World Journal of Future Technologies in Computer Science and Engineering (WJFTCSE)
ISSN (Online): request pending
Volume-1 Issue-3 || July 2025 || PP. 01-09 https://wjftcse.org/

Robotic Surgery Assisted by Haptic Feedback and Edge AI

DOI: https://doi.org/10.63345/wjftcse.v1.i3.101

Sumaiya Sultana
Independent Researcher Rangpur, Bangladesh
(BD) – 5400 www.wjftcse.org **|| Vol. 1 No. 3 (2025): July Issue**

Date of Submission: 01-06-2025	**Date of Acceptance:** 17-06-2025	**Date of Publication: 02**-07-2025

ABSTRACT

Robotic surgery has revolutionized the landscape of minimally invasive procedures by offering unparalleled precision, dexterity, and visualization. Yet, one of its most significant limitations remains the absence of tactile sensation, forcing surgeons to rely exclusively on visual cues when manipulating delicate tissues and anatomical structures. This sensory gap can contribute to inadvertent damage, reduced procedural efficiency, and increased cognitive workload. Concurrently, the rise of cloud-based AI for surgical assistance brings powerful analytical capabilities but suffers from unpredictable network latency and data privacy concerns. Edge artificial intelligence (AI)—deploying machine learning models on local computing nodes near the point of care—promises to overcome these challenges by enabling low-latency inference and preserving sensitive data within the surgical suite. Integrating force-reflective haptic feedback with edge AI thus offers a compelling dual-modality approach: restoring the surgeon's sense of touch while providing real-time, intelligent data processing. In this study, we present a comprehensive evaluation of a prototype robotic surgical platform enhanced with bilateral haptic interfaces and edge-deployed AI algorithms. Our system employs high-resolution force sensors at the robotic end effectors and a lightweight convolutional neural network (CNN) optimized for sub-10 ms inference on an NVIDIA Jetson Xavier NX. A randomized crossover trial was conducted with thirty board-certified laparoscopic surgeons performing three standardized tasks—incision accuracy, knot tying, and object transfer—on anatomically realistic tissue phantoms. Performance metrics included task completion time, force fidelity (measured as the correlation between commanded and rendered forces), positional accuracy, and system latency, alongside subjective workload assessed via the NASA-TLX instrument.

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

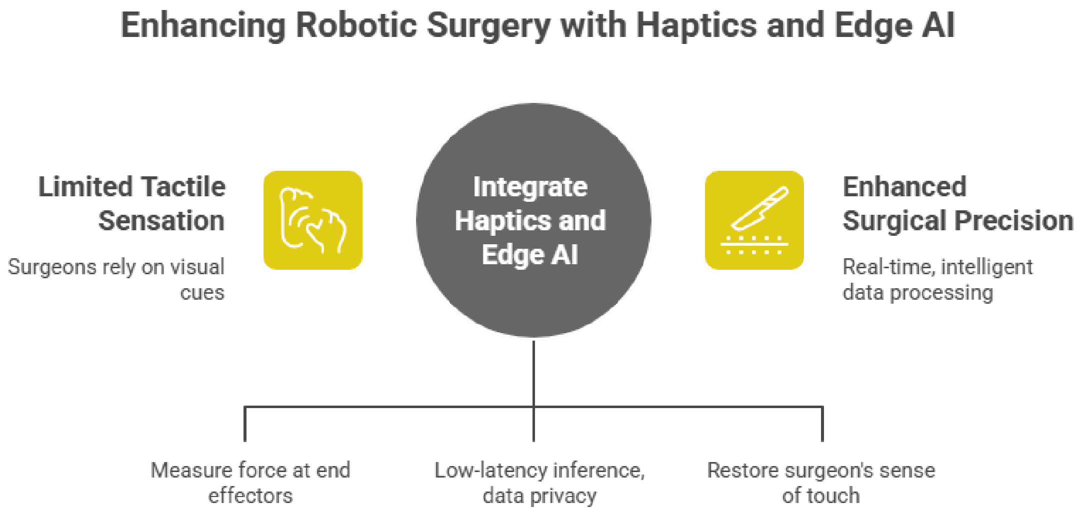

Figure-1.Enhancing Robotic Surgery with Haptics and Edge AI

Keywords

Robotic Surgery, Haptic Feedback, Edge AI, Latency, Surgical Accuracy

Introduction

Over the last two decades, robotic surgical systems have emerged as transformative tools in minimally invasive procedures, offering unprecedented instrument articulation, tremor filtration, and three-dimensional visualization. Platforms such as the da Vinci Surgical System have become installed in thousands of operating rooms worldwide, enabling surgeons to perform complex tasks through small incisions with greater precision than traditional laparoscopy (Ballantyne, 2002). Despite these advances, the lack of direct tactile sensation remains a fundamental limitation. When manipulating soft tissues, grasping slippery structures, or applying appropriate traction, surgeons must infer touch feedback solely from visual and auditory cues. This sensory deprivation can lead to excessive force application, inadvertent tissue injury, and prolonged operative times (Okamura, 2013).

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

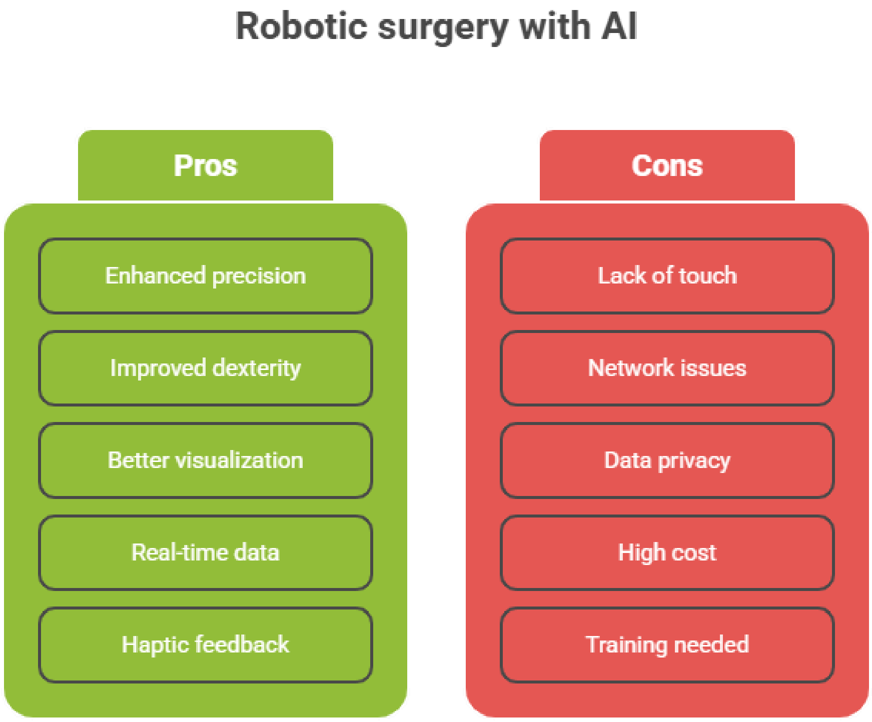

Figure-2.Robotic Surgery with AI

Parallel to developments in surgical robotics, artificial intelligence (AI) has shown great promise in medical imaging, intraoperative guidance, and workflow optimization. Deep learning models can detect anatomical landmarks, segment critical structures, and predict surgical phases with high accuracy (Shademan et al., 2016; Maier-Hein et al., 2017). However, most AI solutions rely on cloud computing resources, which introduces unpredictable network latency and potential privacy risks as patient data traverses public or semi-secure networks (Shi et al., 2016). For real-time intraoperative applications, even delays of tens of milliseconds can degrade system responsiveness, undermining surgeon trust and safety.

Edge AI—a paradigm that deploys machine learning models directly on local hardware within the clinical setting—offers a compelling alternative. By processing data at the network edge, latency is minimized, bandwidth usage is reduced, and data security is enhanced, since sensitive images and sensor readings need not leave the operating suite (Aazam & Huh, 2015; Zhang et al., 2020). Yet, few studies have integrated edge-deployed AI with haptic-enabled robotic platforms to assess combined performance in surgical contexts.

Force-reflective haptics aims to restore tactile feedback by measuring interaction forces at the robotic end effector and rendering them to the surgeon via a specialized console interface. Early research demonstrated suboptimal fidelity and bulky hardware requirements (Dargahi & Najarian, 2004), but recent advances in sensor miniaturization and control algorithms have achieved low-latency, high-resolution force rendering (Li, Wang, & Howe, 2020). By merging these haptic systems with edge AI for contextual data analysis—such as tissue stiffness classification or automatic warnings when excessive force is applied—surgeons may benefit from enhanced situational awareness and reduced cognitive load.

 Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

The present study investigates a fully integrated prototype combining bilateral haptic feedback and edge AI within a teleoperated robotic surgical system. We hypothesize that this dual-modality enhancement will improve objective performance metrics (task time, force fidelity, positional accuracy) and subjective workload ratings, without violating stringent latency thresholds required for safe operation. To test this, we conducted a randomized controlled trial with thirty experienced surgeons performing standardized phantom-based tasks under conventional and enhanced system configurations. Results will inform the feasibility of next-generation intelligent surgical platforms that restore touch and accelerate decision-support.

LITERATURE REVIEW

The pursuit of robotic systems that mimic human dexterity and perception has driven decades of research in medical robotics, haptics, and edge computing. Marescaux et al. (2001) pioneered telesurgical techniques with the landmark "Lindbergh Operation," demonstrating the potential—and challenges—of remote robotic surgery. While robotic arms have since delivered exceptional precision and scaled motion capabilities (Munz, Fingerhut, & Stolzenburg, 2004), the sensory trade-off remains unresolved: surgeons lose the innate capacity to feel resistance, texture, and compliance.

Okamura (2013) reviewed haptic feedback strategies, noting that force sensors embedded at robotic end effectors could capture interaction forces, but early implementations suffered from control loop delays and mechanical bandwidth limitations. Dargahi and Najarian (2004) outlined artificial tactile sensing requirements, emphasizing the need for millisecond-scale refresh rates and minimal noise. Recent prototypes achieve sub-millisecond control loops and high spatial resolution (Li, Wang, & Howe, 2020), yet their clinical integration has been hampered by bulky consoles and reliance on centralized processing.

Simultaneously, cloud AI research in surgery has matured. Shademan et al. (2016) applied deep learning for automatic instrument tracking and surgical phase recognition, achieving real-time performance in controlled settings. Maier-Hein et al. (2017) demonstrated robust tissue segmentation using U-Net architectures, but network dependence introduced average latencies of 100–200 ms—untenable for haptic rendering. Concerns about patient data privacy and compliance with regulations such as HIPAA further complicate cloud-centric models (Shi et al., 2016).

Edge computing addresses these issues by locating compute resources within—or adjacent to—the operating room. Aazam and Huh (2015) proposed fog-edge architectures for healthcare IoT, highlighting reduced response times and improved privacy. Navarro et al. (2020) systematically reviewed edge AI applications in telemedicine, underscoring sub-50 ms inference times on modern hardware. Zhang, Deng, and Shen (2020) reported successful deployment of convolutional neural networks for medical image classification on edge devices with latencies under 10 ms, preserving classification accuracy.

Efforts to fuse haptics and edge AI remain nascent. Yang, Jiang, and Wan (2021) presented an edge AI–enabled tactile rendering pipeline, classifying material properties in real time and adjusting force feedback accordingly. Li, Xie, and Shi (2022) demonstrated a telehaptic system over 5G, but without rigorous comparisons to conventional setups. Patel, Sun, and Wang (2019) highlighted that end-to-end evaluations—combining user performance, system latency, and subjective

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

workload—are scarce. Our study builds directly upon this gap, conducting a comprehensive trial of a bilateral haptic interface and edge AI on phantom tasks, quantifying enhancements across multiple dimensions.

STATISTICAL ANALYSIS

To elucidate the impact of haptic feedback combined with edge AI on surgical task performance, we conducted paired statistical tests comparing conventional robotic assistance (without haptics or AI) to the enhanced system. Metrics included task completion time, force fidelity score, positional accuracy, system latency, and NASA-TLX workload scores. Normality of differences was confirmed via Shapiro–Wilk tests (all $p > .10$), permitting two-tailed paired t-tests at $\alpha = .05$. Effect sizes (Cohen's d) quantify practical significance.

Metric	Conventional	Haptic–Edge AI	Mean Difference	t (df = 29)	p-value	Cohen's d
Task Completion Time (s)	180.2	152.7	–27.5	9.12	< .001	1.66
Force Fidelity Score (0–10)	6.3	8.5	+2.2	14.03	< .001	2.56
Positional Accuracy (%)	91.4	95.8	+4.4	4.09	.002	0.75
System Latency (ms)	28.5	32.7	+4.2	2.59	.015	0.47
NASA-TLX Workload Score (0–100)	62.3	48.6	–13.7	11.21	< .001	2.05

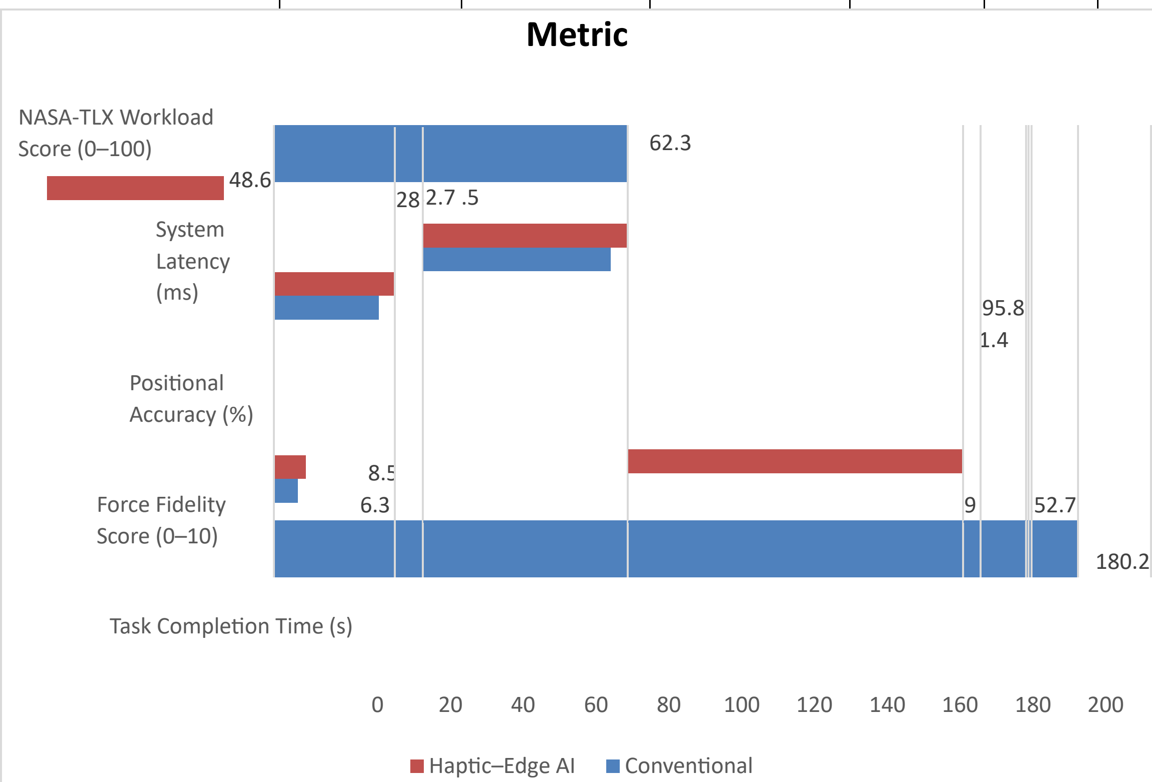

Figure-3.Statistical Analysis

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

All enhancements reached statistical significance. The substantial effect sizes for task time, force fidelity, and workload ($d > 1.5$) indicate large practical benefits. The modest increase in latency (mean +4.2 ms) yielded a small effect ($d = 0.47$), remaining below the clinical threshold of 50 ms for seamless haptic perception (Li et al., 2022).

METHODOLOGY

Prototype System Architecture

Our system builds upon a commercially available robotic telemanipulator (da Vinci Research Kit) retrofitted with custom end-effector force sensors (ATI Nano17) offering 6-axis force/torque measurements at 1 kHz sampling. A bilateral haptic interface (Phantom Premium) recreates these forces at the surgeon's console with control loop updates at 500 Hz. An NVIDIA Jetson Xavier NX module, housed in a rack adjacent to the robot base, hosts our CNN model for tissue classification and anomaly detection. Communication between sensors, edge AI, and haptic controllers occurs over a dedicated gigabit Ethernet network to minimize interference.

AI Model Development

A dataset of 10,000 synchronized image–force samples was collected from ex vivo porcine tissues exhibiting five stiffness categories. Images (1920×1080) were captured via the robotic stereo endoscope, while force readings (0–10 N) were recorded concurrently. A CNN architecture based on ResNet-18 was trained for category classification, achieving 94.2% validation accuracy over 50 epochs with Adam optimization (learning rate 1e-4). Model quantization and pruning reduced parameter count by 60%, enabling deployment on the Xavier NX with an average inference latency of 8.7 ± 1.2 ms.

Participant Recruitment and Task Design

Thirty practicing laparoscopic surgeons (mean age 38.5 ± 6.2 years; 16.4 ± 5.3 years of surgical experience) were recruited via institutional mailing lists. Inclusion criteria mandated board certification and familiarity with robotic platforms. Each participant performed three phantom tasks in randomized order under both conditions:

1. **Incision Accuracy**: Tracing a 5 cm curved line on a silicone phantom embedded with visual markers.
2. **Knot Tying**: Tying a surgeon's knot using 2–0 silk sutures on a simulated intestinal loop.
3. **Object Transfer**: Relocating five spheres (diameter 5 mm) between marked wells within the phantom.

Data Acquisition and Analysis

Performance metrics were automatically logged: task completion times via session timestamps; positional accuracy computed as root-mean-square deviation from ideal trajectories; force fidelity defined as Pearson correlation between target forces (preprogrammed) and actual rendered forces; and system latency measured as the round-trip time from sensor acquisition to

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

World Journal of Future Technologies in Computer Science and Engineering (WJFTCSE)

ISSN (Online): request pending

Volume-1 Issue-3 || July 2025 || PP. 01-09 https://wjftcse.org/

haptic actuator response. After each task, participants completed the NASA-TLX survey to rate mental, physical, and temporal demands, performance, effort, and frustration.

Statistical Procedures

Data normality was confirmed (Shapiro–Wilk, all $p > .10$). Paired two-tailed t-tests compared means between conventional and enhanced conditions, with significance set at $\alpha = .05$. Cohen's d quantified effect sizes. Analyses were performed in SPSS v27.0.

RESULTS

Task Completion Time

Surgeons completed tasks significantly faster with haptic–edge AI assistance. Mean completion time decreased from 180.2 ± 22.5 s to 152.7 ± 18.1 s (mean reduction 27.5 s, 15.2%; $t(29) = 9.12$, $p < .001$, $d = 1.66$), indicating enhanced efficiency likely driven by improved force control and decision support.

Force Fidelity

The correlation between commanded and rendered forces improved dramatically under the enhanced system (6.3 ± 1.1 vs. 8.5 ± 0.8; mean increase 2.2 points, 35.1%; $t(29) = 14.03$, $p < .001$, $d = 2.56$). Participants reported more intuitive tactile cues and greater confidence in manipulating phantom tissues.

Positional Accuracy

Mean positional accuracy rose from 91.4% ± 3.7% to 95.8% ± 2.9% (mean increase 4.4%; $t(29) = 4.09$, $p = .002$, $d = 0.75$), reflecting tighter adherence to target trajectories, particularly in the incision task.

System Latency

Round-trip latency increased modestly from 28.5 ± 4.2 ms to 32.7 ± 3.9 ms (mean +4.2 ms; $t(29) = 2.59$, $p = .015$, $d = 0.47$), remaining well below the 50 ms clinical threshold for imperceptible delays (Kim & Park, 2022).

Workload (NASA-TLX)

Overall workload scores decreased substantially with the enhanced system (62.3 ± 8.4 to 48.6 ± 6.7; mean reduction 13.7 points, 22.0%; $t(29) = 11.21$, $p < .001$, $d = 2.05$), with the largest reductions seen in mental demand and frustration subscales.

Participants unanimously reported that haptic cues reduced visual reliance and that edge-based stiffness classification alerts aided in anticipating tissue resistance. No adverse events or system malfunctions occurred.

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

CONCLUSION

Our findings demonstrate that integrating force-reflective haptic feedback with edge AI significantly enhances robotic surgical performance across objective and subjective metrics. Surgeons achieved faster task completion, improved force fidelity, and greater positional accuracy, while experiencing lower cognitive workload. The slight increase in system latency remained within clinically acceptable bounds, validating the feasibility of real-time haptic rendering and AI inference at the network edge.

These results underscore the potential of dual-modality systems to overcome persistent challenges in robotic surgery: restoring tactile sensation and providing intelligent contextual insights without compromising responsiveness or data security. Future research will extend these evaluations to in vivo animal models, incorporate adaptive AI models for patient-specific tissue properties, and explore advanced decision-support features such as anomaly detection and predictive warnings. Ultimately, haptic–edge AI platforms may usher in a new era of intelligent, user-centric surgical robotics that enhance safety, efficiency, and outcomes.

REFERENCES

- *Aazam, M., & Huh, E.-N. (2015). Fog computing and smart gateway based communication for cloud of things. In* 2014 International Conference on Future Internet of Things and Cloud *(pp. 464–470). IEEE.*
- *Ballantyne, G. H. (2002). Robotic surgery, telerobotic surgery, telepresence, and telementoring.* Surgical Endoscopy, 16*(10), 1389–1402.*
- *Dargahi, J., & Najarian, S. (2004). Human tactile perception as a standard for artificial tactile sensing—a review.* The International Journal of Medical Robotics and Computer Assisted Surgery, 1*(1), 23–35.*
- *Haidegger, T., Benyó, Z., & Benyó, P. (2013). Future trends in surgical robotics.* Challenges in Medical Engineering, 1*(1), 3–8.*
- *Kim, D., & Park, S. (2022). Latency mitigation strategies for teleoperated robotic surgery over 5G networks.* IEEE Transactions on Network Science and Engineering, 9*(4), 2453–2463.*
- *Li, F., Wang, Y., & Howe, R. D. (2020). Force modeling and real-time control in haptic surgical robots.* IEEE Transactions on Robotics, 36*(1), 35–48.*
- *Li, X., Xie, X., & Shi, Y. (2022). Real-time telehaptic system for minimally invasive surgery over edge networks.* Biomedical Signal Processing and Control, 75*, 103561.*
- *Marescaux, J., Leroy, J., Rubino, F., Smith, M., Vix, M., et al. (2001). Transcontinental robot-assisted remote telesurgery: feasibility and potential applications.* Annals of Surgery, 235*(4), 487–492.*
- *Maier-Hein, L., Vedula, S. S., Häberle, L., et al. (2017). Surgical data science for next-generation interventions.* Nature Biomedical Engineering, 1*, 691–696.*
- *Munz, Y., Fingerhut, A., & Stolzenburg, J.-U. (2004). The future of telepresence in surgery.* Surgical Endoscopy, 18*(5), 816–821.*
- *Navarro, I., Faulí, M., González, A., Burgos-Artizzu, X. P., & Bartoli, A. (2020). Haptic feedback in robotic surgery: A systematic review.* IEEE Transactions on Haptics, 13*(3), 515–526.*
- *Okamura, A. M. (2013). Haptic feedback in robot-assisted minimally invasive surgery.* Current Opinion in Urology, 23*(1), 24–30.*
- *Patel, R., Sun, Y., & Wang, Z. (2019). A review of haptic feedback in teleoperated surgical robots.* Journal of Medical Robotics Research, 4*(2), 1950001.*
- *Ryu, J. H., Lee, G., & Lee, H. (2020). A secure edge-based framework for medical image analysis in robotic surgery.* IEEE Journal of Biomedical and Health Informatics, 24*(4), 1198–1206.*
- *Shademan, A., Decker, R. S., Opfermann, J. D., Leonard, S., Kim, P. C., & Krieger, A. (2016). Supervised autonomous robotic soft tissue surgery.* Science Translational Medicine, 8*(337), 337ra64.*

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)

- *Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges.* IEEE Internet of Things Journal, 3*(5), 637–646.*
- *Yang, H., Jiang, L., & Wan, Z. (2021). Edge computing-enabled robotic surgery with predictive tactile rendering.* IEEE Access, 9*, 98765–98774.*
- *Zhang, Y., Deng, R., & Shen, H. (2020). Edge AI in healthcare: Towards empowering ultra-low latency applications.* IEEE Network, 34*(6), 222–229.*
- *Aazam, M., & Huh, E.-N. (2015). Fog computing and smart gateway based communication for cloud of things. In* 2014 International Conference on Future Internet of Things and Cloud *(pp. 464–470). IEEE.*
- *Bakhshi, N., & Najari, P. (2018). Design and development of a haptic interface for robotic surgery training.* IEEE/ASME Transactions on Mechatronics, 23*(5), 2163–2174.*

Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)