VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY
An Autonomous Institute Affiliated to University of Mumbai
Department of Computer Engineering

Project Report on

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

In partial fulfillment of the Fourth Year, Bachelor of Engineering (B.E.) Degree in Computer Engineering at the University of Mumbai Academic Year 2023-24

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(2023-24)

VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY
Department of Computer Engineering

Certificate

This is to certify that **Gaurav Amarnani (D17A, 02)**, **Chetaniya Bajaj (D17A, 04)**, **Kaplesh Mulchandani (D17A, 45)** and **Jayesh Repale (D17A, 56)** of Fourth Year Computer Engineering studying under the University of Mumbai have satisfactorily completed the project on "**ReUnite AI: Harnessing Face Detection and Age Progression for missing person identification**" as a part of their coursework of PROJECT-II for Semester-VIII under the guidance of their mentor **Mrs. Yugchhaya Galphat** in the year 2023-24.

This project report entitled **ReUnite AI: Harnessing Face Detection and Age Progression for missing person identification** by ***Gaurav Amarnani, Chetaniya Bajaj, Kaplesh Mulchandani*** and ***Jayesh Repale*** is approved for the degree of **B.E. Computer Engineering.**

Programme Outcomes	Grade
PO1,PO2,PO3,PO4,PO5,PO6,PO7, PO8, PO9, PO10, PO11, PO12 PSO1, PSO2	

Date:
Project Guide:

Project Report Approval
For
B. E (Computer Engineering)

This thesis/dissertation/project report entitled ***ReUnite AI: Harnessing Face Detection and Age Progression for missing person identification*** by ***Gaurav Amarnani, Chetaniya Bajaj, Kaplesh Mulchandani, Jayesh Repale*** is approved for the degree of ***B.E. Computer Engineering***.

Internal Examiner

External Examiner

Head of the Department

Principal

Date:
Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Computer Engineering Department
COURSE OUTCOMES FOR B.E PROJECT

Learners will be to,

Course Outcome	**Description of the Course Outcome**
CO 1	Able to apply the relevant engineering concepts, knowledge and skills towards the project.
CO2	Able to identify, formulate and interpret the various relevant research papers and to determine the problem.
CO 3	Able to apply the engineering concepts towards designing solutions for the problem.
CO 4	Able to interpret the data and datasets to be utilized.
CO 5	Able to create, select and apply appropriate technologies, techniques, resources and tools for the project.
CO 6	Able to apply ethical, professional policies and principles towards societal, environmental, safety and cultural benefit.
CO 7	Able to function effectively as an individual, and as a member of a team, allocating roles with clear lines of responsibility and accountability.
CO 8	Able to write effective reports, design documents and make effective presentations.
CO 9	Able to apply engineering and management principles to the project as a team member.
CO 10	Able to apply the project domain knowledge to sharpen one’s competency.
CO 11	Able to develop a professional, presentational, balanced and structured approach towards project development.
CO 12	Able to adopt skills, languages, environment and platforms for creating innovative solutions for the project.

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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*

Chapter 1: Introduction

1.1 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.

1.2 Motivation

The motivation behind the Reunite project is deeply rooted in the global challenge of missing persons, a predicament that affects every corner of the world, including India. The emotional turmoil experienced by families and communities when a loved one disappears is immeasurable. In India alone, thousands of people go missing each year, with the numbers steadily increasing. According to the National Crime Records Bureau (NCRB), in 2019, the country reported a staggering 66,000 missing person cases, reflecting a 10% increase from the previous year. This statistic is not just a number; it represents the heartache and anguish faced by countless families across the nation. The motivation to address this issue goes beyond statistics. It is about acknowledging the profound human suffering that ensues when someone disappears without a trace. Families are left in a perpetual state of uncertainty, with questions haunting their every moment. The burden of not knowing a loved one's fate takes an emotional toll that cannot be measured in mere numbers. Reunite is driven by a vision of hope, a vision that embraces technological innovation as a powerful tool to alleviate the suffering of those left behind. In India, where the sheer scale of the problem is daunting, the need for effective solutions is particularly acute. The country's diverse demographics, vast geography, and complex socio-cultural landscape present unique challenges in the realm of missing person identification. However, it is precisely these challenges that motivate us to harness cutting-edge technology to make a difference. Overall, the Reunite project is deeply motivated by the pressing need to address the issue of missing persons in India and around the world. We are driven by the belief that technology can be a beacon of hope for those trapped in the limbo of uncertainty. Our mission is to reunite families, heal wounds, and provide answers to the questions that have haunted them for far too long. Together, we can make a difference, one face at a time.

1.3 Problem Definition

The project addresses the critical issue of finding missing persons, which is a deeply distressing and emotional concern for families, friends, and communities. Current methods for identifying missing persons often rely on time-consuming manual efforts, which may yield limited results. Moreover, identifying missing persons over time can be challenging due to age progression, making it difficult to recognize individuals based on outdated images.

1.4 Existing systems

1.4.1 Amber Alert Systems

Amber Alert systems are emergency response systems that disseminate information about abducted children to law enforcement agencies and the public. These systems often include software components for managing alerts, coordinating responses, and disseminating information across various platforms.

1.4.2 Facial Recognition Systems

Facial recognition technology has been increasingly used in law enforcement to help identify and locate missing persons. Software such as Clearview AI, NEC's NeoFace, and Amazon Rekognition offer facial recognition capabilities that can be integrated into broader missing person search systems.

1.4.3 Law Enforcement Databases

Law enforcement agencies maintain databases of missing persons, which can be accessed by authorized personnel to search for and compare information about missing individuals. These databases may include software tools for managing and querying data effectively.1.4.4 Social Media Platforms

Social media platforms like Facebook, Twitter, and Instagram have been used to spread information about missing persons rapidly. Some organizations and law enforcement agencies use software tools to monitor social media for relevant posts and information.

1.4.5 GPS Tracking Systems

GPS tracking systems can be useful in locating missing persons who have access to devices with GPS capabilities, such as smartphones or personal tracking devices. Software applications like Find My iPhone and Google's Find My Device allow users to locate their devices remotely

1.5 Lacuna of the existing systems

In India:

1. **NCRB Database:** While NCRB's national database is a significant step, it's essential to ensure the accuracy and completeness of the data. This system's effectiveness depends on timely and accurate reporting from law enforcement agencies across the country, which may not always be the case.
2. **Aadhaar Integration:** Aadhaar is a powerful tool, but it also raises privacy and security concerns. There's a need for robust data protection measures to prevent misuse and unauthorized access to biometric information. Moreover, not everyone in India has an Aadhaar card, which may leave out certain individuals from the system.
3. **State Police Portals:** These portals are beneficial, but their effectiveness depends on how well they are maintained and updated. If information becomes outdated or the portals are not user-friendly, they may not be as helpful as intended.
4. **Mobile Applications:** The use of mobile apps is a good idea, but accessibility remains a concern. Not everyone in India has access to smartphones or is tech-savvy. This can result in a digital divide where those who need these services the most cannot effectively use them.

Outside India:

1. **AMBER Alert System (USA):** The AMBER Alert system is effective for missing children, but it focuses primarily on children. There is a need for similar systems for missing adults. Also, the effectiveness of AMBER Alerts depends on the immediate notification of law enforcement agencies, which may not always happen in time.

2. **Interpol's I-24/7 Network:** While Interpol's system is powerful, international cooperation can be challenging due to legal and political barriers between countries. In some cases, it may be difficult to get timely responses from all the countries involved.
3. **Facial Recognition Technology (UK):** The use of facial recognition technology raises privacy concerns and potential misuse. There's a need for strict regulations and oversight to protect individuals' rights. False positives and inaccuracies in facial recognition technology can also lead to wrongful identifications.
4. **The Doe Network:** The Doe Network is a valuable resource, but it relies heavily on volunteers and may not have access to the same resources and technology as law enforcement agencies. There may be gaps in coverage and capabilities.

1.6 Relevance of the Project

The "Reunite: Harnessing Face Detection and Age Progression for Missing Person Identification" project holds immense relevance in addressing several critical aspects of the current landscape of missing person identification and reunification efforts. Here are some key points highlighting the project's relevance:

Humanitarian Impact: Missing persons cases have a profound humanitarian impact, affecting not only the individuals who have gone missing but also their families, communities, and society at large. By enhancing the accuracy of identification, the project directly contributes to reuniting missing persons with their loved ones, alleviating suffering, and providing closure.

Cross-Disciplinary Collaboration: It encourages cross-disciplinary collaboration between computer science, artificial intelligence, and law enforcement, fostering innovation and knowledge sharing across sectors. This interdisciplinary approach is vital for solving complex societal challenges.

Global Applicability: The project's outcomes can be applied not only in India but also in other countries facing similar challenges with missing person identification. The universal nature of this issue means that the solutions developed can have global relevance.

Chapter 2: Literature Survey

The literature survey chapter provides insights from existing research related to systems for finding missing people. It informs the project's development by identifying methodologies, technologies, tools employed and challenges from prior work, guiding the implementation of effective methodologies and technologies, ensuring a solid foundation for the proposed solution.

A. Brief Overview of Literature Survey

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.

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.

B. Related Works

2.1 Research Papers Referred

Sr.	Title	Dataset used	Summary
1	Searchious: Locating missing people using an optimized face recognition algorithm	VGG-Face Dataset	The paper references related work in the field of face recognition and highlights the significance of citizen involvement in assisting law enforcement in tracing missing persons. It also provides details about the training results of Support Vector Machine (SVM) and KNN algorithms for face recognition, showing their accuracy and time efficiency.
2	Efficient MAP/ML Similarity Matching for Visual Recognition	ARPA FERET	The authors have given a probabilistic approach to image matching and retrieval. They have introduced a similarity measure that incorporates bayesian analysis to assess differences between two images.
3	Age Progression using Generative Adversarial Networks	MORPH, FG-NET, UTK Face	This study introduces a technique for generating age-progressed facial images using conditional generative adversarial networks (c-GANs). The best model achieved an accuracy of 91.93%, False Omission Rate of 0.45%. This study also incorporates dataset of uneven ages to account for rapid aging in toddlers.
4	Unique Face Identification System using Machine Learning	Eigenfaces	This paper discusses facial identification using Principal Component Analysis (PCA), Haar cascade, and Support Vector Machine (SVM) algorithms.
5	What is the Challenge for Deep	IJB-A, FaceScrub	In this paper, the authors are addressing the challenges of unconstrained facial recognition focusing on image quality variations. Their study

	Learning in Unconstrained Face Recognition?		revealed deep learning algorithms will struggle when matching face images with large quality gaps.
6	Identifying Missing Children: Face Age-Progression via Deep Feature Aging	MORPH-II, CACD, FG-NET, UTKFace, ITWCC, CLF, CFA	This study involves a Feature Aging Module (FAM) that ages deep face features and an Image Generator to synthesize realistic aged face images. FAM simplifies the complex transformation of face features from one age domain to another. Both FAM and the Image Generator are trained to preserve identity information while aging.

Table 1. Summary of literature survey

2.2 Patent search

2.2.1 Method and device for cross-age face recognition and model training thereof

The invention discloses a method and a device for cross-age face recognition and model training thereof, a computer readable storage medium and electronic equipment. The model training method for cross-age face recognition comprises the following steps: extracting feature vectors of face images in an age-crossing face database through a convolutional neural network, wherein the age-crossing face database comprises a plurality of face images classified according to age features and classification features of faces; acquiring a norm and a normalized vector of the feature vector, updating age loss corresponding to the norm based on the age feature of the face image, and updating classification loss corresponding to the normalized vector based on the classification feature of the face image; and training the convolutional neural network based on the combined loss of the age loss and the classification loss. Based on the scheme of the embodiment, the performance of the model cross-age face recognition can be improved.

2.2.2 Facial recognition

An example method includes receiving a first image and a second image of a face of a user, where one or both images have been granted a match by facial recognition. The method further includes detecting a liveness gesture based on at least one of a yaw angle of the second image relative to the first image and a pitch angle of the second image relative to the first image, where the yaw angle corresponds to a transition along a horizontal axis, and where the pitch angle corresponds to a transition along a vertical axis. The method further includes generating a liveness score based on a yaw angle magnitude and/or a pitch angle magnitude, comparing the liveness score to a threshold value, and determining, based on the comparison, whether to deny authentication to the user with respect to accessing one or more functionalities controlled by the computing device.

2.2.3 Age invariant face recognition using convolutional neural networks and set distances

Time lapse, characteristic of aging, is a complex process that affects the reliability and security of biometric face recognition systems. Systems and methods use deep learning, in general, and convolutional neural networks (CNN), in particular, for automatic rather than hand-crafted feature extraction for robust face recognition across time lapse. A CNN architecture using the VGG-Face deep (neural network) learning produces highly discriminative and interoperable features that are robust to aging variations even across a mix of biometric datasets. The features extracted show high inter-class and low intra-class variability leading to low generalization errors on aging datasets using ensembles of subspace discriminant classifiers.

2.3 Comparison with the existing system

The ReUnite AI project distinguishes itself from existing systems in several key aspects:

- **Advanced Facial Recognition**: Utilizing deep learning algorithms such as PCA, ReUnite achieves higher accuracy in identifying missing individuals compared to traditional methods.

- **Dynamic Age Progression Modeling:** By employing generative adversarial networks (GANs), ReUnite generates realistic representations of how a missing person's appearance changes over time, enhancing its effectiveness.

- **Comprehensive Training Dataset:** Trained on a diverse dataset of facial images, ReUnite ensures robust performance across demographics and aging trajectories, mitigating biases seen in some existing systems.

- **Rigorous Evaluation**: Through rigorous evaluations and case studies, ReUnite demonstrates its efficacy across varying age ranges and temporal intervals, providing empirical evidence of its effectiveness.

- **Integration of State-of-the-Art Technology:** By integrating state-of-the-art facial recognition and age progression techniques, ReUnite addresses the critical challenge of missing person identification more comprehensively than existing systems.

Chapter 3: Requirement Gathering for the Proposed System

In this chapter, we delve into the process of understanding and gathering the requirements for the ReUnite AI project. We explore the resources utilized, the analysis of user needs, and the delineation of functional and non-functional requirements. Additionally, we outline the hardware, software, and technologies employed in the development of the system.

3.1 Introduction to requirement gathering

The Requirement Gathering is a process of requirements discovery or generating list of requirements or collecting as many requirements as possible by end users. It is also called as requirements elicitation or requirement capture.

The requirements gathering process consists of six steps :

- Identify the relevant stakeholders: Engage with stakeholders such as developers, end-users, and domain experts to understand their perspectives and requirements for the ReUnite AI project.
- Establish project goals and objectives: Define clear project goals and objectives, including facilitating the identification of missing persons using facial recognition and age progression technologies.
- Elicit requirements from stakeholders: Conduct interviews, surveys, and workshops to elicit and capture stakeholders' requirements, preferences, and expectations regarding the functionality and performance of ReUnite AI.
- Document the requirements: Document the gathered requirements in a structured format to ensure clarity, completeness, and traceability throughout the project lifecycle.
- Confirm the requirements: Validate and verify the documented requirements with stakeholders to ensure accuracy and alignment with their needs and expectations.

- Prioritize the requirements: Prioritize the documented requirements based on their criticality, feasibility, and impact on the success of ReUnite AI.

Use Case	**Description**
Register and Login	Users including administrators and researchers register and log in to the ReUnite AI system.
Input Missing Person Data	Users input data such as images and relevant information about missing persons into the system.
Analyze Facial Features	The system analyzes facial features of missing persons using deep learning algorithms.
Generate Age-Progressed Images	Age progression models generate updated representations of missing persons' appearances over time.
Compare with Database	The system compares analyzed features and age-progressed images with a database of missing persons.
Notify Matching Results	If a match is found, the system notifies the user and relevant authorities, expediting further investigation.
Manage User Accounts	Administrators manage user accounts, including registration and permissions.
View System Logs	Administrators view system logs for auditing and troubleshooting purposes.

Table 2. Requirements of the system

3.2 Functional Requirements

- Facial Feature Analysis: The system must be able to analyze facial features of missing persons using deep learning algorithms.
- Age Progression: Age progression models should generate updated representations of missing persons' appearances over time.
- Database Comparison: The system should compare analyzed features and age-progressed images with a database of missing persons for identification.

- Notification System: A notification system must promptly inform users and relevant authorities of matching results.
- User Management: Administrators should be able to manage user accounts, including registration, login, and permissions.

3.3 Non-Functional Requirements

- User Interface: The user interface should be intuitive and easy to navigate, ensuring a seamless user experience.
- Accuracy and Reliability: The system's analysis and matching algorithms must be highly accurate and reliable to minimize false positives and negatives.
- Data Security: Strict measures should be implemented to ensure the security and confidentiality of sensitive user data.
- Performance: The system should perform efficiently, delivering timely results even when processing large datasets.
- Scalability: The system should be scalable to accommodate potential increases in user and data volume over time.

3.4 Hardware & Software Requirements

A. **Hardware Requirements:**

   a. Minimum 8 GB RAM

   b. Core i5 7th Gen processor

   c. NVIDIA GPU

   d. Disk space of 4GB

B. **Software Requirements:**

   a. Python

b. Django

c. Google Colab/Jupyter Notebook

3.5 Technology and Tools utilized

A. Technologies:

a. **Python:** Python is a high-level, general-purpose programming language known for its simplicity and readability. It's widely used in various fields, including web development and machine learning.

b. **Django:** Django is a high-level Python web framework that encourages rapid development and clean, pragmatic design. It simplifies the process of building web applications by providing various built-in features.

c. **Google Colab/Jupyter Notebook:** These are interactive computational notebooks that allow you to write and execute Python code in a collaborative environment. They are particularly useful for data analysis, machine learning, and deep learning tasks.

B. Tools:

a. **Vscode:**Visual Studio Code is a popular source code editor developed by Microsoft. It offers features such as debugging, syntax highlighting, and Git integration, making it a versatile tool for software development.

b. **Google Colab:** Google Colaboratory, or "Colab" for short, is a hosted Jupyter notebook service provided by Google. It allows users to write and execute Python code in a browser-based environment, with access to free GPU resources for machine learning tasks.

3.6 Constraints of working

Data Privacy: The system must comply with data privacy regulations and ensure the protection of individuals' privacy rights.

Resource Limitations: The system's performance may be constrained by hardware resources such as processing power and memory.

Chapter 4: Proposed Design

In this chapter, the proposed system's design is presented, including its architecture and interfaces. It emphasizes the models used for face recognition and age progression. It also focuses on integrating those models for finding missing people.

4.1 Block diagram of the system

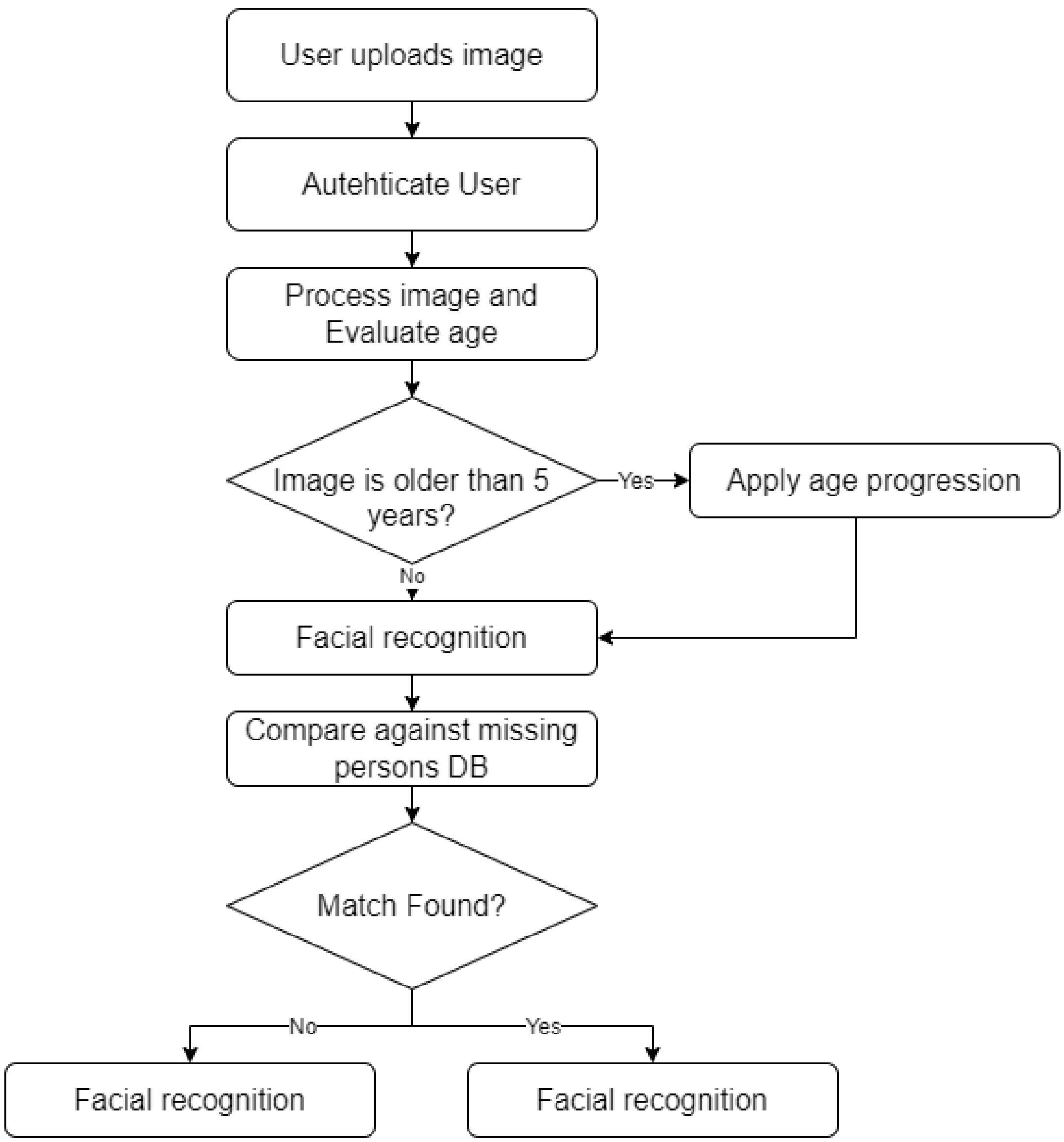

Figure 1. Block Diagram

4.2 Modular design of the system

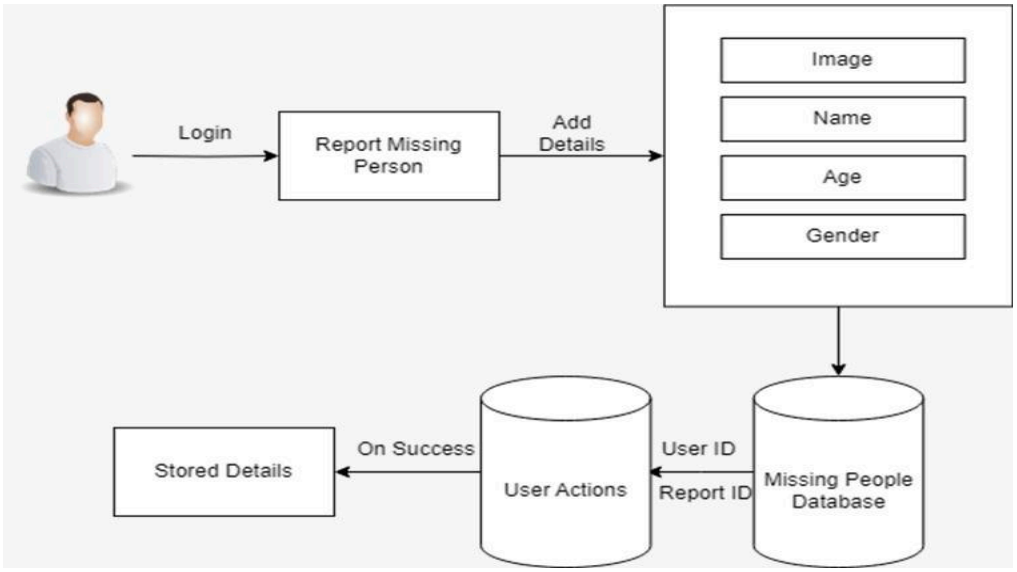

Figure 2. Complaint Module

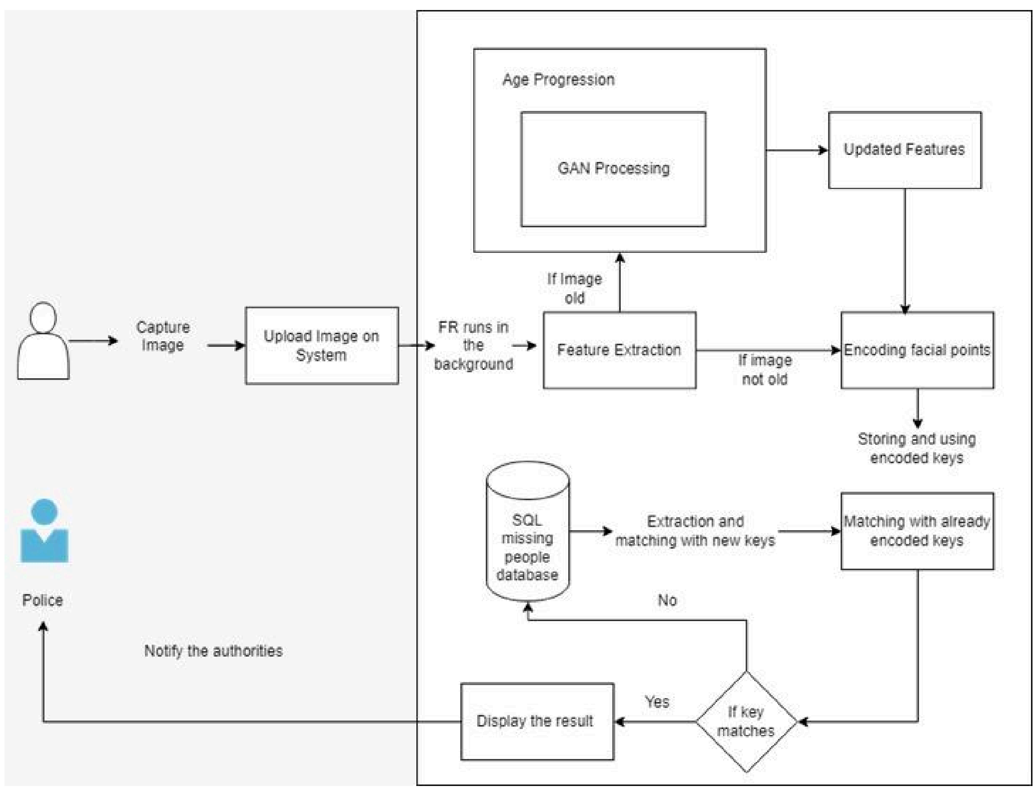

Figure 3. Processing Module

- User Engagement and Image Submission: Users interact with the ReuniteAi platform by uploading images of missing individuals or those they suspect might be missing, initiating the identification process.
- Authentication and Image Processing: The system authenticates users and proceeds to process the uploaded images. This processing involves evaluating the age of the image and determining whether age progression techniques are necessary.
- Age Progression Techniques: For images older than 5 years, sophisticated age progression techniques are employed to generate updated images reflecting the potential appearance of the individual at the current time. This augmented image is then compared with the original for comprehensive analysis.
- Facial Recognition Algorithms: If the uploaded image falls within the 5-year timeframe, the system directly employs facial recognition algorithms. Advanced facial feature extraction methods are utilized to compare the uploaded image against a comprehensive Missing Persons Database.
- Identification Outcome Notification: Upon completing the identification process, the system promptly notifies the user of the outcome. If a match is found, the user is informed, and simultaneous notifications are dispatched to relevant authorities, expediting further investigative procedures.
- No Match Notification: 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.
- Commitment to Efficiency and Accuracy: 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.

4.3 Detailed Design

4.3.1 Flowchart for the proposed system

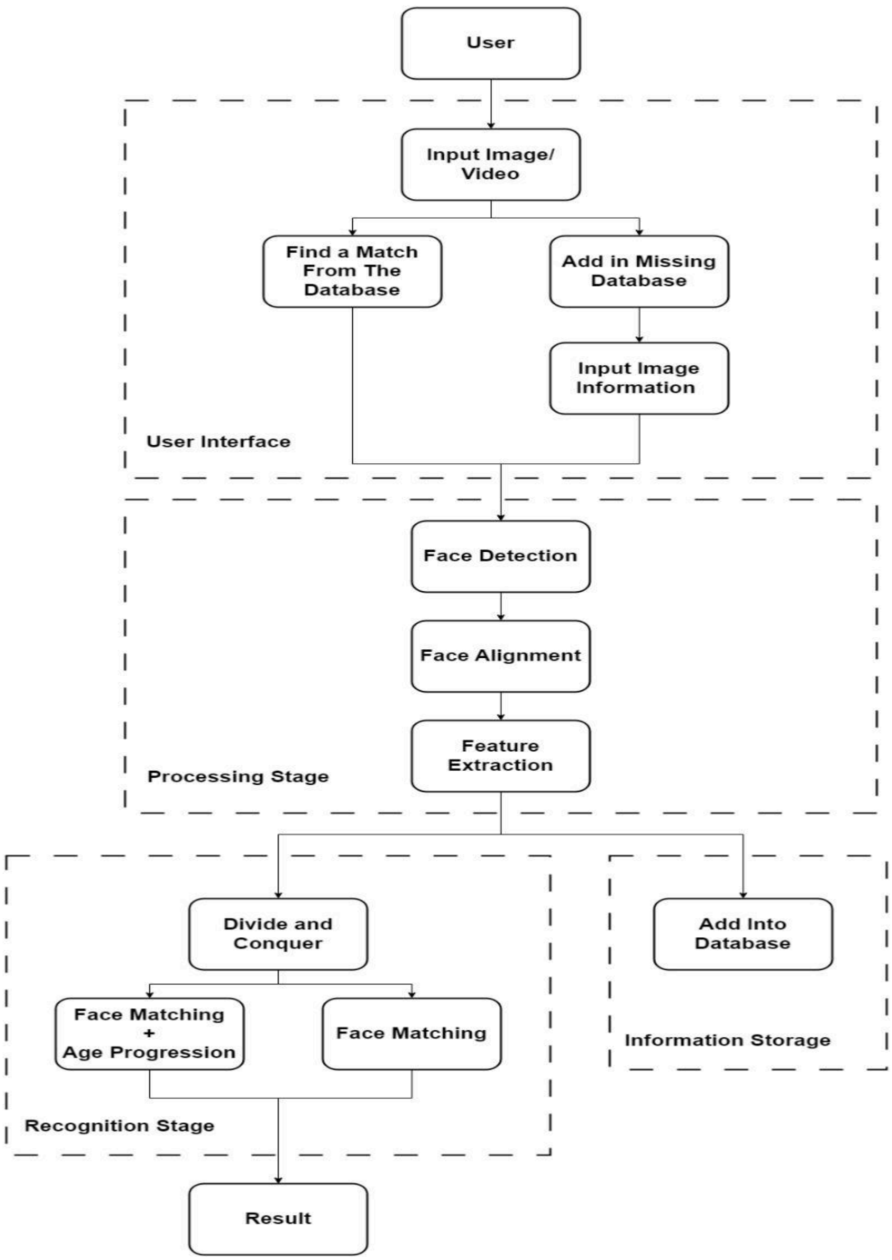

Figure 4. Flowchart of system

4.4 Project Scheduling & Tracking using Timeline / Gantt Chart

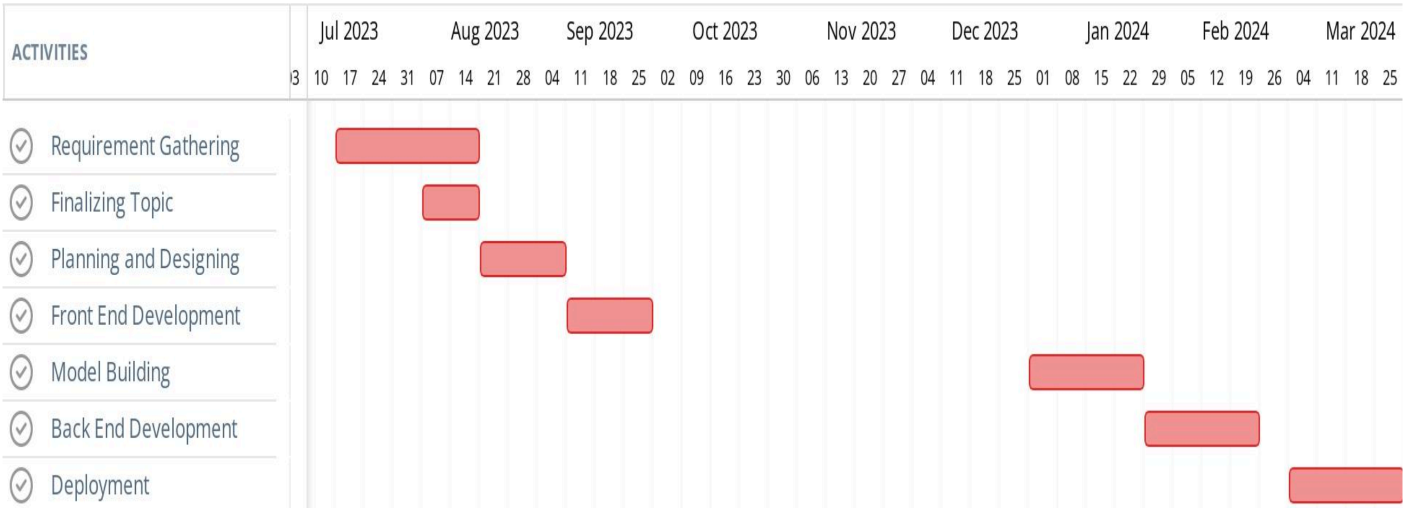

Figure 5. Gantt Chart

Chapter 5: Implementation of the Proposed System

5.1. Methodology employed for development

ReuniteAi serves as an integrated platform dedicated to facilitating the identification and reunification of missing persons with their families and loved ones. Through a user-friendly interface, individuals can upload images of missing persons or those they suspect may be missing, initiating a series of automated processes aimed at maximizing identification accuracy.

The system begins by authenticating users and processing the uploaded images. It evaluates the age of the image, utilizing sophisticated age progression techniques for images older than 5 years to generate updated representations of the individual's potential appearance at the current time. For images within the 5-year timeframe, facial recognition algorithms are directly employed, meticulously comparing uploaded images against a comprehensive Missing Persons Database.

Upon completing the identification process, users are promptly notified of the outcome. If a match is found, simultaneous notifications are dispatched to relevant authorities, expediting further investigative procedures. In cases where no match is established, users receive respectful notifications expressing regret for the inability to provide a positive identification.

Moreover, ReuniteAi is dedicated to continuous refinement and expansion, collaborating with law enforcement agencies and organizations to enhance its identification capabilities. Prioritizing user privacy and data security, the platform employs robust encryption methods to safeguard sensitive information, fostering a supportive environment where users feel empowered to contribute to the search for missing loved ones.

Additionally, ReuniteAi provides resources and support for families and friends of missing persons, offering guidance on platform utilization and access to additional assistance. By fostering a sense of community and collaboration, ReuniteAi aims to make a meaningful impact in reuniting missing individuals with their loved ones and bringing closure to those affected by their disappearance.

5.2 Algorithms and flowcharts for the respective modules

We have mainly used three algorithms for our project:

5.1.1 Principal Component Analysis (PCA) :

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. 5.2, encapsulate the dominant characteristics of a face. The steps for implementing the PCA algorithm are elaborated by S. Sehgal.

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:

$$q = x - m \quad (2)$$

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

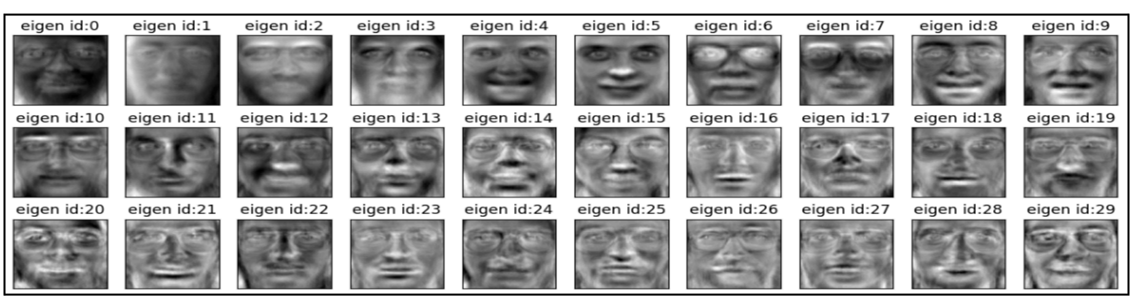

Figure 6. Eigen Faces

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

Where q is Standardized face with unique features, A is Set of Eigen Faces as depicted in Fig. 5.1.

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

$C = A * A^T$ (4)

where A = q1, q2, q3, ...

Where, A is Eigenfaces. AT 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.

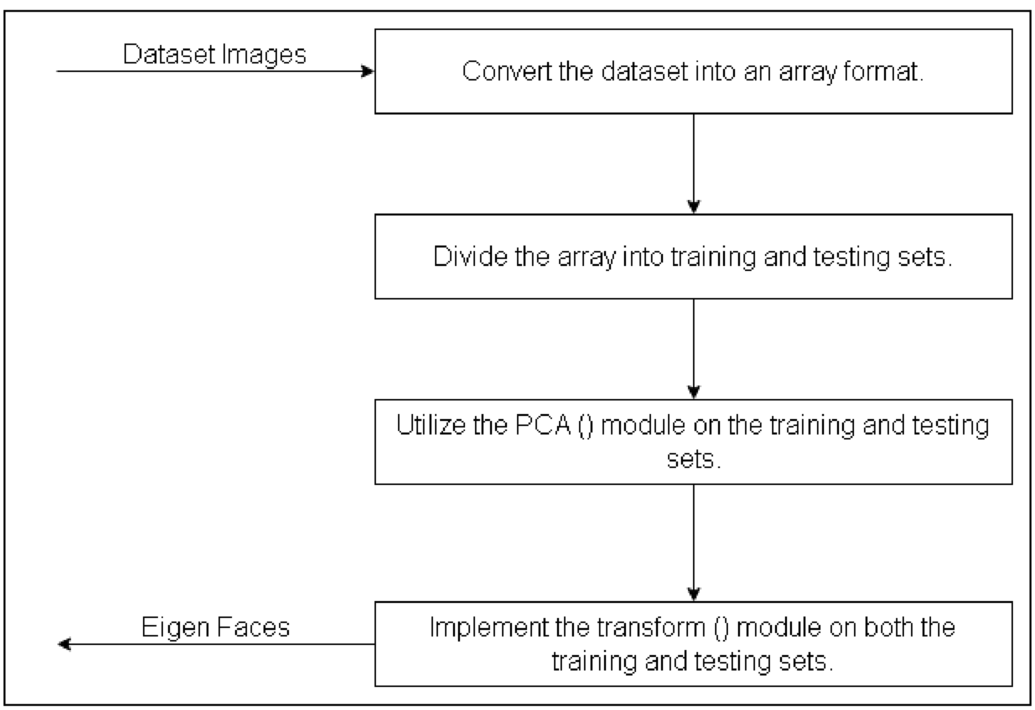

Figure 7. PCA Flowchart

5.2.2 Linear Discriminant Analysis (LDA):

A methodology integrating Principal Component Analysis (PCA) followed by Linear Discriminant Analysis (LDA) to improve feature extraction and classification, as depicted in Fig. 5.3 is being used for our project. 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.

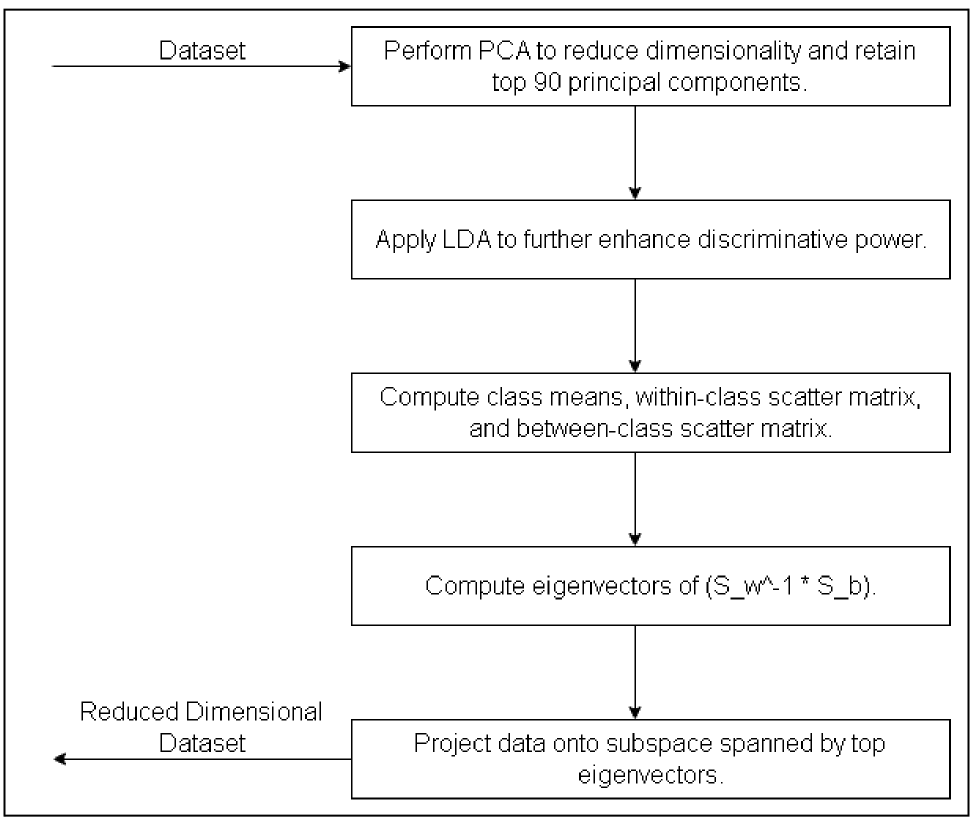

Figure 8. LDA Flowchart

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

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

Where i represents the mean of class i, xi denotes the features belonging to class i, and ni 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:

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

Where Sw is the within-class scatter matrix, xij represents the jth sample of class i, and 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:

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

Where Sb is the between-class scatter matrix, ni represents the number of samples in class i, i is the mean of class i, and is the overall mean.

The eigenvectors of the matrix Sw-1 Sb 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.

5.2.3 Conditional Generative Adversarial Network (cGAN):

Zhang and colleagues pioneered the use of Generative Adversarial Networks (GANs) with age labels for facial age progression. Fig. 5.4 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.

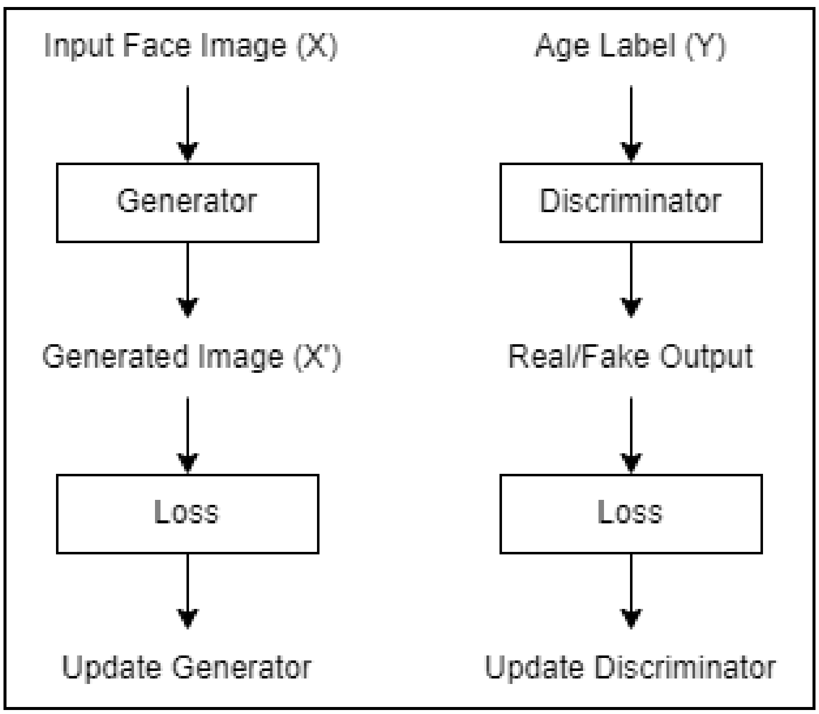

Figure 9. cGAN Flowchart

5.3 Datasets source and utilization

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.

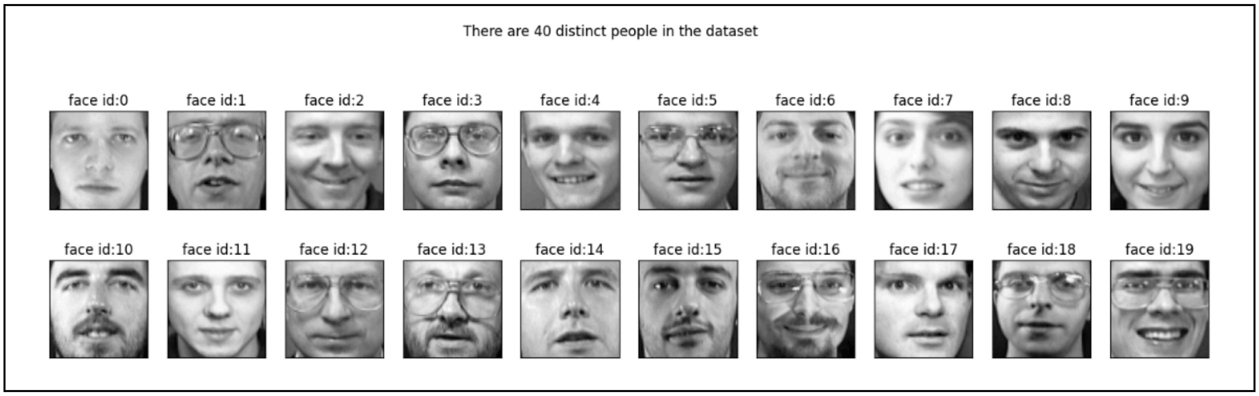

Figure 10. Olivetti Dataset: Distinct images of 40 people

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. 5.5 and Fig.5.6 each represent the images of different people and the distinct images of those people respectively.

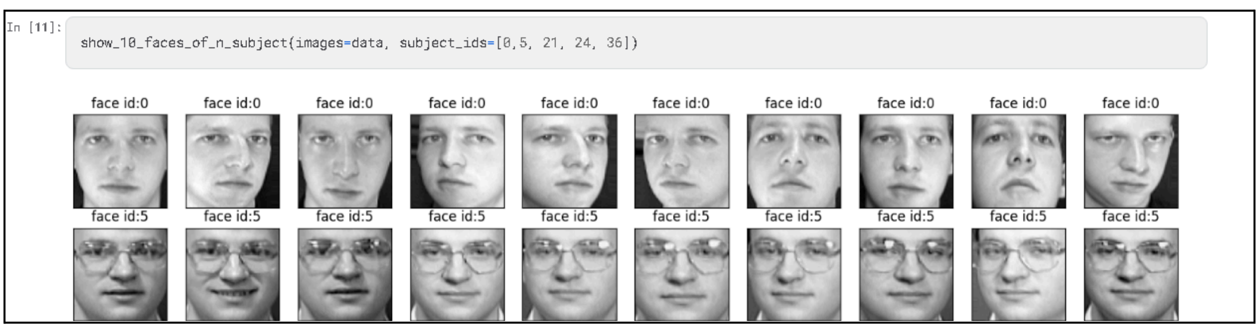

Figure 11. Olivetti Dataset: 10 images of each person

Chapter 6: Testing of the Proposed System

6.1 Introduction to Testing :

Software Testing is a crucial aspect of the ReUnite AI project, ensuring that the system meets the expected requirements and operates defect-free. It involves executing various components of the system using both manual and automated tools to assess their performance and functionality. The primary purpose of software testing in the context of ReUnite AI is to identify any errors, discrepancies, or missing functionalities compared to the specified requirements. In essence, it involves verifying the functionality, usability, interface, compatibility, performance, and security aspects of the system.

A test case within the ReUnite AI project consists of a set of actions executed to verify specific features or functionalities of the system. Each test case includes test steps, test data, preconditions, and postconditions tailored to specific test scenarios, allowing testing engineers to compare expected outcomes with actual results.

6.2 Types of tests considered :

6.2.1 Functionality Testing:

- Verify the absence of dead pages or invalid redirects.
- Validate all fields (registration, login, billing details, etc.) with appropriate error handling.
- Test the workflow of the system, ensuring error-free processes from adding to cart to billing.
- Verify the integrity of data stored in the database, ensuring validity and consistency.

6.2.2 Usability Testing :

- Test navigation and controls, including hyperlinks, buttons, and other DOM elements.
- Verify content displayed matches user expectations.
- Assess user intuition to explore the web application effectively.

6.2.3 Interface Testing:

- Verify the functionality and data flow between different system components.
- Ensure all website components work seamlessly.

6.2.4 Compatibility Testing:

- Test browser compatibility across various browsers like Safari, Chrome, and Firefox.
- Validate operating system compatibility, ensuring functionality on Linux, Windows, etc.
- Check compatibility with different devices such as notebooks, mobile phones, etc.

6.2.6 Security Testing:

- Test for injection vulnerabilities to prevent database corruption.
- Verify proper authentication and session management.
- Mitigate cross-site scripting (XSS) vulnerabilities.
- Ensure security configurations are correctly implemented.
- Protect sensitive data from exposure.
- Prevent unvalidated redirects and forwards to maintain data integrity.

6.3 Various test case scenarios considered :

Sr. No.	Test Case Description	Input	Expected Output	Actual Output	Result
1.	Missing Person Reporting	User provides missing person details	Confirmation message of successful reporting	Confirmation message displayed	Pass
2.	Found Person Verification	User uploads images for verification	Matching found person details displayed	Matching details displayed	Pass
3.	Age Progression	System predicts aging of uploaded images	Updated images showing aging progression	Aging progression images displayed	Pass

4.	Facial Recognition	System compares uploaded image with database	Matching person identified	Person identified	Pass
6.	Facial Recognition	System compared uploaded image with database	Matching person is not identified as he/she is not in the missing database.	Person not identified.	Pass
5.	Notification Delivery	System sends notifications to users	Users receive timely notifications	Notifications received	Pass

Table 3. Test cases

6.4 Inference drawn from the test cases :

Upon completing the testing process for ReUnite AI, it is evident that the system performs effectively across various functionalities. The thorough testing conducted ensures that the system operates as expected, with accurate results and timely notifications delivered to users. The successful execution of test cases validates the robustness and reliability of the ReUnite AI system in identifying missing persons and facilitating reunification with their families.

Chapter 7: Results and Discussion

7.1 Screenshots of User Interface (UI) for the respective module

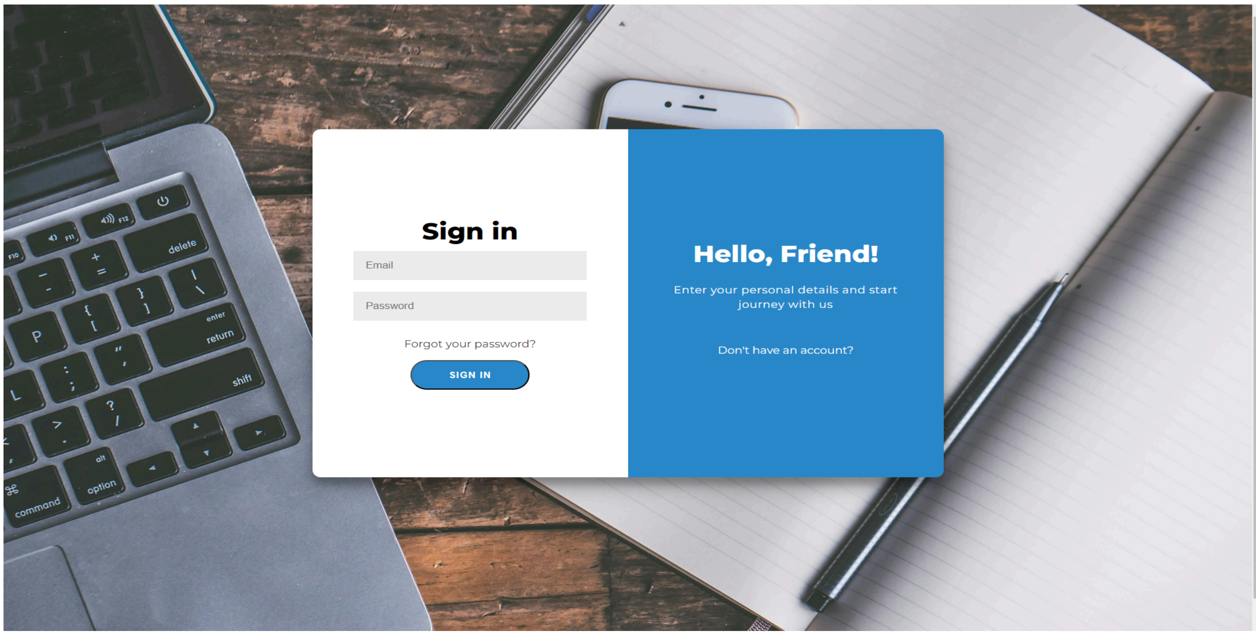

Figure 12. Screenshot for Login page

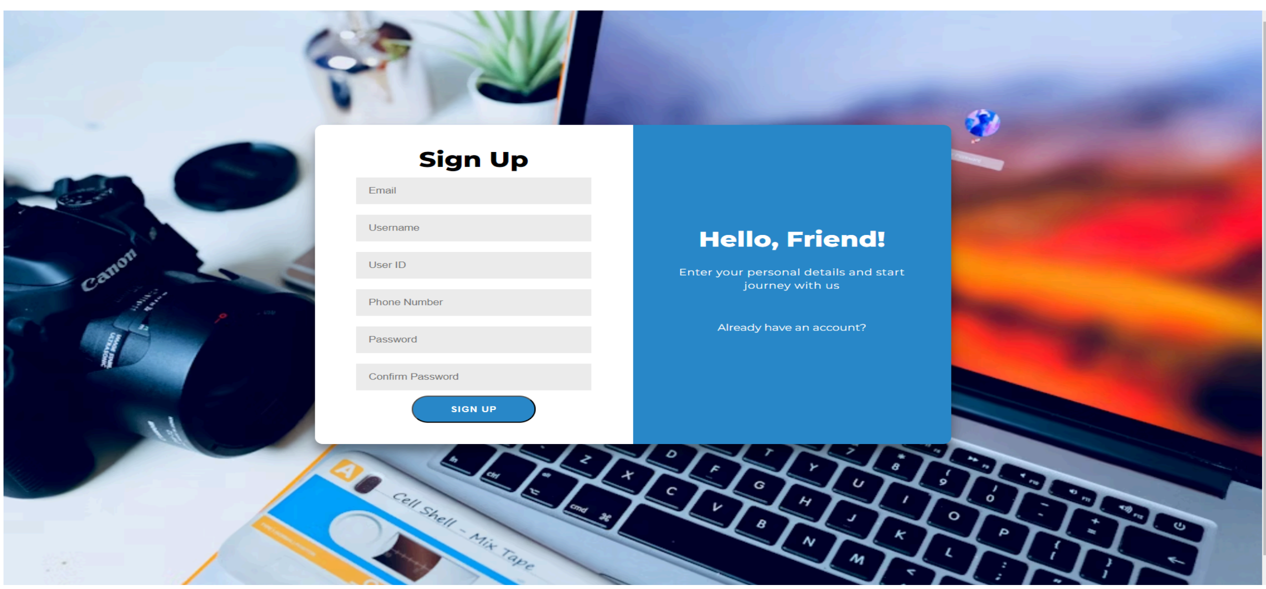

Figure 13. Screenshot for Register page

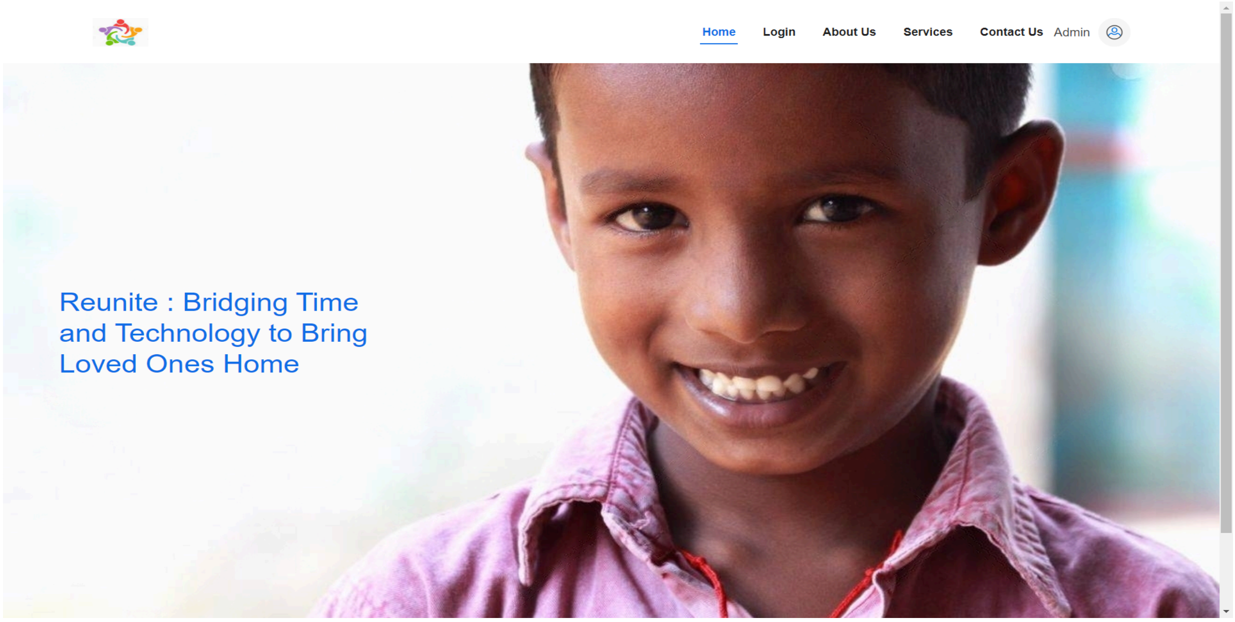

Figure 14. Screenshot for Home Page

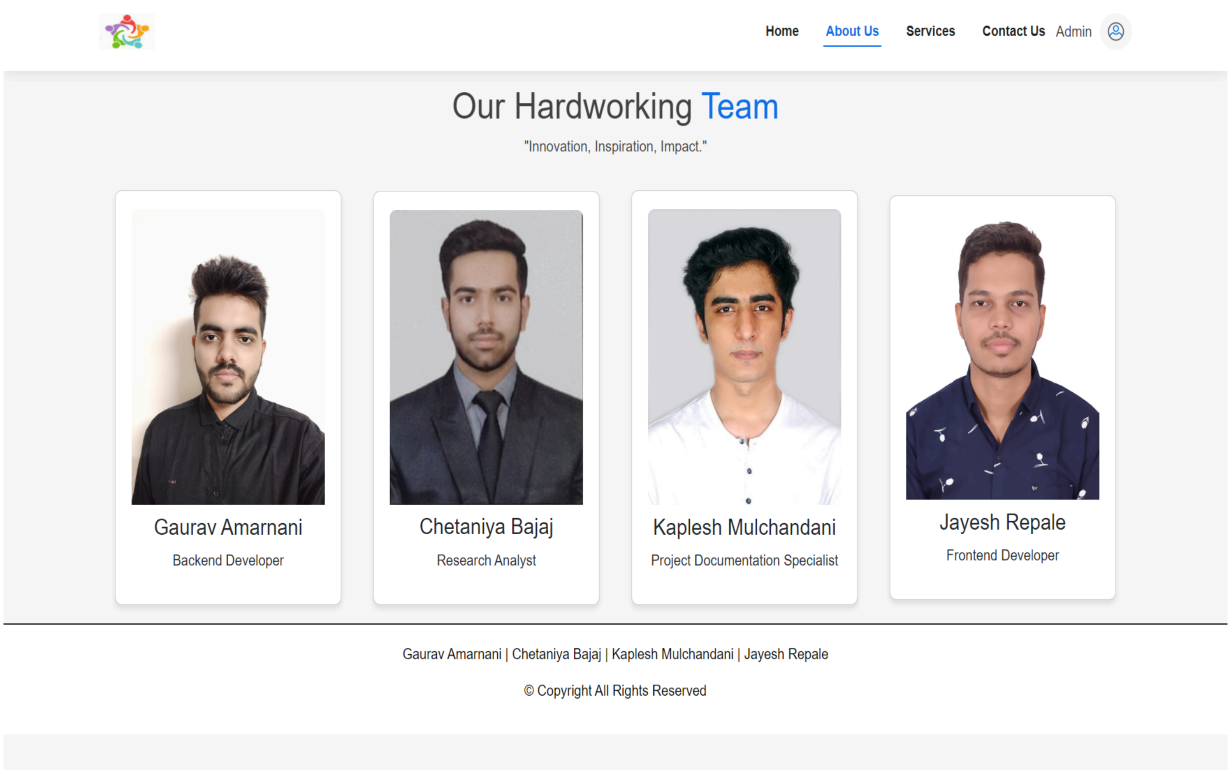

Figure 15. Screenshot for About Us page

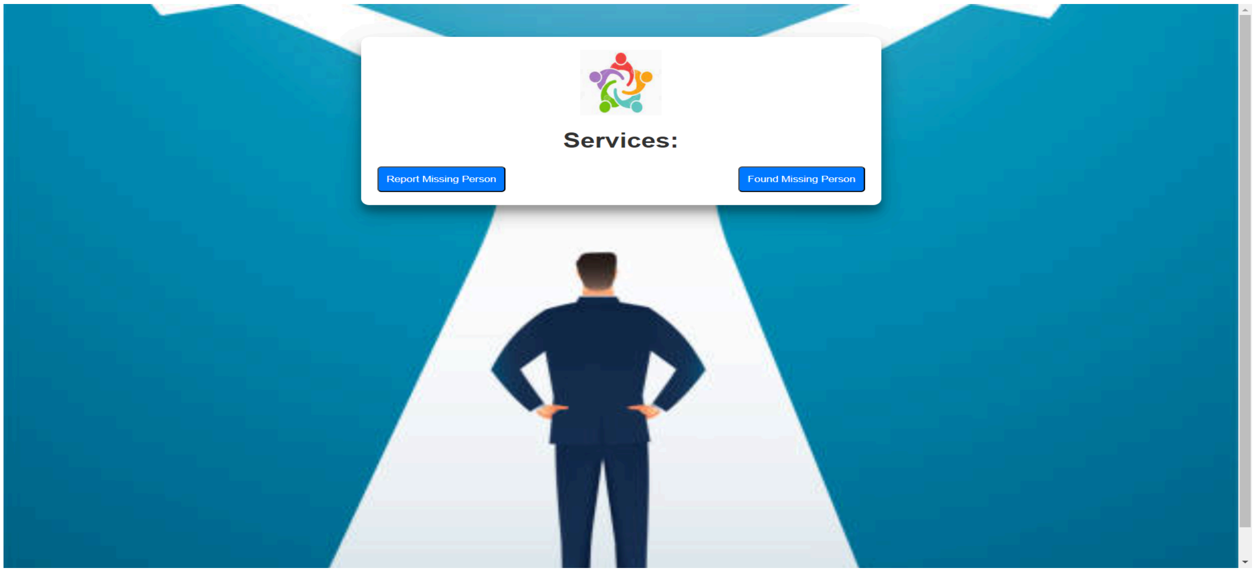

Figure 16. Screenshot for Services Page

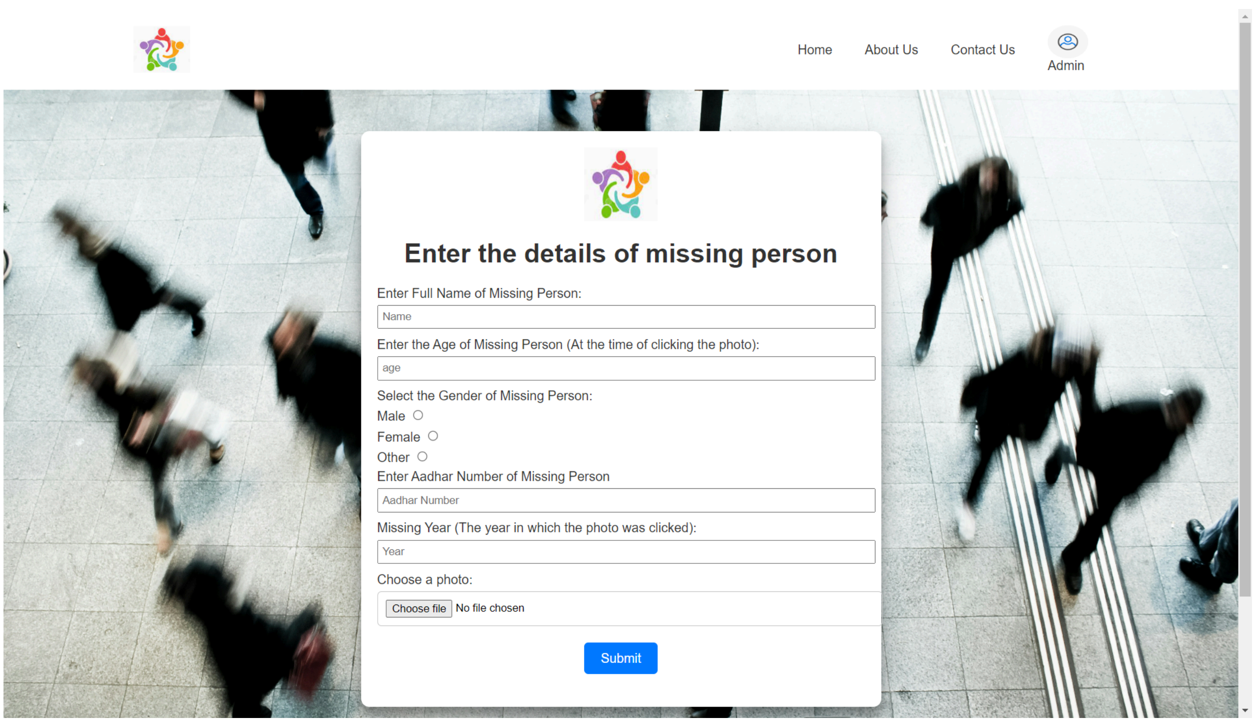

Figure 17. Screenshot for report missing person page

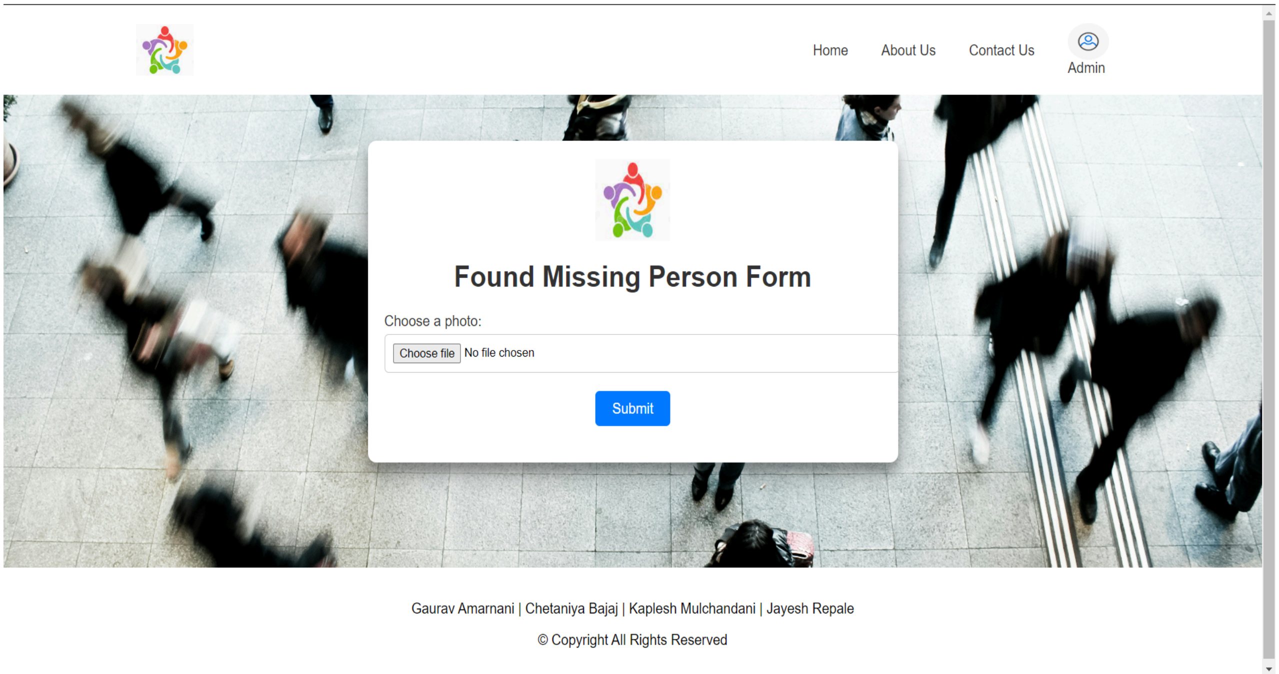

Figure 18. Screenshot for found missing person page

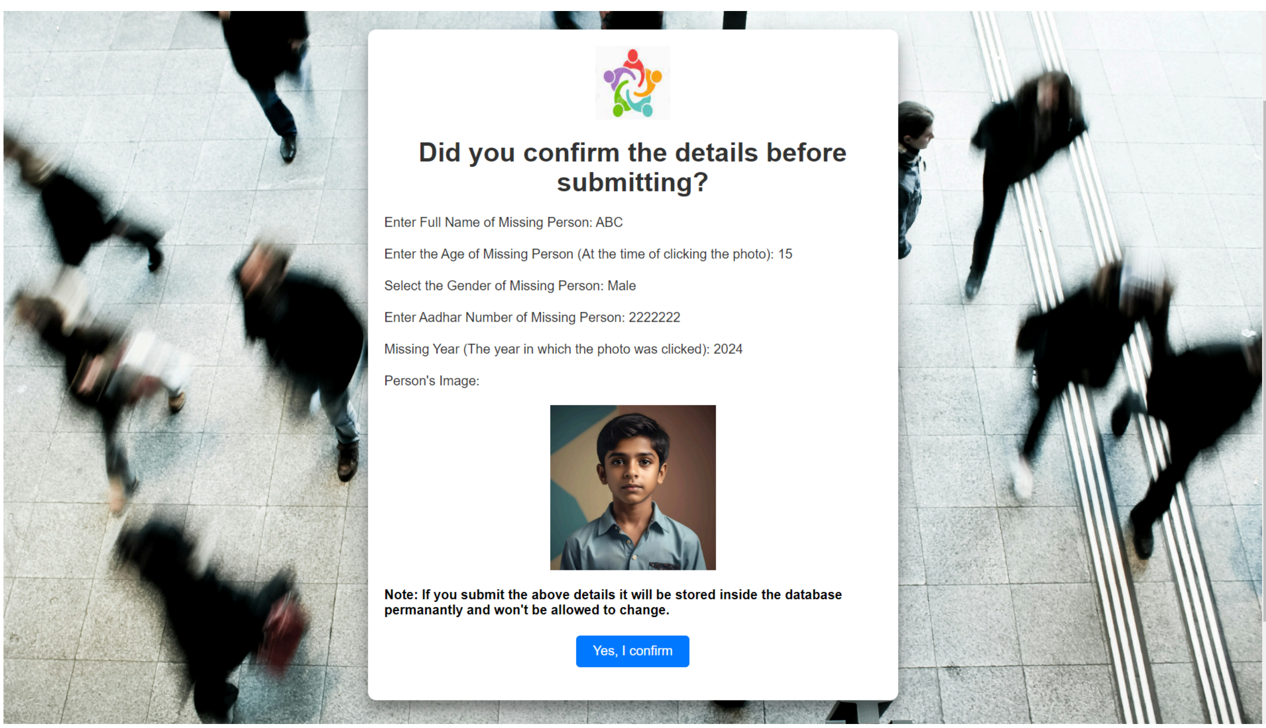

Figure 19. Screenshot for confirmation of details page

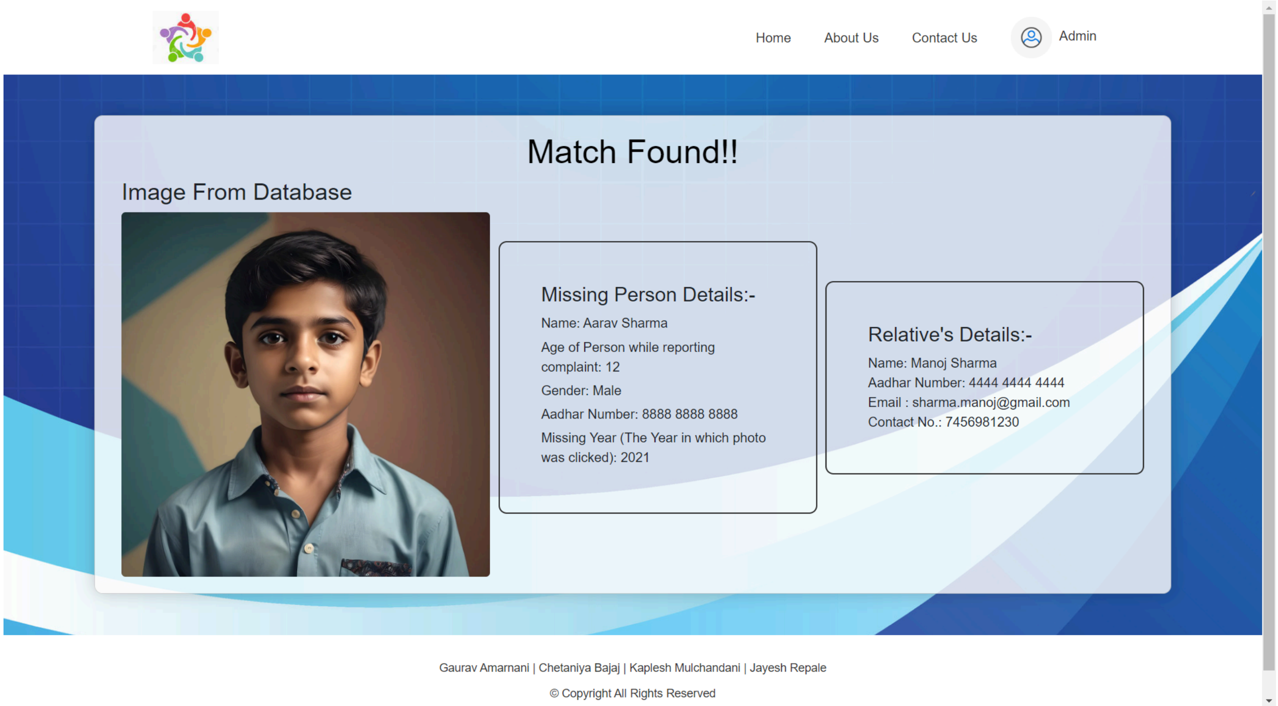

Figure 20. Screenshot for Match Found page

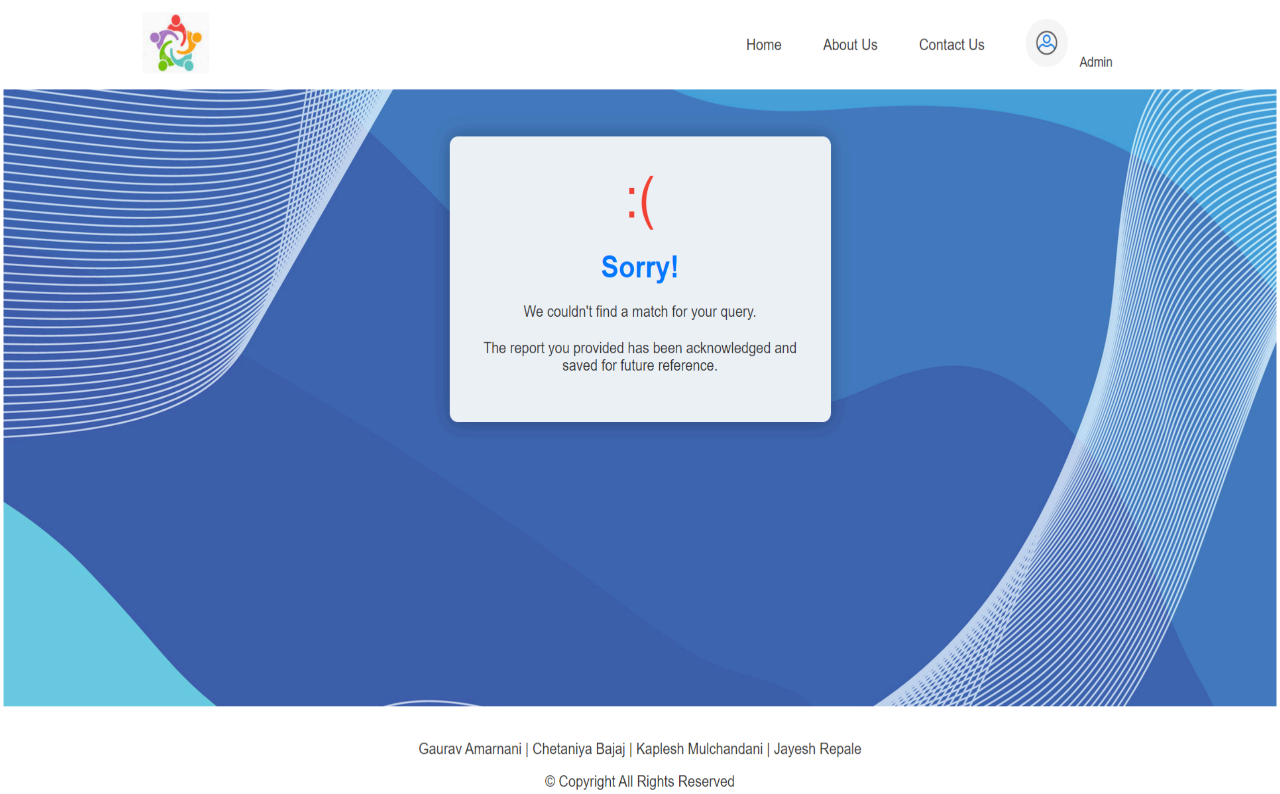

Figure 21. Screenshot for Match Not Found page

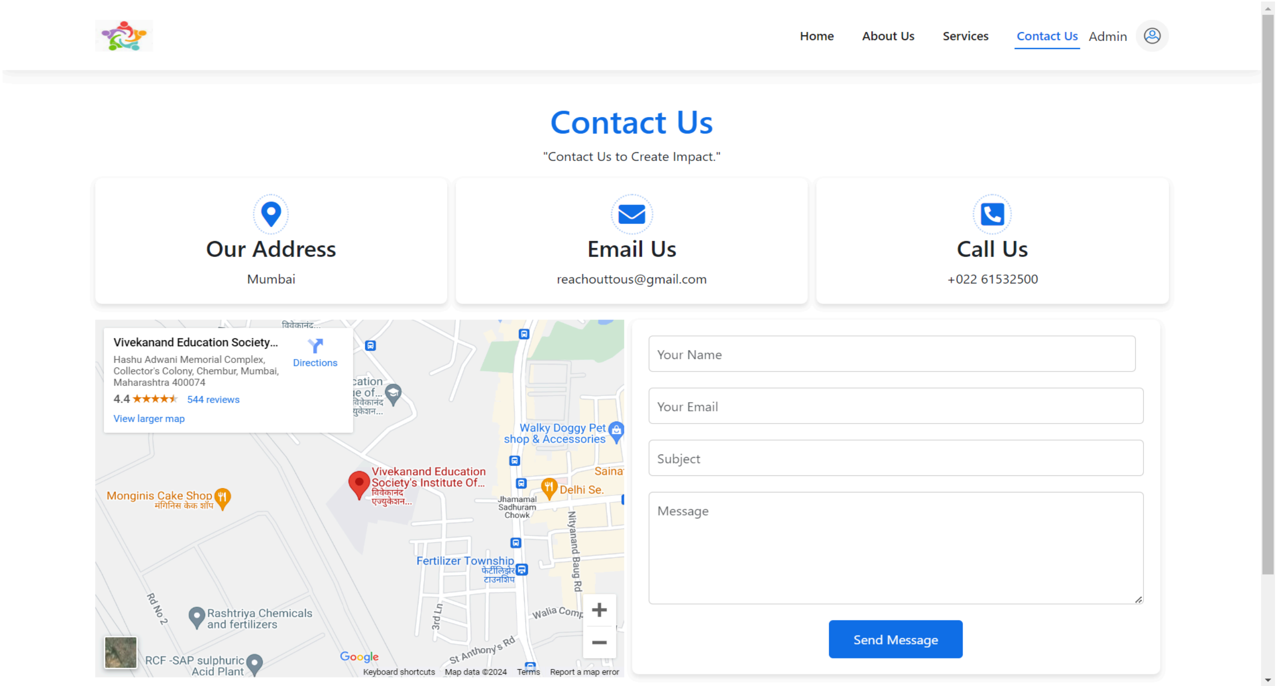

Figure 22. Screenshot for Contact Us page

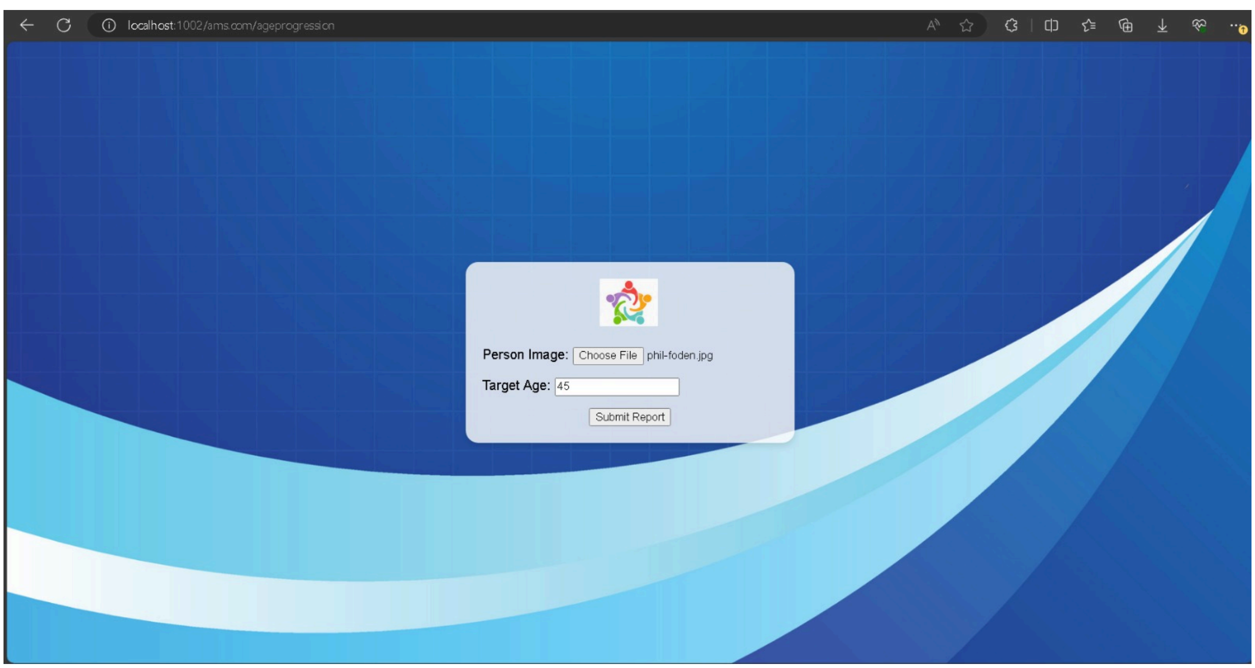

Figure 23. Screenshot for Age Progression Form

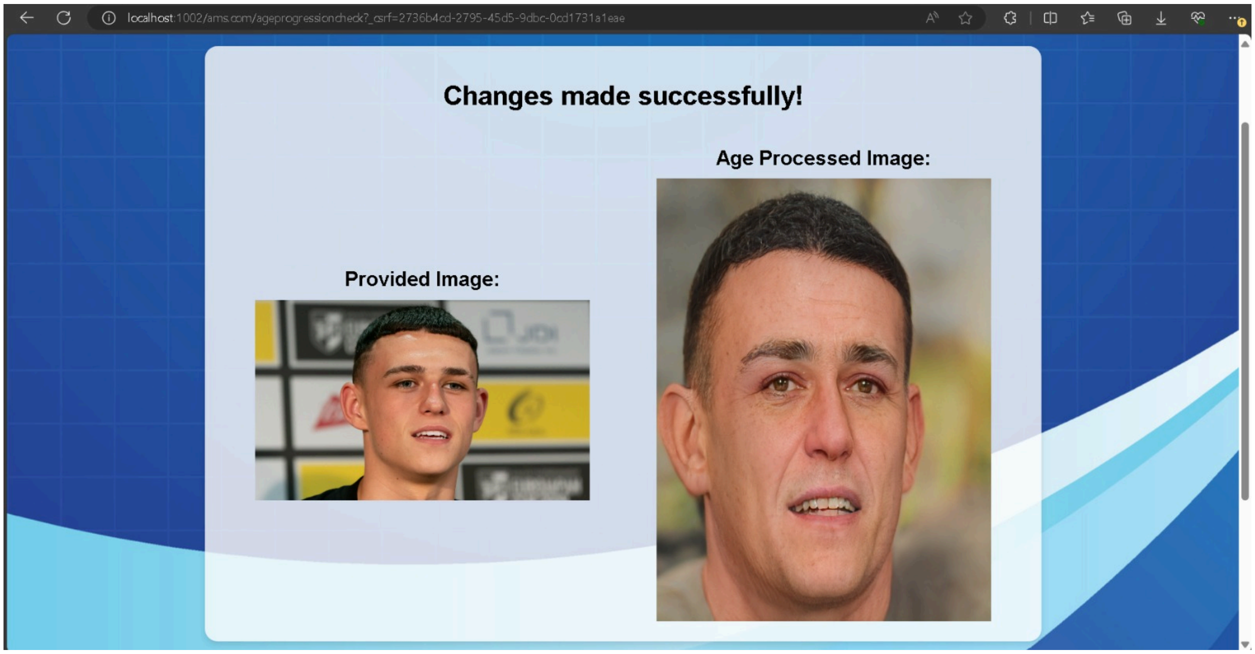

Figure 24. Screenshot for Age Progression Result

7.2 Performance Evaluation measures

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 performance metrics garnered from the implemented machine learning models.

- **Accuracy:** The primary measure of ReUnite's effectiveness in correctly identifying missing individuals by matching facial features and age-progressed representations accurately.
- **Precision and Recall:** Balancing the proportion of correctly identified missing individuals (precision) against the proportion of actual missing individuals correctly identified (recall) to minimize false positives and false negatives.
- **Efficiency:** Assessing computational time and resource utilization to ensure timely identification of missing individuals without excessive computational overhead.
- **Robustness to Demographic Diversity:** Evaluating performance across diverse demographic groups to prevent biases and ensure equitable outcomes.

- **Generalization:** Assessing the system's ability to perform accurately on unseen data, indicating adaptability to new cases or scenarios beyond the training dataset.

7.3 Input Parameters / Features considered

7.3.1 Input Parameters/Features in Face Recognition Models

- **Facial Features:** Face recognition models analyze various facial features, including the overall shape of the face, the arrangement of facial landmarks, and the distribution of features such as eyes, nose, and mouth. These features are extracted and compared to identify individuals accurately.
- **Texture and Color:** Texture patterns and color variations on the face provide additional information for face recognition models. These features capture details such as skin texture, scars, freckles, and other unique facial characteristics that aid in distinguishing one individual from another.
- **Deep Learning Features:** Face recognition models often utilize deep learning techniques, such as convolutional neural networks (CNNs), to automatically extract relevant features from raw input images. These features capture complex patterns and relationships within facial images, improving the models' accuracy and performance.
- **Training Data:** The quality and diversity of the training dataset are crucial input parameters for face recognition models. A comprehensive dataset that includes a wide range of individuals, ethnicities, genders, and facial variations ensures that the model can generalize well and accurately identify individuals across diverse populations.

7.3.2 Input Parameters/Features in Age Progression Models

- **Facial Landmarks:** Age progression models utilize facial landmarks, such as the eyes, nose, mouth, and jawline, as anchor points for feature extraction and analysis. These landmarks help in mapping the changes in facial structure over time.
- **Facial Geometry:** The geometric features of a face, including the shape of the face, distances between facial landmarks, and angles formed by facial features, are important input parameters for age progression models. Changes in facial geometry, such as the

growth of bones and changes in facial proportions, are considered to predict how a person's appearance may evolve with age.

- **Texture and Color:** Age progression models take into account texture patterns and color variations on the face, capturing details such as skin texture, wrinkles, freckles, and other age-related characteristics. Changes in skin texture and color over time contribute to predicting age-related changes accurately.
- **Age-related Features:** Age progression models specifically incorporate features that change with age, such as wrinkles, sagging skin, changes in facial fat distribution, and the appearance of age-related markers like gray hair. These features are essential for accurately predicting how a person's appearance may evolve over time.

7.4 Graphical and statistical output

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

Table 4. Results for various machine learning models

The classification results for various machine learning models applied to the dataset are as compared in TABLE 3. 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.

7.5 Comparison of results with existing systems

Aspect	**Existing Systems**	**Our System**
Facial Recognition Technology	Utilizes basic facial recognition algorithms or manual comparison.	Utilizes advanced deep learning algorithms like principal component analysis (PCA) for facial recognition.
Age Progression Techniques	Limited age progression methods, if any, often simplistic.	Implements generative adversarial networks (GANs) for dynamic age progression modeling, providing realistic representations of aging.
Training Data	Relies on limited or biased datasets, potentially impacting accuracy and inclusivity.	Trained on a comprehensive dataset of facial images to ensure robust performance across diverse demographics and aging trajectories.
Accuracy	Accuracy may vary depending on the quality of algorithms and training data.	Demonstrates higher accuracy due to advanced algorithms and comprehensive training data, reducing false positives and false negatives.

Table 5. Comparison of results with existing systems

7.6 Inference drawn

- **Technological Advancements:** The ReUnite project represents a significant advancement in missing person identification by leveraging advanced facial recognition and age progression technologies. In contrast, existing systems often rely on basic algorithms or manual comparison methods, lacking the sophistication and accuracy provided by modern deep learning techniques.
- **Accuracy and Reliability:** ReUnite demonstrates higher accuracy and reliability compared to existing systems, thanks to its utilization of state-of-the-art algorithms and

comprehensive training data. This results in reduced false positives and false negatives, improving the overall effectiveness of the system in identifying missing individuals.

- **Robustness and Inclusivity:** ReUnite ensures robust performance across diverse demographics and aging trajectories, mitigating biases and ensuring equitable outcomes. In contrast, existing systems may exhibit biases or inaccuracies, particularly across diverse populations, due to limited or biased training data.
- **User Satisfaction and Practical Utility:** Positive user feedback for ReUnite indicates its practical utility and effectiveness in real-world scenarios, enhancing stakeholder satisfaction. This underscores the importance of integrating advanced technology to address critical societal challenges effectively and gain user acceptance.

Chapter 8: Conclusion

8.1 Limitations

1. Data Quality: The effectiveness of the system heavily depends on the completeness and accuracy of data within the Missing Persons Database, which may be incomplete or biased.
2. Resource Constraints: Developing and maintaining a comprehensive database requires significant resources, which may limit scalability and accessibility in regions with limited resources.
3. Legal and Regulatory Compliance: Compliance with data protection laws and regulations presents challenges, particularly in navigating varied legal frameworks across jurisdictions.

8.2 Conclusion

In summary, the Reunite AI project stands as a beacon of hope in the realm of technology-driven solutions for locating missing persons. By leveraging sophisticated techniques like facial recognition and age progression, our system offers a ray of light to families enduring the anguish of separation and provides vital support to law enforcement and humanitarian organizations in their search efforts.

Our commitment to continuous improvement drives us to refine algorithms for more precise face detection and explore innovative age progression methods for generating realistic depictions of individuals over time. These efforts aim to enhance the system's effectiveness in locating missing persons and expediting their reunification with loved ones.

Looking ahead, we see vast potential in expanding the capabilities of the Reunite AI system. Integrating real-time data sources, such as social media platforms and surveillance footage, could further bolster our ability to respond swiftly and effectively to evolving situations, ultimately increasing the likelihood of positive outcomes in missing person cases.

In essence, the Reunite AI project represents a convergence of technology, compassion, and commitment to service. As we continue to push the boundaries of innovation, we remain steadfast in our mission to make a meaningful impact in the lives of those affected by the trauma of separation, one reunion at a time.

8.3 Future Scope

- Algorithm Refinement: Improve facial recognition and age progression algorithms for better accuracy.
- Real-Time Data Integration: Incorporate real-time data sources like social media to speed up identification.
- Mobile App Development: Create a mobile app for easier access and user engagement.
- Community Partnerships: Collaborate with organizations to expand reach and involvement.
- Ethical Guidelines: Establish clear ethical standards for data use and transparency.

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

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***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.

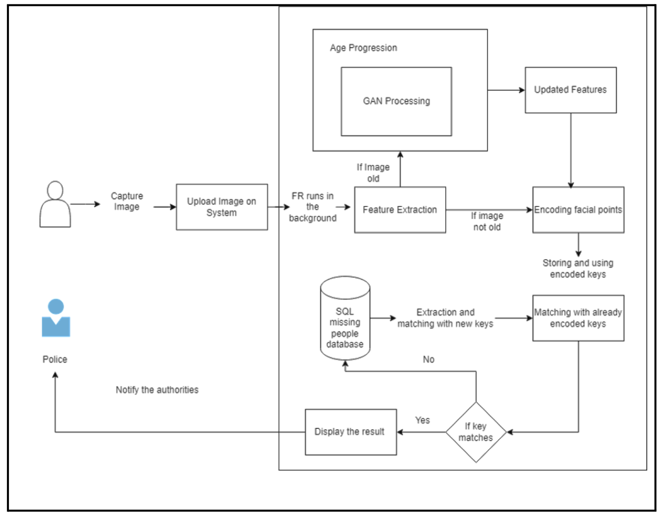

Fig. 1. ReUnite AI: System Architecture.

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.

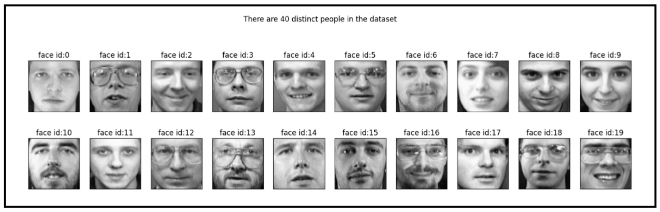

Fig. 2. Olivetti Dataset: Distinct images of 40 people.

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.

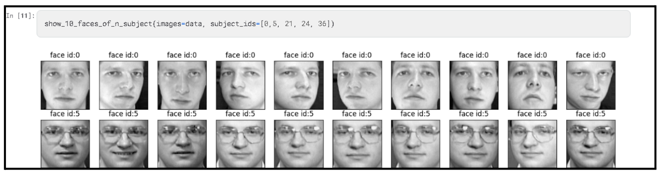

Fig 3. Olivetti Dataset: 10 images of each person.

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:

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

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.

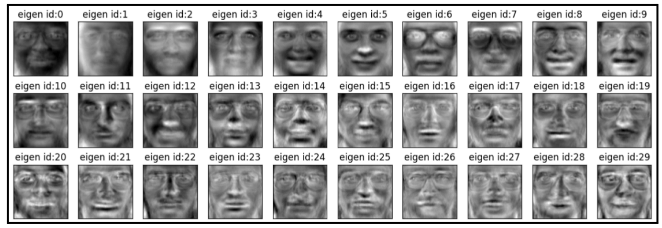

Fig. 4. Eigen Faces.

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

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.

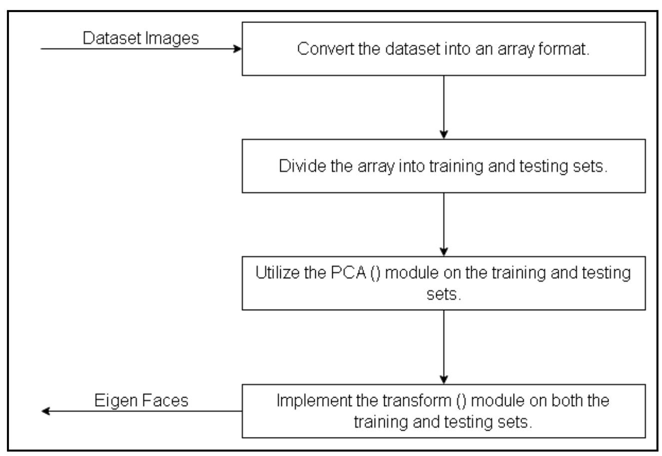

Fig 5. PCA Flowchart.

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.

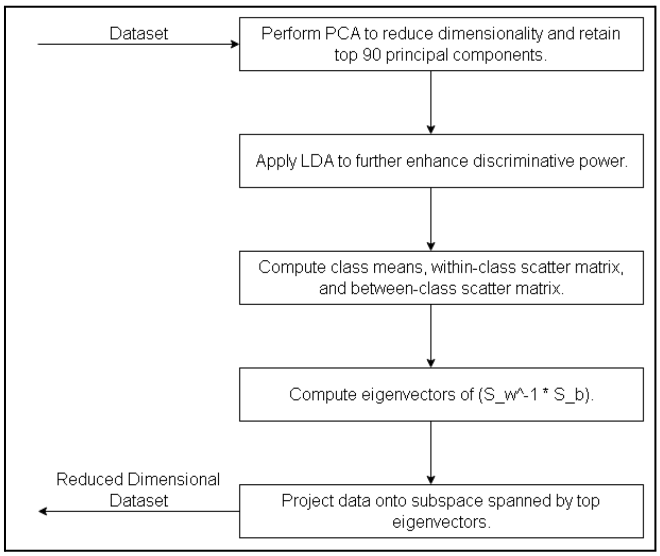

Fig. 6. LDA Flowchart.

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

$$\mu_i = \Sigma\left(x_i\right) / n_i \qquad (5)$$

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:

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

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:

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

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.

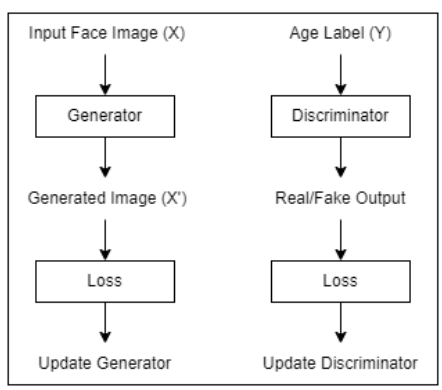

Fig. 7. cGAN Flowchart.

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.

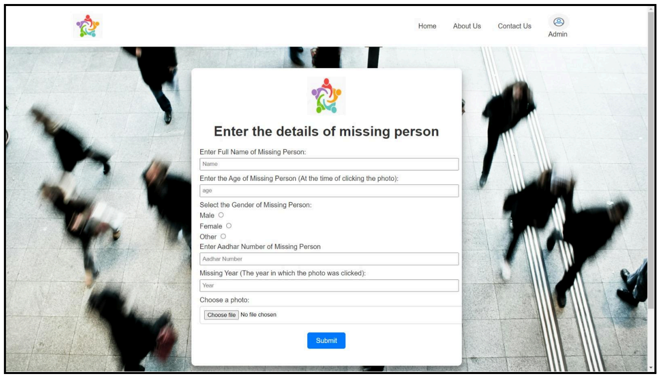

Fig. 8. Reporting missing person

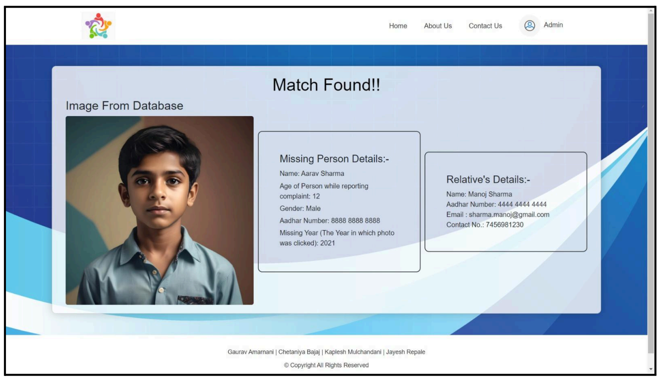

Fig 9. Displaying information in case of match found

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.

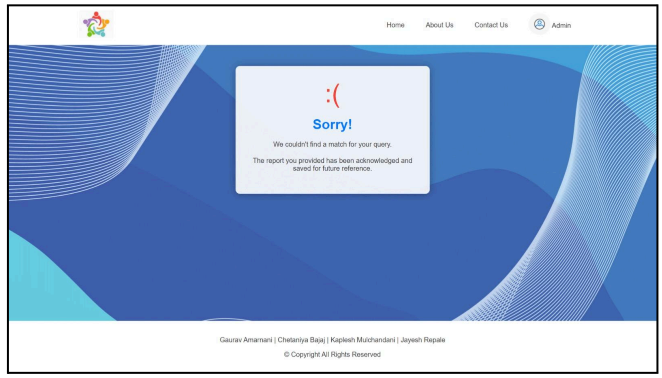

Fig 10. Displaying results in case of no match

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.

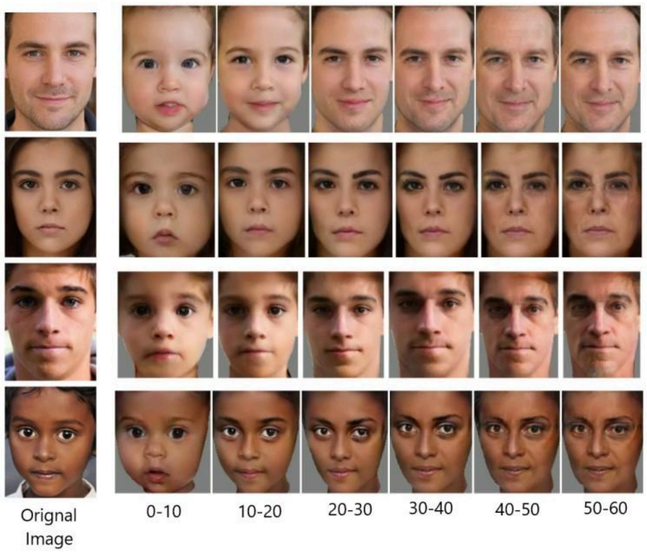

Fig 11. Age Progression Results

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.

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ReUnite AI

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Exploring Techniques For Age Progression In Facial Images: A Comprehensive Survey

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***Abstract*—Facial age progression has emerged as a critical domain in computer vision, finding applications across various fields including forensics and entertainment. This survey thoroughly investigates the methodologies utilized in age progression, encompassing both traditional and deep learning approaches. Beginning with an examination of traditional approaches, we delineate their strengths and limitations. Subsequently, focusing on deep learning methodologies, particularly generative adversarial networks (GANs), which have significantly enhanced the accuracy and realism of age progression. Additionally, addressing challenges associated with age progression, including dataset biases, privacy concerns, and ethical considerations, emphasizing the imperative to mitigate these challenges for the responsible deployment of age progression technologies. Finally, providing an outlook on future directions, discussing emerging trends such as novel data augmentation techniques, improved interpretability of deep learning models, and considerations for the societal implications of widespread age progression applications.**

***Keywords*—Age Progression, Image to Image Translation, Generative Adversarial Networks**

I. Introduction

Facial age progression, the process of synthetically rendering an individual's face at different ages, has emerged as a crucial area of research in computer vision and pattern recognition, with far-reaching implications across various domains. This technology holds significant potential in fields such as forensics, biometrics, and human-computer interaction, where the ability to accurately predict an individual's facial appearance at different ages can prove invaluable.

Facial age progression technology offers a plethora of real-world applications and relevance across diverse fields due to its capability to synthetically depict how an individual's face may change over time. In law enforcement, this technology serves as a crucial tool for identifying missing persons or suspects, as well as aiding in their recovery. By generating age-progressed images, law enforcement agencies can provide updated representations of individuals' potential appearances at different ages, thereby enhancing the chances of locating and rescuing missing persons or apprehending suspects who may have altered their appearance over time. Furthermore, in forensic investigations, facial age progression plays a pivotal role in reconstructing facial features of suspects or victims based on limited information, such as aged photographs or witness descriptions. This aids investigators in generating leads and narrowing down potential suspects, contributing valuable insights to criminal cases.

Beyond law enforcement and forensics, facial age progression technology finds applications in biometrics and human-computer interaction. In biometrics, accurately predicting an individual's facial appearance at different ages enhances the effectiveness of facial recognition systems for identification and authentication purposes. By accounting for age-related changes in facial features, such as wrinkles, sagging skin, and changes in facial structure, biometric systems can maintain accuracy over time, ensuring reliable identification across various age groups. Additionally, in human-computer interaction, facial age progression facilitates the development of age-aware technologies that adapt to users' changing needs and preferences as they age. This enables the creation of more personalized and intuitive user interfaces in applications ranging from digital assistants to virtual reality environments, enhancing user experience and engagement.

Moreover, facial age progression technology holds significant relevance in healthcare and aging research. By accurately predicting facial aging trajectories, clinicians and researchers can gain insights into the effects of aging on an individual's health and well-being. This includes assessing age-related changes in facial morphology associated with certain medical conditions, monitoring disease progression, and developing personalized interventions for age-related health concerns. Additionally, facial age progression aids in raising awareness about the importance of healthy aging and preventive care by visually demonstrating the potential effects of lifestyle choices, such as sun exposure, smoking, and skincare routines, on facial aging.

Facial age progression is a challenging task due to the complex and highly individualized nature of facial aging. The process involves modeling intricate transformations in facial features, textures, and shapes that occur as individuals age. These changes are influenced by various factors, including genetics, environmental conditions, and lifestyle choices, making it difficult to capture the nuances of aging accurately.

Researchers have explored various methods to tackle facial age progression, each with its unique strengths and limitations. The success of these methods heavily relies on the availability of high-quality and diverse datasets. Several publicly available datasets have been widely used in facial age progression research. However, these datasets often suffer from limitations, including biases in terms of age, ethnicity, and demographic representation, posing significant challenges for researchers in terms of data collection and curation.

The rest of the research paper is structured as follows: Section II provides an in-depth examination of the state-of-the-art methodologies used in facial age progression. It explores both feature-based techniques and deep generative models, delving into their complexities. Section III conducts a critical evaluation of the existing datasets employed for training and validation, highlighting their strengths, limitations, and potential biases. Additionally, ethical considerations surrounding facial age progression datasets are examined, emphasizing the necessity of responsible deployment and the mitigation of risks related to privacy and bias. Section IV centers on the diverse evaluation methods available to assess the accuracy of the algorithms discussed in the paper. Section V concludes the whole paper while Section VI mentions the current challenges faced in face age progression and potential for future work.

II. Methods and Approaches

In the realm of facial age progression, two prominent methodologies emerge: the traditional feature-based approach and the deep learning approach, often powered by Generative Adversarial Networks (GANs). These methodologies embody distinct strategies for predicting how a person's face evolves over time, each offering unique advantages and applications. The feature-based method entails the manual extraction and analysis of specific facial features, such as wrinkles and contours, to estimate aging effects based on statistical models and expert insights. In contrast, the deep learning approach harnesses the power of neural networks, particularly GANs, to autonomously generate realistic aged facial images by learning from large datasets. Fig. 1 illustrates examples of age-progressed images generated using cGAN.

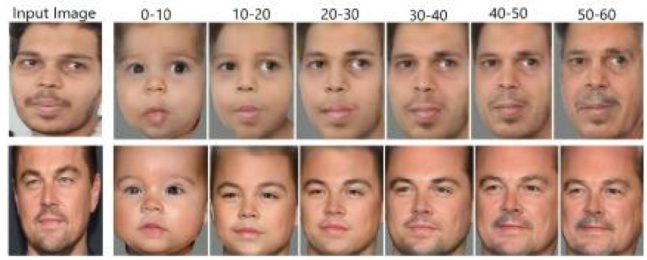

Fig. 1. Face Age Progression

A. Features Based approach

Features based approaches rely on established methods that have been foundational in understanding how a person's face changes with time. These methods often involve the manual or semi-automated analysis of specific facial features, such as wrinkles, skin texture, and facial contours, that are known to undergo alterations with age. Feature-based methods, for instance, extract key landmarks and descriptors from facial images to quantify aging-related changes statistically. They may employ techniques like linear regression or principal component analysis to model the relationship between these features and age labels, providing insights into the aging process. Additionally, template-based methods utilize age-labeled facial images as references for generating aged versions of new faces. By aligning facial features between templates and target images, these methods deform the facial structure to reflect typical aging patterns observed in the templates.

I. Kemelmacher-Shlizerman [1] introduced an innovative, fully automated method for facial age progression, specifically focusing on the challenge of aging young children. This methodology presents a comprehensive approach to automatically progressing facial images across different age ranges. It initiates with the assembly of a substantial dataset covering ages ranging from infancy to adulthood, sourced from diverse online platforms. Leveraging this dataset, the approach involves the creation of aligned and relightable average images for each age group, facilitating the incorporation of realistic shading effects. To generate relightable average images, techniques such as singular value decomposition (SVD) applied to flow-aligned images and the computation of rank-4 approximations are employed. Optical flow methodologies are then utilized to estimate the flow between different age clusters, enabling the computation of age transformations. Additionally, the methodology incorporates algorithms for adjusting aspect ratios and varying skin tones. Because the algorithm's performance heavily depends on the quality and diversity of the training dataset, without sufficient representation across demographics, ethnicities, and facial features the algorithm may struggle to accurately capture age progression for different groups.

X. Shu [2] introduces a novel approach consisting of offline training and online synthesis phases. Short-term aging pairs are collected from various databases to create aging dictionaries covering diverse aging characteristics. A personality-aware coupled dictionary learning model is developed, considering individualized details like birthmarks and scars. Principal Component Analysis (PCA) reduces data dimensionality. In the online synthesis phase, aging faces are rendered iteratively in successive age groups. Sparse coefficients and personalized layers are updated iteratively for optimal aging results, reflecting a short-term coupled learning approach due to limited long-term aging data. The process involves iterative updates until convergence, aiming for consistency with the training phase and producing personalized and natural-looking aging faces through data-driven learning and iterative optimization techniques.

X. Shu [3] presents notable improvements over prior work by addressing the practical challenge of obtaining long-term aging sequences. It achieves this by utilizing dense short-term aging pairs, enhancing the method's applicability for real-world scenarios. The introduction of a bi-level dictionary learning approach, incorporating personalized layers, enhances the capture of individual-specific aging characteristics, resulting in more realistic and personalized aging faces. Furthermore, optimizations in the age progression synthesis process reduce computational complexity, leading to faster convergence and requiring fewer iterations for generating aging faces. Collectively, these enhancements enhance the accuracy, realism, and efficiency of the age progression method, making it suitable for various applications in facial aging analysis and synthesis.

The approach presented by *Shintaro* [4] is for altering facial age in videos while accounting for changes in facial expressions. The methodology primarily focuses on synthesizing aging facial videos while considering the temporal dynamics of wrinkles induced by facial expressions. Initially, the process involves aligning facial expressions between the target video and a database of videos exhibiting similar expressions. This alignment is facilitated using local binary patterns (LBPs) as descriptors for facial expressions, complemented by dynamic time warping (DTW) to ensure temporal coherence. Subsequently, each frame of the database undergoes deformation to match the shape of the corresponding frame in the target video, employing radial basis functions (RBF) interpolation. Additionally, the methodology encompasses the synthesis of an aged video by blending textures from chosen individuals in the database, taking into account attributes like color and wrinkles. The preservation of wrinkles emerges as a critical aspect, entailing the identification of optimal facial regions and the blending of expressions and neutral faces to uphold natural wrinkle depth.

Riaz [5] outlines their methodology for constructing and simulating gender-specific 3D aging models. Initially, they convert 2D images from various datasets into 3D frontal-face models, which serve as the basis for creating aging spaces for both shape and texture. The construction of the 3D aging models involves mapping 2D images to 3D face models using facial landmarks and active shape modeling techniques. Principal Component Analysis (PCA) is separately applied to male and female 3D faces with available age labels to construct shape and texture models. Interpolation methods are utilized to address missing data in the aging patterns. Aging simulation entails fitting input images to the shape aging space and generating corresponding texture patterns. Subsequently, color and flare correction techniques are applied to ensure consistency between the simulated images and the original background. Finally, the age-simulated images are composited onto the original backgrounds using landmark points and an edge-smoothing algorithm to achieve realistic integration.

Elmahmudi [6] proposes an approach that relies on ethnicity-based face templates constructed from age, gender, color, and texture characteristics extracted from faces of principal ethnic groups. The system consists of two main components: firstly, a mathematical method for constructing ethnicity-specific aging templates using average faces; and secondly, the application of these templates to target faces for age generation, incorporating control parameters for color and texture. Additionally, a framework for verifying the accuracy of generated faces through similarity comparison using Convolutional Neural Networks (CNNs) is proposed. Data collection involved multiple phases, including the gathering of images from diverse sources and their normalization to a reference frame. The methodology encompasses techniques for facial landmark detection, template generation, wrinkle mapping, and labeling. Age progression or regression is achieved through image morphing and cross-dissolving, with parameters controlling shape and color fidelity.

While traditional approaches have offered valuable insights into facial aging dynamics, they often rely on simplifications and may struggle to capture the full complexity of age-related changes. As a result, contemporary methods, particularly those based on machine learning and deep learning, have emerged to address these limitations and enhance the accuracy and realism of facial age progression models.

B. Generative Adversarial Networks

In contrast to feature-based approaches, GANs [7] have emerged as a powerful alternative in the realm of face age progression. GANs leverage the concept of adversarial training, where two neural networks, namely the generator and the discriminator, are pitted against each other in a competitive manner. In the context of face age progression, the generator network is tasked with synthesizing realistic images of faces at different ages, while the discriminator network aims to distinguish between real and generated images. In simpler terms, they engage in a min max game. Explained further using equation (1).

$$min\, G\, max\, D\, V(D, G) = E_{x\sim Pdata(x)}[log\, D(x)] + E_{z\sim Pz(z)}[log(1 - D(G(z)))] \tag{1}$$

The Generator G takes random noise samples z from a prior distribution $pz(z)$ and transforms them into data samples $G(z;\ \theta g)$, where θg represents the parameters of the generator. Essentially, $G(z;\ \theta g)$ maps the noise space to the data space, generating synthetic data that ideally mimics the distribution of real data.

The Discriminator D evaluates data samples x and assigns a probability $D(x;\ \theta d)$ representing the likelihood that the sample came from the real data distribution rather than from the generator's distribution. It's represented as a function $D(x;\ \theta d)$, where θd denotes the parameters of the discriminator.

In the training process, the discriminator is trained to maximize the probability of correctly labeling both real data samples and generated samples. This is captured by the term $[log\, D(x)]$ in the equation, where $D(x)$ represents the probability assigned by the discriminator to real data samples. The goal is for $D(x)$ to approach 1 for real data.

Simultaneously, the generator is trained to minimize the discriminator's ability to correctly classify its generated samples as fake. This is achieved by minimizing the log probability of the discriminator outputting 1 when given generated data. This objective is represented by the term $[log(1\ -\ D(G(z)))]$, where $G(z)$ represents the generated data and $D(G(z))$ represents the probability assigned by the discriminator to generated samples. The generator aims to make $D(G(z))$ approach 0, indicating that the discriminator is unable to distinguish between real and generated data effectively. This adversarial process drives both networks to improve iteratively until an equilibrium is reached, ideally resulting in the generator producing high-quality synthetic data samples.

The Conditional Adversarial Autoencoder (CAAE) network, introduced in Paper [8], Unlike traditional GANs which often suffer from instability and produce noisy outputs, integrates an encoder, generator, and discriminators to effectively learn a manifold of facial features. This manifold facilitates smooth transitions in age while preserving unique individual characteristics. By converting input facial images into feature vectors using the encoder, and then combining them with age labels for guidance during generation by the generator, the CAAE ensures accurate and personalized image synthesis. Furthermore, the objective function of the CAAE balances several factors, including reconstruction accuracy, distribution regularity, and image realism, to optimize the quality of the generated images. What distinguishes the CAAE from other generative models, such as Variational Autoencoders (VAEs) [9] and Adversarial Autoencoders (AAEs) [10], is its innovative use of discriminators on both the encoder and generator. This unique approach sets the CAAE apart, making it a promising upgrade over traditional GANs.

G. Antipov [11] introduces two significant contributions: Age-cGAN, an iteration of GANs tailored to craft impeccable synthetic images categorized by age, and an innovative method for optimizing latent vectors to uphold the distinct identity of the original person during facial reconstruction. The proposed approach to facial aging unfolds in a methodical two-step process: initially approximating the latent vector, followed by optimization. The intricacies of Age-cGAN are detail\\ed, showcasing its adept use of conditional data to generate images falling within predefined age brackets. Additionally, the technique for approximating facial reconstruction places a strong emphasis on preserving identity, effectively mitigating issues like blurriness and irrelevant details.

X. Tang [12] introduces Identity-Preserved Conditional Generative Adversarial Networks (IPCGANs) for facial aging. It proposes a method to divide facial images into age groups and generate lifelike faces within specific age ranges while maintaining the original identity. IPCGANs consist of three essential components: CGANs for realistic face synthesis, an Identity-Preserved module to retain identity features, and an age classifier to ensure the generated faces match the desired age group. The CGANs module employs Conditional Least Squares Generative Adversarial Networks (LSGANs) to produce high-quality images, while the Identity-Preserved module utilizes perceptual loss to safeguard identity characteristics. Additionally, an age classification module is incorporated to enforce age coherence in the generated faces. The combined objective function integrates adversarial loss, identity preservation loss, and age classification loss. The network architecture comprises a generator, discriminator, and age classification network, each customized for its specific role. The generator employs residual blocks and integrates age conditions before the initial convolution layer, while the discriminator's architecture draws inspiration from invertible conditional GANs, incorporating condition injection after the first convolution layer. Lastly, the age classification network, based on AlexNet [13], is enhanced with fully connected layers and dropout to prevent overfitting.

H. Yang [14] combines GANs, age-specific feature extraction, and identity preservation techniques. The framework involves a generator network, encoder-decoder architecture, and discriminator network. Identity preservation is addressed by measuring the input-output distance in a feature space sensitive to identity changes. The loss function comprises adversarial loss, pixel-wise loss for color aberration, and identity loss, with weighting factors regulating their contributions.

Y. Liu [15] introduces a framework based on GANs to tackle the challenge of learning age-specific transformations in unpaired face image datasets. This framework consists of a generator network and a discriminator based on wavelet analysis. The generator is designed to incorporate both low-level image details and high-level semantic facial attributes, aiming to stabilize the translation process between young and aged faces. To capture age-related textures effectively, the model utilizes wavelet packet transform, enabling multi-scale texture analysis while keeping computational demands low. The training process involves minimizing adversarial loss, pixel loss to maintain image-level consistency, and identity loss to preserve personalized facial features.

The S2GAN framework introduced by *Z. He* [16] is a novel approach to face aging by incorporating personalized aging factors and age-specific transformations. It comprises three main components: establishing personalized aging bases using a deep encoder, transforming these bases into age representations for different age groups, and decoding these representations to generate aged faces. Unlike traditional GANs, S2GAN optimizes the model with three objectives: age group classification loss, L1 reconstruction loss for identity preservation, and adversarial loss for fidelity. The age-specific transforms, shared across individuals but distinct for different ages, enable continuous aging interpolations, providing more natural and practical results compared to methods with discrete age groups.

TABLE I

Summary of Age Progression Algorithms and Methods

Paper Title	ML Model	Dataset	Parameters	Results	Comments
Personalized Age Progression with Aging Dictionary - 2015 [2]	PCA	CACD, MORPH, FGNET	Comparison to ground truth	Out of 12,300 visual comparisons done by 50 people 45.35% preferred this model, 36.45 preferred the prior works, while 18.20% found them comparable.	One of the earliest methodologies provided for age progression
Personalized Age Progression with Bi-Level Aging Dictionary Learning - 2018 [3]	PCA	CACD, MORPH	Comparison to ground truth	Out of 13,050 visual comparisons done by 50 people 36.5% preferred BDL-PAP, 34.8% preferred CDL-PAP, 26.7% preferred prior works and 2.0% were not satisfied.	BDL-PAP is more time efficient than CDL-PAP.
A framework for facial age progression and regression using exemplar face templates - 2021 [6]	CNN, GAN	FEI, MORPH II	CNN Face recognition	Similarity value of higher than 70% on the FEI dataset.	Ethnicity-based age progression method validated by CNN
Age Progression/Regression by Conditional Adversarial Autoencoder - 2017 [8]	CAAE	MORPH, CACD	Comparison to ground truth	Out of 1508 votes from 47 people 52.77% preferred CAAE, 28.99% preferred prior works and 18.24% thought they were equal.	Introduced Conditional Adversarial Autoencoder (CAAE) and integrated encoder in GAN
Face aging with conditional generative adversarial networks - 2017 [11]	CGAN	AGE-eGAN	Identity-Preserving Face Reconstruction and Aging	After Face reconstruction, The software 'OpenFace' gave these scores After Initial Reconstruction 53.2%, Pixelwise Optimization 59.8%, Identity-Preserving Optimization 82.9%.	GAN iteration for generating high-quality synthetic images
Face Aging with Identity-Preserved Conditional Generative Adversarial Networks - 2018 [12]	IPCGAN	CACD	Face Verification	After conducting face verification testing, CAAE scored 91.53%, acGAN scored 85.83%, IPCGAN scored 96.90%.	Integrated CGANs with an Identity-Preserved module and an age classifier
Attribute-Aware Face Aging With Wavelet-Based Generative Adversarial Networks - 2019 [15]	GAN	MORPH, CACD	Face Verification	On the MORPH dataset, the face verification score for CAAE was 11.77%, GLCA-GAN was 95.39%, PAG-GAN was 97.33%, Proposed model 99.42%.	Utilized wavelet analysis in the discriminator to stabilize translation
S2GAN: Share Aging Factors Across Ages and Share Aging Trends Among Individuals - 2019 [16]	S2GAN	MORPH, CACD	Aging Accuracy	On the MORPH dataset, Aging accuracy score for CAAE was 47.38%, IPCGAN was 64.42%, Proposed S2GAN was 93.0%.	Optimized with classification, reconstruction, and adversarial losses
Face Aging with Conditional Generative Adversarial Network Guided by Ranking-CNN - 2020 [17]	Ranking-CNN, GAN	CACD	Aging Accuracy	On the CACD dataset, Aging accuracy score for CAAE was 27.01%, IPCGAN was 47.98%, Proposed model was 52.08%.	Implemented Conditional GAN supervised by Ranking-CNN
CAN-GAN: Conditioned-attention normalized GAN for face age synthesis - 2020 [18]	CAN-GAN, CAAC	CACD, MORPH, FGNET	Face Verification	On the MORPH dataset, the face verification score for GLCA-GAN 95.39%, Yang et al. 97.00%, WaveletGLCA-GAN 99.80%, CAN-GAN 99.99%	Used CAN for age-based normalization and CAAC to improve age determination accuracy
An Improved Technique for Face Age Progression and Enhanced Super-Resolution with Generative Adversarial Networks - 2020 [19]	Cycle-GAN, ESRGAN	IMDB-WIKI, CACD, UTKFace, FGNET, CELEB-A	Age Estimation	On the IMDB-WIKI dataset, FACE++ software estimates the average age of the synthesized images as 30.2 for the age group 19 - 35. average age of 36.5 for age group 35 - 60 and average age of 61.7 for age group 60 and above	Combined CycleGAN for age progression and ESRGAN for image enhancement
PFA-GAN: Progressive Face Aging With Generative Adversarial Network - 2021 [20]	PFA-GAN	MORPH, CACD	Face Verification	On the MORPH dataset, FACE++ is used for Face Verification PFA-GAN 99.70%, CAAE 44.02%, IPCGAN 99.21%, WGLC-CAN 99.27%.	Introduced multiple sub-networks to capture aging dynamics, preserve facial identity, and mitigate overfitting
Face aging using global and pyramid generative adversarial networks - 2021 [23]	GAN	UTKFace, CACD	Age Classification	The age classification accuracy for GFA-GAN is 27.45%, for PFA-GAN it is 39.72%, for CAAE it is 17.64%, and for IPCGANs it is 17.88%.	Introduced weight sharing in GFA-GAN and pyramid weight sharing in PFA-GAN

Furthermore, S2GAN offers lower computational cost and storage requirements by utilizing a single model for all target ages and sharing the personalized basis across ages, making it more efficient and scalable for face aging tasks.

The approach by *M. Sheng* [17] aims to improve the precision of face aging through the utilization of a conditional GAN under the supervision of Ranking-CNN. It categorizes facial images into five distinct age groups and employs a combination of a generator, discriminator, pretrained Alexnet network [13], and Ranking-CNN within its framework. Diverging from conventional GANs, this technique integrates a perceptual loss mechanism to uphold identity preservation and integrates Ranking-CNN to enforce more rigorous age constraints on the generator. Additionally, it adopts conditional Least Squares GAN (LSGAN) [18] for adversarial loss implementation to ensure consistent and high-quality image synthesis.

Shi [18] introduces The CAN-GAN framework. At its core lies the Conditional Attention Normalization (CAN) which is integrated into both the generator and discriminator units. Unlike conventional approaches, CAN utilizes age disparities instead of age labels for normalization, thereby adeptly capturing age-related facial characteristics while diminishing irrelevant ones. Furthermore, the model integrates the Conditional Age Attribute Classifier (CAAC) to assess the significance of individual facial attributes in age determination, thereby enhancing accuracy. The model's objective function merges adversarial loss, reconstruction loss, and age classification loss to effectively train the CAN-GAN model.

Sharma [19] introduces an integrated approach Leveraging techniques such as CycleGAN for age progression and Enhanced Super-Resolution GAN (ESRGAN) for image enhancement. The method aims to transform input face images into aged versions while preserving original features and improving image quality. By incorporating advancements like age-conditional GANs, progressive GANs, and cGANs, the model ensures better resolution and guidance in data generation. Although requiring substantial computational resources for training, This integration of face age progression and super-resolution techniques offers a promising solution to generating high-quality aged face images.

The progressive face aging framework proposed by Zhizhong [20] diverges from traditional GANs by concentrating specifically on capturing the aging dynamics of facial images. While conventional GANs typically generate images from random noise, this framework redefines the aging process through a progressive neural network structure composed of multiple sub-networks. These sub-networks specialize in learning the aging effects between neighboring age groups, facilitating controlled and lifelike age transitions. Through the integration of residual skip connections and binary gates, the framework effectively preserves facial identity and mitigates overfitting issues during the aging process. Moreover, by training the model end-to-end, it addresses cumulative error concerns, ensuring robust age progression across various age groups and conditions, a distinct feature from the separate training paradigm of traditional GANs.

H. Tang [21] proposes Attention-Guided Generation Scheme I and Scheme II. In Scheme I, attention-guided generators G and F are employed to learn mappings between image domains X and Y. Here, attention masks are generated to selectively adjust foreground content while preserving background elements. However, Scheme I encounters challenges with complex tasks due to its reliance on a single attention and content mask generation process. To overcome these limitations, Scheme II introduces distinct sub-networks for generating attention and content masks, enabling more adaptable learning and translation of both foreground and background content. Moreover, attention-guided discriminators are proposed to emphasize discriminative content and enhance translation quality. Both schemes incorporate cycle-consistency loss [22] and supplementary regularization methods to effectively optimize the translation process.

The methodology proposed by Pantraki [23] treats age progression as an unsupervised task of translating images across different age groups, employing the UNIT network [24] for this purpose. Each age group is represented through three key components: an encoder, a decoder/generator, and a discriminator. In GFA-GAN, weight sharing is introduced using a combination of encoders and generators, capturing both localized and global features. PFA-GAN builds upon this approach by introducing a pyramid weight sharing mechanism to emulate the gradual aging process. Throughout the training process, the framework aims to minimize various losses such as cycle consistency and total variation, ensuring faithful translations between diverse age groups.

Table I presents a comprehensive summary of the algorithms employed in facial age progression research, along with the datasets utilized to train and evaluate these algorithms. Each algorithm is meticulously analyzed in terms of its year of publication, the specific dataset employed, and any noteworthy features or contributions.

III. DATASET

Collecting a comprehensive dataset relevant to facial aging is a challenging task, necessitating careful consideration of various factors. One of the critical criteria in the data collection process is ensuring diversity in age representation among subjects. This ensures that the dataset covers a broad spectrum of aging patterns, facilitating the development of robust facial aging models. However, while sequential images of the same individual at different ages are often preferred, certain methodologies in facial aging research can effectively discern aging patterns without this requirement.

The success of Generative Adversarial Networks (GANs) in producing realistic facial aging progression hinges on the diversity and quality of the training dataset, crucial for capturing the nuanced complexities of aging with accuracy.

The various datasets commonly used in research related to facial age progression and related fields vary in terms of size, subject type, labeling criteria, and distribution of images across age groups. Several datasets focus on celebrity faces, such as CACD [26], IMDB-WIKI [27], and CelebA [28], with large numbers of images spanning different age categories. Other datasets, like FFHQ [30], UTKFace [8], VGG Face 2 [34], Morph [29], AgeDB [35] are collected from general populations, encompassing a range of ages and genders. The labeling criteria predominantly include age and gender, although some datasets also include additional attributes such as race. While most datasets exhibit non-monotone distributions across age groups, indicating a varied representation of ages, some datasets, like FGNET [31] and Olivetti [33], feature monotone distributions primarily focused on specific age ranges. Additionally, there are datasets like WebFace260M [32], WebFace42M [32], DigiFace1M [36], MegaFace1M [37] that provide extensive collections of facial images without specific labels, catering to various research needs.

Ethical concerns surrounding facial aging datasets, especially those containing images of children, are paramount. While these datasets offer valuable insights, they raise significant privacy and consent issues. Mitigating these concerns is essential to ensure responsible research practices, often prompting the exploration of alternative methods like generating synthetic images. One notable paper addressing this challenge is ChildGAN [25]. It introduces a novel method for generating synthetic images of children that closely resemble real faces while avoiding the need to use actual images of minors.

The methodology proposed in the aforementioned paper comprises three main phases: firstly, gathering synthetic data for initializing training datasets; secondly, separately training ChildGAN models tailored for boys and girls using StyleGAN2; and finally, employing techniques for editing the latent space to modify facial attributes. Synthetic data from diverse origins undergoes a rigorous filtering process and is categorized into two distinct classes. ChildGAN, constructed upon StyleGAN2, undergoes training via transfer learning to generate high-fidelity facial images of children. The manipulation of facial attributes, such as expressions and lighting conditions, is facilitated through latent space editing. This approach seamlessly combines sophisticated deep learning techniques with meticulous data curation to create lifelike synthetic facial images of children.

IV. Conclusion

In conclusion, facial age progression research represents a dynamic and evolving field at the intersection of computer vision, machine learning, and ethics. The methodologies discussed, ranging from traditional feature-based approaches to advanced deep learning techniques utilizing Generative Adversarial Networks (GANs), underscore the complexity and diversity of strategies employed to predict facial aging accurately. While each approach offers distinct advantages and contributions, the success of these methods critically hinges on the quality and diversity of datasets utilized for training and evaluation. Ethical considerations surrounding data collection, particularly concerning the inclusion of images of children, necessitate careful navigation to ensure privacy protection and mitigate potential harms. Moreover, the comprehensive overview of publicly available datasets provided herein underscores the foundational importance of diverse and well-annotated data repositories in advancing facial age progression research. Moving forward, continued interdisciplinary collaboration and ethical awareness will be paramount in harnessing the full potential of facial age progression technologies for societal benefit while addressing associated ethical concerns.

V. Challenges and future work

Challenges and future directions in the domain of facial age progression (FAP) encompass several critical aspects that researchers are actively addressing. One significant challenge lies in achieving a balance between visual fidelity, aging accuracy, and identity preservation in synthesized images. While advancements have been made in improving these aspects individually, achieving optimal results across all dimensions simultaneously remains a complex task. Future research efforts can be focused on developing novel algorithms and techniques that strike a harmonious balance between these competing objectives.

Another challenge in facial age progression is the availability and quality of training data. Current datasets often suffer from biases, such as underrepresentation of certain age groups or ethnicities, which can impact the performance and generalization capabilities of facial age progression models. Addressing these biases and curating more diverse and comprehensive datasets will be crucial for improving the robustness and reliability of facial age progression systems.

Ethical considerations also pose significant challenges in the development and deployment of facial age progression technology. Concerns related to privacy, consent, and potential misuse of synthesized images underscore the need for robust ethical frameworks and guidelines. Future research will need to explore ethical implications in greater depth and develop mechanisms to ensure responsible use of facial age progression technology.

Furthermore, scalability and computational efficiency are ongoing challenges in facial age progression, particularly as the demand for real-time or large-scale age progression applications grows. Optimizing algorithms for faster inference and reducing computational resource requirements will be essential for practical deployment in various domains, including law enforcement, entertainment, and healthcare.

Looking ahead, future work in facial age progression will likely focus on exploring new avenues such as generative models with improved interpretability, incorporating domain knowledge from related fields like psychology and gerontology, and leveraging emerging technologies such as augmented reality (AR) and virtual reality (VR) for more immersive and interactive age progression experiences. By addressing these challenges and pursuing innovative research directions, the field of facial age progression holds tremendous potential for transformative advancements with far-reaching societal impacts.

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Plagiarism Report

Exploring Techniques For Age Progression In Facial Images: A Survey

ORIGINALITY REPORT

3%	2%	4%	1%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

Project Review Sheet 1

Inhouse/ Industry _Innovation/Research:

Sustainable Goal:

Project Evaluation Sheet 2023 - 24

Class: D17 A/B/C

Group No.: 44

Title of Project: Reunite: Harnessing Face Detection and Age Progression for missing people identification

Group Members: Gaurav Amarnani (2), Kaplesh Mulchandani (45), Chetaniya Bajaj (4), Jayesh Repale (56)

Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life-long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(3)	(5)	(50)
4	3	3	2	2	2	2	2	2	2	2	3	2	2	–	33

Comments: Research paper.

Sujata K 10/02/24

Name & Signature Reviewer1

Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life-long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(3)	(5)	(50)
4	4	3	2	2	2	2	2	2	2	3	3	2	2	–	36

Comments: → Age progression model need to shown,
→ Topic/problem statement should be explained with clarity
→ Research Paper not shown

Date: 10th february, 2024

Yugchhaya 10/02/24

Name & Signature Reviewer 2

Project Review Sheet 2

Inhouse/ Industry _Innovation/Research:

Sustainable Goal:

Project Evaluation Sheet 2023 - 24

Class: D17 A/B/C

Group No.: 44

Title of Project: Reunite AI: Harnessing Face Detection and Age Progression for missing person identification.

Group Members: Gaurav Amarnani (2), Kaplesh Mulchandani (45), Chetaniya Bajaj (4), Jayesh Repale (56)

Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life-long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(3)	(5)	(50)
4	4	4	3	4	2	2	2	2	2	02	3	2	2	4	42

Comments:

Name & Signature Reviewer1

Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg&Mgmt principles	Life-long learning	Professional Skills	Innovative Approach	Research Paper	Total Marks
(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(3)	(5)	(50)
04	04	04	03	04	02	2	02	02	01	02	03	02	02	03	40

Comments: Use case based demonstration need to be shown & with clear understanding depth.

Date: 9th March, 2024

Yugchhaya

Name & Signature Reviewer 2