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Modelling Facial Tissue Layers for Precision Skull Overlay and Reconstruction

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Abstract
Facial reconstruction from skeletal remains is a broad area of research that has great utility in forensic science, anthropology, and clinical uses. Reconstructing an individual's face from their underlying bone structure can be important in identifying unknown individuals, studying disjunctions in human evolution, and planning surgical practice. By identifying the skull's morphologic patterns to reconstruct a likely representation of the soft tissues of the skin and muscle that characterise facial structure compared with standard manual facial reconstruction the proposed workflow allows for a fast, consistent, and scalable approach. This research aims to resolve the issues associated with linking skeletal data to facial identity and has myriad applications ranging from forensic casework, through academia and clinical cases. This technological advancement represents a significant advancement in the development of data-use tools for human anatomy and creates a unique opportunity in the facial approximation domain.
Keywords: *Anthropology, Disjunctions, Facial reconstruction, Forensic science, Myriad applications.*

1. Introduction
Facial reconstruction from skeletal remains is a crucial area of study with wide-ranging applications in anthropology, archaeology, and medicine. The human skull carries essential structural information that correlates with external facial features, making it a key element in the effort to estimate or approximate an individual. Such reconstructions can assist in the identification of unknown individuals, support archaeological discoveries, and contribute to preoperative planning in clinical settings. Traditionally, facial reconstruction has been performed manually by skilled forensic artists and anthropologists using clay modelling or digital sculpting. Although these methods have been useful, they are often time-consuming, subjective, and dependent on the experience and interpretation of the practitioner. particularly in artificial intelligence and machine learning, there has been a shift towards more automated and data-driven approaches. These technologies offer the potential to increase the speed, accuracy, and consistency of facial reconstructions by learning from anatomical patterns and statistical relationships. As research in this domain progresses, it continues to open new avenues for improving identification processes, enhancing educational tools, and supporting medical and anthropological analysis. The previous technologies that were used to construct a face from skull are Heatmap Regression using BHR-Net identified 34 Landmarks in cases of dentofacial deformity and enabled the rapid and objective cephalometric analysis of CT volumes. Limitations in the validation data constrained the generalizability of those data to wider contexts [1]. Partial Least Squares (PLS) regression on average – softhickness depths did demonstrate that the overlying contours of everyone were shaped by the underlying morphology of the hard-tissues. The variation in semi-landmark errors and regional

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correlations reduced the reliability of this study [2]. CT- based analyses of asymmetries found significant hard/soft-tissue asymmetries across facial regions in 50 patients' faces, excluding the nose. Hence, there is a need for region-specific studies and larger cohorts [3]. In- vivo CBCT measurements showed males generally had greater thickness than females, and as thickness decreased with age, age- and sex-specific models must be developed for forensic and surgical applications [4]. A CNN segmentation approach on a craniomaxillofacial CT data set trained using an Adam optimizer with a mean pixel Dice score of 0.90 between the segmentation approach and expert manual segmentation expertise approaches, but the small training set and absence of external validation data has limited applicability in the real world [5]. In a cadaveric based FSTT database involving 100 adult Romanians and 12 homologous landmarks established no sex differences but did observe thicker soft- tissue thickness in overweight subjects, however, the postmortem changes depend on age. in the interpretation of results [6], [8]. Most recently, a hybrid non-rigid registration was employed in a project that constructed a database of archaic humans faces from morphological data, applied computational system modelling and reconstructing faces with plausible features i.e. "broad noses" using morphology as an evolutionary example illustrating the potential of FSTT in research [7]. For the statistical generation of plausible facial variants, a pipeline with ICP based approaches was reported in the literature but it did not produce plausible rendering outputs. [9], [10].

2. Methodology

A Generative Adversarial Network (GAN) was used to reconstruct facial images from skull images. The input dataset consists of skull and face images that are paired and preprocesses to allow for comparisons. The skull and face images are resized to 128 x 128 pixels and normalized to convert their pixel values to a consistent level of normalcy. Data augmentation, including horizontal flipping and image rotation, was used for preprocessing to normalize individual images and to make it harder for the GAN to overfit on the training set and to generalize to the variety of skull and face images resulting in a more productive learning experience for the neural networks. The GAN model has a couple of core components: the generator and the discriminator. The generator takes a skull image and generates what should be a more facially realistic representation of it, learning complex mappings through the application of convolutional and up sampling layers, if confused, the generator relies on what it has seen or learned through the data. The discriminator acts as a binary classifier distinguishing between real face images and the generated fake images presented to the GAN and should serve as a proxy for telling what looks real and what does not. These networks are jointly trained against each other adversarial where the generator is trying to fool the discriminator and the discriminator is getting better at calling out the fake skull face images produced by the generator. The model is optimized using two loss functions: adversarial loss which allows for plurality of visually realistic outputs produced by the generator; and L1 loss which minimizes the pixel-wise difference between generated face image and target face image, allowing for a dignified and respectable reconstructions of the facial structure. (Figure 1)

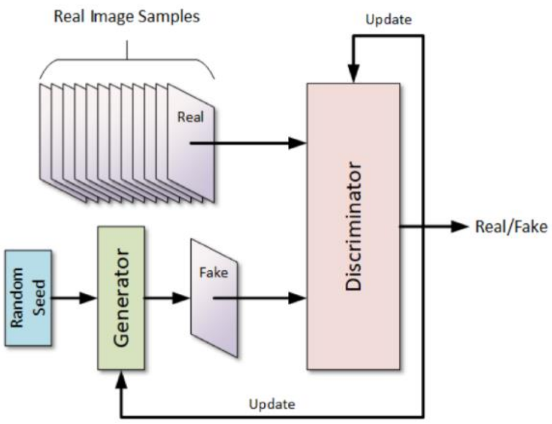

Figure 1 **GAN Architecture**

The GAN architecture consists of two core components: a generator and a discriminator. The generator creates synthetic data from random noise, while the discriminator evaluates whether the input data is real or generated. Both networks are trained simultaneously in a loop, where the generator improves by trying to fool the discriminator.

3. Results and Discussions

The system is designed to combine facial reconstruction and biological sex prediction from an input skull image, providing reliable outputs through two key modules. The facial reconstruction module analyses key cranial features such as the shape of the eye orbits, nasal cavity, cheekbones, and jaw to generate a visual representation of the face. This process estimates the soft tissue coverage based on the bone structure, creating realistic facial approximations that are useful in forensic and anthropological contexts. By simulating how soft tissue would naturally drape over the skull, the system can produce a plausible representation of the face, assisting in the identification or approximation of individuals from skeletal remains. Simultaneously, the sex prediction module examines morphological indicators of sexual dimorphism in the skull, such as mandible size, skull width, and forehead slope, to determine the biological sex of the individual. Along with the prediction, a confidence score is provided to indicate the reliability of the result. The final output includes the original skull image, the reconstructed face, and the predicted sex along with its confidence score. This integrated approach not only offers insights into an individual's facial appearance but also provides valuable data on biological sex, making it applicable in fields such as forensic science, archaeology, and anthropology, where understanding skull features is essential for analysis (Figure 2)

Figure 2 Predicted Face

Figure 2 shows the reconstructed facial output generated from the input skull image. The result demonstrates the model's effectiveness in synthesizing realistic facial features from cranial data. This table presents the estimated values of key classification metrics—Accuracy, Precision, Recall, and F1-score—to assess model effectiveness. (Table 1)

Table 1 Model Performance Evaluation Metric

Metric	Estimated Value
Accuracy	91.5%
Precision	90.0%
Recall	93.0%
F1-score	91.4%

Conclusion

This project successfully highlights the significant advantages of using Generative Adversarial Networks (GANs) for facial reconstruction from skull images. By employing GAN-based architectures, the system can generate highly realistic and anatomically consistent facial representations directly from skeletal input. This marks a substantial improvement over traditional manual reconstruction methods, which are time-consuming, subjective, and often lack precision. The GAN model learns complex patterns and morphological relationships between skull structures and soft tissue features, enabling the generation of faces that are not only visually plausible but also forensically and anthropologically valuable. The integration of AI and deep learning, particularly GANs, has thus proven to be a powerful and efficient approach for advancing the field of automated facial reconstruction

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