Enhancing Surgical Visualization: Feasibility Study on GAN-Based Image Generation for Post Operative Cleft Palate Images

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Abstract: Cleft Lip/Palate (CL/P) is a prevalent maxillofacial congenital anomaly arising from the failure of fusion in the frontonasal and maxillary processes. Currently, no internationally agreed gold standard procedures for cleft lip repair exists, and surgical approaches are frequently selected based on the surgeon's past experiences and the specific characteristics of individual patient cases. The Asher-McDade score, a widely employed tool in assessing unilateral cleft lip surgeries, relies on criteria related to aesthetics and symmetry of maxillofacial region. However, no objective metric has been developed for assessing surgical success. This study aims to incorporate deep learning and Generative Adversarial Network (GAN) methods to construct an image generation framework to produce post-operative lip images that can serve as a standardized reference for assessing surgical success. We introduce an image similarity score based on the image embeddings which we use to validate the generated images. Our method paves the way to a set of techniques for the generation of synthetic faces which can guide surgeons in assessing the outcomes of CL/P surgery.

1 INTRODUCTION

Cleft lip/Palate(CL/P) stands as the most common maxillofacial birth defect, resulting from the failure of fusion in frontonasal and maxillary processes. This failure leads to the physical separation of either one side, termed a unilateral cleft or both sides, referred to as a bilateral cleft, in the upper lip (Agrawal, 2009). On a global scale,1 in 600-800 children are born with this condition, leading to an annual occurrence of nearly 220,000 cases (Vyas et al., 2020; Cobourne, 2004; Yilmaz et al., 2019). Children born with the cleft lip condition experience speech and hearing issues, high susceptibility to dental cavities, difficulty in feeding and they often undergo social and mental development disorders (Chaudhari et al., 2021). It also causes significant psychological and socioeconomic effects on parents as well as caretakers.

Cleft lip is treated with surgical procedures followed by rehabilitation starting as early as 10-12 weeks of age and follow up surgeries from the age of 1 year (Shkoukani et al., 2013). Most of the cases undergo at least two surgeries where more follow up surgeries are required for complex conditions. Ideally cleft lip repair surgeries should result in symmetric and naturally looking upper lips (Mosmuller et al., 2016). But in most of the patients, surgical scars can be noticed in upper lip and philtrum which is the area between upper lip and nose. Cleft lip surgeries restore or repair speech, appearance and normal feeding. Cleft lip surgical procedures are complex and rely on the collective expertise drawn from multiple clinical domains (Yilmaz et al., 2019).

Machine learning and deep learning methods to model the face have experienced a surge of interest in recent years. In particular, facial GANs have emerged as an active research topic and poses a number of interesting challenges, largely due to the fact that the human face is a very complex object which can be represented in 2D or 3D and we often need to account for dynamic poses and facial expression which modify the features considerably (Kammoun et al., 2022). There are some recent efforts to develop methods to assist and guide clinicians performing CL/P surgical repairs. (Li et al., 2019) have trained a model to locate surgical markers and incisions which helps surgeons prepare for the procedure particularly in circumstances where they may lack experience. In (Chen et al., 2022) GAN inpainting methods are proposed to generate non-cleft lips from images with

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cleft lip. Despite the advances in facial recognition and modelling, the application of these methods in plastic surgery is still very limited. In part, this is due to the lack of good quality datasets for training and in our case to a particular lack of datasets with faces of children.

At present, there is no established standard surgical procedure for restoring cleft lip and palate. As a result, a diverse range of surgical approaches exists for CL/P repair (Wadde et al., 2022). (Asher-Mcdade et al., 1991) introduced a standardised rating method for evaluating different cleft lip treatment approaches. This widely used index serves as a common measure to evaluate the success of cleft lip surgeries, focusing on the aesthetics of the nasolabial region. More recently, the Cleft Aesthetic Rating Scale (CARS) (Mosmuller et al., 2016) has been developed, but the Asher-McDade scale is considered superior and is still the most widely used. One of the major issues with both of the scales is the subjectivity involved, whereby the assessments by clinicians do not accord well with those of the cleft patients and other lay people (Duggal et al., 2023).

In light of this, we intend to develop methods which can be used to provide an automated and standardised scoring scale for cleft lip patients based on objective and explainable analysis. The method relies on generation of synthetic facial features including the upper lip and philtrum (groove between the base of the nose and the upper lip) and detailed comparison of the generated features with the original faces to provide an objective and reliable score for post-operative assessment.

The main contributions of this study are therefore:

- KidsLips. A curated dataset of lips and philtrum of children suitable for training image generation models.
- Lip Image Inpainting. This is the first study of image inpainting with a specific focus on details of lips and philtrum.
- We propose a pipeline for post surgical assessment of cleft palate repair.

The code[1] and dataset[2] for training the gan-inpainting model are available online.

[1]https://github.com/danielanojan/Cleft_Inpainting.git

[2]https://doi.org/10.5281/zenodo.10498842

2 RELATED WORK

2.1 ML Applications on CL/P

Despite the widespread applications of machine learning and deep learning in the medical domain in recent years, it is noteworthy that only a limited volume of research has been directed towards addressing issues associated with the cleft lip condition. (Lin et al., 2021) worked on predicting the need for cleft lip repair surgery at a later age from cephalometric features based on the radiographic images taken at an early stage. (Li et al., 2019) developed a CNN based algorithm to automate the localisation of surgical markers for cleft lip surgeries. (Agarwal et al., 2018) worked on classifying unilateral and bilateral cleft lips from healthy lips. To our knowledge, there is no machine learning research to date has investigated the success of the cleft lip surgical procedures with the goal of assisting surgeons in choosing the best-fit surgical procedure. For CL/P repair, (Chen et al., 2022) proposed an image inpainting on pre-op CL/P images to predict the post-op repaired CL/P images which would guide surgeons on surgical planning and educate patients and caretakers on surgical outcomes. In particular, this work used images of faces with a resolution of 224x224 pixels, at which size it is difficult to discern the relevant features on the lip and philtrum. In addition, the model is trained on the CelebA (Liu et al., 2015) dataset which consists of mid age to old age celebrity faces.

2.2 GAN Inpainting

Image generation has been studied in detail over the years and with the development of GAN, VAE realistic images can be generated. StyleGAN (Karras et al., 2020) succeeded in generating high resolution realistic looking human faces. In medical imaging, skin lesion images, brain MRI images and lung cancer nodule images are generated using GANs (Ali et al., 2022; Wang et al., 2022). These methods pave the way for better analysis by generating realistic training images for data hungry deep learning modalities. Image Inpainting is used to synthesize missing parts of an image maintaining the semantic meaning. Generative models are proven to be the state of the art in Image inpainting. In medical imaging, inpainting is used to remove occlusions such as metallic implants (Armanious et al., 2018) and reconstructing distorted portions in CT (Tran et al., 2021) and removing light distortions caused by endoscopes (Daher et al., 2022). Face inpainting is complex task due to the unique and complex facial structures and generative models are

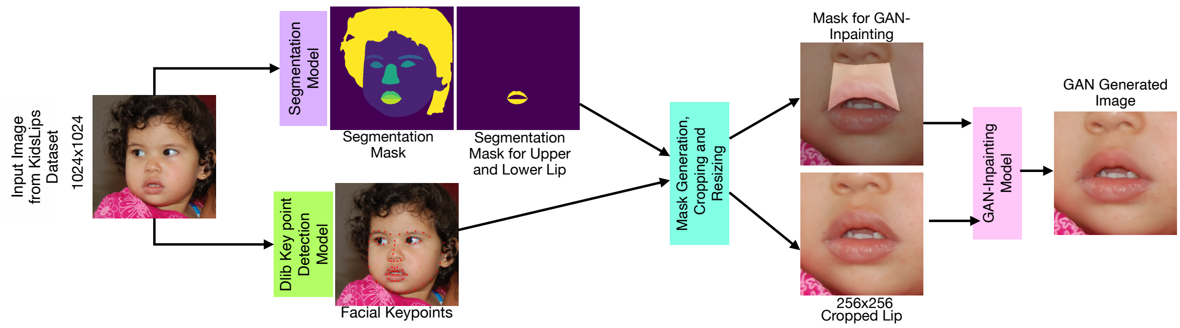

Figure 1: KidsLips Dataset preparation Pipeline. We obtain lip area and corresponding masks from high-res faces. For this purpose, use LaPa (Liu et al., 2020) segmentation of Upper lip and nose keypoints detected by Dlib (King, 2009) to guide the region selection.

coupled with transformers to reduce the inductive bias and learn semantically appealing features (Deng et al., 2022).

2.3 Siamese Network

Siamese networks (Koch et al., 2015) are a subclass of neural networks, in which two identical sub-networks learn a similarity function from the input pairs by comparing feature embeddings. With the ability of the network to learn with image pairs which resemble a one-shot learning process, Siamese networks can handle imbalanced classes which usually cause serious problems for traditional CNNs. Also as the network learns the distance between image embeddings, it can learn features resembling semantic similarity and this helps in this study, as we want to quantify the similarity between image pairs. (Pei et al., 2023) have used Siamese network to identify face spoofing. We use contrastive loss, due to its ability to reduce inter-class variance and and increase intra-class variance.

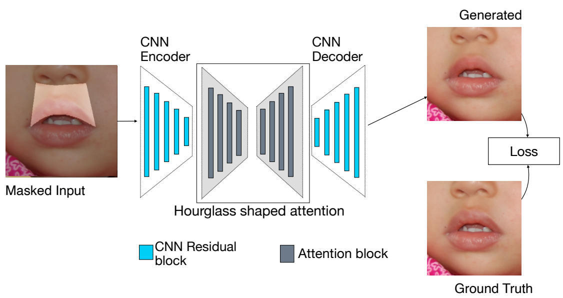

Figure 2: Hourglass Attention Network for Generation of Upper Lip Area.

3 METHODOLOGY

3.1 Dataset Acquisition

An overview of the data preparation pipeline is shown in Figure 1. We start with high quality images of children's faces from our curated KidsLips dataset. We extract the facial keypoints using standard methods, but the keypoints alone are not sufficient to locate the regions of interest. We also apply a segmentation model to identify precise masks for the upper and lower lips regions. Using the masks and keypoints, we mask, crop and resize the image in preparation for GAN-inpainting. The GAN-inpainting model is applied to the cleft-lip images to inpaint the upper lip and philtrum regions and generate faces without cleft.

The fully anonymised post-op Cleft lip surgery dataset was collected in Childrens's Health Ireland at Temple Street between 2009-2012 and obtained under a research agreement between Children's Health Ireland at Temple Street and University College Dublin.

The cleft repair surgery had been performed when the children were between 6 months to 1 year old but the actual images have been taken by surgeons during follow ups when the children reached the age of 5. Due to GDPR constraints, the images are anonymised and have been cropped to lip and surrounding area only. The images were not taken in a controlled environment and the variations in lighting, angle and resolution are apparent. The original dataset consists of 174 images. Subsequently due to insufficient lighting or blurring, the poor quality images had to be excluded. This resulted in the final dataset containing 147 images with a combination of both unilateral and bilateral clefts which was used in the study. For the purposes of this study, these images are used only for inference and do not appear in any training dataset.

Deep learning models are data hungry and they

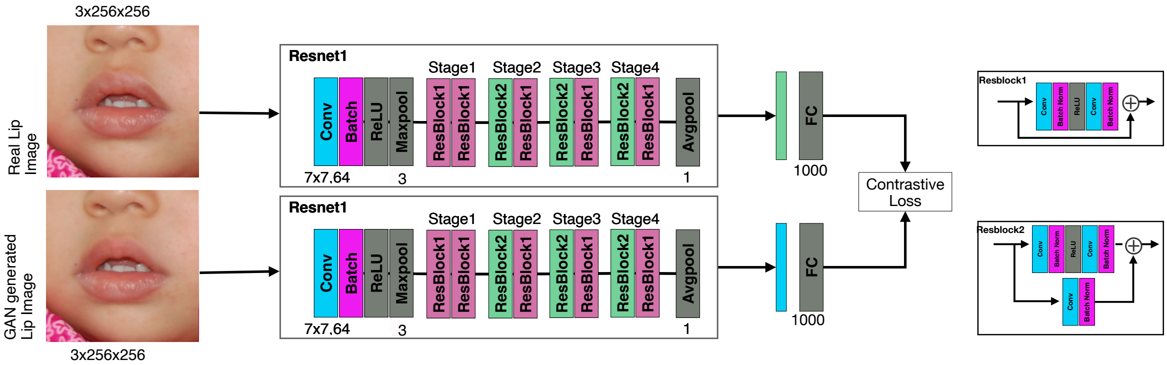

Figure 3: Siamese Network architecture for image similarity prediction. The GAN-inpainted image and the real image are fed as inputs to the Siamese network which is trained with contrastive loss. The distance between the image embeddings is used to compute a similarity score.

require significant amounts of labelled data of similar distribution of that of target domain for training. In the context of this study, we require 256x256 pixel regions of the cropped area as shown in Figure 1. This requirement is challenging as there are no publicly available image datasets specifically tailored to children's lips or faces. Though YLFW (Medvedev et al., 2023) contains a substantial number of children's faces, the images are low-resolution and not suitable for this study. Consequently, we address this gap by mining existing high resolution face datasets as sources for extracting lip images relevant for this study. We use the FFHQ dataset (Karras et al., 2018) for this purpose. FFHQ consists of 70000 faces sourced from Flickr.com with a resolution of 1024x2024, and includes a variety of ages, ethnicities and image backgrounds. For this study we manually scrape children's faces in the age range 0-10. We are releasing this curated dataset as KidsLips and hope it will be of use to the community for future research and development.

We use keypoints in association with a segmentation model to build masks of the facial region of interest. Our GAN-inpainting model is used to generate synthesised upper lips and philtrum and we condition the generation of these regions on the lower lip. The lower lip is suitable for conditioning the GAN generation, as it is usually unaffected by the cleft. We find the exact boundary of the upper lip by joining keypoints. We leverage the segmentation model of LaPa (Liu et al., 2020) to get the lip boundaries at pixel level and fuse it with the nose keypoints extracted by Dlib (King, 2009) to form a polygon and generate the mask region, as show in Figure 1. This mask generation is different from other state of the art inpainting methods where random masks are commonly used. In contrast, we condition the mask on the lower lip for all cases.

As shown in Figure 1 images are then cropped to include lip and philtrum area based on keypoints from the nose and lip areas. Subsequently, both the cropped images and their corresponding masks are reshaped to 256x256 pixels. The dataset is then manually inspected, and images featuring occluded or blurry lip regions are excluded. The resulting dataset comprises of 6,508 high-quality images of healthy children's lips of diverse ethnicity. We refer to this curated dataset as KidsLips dataset. Within this KidsLips dataset, 5,900 images are randomly assigned for training the GAN inpainting model, while the remaining 608 images are further partitioned in an 80:20 ratio to facilitate the training and validation of a Siamese similarity model.

The face keypoint models cannot be used on partial face images as they are trained on full faces. Due to this limitation, we manually annotate the masks on the cleft lip dataset to generate the upper lip and philtrum area.

3.2 GAN Inpainting Network for Upper Lip Generation

We use the Hourglass Attention network(Deng et al., 2022) for GAN inpainting to generate the upper lip and philtrum area. The network is constructed with symmetric structure similar to the UNet model (Ronneberger et al., 2015). The base building blocks are constructed from CNN encoder and decoder and hourglass-shaped attention modules as shown in Figure 2. The encoder captures contextual information as hierarchical features and passes it to the attention module. The hourglass attention block is similar to a multi-head self attention module with laplacian prior referred to as laplacian attention module. This prior calculates the distance between feature maps and constitutes the spatial locations as a laplacian distribution. The model generates esthetically appealing images well-suited for this study. The GAN inpainting model is trained with our KidsLips dataset along with the corresponding generated masks.

3.3 Training Siamese Network to Identify Image Similarity

We use pairs of images to train a Siamese network to determine if the pair of images are from same, or different child. This training process is chosen to train the baseline network weights to capture the similarities in images while penalising defects for example post operative scaring. During training, we present the networks with different pairs of images, which could be real and GAN-inpainted images of the same child or real and GAN-inpainted images of different children. If both the images are of same child, this is a positive pair otherwise they it is a negative pair.

We use the ResNet18 (He et al., 2015) architecture, pretrained on ImageNet as the backbone network for the Siamese network which is shown in Figure 3. The embeddings from the fully connected layer are trained with contrastive loss to optimize the network. We use the contrastive loss function due to its ability to reduce inter-class variance and increase intra-class variance (Shorfuzzaman and Hossain, 2021).

The contrastive loss is defined as

$$L = \frac{1}{2}(1-Y)(D_e)^2 + (Y)\frac{1}{2}max(0, m-D_e)^2 \quad (1)$$

where Y is the label, D_e is the euclidean distance between the feature embeddings of the image pair defined below and m is the margin.

$$\|D_e(f_1, f_2)\|_2 = \left(\sum_{i=1}^{n} |(f_1 - f_2)|^2\right)^{1/2} \quad (2)$$

Here f_1 and f_2 are image embeddings obtained from Siamese network. The threshold value for contrastive loss is updated after each epoch based on the updated mean values between two classes.

3.4 Similarity Between Post-Op Cleft Lip Images and Generated Images

We use images of cleft lip patients and the corresponding GAN-inpainted images with the pre-trained Siamese network to calculate the euclidean distance between embeddings. Finally, we determine the similarity score as the inverse of the distance.

4 EXPERIMENTS

We use the hyperparameters from (Deng et al., 2022) and the GAN-inpainting model is trained for 1000000 iterations. No image augmentation is used. A learning rate of 1x10-5 is applied with learning rate decay. The model is trained with Adam optimizer and the batch size is 4. For training the Siamese network, images are augmented with Random Flip and Random Rotation with an angle of 0-10 degrees. Grid search is used for hyper parameter tuning. We used a batch size of 1, the learning rate is 0.001 and the model is trained with the Adam optimizer. The initial contrastive loss threshold was chosen to be 2.4 and updated after each epoch. The accuracy is calculated if the euclidean distance between image embeddings are smaller than a predefined distance threshold of 1.5. The validation accuracy was reported as 0.972. We implement both networks using PyTorch (Paszke et al., 2017) Framework.

5 RESULTS & DISCUSSION

Figure 5 shows the similarity scores between post-operative CL/P images and GAN-generated images. We use euclidean distance of 1.5 as the threshold for GAN-generated image to be classified as a match and the results show that 80% of the generated post-op cleft upper lips have the euclidean distance less than 1.5. We observe that the network trained on healthy children's images generates highly realistic images of post-operative faces, preserving the large scale features of the faces while removing the post-surgical scars. The model shows great ability to adapt to the domain of cleft lip images, even though these images are not used in training. The similarity score captures the differences in images and coincides well with a visual assessment. It should be noted that the visible scars in the post-op images are captured by the similarity score. For example, Figure 5(c) and Figure 5(d) have a high similarity score and we do indeed see that the generated images have upper lip structure which is visually similar to the ground truth upper lips. However, Figure 5(c) contains noticeable scars, resulting in a lower score compared to Figure 5(d), which has much less noticeable post-operative scarring.

The GAN-inpainting model fails to generate images of vertically asymmetric lips where the upper lips are vertically elongated compared to the lower lips. In those cases, flat lips are generated and it is penalized while calculating the similarity score as shown in Figure 5(a) and Figure 5(b). This is due to the fact that the KidsLips training dataset contains

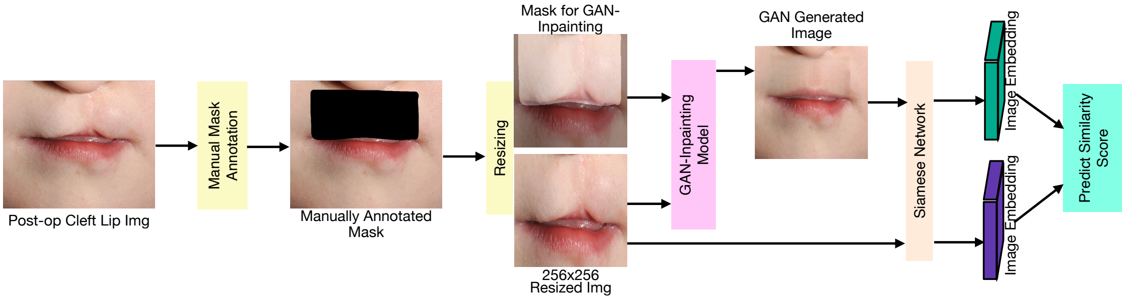

Figure 4: Inference Pipeline for post-op CL/P. Images are annotated and reshaped to 256x256 and passed to the pretrained GAN inpainting model to generate corresponding lip image. Then the similarity score is calculated between GAN generated image and real image using pretrained Siamese Network.

mostly lips with a flat shape. It is also noted that the model fails to capture the texture of the philtrum for a small proportion of cases, resulting in blurry regions or the region with patches as shows in Figure 5(a)(b).

For the cases with low similarity score, the GAN-inpainting model is unable to produce a realistic synthetic image and these cases are not suitable for use in surgical assessment.

6 CONCLUSION AND FUTURE WORK

Our goal in this work is to develop an image inpainting method tailored for post-op cleft lip generation in children to be used as a ground truth automated scoring method for assessing the success of cleft lip surgery. It is evident that the GAN-inpainting models can generate visually appealing images, it can be used as the reference to score the success of the surgery.

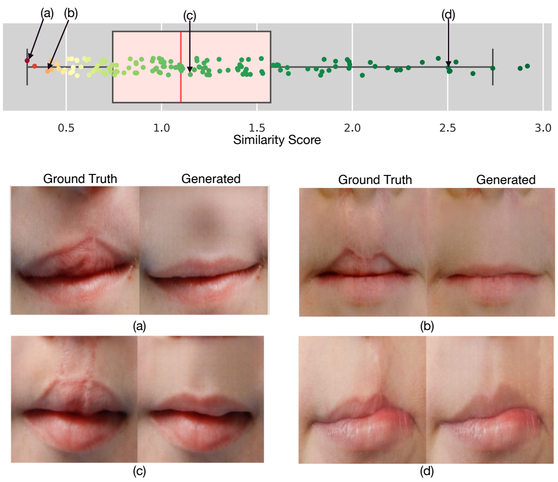

Figure 5: Similarity score distribution calculated using Siamese Network. Image pairs with high similarity scores have a strong visual resemblance.

The Siamese-based image similarity distance calculation is proven to be a good measure in validating the image generation. We make the KidsLips dataset available to facilitate further research in this area. In our future work, we will perform assesements with the clincians and surgeons and ask them to validate the scoring methods detailed in this work.

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