ReUnite AI: Harnessing Face Detection and Age Progression for missing person identification

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***Abstract*—ReUnite AI is a system that has been engineered to address the extensive issue of missing individuals, by leveraging advanced face detection and age progression techniques.It offers a comprehensive solution catering to both the general public and law enforcement agencies. Deep learning algorithms are employed in the system to analyze and match facial features from input images against a database of missing individuals. ReUnite AI utilizes Principal Component Analysis (PCA) and Generative Adversarial Networks (GANs) to achieve accuracy and efficiency. System is integrated with age-progression model that generates realistic images depicting how a missing person might appear after a period of time thereby enhancing the identification process . This paper introduces a robust system and provides detailed implementation strategies, showcasing significant potential in locating missing persons.**

Keywords—Missing persons, Facial recognition, Age progression, Reunite AI project, Deep learning algorithms, Societal challenges

I. Introduction

Kidnapping emerges as the predominant cause for individuals being reported missing, with children under six being especially vulnerable. Within India, hourly statistics reveal a staggering rate of disappearance, with 88 women, children, and men disappearing, culminating in 2,130 individuals vanishing daily and 64,851 monthly.

The proposed system aims to address the critical issue of locating missing persons by utilizing advanced face recognition and age progression techniques. The system will accept images or videos as input, containing one or multiple faces, and compare them against a database of stored images of missing individuals. By integrating an age progression algorithm, the software will also predict the aging of the person if need be, further aiding in the identification process. The application targets both the general public and law enforcement, offering a powerful tool to expedite and optimize the search for missing persons and potentially bring closure to their families and loved ones.

At the heart of Reunite lies the utilization of PCA for dimensionality reduction and feature extraction, enabling the discernment of salient facial characteristics essential for accurate identification. By distilling complex facial data into its constituent components, PCA empowers Reunite to navigate the intricate nuances of facial recognition with precision and efficiency.

Complementing the discerning capabilities of PCA, Reunite harnesses the transformative potential of GANs in the realm of age progression modeling. GANs, with their unparalleled capacity to generate synthetic data through adversarial training, facilitate the creation of realistic and temporally accurate representations of individuals' appearances over time. Through the iterative interplay of generator and discriminator networks, GANs enable Reunite to envisage and forecast the progression of facial features with unprecedented fidelity.

The integration of PCA and GANs within Reunite underscores a commitment to innovation, efficacy, and ethical stewardship. Through rigorous experimentation and validation, we seek to elucidate the capabilities and limitations of our approach, ensuring its robustness across diverse demographic cohorts and aging trajectories. Moreover, we remain steadfast in our dedication to safeguarding the privacy and dignity of individuals involved in missing person investigations, upholding the highest standards of data protection and ethical conduct.

In this paper, we elucidate the pivotal role of PCA and GANs within the framework of Reunite, delineating their technical intricacies and practical applications within the context of missing person identification. Through empirical validation and case studies, we demonstrate the transformative potential of our approach in accelerating the pace of missing person investigations and fostering collaboration among stakeholders.

II. Related work

Vishakha et al. [1] present Searchious, a system combining an Android app for civilians and desktop software for police to enhance face recognition using the K-Nearest Neighbors (KNN) algorithm on the FaceScrub dataset. The architecture facilitates rapid tracking and tracing, alerting authorities and citizens. Citizens can upload photos for immediate cross-verification against the police database, initiating new cases. Employing KNN learning and Dlib for facial mapping, Searchious achieves around 59% recognition accuracy.

Lahaw, Essaidani, and Seddik [2] introduced a face recognition methodology integrating linear discriminant analysis (LDA), independent component analysis (ICA), principal component analysis (PCA), and support vector machines (SVMs). Evaluated on the AT&T Database comprising 400 grayscale face images of 40 subjects with

10 images per subject in varying poses, expressions, and scenarios including wearing sunglasses, their approach achieved 96% recognition accuracy. This was accomplished through a hybrid method employing the Discrete Wavelet Transform (DWT) coupled with either PCA or LDA for dimensionality reduction, followed by SVM classification on the reduced feature space.

Chen [3] introduces a Python-based system integrating motion sensors and face identification for detecting suspicious individuals and alerting authorities. The approach was evaluated on video recordings to assess detection efficiency.

N. Sabri et al. [4] conducted a comparative study on different machine learning algorithms. Multi-Layer Perceptron (MLP), Naive Bayes, and Support Vector Machine (SVM) for human face classification using geometric distance measurements. Their experiments showed Naive Bayes as the top performer with a classification accuracy of 93.16%, indicating its simplicity and robustness.

Jahan et al. [5] introduce a new security enhancement method for university premises using live video feed analysis and face detection. They propose a cascading monitoring system to detect human faces from video streams. Facial embeddings, derived from facial measurements using a deep residual network, serve as the primary feature set. A K-Nearest Neighbors (KNN) classifier is then utilized to classify these embeddings, enabling identification of individuals in the video feed.

A. Adouani et al. [6] provide an extensive comparison of three popular face detection methods: Histogram of Oriented Gradients (HOG), Haar Cascade with Linear Binary Patterns (LBP), and Support Vector Machines (SVMs). They assess these techniques using Python programming language with Dlib and OpenCV libraries. Results indicate that the HOG + SVM approach exhibits exceptional robustness and efficiency, surpassing both LBP and Haar cascade methods, achieving an impressive overall recognition rate of 92.68%.

Yadav and Singha [7] introduce an algorithm that aims to enhance the accuracy of facial landmark detection compared to the widely adopted Viola-Jones algorithm. Their proposed approach leverages the combination of detected facial landmarks to extract relevant features. The methodology involves acquiring input images and subsequently cropping seven significant facial regions. These cropped regions are then processed to retrieve and store features pertaining to facial expressions.

Firoz et al. [8] proposed a face recognition system employing the Linear Discriminant Analysis (LDA) algorithm, which is also utilized for dimensionality reduction. The authors provide a comprehensive analysis of the benefits and limitations of LDA in comparison to Principal Component Analysis (PCA), both of which are linear transformation techniques. The authors highlight LDA's ability to derive discriminative features more effective for classification tasks, such as face recognition, by explicitly considering class separability during the transformation process. This fundamental distinction in approach enables LDA to outperform PCA in scenarios where class discrimination is crucial, albeit at the potential cost of increased computational complexity.

H. S. Karthik [9] suggests a method that uses the Viola-Jones algorithm for facial detection and integrates it with Principal Component Analysis (PCA) for recognition. This approach achieves fast detection and high precision rates, evidenced by its evaluation on a dataset of over 1,000 images, where it achieved a notable 90% accuracy, albeit with some false positives. In the PCA framework, Eigenvalues and Eigenvectors are pivotal, indicating the variance retained by each principal component and defining their directions, respectively. By discarding principal components associated with small Eigenvalues containing insignificant information, the authors reduce feature space dimensionality, thereby enhancing computational efficiency without compromising recognition performance.

Sasankar and Kosarkar [10] introduce an upgraded face identification system, utilizing Principal Component Analysis (PCA) for both feature extraction and dimensionality reduction of facial images, along with the K-Nearest Neighbors (KNN) algorithm for data classification. The authors emphasize the importance of color information, which becomes crucial when images are captured under low illumination conditions. Their approach synergizes PCA's ability to derive compact yet informative feature representations from high-dimensional image data with KNN's proven efficacy in pattern classification tasks.

Z. Zhang [11] presents a Conditional Adversarial Autoencoder (CAAE) network designed for age progression and regression in facial images. It surpasses existing methods by generating photo-realistic faces while maintaining individual personality traits. Assessment, conducted on various datasets including Morph and CACD confirms CAAE's efficacy. Approximately 48.38% of participants in a survey deemed the generated faces indistinguishable from real ones, with 52.77% preferring CAAE over previous approaches. These results underscore CAAE's practical potential and its ability to tackle age-related tasks effectively.

Eric Patterson [12] introduces and evaluates age-progression techniques using the Wide Age-Range Progression (WARP) dataset, addressing the lack of standardized metrics. It compares AAMAP and AAMDT algorithms, with AAMDT generally outperforming in representing aging effects accurately. The study stresses the importance of standardized evaluations.

G. Antipov [13] introduces Age-cGAN, a GAN focused on preserving identity during face aging. Using the IMDB-Wiki dataset, it significantly improves identity preservation compared to traditional methods. Through experiments, it enhances face recognition scores, contributing to more reliable recognition systems across age groups.

Continued advancements in the application of Generative Adversarial Networks (GANs) for age progression have been demonstrated through recent research findings. [15] introduces a novel approach utilizing a multi-layered pyramid GAN architecture. In [16], a Conditioned Attention Normalization layer GAN is proposed, aiming to enhance performance in age progression tasks. Furthermore, [17] contributes to the field by enhancing the efficiency of the loss function through the integration of a ranking CNN algorithm alongside GAN methodologies. These developments underscore the ongoing refinement and innovation within the realm of GAN-based age progression techniques.

III. Proposed System

A. System Architecture

Now considering a scenario that explains the working of the system, a missing person, a young child disappears from a local park, prompting a frantic search. The authorities use the system to add recent photos of the child, which in turn the system stores in our database after analyzing it. The system also generates age-progressed images after the set threshold time. After two years, the child is found by the police. They use the system to check if the child's details match any in the missing people database. The system quickly identifies the child and provides information about the family to the reporting authority. As soon as the successful match is confirmed, the system immediately notifies the family that their child has been found and provides contact details of the officer who initiated the search, facilitating a swift reunion of loved ones.

In another scenario, a lost elderly person/child is found wandering at a busy railway station, bus stop or any crowded places trying to locate his family or relatives . Any common responsible citizen reports this case to a police officer, who uploads the person's details in the system along with its photograph . The system analyzes the information and matches it with a record in the missing people database. The system then provides the family’s information to the officer, who informs them that their loved one has been found. The system ensures that the family is immediately notified and given the contact details of the reporting officer.

ReUniteAI functions as an integrated platform designed to facilitate the identification of missing persons through a user-friendly interface. Users engage with the system as shown in Fig. 1, where they are either allowed to report a missing person by uploading an image of the person (a relative or a friend or just someone known) who has gone missing. As shown in Fig 2, the government officials who have come across the case of a missing person can check if the found missing person exists in the missing people database or not.

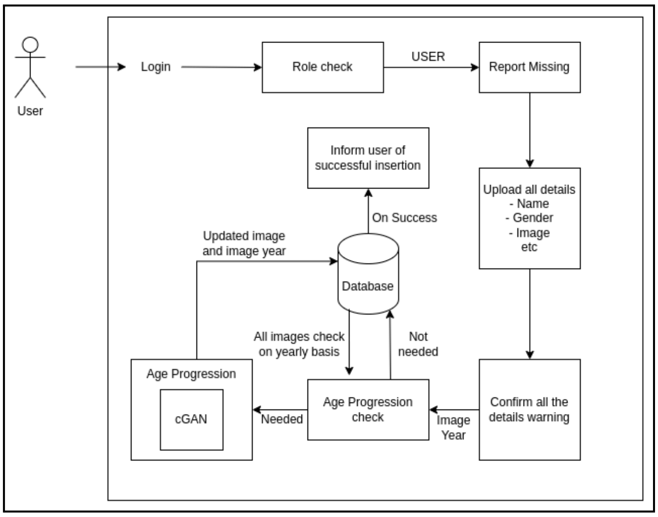

Fig. 1. Report missing person architecture

The System authenticates the users and they are given a role based on the credentials they provide, they can belong either in a normal user group or a government official group. Both the groups have different sets of actions that they are permitted to perform. The USER role can only be allowed to report a missing person and the ADMIN role is allowed to check if a found person exists in the missing people database or not. The credentials of users are very safe in this system as it uses BCrypt [18] Encryption technique to store their passwords.

Now, focusing on the Report Missing Person module, it encompasses several critical steps aimed at maximizing the accuracy of identification. It basically asks for all the details of the person who has gone missing, the details usually include full name, address, Aadhar card number, gender, age, image year, Place from where he or she is missing . Age is an important parameter while applying Age Progression on the image to generate an age-progressed image from the previous age to the current date's age. Lastly, image year is very important as it is the factor which helps to decide when to apply age progression. If the image we have been provided by the user is older than 5 years or it gets older than 5 years at some point whilst inside the database, age progression will be applied on the image to generate a newer image of the person . This progressed image will now be used for all the tasks of identification and further checking.

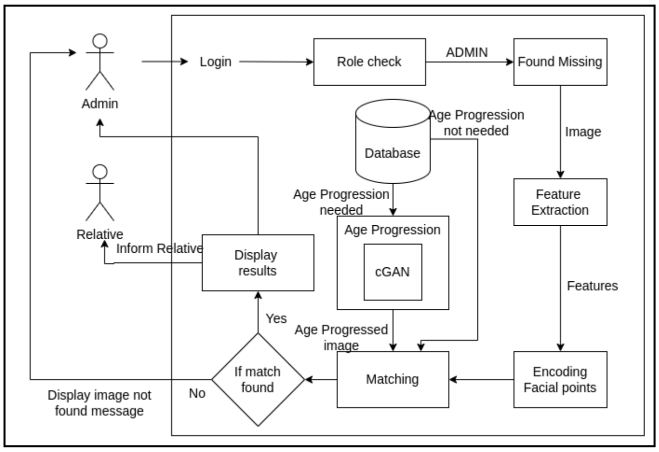

Fig. 2. Found missing person architecture

Fig 2. illustrates the process of handling missing/ abundant found cases. This might happen when such a person has no recollection of where he/she is from or who are his/her family members , their identification number, several etc.In such scenarios police have to try to find the person's details, they can look it up in the system's missing people database. They will just have to provide the image of the found missing person into the found missing people database and the system will perform all the checks. As soon as the ADMIN will provide the image to the system the facial recognition model comes into picture . It leverages advanced facial feature extraction methods to meticulously compare the uploaded image against a comprehensive missing persons database this database houses a repository of images and pertinent information regarding individuals reported missing. Through intricate comparison algorithms, potential matches are identified based on similarities in facial features and other relevant identifiers.

Upon completion of the identification process, if the match is found the system promptly displays the results to the Admin and notifies the User who had reported this person to be missing with the details of the Admin so User can get in contact. same for the Admin, it displays all the information about the missing person and the details of the relative who reported the person as missing. Conversely, if no match is established, the Admin receives a notification accompanied by a respectful message expressing regret for the inability to provide a positive identification. Throughout these interactions, the system maintains an unwavering commitment to efficiency and accuracy, ensuring timely feedback and facilitating the swift resolution of missing person cases.

B. Dataset

Dataset used for training and testing of the face recognition model is the Olivetti dataset [20]. Olivetti dataset is a well-known benchmark dataset in the field of face recognition and machine learning. It consists of a 40 collection of grayscale facial images of 40 distinct subjects, with 10 images per subject resulting in a total of 40 * 10 = 400 images in the dataset. Leave one out cross validation technique was applied for the training and testing of the age progression model.

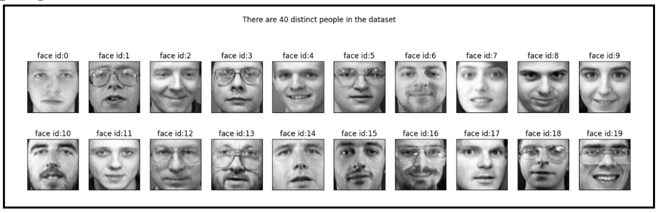

Fig. 3. Olivetti Dataset: Distinct images of 40 people.

For testing of the age progression model, and face recognition model, random images of celebrities sourced from the Celeb-A [21] and MillionCelebs [19] datasets were utilized specifically focusing on younger iterations of these celebrities.

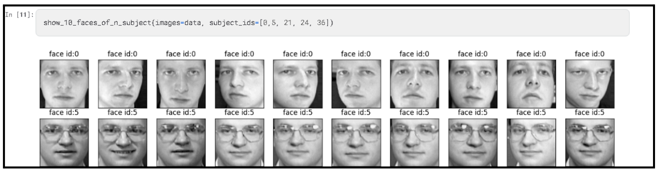

Fig 4. Olivetti Dataset: 10 images of each person.

C. Principal Component Analysis

To address the challenge of overfitting, which arises when a model attempts to capture intricate trends in densely populated data, a solution was introduced leveraging Principal Component Analysis (PCA). Overfitting occurs when a model becomes excessively complex, with numerous parameters, causing it to capture noise rather than signal, thereby hindering its generalizability to new datasets. PCA serves as a method of dimensionality reduction, particularly in extracting Eigenfaces, which represent the most prominent facial features. These Eigenfaces, depicted in Fig. 5, encapsulate the dominant characteristics of a face. The steps for implementing the PCA algorithm are elaborated by S. Sehgal [14].

Mean Calculation: Initially, the mean of the facial images is computed, capturing the shared characteristics across all images within the dataset. Consider a collection of facial images:

$$X = \{x1,\ x2,\ x3,\ ....\} \tag{1}$$

Where, x = Faces captured and X = Set of faces captured for a single person.

Standardization: The facial images undergo standardization by subtracting the mean face from each individual image. This normalization process yields distinct features, which are essentially the Eigenfaces. The calculation for normalization is as follows:

$$q = x - m \tag{2}$$

Where q is Unique features of a face, x is Face capture, m is Mean face.

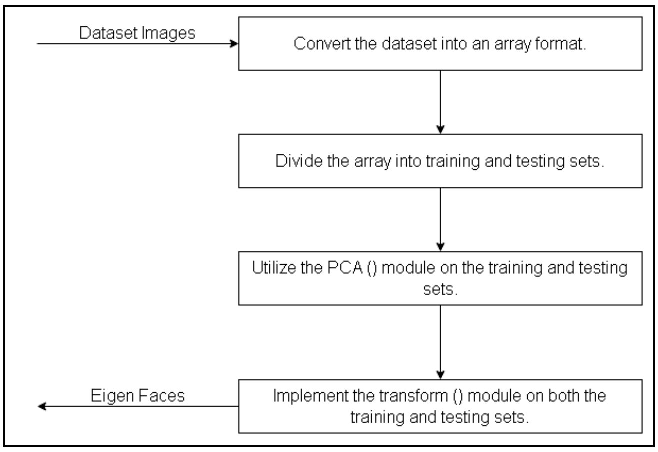

Fig 5. PCA Flowchart.

$$A = \{q1,\ q2,\ q3,\ ....\} \tag{3}$$

Where q is Standardized face with unique features, A is Set of Eigen Faces as depicted in Fig. 6.

Eigenvector Generation: The Eigenvector is derived from the covariance matrix, computed through the following procedure:

$$C = A * A^T \tag{4}$$

where $A = \{q1,\ q2,\ q3,\ ....\}$

Where, A is Eigenfaces. A^T is Transform of A, C is a Covariance matrix.

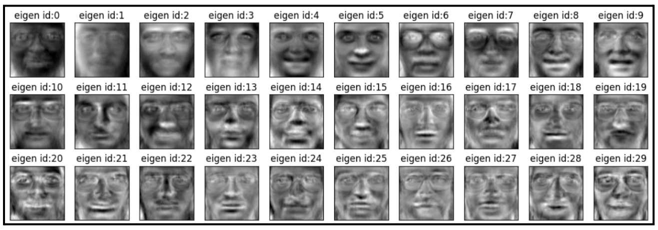

Fig. 6. Eigen Faces.

Organizing the matrix in descending order, the topmost vector corresponds to the Eigenvector with the highest Eigenvalue, representing the principal component. Upon obtaining the Eigenfaces, they are divided into training and testing datasets. The training and testing datasets encompass 75% and 25% of the total available Eigenfaces, respectively.

D. Linear Discriminant Analysis

Z. B. Lahaw and colleagues [2] introduce a methodology integrating Principal Component Analysis (PCA) followed by Linear Discriminant Analysis (LDA) to improve feature extraction and classification, as depicted in Fig. 7. Initially, PCA is utilized to decrease the data dimensionality and identify the top 90 principal components. This process efficiently captures the dataset's maximum variance while retaining crucial information, mitigating overfitting and improving generalization.

Following PCA, LDA is applied to further enhance the discriminative power of the features. Operating on the reduced dataset obtained from PCA, LDA aims to maximize the separation between different classes while minimizing within-class variance. By computing class means, within-class scatter matrix, and between-class scatter matrix, LDA identifies discriminant directions that effectively separate the classes and improve classification performance.

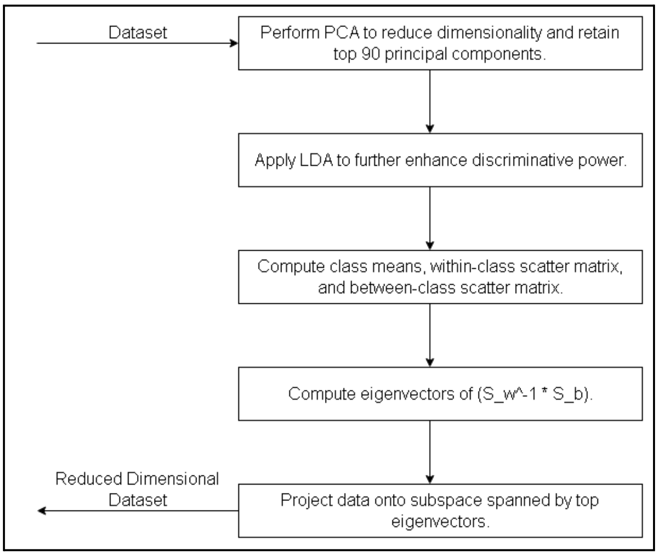

Fig. 7. LDA Flowchart.

Class Mean Calculation: Initially, the mean of features for each class is computed, capturing the average characteristics within each class:

$$\mu_i = \Sigma(x_i) / n_i \tag{5}$$

Where μ_i represents the mean of class i, x_i denotes the features belonging to class i, and n_i is the number of samples in class i.

Within-Class Scatter Matrix: The within-class scatter matrix is calculated to capture the spread of data within each class:

$$S_w = \Sigma\left(\left(x_{ij} - \mu_{ij}\right)\left(x_{ij} - \mu_i\right)^T\right) \tag{6}$$

Where S_w is the within-class scatter matrix, x_{ij} represents the j^{th} sample of class i, and μ_i is the mean of class i.

Between-Class Scatter Matrix: Similarly, the between-class scatter matrix is computed to measure the separation between different classes:

$$S_b = \Sigma\left(n_i * \left(\mu_i - \mu\right)^T * \left(\mu_i - \mu\right)\right) \tag{7}$$

Where S_b is the between-class scatter matrix, n_i represents the number of samples in class i, μ_i is the mean of class i, and μ is the overall mean.

The eigenvectors of the matrix $\left(S_w^{-1} * S_b\right)$ are computed to represent the discriminant directions, and the data is projected onto the subspace spanned by these eigenvectors. This projection focuses on the most relevant discriminant features, optimizing the classification process and improving accuracy. Overall, the combined use of PCA and LDA enhances feature extraction and classification performance, leading to improved accuracy and efficiency in pattern recognition tasks.

E. Conditional Generative Adversarial Networks

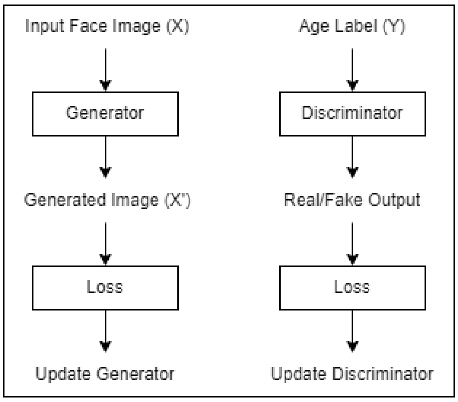

Fig. 8. cGAN Flowchart.

Zhang and colleagues [11] pioneered the use of Generative Adversarial Networks (GANs) with age labels for facial age progression. Fig. 8 illustrates the architecture and training methodology of a Conditional Generative Adversarial Network (cGAN) tailored for this purpose. The cGAN comprises two key components: the Generator and the Discriminator. The Generator takes an original face image and an age label as inputs to produce a new image representing the input face at the specified age. Meanwhile, the Discriminator evaluates the authenticity of generated images compared to real ones. This feedback loop guides both the Generator to create realistic images and the Discriminator to refine its ability to differentiate real from fake images. The training process involves iteratively updating both networks based on their performance loss until the Generator can produce convincing images aligned with the specified age labels, while the Discriminator struggles to distinguish between real and generated images. Through this adversarial training, the cGAN learns to generate facial images that accurately portray the aging process.

IV. RESULTS AND EVALUATION

A. *Results*

In analyzing the outcomes of the face recognition and age progression it's imperative to delve into the results and evaluations obtained. The following presents a comprehensive overview of the findings and performance metrics garnered from the implemented machine learning models. It displays an example set of images from the missing people database. Along with the images the matching accuracy of the target image with all the missing people images by the facial recognition model is also displayed.

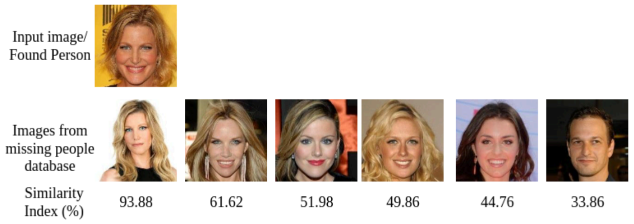

Fig. 9. Face Recognition demonstration

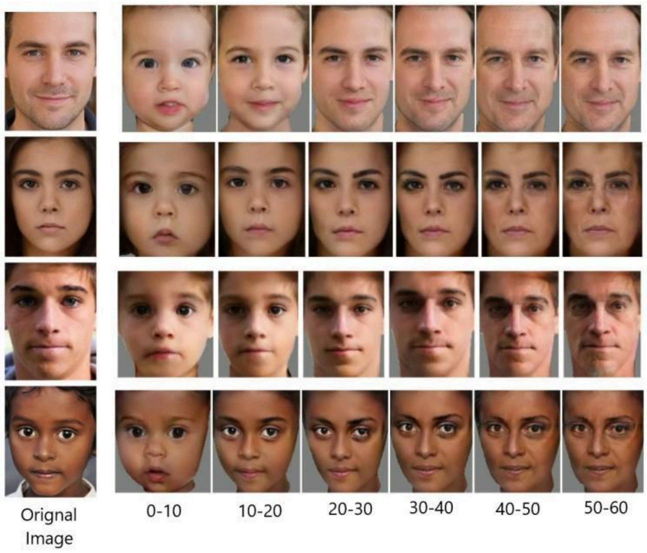

Fig. 10. Age Progression demonstration

Fig. 9 illustrates a single example of matching an input image of a found person with a missing person database. These images were taken from the Celeb-A dataset [21]. The image that crosses the threshold (similarity index 85%)and has the highest similarity index is displayed as match found , if no image crosses the threshold the results will be no match found then it will .Further tests were performed on the facial recognition algorithm by using images of from the Olivetti dataset [20] that were not part of the training data. The face recognition algorithm achieved a 93% accuracy rate by correctly identifying True Positives and True Negatives while minimizing False Positives and False Negatives. This evaluation utilized images from the Celeb-A dataset to assess the algorithm's performance in recognizing faces.

Fig. 10 illustrates the functionality of the age progression module. The images are generated in various age groups. These images were sourced from MilionCelebs [19].

Evaluating the system as a whole required collecting older images of various celebrities, around 10 years older, from various sources like MilionCelebs [19] and Celeb-A dataset [21]. In Fig. 11 an example of comparing the current images of celebrities with the age-progressed version of their old images by using age progression algorithm and comparison with help of face-recognition algorithm is represented. In our test with 30 images, it was found that, on average, the similarity score was 84.80%.

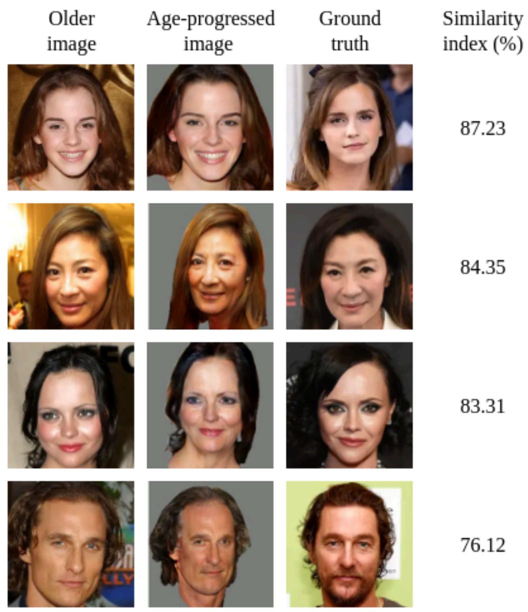

Fig. 11. Similarity index of age progressed images

B. *System Screenshots*

The ReUnite AI system facilitates two primary functions for its users: reporting a missing individual and reporting a found missing whose details necessitate verification. When users report a missing person, they are prompted to provide the individual's name, age, gender, Aadhar card details, and the most recent available image, as illustrated in Fig. 12.

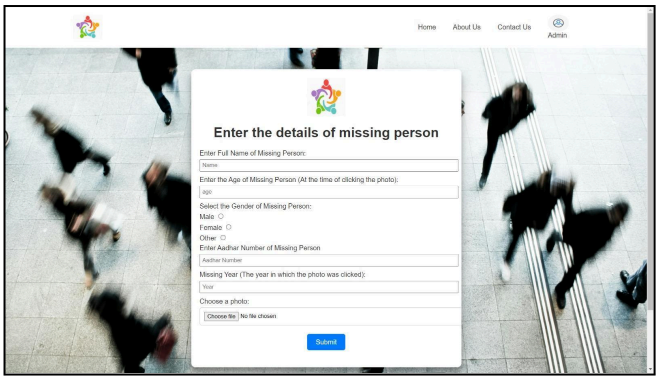

Fig. 12. Reporting missing person

Fig. 13. Displaying information in case of match found

Conversely, when admin reports for a found abundant individual, they have to submit the image of the individual. Subsequently, users are promptly notified of any matches or the absence thereof, as depicted in Fig. 13 and Fig. 14.

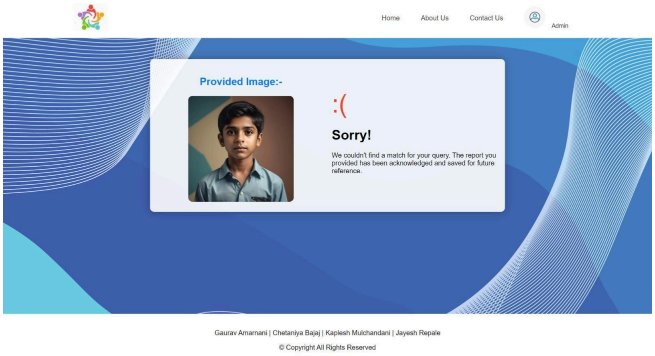

Fig. 14. Displaying results in case of no match

V. Conclusion and Future Work

In summary, the Reunite AI project represents a beacon of hope in utilizing advanced technologies such as facial recognition and age progression to tackle the challenge of locating missing individuals. By incorporating these methods, our system serves as a powerful tool for both law enforcement agencies and humanitarian organizations, facilitating the reunification of missing persons with their loved ones and communities. Our ongoing efforts are directed towards continuous refinement, focusing on improving algorithms for more precise face detection and exploring sophisticated age progression techniques to generate realistic depictions.

This system can be extended by Exploring ways to integrate live social media feeds, CCTV footage, and other surveillance data that would enable the system to provide more immediate and accurate updates on missing persons. By employing advanced data fusion techniques and enhancing machine learning algorithms for real-time analysis, ReUnite AI could enhance the it's effectiveness in dynamic situations.

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