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

Mrs. Yugchhaya Galphat
Department of Computer Engineering
Vivekanand Education Society's
Institute of Technology
Chembur, India
yugchhaya.dhote@ves.ac.in

Mr. Gaurav Amarnani
Department of Computer Engineering
Vivekanand Education Society's
Institute of Technology
Chembur, India
d2020.gaurav.amarnani@ves.ac.in

Mr. Chetaniya Bajaj
Department of Computer Engineering
Vivekanand Education Society's
Institute of Technology
Chembur, India
2020.chetaniya.bajaj@ves.ac.in

Mr. Kaplesh Mulchandani
Department of Computer Engineering
Vivekanand Education Society's
Institute of Technology
Chembur, India
d2020.kaplesh.mulchandani@ves.ac.in

Mr. Jayesh Repale
Department of Computer Engineering
Vivekanand Education Society's
Institute of Technology
Chembur, India
d2020.jayesh.repale@ves.ac.in

***Abstract*—The Reunite AI project aims to facilitate reconnecting missing individuals with their families by leveraging facial recognition and age progression technologies. Reunite employs deep learning algorithms to analyze facial features of missing persons and generate updated representations of their appearances over time using age progression models. The system is trained on a comprehensive dataset of facial images to ensure robust performance across diverse demographics and aging trajectories. The core components include principal component analysis (PCA) for facial recognition and generative adversarial networks (GANs) for age progression modeling. Rigorous evaluations and case studies demonstrate Reunite's efficacy in identifying missing persons across varying age ranges and temporal intervals. This integration of state-of-the-art technology addresses the critical societal challenge of missing person identification.**

Keywords—Missing persons, Facial recognition, Age progression, Reunite AI project, Kidnapping, 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

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 upload images of missing individuals or those they suspect might be missing. Upon image submission, the system initiates a series of automated processes to analyze the uploaded content.

The system authenticates the user and then proceeds to process the uploaded image. This processing phase encompasses several critical steps aimed at maximizing the accuracy of identification. The system begins by evaluating the age of the uploaded image, discerning whether it exceeds a threshold of 5 years. For images older than 5 years, the system engages sophisticated age progression techniques to generate an updated image that reflects the potential appearance of the individual at the current time. This augmented image is juxtaposed with the original for comprehensive comparative analysis.

Conversely, if the uploaded image falls within the 5-year timeframe, the system forgoes the age progression step and instead directly employs facial recognition algorithms. Leveraging advanced facial feature extraction methods, the system meticulously compares the uploaded image against a comprehensive Missing Persons Database as mentioned in Fig. 1. 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.

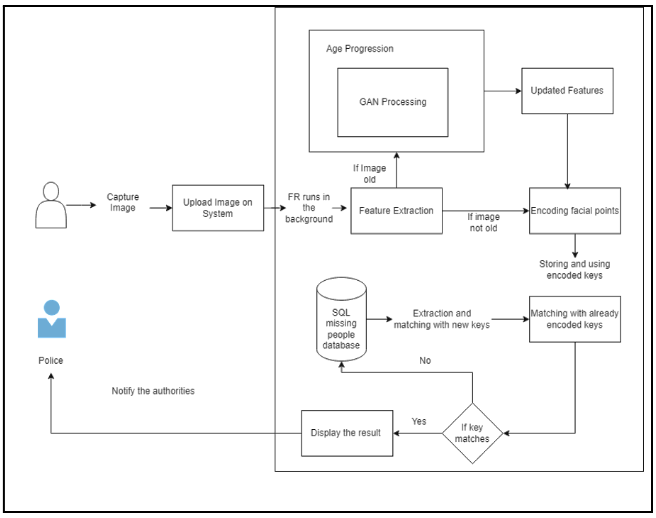

Fig. 1. ReUnite AI: System Architecture.

Upon completing the identification process, the system promptly notifies the user of the outcome. In cases where a match is found, the user is promptly informed, and simultaneous notifications are dispatched to relevant authorities, expediting further investigative procedures. Conversely, if no match is established, the user 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 the model is the Olivetti dataset. Olivetti dataset is a well-known benchmark dataset in the field of face recognition and machine learning. It was created by AT&T Laboratories Cambridge and consists of a collection of grayscale facial images of 40 distinct subjects, with 10 images per subject. Each image is 92 pixels wide and 112 pixels tall, resulting in a total of 40 * 10 = 400 images in the dataset.

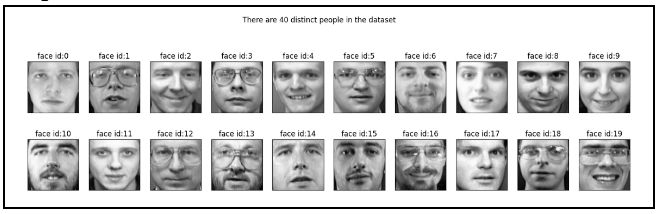

Fig. 2. Olivetti Dataset: Distinct images of 40 people.

The images were captured in a controlled environment, with consistent lighting conditions and facial expressions. Each subject was photographed under different poses, lighting conditions, and facial expressions, to test the robustness of face recognition algorithms. Fig. 2 and Fig.3 each represent the images of different people and the distinct images of those people respectively.

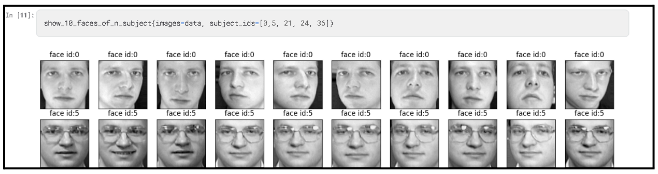

Fig 3. Olivetti Dataset: 10 images of each person.

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:

$$X = \{x1, x2, x3, ...\} \quad (1)$$

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.

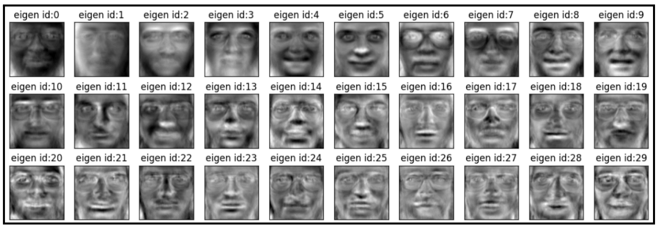

Fig. 4. Eigen Faces.

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

Where q is Standardized face with unique features, A is Set of Eigen Faces as depicted in Fig. 4.

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.

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.

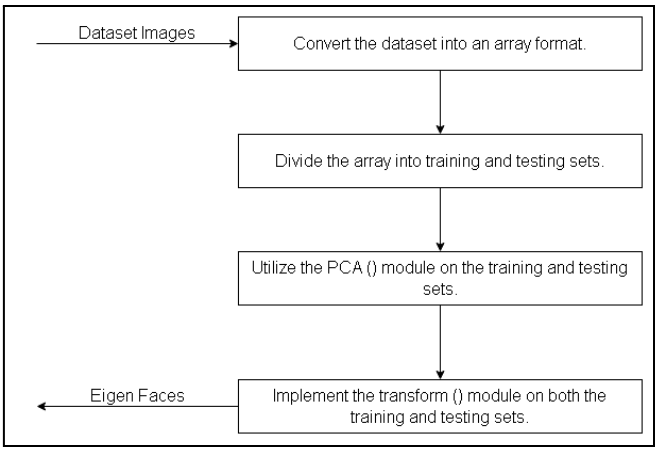

Fig 5. PCA Flowchart.

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. 6. 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.

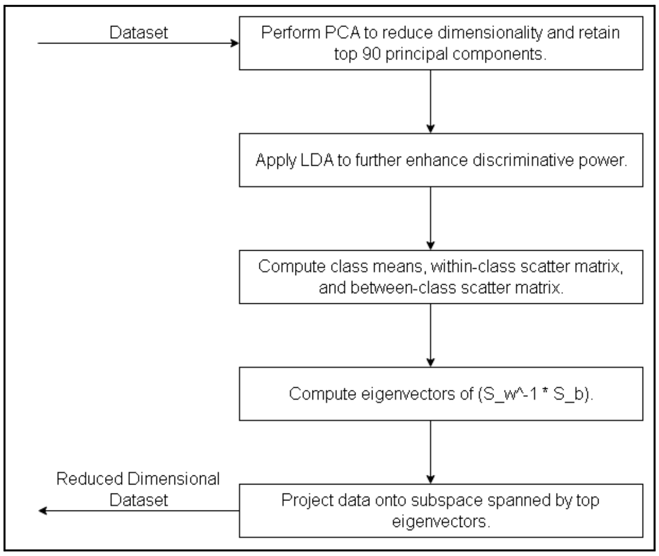

Fig. 6. LDA Flowchart.

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

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

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

Zhang and colleagues [11] pioneered the use of Generative Adversarial Networks (GANs) with age labels for facial age progression. Fig. 7 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.

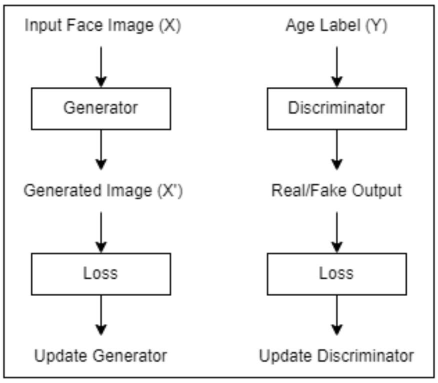

Fig. 7. cGAN Flowchart.

F. Use Case Demonstration

The ReUnite AI system facilitates two primary functions for its users: reporting a missing individual and reporting a found person whose details necessitate verification. When users report a missing person, they are prompted to provide comprehensive information including the individual's name, age, gender, Aadhar card details, and the most recent available image, as illustrated in Fig. 8. This data undergoes thorough validation processes before being securely stored within the missing persons database.

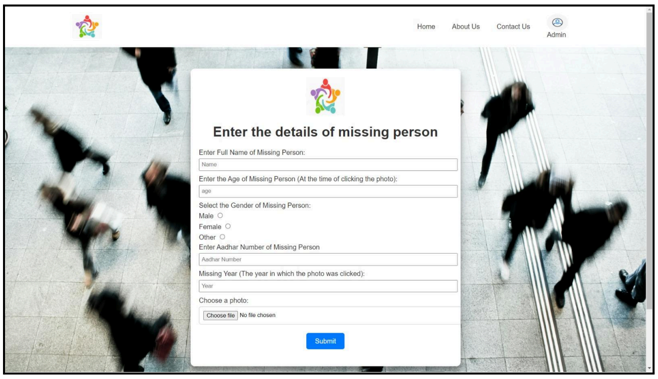

Fig. 8. Reporting missing person

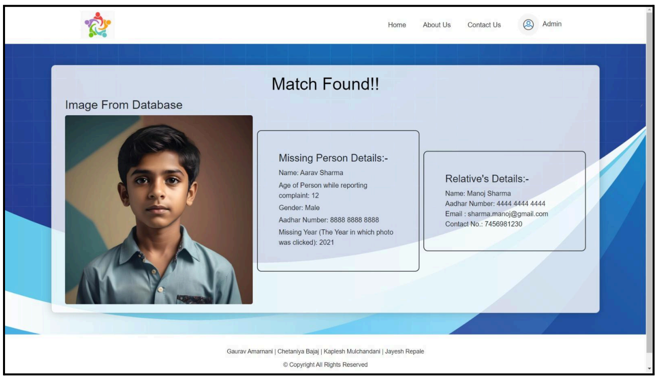

Fig 9. Displaying information in case of match found

Conversely, when users report for a found abundant individual, they have the option to submit up to 10 images of the individual. The system then utilizes these images to undergo training, aiming to achieve optimal accuracy in determining whether the found person matches any existing entries within the missing persons database from either the image provided by the relatives of the missing person, or the age progressed version of that image based on how old the particular image is. Subsequently, users are promptly notified of any matches or the absence thereof, as depicted in Fig. 9 and 10. Additionally, users have the flexibility to choose whether they wish to receive notification via email regarding any matches, instead of viewing the information directly on the interface.

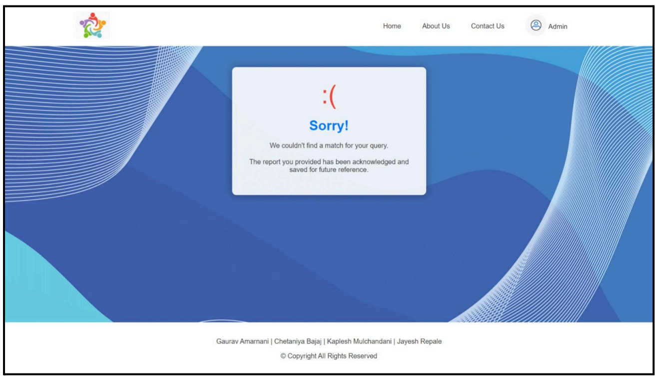

Fig 10. Displaying results in case of no match

IV. Results and Evaluation

In analyzing the outcomes of the face recognition and age progression project, 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.

TABLE I

Results for various machine learning models

Machine Learning Algorithm	Accuracy score
Linear Discriminant Analysis (LDA)	0.93
Linear Regression (LR)	0.93
Naïve Bayes (NB)	0.86
K-Nearest Neighbour (KNN)	0.70
Decision Tree (DT)	0.66
Support Vector Machine (SVM)	0.92

The classification results for various machine learning models applied to the dataset are as compared in TABLE I. Linear Discriminant Analysis (LDA) and Logistic Regression (LR) achieved an accuracy score of 0.93, showcasing robust classification performance. Gaussian Naive Bayes (NB) exhibited a slightly lower accuracy score of 0.86, while K-Nearest Neighbors (KNN) and Decision Trees (DT) yielded less effective results with accuracy scores of 0.70 and 0.66, respectively. Support Vector Machines (SVM) demonstrated strong performance with an accuracy score of 0.92. Cross-validation scores further validated the models' performance, with LDA achieving the highest mean score of 0.98, followed by LR with 0.93. NB, KNN, DT, and SVM yielded mean cross-validation scores of 0.79, 0.68, 0.50, and 0.86, respectively. Additionally, the Linear Discriminant Analysis model attained an accuracy score of 0.93 when applied to the test data. These findings offer insights into the comparative effectiveness of different machine learning algorithms for the classification task.

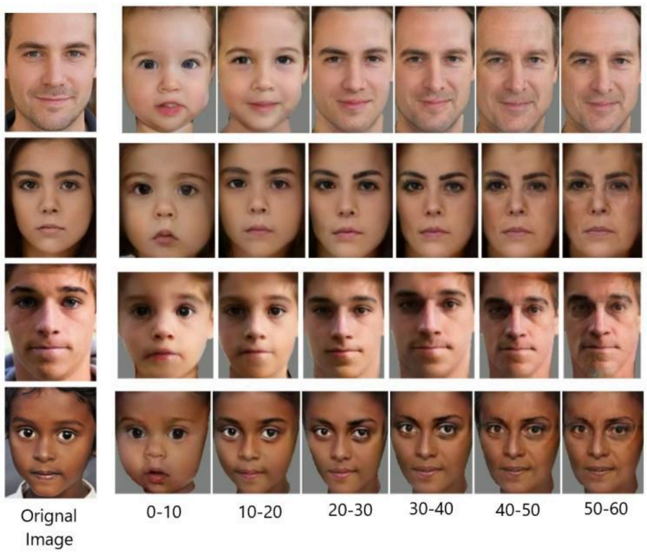

Fig 11. Age Progression Results

Fig. 11 illustrates the functionality of the age progression module. The images used are from various sources, including random selections from Google. Through our algorithm, we produced age-progressed images representing individuals across different age ranges. This demonstration aims to showcase the effectiveness and adaptability of our method in predicting facial changes over time.

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 real-time data sources, such as social media platforms or surveillance footage, to assist in the timely identification of missing persons and enhance the system's effectiveness in dynamic situations.

References

[1] Vishakha Shelke, Gunjan Mehta, Prajakta Gomase, Trisha Bangera "Searchious: Locating missing people using an optimized face recognition algorithm", 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), Vasai, India, 2021

[2] Z. B. Lahaw, D. Essaidani and H. Seddik, "Robust Face Recognition Approaches Using PCA, ICA, LDA Based on DWT, and SVM Algorithms," 2018 41st International Conference on Telecommunications and Signal Processing (TSP), Athens, 2018, pp. 1-5. doi: 10.1109/TSP.2018.8441452

[3] Dr. Joy long Zong Chen, "Smart Security System for Suspicious Activity Detection in Volatile Areas", Journal of Information Technology and Digital World, 2020

[4] N. Sabri et al., "A Comparison of Face Detection Classifier using Facial Geometry Distance Measure," 2018 9th IEEE Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, 2018

[5] Nusrat Jahan, Pranta Kumer Bhuiyan, Parves Ahmed Moon and Md Ali Akbar, "Real Time Face Recognition System with Deep Residual Network and KNN", International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020

[6] A. Adouani, W. M. Ben Henia and Z. Lachiri, "Comparison of Haar-like, HOG and LBP approaches for face detection in video sequences," 2019 16th International Multi-Conference on Systems, Signals & Devices (SSD), Istanbul, Turkey, 2019

[7] Kuldeep Singh Yadav and Joyeeta Singha, "Facial expression recognition using modified Viola-John's algorithm and KNN classifier", Springer, 2020

[8] Firoz Mahmud, Mst. Taskia Khatun, Syed Tauhid Zuhori, Shyla Afroge, Mumu Aktar, Biprodip pal Face Recognition using Principal Component Analysis and Linear Discriminant Analysis IEEE:(ICEEICT) 2015

[9] H. S. Karthik and J. Manikandan, "Evaluation of relevance vector machine classifier for a real-time face recognition system," 2017 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia), Bangalore,2017

[10] Prof. Prachi Sasankar and Prof. Usha Kosarkar, "A study for Face Recognition using techniques PCA and KNN.", Easy Chair, 2021

[11] Z. Zhang, Y. Song and H. Qi, "Age Progression/Regression by Conditional Adversarial Autoencoder," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017

[12] Eric Patterson and Devin Simpson. 2017. Dataset and Metrics for Adult Age-Progression Evaluation. In Proceedings of the SouthEast Conference (ACM SE '17). Association for Computing Machinery, New York, NY, USA, 248–251.

[13] G. Antipov, M. Baccouche and J. -L. Dugelay, "Face aging with conditional generative adversarial networks," 2017 IEEE International Conference on Image Processing (ICIP), Beijing, China, 2017

[14] S. Sehgal, H. Singh, M. Agarwal, V. Bhasker and Shantanu, "Data analysis using principal component analysis," 2014 International

Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom), Greater Noida, India, 2014

[15] H. Yang, D. Huang, Y. Wang and A. K. Jain, "Learning Face Age Progression: A Pyramid Architecture of GANs," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA

[16] Shi, Chenglong et al. “CAN-GAN: Conditioned-attention normalized GAN for face age synthesis.” Pattern Recognit. Lett. 138 (2020): 520-526.

[17] M. Sheng, Z. Ma, H. Jia, Q. Mao and M. Dong, "Face Aging with Conditional Generative Adversarial Network Guided by Ranking-CNN," 2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Shenzhen, China, 2020