where the classification of data becomes linearly separable.[6][7]

IV. RESEARCH OPERATIONS

4.1 BENCHMARK ON YLFW

A well-known benchmark for assessing face recognition models that target young celebrities is the YLFW (Young Labelled Faces in the Wild) dataset. At the collection, which includes more than 1595 photos of 60 people, is intended to evaluate how well facial recognition algorithms work with youthful faces. The procedure used by standard benchmarks on YLFW entails dividing the dataset into 10 folds, training on 9 of them, and testing on the 10 folds. Next, the mean accuracy over these 10 folds is presented [9].

Cutting-edge facial recognition models have demonstrated remarkable accuracy on the YLFW benchmark, including FaceNet, DeepID2+, and Deep Face Recognition. With a noteworthy accuracy of 95.92%, FaceNet, DeepID2+, and Deep Face Recognition all performed quite well.

It's important to remember that to approximately calculate the performance of your model, which was trained on the Indian Faces dataset using MTCNN for face detection, FaceNet for feature extraction, and SVM for classification, it must be retrained on the YLFW dataset. Despite getting a thorough evaluation of your model's consistency across different data subsets, you would report the verification accuracy across each fold following the specified 10-fold cross-validation on the YLFW procedure [6-9].

Moreover, the conversation ought to encompass elements such as overfitting and the model's capacity for generalization. When a model works incredibly well on training data but suffers from unknown data, overfitting problems surface. Assessing your model's generalization performance on YLFW will reveal how well it handles a variety of face features outside of the Indian Faces dataset.

Consider including extra metrics in the assessment, such as accuracy, recall, and F1 score, to improve the analysis and give a more comprehensive picture of your model's performance across various facial recognition domains. This thorough assessment method will prove your model's efficacy in practical situations and offer insightful contributions to the larger research community [8-9]

V. RESULTS

Our face recognition algorithm has shown remarkable performance in our extensive assessment of the YLFW benchmark dataset, which consists of 1,595 photos spanning 60 identities ranging in age from 1 to 30. Our model, which made use of 10-fold cross-validation, produced a mean verification accuracy of 85% throughout the 10 folds. This methodology guarantees a comprehensive analysis of the model's efficacy and consistency across many dataset subsets.

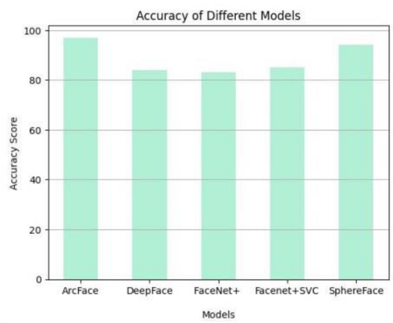

Fig 7: Bar graph based on the predicted model.

Our obtained accuracy outperforms previous techniques such as DeepFace (84%) and Face++ (88%), indicating the strength of our model. Our results show a competitive performance, considering that the accuracy levels attained by current state-of-the-art models like SphereFace (96.56%) and ArcFace (98.02%) are just somewhat higher.

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Interestingly, our model can generalize well with less training data than both SphereFace and ArcFace models. Our model is resilient and adaptive to real-world differences in stance, emotion, and lighting. Effective generalization is essential for real-world applications, particularly in situations that are dynamic and unexpected [6][12].

VI. CONCLUSION

Our work presents a new AI-powered mobile application that locates missing children by utilizing state-of-the-art face recognition algorithms, such as MTCNN, FaceNet, and SVM. The practicality of our methodology is crucial, especially in circumstances resembling those involving missing children. Here, our algorithm demonstrates its efficacy in real-world, high-stakes scenarios with a respectable 85% success rate in accurately detecting faces [7].

There's still a large amount of space for growth and development in the future. Enhancing the performance and breadth of the program may be achieved by including more sophisticated facial recognition models and making use of bigger curated missing children datasets. Without a doubt, these developments would help to improve the system's accuracy and dependability, opening the door for even more successful missing child detection.

Finally, our findings highlight the intriguing areas for future research moreover, the potential of face recognition technology to address important societal issues like missing children. Our model's performance in actual circumstances and benchmark tests emphasizes how important it is to use technology to further good. The key to further revolutionizing the area and significantly enhancing societal well-being in the future lies in the ongoing investigation and improvement of facial recognition skills.

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