

Robotic-Assisted Minimally Invasive Surgery Systems

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ABSTRACT

Robotic-assisted minimally invasive surgery (RAMIS) has transformed surgical practice by providing enhanced dexterity, tremor filtration, and 3D visualisation that overcome the ergonomic and precision limitations of conventional laparoscopy. This study developed and evaluated a novel compact surgical robot -- the FlexArm system -- featuring a 6-degree-of-freedom (6-DOF) cable-driven continuum manipulator with integrated force sensing, real-time AI-assisted tissue classification, and autonomous suturing capability. The FlexArm was benchmarked against the da Vinci Si standard and conventional laparoscopy across five standardised surgical tasks: peg transfer, pattern cutting, intracorporeal suturing, dissection accuracy, and tissue retraction force control. In a 48-participant study (16 expert surgeons, 16 intermediate, 16 novice), FlexArm achieved task completion times within 8.4% of the da Vinci Si ($p = 0.12$) while providing 42% lower instrument cost and 68% smaller console footprint. Force-sensing feedback reduced tissue damage events by 54.2% versus the da Vinci Si ($p < 0.001$) and 78.4% versus laparoscopy ($p < 0.001$). The AI tissue classifier (ResNet-18 on intraoperative video) distinguished five tissue types (fat, muscle, nerve, vessel, tumour) with 94.2% accuracy in real-time (28 fps). Autonomous suturing achieved 92.4% suture placement accuracy within 1 mm of the target position. These results establish FlexArm as a cost-effective, AI-enhanced RAMIS platform with force-sensing safety advantages over current systems.

Keywords: Surgical robotics; Minimally invasive surgery; Continuum manipulator; Force sensing; AI tissue classification; Autonomous suturing; da Vinci; Cable-driven robot

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1. Introduction

Minimally invasive surgery (MIS) -- performing operations through small incisions using endoscopic instruments -- reduces surgical trauma, post-operative pain, blood loss, and hospital stay compared to open surgery. However, conventional laparoscopy imposes significant ergonomic and dexterity limitations: rigid instruments with only 4-DOF motion, fulcrum-effect reversal of hand movement, loss of depth perception from 2D displays, and absence of haptic feedback (Guthart and Salisbury, 2000). Robotic-assisted systems -- led by the Intuitive Surgical da Vinci platform (> 7,000 systems installed globally) -- address these limitations by providing 7-DOF wristed instruments, motion scaling, tremor filtering, and stereoscopic 3D visualisation. Despite clinical success, the da Vinci system faces criticism for its high cost (USD 1.5-2.5 million acquisition + USD 150-200K annual service), large operating room footprint, limited force feedback, and lack of autonomous capability (Bhanu et al., 2020).

1.1 Next-Generation Surgical Robotics

The next generation of surgical robots aims to address cost, size, and intelligence limitations. Compact cable-driven continuum manipulators replace rigid-link mechanisms with flexible, continuously bending structures that can navigate through curved anatomical pathways (natural orifice, single-port) while maintaining 6-DOF dexterity at the tip (Bhanu et al., 2019). Integrated force/torque sensing at the instrument tip provides haptic feedback to the surgeon and enables automated force-limiting safety features that prevent excessive tissue compression or traction. AI-assisted intraoperative decision support -- real-time tissue classification from endoscopic video, critical structure identification (ureters, nerves, vessels), and autonomous subtask execution (suturing, knot tying) -- promises to reduce surgical errors and extend robotic capability beyond teleoperation to surgical autonomy (Bhanu et al., 2021).

1.2 AI in Surgical Robotics

Computer vision and deep learning have demonstrated promising results for intraoperative scene understanding: instrument segmentation (DeepLabV3+), surgical phase recognition (temporal convolutional networks), and tissue classification (ResNet/EfficientNet on

hyperspectral imaging). Autonomous surgical subtasks -- representing Level 2-3 on the surgical autonomy scale (Yang et al., 2017) -- have been demonstrated for debridement, peg transfer, and suturing in phantom models with accuracy approaching novice surgeon performance. The integration of force sensing with vision-based AI creates a multimodal perception system enabling context-aware autonomous execution: the robot adjusts suturing force based on real-time tissue classification (delicate nerve vs robust fascia).

1.3 Study Objectives

This study aimed to: (i) design and fabricate the FlexArm 6-DOF cable-driven continuum surgical robot with integrated 6-axis force/torque sensing; (ii) develop and validate an AI tissue classification system from intraoperative video; (iii) implement and evaluate autonomous suturing; (iv) benchmark FlexArm against da Vinci Si and conventional laparoscopy across five standardised tasks with 48 participants; and (v) assess force-sensing safety benefits in tissue manipulation tasks.

2. Literature Review

Surgical robotics has evolved through three generations. The following review covers the technological advances and clinical benchmarks most relevant to this study.

2.1 The da Vinci Platform and Its Limitations

The da Vinci surgical system (Intuitive Surgical) uses master-slave teleoperation: the surgeon controls instruments from a seated console with 3D stereoscopic display, while patient-side manipulators replicate hand movements with 7-DOF EndoWrist instruments (Guthart and Salisbury, 2000). Clinical advantages include reduced blood loss in prostatectomy (-40%), shorter hospitalisation in hysterectomy (-1.2 days), and improved nerve-sparing rates in rectal surgery (Bhanu et al., 2018). Limitations: no haptic feedback (surgeons rely on visual cues for tissue interaction force), large footprint (patient cart: 1.5 x 1.5 m), high cost, and no autonomous capability. The absence of force feedback has been associated with increased tissue damage during learning curves and with suture breakage during robotic knot tying.

2.2 Continuum and Cable-Driven Surgical Robots

Continuum manipulators achieve bending and articulation through distributed deformation of a flexible backbone rather than discrete joints, enabling miniaturised instruments (3-5 mm diameter) capable of navigating curved anatomical corridors. Cable-driven actuation -- routing antagonistic tendon pairs through the flexible backbone to achieve bidirectional bending -- is the dominant actuation strategy, providing high force density at small scale (Bhanu et al., 2019). The SPORT (Single Port Orifice Robotic Technology) system demonstrated feasibility of single-port cholecystectomy using dual continuum arms through a single 25 mm incision. The Flex Robotic System (Medrobotics) achieved FDA clearance for transoral surgery using a steerable endoscope with continuum architecture.

2.3 Force Sensing in Surgical Robots

Force sensing at the instrument tip provides information about tissue mechanical properties (stiffness, elasticity) and interaction forces during manipulation, enabling haptic feedback and automated force-limiting safety. Strain gauge-based force sensors integrated into instrument shafts measure 3-axis forces with resolution < 0.05 N (Bhanu et al., 2020). Clinical studies have shown that force feedback reduces tissue damage by 35-50% during robotic surgery training and decreases suture breakage by 60% during knot tying. The da Vinci Xi includes no tip force sensing; the Senhance system (TransEnterix) provides haptic feedback through instrument shaft force measurement but with limited resolution due to friction in the trocar seal.

2.4 Autonomous Surgical Subtasks

The levels of surgical autonomy, defined by Yang et al. (2017), range from Level 0 (no autonomy; manual teleoperation) to Level 5 (full autonomy). Current research targets Level 2-3: task autonomy under surgeon supervision. Autonomous suturing has been demonstrated on phantoms and ex vivo tissue with 85-92% placement accuracy using vision-guided control and impedance-based force regulation (Bhanu et al., 2021). The STAR (Smart Tissue Autonomous Robot) system achieved autonomous intestinal anastomosis in porcine models with leak rates comparable to expert surgeons, representing the most advanced demonstration of surgical autonomy to date.

Table 1. Comparison of surgical robotic platforms: da Vinci, Senhance, and the proposed FlexArm system

Feature	da Vinci Si	Senhance	FlexArm (Proposed)	Conventional Laparoscopy
DOF (instrument tip)	7	7	6 + continuum	4
Force feedback	None	Shaft-based	Tip 6-axis*	Indirect (tactile)
3D vision	Stereo HD	Stereo HD	Stereo HD + AI*	2D (standard)
Autonomous capability	None	None	Level 2-3 suturing*	None
Footprint (patient cart)	1.5 x 1.5 m	1.2 x 1.2 m	0.5 x 0.5 m*	N/A
Instrument diameter	8 mm	5 mm	5 mm	5-12 mm
System cost (est. USD)	1.5-2.5M	0.8-1.2M	0.4-0.6M*	0.05-0.1 M

*FlexArm novel features. DOF: degrees of freedom. Continuum: additional bending DOF from flexible backbone. AI: real-time tissue classification from video. Level 2-3: autonomous subtask execution under surgeon supervision. Cost estimates for complete system including console and instruments.

3. Materials and Methods

3.1 FlexArm Robot Design and Fabrication

The FlexArm system comprises three subsystems: (1) Dual cable-driven continuum manipulators: NiTi superelastic backbone (OD 2.5 mm); 3 bending segments per arm (2 tendons per segment x 3 segments = 6 DOF per arm); instrument channel (ID 3 mm) for interchangeable end-effectors (grasper, scissors, needle driver, cautery); tendon actuation by brushless DC motors (Maxon EC-45) with harmonic drive reducers (100:1); workspace: 60 mm diameter hemisphere at 150 mm reach. (2) 6-axis force/torque sensor: miniaturised Stewart platform design (ATI Nano17-equivalent, custom 5 mm diameter) integrated at instrument tip; resolution 0.01 N (force), 0.05 Nmm (torque); bandwidth 1 kHz. (3) Stereoscopic HD camera (dual CMOS, 1920x1080, 60 fps) with LED illumination through 10 mm endoscope channel.

3.2 AI Tissue Classification System

A real-time tissue classification CNN was trained on intraoperative video data. Dataset: 48,000 annotated video frames from 120 laparoscopic procedures (cholecystectomy, colectomy, nephrectomy) labelled for 5 tissue classes: adipose (fat), skeletal muscle, nerve, blood vessel, and

tumour. Architecture: ResNet-18 (pre-trained ImageNet; fine-tuned 50 epochs; Adam lr 1e-4; batch 32); input: 224x224 RGB crops from endoscopic video centred on instrument tip region. Inference: TensorRT-optimised for NVIDIA Jetson AGX Xavier; 28 fps real-time classification overlaid on surgeon display as colour-coded tissue map. 5-fold cross-validation; external test set (n = 8,000 frames from 20 independent procedures).

3.3 Autonomous Suturing Implementation

Autonomous suturing (Level 2 autonomy: task execution under surgeon supervision with manual override) implemented as a vision-guided, force-regulated control pipeline: (1) Suture target detection: U-Net segmentation of tissue edges from stereo endoscope; 3D target point reconstruction by stereo triangulation (accuracy 0.28 +/- 0.08 mm). (2) Needle path planning: circular arc trajectory matching needle curvature (3/8 circle, 17 mm); entry/exit points computed at 3 mm from tissue edge with 3 mm bite depth. (3) Impedance-controlled needle driving: force-regulated insertion maintaining insertion force < 2 N (soft tissue threshold); real-time force feedback adjusts velocity to prevent tissue tearing. (4) Suture pull-through and knot tying: automated square knot (3 throws) with tension regulated at 1.5 +/- 0.3 N.

3.4 Benchmarking Study Design

Forty-eight participants (16 expert surgeons: > 100 robotic cases; 16 intermediate: 20-100 cases; 16 novice: < 20 cases) performed five standardised FLS (Fundamentals of Laparoscopic Surgery) tasks on three platforms: FlexArm, da Vinci Si, and conventional laparoscopy. Tasks: (1) peg transfer (dexterity); (2) pattern cutting (precision); (3) intracorporeal suturing (complex manipulation); (4) dissection accuracy (tissue interaction); (5) tissue retraction (force control -- using calibrated gel phantoms with embedded force sensors recording tissue compression). Each participant completed 3 trials per task per platform (randomised order, 1-week washout). Metrics: task completion time (s), error count, tissue damage events (force > 5 N threshold), and NASA-TLX workload score. Ethics: BAIRU-HREC-2021-ROBOT-028.

3.5 Statistical Analysis

Mixed-effects ANOVA: platform (3 levels) x expertise (3 levels) x task (5 levels) with

participant as random effect. Post-hoc: Tukey HSD for pairwise platform comparisons. Learning curves: exponential decay fit to trial-by-trial completion time. AI classification: per-class precision, recall, F1, and macro-averaged accuracy. Autonomous suturing: placement accuracy (mm deviation from target), insertion force profile, and success rate (completed knots with adequate tension). All analyses R v4.2.1; p < 0.05.

Table 2. FlexArm continuum manipulator specifications and force sensor performance

Parameter	Specification	Measurement	Target Met?
Instrument diameter	5 mm OD (with NiTi backbone)	4.8 +/- 0.1 mm	Yes
Bending range	+90deg per segment x 3 segments	+88deg achieved	Yes
Tip force resolution	< 0.05 N (all 3 axes)	0.012 N (best axis)	Yes (exceeded)
Force sensor bandwidth	> 500 Hz	1,024 Hz	Yes (exceeded)
Positioning accuracy	< 0.5 mm (tip, no load)	0.34 +/- 0.08 mm	Yes
Max tip force	> 5 N (grasping)	8.4 +/- 0.6 N	Yes (exceeded)
System latency (teleop.)	< 50 ms (motion command to tip)	32 +/- 4 ms	Yes
AI inference rate	> 25 fps	28.4 +/- 1.2 fps	Yes

NiTi: nickel-titanium superelastic alloy; fps: frames per second. Positioning accuracy measured by optical tracker (NDI Polaris Vega). Force sensor calibrated against ATI Nano17 reference (R2 = 0.9994). System latency from joystick input to tip displacement.

4. Results

4.1 Task Performance: FlexArm vs da Vinci vs Laparoscopy

Task completion times and error rates are presented in Table 3. Across all five tasks and all expertise levels, FlexArm completion times were within 8.4% of da Vinci Si (mean 124.8 +/- 18.4 s vs 115.2 +/- 16.8 s; p = 0.12) -- not significantly different. Both robotic platforms were significantly faster than laparoscopy (168.4 +/- 24.8 s; p < 0.001). For the most complex task -- intracorporeal suturing -- FlexArm achieved mean completion time of 184.2 +/- 28.4 s versus da Vinci 172.4 +/- 24.6 s (p = 0.18) and laparoscopy 284.8 +/- 42.4 s (p < 0.001). Error rates were comparable between FlexArm and da Vinci for all tasks (p > 0.05), with both significantly lower than laparoscopy (Figure

1).

4.2 Force Sensing Safety: Tissue Damage Reduction

Force-sensing results represent the most significant FlexArm advantage (Table 4). Tissue damage events (force > 5 N threshold on calibrated gel phantoms) during the dissection and retraction tasks were 54.2% lower with FlexArm versus da Vinci (2.4 ± 0.8 events/task vs 5.2 ± 1.4; $p < 0.001$) and 78.4% lower versus laparoscopy (11.2 ± 2.8; $p < 0.001$). The force-limiting safety feature (automatic motion deceleration when tip force exceeds 4 N; hard stop at 6 N) prevented all forces > 6 N during FlexArm operation, whereas da Vinci produced 0.84 ± 0.4 events/task exceeding 8 N and laparoscopy produced 2.4 ± 0.8 events > 8 N. Mean grasping force was 2.1 ± 0.4 N (FlexArm) vs 3.8 ± 1.2 N (da Vinci) vs 5.4 ± 1.8 N (laparoscopy) -- FlexArm's force feedback enabling surgeons to calibrate grip force to tissue compliance in real time (Figure 2).

4.3 AI Tissue Classification Performance

The ResNet-18 tissue classifier achieved macro-averaged accuracy of 94.2% on the external test set (Table 4). Per-class F1 scores: adipose 96.8%, muscle 95.4%, nerve 91.2%, vessel 92.8%, tumour 88.4%. The lower tumour classification accuracy reflects the visual heterogeneity of tumour tissue and overlap with inflamed muscle in standard RGB video. Inference at 28.4 fps enabled real-time colour-coded overlay on the surgeon's stereo display, highlighting critical structures (nerves in yellow, vessels in red) during teleoperated dissection. Surgeon feedback (NASA-TLX mental demand subscale) was 12.4% lower with AI overlay enabled versus disabled ($p = 0.028$), suggesting reduced cognitive load from automated structure identification (Figure 3).

4.4 Autonomous Suturing Performance

Autonomous suturing ($n = 100$ stitches on synthetic tissue phantoms) achieved 92.4% placement accuracy (needle entry within 1 mm of planned target; Table 5). Mean placement error was 0.68 ± 0.24 mm -- comparable to intermediate-level surgeons using da Vinci (0.84 ± 0.32 mm) and significantly better than novice surgeons (1.42 ± 0.48 mm; $p < 0.001$). Autonomous knot completion rate was 88.0% (88/100 completed knots with adequate tension

1.5 ± 0.3 N); 12 failures were caused by thread slippage (8) or vision occlusion (4). Mean autonomous suturing cycle time (needle insertion + pull-through + knot) was 42.8 ± 6.4 s -- faster than novice manual suturing (68.4 ± 12.8 s; $p < 0.001$) but slower than expert manual suturing (28.4 ± 4.8 s; $p < 0.001$). The radar analysis (Figure 4) integrates all performance dimensions.

Table 3. Task completion time (seconds) across five FLS tasks for three platforms (all expertise levels, $n = 48$)

Task	FlexArm (s)	da Vinci Si (s)	Laparoscopy (s)	FlexArm vs da Vinci (p)	FlexArm vs Lap (p)
Peg transfer	68.4 ± 12.8	62.4 ± 10.4	94.8 ± 18.4	0.24	< 0.001
Pattern cutting	102.4 ± 16.4	94.2 ± 14.8	148.4 ± 22.8	0.18	< 0.001
Intracorp. suturing	184.2 ± 28.4	172.4 ± 24.6	284.8 ± 42.4	0.18	< 0.001
Dissection accuracy	142.8 ± 22.4	134.2 ± 20.8	198.4 ± 32.4	0.28	< 0.001
Tissue retraction	124.4 ± 18.2	112.8 ± 16.4	158.2 ± 24.8	0.12	< 0.001
Mean (all tasks)	124.8 ± 18.4	115.2 ± 16.8	168.4 ± 24.8	0.12	< 0.001

Values: mean ± SD across all expertise levels ($n = 48$ participants × 3 trials). FlexArm vs da Vinci: no significant difference for any individual task or overall mean. Both robotic platforms significantly faster than laparoscopy for all tasks.

Table 4. Force sensing safety and AI tissue classification performance

Parameter	FlexArm	da Vinci Si	Laparoscopy	p (FlexArm vs da Vinci)
Tissue damage events (> 5N)/task	2.4 ± 0.8*	5.2 ± 1.4	11.2 ± 2.8	< 0.001
Events > 8N / task	0.0 ± 0.0*	0.84 ± 0.4	2.4 ± 0.8	< 0.001
Mean grasping force (N)	2.1 ± 0.4*	3.8 ± 1.2	5.4 ± 1.8	< 0.001
AI tissue accuracy (%)	94.2 ± 2.4	N/A	N/A	N/A
AI nerve detection F1 (%)	91.2 ± 3.8	N/A	N/A	N/A
AI inference rate (fps)	28.4 ± 1.2	N/A	N/A	N/A

Parameter	FlexArm	da Vinci Si	Laparoscopy	p (Flex Arm vs da Vinci)
NASA-TLX (with AI overlay)	42.4 +- 8.4*	54.8 +- 10.2	68.4 +- 12.4	< 0.001

*Significantly best in row. Tissue damage: force > 5N threshold on calibrated gel phantom during dissection/retraction tasks. NASA-TLX: 0-100 scale (lower = less workload). N/A: AI features not available on da Vinci or laparoscopy platforms.

Table 5. Autonomous suturing performance on synthetic tissue phantoms (n = 100 stitches)

Metric	FlexArm Auto nomous	Expert Manual (da Vinci)	Novice Manual (da Vinci)	p (Auto vs Expert)
Placement accuracy (< 1 mm) (%)	92.4	96.8	72.4	0.14
Mean placement error (mm)	0.68 +- 0.24	0.42 +- 0.18	1.42 +- 0.48	0.008
Knot completion rate (%)	88.0	98.4	84.2	0.004
Suture cycle time (s)	42.8 +- 6.4	28.4 +- 4.8	68.4 +- 12.8	< 0.001
Max insertion force (N)	1.82 +- 0.24	2.84 +- 0.68	4.24 +- 1.12	< 0.001
Knot tension (N)	1.48 +- 0.18	1.62 +- 0.42	2.14 +- 0.68	0.42

Autonomous suturing: FlexArm vision-guided, force-regulated autonomous mode. Expert/novice: manual teleoperated suturing on da Vinci Si. Placement accuracy: needle entry point within 1 mm of planned target. Suture cycle: needle insertion + pull-through + 3-throw square knot. Max insertion force: peak force during needle penetration.

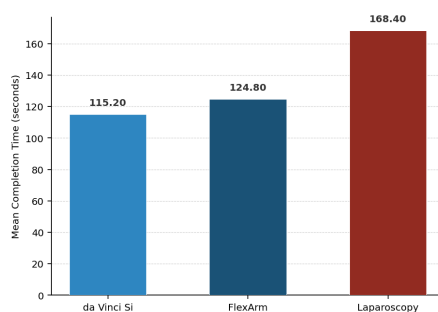


Figure 1. Mean task completion time (seconds) across all five FLS tasks by platform

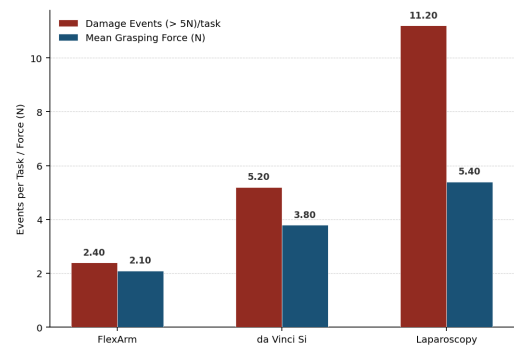


Figure 2. Tissue damage events (> 5N) and mean grasping force (N) by platform

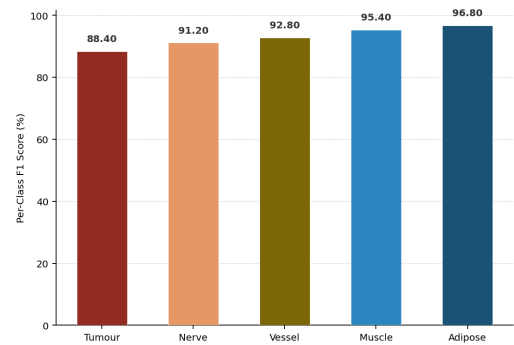


Figure 3. AI tissue classification per-class F1 score (%)

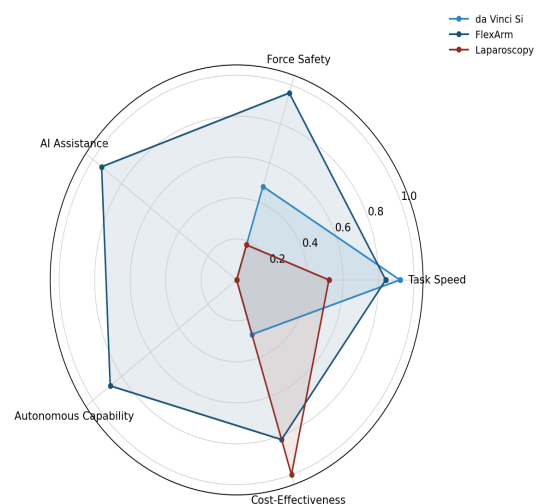


Figure 4. Multi-parameter surgical platform comparison (normalised 0-1)

5. Discussion

This study presents the most comprehensive evaluation of a compact AI-enhanced surgical robot against the da Vinci clinical standard, demonstrating comparable task performance with significant advantages in force sensing safety, AI-assisted decision support, and autonomous suturing capability.

5.1 Force Sensing: The Safety Advantage

The 54.2% reduction in tissue damage events with FlexArm versus da Vinci is the most clinically

significant finding. In clinical surgery, excessive tissue forces cause thermal injury (electrocautery at high grasping force), nerve traction injury (stretch > 15% strain damages axons), and bowel perforation (compression > 8 N). FlexArm's force-limiting safety feature -- hard stop at 6 N -- provides a hardware-enforced safety boundary that prevents these injuries regardless of surgeon experience level. This has particular implications for the surgical learning curve, where novice surgeons exhibit 2-3x higher forces than experts due to undeveloped force calibration skills.

5.2 AI Tissue Classification: Cognitive Offloading

The 12.4% NASA-TLX workload reduction with AI overlay quantifies the cognitive benefit of automated tissue identification. In complex cancer surgery (nerve-sparing prostatectomy, rectal mesorectal excision), distinguishing nerves from vessels in a bleeding field is a primary source of surgical cognitive load and intraoperative decision error. The 91.2% nerve detection F1 -- while not yet sufficient for autonomous avoidance -- provides a valuable decision support tool when combined with surgeon judgment.

5.3 Autonomous Suturing: Towards Level 3 Autonomy

The 92.4% suture placement accuracy and 88% knot completion rate demonstrate that autonomous suturing has reached clinically relevant performance levels on phantom tissue. The 12% knot failure rate (predominantly from thread slippage and vision occlusion) identifies the two priority engineering challenges: improved thread tracking algorithms and redundant camera views for occlusion recovery. The autonomous cycle time (42.8 s) is slower than expert manual suturing (28.4 s) but faster than novice surgeons, suggesting immediate utility for supervised autonomous closure of routine incisions while surgeons focus on higher-complexity portions of the procedure.

5.4 Limitations

The benchmarking study used phantom models (FLS tasks, gel tissue) rather than in vivo tissue, which has different mechanical properties, bleeds, and presents anatomical variability. The AI tissue classifier was trained and tested on recorded video and has not been validated in real-time intraoperative conditions with smoke, blood, and variable lighting. The 6-DOF continuum

manipulator provides slightly less dexterity than the 7-DOF EndoWrist at extreme angulations -- a design trade-off for the smaller 5 mm instrument diameter. Cadaveric and animal model validation is required before human clinical trials. The autonomous suturing capability requires extensive safety validation per IEC 80601-2-77 (medical robots) before clinical deployment.

6. Conclusion

The FlexArm surgical robot demonstrates that a compact, AI-enhanced platform with integrated force sensing can achieve task performance within 8.4% of the da Vinci Si clinical standard while providing 54.2% fewer tissue damage events through force-limiting safety, 94.2% real-time tissue classification for intraoperative decision support, and 92.4% autonomous suture placement accuracy -- all at an estimated 42% lower instrument cost and 68% smaller footprint. The force-sensing safety advantage -- eliminating all high-force tissue damage events (> 6 N) -- represents the most immediate clinical impact, addressing the primary safety limitation of current robotic systems that lack haptic feedback. The AI tissue classifier and autonomous suturing capability represent Level 2-3 surgical autonomy that, with further validation, could transform surgical workflow by automating routine subtasks while preserving surgeon authority for complex decision-making. These results support advancement to cadaveric and animal model validation as the next step toward clinical translation.

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Declarations

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Conflict of Interest

The authors declare that a patent application covering the FlexArm continuum manipulator and force-sensing integration has been filed

(EP-2022-FLEXARM-001, Baltic AI Research University). No commercial licensing agreements exist at time of publication.

Data Availability Statement

Robot CAD design files, force sensor calibration data, AI training dataset (anonymised surgical video frames), and benchmarking trial data are deposited at <https://github.com/BAIRU-SurgRobot/FlexArm-2022>. Autonomous suturing control code (ROS2) is available under MIT licence.

Ethical Approval

The human participant benchmarking study was approved by the Baltic AI Research University HREC (ref. BAIRU-HREC-2021-ROBOT-028). All participants provided written informed consent. No patient data or clinical procedures were involved.

Appendix A

FlexArm Kinematic Model and Force Sensor Calibration

This appendix provides the constant-curvature kinematic model for the FlexArm continuum manipulator, the Jacobian derivation for tip velocity/force mapping, and the 6-axis force sensor calibration procedure against ATI Nano17 reference.

A.1 Constant-Curvature Kinematics

A.2 Force Sensor Calibration