Deepfake: A Boon for Pediatric Dental Patients

Aditi Tasgaonkar
Department of Pediatric and Preventive Dentistry, Dr. D.Y. Patil Dental College and Hospital, Pimpri, Pune, Maharashtra, India
aditi.tasgaonkar98@gmail.com

Rujuta Joshi
Department of Computer Science, University of Texas at Arlington, Arlington, Texas, USA
rujutasj@gmail.com

Harshada Chavan
Barclays, Pune, India
harshada.hs.chavan@gmail.com

Madhuri Tasgaonkar
Department of Computer Engineering, Cummins College of Engineering for Women, Karvenagar, Pune, Maharashtra, India
madhuri.tasgaonkar@cumminscollege.in

Nilesh Rathi
Department of Pediatric and Preventive Dentistry, Dr. D.Y. Patil Dental College and Hospital, Pimpri, Pune, Maharashtra, India
nilesh.rathi@dpu.edu.in (corresponding author)

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ABSTRACT

Deepfake refers to a technique that utilizes Generative Adversarial Networks (GANs), a type of Artificial Intelligence (AI), to generate synthetic visual content such as images and videos. Although commonly associated with misinformation, this technology also offers positive applications in domains including medical training, education, and imaging. However, its use in personalized behavioural management of pediatric dental patients remains unexplored. This study seeks to develop a real-time application leveraging deepfake technology to reduce dental anxiety in children. The application replaces the face of an anxious pediatric dental patient with an alternative face in a video, providing a personalized distraction during treatment. Three widely used tools for face swapping and deepfake generation—DeepFaceLab, Roop, and MobileFaceSwap—were evaluated, with their architectural characteristics, advantages, and limitations analysed in the context of this use case. A pilot study involving 20 anxious pediatric patients demonstrated that the application significantly reduced anxiety and fear associated with dental treatment.

Keywords-Generative Adversarial Networks (GANs); deepfake; behavioural management

I. INTRODUCTION

Approximately 32% of adults experience dental anxiety [1, 2], and this percentage increases to 75% among children aged 3-18 years [3-5]. Despite the progress in dental technology, anxiety remains a significant factor that potentially leads to dental avoidance, compromised oral health, and more invasive and costly future treatments. Therefore, behavior management is a critical aspect of pediatric dentistry. Traditional behavior management techniques include positive reinforcement, tell-show-do, distraction, voice control, and parental presence/absence strategies [6, 7]. Recent advancements in digital technologies have created new opportunities for more engaging and effective patient management, including non-invasive or minimally invasive approaches such as Virtual Reality (VR) and, more recently, deepfake technology [8, 9].

Deepfake technology, based on deep learning algorithms such as Generative Adversarial Networks (GANs), enables the realistic presentation and generation of audiovisual content. In healthcare, deepfakes have been applied in diagnosis, medical education, telemedicine, and virtual therapy [10]; however, their application in dentistry remains largely unexplored.

Deepfakes in dental care can be employed as a promising strategy for alleviating children's fear by using visual familiarity and modelling, where children view images or videos that help them anticipate the dental experience. Unlike conventional marketing strategies, this approach focuses on promoting positive behavioral change. In this study, we used Artificial Intelligence (AI)-generated visuals to make dental procedures appear less intimidating and more relatable, thereby increasing children's confidence and cooperation. The contributions of this study are as follows:

- Development of a computer-based application that applies deepfake technology to replace the faces of anxious pediatric patients in dental procedure videos with those of calm, cooperative individuals.
- Creation of a localized tool to visually model cooperative behavior and reduce anxiety in uncooperative children.
- Evaluation of the effectiveness of deepfake-based videos in alleviating pediatric dental anxiety.
- Assessment of the feasibility of implementing this approach in clinical settings.

This research also addresses the ethical implications of using deepfake technology in medical contexts. Overall, it contributes to the emerging body of work on deepfake applications in healthcare.

II. LITERATURE REVIEW

Digital tools have emerged as promising adjuncts to pediatric behavior management. Audio distraction, VR, Augmented Reality (AR), animated educational videos, and mobile applications have demonstrated effectiveness in reducing anxiety and enhancing cooperation during dental procedures [9, 11-13]. These approaches leverage children's familiarity with digital media to create more engaging and less intimidating treatment environments.

Deepfake technology involves the use of GANs to generate highly realistic audiovisual simulations, allowing for the creation of personalized and interactive media. For instance, AI-based tools for screening the mental health of the young population [14] and AI-generated avatars have been used to deliver Cognitive Behavioral Therapy (CBT) to children, providing tailored emotional support [15]. Similarly, Natural Language Processing (NLP)-based multilingual models for patient communication [16] and digital twins have been found useful in pediatric oncology to deliver personalized educational content and emotional comfort [17].

The literature highlights applications of deepfakes in medical imaging, training, telemedicine, and patient engagement [10, 18]. However, studies on their use in dentistry are virtually absent. Potential applications in pediatric dentistry include:

- Using familiar characters (e.g., cartoons, superheroes) to promote healthy habits or model cooperative behavior.
- Creating personalized motivational videos featuring dentists or trusted figures.
- Designing interactive, emotionally adaptive videos that respond dynamically to a child's anxiety level or behavior.

Such approaches may enhance engagement, reduce fear, and encourage cooperation by leveraging social and emotional familiarity. Nonetheless, these applications require validation through empirical research [19-22].

The technology needed to produce these distractions requires the use of GANs; several GAN versions have been studied in the literature [23, 24]. For instance, StyleGAN is an advanced version of GANs that generates high-quality, realistic images. A key strength of StyleGAN lies in its ability to provide fine-grained control over image synthesis, which makes it especially suitable for applications such as face generation and artwork creation. Its capacity to produce detailed, high-resolution imagery represents a significant advancement in image synthesis [25]. Unlike traditional GANs that rely on aligned image pairs (e.g., a photo and its sketch), CycleGAN learns mappings between unpaired datasets. Its primary advantage is the ability to perform domain-to-domain image translation without requiring paired samples. The "cycle" aspect is achieved through cycle-consistency loss, which enforces that a translated image can be mapped back to the original domain with minimal loss [26].

Image animation is another critical aspect of deepfake generation, where an object in a source image is animated based on the motion in a driving video. The First-Order Motion Model (FOMM) addresses this challenge without relying on annotated datasets or prior object-specific knowledge. After being trained on video collections from a given category (e.g., human faces or bodies), FOMM can animate any object from the same category [27]. Furthermore, DeepFaceLab is a widely used framework for highly realistic face-swapping tasks. Its modular and comprehensive pipeline processes a video frame by frame, performs face replacement, and then reassembles the frames into a coherent output video. Owing to its adaptability and extensibility, DeepFaceLab remains a benchmark tool in deepfake research and applications [28].

Shaoanlu's Faceswap-GAN employs a GAN-enhanced autoencoder architecture for face swapping. It utilizes a shared encoder with dual decoders: one for reconstructing the source face and another for transforming it into the target identity. This design allows for more natural transitions and realistic swapped outputs [29]. Similarly, Roop is a streamlined video face replacement tool built on InsightFace models and other pretrained utilities for detection, alignment, recognition, and identity transfer. Its pipeline consists of face detection and alignment, embedding extraction, and identity mapping, resulting in efficient face replacement with minimal preprocessing overhead [30]. Lastly, MobileFaceSwap is a streamlined, real-time face-swapping model tailored for mobile and edge devices. It employs lightweight architectures with quantized weights, depth-wise separable convolutions, and batch size optimization to ensure fast performance without sacrificing visual quality. This makes it particularly suitable for deployment in resource-constrained environments such as mobile CPUs, NPUs, or GPUs [31]. The comparative discussion of these GAN-based models is summarized in Table I.

TABLE I. COMPARATIVE ANALYSIS OF GAN-BASED DEEPFAKE GENERATORS

Model / Tool	Image Quality	Identity Preservation	Control over Output	Data Requirements	Training Complexity	Real-Time Capable	Notes
StyleGAN3	Excellent	Very good	Excellent	High	High	No	Top-tier face synthesis; great for generating novel identities.
CycleGAN	Good	Good	Good	Low (unpaired)	Low	No	Suitable for unpaired translations; less consistent faces.
FOMM	Good	Very Good	Average	Low	Moderate	Yes	Animation of static images using motion video; real-time capable.
DeepFaceLab	Very Good	Excellent	Good	High	High	No	Industry standard for face-swapping videos; very customizable.
Shoanlu/Faceswap-GAN	Very Good	Very Good	Good	Moderate	Moderate	No	GAN-based face-swapping with autoencoders; better than basic GANs.
Roop	Very Good	Excellent	Average	Very Low (pretrained)	None	Yes	One-click face swapping using pretrained pipelines; simple and effective.
MobileFaceSwap	Good	Good	Average	Very low (pretrained)	None	Yes	Lightweight and optimized for mobile devices; trades some quality for speed and portability.

III. PROPOSED METHOD

Developing and implementing the proposed deepfake application required meeting several criteria established by dental practitioners. First, the system needed to enable near real-time video transformations to ensure practicality in a clinical setting. Second, the face-swapping quality had to be sufficiently realistic to capture and sustain the attention of uncooperative pediatric patients. Finally, the video background needed to replicate an authentic clinical environment to maintain contextual relevance.

To achieve these goals, we evaluated whether to design custom deep networks for face recognition [32] or to leverage existing pretrained models. To capitalize on the efficiency of pretrained frameworks, three GAN-based models were selected for experimentation: DeepFaceLab, Roop, and MobileFaceSwap. The selection was guided by two primary criteria: output image quality and real-time inference capability. The major architectural components of these models are depicted in Figure 1.

During the comparative analysis of the models, the following observations were made:

- All three models extract frames from input videos, with options for pre- or post-processing.
- Users can select the Frames Per Second (FPS) rate to balance video quality against computational efficiency.
- Roop and MobileFaceSwap are pretrained frameworks, whereas DeepFaceLab requires training during the face-swapping process.

Based on this analysis, the GAN pipeline was modified as shown in Figure 2. Specifically, the frame generation step was employed as a pre-processing phase. The generated frames were used for background replacement (removing the green screen and inserting a real clinical background), followed by frame-wise face swapping and final video reconstruction.

For data collection, videos of commonly performed pediatric dental procedures were recorded using a handheld Digital Single-Lens Reflex (DSLR) camera against a green background (Figure 3). Dental practitioners were asked to photograph their clinical environment, which was then used as the background for the generated videos (Figure 3).

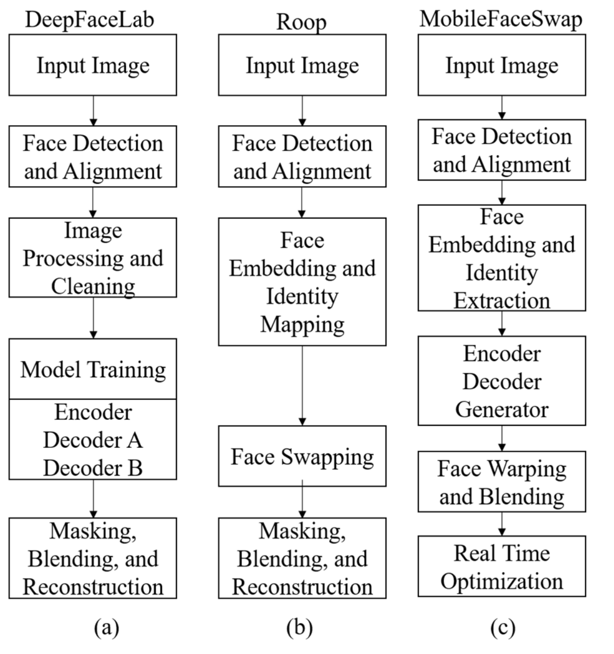


Fig. 1. Architectures of (a) DeepFaceLab, (b) Roop, and (c) MobileFaceSwap.

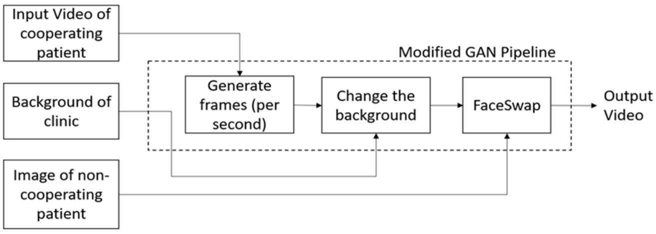
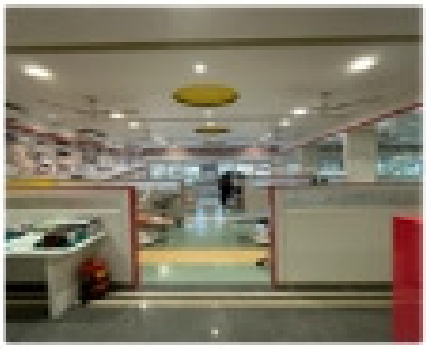


Fig. 2. High-level architecture of the proposed method.

(a)



(b)

Fig. 3. (a) A screenshot of the recorded video with a green background, (b) the real background of a clinic.

A. Hardware Setup

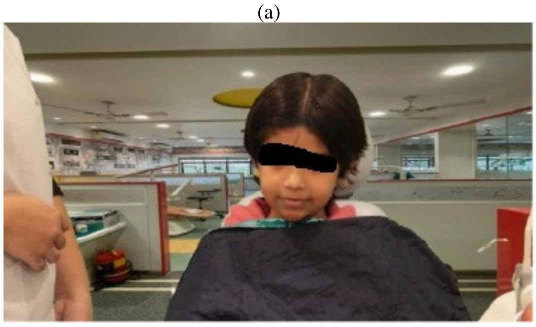
Experiments were conducted on a laptop equipped with an Intel Core i7 processor, 16 GB Random Access Memory (RAM), and an NVIDIA RTX 4070 Graphics Processing Unit (GPU) (8 GB GDDR6).

B. Patient Exposure to the Application

The study was conducted in the Department of Pediatric and Preventive Dentistry, Dr. D. Y. Patil Dental College and Hospital, using the following procedure:

- Non-cooperative, anxious patients aged 7-10 years were recruited after obtaining informed parental consent.
- A facial image of each patient was captured, and an AI-generated video was created in real time. The system replaced the original face in a pre-recorded dental procedure video with that of the patient (Figure 4).
- The personalized video was shown to the child immediately before the dental treatment (Figure 5).
- Anxiety was measured both before and after video exposure using a validated behavioral scale combined with heart rate monitoring. Fear parameters were noted using the Children's Fear Survey Schedule Dental subscale (CFSS-DS), and anxiety parameters were noted using the Modified Child Dental Anxiety Scale Faces (MCDASf). A pulse oximeter was used to check vital parameters.

(a)



(b)

Fig. 4. (a) Screenshot of input video and (b) screenshot of output video with updated green screen.

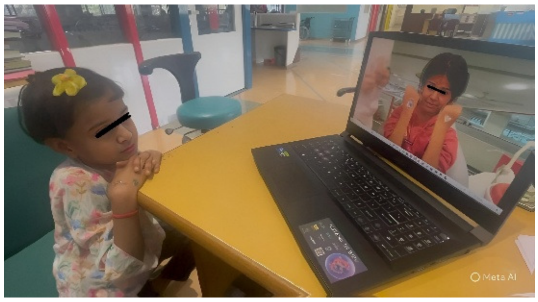


Fig. 5. Experimental set-up for demonstration.

C. Ethical and Practical Considerations

The use of deepfake technology in pediatric care introduces ethical concerns that must be addressed. During such studies, informed consent from parents and dental practitioners is of utmost importance. Transparency regarding the artificial nature of the generated content was emphasized to maintain trust. Strict measures were followed to ensure data privacy and security, particularly when handling sensitive audiovisual material [33].

Clinical and ethical guidelines were strictly adhered to during the study. Parents were provided with detailed explanations and demonstrations of the generated videos prior to experimentation. No child participated without explicit parental consent. Additionally, all generated videos were permanently deleted after the dental procedures were completed.

IV. RESULTS AND DISCUSSION

Three selected models (DeepFaceLab, Roop, and MobileFaceSwap) were tested on four videos using the Python library. The hardware configuration was kept constant throughout the experiments, and the frame rate was fixed at 60 FPS for all models.

The DeepFaceLab model required approximately 8 hours of training for Video 1 before producing an output. Although the generated images and videos were of high quality, the requirement for near-real-time output disqualified the DeepFaceLab model from further consideration. A comparative performance summary of Roop and MobileFaceSwap is provided in Table II.

Table II also indicates that MobileFaceSwap was the fastest model, demonstrating strong real-time performance. However, the generated outputs often contained blurred and deformed images, which reduced overall video quality (Figure 6). By contrast, Roop produced more consistent outputs at the expense of slightly higher processing time.

TABLE II. PERFORMANCE ANALYSIS OF ROOP AND MOBILEFACESWAP

Video and duration	Frames generated	Processing time	
		Roop	MobileFaceSwap
Video 1 (90 s)	5,400	11 min	9 min
Video 2 (37 s)	2,220	4.5 min	3.8 min
Video 3 (25 s)	1,500	3 min	2.55 min
Video 4 (54 s)	4,860	10 min	8.3 min

(a) (b)

Fig. 6. Deformities and blur experienced at the output of MobileFaceSwap.

The performance of GAN-based face swapping depends on multiple pipeline phases, including source face detection, segmentation, feature extraction, and target face alignment:

- DeepFaceLab uses the Single Shot Scale-Invariant Face Detector (S3FD) for source face detection and the XSeg model for masking and segmentation. Landmark-based alignment is performed with Dlib or the Face Alignment Network (FAN). XSeg supports custom segmentation training, resulting in high-quality but slow outputs.
- Roop employs RetinaFace (from InsightFace) for face detection, with automatic alignment via a 512-dimensional vector embedding from InsightFace. Segmentation is integrated within the alignment stage, enabling efficient performance with moderate resources.
- MobileFaceSwap is optimized for speed and portability. It uses BlazeFace for detection, 128-dimensional embeddings for encoding, and BiSeNet for segmentation. Alignment relies on BlazeFace, particularly eye positioning. These lightweight components make it highly efficient but at the cost of reduced output fidelity.

The summarized components of each framework are presented in Table III. Based on experimental results and predefined requirements, Roop was selected for further application testing with cooperative and anxious pediatric patients.

TABLE III. THE SUMMARY OF FRAMEWORKS AND THEIR COMPONENTS USED

Framework	Face Detection	Face Segmentation	Face Alignment
DeepFaceLab	S3FD	XSeg	Dlib/FAN-based frontalization
Roop	RetinaFace (InsightFace)	No segmentation	InsightFace built-in
MobileFaceSwap	BlazeFace	BiSeNet	Light alignment via eyes using BlazeFace

As this was a pilot study, 20 children were assigned to the experimental group (Group 1) and 20 to the control group (Group 2). Both groups' fear and anxiety scores for dental procedures were examined based on a questionnaire of six items (A-F) corresponding to specific dental experiences. These included: A→going to the dentist, B→undergoing an oral checkup, C→having the teeth scraped or polished, D→receiving a gum injection, E→undergoing a tooth filling, and F→having a tooth extracted. Higher scores indicate greater levels of fear or anxiety.

Figure 7 compares pre- and post-intervention results, showing a significant reduction in children’s anxiety and fear across all dental procedures.

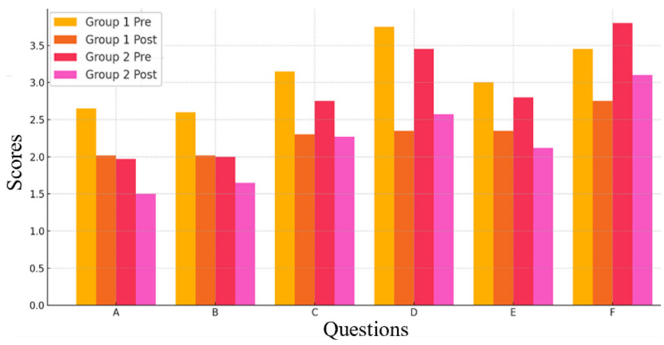


Fig. 7. Comparison of fear and anxiety scores for dental procedures across groups.

Additionally, heart rate measurements decreased noticeably, suggesting that children were more relaxed following exposure to the deepfake-based intervention prior to the dental procedure. Figure 8 illustrates the heart rate and oxygen saturation values for both groups before and after the intervention. Heart rate decreased significantly post-intervention, confirming reduced anxiety, while oxygen saturation improved slightly, suggesting enhanced physiological calmness.

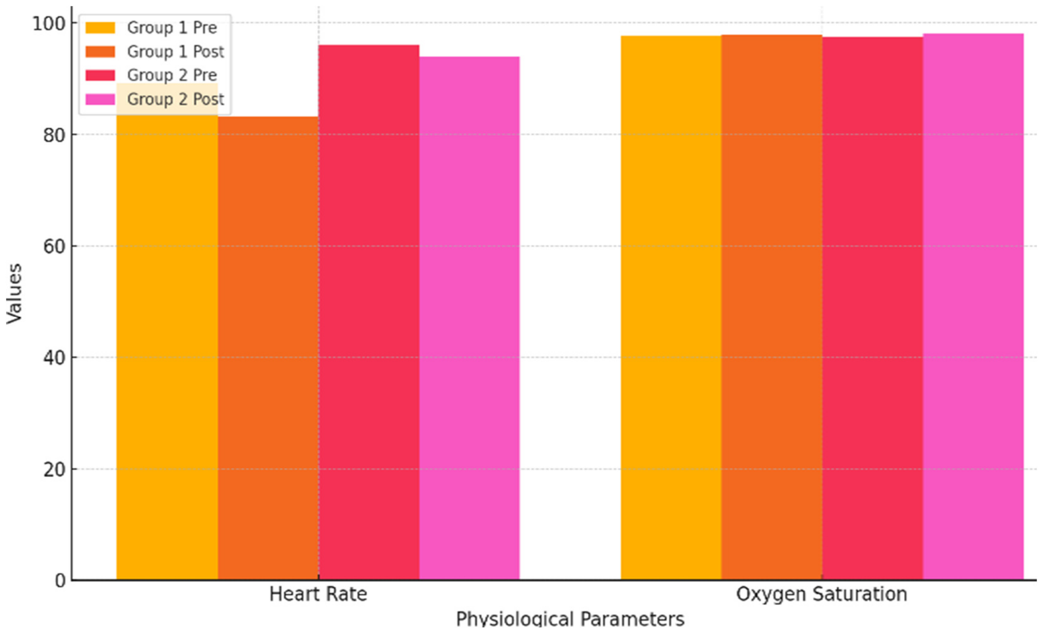


Fig. 8. Heart rate and oxygen saturation values across the groups.

V. CONCLUSION

This research demonstrates that digital behavior management tools can play a pivotal role in pediatric dentistry, and deepfake technology introduces a novel opportunity to further enhance patient experiences. By generating personalized, engaging, and emotionally resonant content, deepfakes have the potential to complement and strengthen traditional methods of managing pediatric dental anxiety. The study, however, was conducted on a limited sample size within a narrow age group and on a local Graphics Processing Unit (GPU)-enabled workstation, which constrains its broader applicability. Future work should explore deployment in cloud-based environments, enabling scalability and accessibility for dental professionals across diverse clinical settings. Expanding the patient pool to include a larger, demographically diverse, and wider age range will also provide more comprehensive insights into the model's effectiveness. Additionally, the current system faces certain technical limitations, such as the inability to modify hairstyles and other non-facial attributes, which reduces the overall personalization effect. Addressing these limitations through more advanced generative models could further improve the user experience.

Ultimately, ethical considerations, parental consent, and professional oversight remain essential for safe and effective implementation. When developed responsibly, deepfake-based applications can serve as a valuable adjunct to conventional behavior management strategies, offering an enriched, child-friendly, and cooperative dental care environment.

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AUTHORS PROFILE

Dr. Aditi Tasgaonkar is currently a third-year Master of Dental Surgery student at D.Y. Patil Dental College and Hospital, Pimpri, Pune, specializing in Pediatric and Preventive Dentistry. She has a keen interest in the behavioral management of pediatric patients.

Miss Rujuta Joshi is currently pursuing her Master's degree in Computer Science at the University of Texas at Arlington. She is an alumna of Cummins College of Engineering for Women.

Miss Harshada Chavan is currently working as a Data Engineer at Barclays and is an alumna of Cummins College of Engineering for Women.

Dr. Madhuri Tasgaonkar is an Assistant Professor at Cummins College of Engineering for Women, Pune. She holds a Ph.D. in Electronics Engineering, with research interests in Image Processing, Artificial Intelligence, and Machine Learning. She has over 25 years of teaching experience.

Dr. Nilesh Rathi is Professor and Head of the Department of Pediatric and Preventive Dentistry at D.Y. Patil Dental College and Hospital, Pimpri, Pune. He has been honored with a Fellowship in Pediatric Orthodontics and has over 15 years of experience, with more than 85 publications to his credit.