Exploring the Sphenoid Sinus as a Biometric Marker for Human Identification*

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Abstract

Background: Human identification in forensic contexts becomes challenging when fingerprints, dental records, or DNA are unavailable. The sphenoid sinus, owing to its protected anatomical location and high inter-individual variability, offers potential as a biometric marker.

Methods: We first replicated a YOLOv8-nano segmentation experiment using annotated CT scans in DICOM data format. Images were preprocessed with soft-tissue windowing and converted into high-quality PNGs for training. Model performance was evaluated with standard segmentation metrics. Based on observed limitations, we decided for 3D modelling approaches involving manual, semi-automatic, and normalization-based segmentation pipelines.

Results: The YOLOv8 model achieved high validation performance (mAP50 = 0.921; true positive rate = 91%; true negative rate = 100%), which is promising for the future implementation. However, its reliability for consistent sphenoid sinus segmentation was limited by anatomical complexity and heterogeneous datasets. In contrast, 3D modelling methods produced more robust and accurate reconstructions of the sphenoid sinus.

Conclusion: While deep learning-based 2D segmentation provides a strong baseline for sinus analysis, 3D modelling approaches currently offer greater reliability for forensic applications. Combining both strategies may pave the way toward fully automated, scalable identification frameworks based on sphenoid sinus morphology.

Keywords

sphenoid sinus, biometric identification, forensic medicine, CT imaging, deep learning segmentation, 3D modelling

1. Introduction

The accurate identification of human remains is a critical challenge in forensic medicine is an endeavor often impeded when conventional methods such as fingerprints, dental records, or DNA analysis are unavailable due to decomposition, trauma, or resource limitations. In such situations, skeletal structures, particularly the paranasal sinuses, offer valuable alternatives. Among them, the sphenoid sinus is an anatomically deep-seated and highly variable paranasal cavity, which has emerged as a promising biomarker for forensic identification due to its structural uniqueness and resilience to external damage [1].

The sphenoid sinus demonstrates remarkable inter-individual variability in terms of pneumatization, shape, size, and septal asymmetry [2]. Its location deep within the sphenoid bone

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renders it less susceptible to external trauma, enhancing its reliability as a potential forensic identifier. Historically, forensic experts have relied on manual or semi-automatic methods to analyze sphenoid sinus morphology, but these approaches are time-consuming, operator-dependent, and subject to considerable variability [3].

In response, recent advances in computational methods have yielded promising results in automating both segmentation and recognition of the sphenoid sinus. One seminal study proposed a fully automatic 3D reconstruction pipeline, combining fuzzy c-means clustering and mathematical morphology for sphenoid segmentation, followed by feature extraction via a stacked convolutional auto-encoder. This approach achieved perfect identification accuracy (100%) on a dataset of 85 CT scans from 72 individuals [1]. More recently, deep learning techniques have been leveraged with even larger datasets. For example, a convolutional neural network trained on 1,475 noncontrast thin-slice CT scans achieved a Rank-1 accuracy of 93.94% and Rank-5 accuracy of 99.24%, performing each identification in under a minute [4].

Along a parallel trajectory, point cloud methods have been applied to enhance the robustness of sphenoid sinus-based identification. A geometric self-attention network (GSA-Net) operating on 3D point cloud representations achieved Top-1 accuracy of 99.55% and Top-3 accuracy of 100% across 220 individuals, demonstrating strong resilience to rotational transformations [5].

In the realm of segmentation, the U-Net architecture has revolutionized biomedical image processing through its encoder–decoder structure, facilitating highly precise segmentation even with limited training data. Its variants have since been widely adopted across medical imaging tasks. However, most work applying deep learning to paranasal sinuses focuses on CT images and maxillary or frontal sinuses [6]. Recently, an nnU-Net v2 model was developed to segment sphenoid sinus and adjacent skull base structures in cone-beam CT (CBCT) volumes. This model reached a Dice coefficient of 0.96 for the sphenoid sinus demonstrating exceptional segmentation accuracy and moderate performance on other nearby anatomical structures [7].

Collectively, these findings underscore the potential of combining high-fidelity segmentation with advanced recognition models such as U-Net–based or point cloud–based neural networks to develop an end-to-end, automated framework for human identification via sphenoid sinus morphology [8]. Such a framework would offer high accuracy, operator independence, and scalability qualities paramount in forensic contexts where rapid and reliable identification is required.

The aim of this study was to perform 2D segmentation using the YOLOv8 model and to investigate preprocessing of 3D data of the sphenoid sinus for the person recognition task using manual, semi-automatic and normalization methods

2. Material and Methods

This study investigated the segmentation of the sphenoid sinus from cranial CT scans as a potential biometric structure for forensic human identification. The study was approved by the Bioethics Committee of Kharkiv National Medical University (Minutes of the meeting of the commission No. 5 dated November 11, 2018). Data were collected from two sources: (i) heterogeneous CT datasets provided by collaborating institutions, characterized by variable image quality, slice thickness, and orientations, and the publicly available NasalSeg dataset comprising 130 expert-annotated CT scans. While NasalSeg does not directly annotate the sphenoid sinus, it provided a standardized reference dataset for testing preprocessing and segmentation pipelines.

As a preliminary step, we conducted experiments based on nasal sinus segmentation with YOLO v8 [10]. A dataset of 24 patient DICOM scans (12-bit depth) with JSON annotations was processed. Soft-tissue windowing was applied to the raw DICOM data to enhance anatomical contrast, and the images were converted into high-quality, lossless 8-bit PNGs. These were used to train a YOLOv8-HD95 segmentation model (yolo v8n-seg) for 100 epochs at 512×512 resolution on an NVIDIA RTX 3060 GPU. All experiments and evaluation pipelines were implemented within a structured project environment, which is publicly available for reproducibility. The finalized submission package (“BIKO_UA_Nasal_Sinus_Segmentation_via_DeepLearning.zip”) includes the complete, cleaned project directory with two main modules: 3D_Attention_UNet and YOLOv8_Segment. Each module contains its full source code (/src), training and evaluation results (CSV format under /results), and corresponding dependency files (requirements.txt). The trained model files (best_dice_model.pth and best.pt) exceed 300 MB and were therefore not included in the ZIP archive. All versioned code and model weights are hosted publicly on GitHub: https://github.com/Simsalasigsauer/Sinus-Segmentation-UNet-vs-YOLO.

Detailed quantitative evaluation tables for both models (Dice, IoU, Hausdorff Distance HD95, Average Surface Distance ASSD) are included in the project README.Additionally, the README outlines follow-up analyses regarding generalization across sites and downstream identification tasks.Some advanced experiments (Rank-1/Rank-5 accuracy, cross-site inference) were not conducted, as the current project stage focused on segmentation benchmarking rather than full identification pipelines.

Then three complementary preprocessing approaches for 3D data were evaluated:

1. Manual segmentation. Expert annotations of the sphenoid sinus were processed using custom Python scripts. DICOM images and JSON-based masks were converted into 3D volumetric data and point clouds. These were subsequently meshed in Blender using metaball algorithms combined with marching cubes reconstruction [11]. This workflow allowed the generation of anatomically plausible sinus models but required significant computational and manual effort.
2. Semi-automatic segmentation. Semi-automated region-growing algorithms were applied in Materialise Mimics [12] and 3D Slicer [13]. Mimics provided an intuitive interface and fast processing (3–10 minutes per case), while 3D Slicer, as an open-source tool, required more manual refinement but offered broader functionality and flexibility. Comparative evaluations focused on segmentation accuracy, mesh quality, processing time, and software accessibility [14, 15].
3. Image normalization. To address variability in CT quality, multiple preprocessing methods were implemented [16]. Percentile normalization (5–98%) was used to suppress outlier intensities such as those caused by dental implants, while preserving relevant anatomical detail. Windowing was applied to improve the visibility of soft tissue and bone structures within defined Hounsfield ranges. Finally, an extended Nyúl-Shah normalization method was explored but not fully optimized within the project timeframe. These methods aimed to harmonize heterogeneous datasets for downstream learning-based analyses.

In addition, anatomical distinctiveness of paranasal sinuses has been reported in prior studies [17], and volumetric evaluations of sphenoid sinus morphology have highlighted their forensic potential [18].

3. Results

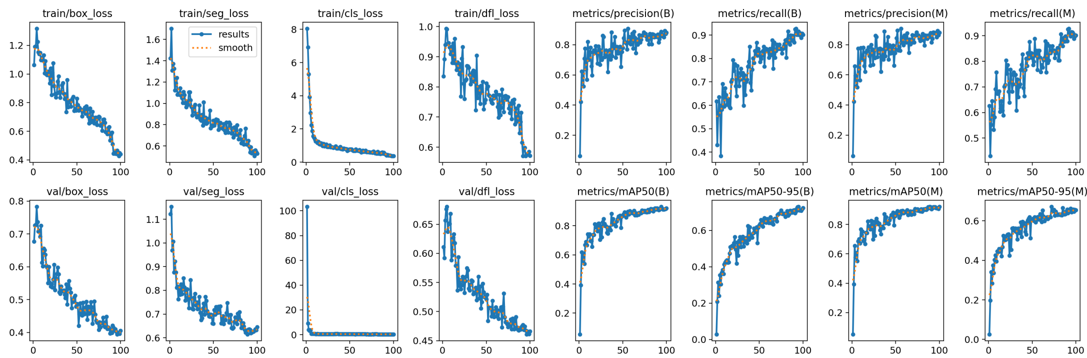

Figure 1: Result for images in axial plane using YOLOv8

Manual segmentation successfully reconstructed the sphenoid sinus in three dimensions, confirming the feasibility of this approach as a ground truth reference.

However, the process was labor-intensive and limited by mesh artifacts such as unnatural connections and excessive smoothing in Blender reconstructions. Consequently, this method was deemed impractical for large-scale dataset generation.

The YOLOv8 model converged stably and achieved strong segmentation performance on the validation set. The predicted masks were smooth and anatomically precise, with a mask mAP50 of 0.921. The model reached a true positive rate of 91% and a true negative rate of 100%. These results confirmed the technical feasibility of using deep learning for sinus segmentation.

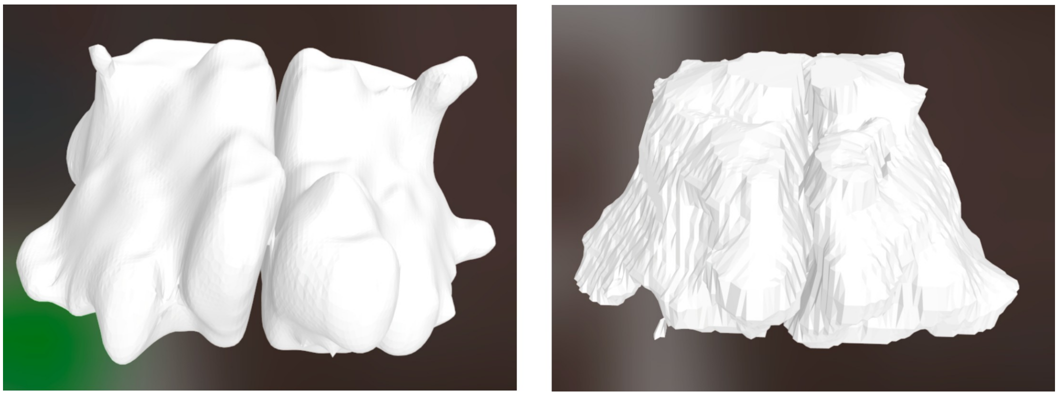

Figure 2: Mesh results for 3D Slicer (left) and Materialize Mimics (right)

Semi-automatic segmentation provided more efficient results. Mimics consistently produced accurate 3D reconstructions with minimal user intervention, albeit at high licensing costs. 3D Slicer required more extensive manual correction but yielded smoother and more organic meshes, particularly when slice thickness was small. Across both tools, 63 segmentations were completed (23 from the local dataset, 40 from NasalSeg). While the NasalSeg data enabled clean reconstructions, scans from the local dataset were often compromised by poor resolution, orientation errors, and incomplete fields of view.

Normalization markedly improved data quality and comparability. Percentile normalization reduced histogram variability and mitigated the effects of overexposure artifacts, while windowing enhanced contrast within the sinus cavities. Optimal results were achieved using percentile thresholds of 5–98% combined with window values between 8,000 and 40,000 HU, producing sharper anatomical boundaries while maintaining tissue differentiation. Attempts to implement Nyúl-Shah normalization suggested potential advantages for standardizing multi-center data, but further refinement was required.

4. Discussions

This work demonstrates the potential of the sphenoid sinus as a biometrically distinctive and resilient structure for forensic human identification. Manual segmentation confirmed the anatomical uniqueness of the sinus but was not scalable due to its high time demands. Semi-automatic approaches proved to be a practical compromise, combining acceptable accuracy with efficiency. The comparison between Mimics and 3D Slicer highlights a trade-off between commercial accessibility and open-source flexibility: Mimics excelled in usability and speed, while 3D Slicer provided broader functionality and cost-free access, albeit with higher operator involvement [19, 20].

While the YOLOv8-based segmentation demonstrated high accuracy, its direct application to the sphenoid sinus proved less effective for our forensic identification goals. The method was highly optimized for general nasal sinus segmentation, but the sphenoid's deep location and complex anatomical variation limited reliability in practice. Additionally, despite strong validation metrics, qualitative inspection revealed inconsistencies when working with heterogeneous CT data and variable acquisition parameters. These limitations motivated us to move beyond 2D slice-based segmentation toward more robust 3D modelling strategies.

Normalization emerged as a critical step for ensuring comparability across heterogeneous CT datasets. Percentile normalization effectively reduced variability, while windowing provided targeted contrast enhancement. These methods collectively improved segmentation performance and prepared the datasets for integration into machine learning frameworks. Although Nyúl-Shah normalization was not fully realized, its theoretical potential suggests it could further standardize data across institutions and scanners.

Table 1
Comparison of Materialize Mimics and 3D Slicer

Materialize Mimics	3D Slicer
Good user interface; easy to understand and intuitive	Requires more familiarization, but offers many features
Efficient algorithms for region growing and post-processing	More manual post-processing required and somewhat more labor-intensive
3D mesh quality somewhat more precise but more angular; scans with large slice thickness appear unnatural; higher accuracy expected with high resolution	3D mesh more smoothed, appears more organic; some loss of detail expected
Faster processing time per image (approx. 3–10 minutes)	Longer processing time per image, though likely improves with experience
Commercial software – associated with high costs	Freely available

A comparison between Mimics and 3D Slicer (see table 1) highlighted clear trade-offs between commercial and open-source approaches. Mimics offered an intuitive and user-friendly interface (see Fig. 3) with efficient algorithms for both region growing and post-processing. Processing times were shorter (approximately 3–10 minutes per image), and mesh accuracy was higher, though reconstructions tended to appear angular, particularly with scans of larger slice thickness. Its main drawback was the high licensing cost. By contrast, 3D Slicer required more familiarization and greater manual effort for post-processing, which initially increased segmentation time. However, it provided a broader range of features and the advantage of being freely available. Reconstructions generated with 3D Slicer appeared more smoothed and organic, albeit with some expected loss of fine detail [20]. Overall, Mimics proved advantageous for speed and precision at high resolution, while 3D Slicer offered flexibility and accessibility for extended research use.

The study underscores the importance of preprocessing and segmentation as foundational steps toward automated identification pipelines. Future work should integrate these methods into deep learning frameworks, such as GSA-Net, which have demonstrated near-perfect accuracy in sphenoid sinus–based identification tasks [21, 22]. By coupling robust normalization with advanced segmentation and classification models, fully automated and scalable forensic identification based on sinus morphology may become feasible.

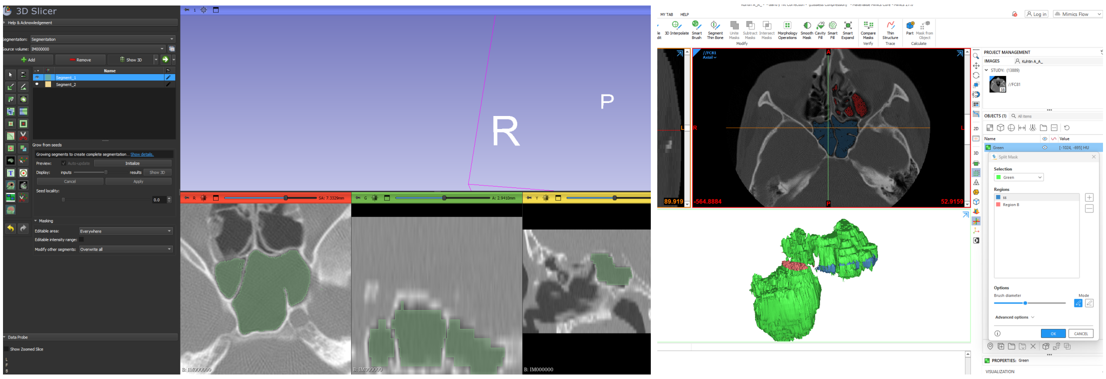

Figure 3: Materialize Mimics and 3D Slicer comparison

The YOLOv8 segmentation experiments established a strong technical baseline, confirming that deep learning can generate anatomically coherent masks of the paranasal sinuses. However, the limitations observed when focusing on the sphenoid sinus highlighted the need for alternative methods. Consequently, we transitioned to 3D reconstruction and modelling approaches, which offered greater anatomical fidelity and potential for forensic identification.

5. Conclusions

This study represents an initial attempt to use sphenoid sinus morphology from CT imaging as a biometric marker for human identification. Through the evaluation of manual, semi-automatic, and preprocessing-based segmentation methods, we demonstrated both the feasibility and the limitations of current approaches. While manual segmentation provides accurate anatomical references, it is not scalable; semi-automatic tools such as Mimics and 3D Slicer offer a practical balance between usability and accuracy, though with different trade-offs. Image normalization proved essential for harmonizing heterogeneous datasets and improving the comparability of scans. Together, these findings establish a methodological foundation for future research aimed at integrating advanced deep learning models for fully automated and scalable forensic identification.

Declaration on Generative AI

During the preparation of this work, the authors used GPT-4 in order to: Grammar and spelling check. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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