Comment on "Just a quick pic: Ethics of medical photography:" Generative adversarial networks could be a solution

To the Editor: We were interested to read the article about the ethical problem of medical photography in dermatology.[1] Photography in dermatology is an important clue to diagnosis, and unlike radiologic medical imaging, infringing on patients' privacy is always a problem with photography,[2] particularly when photographs in medical journals are available to unspecified numbers of people. Informed consent is essential for medical photography, but regulations or guidelines regarding which level of consent to achieve is not established. Moreover, if dermatologists hesitate to report their own cases to avoid unnecessary ethical or legal disputes, medical progress can be hindered.

Generative adversarial networks (GANs) are kinds of deep-learning algorithms.[3] GANs consist of 2 conflicting models: generative and discriminative. Generative models provide fake and nonexistent images, and discriminative models determine whether the generated image was acquired from the distribution of the model or the data. The relationship between these 2 models is often referred to as the counterfeiter and the police. As the learning algorithm progresses, the generative model generates an image that is increasingly difficult to distinguish, eventually deceiving the discriminative model. The recent GAN architecture can also extract mutual information to create a variety of images with consistent characteristics.[4] Burlina et al[5] reported that GAN-generated, high-resolution synthetic retinal images were realistic, even to retinal specialists. Besides medical image synthesis, GANs could also be applied to detecting anomalies, denoising radiologic images, and transferring radiologic images from different modalities.[5]

In medical photographs, dermatologists' interests are mainly in skin lesions, while the part related to the patient's privacy is usually in the surrounding area. For example, physicians might be interested in the size, shape, and location of squamous cell carcinoma on the face, but the face itself is not a doctor's concern. From this perspective, if a report posts photography of a body part, the process of publishing could be changed as follows: first, the patient's real photograph will be viewed only by the reviewers. Second, before publication, body parts, except for the lesion area, can be replaced with a GAN-generated image same in sex, age, and skin type (Fig 1). Thus, preserving information about the lesion and the surrounding body is possible, while minimizing privacy infringements.

Many obstacles remain before such a method is fully introduced. Current GAN algorithms deal well with the face, which is typical and easy to collect; however, photographs of various other body parts are not easy to collect for training. Even if new processes are introduced, informed consent will remain an important procedure for medical photography.

In conclusion, generative deep-learning techniques can alleviate the dilemma of medical photography between privacy and research. Dermatologists need to be involved with this novel algorithm.

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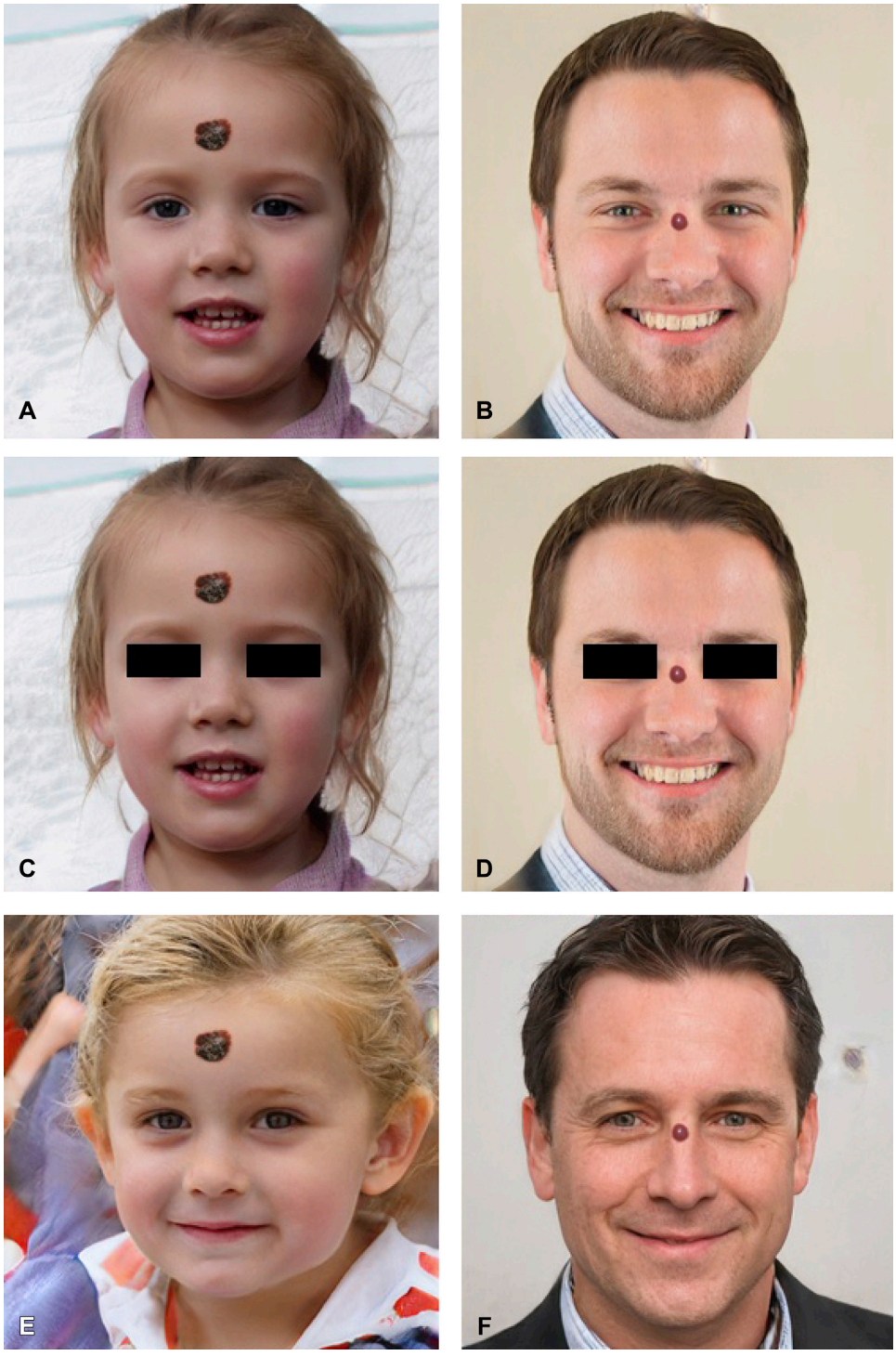

Fig 1. Examples of generative adversarial networks constructing dermatologic images. **A**, White girl with melanoma lesion on forehead. **B**, White adult male with pyogenic granuloma on nose. **C** and **D**, Typically, the eye area is blinded in this kind of photography. **E** and **F**, The generative adversarial network algorithm can make fake images of the same sex, age, and skin type. (All images are generated from styleGAN; https://thispersondoesnotexist.com. Skin lesions were synthesized manually from other photographs containing skin lesions.)