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Review Article

AI-augmented clinical anatomy: Integrating radiomics and cadaveric correlation for precision surgery

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Abstract

Clinical anatomy has conventionally depended on cadaveric dissection as the gold standard in understanding structural relationships in surgical practice. However, with the advent of radiomics, artificial intelligence (AI), and three-dimensional imaging techniques, anatomical understanding has transformed from a static science to a dynamic one. AI-assisted radiologic analysis now allows the quantitative evaluation of radiomic features that have been shown to relate to microanatomy, vascular variability, facial planes, and neural networks. The combination of radiomic analysis with cadaveric correlation is proposed as an emerging framework in precision surgery and personalized anatomical understanding. In this review, we explore the interface between AI, radiomics, and clinical anatomy from an evolving perspective with specific emphasis on their potential applications in neurosurgery, hepatobiliary surgery, vascular interventions, and minimally invasive surgical procedures. By fusing radiologic intelligence with traditional anatomical understanding, AI-enhanced clinical anatomy promises to revolutionize surgical practice in the future.

Keywords: Artificial intelligence, Radiomics, Clinical anatomy, Cadaveric correlation, Precision surgery, 3D reconstruction, Surgical navigation, Anatomical variation, Personalized medicine, Machine learning

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1. Introduction

Clinical anatomy is the backbone of surgical science. It influences the way we expose anatomy during surgeries, the way we avoid risks, and the way we preserve important nerves, vessels, and other structures. For a long time, the gold standard for understanding anatomical relationships and their variability among individuals has been cadaveric dissection.[1] Dissection provides unparalleled spatial understanding, but it is a passive technique, only applicable to the population studied, and unable to account for the individual variability necessary for precision surgery.[2] In the last decade, advances in imaging technologies such as MDCT, MRI, and DTI have started to reveal the intricacies of anatomical structures in vivo.[3,4] However, the most significant revolution in the field was the advent of radiomics, which has the ability to transform images into data using texture, shape, intensity, and spatial features that can be analyzed using machine learning.[5-7]

Artificial intelligence, particularly machine learning and deep learning technologies like CNNs, has hastened this process. Convolutional neural networks and other AI technologies enable the automation of segmentation, the detection and classification of structures, the recognition of subtle variations, and the estimation of surgical risks.[8-10] In brain surgeries, tractography using AI technologies helps to create a map of white matter tracts to create a safer surgical corridor.[11] In liver and biliary surgeries, vascular segmentation using AI technologies helps to create a pre-surgical map of the hepatic arteries and portal venous variations.[12] This trend is now being applied to vascular, orthopedic, and cardiothoracic surgeries.[13,14] However, the anatomy depicted by imaging modalities needs to be correlated to the gold standard, which is dissection. Cadaveric studies are important to validate whether the features extracted from the images accurately reflect the anatomy, whether the AI segmentation accurately reflects the

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anatomy, and to extend the limits of spatial resolution.[15] Connecting the cadaveric database to the imaging database improves the way the algorithm learns from the images and reduces the misclassification of complex anatomical variations.[16] A hybrid approach using a combination of radiology and cadaveric data has demonstrated higher precision in the delineation of fascial planes, skull base foramina, pelvic autonomic plexuses, and vascular branching.[17-19]

Anatomical variations are a major cause of intraoperative difficulties. Variations in the hepatic artery, Circle of Willis, renal vessels, and brachial plexus can alter the approach and outcome of a surgical procedure.[20-22] Today, it is possible to use AI-based predictive models to identify anatomical variations prior to surgery with high consistency. This could lead to time savings and minimize unintended tissue damage.[23] Using large-scale imaging data and dissecting anatomical atlases, we are getting closer to accurate anatomical profiling.[24] Improvements in 3D reconstruction and augmented reality are bringing the images and the actual field closer. Using AI-based 3D models, surgeons can now navigate the patient's unique anatomy, simulate the resection margins, and even forecast the areas where vessels and nerves could interfere.[25-27] This is the juncture of computational anatomy, surgical navigation, and precision medicine.

The transition to AI-based clinical anatomy has its methodological and ethical implications. Heterogeneity of data, segmentation bias, overfitting, and lack of external validation are the challenges in the transition.[28] Explainability and reproducibility of AI-based anatomical prediction are critical in the safe application of AI-based clinical anatomy in surgery.[29] Strengthening cadaver correlation studies, standardization of radiomic data, and interprofessional collaboration are critical in ensuring the reliability of AI-based anatomical prediction.[30] In the review, we discuss the concepts and methods of AI-based clinical anatomy, its current translational applications in various surgical specialties, and its future directions. Combining radiomics and cadaver correlation studies, clinical anatomy has evolved beyond its traditional descriptive and morphological limits and has entered the era of precision surgery.

2. Conceptual Framework: Radiomics and Computational Clinical Anatomy

The process of radiomics is defined as "the extraction of large numbers of quantitative features from conventional clinical imaging data, converting visual images into data for analysis.[5,6]" This means that in clinical anatomy, we are now able to quantitatively define what we see in terms of the shape of structures, the branching pattern of blood vessels, the number of tissue layers, and the paths of nerves. This is unlike conventional radiology, which relies upon what we see and feel by visual inspection. Spatial heterogeneity, surface curvature, volume differences, and texture are now quantified by the use of a computational approach to clinical anatomy.[7] This new era in clinical anatomy is based upon three fundamental ideas:

1. **Image acquisition standardization:** The accuracy of anatomical detail relies upon the standardization of imaging parameters. This means that the resolution and contrast schemes used to define the imaging parameters are crucial. For example, variations in slice thickness and the use of specific parameters for each imaging modality mean that standardization protocols are crucial before any analysis takes place.[28]
2. **Segmentation and feature extraction:** This means that AI segmentation allows for the use of convolutional neural networks to automatically define areas such as the cranial nerves, vessels of the liver, and fascial planes.[8-10] Once this takes place, hundreds of features are extracted to define the shape, basic statistics, and texture features.[6,7] This means that a morphological fingerprint of anatomy at both macroscopic and microscopic levels is now possible.
3. **Machine learning integration:** This means that both supervised and unsupervised learning models allow for the integration of features to categorize anatomy or to forecast the complexity of a procedure.[23] For example, clustering allows for the identification of vascular branching that was not previously known.[20,21] This means that deep learning models allow for the automatic labeling of anatomy and 3D reconstruction.[25]

This means that the use of a computational approach to clinical anatomy allows for a probabilistic prediction system to be used to guide clinical practice. This means that the results from any algorithm have to be interpreted in relation to what we already know from conventional anatomy.[1,15]

3. Methodological Integration: Imaging–Cadaveric Validation Models

Even as the precision of AI-assisted analysis improves, there is no substitute for the reality check of cadaver dissection.[1,15] Most integration strategies follow one of three models:

Direct Radiologic-Cadaveric Correlation: In this strategy, the cadaveric specimens undergo imaging using CT scans or MRI scans. Subsequently, dissection is performed to validate the exact anatomical locations and to compare the accuracy of the results obtained from the automated process.[16,17] This strategy has been found to be particularly effective in:

1. Mapping the Skull Base Foramina
2. Describing the Pelvic Autonomic Plexus
3. Tracing Microvascular Branches

By undertaking these correlation studies, the training data for the algorithm is refined, and the spatial accuracy limits are increased.[18,19]

4. Hybrid Anatomical Atlas Construction

In this strategy, imaging population data is combined with morphometric data from cadavers to create atlases.[24] AI systems are trained using these atlases to refine the prediction of anatomical variations:

1. Hepatic Artery Variants in Liver Surgery.[12,20]
2. Circle of Willis Variants in Neurosurgery.[21]
3. Renal Vascular Variants in Kidney Transplant Surgery.[22]

By using these atlases, the external validity of the results is increased, and the bias in the segmentation process is reduced.[28]

5. 3D Reconstruction and Surgical Simulation

High-resolution imaging combined with cadaveric correlation results in the development of patient-specific anatomical models.[25-27] AI-assisted reconstruction improves visualization:

1. Safe Entry Zones in Skull Base Surgery
2. Kambin's Triangle in Minimally Invasive Spine Surgery
3. Interfascial Planes in Regional Anesthesia

Augmented reality displays, which are generated using the results from the cadaveric correlation process, help the surgeon to superimpose the images over the surgical site, thus reducing the need to rely on mental reconstruction.[26]

6. Translational Clinical Applications in Precision Surgery

The thread of AI-augmented clinical anatomy now runs through many surgical specialties.

1. **Neurosurgery:** By using diffusion tensor imaging in conjunction with AI-assisted tractography, the precision of the white matter tractography improves, thereby allowing the surgeon to aim for the best tumor resection even in eloquent areas.[11] Radiomics analysis provides another layer to identify the interfaces between tumors and the brain, thus improving the way we plan the surgical approach. This is then combined with cadaveric fiber dissection studies.[15]
2. **Hepatobiliary and pancreatic surgery:** In hepatobiliary and pancreatic surgery, the anatomical variation in the hepatic arteries and portal veins may impact the surgical approach to resection.[20] AI-assisted vascular segmentation from multiphase CT scans now helps classify these variations preoperatively.[12] Radiomics-based vascular modeling reduces the risk of intraoperative bleeding.[13]
3. **Vascular and endovascular surgery:** AI-assisted calculation of the geometry of the aneurysm neck, arterial tortuosity, and branching angles helps the surgeon decide which device to use for the repair.[14] Cadaveric studies validate these findings.[16]
4. **Orthopedic and spine surgery:** In spine surgery, anatomical corridors such as Kambin's triangle are important. AI-assisted three-dimensional reconstructions help in the mapping of the safe zone.[27]
5. **Pelvic and robotic surgery:** In robotic-assisted pelvic surgeries, robotic magnification helps the surgeon visualize the autonomic nerves. AI-assisted mapping may be more effective in the preoperative planning to identify the variation in the hypogastric plexus.[18,19] Radiology findings combined with cadaveric studies are the key to maintaining sexual and urinary functions during tumor resections.

However, the following hurdles need to be addressed:

1. Reproducibility of radiomics findings between imaging modalities.[28]
2. Bias in the training dataset and the risk of overfitting in AI-assisted models.[29]
3. Explainability of AI-assisted findings to the surgeon for decision-making.[30]
4. Lack of integration of traditional dissection-based anatomical education into AI-assisted anatomical education.

To develop AI-augmented clinical anatomy as a precision surgical discipline, we need to standardize imaging protocols and develop open anatomical datasets.

7. Discussion

The advent of artificial intelligence in clinical anatomy is a significant change from the traditional focus of anatomy to a predictive and data-driven approach to structural medicine. Anatomy is traditionally considered a foundational and static field—a training ground for what the next surgical steps will be. It is now quantified and made computable with the advent of artificial intelligence-powered radiomics.[5-7] This is a significant advantage of the new paradigm because it allows for the accurate mapping of anatomical variations. Variations in hepatic arteries, cerebral vessels, renal pedicles, and peripheral nerves are all well-known risk factors for intraoperative outcomes.[20-22] The ability of artificial intelligence-powered tools to classify these variations is an advantage because it reduces the variability of radiologic judgment.[8-10,23] It has been observed to have better structural accuracy when compared to cadaveric truth.[15-17]

In the case of neurosurgery, the AI models that use tractography indicate the need for a combination of computational approaches and conventional knowledge obtained from fiber dissections.[11,15] Otherwise, there will be false-positive nerve paths or missing nerve paths in the map obtained from the models. In the case of hepatobiliary and vascular surgery, the radiomic features of the vessels must correspond with the actual lumen and vessel patterns obtained from dissection models.[12,16] The actual value of AI-assisted anatomy will become evident in minimally invasive and robotic surgeries, where tactile feedback and visual exposure are limited, and the accuracy of surgical anatomy will become more important. However, there are methodological challenges that need addressing before radiomic and AI-assisted approaches in surgical anatomy become a norm in the medical community.[25-27] For one, radiomic features are image-dependent, and image acquisition, segmentation, and radiomic feature extraction are all prone to errors and inconsistencies.[28] Second, the lack of explainability in deep learning models will become a major challenge in gaining the trust of the medical community and regulatory bodies.[29,30] Third, the over-reliance on algorithmic approaches and the lack of proper anatomical knowledge will give rise to a new form of cognitive dependency in surgical education and training. Therefore, AI-assisted clinical anatomy should be viewed as an extension and synergy with conventional dissection techniques. The foundation of AI-assisted models in anatomy will remain cadaveric validation to ensure that they are based on anatomical facts.[1,15] The most accurate models will be those that incorporate multimodal imaging, dissection-based morphometry, and transparent machine learning models.

8. Future Directions and Clinical Translation

The next generation of AI-assisted clinical anatomy will likely be an evolution in four areas:

1. ***Development of globally validated anatomical data banks:*** The development of large-scale imaging databases in conjunction with cadaveric morphometric data will be useful in improving the accuracy of AI algorithms and will also help to reduce bias in anatomical models based on imaging data from different populations worldwide.[24,28]
2. ***Explainable AI in anatomical predictions:*** The next generation of AI algorithms will be based on transparent models that will be able to identify the specific radiomic features that influence anatomical predictions or risk predictions.[29]
3. ***Integration of AI in real-time intraoperative procedures:*** The next generation of AI algorithms will be integrated with anatomical atlases to provide real-time anatomical structures during surgical procedures with the help of intraoperative navigation and augmented reality technology.[25,26]
4. ***Evolution of anatomical education:*** The next generation of anatomical education will be based on a combination of conventional dissection techniques and AI-assisted models that will be integrated with conventional anatomical knowledge to provide a better understanding of anatomical structures.[27]

The key to bringing this into everyday surgical practice will depend on prospective validation studies demonstrating fewer minutes of surgery, fewer complications, and less blood loss. However, the regulatory framework must address the issue of data governance, validation standards, and auditing of algorithms.[30]

9. Conclusion

AI-assisted clinical anatomy represents a paradigm shift where radiomics, machine learning, and dissection science converge. By making imaging data quantifiable and structurally relevant and cross-checking it with dissection science, clinical anatomy transitions from a descriptive science into a predictive and personalized science. While challenges persist, such as reproducibility, explainability, and standardization, the marriage of computational and dissection science appears a promising way forward in the quest for precision surgery. AI does not supplant dissection science but extends its reach into the digital era, and clinical anatomy assumes its rightful place at the vanguard of personalized surgical practice.

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11. Conflict of Interest

None.

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