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Review Article

Roles of Artificial Intelligence in Soft Tissue Surgery: A Review

Mohammad Mehdi Ranjbar Kamrani[1]*, Abdolhossein Malekian[2], Mahsa Onagh[3], Mohammad Manian[4], Mohammad Shahraki[5]**, and Maedeh Vasei[2]

[1] Faculty of Veterinary Medicine, Islamic Azad University, Shabestar Branch, East Azerbaijan Province, Iran
[2] Faculty of Veterinary Medicine, Islamic Azad University, Garmsar Branch, Semnan, Iran
[3] Faculty of Veterinary Medicine, University of Zabol, Zabol, Iran
[4] Department of Clinical Sciences, Faculty of Veterinary Medicine, Shiraz University, Shiraz, Iran
[5] Department of Clinical Sciences, Faculty of Veterinary Medicine, Shahid Bahonar University of Kerman, Kerman, Iran

* *Corresponding author:* Mohammad Mehdi Ranjbar Kamrani, Faculty of Veterinary Medicine, Islamic Azad University, Shabestar Branch, East Azerbaijan Province, Iran. Email: Mahdikamrani6500@gmail.com

** *Corresponding author:* Mohammad Shahraki, Department of Clinical Sciences, Faculty of Veterinary Medicine, Shahid Bahonar University of Kerman, Kerman, Iran. Email: Shahraki990@gmail.com

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ABSTRACT

Artificial intelligence (AI) is gradually transforming surgical approaches in human and veterinary medicine, but its application in soft tissue surgery is still in its early stages. The present study aimed to comprehensively examine the roles of AI in soft-tissue surgery and to outline the prospects for using AI in veterinary medicine based on *in vivo* studies. A comprehensive search was performed across PubMed, Scopus, Web of Science, and the Cochrane Library for peer-reviewed articles published from January 2020 to January 2026. Subsequently, 17 studies were selected and evaluated. The current findings indicated that deep learning algorithms, especially convolutional neural networks and computer vision-based models, have been successful in different areas. These areas included preoperative and intraoperative image navigation and recording, automatic detection of tissue edges and differentiation of vital structures from damaged tissues, and guidance of surgical robots during delicate cutting and suturing movements. *In vivo* studies in small animal models (rats and rabbits) have confirmed the high accuracy of AI-based technologies under physiological conditions, yet there remains a significant gap between these technologies and their routine clinical application in veterinary medicine. Main challenges in translating AI systems from experimental *in vivo* studies to routine clinical application in veterinary medicine included the need for large amounts of labeled data across different animal species, anatomical variation between breeds, the high cost of robotic hardware, and the lack of common evaluation guidelines. The present study indicated that veterinary medicine is moving towards the development and use of real-time decision-support systems, telesurgery, and multimodal data integration.

1. Introduction

Soft tissue surgery in veterinary medicine has a wide range of interventions, including tumor removal, visceral repair, hepatorenal surgery, and diaphragmatic repair[1]. Soft tissues present particular challenges due to their deformability, movement during respiration and heartbeat, and lack of fixed spatial landmarks[2].

In the last decade, artificial intelligence (AI), especially in the fields of deep learning and computer vision, has revolutionized human medicine[3,4]. From automatic tumor detection in radiological images to predicting postoperative complications, intelligent algorithms have achieved many goals[5,6]. In the field of surgery, AI-based navigation systems and new-generation surgical robots, such as the da Vinci, have made great steps in minimally invasive surgery, but most of the successes have been limited to orthopedic, craniocerebral, and spinal surgeries in humans[7,8]. Despite significant advances, the application of AI in soft tissue surgery has not been fully evaluated[9].

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The primary cause of this delay is the nonlinear and unpredictable nature of soft-tissue deformation during surgical procedures. Unlike a vertebra or femur, a liver or kidney constantly undergoes deformation during surgery due to instrument movement, changes in patient positioning, or even breathing[10]. This situation, known as tissue deformation, poses a significant challenge for accurately registering preoperative and intraoperative images[11]. Prior to deploying an algorithm in real patients, it should be validated *in vivo* rather than solely on static images or laboratory models. Farokhmoradi and Salari-Kakhk[12] emphasized that even well-designed algorithms can be undermined by poor study design, hidden contaminants, and uncontrolled confounding factors in animal studies. In the field of soft tissue surgery, *in vivo* studies in mice, rabbits, pigs, and dogs have provided valuable insights into the accuracy of smart navigation, the safety of automated cutting, and how well algorithms learn and adapt to changing conditions[13,14].

The veterinary field has a strategic advantage for developing AI in soft tissue surgery in two ways. First, the enormous anatomical diversity across species (from dogs and cats to horses, cows, and exotic animals) posed a challenge that drives AI engineers to design more generalizable algorithms[14]. Second, the ethical and legal issues of using animal models in veterinary medicine are less restrictive than in human medicine, as veterinary surgery inherently deals with nonhuman patients[15]. Hence, the present study aimed to systematically and comprehensively assess the application of AI in soft tissue surgery, with particular focus on findings that are applicable to veterinary medicine.

2. Materials and Methods

A comprehensive search was conducted in PubMed, Scopus, Web of Science, and the Cochrane Library for peer-reviewed articles published between January 2020 and January 2026. The search strategy combined keywords related to AI, such as artificial intelligence, deep learning, convolutional neural network, computer vision, and machine learning. Soft tissue surgery terms, including soft tissue surgery, image navigation, tissue segmentation, surgical robot, and *in vivo* animal model terms such as *in vivo*, rat, rabbit, canine, porcine, and animal study. Boolean operators such as AND, OR, and truncation were applied as appropriate. The inclusion criteria included original peer-reviewed studies excluding reviews, editorials, and conference abstracts, studies applying AI algorithms to soft tissue surgery, *in vivo* or *ex vivo* animal studies with direct surgical relevance, and English-language studies. The exclusion criteria were studies focused solely on human surgery without animal validation, *in silico* (simulation-only) or static-image studies, case reports with fewer than 3 animals, and duplicate publications. After duplicate removal, the initial search yielded 247 records. Following title/abstract screening and full-text assessment against the eligibility criteria, 17 studies were selected and included in the final analysis.

3. Applications of artificial intelligence in veterinary medicine

3.1. Deep learning image recognition revolution

The first and most widespread area of AI penetration in veterinary medicine is image recognition[16]. Deep learning algorithms, particularly convolutional neural networks (CNNs), have been able to interpret veterinary radiographs, ultrasounds, and magnetic resonance imaging (MRI) images with accuracy comparable to that of experienced radiologists[17-19]. Automated systems for diagnosing hip dysplasia in dogs, identifying lung metastases in cats, and classifying mammary tumors in female dogs have great potential for future studies[20]. Artificial intelligence tools not only reduce interpretation time but also enable mass screening in areas where expert veterinarians are scarce.

3.2. Telemedicine and decision support systems

The second major application of AI in veterinary medicine involves creating clinical decision support systems (CDSS) and smart telemedicine platforms[21]. Intelligent telemedicine platforms, by simultaneously analyzing laboratory data (hematology, biochemistry), vital signs, clinical history, and images, can prioritize differential diagnoses and even suggest possible treatments[22]. In urgent conditions, telemedicine and decision support systems can estimate the risk of septic shock, renal failure, or poisoning in less than a few seconds[23]. Telemedicine has greatly increased efficiency, especially in large industrial livestock farms where a veterinarian is responsible for thousands of animals' lives.

3.3. Preoperative planning and surgical simulation

One of the most valuable applications of AI directly related to soft tissue surgery is 3D preoperative planning and surgical simulation[24]. Machine learning algorithms can reconstruct accurate 3D models of soft organs, such as the spleen, liver, or kidney, from simple computed tomography (CT) or MRI images and then predict the optimal incision path, location of vital vessels, and tumor safety margins[11,25]. Surgical simulation is particularly critical in veterinary oncology surgeries where the goal is to completely remove a tumor without damaging adjacent organs[26].

3.4. AI-guided surgery

In veterinary orthopedic surgery, computer vision algorithms have been used to accurately determine bone-cutting angles during surgeries to correct limb deformities[26]. In spinal surgery, intelligent navigation systems have enabled the precise placement of lumbar screws with errors of less than one millimeter. Moreover, in minimally invasive veterinary laparoscopic surgery, the implementation of image stabilization and instrument-tracking algorithms enhanced visual quality for surgeons[23]. AI-guided surgery has demonstrated that veterinary hospitals may be ready to expand into soft-tissue surgery.

4. Technical basics of artificial intelligence in soft tissue surgery

The basic difference between soft tissue surgery and bone surgery lies in the dynamic and changing nature of the target tissue[27,28]. In orthopedic surgery, bone is a rigid body. Markers placed on it can be tracked throughout the procedure with submillimeter accuracy[29]. But soft tissues such as the liver, kidney, spleen, or intestine have opposite characteristics; continuous deformation caused by breathing and heartbeat, displacement due to pulling or pushing by surgical instruments, and the lack of fixed anatomical points that can be relied upon as references[30]. Since tissues deform once the body is opened, preoperative images often do not accurately reflect the tissue's real-time state[31]. These technical challenges and AI-based solutions are directly transferable to veterinary soft tissue surgery, as species such as dogs, cats, pigs, and rabbits exhibit similar tissue deformation, anatomical variation, and real-time navigation needs during procedures such as liver resection, nephrectomy, or bowel surgery[32]. To address the challenge of tissue deformation, three main categories of AI architectures have been used[33]. Firstly, convolutional neural networks (CNNs) can extract visual features, including edges, surface textures, and blood vessel patterns, from intraoperative images[34]. The CNN networks can distinguish the tumor border from healthy tissue in a second[34]. Second, recurrent neural networks (RNNs) and their variants, such as long short-term memory, are designed for sequential data (sequential images from surgical videos). Recurrent neural network architectures can predict tissue deformation over time and estimate the next point displacement of the tissue[35,36]. Third, geometric deep learning directly models 3D data from surface scanners or structure-from-motion reconstructions onto tissue mesh[37].

Intelligent navigation in soft-tissue surgery is divided into two general categories, including marker-based and marker-free[38]. In marker-based approaches, physical reference points, such as reflective disks or electromagnetic markers, are implanted on the tissue surface or near the surgical site, and optical or electromagnetic tracking systems determine their position in 3D space[38]. Although this approach has high accuracy, it requires invasive marker implantation in tissues. In contrast, markerless approaches, enabled by advances in computer vision, utilize natural features of the tissue surface, such as the pattern of superficial blood vessels, scar tissue, or even the natural folds of the organ capsule[39].

The next-generation surgical robots use AI not only for navigation but also for active control of the instruments[40]. In a closed-loop control system, intraoperative cameras send images of the tissue at 30 to 60 frames per second to an intelligent algorithm[41]. The algorithm determines the current position of the instrument, such as a scalpel or forceps, and the state of the tissue, then compares it with the programmed path, and sends a corrective signal to the robot arms when there is a deviation[42]. This cycle of imaging, analysis, action, and reimaging is repeated up to a thousand times per second. In addition to the images, force sensors at the end of the instrument measure the tissue's resistance to shear or compression, allowing the algorithm to estimate the tissue's stiffness (Figure 1).

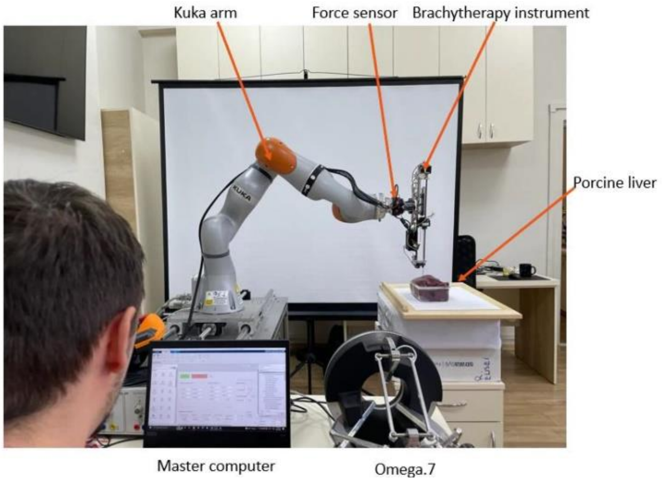

Figure 1. Experimental setup for force measurements using robotic-assisted brachytherapy. In this experimental setup, the Kuka robotic arm is guided by the Omega.7 haptic device, and a master computer positions the brachytherapy instrument into the porcine liver. The force sensor simultaneously measures the insertion forces applied to the instrument during the procedure (Source: MDPI Copyright, 2022)[42].

A set of quantitative metrics has been defined to assess the performance of AI systems in soft-tissue surgery. The most important of AI systems in soft-tissue surgery is the target registration error (TRE), which represents the distance between the actual position of a point in the tissue (determined by a reference sensor or post-operative dissection) and the position predicted by the intelligent system[43]. Another metric is system latency, which measures the time between the actual movement of the tissue/instrument and the corrected display on the surgeon's monitor[44]. Latencies above 100 milliseconds may lead to surgical errors. Accurate tissue recognition is crucial for distinguishing damaged tissue from healthy tissue, and this accuracy is usually evaluated through metrics such as sensitivity[45,46].

5. Clinical challenges of implementing artificial intelligence in soft tissue surgery

The first and most important challenge to implementing AI in veterinary soft-tissue surgery is the lack of large, diverse, and well-established databases[21,47]. Deep learning algorithms typically require thousands or even tens of thousands of labeled images to achieve acceptable accuracy[47]. Furthermore, species and breed diversity compound the problem. For instance, an algorithm trained on surgical images of a Labrador Retriever's liver is likely to perform poorly on a cat's liver or even on a Greyhound's liver with different anatomy. Even if a highly accurate intelligent algorithm is developed, its implementation in the veterinary operating room faces several technical challenges[22,48]. While human medicine projects, such as the Cancer Genome Atlas (TCGA) and Brain Tumor Segmentation (BraTS), provided large datasets, in veterinary medicine, such structures are almost nonexistent[49].

One of these challenges is the cost of equipment, such as high-frame-rate computer vision systems, 3D cameras, force sensors, and powerful graphics processing units (GPUs)[49]. The second problem in veterinary soft tissue surgery is latency; deep learning algorithms require time to analyze each image frame. When this latency exceeds 50 to 100 milliseconds, the navigation system is no longer considered real-time, and the surgeon may be confused rather than helped[50]. Another barrier is the mental and behavioral resistance of veterinary surgeons to adopting smart technologies[51]. Additionally, the learning curve involved in operating intelligent navigation systems and robotics can be achieved[52]. A final major challenge is the generalizability of algorithms from a controlled laboratory setting to real-world clinical situations[53,54]. Most *in vivo* studies are performed under ideal conditions, including the deep anesthesia, immobility of the patient, a clean surgical field without significant bleeding, and the target organ in a standard anatomical position[55]. An intelligent algorithm that is 98% accurate under ideal conditions may fall to 70% in the real operating room[56]. Additionally, there are special ethical considerations in veterinary medicine: unlike in human medicine, where the patient gives informed consent, in veterinary medicine, the animal owner is the decision-maker.

6. Explainable artificial intelligence and future prospects

One of the most promising horizons for veterinary medicine is remote surgery guided by AI[57]. Surgery guided by AI could bridge the deep gap between areas with and without specialized veterinary services.

One of the main barriers to the adoption of AI in surgery is the black box nature of deep learning algorithms[58]. The future of soft tissue surgery is moving towards the development of explainable AI (XAI); systems that not only make a decision, but also visually and textually present the reasons and evidence behind that decision to the surgeon[59,60]. For instance, the algorithm can display a heatmap on the intraoperative image to show why a particular area was identified as a vital vessel (due to wall thickness, visible pulsation, or a specific branching pattern)[61]. This transparency would build the surgeon’s trust and enable them to make the final judgment in borderline cases. Artificial intelligence could integrate imaging data (MRI, CT, Doppler ultrasound, fluoroscopy), physical data (force sensors, temperature, tissue pH), and physiological data (heart rate, blood pressure, oxygen saturation) into a dynamic 3D model of animals and humans[62]. For instance, during the excision of a hepatic tumor, a surgeon can concurrently observe the tumor boundary via MRI, the vascular map obtained from Doppler ultrasound, and the tissue perfusion rate through laser sensors integrated into an augmented reality (AR) headset[63]. The AI algorithm functions as a virtual coach, analyzing every action of the surgeon, identifying areas for improvement, such as excessive pressure on the tissue, improper cutting angles, or delays in ligating vessels, and delivering immediate, personalized feedback[9].

7. Conclusion

The present study emphasized that artificial intelligence (AI) is increasingly evolving from a purely theoretical, laboratory-based tool into a practically valuable asset in veterinary soft-tissue surgery. The most immediate and impactful contributions of AI are observed in preoperative planning and postoperative risk assessment. Preoperatively, AI can accurately predict surgical margins from imaging data. Postoperatively, AI anticipates complications such as surgical site infections and wound-healing issues by analyzing health records. In contrast, real-time intraoperative applications such as robotic dissection and decision support remain in early development. Major limitations were the scarcity of large-scale, cross-species labeled datasets and a lack of multicenter evidence. Therefore, future studies should focus on international data-sharing efforts, long-term outcome studies that evaluate complication rates and cost-effectiveness, and the creation of regulatory frameworks by veterinary organizations to manage liability and approve algorithms.

Declarations

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Authors’ contribiutions

Mohammad Mehdi Ranjbar Kamrani was responsible for the conceptualization and overall supervision of the review, defining the scope from laboratory to clinical application. Abdolhossein Malekian developed the methodology and curated the data, focusing on AI applications in preoperative planning and postoperative risk stratification. Mahsa Onagh performed the formal analysis and visualization, identifying key translational barriers such as limited veterinary datasets and algorithm generalizability. Mohammad Manian drafted the original manuscript, including the final synthesis of results on AI's impact on surgical margin prediction and wound healing. Mohammad Shahraki critically reviewed and edited the manuscript, refining the discussion on clinical workflow integration and species-specific challenges; and Maedeh Vasei handled project administration and validation, ensuring the conclusions remained evidence-based and relevant to veterinary soft tissue surgery practice. All authors read and approved the final edition of the manuscript.

Availibility of data and materials

Datasets are available upon request from the corresponding author.

Competing interest

Authors declared that they have no competing interests.

Ethical considerations

The authors confirmed that ethical concerns, such as plagiarism, permission to publish, research misconduct, data fabrication or falsification, duplicate submissions, and redundant publication, have been thoroughly reviewed. No AI-assisted technologies were used in the generation of this manuscript. After the content was fully written, an AI-powered tool was exclusively used to review and refine the chapter's grammar, punctuation, and overall linguistic flow. The AI tool (Grammarly) was used strictly as a proofreading and language refinement assistant and was not employed at any stage for generating content, ideas, or writing chapter sections.

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