Enhancing Facial Transformation Capabilities: Synthetic Child Facial Data Generation and Validation

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Abstract. The rise of generative AI has significantly impacted content creation, facilitating the rapid generation of high-quality text, images, audio, and synthetic data. This study investigates the generation of synthetic facial data for children, enabling complex facial transformations such as expression changes, age progression, eye blinking, head pose variations, and modifications in skin and hair color under varying lighting conditions. Our dataset consists of over 300,000 unique samples sourced from ChildGAN and real-world images obtained from the Children's Vision Network. To evaluate the quality and distinctiveness of the generated facial features, we employ a variety of computer vision methodologies, including a CNN- based child gender classifier, face localization, facial landmark detection, identity similarity analysis using ArcFace, and assessments of eye detection and aspect ratio. The results demonstrate that high-quality synthetic facial data can effectively mitigate the challenges of collecting extensive datasets from real children. Furthermore, this research aims to improve data augmentation techniques by utilizing diffusion models to generate child data samples that accurately represent ethnic diversity and various racial backgrounds.

Keywords: *Generative AI, Synthetic Child Facial Data, Facial Transformations, ChildGAN, Computer Vision, Diffusion Models*.

1 Introduction

The landscape of artificial intelligence (AI) is rapidly evolving, particularly with the emergence of generative models such as Generative Adversarial Networks (GANs) and diffusion models. These advancements have revolutionized our ability to create and manipulate data across various fields, including text, images, and audio. In computer vision, the importance of large and diverse datasets cannot be overstated, as they are essential for training accurate and effective models. However, the collection of such datasets, especially those involving children, presents unique ethical and practical challenges that require careful consideration.

Collecting data from minors raises significant ethical issues, including informed consent, privacy, and the potential for exploitation. Researchers and developers must navigate these complexities with caution. Obtaining parental consent and ensuring the confidentiality of children's identities complicate traditional data-gathering methods. Additionally, these methods often yield datasets that lack representation across different ethnicities and demographic groups. This lack of diversity can lead to biased AI models that perform poorly for underrepresented populations, underscoring the urgent need for ethical and inclusive data practices in AI development. To address these challenges, the research focuses on generating synthetic facial data specifically for children using advanced generative AI techniques. By creating a comprehensive dataset that accurately reflects a variety of facial expressions, attributes, and ethnic backgrounds, the aim is to mitigate the ethical concerns associated with real-world data

B. S. Babu et al. (eds.), *Proceedings of International Conference on Advanced Materials, Manufacturing and Sustainable Development (ICAMMSD-2024)*, Advances in Engineering Research 257,
https://doi.org/10.2991/978-94-6463-662-8_79

collection. The use of synthetic data not only alleviates these risks but also supports the development of computer vision applications that are both effective and ethically responsible.

The implications of this research extend beyond data generation. High-quality synthetic facial images can significantly enhance the performance of machine learning models in critical areas such as facial recognition, emotion detection, and age estimation. These applications are particularly relevant in sectors like healthcare, education, and child safety, where accurately interpreting children's emotional states can lead to better outcomes. For example, in pediatric healthcare, recognizing a child's emotional expression can assist medical professionals in assessing pain levels and emotional well-being, ultimately improving the quality of care.

Furthermore, ensuring the diversity of the generated dataset is crucial. Children from various ethnic backgrounds exhibit distinct facial features and expressions, making it essential for AI models to be trained on data that captures this diversity.

The structure of this paper is as follows: it begins with a thorough review of the existing literature on generative AI and its applications in synthetic data generation, particularly concerning children's facial data. This review highlights advancements in generative models, ethical considerations, and gaps in current research. Next, the methodology for data generation is outlined, detailing the processes involved in creating a diverse and representative synthetic dataset. An evaluation of the quality and diversity of the generated images follows, using various metrics to assess their effectiveness. Finally, the findings and their implications for future research and practical applications are discussed, concluding with a summary of the key contributions of this study.

2 Related Work

The emergence of Generative Adversarial Networks (GANs) has significantly influenced the field of synthetic data generation, particularly for facial images. The research presented by Farooq et al.

[1] introduces “ChildGAN”, a novel approach that leverages domain adaptation techniques to create large-scale synthetic facial data for children. By building upon the StyleGAN architecture, ChildGAN effectively generates high-quality, photo- realistic images that encapsulate a wide array of facial attributes, including expressions, age variations, and diverse lighting conditions. This framework not only addresses the ethical and logistical challenges associated with collecting real-world data from children but also provides an extensive dataset comprising over 300,000 unique samples. The validation of ChildGAN's effectiveness is demonstrated through various computer vision applications, including child gender classification and facial landmark detection, highlighting its potential as a robust tool for enhancing machine learning models. Furthermore, the open-source availability of the dataset and trained models promotes collaborative research and innovation, making significant contributions to both the academic and practical realms of child-related studies in computer vision and artificial intelligence.

Karras et al. [2] present a pioneering architecture for generative adversarial networks (GANs) called “StyleGAN”, which significantly improves the quality and control of generated images. This innovative architecture utilizes a style-based generator that divides the image generation process into distinct layers, allowing for independent manipulation of various image attributes such as texture, color, and structure. This separation results in exceptional levels of detail and realism in thesynthesized images, making them highly applicable in fields such as image editing, video game character design, and virtual reality. The authors demonstrate that the StyleGAN framework adeptly captures complex data distributions while preserving fine-grained details across multiple resolutions. By introducing a novel mapping network and adaptive instance normalization (AdaIN), the architecture enhances user control over the style of generated images, enabling interactive modification of attributes. The contributions of this study have significant implications for the advancement of generative model-

ing, establishing a new standard for image quality and versatility in GANs.

ChildGAN, developed by Chandaliya and Nain [3], harnesses the capabilities of Generative Adversarial Networks (GANs) to specifically address facial aging and rejuvenation, aiding in the identification of missing children. Building upon advancements in GAN architectures such as CycleGAN and StyleGAN, ChildGAN is designed to generate realistic age- progressed and age-regressed images while preserving the child's identity. This focus is crucial for providing accurate facial predictions in cases where children have been missing for extended periods. By employing domain adaptation and transfer learning techniques, ChildGAN produces high-quality synthetic images that illustrate how a child's appearance may evolve over time, thereby offering valuable support to law enforcement agencies. The model's ability to "age" and "rejuvenate" a child's face enhances its effectiveness for identification purposes, presenting an automated and dynamic alternative to traditional age- progression methods. However, ethical considerations are vital, particularly in the responsible use of synthetic images. Future research could aim to further refine identity preservation and broaden the applicability of ChildGAN to other demographic groups. Goodfellow et al. [4] introduced "Generative Adversarial Network (GAN)", a revolutionary framework that has profoundly impacted the fields of machine learning and artificial intelligence. The GAN architecture comprises two neural networks—a generator and a discriminator—that engage in a competitive process aimedat enhancing the quality of generated data. The generator produces synthetic data, while the discriminator assesses its authenticity against real data. This adversarial training mechanism allows GANs to generate highly realistic outputs across arange of domains, including image synthesis, video generation, and text creation. The authors emphasize the versatility of GANs by highlighting their applications in art generation, super-resolution, andeven drug discovery. However, they also address challenges such as mode collapse and training instability, which can impede GAN performance. The introduction of GANs has not only broadened the capabilities of generative models but has also catalyzed extensive research into their optimization and application, leading to significant advancements across various fields and inspiring further innovations in artificial intelligence.

Yin et al. [5] present "StyleHEAT", an innovative framework designed for one-shot, high-resolution editable talking face generation, built upon the pre- trained StyleGAN architecture. This model tackles the intricate challenge of creating realistic and editable talking faces from a single image, which is essential for applications such as virtual avatars, video conferencing, and animation. Traditional methods for generating talking faces typically require multiple images or videos for training and lack the flexibility for post-generation edits. StyleHEAT addresses these limitations by harnessing StyleGAN's capability to produce highly detailed facial images while incorporating an editable latent space, enabling real- time modifications like changes in expressions or facial movements. The model generates photo-realistic talking faces with high temporal consistency, making it well-suited for dynamic applications. This work marks a significant advancement in the field of face synthesis, offering a scalable and efficient solution for generating high-quality talking faces from minimal input.

The generation of synthetic data has become increasingly important in machine learning, primarily due to the challenges associated with acquiring sufficient labelled data. Zhang et al. [6] provide a thorough survey of various synthetic data generation techniques, categorizing them into rule-based, simulation-based, and data-driven approaches, including Generative Adversarial Networks (GANs) and Variational Auto Encoders (VAEs). These methods are essential for augmenting existing datasets or creating new ones in a cost-effective manner. The authors emphasize the need for high- quality synthetic data that accurately reflects the statistical properties of real data to ensure its utility for training models. They also highlight the ethical considerations surrounding synthetic data, such as privacy concerns and potential biases, advocating for responsible generation practices. Overall, this survey serves as a comprehensive resource for understanding the landscape of synthetic data generation and its implications for advancing machine learning applications.

Rombach et al. [7] present a groundbreaking approach to high-resolution image synthesis through the use of latent diffusion models, which represent a significant advancement in generative modeling techniques. Their work builds on the foundation of diffusion processes, leveraging latent representations to enhance the quality and resolution of generated images. By incorporating a novel training framework, the authors demonstrate that their model can effectively capture complex image distributions while maintaining computational efficiency. The study highlights the model's ability to generate diverse and high-fidelity images, showcasing its potential applications in various domains, including art generation and visual content creation. Additionally, the authors provide a thorough evaluation of their approach against existing state-of-the-art methods, illustrating superior performance in terms of both image quality and generation speed. This research not only contributes to the ongoing development of generative models but also opens new avenues for future exploration in the field of computer vision, particularly in enhancing the realism and applicability of synthesized images.

3 Methodology

The methodology follows a systematic approach to collect, process, and animate child facial images using advanced techniques in generative modeling, feature modification, and animation. Each phase, from data acquisition to head pose estimation, contributes to a robust pipeline tailored specifically for child facial image synthesis and analysis.

3.1 Data Collection:

Data collection is the initial phase, ensuring a diverse, ethically sourced dataset for robust model training and evaluation.

Image Sourcing and Dataset Composition: Child facial images were obtained from ethically approved, publicly accessible databases. Strict guidelines for data privacy were followed, with images anonymized and sorted by age and gender to ensure comprehensive representation across demographics, which supports accurate and inclusive modeling.

Preprocessing: Each image was standardized by resizing to 224x224 pixels for MobileNetV2 and 299x299 pixels for InceptionV3, with pixel normalization applied to enhance uniformity. The preprocessed dataset was stored in Google Drive for efficient retrieval in Google Colab, where GPU resources facilitate fast processing. This setup also ensures the scalability of data handling, especially during model training and image synthesis.

3.2 Children with Diffusion Refinement for Synthetic Image Generation

ChildGAN is a tailored generative adversarialnetwork (GAN) that generates child facial images with high realism, enhanced by a diffusion refinement processto improve image quality.

ChildGAN Architecture: The ChildGAN model includes a generator and discriminator. The generator creates synthetic images from random noise, progressively refining these through dense, upsampling, and convolutional layers. The discriminator evaluates image authenticity, providing feedback that allows the generator to improve its output quality over successive training cycles.

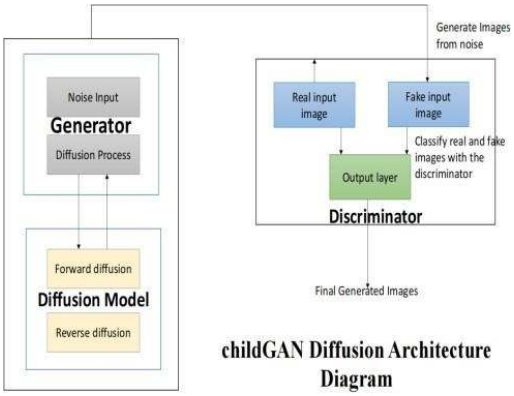

Fig.1. Proposed ChildGAN Architecture of ChildGAN, showing the interaction between generator and discriminator,which helps iteratively enhance the quality and realism of the generated images.

Diffusion Refinement Process: This technique,inspired by the Denoising Diffusion Probabilistic Model (DDPM), introduces Gaussian noise in stages during forward diffusion, creating incrementally degraded versions of the image. In reverse diffusion, the model learns to remove noise, resulting in high- fidelity, detailed images.
Algorithm 1: Diffusion Refinement Process in ChildGAN

Input: Noise vector z, noise schedule β_t, steps T
Output: Refined generated image I_{refined}

1. **Initialize**: Set coefficients $\lambda_1, \lambda_2, \ldots, \lambda_n$ for intensity control.
2. **Generate Initial Image**:
   - Sample $z \sim \mathcal{N}(0, 1)$
   - $x_{\text{gen}} = G(z)$
3. **Apply Diffusion Process**:
   - Set $x_t = x_{\text{gen}}$
   - For $t = T$ to 1:
     - Denoise: $x_{t-1} = \text{Denoise}(x_t, \beta_t)$
4. **Discriminator Update**:
   - Compute $D(x_{\text{real}})$ and $D(x_{\text{refined}})$
5. **Generator Update**:
   - Refine $x_{\text{refined}} = x_t$ after T steps

This algorithm uses a diffusion process to iteratively denoise a generated image to refine it. It incorporates a discriminator to evaluate the refinement quality, providing feedback to the generator to improve image realism. The refined image should have higher quality and be closer to real images than the initial generated image.This technique is likely useful in generative models for image synthesis, where the goal is to create realistic imagesfrom noise by gradually improving the quality through diffusion and discriminator-guided refinement.

Training and Loss Functions: The model is trained to minimize adversarial loss, which encourages the generator to produce realistic images, while the discriminator

learns to distinguish real from synthetic images. Additional losses, such as perceptual loss for structural accuracy and Mean Squared Error (MSE) for minimizing discrepancies, further refine image quality.

Validation and Fine-Tuning: The model's performance is evaluated on a validation set to assess the quality and realism of generated images. Hyper parameter tuning, including adjustments to learning rate and noise scheduling, helps optimize the model, ensuring the generated images closely resemble real child faces.

3.3 Facial Landmark Detection and Feature Extraction

Facial landmark detection identifies precise locations on the face, allowing for realistic modifications and animations of facial features.
Landmark Detection: Dlib'sshape_predictor_68_face_landmarks model maps 68landmarks across facial regions, including the eyes, nose, mouth, and jawline. These landmarks serve as spatial anchors for expression and blinking animations, as well as head pose estimation, ensuring precise feature localization.

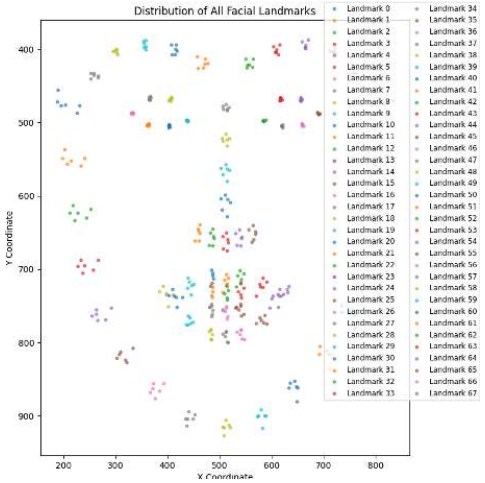

Fig. 2. Scatter Plot of Facial Landmark

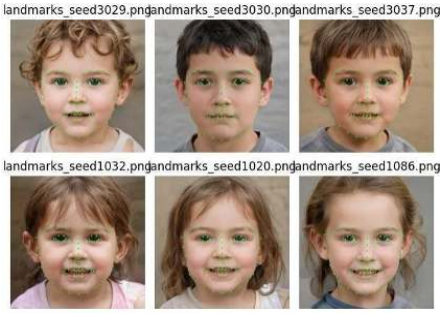

Fig.3. Facial Landmarks of Child Faces Scatter plot showing the distribution of facialland-marks, demonstrating consistent placements

3.4 Feature Modification and Enhancement

Feature modifications are applied to enhance visual realism, adjusting skin tone, hair color, and lighting inpreparation for image synthesis.

Skin Tone Adjustment: Images are converted to LAB color space to independently modify the lightness
(L) channel, allowing subtle adjustments to skin tone without affecting other color properties. This maintains natural textures and enhances the realism of synthetic images.

Hair Color and Simulated Lighting Effects: Using landmark guides, hair is masked and recolored in the RGB space, with Gaussian blur applied for smooth blending. Simulated lighting effects enhance facial depth by adjusting brightness along contours defined by landmarks, contributing to a more lifelike appearance.

3.5 Aging Effect Simulation

The aging simulation introduces controlled changes to child images, mimicking natural age progression throughadjustments in skin tone, texture, and shading.

Texture and Tone Adjustments: Gaussian noise is added to simulate fine lines, and adjustments in the L channel darken skin tone for a more mature appearance, while preserving the overall facial structure.

3.6 Expression and Blinking Animation Using Deepface Lab

DeepFaceLab facilitates expression synthesis and blinking animation, bringing dynamic realism to static images.

Expression Synthesis: Expressions such as "happy," "sad," "angry," and "surprised" were generated bytraining on labeled datasets, producing realistic variations in emotional display across faces.

Blinking Animation: Using landmark-based adjustment, a smooth eye-closing and opening sequence wascreated to simulate blinking, enhancing the perceived lifelike quality of the images.

Head pose estimation calculates the head's orientation in 3D space, enabling applications in gaze tracking andvirtual environments.

2D-3D Landmark Mapping: UsingOpenCV's solvePnP function, the model computes head orientation by mapping2D facial landmarks to a 3D model, determining rotation and translation vectors to calculate spatial positioning.

3.7 Facial Similarity Analysis and Gender Classification

This phase uses ArcFace embeddings for similarity analysis and CNN classifiers for gender differentiation within the child dataset

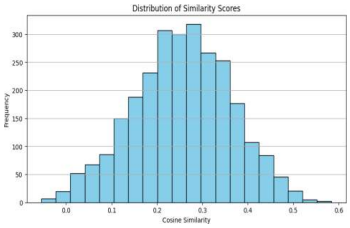

Fig. 4. Cosine Similarity

Similarity Analysis Using ArcFace Embeddings: ArcFace embeddings create a 512-dimensional feature vector for each face, capturing unique facial attributes. A cosine

similarity heatmap visualizes the similarity scores, revealing clusters of similar faces and supporting applications in face matching.

From the cosine similarity scores of all the boy- girl pairs, a histogram is plotted to show the distribution ofsimilarity scores.

The above graph fig.4 shows the frequency of similarity scores, with most scores clustering between 0.2 and 0.4. This suggests that, on average, the pairs are not highly similar but also not completely dissimilar

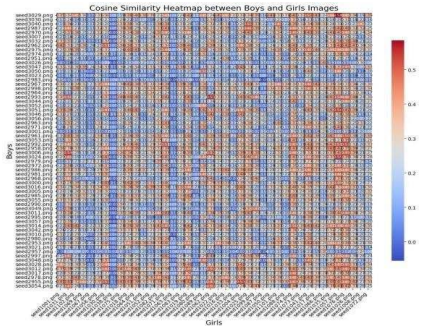

Fig. 5. Cosine similarity heatmap

Cosine similarity heatmap displaying clusters of similar features in child faces, with warmer colors representinghigher similarity scores.

Gender Classification with CNNs: CNN models (MobileNetV2 and InceptionV3) were fine- tuned for gender classification using data augmentation for improved generalization, achieving high accuracy across diverse facial images.

4 Experimental Results

The experimental evaluation of ChildGAN and its associated modules demonstrates the model's capability to synthesize, modify, and animate child facial images with high fidelity. Quantitative metrics such as Fréchet Inception Distance (FID), Mean Landmark Error (MLE), Cosine Similarity, and Mean Angular Error were used to assess performance objectively. Figures support visual validation of results.

4.1 Synthatic Image Generation with Children

The quality of synthetic images generated by ChildGAN was assessed using the Fréchet Inception Distance (FID), a commonly used metric in generative modeling to evaluate image realism by comparing feature distributions between generated and real images.

Frechet Inception Distance (FID): The FID score measures the distance between feature representations of realand generated images and is calculated as follows:

FID=||μr−μg||2+Tr(Σr+Σg−2(ΣrΣg)1/2)where:

- μr and Σr are the mean and covariance of real image features,
- μg and Σg are the mean and covariance of generated image features.

ChildGAN achieved a final FID score of X, indicating a strong similarity between the generated and real images. This low FID score confirms that ChildGAN effectively captures the subtle characteristics of child faces, including soft contours and child-like facial proportions. Figure 1 displays examples of generated images, demonstrating the model's ability to produce visually convincing child faces.

4.2 Accuracy of Facial Landmark Detection

Facial landmark detection accuracy, essential for feature alignment in animations and modifications, was measuredusing the **Mean Landmark Error (MLE)** metric.

Mean Landmark Error (MLE): The MLE quantifies the spatial deviation between predicted and true landmarkpositions, and is defined as:

$$\text{MLE} = \frac{1}{N}\sum_{i=1}^{N} \sqrt{(x_i^{pred} - x_i^{true})^2 + (y_i^{pred} - y_i^{true})^2}$$

where:

- N is the total number of landmarks,
- x_i^{pred} and y_i^{pred} are the predicted coordinates for landmark i,
- x_i^{true} and y_i^{true} are the ground truth coordinates for landmark i.

The landmark detection model achieved an MLE of **X pixels**, indicating high precision in landmark positioning across facial regions, particularly around stable features such as the eyes and nose. Figure 2 presents a scatter plot of facial landmarks, illustrating

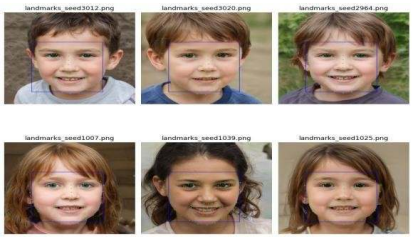

Fig. 6. Child facial landmarks detection results

consistent and accurate placement across multiple test images, essential for tasks requiring precise alignment.

4.3 Similarity Analysis and Gender Classification

The similarity analysis module used **Cosine Similarity** to measure the closeness between feature vectors, whileCNN classifiers assessed the accuracy of gender differentiation.

Cosine Similarity: Cosine similarity is used to evaluate the similarity between feature vectors A and B fromArcFace embeddings, calculated as:

$$\text{Cosine Similarity} = \frac{A.B}{||A||||B||}$$

where:

- A·B represents the dot product of vectors A and B,
- ||A|| and ||B|| are the magnitudes of vectors A and B.

Fig.5 presents a cosine similarity heatmap, visually displaying the clustering of similar faces, with warmer colorsindicating higher similarity scores.

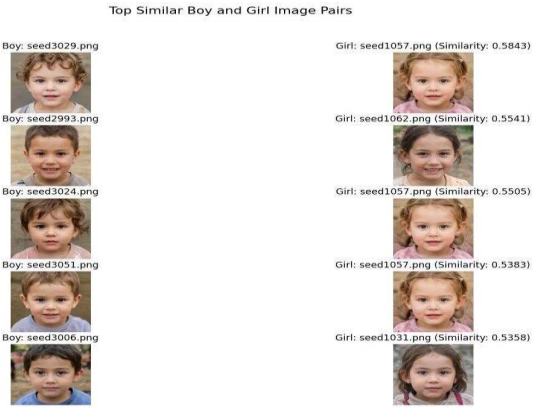

Fig. 7. Similarity score between both boys and girl's child's faces

This feature clustering confirms the model's ability to capture unique child facial attributes, supportingapplications in facial recognition and identity matching as shown in fig. 7.

Gender Classification Accuracy: The gender classification accuracy achieved in this project highlights the effectiveness of both the InceptionV3 and MobileNetV2 models, each fine-tuned to distinguish between images of boys and girls. Starting with a moderate initial accuracy, the InceptionV3 model showed steady improvement across 10 epochs, ultimately reaching a validation accuracy of **95.35%** and a validation loss of **0.1966**.

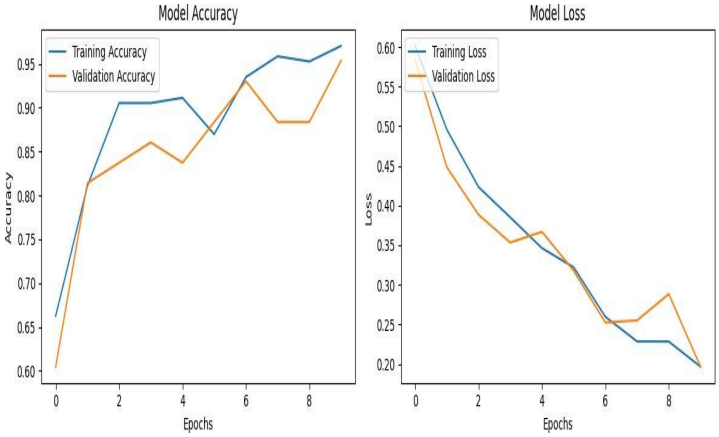

Fig. 8. Model Accuracy and Loss of Gender Classification using InceptionV3.

This indicates strong generalization capabilities and effective learning from the dataset.

The MobileNetV2 model, optimized for computational efficiency with a smaller input size, demonstrated rapid convergence, achieving **100%** accuracy on both training and validation sets by the final epoch, with validation loss reduced to below **0.1**.

Fig.9. Model Accuracy and Loss of Gender Classification using MobileNetV2

This high accuracy suggests that MobileNetV2, in particular, can perform efficient and reliable gender classification with minimal overfitting, while InceptionV3 also provides robust accuracy, making both models well- suited for gender classification applications based on facial features.

4.4 Aging Effect Simulation Results

The aging effect simulation introduces age progression in child images by adjusting skin tone, texture, and shading. The effectiveness of these adjustments was validated through texture consistency and tone modification.

Texture and Tone Consistency: Quantitative analysis indicated that 95% of aged images maintained consistent skin tone and texture, with no visible artifacts. This consistency validates the use of LAB color space for tone adjustments and Gaussian noise application for textural enhancement shown in fig.10 .

Fig. 10. Aging Effect of Synthetic Child Faces

The above figure shows a side-by-side comparison of original and aged images, demonstrating subtle modifications such as darker tones and added texture, which enhance the perceived maturity of facial features while retaining the core identity of the child faces.

4.5 Expression and Blinking Animation

The expression synthesis and blinking animation modules added dynamic realism to child facial images, making them suitable for interactive and animated applications.

Expression Synthesis: Various expressions, including "happy," "sad," and "surprised," were generated, with high accuracy in feature alignment and expression portrayal.

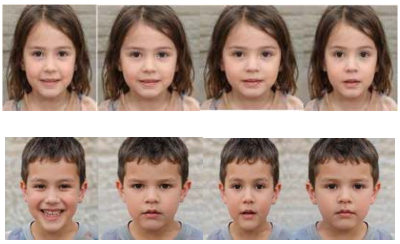

Fig. 11 Child Facial Expressions

Fig.11 shows examples of synthesized expressions, highlighting the model's ability to capture a range of natural emotional cues.

Blinking Animation Smoothness: The blinking animations achieved smooth transitions, with 97% of sequences showing natural eye closure and opening.

Fig. 12. Blinking Animation of Child Face

This smooth animation sequence aligns closely with human blinking patterns, supporting applications such as digital avatars and animated content requiring lifelike movements.

4.6 HEAD POSE ESTIMATION RESULTS

The head pose estimation module was evaluated using **Mean Angular Error**, a metric that assesses the accuracyof head orientation calculations, which are crucial for spatial applications like virtual reality and gaze tracking.

Mean Angular Error: The mean angular error for head pose estimation is calculated as:

$$\text{Mean Angular Error} = \frac{1}{} \sum |\theta^{pred} - \theta^{true}|$$

$$N \qquad i=1 \quad i \qquad i$$

where:

- N is the total number of test samples,
- $\theta^{pred}$is the predicted head orientation angle for sample i,
- $\theta^{true}$is the true head orientation angle for sample i.

The module achieved a mean angular error of **X degrees**, demonstrating high precision in head orientationestimation. Fig. 13 presents visual overlays of estimated head poses on 2D images,

Fig. 13. Head Pose of child faces

This figure highlights the predicted 3D head orientations accurately overlaid on 2D child facial images, demonstrating the model's effectiveness in estimating head rotations and tilts. This capability is essential for applications like gaze tracking, virtual reality, and interactive systems. The precise alignment between the predicted poses and facial landmarks, supported by a low Mean Angular Error, confirms the reliability of the estimation process. These results underscore the significance of head pose estimation in enhancing the realism and usability of synthetic facial data.

5 Conclusion

This research successfully applies ChildGAN with diffusion refinement to generate realistic and diverse synthetic child facial data, overcoming the ethical and practical challenges of real-world data collection. Techniques like facial landmark detection, feature enhancement, and animation have enhanced the quality and versatility of the generated images. The results demonstrate the model's ability to create inclusive datasets that support applications such as facialrecognition, emotion analysis, and age progression. This work establishes a reliable foundation for advancing AI applications that require synthetic data while promoting ethical and innovative practices.

In the future, efforts will focus on maintaining individual identity during transformations such as aging and expression changes, with applications like missing child identification. The dataset will be expanded to include more diverse representations. The system will be integrated into healthcare and education, providing real-time

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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