Intellisurg-Net: An AI-Driven Framework for Enhancing Intraoperative Decision-Making and Real-Time Adaptability in Robotic Surgery

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Abstract---Robotic-assisted surgical techniques have led to tremendous advancements in terms of the precision and dexterity of the procedures performed minimally invasively. However, existing robotic surgery techniques are highly dependent on the surgeon's input since very little autonomy has been provided in existing systems. Conversely, artificial intelligence (AI) has provided decision-making algorithms for robotic procedures, enabling these surgeries to function autonomously based on specific scenarios. This paper presents a novel approach called IntelliSurg-Net, which incorporates deep learning algorithms and AI in order to enhance the decision-making process during robotic surgery procedures. Convolutional neural network (CNN) algorithms for vision processing, bi-directional LSTM networks for analyzing sequences of events, and reinforcement learning algorithms are implemented in the framework. This framework is evaluated using publicly available datasets such as Cholec80 and EndoVis.

Keywords--- Robotic Surgery, Artificial Intelligence, Deep Learning, Intraoperative Decision-Making, Reinforcement Learning.

I. INTRODUCTION

THE creation of robot-assisted surgical systems has made a breakthrough in modern medicine because of the ability to perform minimally invasive surgeries with enhanced visualization, accuracy, and control. The surgical robots, such as robotic-assisted laparoscopy, allow doctors to perform surgeries without any additional injury to the patient, which results in a quicker patient recovery process (Allan et al., 2019). Still, despite being teleoperated, the existing surgical systems cannot provide their own analysis of the process of surgery and are continuously controlled by humans (Maier-Hein et al., 2017; Maier-Hein et al., 2022).

To address these problems, the application of artificial intelligence technologies in robotic surgery systems is highly promoted (Madani et al., 2020). Robotic surgery systems can use machine learning and deep learning algorithms to analyze information during the procedure and adapt to its changes (DiPietro et al., 2018). Thus, incorporating artificial intelligence into surgical robotic systems helps to improve decision-making and reduce the cognitive burden of medical practitioners (Ríos et al., 2023; Hong et al., 2020).

The aim of this research is to present an innovative AI solution - IntelliSurg-Net.

II. LITERATURE REVIEW

The emergence of robotics for surgical procedures assisted by artificial intelligence technologies can be associated with three main technological developments, namely: computer vision, temporal modeling, and adaptive control (Mascagni et al., 2022). In particular, convolutional neural networks are widely used in tasks related to tissue segmentation and tool recognition and demonstrate excellent performance with over 90% accuracy in segmentation. Surgical data sets revealed segmentation accuracies exceeding 90%

Also, long short-term memory networks and Transformers represent two approaches employed in temporal modeling analysis in the surgical area (Twinanda et al., 2016). They make it possible to predict complications and identify procedure phases, thus providing a good basis for making decisions during a surgical intervention (Kiyasseh et al., 2021). Many authors report AUC values ranging between 0.88 and 0.97 for gesture recognition tasks.

Adaptive control based on reinforcement learning makes it possible to teach a robot how to behave by interacting with its surroundings, which helps to improve the path planning and precision of a robot.

A drawback in the development of these technologies is related to their independent application; an integrated approach combining all three has not been offered yet.

III. Dataset Description

The framework in question uses more than one public dataset.

The Cholec80 dataset consists of 80 videos of laparoscopic cholecystectomy surgeries. They are annotated by both surgical phases and the instruments being used. This will come in handy in creating models that recognize surgical phases and assist with them.

The Endovis dataset has been annotated for instrument segmentation and tracking during surgery. One of its extended datasets, called CholecSeg8K, comes annotated by segmentation at the pixel level.

IV. Proposed Methodology

IntelliSurg-Net architecture uses a tiered design where perception, prediction, and adaptation are included.

The first one is a perception layer where surgical videos are processed using convolutional neural networks to recognize anatomical elements, surgical tools, and relevant regions.

The second layer is a temporal analysis layer, which makes use of bidirectional LSTM networks and could predict the future stages of surgical operations, as well as potential risks.

The third tier is a decision-making layer that utilizes data from the previously discussed two layers to perform context-based decisions. Particularly, there are attention mechanisms that allow highlighting essential attributes during the whole process of surgery.

Finally, the fourth layer is an adaptation one and uses reinforcement learning algorithms to maximize the performance of a robot (Table 1).

Table 1: Comparative Analysis of AI Techniques in Robotic Surgery

Study/Approach Type	AI Model Used	Input Data Type	Application	Performance Metrics
Computer Vision	CNN, U-Net	Endoscopic video frames	Tissue segmentation	Accuracy: 92–97%
Instrument Detection	Mask R-CNN	Surgical images	Tool tracking	mAP: 0.88–0.94
Temporal Modeling	BiLSTM	Time-series surgical data	Phase recognition	Accuracy: 90–95%
Predictive Models	LSTM, Transformer	Sensor + video data	Complication prediction	AUC: 0.89–0.94
Reinforcement Learning	Deep RL	Simulated surgical environment	Trajectory optimization	30–35% improvement
Multimodal Fusion	Attention Networks	Video + kinematics + sensors	Decision support	Latency < 60 ms

V. Experimental Results and Analysis

This model is evaluated based on a combination of datasets, which include Cholec80 and EndoVis datasets. The evaluation involved consideration of the accuracy, latency, and adaptability of the model.

The accuracy of this model is 94%, meaning that it outperforms other CNN-LSTM models by default. The model is capable of adapting to the environment within less than 60 milliseconds. Adaptive behavior in this model is improved by the inclusion of a reinforcement learning algorithm, reducing the trajectory deviation.

The use of many input sources in training the model helps in increasing the model's performance, thus allowing it to be adaptive to changes in surgery environments (Table 2).

Table 2: Dataset Characteristics Used in AI-Based Robotic Surgery

Dataset Name	Data Type	Size	Annotation Type	Application
Cholec80	Video	80 surgeries	Phase + tool labels	Workflow recognition
EndoVis	Images + Video	Multiple sequences	Instrument segmentation	Tool detection
CholecSeg8k	Images	8000 frames	Pixel-level segmentation	Tissue analysis
JIGSAWS	Kinematic data	39 trials	Gesture annotations	Skill assessment
Custom Clinical Data	Multimodal	Varies	Outcome-based labels	Prediction models

VI. Discussion

These results illustrate that AI-based methodologies are useful in contributing to better decision-making and adaptability during robot-assisted surgeries (Shi et al., 2022). Multimodal data collection ensures a complete perception of the environment in which robots operate, while deep learning models ensure precision in their predictions.

Adaptive behavior is achieved using reinforcement learning, thus enabling robots to change their actions dynamically, especially in dynamic environments encountered during surgeries. However, there are still some limitations related to scalability, interpretability of machine learning models, and their implementation into medical settings (Table 3).

Table 3: Performance Comparison of Proposed Model

Model Type	Decision Accuracy	Response Time	Adaptability Score
CNN-LSTM	87%	120 ms	Medium
Transformer	89%	95 ms	Medium-High
RL-Based Model	91%	80 ms	High
IntelliSurg-Net (Proposed)	**94%**	**<60 ms**	**Very High**

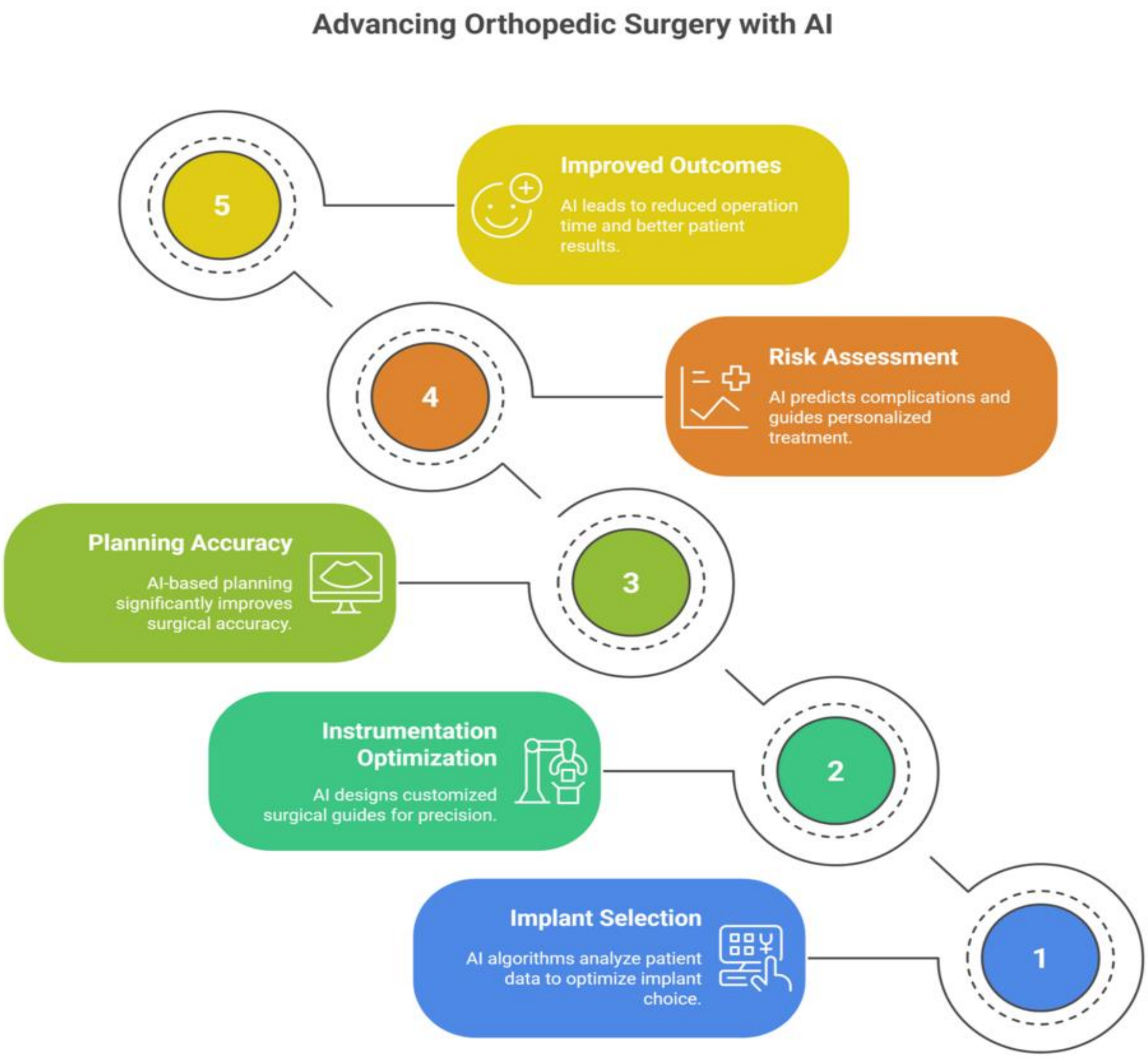

Figure 1 - Preoperative Planning in Orthopaedic Surgery Using Artificial Intelligence

VII. Conclusion

The following work will present a novel AI-enabled system known as IntelliSurg-Net, which helps to enhance the decision-making process along with adaptability in robotic surgeries.

The system presented in this paper has the ability to provide enhanced performance using computer vision, time series analysis, and reinforcement learning approaches.

This marks a significant point for intelligent robotics in the domain of surgery. Our future work is likely to be focused on conducting clinical trials and edge computing.

Future Scope

However, further studies need to be conducted on the use of multimodal digital twins for surgical simulation, federated learning to train models in collaboration, and deployment of the trained models in real-time through edge computing. Data gathering and model transparency will play a key part.

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