



Sarvajani College of Engineering and Technology  
Artificial Intelligence and Data Science  
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# Age Progression using xAI-CPAVAE

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# Introduction

## Overview of the project:

- **Global Challenge:**

- Annually, 60,000 children go missing in India, with many falling victim to trafficking or exploitation.
- Globally, minors account for 28% of trafficking victims, with a gender disparity—girls are disproportionately targeted.

- **Current Solutions:**

- **TrackChild Database (India):** Features a Facial Recognition System (FRS) enabling law enforcement to trace thousands of missing children.
  - Example: Delhi Police identified 3,000 children using FRS.
- **Darpan System (Telangana):** Another successful technological initiative.

# Introduction

## Limitations of Traditional Methods:

- Dependence on outdated photographs for age progression.
- Manual techniques (e.g., forensic sketches) lack scalability and efficiency.

## Hybrid Framework- Combines:

- **CPVAE (Conditional Perceptual Adversarial Variational Autoencoder):** Generates high-quality conditional outputs.
- **xAI-GAN (Explainable AI – Generative Adversarial Network):** Adds interpretability to the generative process.

## Key Features:

- Enables identity tracking over time despite facial changes.
- Provides reliable, efficient, and transparent tools for law enforcement and social welfare organizations.

# Introduction

## Objective:

- **Primary Goals:**

- Create an interpretable, robust model for age progression.
- Enable **feature-level insights** to build trust and refine outputs.

- **Applications:**

- Forensics (missing person identification).
- Healthcare (age-related predictions).

# Challenges Faced

## Problems Encountered:

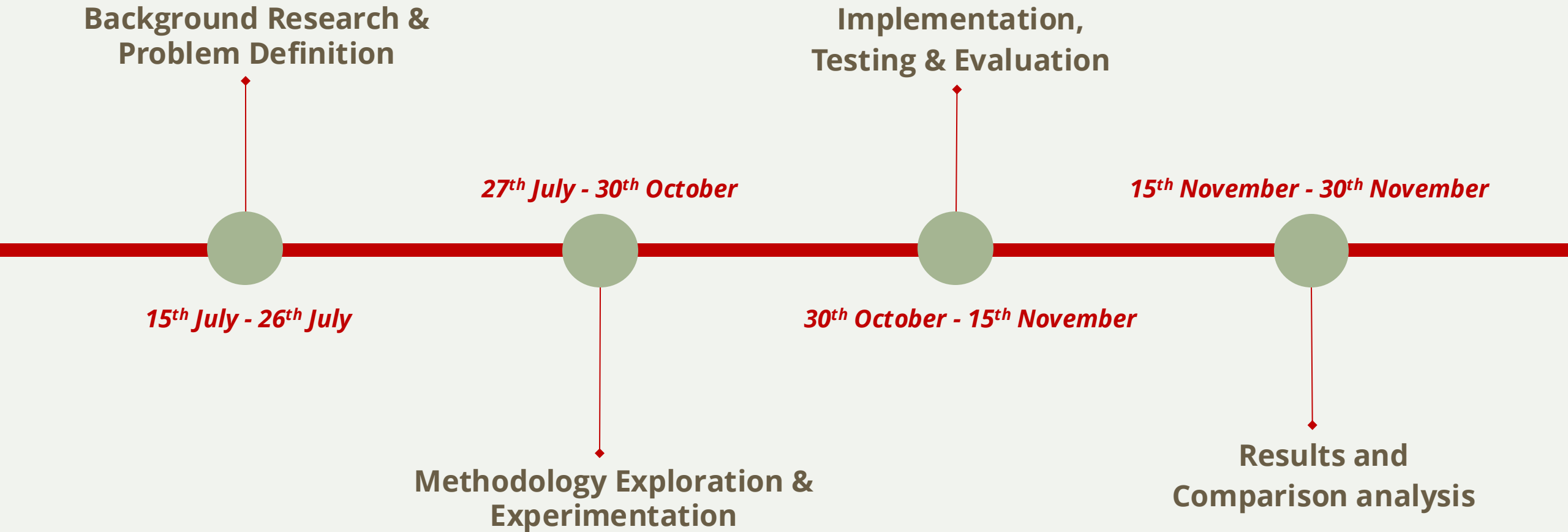
- **Complexity in Gradient Refinement**
  - Difficulty in integrating the explainable matrix  $M$  into generator updates.
- **Ensuring Explainability**
  - Selecting the most effective xAI technique (e.g., Saliency Maps, LIME, DeepSHAP).
- **Maintaining Image Quality**
  - Struggles with retaining stylistic and textural details during adversarial learning.
- **Balancing Loss Functions**
  - Challenges in balancing adversarial loss, perceptual loss, and KL divergence.
- **Computational Overhead**
  - High resource requirements for training with VGG19 and multiple xAI methods.

# Challenges Faced

## How We Addressed the Challenges:

- **Gradient Refinement**
  - Adjusted the generator's gradient update mechanism by careful tuning
- **Optimizing Explainability**
  - Enhanced model interpretability through **xAI tools** (e.g., saliency maps).
- **Loss Function Tuning**
  - Iteratively tuned the weights of loss components to ensure balanced model performance.
- **Managing Computational Resources**
  - Used hardware accelerators (GPUs/TPUs) and efficient data pipelines to reduce training overhead.
- **Improved image quality with perceptual loss.**
- **Leveraged pre-trained models like VGG19 for efficient processing.**

# Project Timeline



# Technical Details

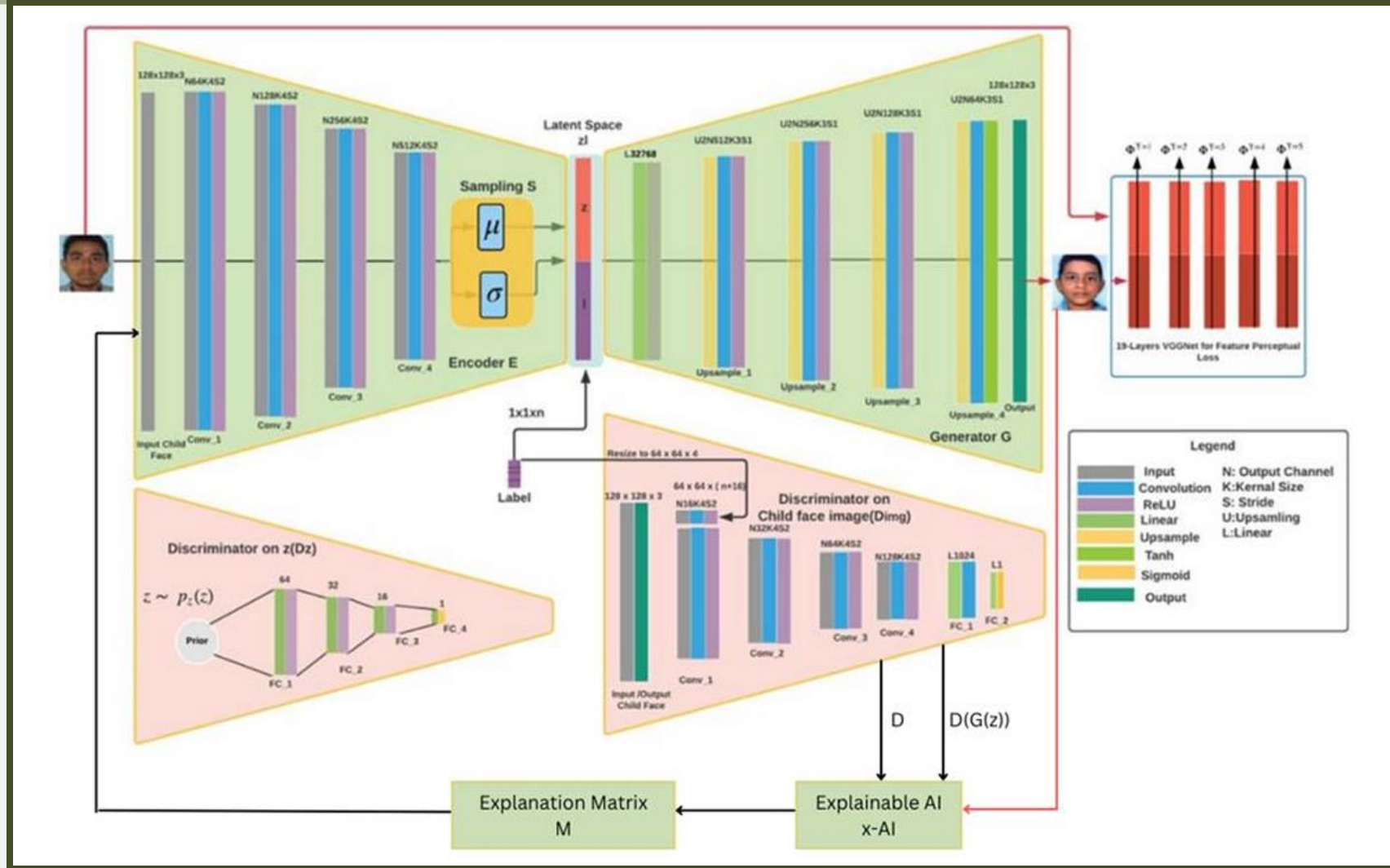


Figure : Major Steps of the proposed approach



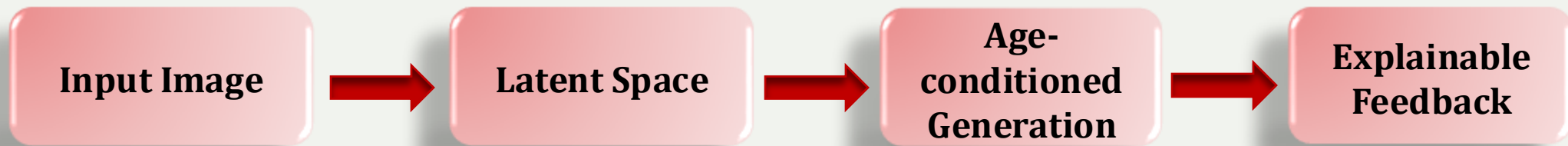
# Technical Details

- **The proposed xAI-CPVAE approach:**

- **Framework Architecture:**

- Encoder, Generator, two Discriminators, Explainable Loss Network, Perceptual Loss Network.
    - Adversarial Learning ensures the generator produces realistic outputs.

- **Process Flow:**



# Technical Details

## Dataset Details:

- **Multi-Racial Child Dataset (MRCD):**

Characteristic	Description
Dataset name	Multi-Racial-Child-Dataset(MRCD)
Number of images	64,965
Race groups	Asian (17,221 images), Black (13,354 images), White (19,297 images), Indian (15,103 images)
Age range	0-20 years

# Technical Details

## Pre-processing Steps:

- Resizing all images to 64x64 pixels.
- Center cropping for symmetry.
- Normalization using values tuned for pre-trained models (e.g., VGG19).

# Technical Details

## Tools and Techniques:

- **Development Environment:**

- PyTorch 2.5, NVIDIA GeForce GPU with CUDA 11.7.

- **Explainability Frameworks:**

- Captum, Saliency Maps, LIME, SHAP.

- **Optimization Strategies:**

- Loss Functions: Perceptual Loss, Adversarial Loss, and KL Divergence.
- Optimizers: Adam

# Technical Details

## Mathematical Formulations:

- **Key Equations:**

- **Perceptual Loss:** Measures spatial discrepancies for high-frequency detail retention.
- **Adversarial Loss:** Ensures realistic image generation.
- **Explainability Matrix (M):** Offers gradient-based insights for interpretability.

# Results and Analysis

**Table: Results of the proposed approach and its comparison with the existing models**

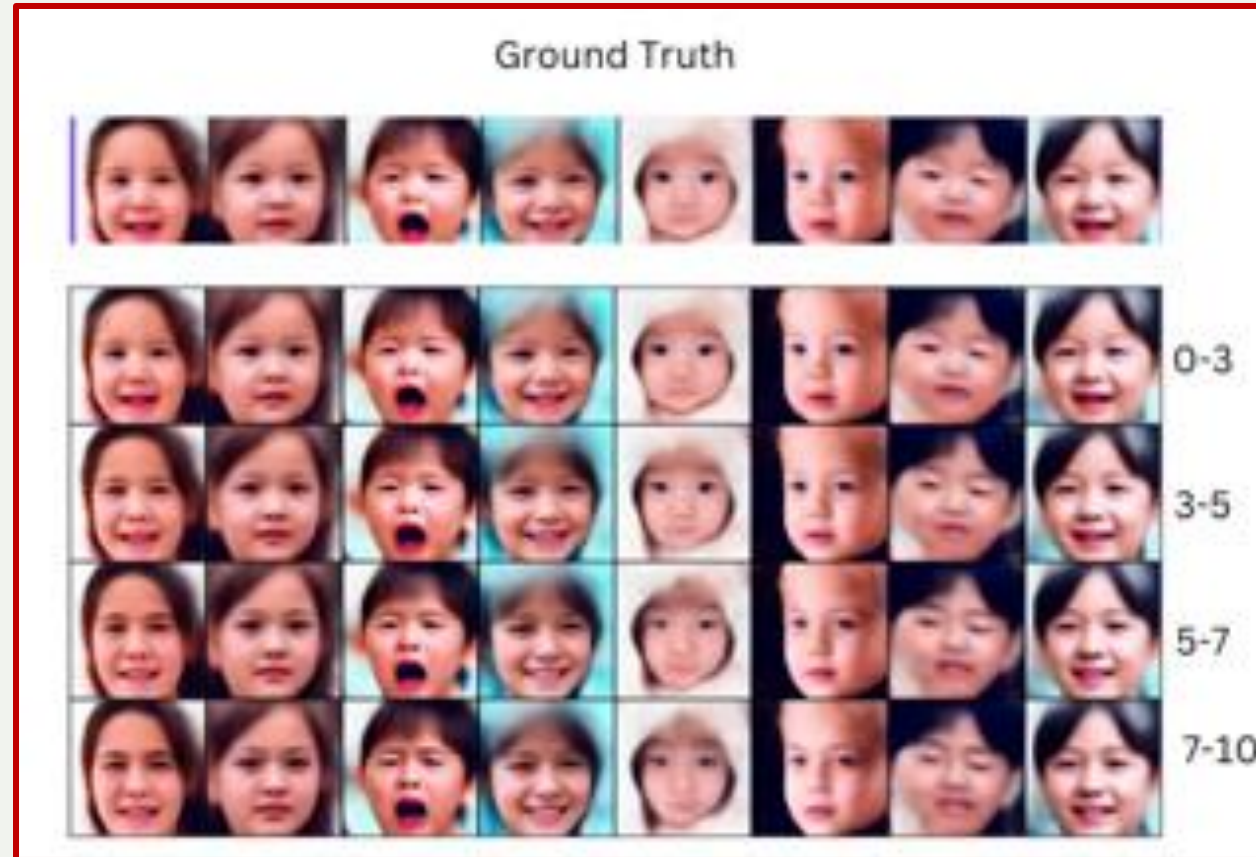
Parameters	CAAE	CPAVAE	XAI-GAN	XAI-CPAVAE
Generator_loss	0.9877	0.9999	3.4478	<b><i>0.9888</i></b>
Discriminator_loss	0.5866	0.0234	0.6171	<b><i>0.0142</i></b>

# Results and Analysis



**Figure: Visualization of the results of xAI-CPVAE for Age Progression**

# Results and Analysis



**Figure: Visualization of the results of CPVAE**



# Results and Analysis



**Figure : Visualization of the results of xAI-GAN**

# Results and Analysis



**Figure : Visualization of results of CAAE**

# Results and Analysis

## Key Findings

- **CAAE** generates visually appealing images but struggles with age transitions and facial feature preservation.
- **CPAVAE** improves feature preservation and smoother age transitions but faces occasional inconsistencies.
- **xAI-GAN** integrates explainability but compromises image realism.
- **xAI-CPAVAE** achieves the best balance of realism, accuracy, and explainability.

# Results and Analysis

## Quantitative Insights

- **xAI-CPAVAE:**
  - Lowest **Discriminator Loss (0.0142)**
  - competitive **Generator Loss (0.9888)**.

## ▪ Visual Comparisons

- **xAI-CPAVAE** excels in:
  - Preserving facial features.
  - Delivering realistic, smooth age transitions.

# Future Work

## 1. Age Rejuvenation & Prediction

- Predict facial changes for forensics, healthcare (e.g., aging diseases), and entertainment (e.g., movies, style simulations).
- Simulate customer appearances with cosmetics and accessories for fashion & retail.

## 2. Cross-Domain Applications

- **Healthcare:** Facial predictions for health conditions, surgery planning, and ageing diseases (e.g., progeria).
- **Education:** Visualizing ageing processes in biology/anatomy classes.

# Future Work

## **3. User-Friendly Interface for Identification**

- Platforms for governments and NGOs to assist in missing person identification.
- Multi-language support for broader adoption.

## **4. Collaboration & Scaling**

- Partner with International Organizations (e.g., Interpol, UNICEF) for broader impact.
- Public-private partnerships for resource-limited settings, enhancing global deployment.

# Conclusion

## Key Takeaways:

- **Innovation Highlight:**

- xAI-CPVAE merges explainability with generative strength to set a new benchmark in facial age progression.

- **Real-World Applications:**

- Potential for transforming forensics, healthcare, and identity management industries.

## Final Thoughts:

- **Impact:**

- Bridges the gap between performance and transparency in generative modelling.
- Scalable for broader datasets and cross-domain tasks.

# Acknowledgements

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**THANK YOU!**