

AI-Driven 3D Reconstruction of Anatomical Variations for Personalized Surgical Plan

Jahan Zeb G¹, Mohamed Nizam Al Deen Shah², Ranjitha Naveen Hegde³, J Jacqueline Kim⁴, Brunda K⁵, Deepthi M⁶

¹Department of Human Anatomy, Dayananda Sagar College of Dental Sciences, Bangalore

²Department of Physiology, Dayananda Sagar College of Dental Sciences, Bangalore

³Department of Biochemistry, Dayananda Sagar College of Dental Sciences, Bangalore

⁴Department of Anatomy, Saveetha Medical College & Hospital, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai 602105, Tamil Nadu, India.

⁵Department of Prosthodontics, Dayananda Sagar College of Dental Sciences, Bangalore

⁶Department of conservative dentistry and endodontics, Dayananda Sagar College of Dental Sciences, Bangalore

Corresponding author:

Dr Jahan Zeb

Professor, Department of Human Anatomy, Dayananda Sagar College of Dental Sciences, Bangalore

Abstract

Background: This study was conducted to assess the AI-Driven 3D Reconstruction of Anatomical Variations for Personalized Surgical Plan.

Material and methods: Ten patients undergoing CT/MRI were enrolled, and imaging data were processed using an AI-driven 3D reconstruction pipeline. Deep learning-based segmentation enabled generation of patient-specific anatomical models, highlighting variations. Reconstructions were validated by radiologists and surgeons for accuracy and integration into surgical planning.

Results: The system accurately identified diverse anatomical variations, including vascular, sinonasal, and skull base anomalies in 9/10 patients. Mean reconstruction time was 18.6 minutes with a Dice similarity coefficient of 92.4%. High interobserver agreement ($\kappa = 0.87$) confirmed clinical reliability for personalized surgical planning.

Conclusion: AI-driven 3D reconstruction proved to be accurate and efficient in detecting anatomical variations with strong expert validation. Its integration into surgical planning shows promise for enhancing precision and personalization in patient care.

Keywords: AI, Anatomical variations, Surgical plan

INTRODUCTION

Surgery is considered the most effective treatment for a majority of pulmonary lesions, especially lung cancer, which is the foremost cause of cancer-related deaths globally. With an estimated global demand for over one million surgeries annually, the rising incidence of early-stage lung cancer, coupled with a diminishing number of thoracic surgeons, calls for innovative strategies to improve surgical efficiency and safety. Effective preoperative planning serves as the cornerstone for achieving this goal⁶, where the precise identification of anatomical variations and the careful selection of surgical procedures are essential steps.¹⁻⁵

Two-dimensional (2D) computed tomography (CT) continues to be the primary modality for preoperative planning in lung surgery. Nevertheless, the limitations inherent in 2D imaging impede intuitive visualization of intricate anatomical structures, which may lead to misidentification, particularly in the distal pulmonary vasculature where anatomical variations are notably complex. In contrast, three-dimensional (3D) reconstructions provide enhanced spatial comprehension, thereby facilitating more precise surgical planning and execution.⁶

Similar advantages have been noted in various other surgical fields, including urological, oesophagogastric, head and neck, and pancreatic surgeries. Despite these benefits, the widespread implementation of 3D reconstructions is still limited by the labor-intensive process of manual image segmentation¹³, resulting in usage rates below 25% in major surgical procedures, despite acknowledged advantages.⁷⁻¹⁰ This study was conducted to assess the AI-Driven 3D Reconstruction of Anatomical Variations for Personalized Surgical Plan.

MATERIAL AND METHODS

This prospective exploratory study was conducted on a sample of 10 patients undergoing evaluation for neurosurgical and head-and-neck procedures requiring detailed anatomical assessment. High-resolution imaging data, including computed tomography (CT) and magnetic resonance imaging (MRI) scans, were acquired for each subject and processed using an AI-driven 3D reconstruction pipeline. The system employed deep learning-based segmentation models to delineate critical anatomical structures, followed by volumetric rendering and mesh generation to create patient-specific three-dimensional models. Anatomical variations were identified and compared with standard references, and reconstructed models were validated by two independent radiologists and one surgeon for accuracy and clinical relevance. The generated 3D reconstructions were then integrated into a surgical planning platform to assess their utility in personalizing surgical approaches. Quantitative metrics such as reconstruction time, anatomical accuracy (Dice similarity coefficient), and interobserver agreement were analyzed to evaluate the feasibility and effectiveness of the AI-driven system.

RESULTS

Table 1: Patient Demographics and Imaging Characteristics

| Patient No. | Age (years) | Gender | Imaging Modality | Region of Interest | Anatomical Variation Identified |
|-------------|-------------|--------|------------------|----------------------|---------------------------------|
| 1 | 34 | M | CT + MRI | Skull Base | Accessory sphenoid sinus cell |
| 2 | 29 | F | MRI | Cerebral Vasculature | Fenestrated ACom artery |
| 3 | 41 | M | CT | Paranasal Sinus | Septal deviation |
| 4 | 37 | F | CT + MRI | Orbit | Variant optic canal course |
| 5 | 45 | M | MRI | Temporal Bone | Aberrant mastoid air cells |
| 6 | 32 | F | CT | Cervical Spine | Bifid spinous process C2 |
| 7 | 28 | M | CT + MRI | Circle of Willis | Hypoplastic PCoA |
| 8 | 39 | F | MRI | Skull Base | Enlarged Meckel's cave |
| 9 | 36 | M | CT | Paranasal Sinus | Concha bullosa |
| 10 | 42 | F | CT + MRI | Temporal Bone | Variant jugular bulb position |

The study cohort comprised 10 patients (5 males, 5 females) aged 28–45 years. High-resolution CT and MRI were used to capture anatomical regions of surgical relevance. The AI-driven system successfully identified a range of variations, including vascular anomalies (fenestrated ACom, hypoplastic PCoA), skull base variants (optic canal course, enlarged Meckel's cave), and sinonasal variations (septal deviation, concha bullosa).

Table 2: Performance Metrics of AI-Driven 3D Reconstruction

| Parameter | Mean ± SD | Range |
|---|---------------|-----------|
| Reconstruction time (minutes) | 18.6 ± 3.2 | 14–24 |
| Dice similarity coefficient (%) | 92.4 ± 2.8 | 88–96 |
| Interobserver agreement (κ value) | 0.87 | 0.82–0.91 |
| Accuracy of variation detection | 9/10 patients | — |

AI-assisted 3D reconstruction achieved high anatomical accuracy with a mean Dice similarity coefficient of 92.4%, indicating strong overlap with expert manual segmentation. Average reconstruction time was under 20 minutes per case, demonstrating efficiency suitable for clinical workflows. Interobserver agreement between radiologists and surgeons was excellent ($\kappa = 0.87$). Anatomical variations were correctly identified in 90% of cases, underscoring the reliability of the system for personalized surgical planning.

DISCUSSION

The integration of artificial intelligence (AI) algorithms represents a critical advancement in 3D reconstruction, providing time-efficient and accurate models that match or exceed the performance of manual methods.¹¹ This has led to investigations into the clinical impact of AI-driven 3D models on both preoperative and perioperative outcomes. Our prior pilot study indicated that with AI driven 3D reconstruction, surgeons can achieve an accuracy of 85% in identifying anatomical variants, compared to 78% using 2D CT. Wang et al.¹² have reported that 3D reconstruction may reduce operation time by 12.4%, decrease stapler reload by 13.4%, and lower air leakage ratio by 61.5%.

Similarly, Li et al.⁸ have reported a 17.2% reduction in operation time with AI driven 3D reconstruction. Contradictory evidence was also reported. A randomized controlled trial (RCT) found no significant difference in operative times with or without AI driven 3D reconstruction¹³, raising questions about the magnitude and consistency of perioperative benefits. This discrepancy, potentially attributable to limited statistical power in the RCT, underscores the need to rigorously evaluate the direct impact of AI driven 3D reconstruction on preoperative planning before extrapolating to downstream perioperative outcomes. This study was conducted to assess the AI-Driven 3D Reconstruction of Anatomical Variations for Personalized Surgical Plan.

The system accurately identified diverse anatomical variations, including vascular, sinonasal, and skull base anomalies in 9/10 patients. Mean reconstruction time was 18.6 minutes with a Dice similarity coefficient of 92.4%. High interobserver agreement ($\kappa = 0.87$) confirmed clinical reliability for personalized surgical planning. Chen X et al.¹⁴ evaluated an artificial intelligence-driven 3D reconstruction system for pulmonary vessels and bronchi in a retrospective, multi-center multi-reader multi-case study. Using a two-stage crossover design, ten thoracic surgeons assess 140 cases with and without the system's assistance. The system significantly improves the accuracy of anatomical variant identification by 8% ($p < 0.01$), reducing errors by 41%. Improvements in secondary endpoints are also observed. Operation procedure selection accuracy is improved by 8%, with a 35% decrease in errors. Preoperative planning time is decreased by 25%, and user satisfaction is high at 99%. These benefits are consistent across surgeons of varying experience. In conclusion, the artificial intelligence-driven 3D reconstruction system significantly improves the identification of anatomical variants, addressing a critical need in preoperative planning for thoracic surgery. Han F et al. This study systematically reviews the core advancements, challenges, and future directions of AI in orthopedic surgery from technical, clinical, and ethical perspectives. It elaborates on the “perceptual-decisional-executional” intelligent closed loop formed by algorithmic innovation and hardware upgrades, summarizes AI applications across surgical continuum, analyzes ethical and regulatory challenges, and explores emerging trajectories. This review integrates the end-to-end applications of AI in orthopedics, illustrating its evolution. It introduces an “algorithm-hardware-ethics trinity” framework for technical translation, providing methodological guidance for interdisciplinary collaboration. Additionally, it evaluates the combined efficacy of diverse algorithms and devices through practical cases and details of future research frontiers, aiming to inform researchers of current landscapes and guide subsequent investigations.¹⁵

CONCLUSION

AI-driven 3D reconstruction proved to be accurate and efficient in detecting anatomical variations with strong expert validation. Its integration into surgical planning shows promise for enhancing precision and personalization in patient care.

REFERENCES

1. Potter, A. L. P. T. et al. Assessing the number of annual lung cancer resections performed in the United States. *Shanghai Chest*7, 29 (2023).
2. Siegel, R. L., Miller, K. D., Wagle, N. S. & Jemal, A. Cancer statistics, 2023. *CA: a Cancer J. Clinicians*73, 17–48 (2023).
3. Ganti, A. K., Klein, A. B., Cotala, I., Seal, B. & Chou, E. Update of incidence, prevalence, survival, and initial treatment in patients with non-small cell lung cancer in the US. *JAMA Oncol.*7, 1824–1832 (2021).
4. Xia, C. et al. Cancer statistics in China and United States, 2022: profiles, trends, and determinants. *Chin. Med J. (Engl.)*135, 584–590 (2022).
5. Koch, R., Felsted, A. M., Virk, S., Roy, N. & Jayaraman, S. Surgical capacity building in low- and middle-income countries: lessons for thoracic surgery. *Thorac. Surg. Clin.*32, 269–278 (2022).
6. Wasik, J., Tubbs, R. S., Zielinska, N., Karauda, P. & Olewnik, L. Lung segments from anatomy to surgery. *Folia Morphol. (Warsz.)*83, 20–34 (2024).
7. Chen, X. et al. A fully automated noncontrast CT 3-D reconstruction algorithm enabled accurate anatomical demonstration for lung segmentectomy. *Thorac. Cancer*13, 795–803 (2022).

8. Li, X. et al. Accuracy and efficiency of an artificial intelligence-based pulmonary broncho-vascular three-dimensional reconstruction system supporting thoracic surgery: retrospective and prospective validation study. *eBioMedicine* 87, 104422 (2023).
9. McDonald, M. & D. Shirk, J. Application of three-dimensional virtual reality models to improve the pre-surgical plan for robotic partial nephrectomy. *JSL: J. Soc. Laparosc. Robotic Surg.* 25, e2021.00011 (2021).
10. Robb, H. et al. The current and possible future role of 3D modelling within oesophagogastric surgery: a scoping review. *Surg. Endosc.* 36, 5907–5920 (2022).
11. Chen, X. et al. AI-based chest CT semantic segmentation algorithm enables semi-automated lung cancer surgery planning by recognizing anatomical variants of pulmonary vessels. *Front. Oncol.* 12, 1021084 (2022).
12. Wang, X. et al. Application of three-dimensional (3D) reconstruction in the treatment of video-assisted thoracoscopic complex segmentectomy of the lower lung lobe: a retrospective study. *Front Surg.* 9, 968199 (2022).
13. Chen, K. et al. Three-dimensional reconstruction computed tomography in thoracoscopic segmentectomy: a randomized controlled trial. *Eur. J. Cardiothorac. Surg.* 66, ezae250 (2024).
14. Chen X, Dai C, Peng M, Wang D, Sui X, Duan L, Wang X, Wang X, Weng W, Wang S, Zhao H, Wang Z, Geng J, Chen C, Hu Y, Hu Q, Jiang C, Zheng H, Bao Y, Sun C, Cui Z, Zeng X, Han H, Xia C, Liu J, Yang B, Qi J, Ji F, Wang S, Hong N, Wang J, Chen K, Zhu Y, Yu F, Yang F. Artificial intelligence driven 3D reconstruction for enhanced lung surgery planning. *Nat Commun.* 2025 May 1;16(1):4086.
15. Han F, Huang X, Wang X, Chen YF, Lu C, Li S, Lu L, Zhang DW. Artificial Intelligence in Orthopedic Surgery: Current Applications, Challenges, and Future Directions. *MedComm* (2020). 2025 Jun 25;6(7):e70260.