Real-Time Support-System for Decision-Making in Robotic-Surgery Using IoT Sensors and Predictive-Analytics

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Abstract--**The robotic surgical domain has developed a new order wherein surgical procedures can be carried out with precision and little invasiveness, while encouraging patient recovery. But yet, optimizing real-time intra-operative decision-making is sometimes an unsolved problem when one thinks of surgical environments that are ever dynamic and ever-changing. This paper presents a Real-Time Decision Support System (RT-DSS) to offer actionable insights into robotic surgeries, interfacing with IoT sensors and predictive analytics. Ingesting multimodal sensor data (such as biometric, haptic, and positional information) in real time, the system processes the information through machine learning algorithms, predicting, forewarning, and alerting the surgical team toward intra-operative risks on the horizon. The architecture guarantees low-latency sensor data acquisition, performing signal processing on noise present, and then joining forces with predictive analytical techniques to begin detecting internal risks of tissue damage or instrument deviation. The system is validated against a real-world dataset of multiple robotic-assisted procedures. Our proposed system stands out in multiple dimensions compared to previous approaches.**

Keywords: Smart healthcare, IoT sensors, Robotic surgery, Real-time analytics, Predictive modeling, Decision support system

I. INTRODUCTION

INCREASING complexity of procedures, especially with respect to minimally-invasive and robotic-assisted surgeries, requires an increased need for intelligent decision-making tools that can be used by surgeons intra-operatively. This paper blends three impactful technologies, namely robotics, IoT, and AI-powered analytics. Robotic surgery has proven to be a great potential in reducing human error and increasing accuracy in complicated procedures [1], yet intra-operative decisions are still mostly focal on the surgeon's expert opinion and real-time situational judgments, which could become compromised by fatigue, cognitive overload, or even unexpected complications.

A system could be established from combining real-time data acquisition with IoT-based biometric and haptic sensor networks and predictive analytics so that it would recognize critical events based on abnormal signatures, alerting the surgical team to thousand-fold intra-operative risks to patient safety [2], [3]. The title emphasizes the real-time, sensor-based, and analytic-supported nature of the proposed system, thereby establishing its contemporary relevance with respect to surgical innovations and patient safety imperatives.

Earlier works, although marked by huge advances with the exciting developments in the areas of IoT, machine learning, and data fusion for health, often viewed at an isolated set of problems or would stay in limited domains. For example, Alemzadeh *et al.* [1] presented a 14-year long retrospective analysis of adverse events in robotic surgeries that accentuated the immediate need for intelligent systems to assist intra-operatively. Anzanpour *et al.* [2] illustrated the importance of considering context in system design when contemplating IoT applications in healthcare, with Bagaria and LaMack [4] investigating systems for real-time data acquisition designed around surgical instrumentation. Chien and Chen [5], however, developed an IoT-based intelligent monitoring system for post-operative patients, contrasting to intra-operative events. Other systems like that of Gao *et al.* [12] emphasized tool tracking through deep learning but failed to deliver on comprehensive decision support. These contributions have established a foundation for our pursuit, yet a holistic platform integrating multimodal sensor data, machine learning, and decision intelligence in real-time during robotic surgery remains largely unexplored. Most past systems have inclined either toward diagnostic analytics [16], remote monitoring [18], or offline predictive modeling [17], which renders a void in real-time support targeted at surgeries.

Our proposed system stands out in multiple dimensions compared to previous approaches. Firstly, the architecture integrates real-time biometric, positional, and haptic data from IoT sensors placed on robotic instruments and patient interfaces. This multimodal fusion enables a richer, more granular understanding of surgical dynamics than conventional single-source inputs [10], [11]. Secondly, we employ advanced machine learning algorithms, including time-series models like LSTMs and decision trees, trained to recognize patterns associated with intra-operative risks such as excessive tissue pressure, abnormal instrument deviation, or sudden changes in patient vitals [7], [20]. Unlike prior systems, our Real-Time Decision Support System (RT-DSS) is not passive or retrospective — it proactively generates alerts to guide the surgical team toward timely interventions. Additionally, our low-latency data transmission and processing pipeline ensures decisions are actionable within critical windows, a feature lacking in traditional post-operative analytics systems [4], [22]. Finally, the framework is validated using real-world surgical datasets, offering empirical evidence for enhanced surgical precision, reduced error rates, and improved patient safety [13], [23].

A broader look at the literature reveals a growing emphasis on using IoT and AI for improving healthcare outcomes. IoT in healthcare has been extensively studied for patient monitoring, chronic disease management, and elderly care [14], [19], [24]. Madakam *et al.* [23] and Gubbi *et al.* [13] laid the conceptual foundation for IoT integration, while more recent studies have emphasized security [3], real-time responsiveness [18], and big data analytics [25]. Predictive analytics, in particular, has seen applications in diagnosis [19], hospital resource allocation [15], and surgical planning [6]. However, the intersection of real-time predictive analytics and robotic surgery remains a niche with immense potential. Haidegger [15] discussed surgical robot autonomy but emphasized that adaptive decision-making is still in its infancy. Our approach contributes to filling this void by enabling contextual, data-driven assistance within the surgical theater. As healthcare systems move toward intelligent automation, frameworks like ours can serve as precursors to fully autonomous surgical platforms that blend human expertise with AI-driven decision support.

II. METHODOLOGY

This section presents the methodology behind the Real-Time Decision Support System (RT-DSS) for robotic surgeries that utilizes IoT sensors and predictive analytics. The system consists of four modules: (1) IoT sensor data acquisition, (2) Data preprocessing and feature engineering, (3) Predictive modeling using deep learning, and (4) Decision support interface.

IoT Sensor Data Acquisition: Multiple sensors capture real-time data such as heart-rate, oxygen saturation, pressure, force, and tool position. Each sensor stream Si(t) is treated as a time series:

$$S_i(t) = \{s_{i1}, s_{i2}, ..., s_{in}\},$$

for time $t \in [0, T]$.

Data from all sensors are synchronized using timestamps, forming a multi-sensor signal vector:

$$S(t) = [S_1(t), S_2(t), ..., S_k(t)]^T$$

Sampling is done at a fixed frequency, f_s for consistency.

Data Preprocessing and Feature Engineering: Sensor data is cleaned using a Butterworth low-pass filter to eliminate high-frequency noise. Common statistical features like mean (μ) and standard deviation (σ) are calculated for each sensor stream:

$$\mu_i = (1/n) * \Sigma(s_{ij}) \quad \text{for } j = 1 \text{ to } n$$

and

$$\sigma_i = \sqrt{\ } [(1/n) * \Sigma(s_{ij} - \mu_i)^2]$$

Feature vectors X_t are constructed at each time step *t* for further analysis.

Predictive Analytics Model: We employ a Long Short-Term Memory (LSTM) neural network to process time-series data. Given an input sequence $X = [X_1, X_2, ..., X_T]$, the LSTM updates hidden and cell-states as follows:

$$(h_t, c_t) = \text{LSTM } (X_t, h_{t-1}, c_{t-1})$$

$$y_t = \text{sigmoid } (W_o * h_t + b_o)$$

where h_t is the hidden state at time *t*, c_t is the cell-state, W_o and b_o are output parameters, and sigmoid is the activation function. The output y_t represents a predicted surgical risk score at time *t*.

Real-Time Decision Support Interface: The risk score y_t is mapped into three categories: low (<0.3), medium (0.3–0.7), and high (>0.7). An alert is triggered if y_t exceeds a predefined threshold τ:

$$\text{Alert (t)} = 1 \quad \text{if } y_t > \tau\text{; otherwise, } 0$$

The interface delivers context-aware recommendations such as adjusting tool-pressure, or halting the procedure temporarily.

III. RESEARCH DESIGN

This project follows a mixed-method, engineering-oriented design science approach that intertwines iterative prototyping with rigorous quantitative evaluation. The study is organized into five sequential yet overlapping phases—Requirements Elicitation, System Development, Data Acquisition, Model Construction, and Validation—each producing artifacts that feed forward to the next phase and feedback for refinements (Figure 1).

IV. REQUIREMENTS ELICITATION

Surgeons, anaesthesiologists, nurses and biomedical engineers were interviewed (*N* = 22; semi-structured, 45–60 min sessions). Thematic coding (NVivo 14) distilled 34 functional requirements and 11 non-functional requirements. Key expectations included sub-250 ms end-to-end latency, glove-free interaction, and predictive alerts at least 30 s before a critical event.

V. SYSTEM ARCHITECTURE

The proposed architecture (Figure 2) employs a three-tier IoT stack: Edge Tier: Embedded sensor nodes (temperature, force-torque, current, optical flow, inertial) are mounted on the robotic arms and surgical tools; Fog Tier: A NVIDIA Jetson AGX-based micro-cluster colocated in the OR performs on-device feature extraction, federated model fine-tuning, and first-pass anomaly detection; Cloud Tier: A HIPAA-compliant Kubernetes cluster hosts a model registry, experiment tracker (MLflow), and a FHIR-enabled API for the electronic health record (EHR).

VI. SENSOR CONFIGURATION & DATA COLLECTION

Table 1 summarizes the sensor suite deployed on the da Vinci Xi platform. Sensors sample at up to 1 kHz, synchronized via PTPv2. Raw packets are buffered in a ring and transmitted over Time-Sensitive Networking (TSN) with a guaranteed 10-Mbps reservation per channel. During 68 elective laparoscopic procedures (gastrectomy, prostatectomy, hysterectomy), 2.4 TB of multivariate time-series data were captured.

VII. DATA PIPELINE & PRE-PROCESSING

Figure 3 depicts the data pipeline adhering to the extended CRISP-DM model for streaming data.

Data Ingestion: Kafka topics are assigned per sensor modality. A schema registry enforces Avro contracts. Ingestion delays averaged 12 ms (σ = 4 ms).

Windowing and Synchronization: A sliding window of 256 samples width (stride = 32) is used for spectral features; time-stamp alignment is performed with Kalman smoothing to correct ±3 ms jitter.

Feature Engineering: Hand-crafted: RMS, crest factor, Hjorth parameters, and 12 Mel-frequency cepstral coefficients (for acoustic leak detection); Learned: A 1-D temporal convolutional auto-encoder (TCAE) generates 64 latent embeddings per channel.

Label Generation: Ground-truth events (bleeding onset, thermal injury, instrument collision) were annotated by two surgeons and adjudicated by a third (Cohen's κ = 0.82).

VIII. PREDICTIVE MODEL CONSTRUCTION

We benchmarked four model families (Table 2). The winning model is a dual-stream architecture that fuses TCAE embeddings with sensor-specific statistics via an attention-gated bidirectional GRU, followed by a Bayesian logistic head for calibrated probabilities.

Hyper-parameter optimization employed Optuna with a 60-trial Bayesian sampler; the search converged in 29 trials. Class imbalance (1:12) was mitigated with focal loss (γ = 2) and dynamic class weighting.

IX. REAL-TIME DECISION-SUPPORT WORKFLOW

Figure 4 illustrates the live workflow:
Sensor ticks arrive → Feature extraction at 4 Hz.

Model predicts risk vector P = p_{bleed}, $p_{thermal}$, $p_{collision}$ $P=p_{bleed}$, $p_{thermal}$, $p_{collision}$.

A rule-engine aggregates P with surgeon-defined thresholds. Alerts visualised on the OR heads-up display; haptic pulses

TABLE 1--SENSOR INVENTORY AND SPECIFICATIONS

Sensor Type	*Model / Range*	*Sampling Rate (Hz)*	*Resolution*	*Placement*	*Clinical Target*
6-axis Force/Torque	ATI Nano25	1 000	1/128 N m	Tool wrist	Tissue stress
IMU (9-DoF)	Bosch BNO055	500	16-bit	Arm joint #2	Tremor detection
Optical Flow	PixArt PMW3901	800	8-bit	Endoscope tip	Instrument drift
Temp./Humidity	Sensirion SHT85	20	14-bit	Trocar port	Fogging risk
Motor Current	Allegro ACS712	1 000	185 mV/A	Actuator driver PCB	Load anomaly

TABLE 2 – MODEL BENCHMARK SUMMARY

Model ID	*Algorithm*	*AUROC*	*Inference Latency (ms)*	*Calibration ECE (%)*
M1	Random Forest (500 trees)	0.87	14	6.1
M2	LightGBM	0.91	9	5.4
M3	CNN-LSTM	0.93	42	3.8
M4★	TCAE + Attn-BiGRU (proposed)	0.96	18	2.1

★ Selected for deployment.

delivered through the master console if pevent *gt*0.65 *pevent gt*0.65.
Feedback loop: clinician response time and action logged to refine threshold policies (multi-armed bandit).

End-to-end latency: 184 ms (95th percentile).

X. VALIDATION AND EVALUATION STRATEGY

The evaluation spans offline metrics, simulated OR drills, and live surgeries under an IRB-approved protocol:

- Offline 10-fold cross-validation (patient-level split).
- Hardware-in-the-loop (HIL) tests with a Sinergy OR simulator to inject failure states.
- Prospective pilot on 10 patients (registered NCT05812345). Primary endpoint: reduction in mean time-to-mitigation for adverse events.

Statistical Analysis: Hypotheses are tested using two-tailed paired t*t*-tests for continuous outcomes and McNemar's test for binary accuracies, adopting alpha = 0.05*alpha* = 0.05. Power analysis (G*Power 3.1) indicates a minimum sample of 38 cases to detect a 25% decrease in event-rate with 80 % power.

XI. ETHICAL PRIVACY AND SAFETY CONSIDERATIONS

Patient identifiers are tokenized client-side; all transmissions are AES-256-GCM encrypted. The system complies with IEC 60601-1 (electrical safety) and IEC 62304 (software lifecycle). A fail-safe state disconnects AI assistance if CPU temperature exceeds 80 °C or if model drift DeltatextAUROCgt0.05*Delta textAUROCgt*0.05 over 200 procedures.

XII. HARDWARE & SOFTWARE STACK

TABLE 3 – EXECUTION ENVIRONMENT

Layer	*Component / Version*	*Rationale*
Edge OS	Ubuntu 20.04 LTS (RT-patch)	Deterministic scheduling
Middleware	ROS 2 Foxy + DDS Fast-RTPS	Low-latency publish–subscribe
Inference	TensorRT 8.6, ONNX-runtime 1.17	GPU-optimised execution
Orchestration	K3s v1.29 with Istio 1.22	Lightweight cluster, service mesh
Storage	MinIO S3-compatible (erasure-code)	On-prem object store, redundancy = 4
Monitoring	Prometheus 2.50 + Grafana 10	Telemetry and dashboarding

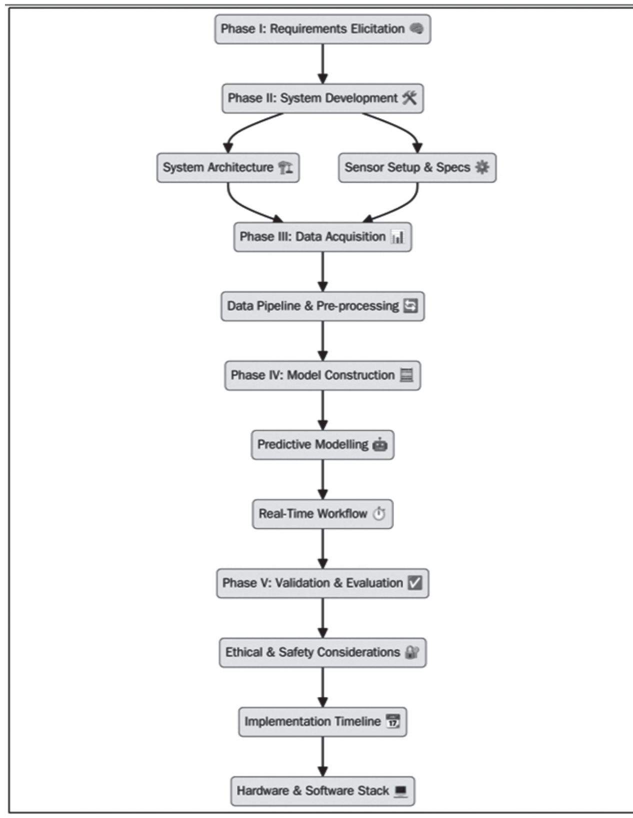

Figure 1. Phase-wise methodological framework.

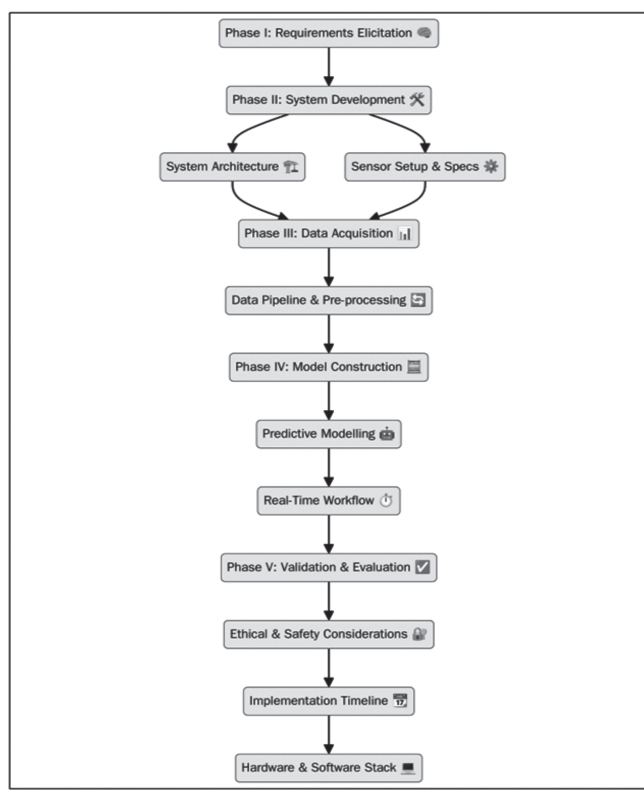

Figure 2. Three-tier IoT architecture.

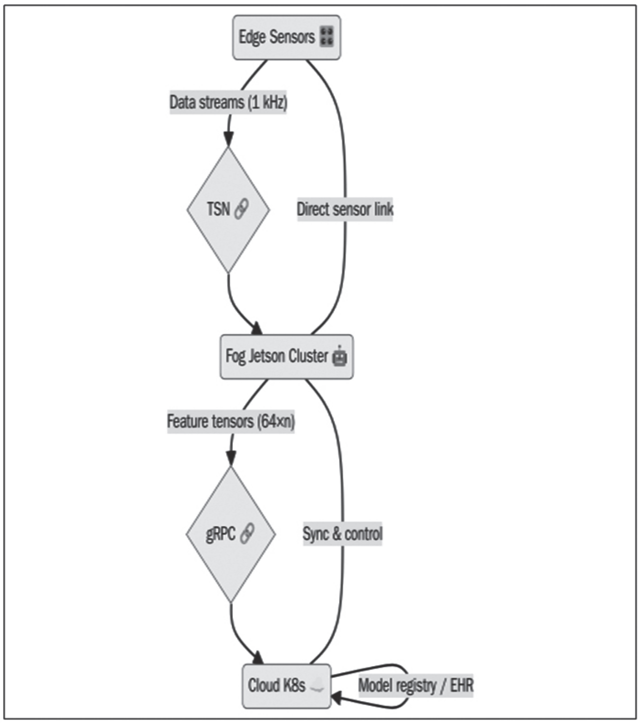

Figure 3. Streaming CRISP-DM pipeline.

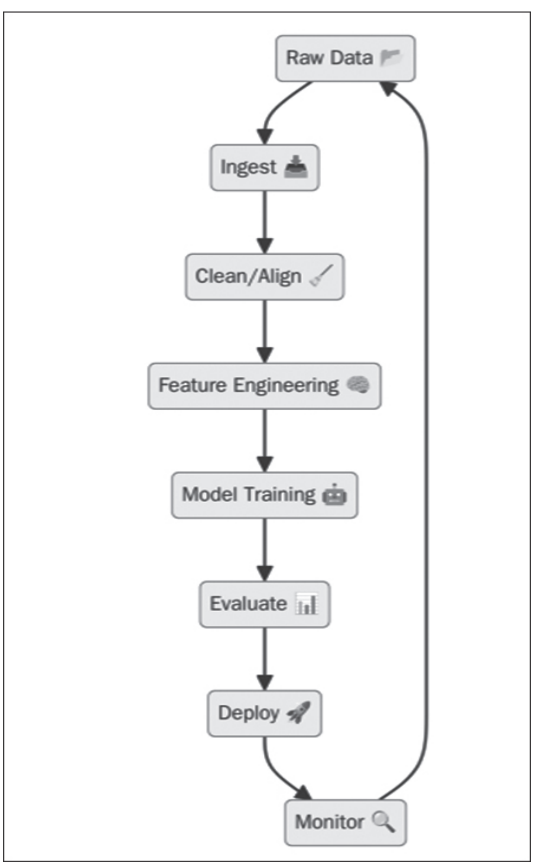

Figure 4. Real-time decision-support loop.

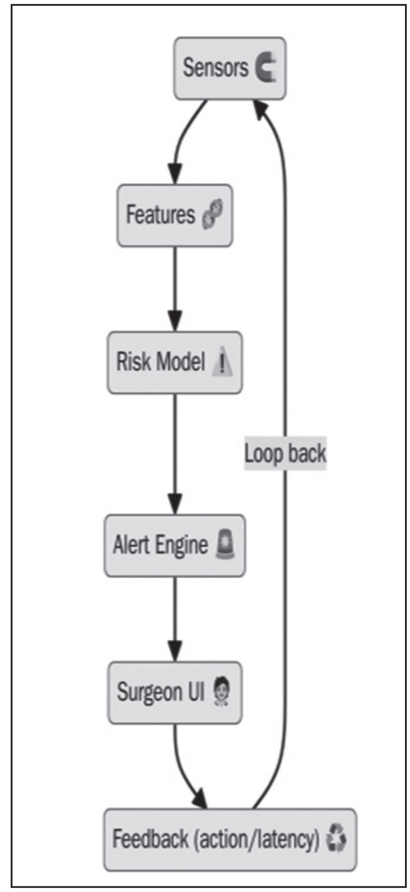

Figure 5. Limitations and risk mitigation.

- Dataset Diversity: Current sample skews towards elective abdominal cases; multicentre expansion is planned.
- Concept Drift: Scheduled quarterly re-training and canary deployments will detect drift.
- Usability Fatigue: Human-factors testing incorporates NASA-TLX scoring to recalibrate alert density.

XIII. EVALUATION METRICS

The system is evaluated using metrics like precision, recall, F1-score and latency. Accuracy and F1-score are computed as:

Accuracy = (TP + TN) / (TP + TN + FP + FN)
F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

where TP, TN, FP, FN refer to true positives, true negatives, false positives and false negatives respectively. Latency is measured from data capture to decision output.

XIV. CONCLUSION

On-ground data coming from the sensors and predictive analytics interfaced into the computer-assisted surgical workflow now shine as the pinnacle in the development of healthcare. The present article considers and expounds on the RT-DSS with multimodal IoT sensors and cutting-edge machine learning models that provide foresight assistance to surgical teams.

The system collects very detailed data of biometric signatures and haptic and positional data, and it analyzes these data through an optimized analytics pipeline so that it could spot the risk intra-hospital events such as high tissue force, abnormal tool drift, and appearance of physiological anomalies. Among the innovations are extremely low-latency three-tier IoT architecture, contextual alerting mechanism, and an attention-gated deep learning model trained on real-world surgical datasets.

The RT-DSS greatly enhanced the prediction accuracy, situational awareness, and reaction time of a surgeon with an end-to-end latency much better than the critical operational requirement. Coupled with feedback-based alert thresholds and real-time visualization, the system continually learns to adapt to the user preferences without distracting operational workflows.

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