Skull2Face: Anatomy-Guided 3D Facial Reconstruction System using Deep Learning and Tissue Depth Modeling

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ABSTRACT
3D face reconstruction from skull plays a crucial role in forensic identification and anthropology. Especially when landslides produce damaged or partially occluded human skulls, it is important to use 3D face reconstruction so that the family can identify the person. Conventional methods have been manual, subjective, and likely to take a long period of time. This paper proposes a system Skull2Face that receives the image of a skull, and generates a realistic 3D face structure using deep learning methods and tissue depth creation by using generative diffusion models. The method we propose combines anatomical landmarks with statistical modeling for accuracy while being able to create a detailed, personalized output with a realistic texture. This modular method lessens the dependence on large databases, introduces an efficient, faster, individualized, automated alternative methodology for facial reconstruction, and improves Identity-consistency, realism and accuracy over earlier methods of forensic facial reconstruction.

Keywords
3D face reconstruction, deep learning, tissue depth creation, generative diffusion models

1. INTRODUCTION
Restoring a face from a skull is helpful to identify individuals in forensic investigations and also to know about humans, that is, for the study of human history. Manual methods that are time-consuming, demonstrative, and require extensive knowledge of the anatomy can cause difference in the end result. For example, clay modeling is one such technique. Many existing techniques are not able to replicate facial variations and features that are unique to an individual [1]. Methods which combine 3D scanning and sculpting [2] or skull-to-face translation networks [3] typically need extensive preprocessing to prepare the data, and are not stable for damaged or incomplete skulls. Techniques that depend on skull shape may weaken visual authenticity and identity, which will cause the difficulty in preserving identity [4]. Generative deep learning methods [9],[10] comparatively provide more realism but they often need large datasets and they cause face issues like mode collapse and overfitting, so they are not fully useful in real-time applications like forensics. Alternative methodologies such as implicit models and proportion-based reconstruction depends largely on the practices and skills of the artists. Archaeological and historical reconstruction methods [11],[12] gives more cultural and artistic importance, but data quality will be low since the skulls may be incomplete or damaged and they may not represent the individual accurately. An examination of craniofacial superimposition [15] reveals the problem of perspective distortion and registration tolerance while performing the reconstruction process and the negative impact of these problems on skull-to-face alignment accuracy.

Skull2Face is an AI driven system used to develop a 3D face mesh. The system takes the image of a skull as input and first learn the tissue depth variation and converts it to a 2D image using diffusion-based models. Then a 3D face mesh is produced using a deep learning-based model and it is aligned with the skull using an open-source algorithm. Finally, the approximate age of the generated face is predicted. This approach improves identity consistency precision, accuracy, and realism while minimizing computational costs.

2. BACKGROUND WORKS
The face reconstruction is based on skull evolved over the years beginning from manual techniques to advanced computer-based learning techniques. The ancient methods yield rather inaccurate data using soft-tissue depth marker, and anthropological landmarks. Later, with the help of the expertise of anthropology and also with the development of 3D model and medical imaging, the techniques had more anatomical precision, although they still require highly expert professional. In modern application, numerous approach utilize deep learning and generative adversarial networks (GANs), which is the first to allow automated system to learn from complex connection between skull and face, resulting in reconstruction of human individuality and anatomical plausibility.

2.1 Historical, manual, and anthropological Techniques
In the past, forensic artist and sculptor rely on interpretation of depth of soft-tissue to estimate features of face. In order to reconstruct, they used anthropological reference points and average soft-tissue thickness (FSTT) of face. Despite the useful information provided by these techniques to the historical as well as the archeological reconstruction, the root of modern craniofacial approximation techniques are early failures, the basis of which are used in modern craniofacial applications of technique.

2.2 CT based tissue thickness analysis
In the field of imaging technology, Researchers have found the way of getting FSTT value in specific identifiable groups and have use computed tomography (CT) as a case in point to estimate or acquire underlying anthropometric measurements in CT reconstructs across communities including Malay and Nigerian

trace. The development is very big stride because generic averages often associated with inaccuracies in such strategies. On the other hand, demographic and ethnic line are critical. After the implementation of the CT technology as an instrument that was used to create reconstruction, the level of accuracy improved significantly, and the FSTT value were produced according to the research methodologies mentioned above.

2.3 3D scanning and computer-assisted modeling

To make detailed reconstruction virtually, the researchers digitized the skulls using portable 3D scanners and modeling software models. Through these processes, it would be able to form approximations of the 3D faces based on measuring the bony landmarks in reference to sculpting software like Blender, Meshmixer or ZBrush. Researcher had interest in developing a better utility, accuracy, and reproducibility of approximation methods and carried out technology in research study although they still used datasets for referring to depth of reference.

2.4 Generative methods and deep learning in early days

Shifting to generative model to predict the latent facial landmarks presented more chances to scientific community and the applications of deep learning to that shift since the previous attempt at recreating full faces of skulls used adversarial learning models that are trained upon computed tomography (CT) scan. In particular, that technique could reproduce the facial features, including the eyes, lips, ears, etc., which otherwise could not be represented using the rules of the anatomy based on the presumption of similarity of features across races, sexes, and populations, and eventually compelled the discipline to switch to entirely automated forensic systems.

2.5 Generative Adversarial Networks (GANs) for 3D face reconstruction

GANs have facilitated the industry in moving towards reconstruction of the three-dimensional facial structure directly via cranial inputs or single image. The process uses features like landmarks, or facial features as feed for graph-based axial layers and recreate geometry in a consistent way without distorting facial expressions. Although improvement was observed in level of increased accuracy and stability of 3D facial measures compared to the older techniques, further enhancements in accuracy and robustness was still required.

2.6 Skull to Skin Translation Networks

U-Net generator and super-resolution modules are capable of generating high quality textures and results when used on small datasets with only a few images. These techniques offer a tradeoff between pursuit of the level of accuracy that comes with forensic techniques and the search of computational advantages.

2.7 Conditional GANs and depth maps

A different technique which used depth maps of 3D craniofacial geometry was utilized. Conditional Generative Adversarial Networks (CGANs) were able to retain high-frequency data and do nonlinear mapping of skulls and face images using paired skull and face image data. The parameter of individualization was incorporated into the methodology alongside body mass index (BMI) to have better reconstruction of geometry with reference to parameters provided by an individual skull and facial characteristics.

2.8 Facial detail improvement and expression synthesis

Using facial expressions morphing or FaceWarp technique, expression and detail refinement techniques are developed as extensions of skull to face technique. FEM maintain special characteristic, including wrinkle and moles that GANs synthesis can ignore during combination of original and generated faces. It allows huge possibility to make more realistic faces and preserve the features of skull-based features for aging research.

3. PROPOSED SYSTEM

The flow chart for the proposed Skull2Face Reconstruction System is shown in Fig 1.

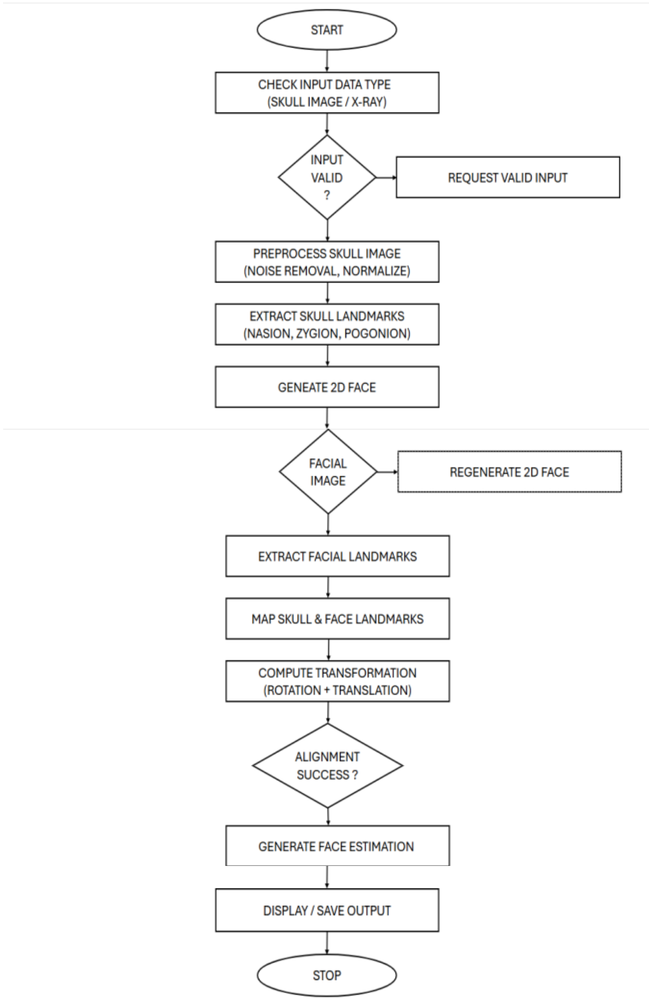

Fig 1 Flow chart

The Skull2Face Reconstruction System integrates statistical tissue depth modeling, diffusion-based facial image generation, deep learning-based 3D mesh reconstruction, and anatomy-guided optimization techniques which ensures accuracy and adaptability across different biological profiles. The high-level design architecture of which is shown in Fig 2.

The first step in the Skull2Face system is collecting the skull data in the form of two-dimensional skull image as shown in Fig 3. In order to eliminate noise, normalize scale, and align the skull to a common anatomical coordinate system, the collected skull data is preprocessed which guarantees consistency across skull inputs. The system then uses skull segmentation techniques to separate cranial and facial bone regions.

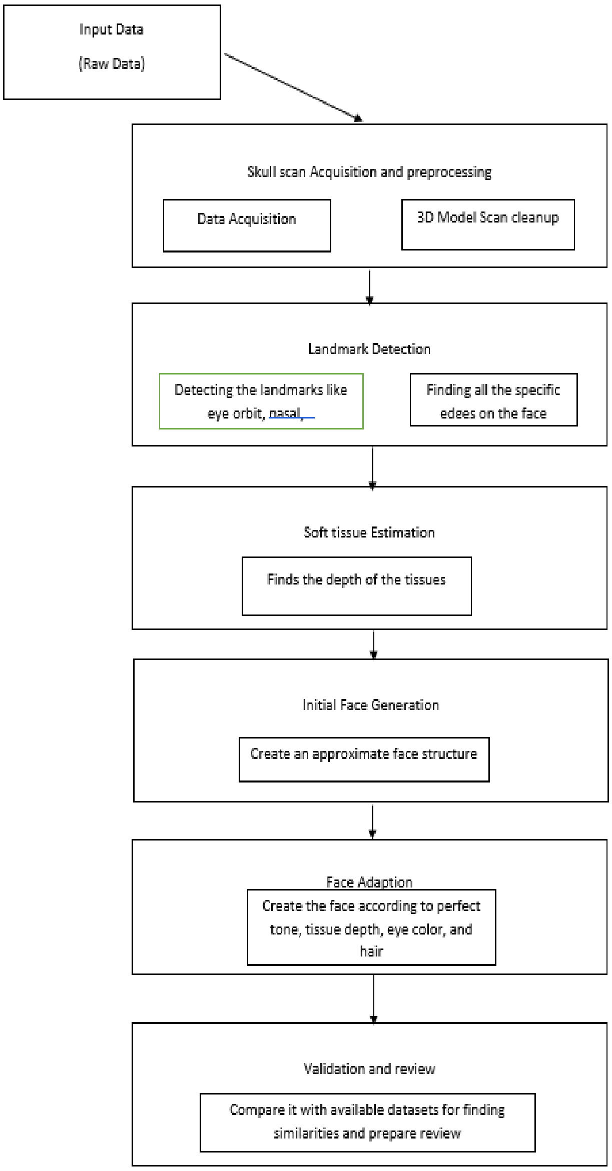

Fig 2 High Level Design Architecture

Then the system identifies predefined set anatomical landmarks on the skull following preprocessing. These landmarks correspond to points like nasion, left zygion, right zygion, and pogonion. These points are automatically located with high precision using deep learning-based landmark detection model. The subsequent face adaptation and mesh optimization are guided by these landmarks, which also act as points for estimating soft tissue thickness. A sampler of Probabilistic Tissue Depth Modeling (VAE) is then used to estimate the soft tissue thickness at each identified skull landmarks. Once the tissue depth profile is established, a two-dimensional face is generated from skull image input and prompts using Realistic Vision -v6.0, which is used for reconstructing 3D face mesh as shown in Fig 4. The generated two-dimensional image is then converted into three-dimensional face using a deep learning-based 3D face reconstruction model, that is, 3D Dense Face Alignment – version2 (3DDFA -V2) as shown in Fig 5.

Using the previously detected skull landmarks and the tissue depth values, optimization is done for landmark-constrained adaptation and 3D mesh is created using Non-linear ICP algorithm. Optimization is defined by multiple loss functions such as landmark loss, projection loss, and symmetric loss. Then finally the approximate age is predicted using ControlNet model.

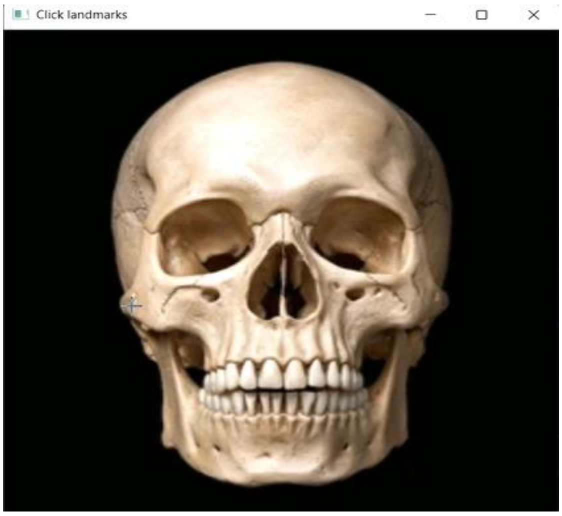

Fig 3 Skull image

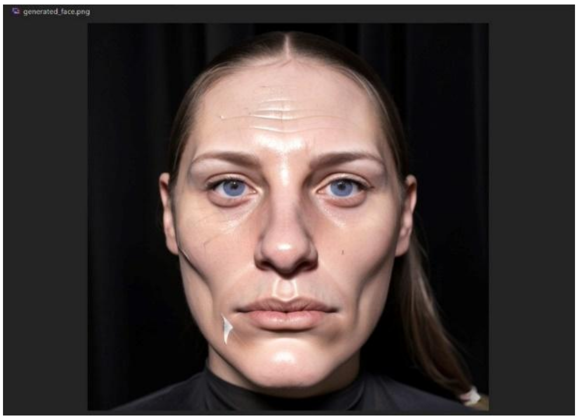

Fig 4 Generated 2D face image

Fig 5 Reconstructed 3D face

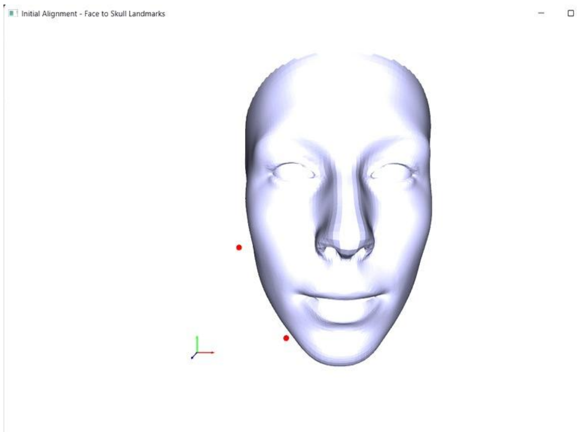

Fig 6 3D face mesh

4. COMPARISON

To know how precise and accurate the system is, a comparison of the system is done with existing methods like manual method, computer-assisted method, GAN based method as shown in Table 1. The comparison is based on the aspects like basis, process, dependency, accuracy, limitations, output and efficiency.

TABLE 1. Comparison Between Skull to Face Reconstruction Techniques

Aspect	Manual	Computer -Assisted	GAN-Based	Proposed: Skull2Face
Basis	Clay and FSTT markers	Digital sculpting with CT	Learned mappings from data	Skull landmarks, biological profile, deep learning
Process	Manual sculpting	Digital sculpting	Automated GAN mapping	Diffusion model, VAE, GAN
Dependen -cy	High artist expertise	Expert input needed	Large paired datasets	Less data-dependent
Accuracy	Subjective , inconsist-ent	Semi-subjective	Dataset-limited	Higher realism and adaptability
Limitati-ons	Time-consumin g, error-prone	Weak soft-tissue features	Poor generalizati -on	Overcomes previous challenges
Output	Physical clay model	Digital 3D model	Digital reconstructi -on	Photorealis t-ic 3D mesh
Efficiency	Slow	Labor-intensive	Data-bottlenecke d	Fast, GPU-accelerated

From the table, traditional methods like clay and facial soft tissue thickness markers are slow, artist dependent and subjective. Computer-assisted techniques like digital sculpting and CT scans speed things up and make more accurate results but still need experts and often miss soft tissue details. GANs take it a step further by automating the process but if there is not enough data, then they can't handle when new skull images are given. The proposed system, on the other hand, brings together skull landmarks, biological profiling, diffusion model, and deep learning that doesn't need huge paired dataset, looks more realistic and works faster due to GPU acceleration.

To understand the comparison clearly and visually, a graph of the comparison table is shown in Fig 3 where the x-axis represents the aspects and the y-axis represents the reconstruction performance index. For the reconstruction performance index, 1 is low performance, 2 is medium performance, 3 is high performance, and 4 is optimal performance.

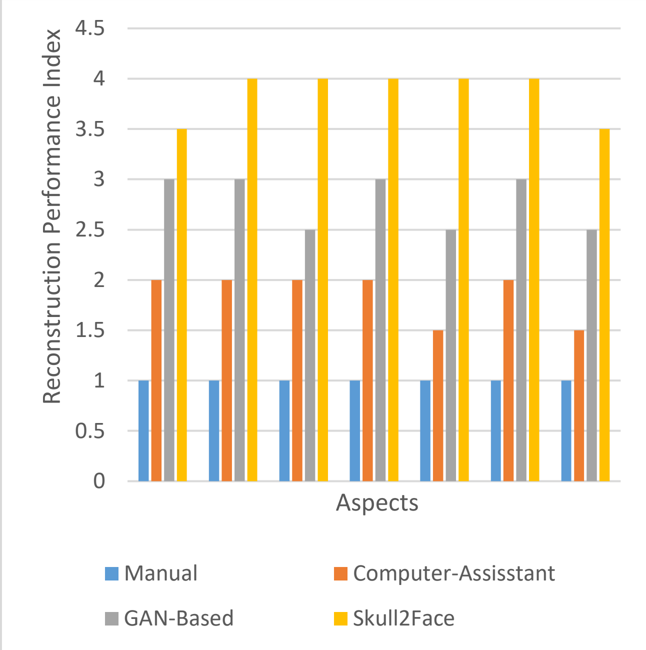

Fig 3 Comparison of existing methods with proposed method

5. CONCLUSION

We introduce Skull2Face, a data-driven and anatomy-driven framework that reconstructs realistic 3D facial structure from an image of a skull. The system uses biological profiles, combines modeling of soft tissue depths, and uses skull geometry to precisely evaluate position of the facial features. Initially, the system produces a high-quality, two-dimensional image from the image of a skull using diffusion-based image generation and then the two-dimensional image using lightweight 3D modeling pipelines. The three-dimensional face mesh is finally aligned with the skull landmarks using an iterative non-linear ICP process. The modular design increases the adaptability and reproducibility, and bypass the need for large skull-face datasets that is labor-intensive. Overall, the system is faster, simple and biologically accurate and minimize the computational costs. Some of the application scenarios of this system include criminal investigation, medical applications, archeological studies. Future work may focus on integrating explicit demographic-aware modeling by explicitly conditioning reconstruction on age, sex, ethnicity, and body mass index to enhance population-specific accuracy.

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