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Machine Learning in Medical Robotics of Diagnostics, Surgery and Rehabilitation

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Abstract:

Recently, the integration of Machine Learning (ML) into medical robotics has revolutionized the fields of diagnosis, surgery and rehabilitation by enabling minimally invasive procedures and improving recovery outcomes and transforming them into assistants capable of interpreting complex data and supporting real-time clinical decisions. This review mainly focuses on ML applications in three areas: diagnostics, surgery, and rehabilitation. In diagnostics, attention-based U-Net variants like OP-U-Net uses optical flow and channel attention for real-time vascular segmentation in robotic ultrasound, and there is also skin cancer detection by using Hybrid Convolutional Neural Network (CNN) frameworks, while voice analysis using supervised ML models enables early Parkinson diagnosis. In surgery, deep learning enables autonomous vascular access and semantic segmentation of instruments by using architecture such as TernausNet and LinkNet. Super-resolution in endomicroscopy is achieved through synthetic data training, overcoming hardware constraints and improving intraoperative imaging. In rehabilitation, reinforcement learning frameworks like Flexible Policy Iteration (FPI) enhance robotic knee control by integrating experience replay and prior knowledge. Additionally, ML-driven wearable systems for stroke rehabilitation enable real-time gesture recognition and robotic hand assistance, supporting at-home recovery. These methods bring substantial improvements in accuracy, adaptability, and clinical relevance. However, challenges in generalizability, interpretability, and data privacy remain. Solving these issues by explainable AI, federated learning, and domain-informed architectures is crucial for the future integration of intelligent robots into everyday healthcare.

Keywords: Machine Learning (ML); medical robotics; diagnostics, surgery, and rehabilitation.

1. Introduction

The development of medical robots has made surgery more precise and dexterous. The application of medical robots such as Da Vinci robot surgical system has enabled surgeons to reach areas that were previously difficult to access with traditional tools and operate with minimal invasiveness on patients. This has helped doctors enhance their surgical capability and enabled patients to recover faster, return to daily life sooner, and have shorter hospital stays.

In the recent decades, research has mainly focus on smart and adaptive robots, with the main products being automated, semi-automated, and rehabilitation robots. In the past five years, recent advances in Artificial Intelligence (AI) have catalysed a new era of intelligent robotics: Al-powered medical robots. The implementation of Machine Learning (ML) into medical robotics is transforming medical robots from passive mechanical assistance into real surgical helper. Machine learning enables medical robots to interpret sensory data to provide doctors with more targeted data and more accurate assistance. With ML, these systems can process complex data in real time, learn from clinical outcomes, support clinicians in decision-making tasks and help them better identify lesions and operate more precise surgeries.

The application of machine learning in medical robots mainly concentrates on 3 fields: diagnostics equipment, surgical robots and rehabilitation robots. In medical diagnostics, Machine Learning primarily involves the field of image recognition. ML can enhance the capabilities of robotic ultrasound systems by enabling data-driven automation, improving diagnostic consistency, and reducing operator dependency. For example, ML techniques—particularly deep learning and reinforcement learning—enable robotic platforms to learn from expert-performed scans, adapt to anatomical variations, and optimize probe trajectories in real time [1]. This learning-based adaptability addresses one of the core limitations of traditional ultrasound: variability due to manual probe manipulation. Complementing this, the comprehensive survey by Jiang underscores how ML supports real-time semantic understanding of ultrasound images, guiding robotic systems toward diagnostically optimal views with greater efficiency and reproducibility [2]. Together, these works illustrate how ML not only boosts the autonomy of ultrasound robots but also lays the foundation for scalable, intelligent imaging systems in diverse clinical settings such as emergency care, remote diagnostics, and intensive care units.

In the field of surgery, the surgical console of a robot-assisted system provides crucial visual data, such as 2D images and videos, to support intra-operative decision making. A key challenge in interpreting this data is accurately segmenting surgical instruments, which is complicated by lighting variations, occlusions like blood or fog, and complex tissue backgrounds. Reliable segmentation is essential for effective instrument tracking, highlighting the need for robust computer vision techniques for semantic segmentation in surgical settings. Shvets et al. demonstrates a technique of using machine learning to achieve highly accurate and robust segmentation of surgical instruments in robot-assisted procedures [3]. By training a Convolutional Neural Network (CNN) model with a training dataset consists of high-resolution stereo camera images acquired from a da Vinci Xi surgical system during several different procedure, this ML model enables precise localization and identification of tools within complex and dynamic environments like the human body. ML improves both the safety and efficiency of minimally invasive surgeries. Moreover, these recognition systems reduce the cognitive load on human operators by providing visual overlays, automating part of the perception tasks, and facilitating semi-autonomous behaviors.

In the field of rehabilitation, ML can be crucial in building robotic knees to assist individuals to regain the ability of walking. ML, especially Reinforcement Learning (RL) can learn directly from data of the robot. It avoids the need for a traditional mathematical model, which is hard to work well in human-robot systems. Thus, RL is considered to be ideal for solving complex controlling problems in robotic knees. Gao et al. addressed a new method in RL robot training called Flexible Policy Iteration (FPI) [4]. FPI integrates experience replay and prior knowledge into RL to ensure convergence, optimality, and system stability. Through simulated applications in robotic knee control, the study shows FPI's effectiveness of using less sample and cycles to achieve better performance compared to other methods like dHDP, NFQCA, and GPI, signalling its potential for high-dimensional control problems in robotic knees.

These advancements collectively mark the trends of reshaping in medical robotic systems with ML applications. Based on this circumstance, this review aims to synthesize the current research of ML applications in medical robotics by underlying their methods, discuss their implications, and evaluate their effectiveness in real-world clinical applications.

2. Method

To investigate how machine learning enhances the performance of medical robots across diagnostics, surgery, and rehabilitation, this section will review the core methodologies adopted by researchers in each domain.

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They have implemented various machine learning techniques to develop robotic systems capable of interpreting complex medical data and adapting to dynamic clinical environments. The following examples illustrate how these machine learning techniques have been practically implemented across different types of medical robotic systems, highlighting the algorithms, models, and training approaches used in each application:

2.1 Medical Diagnosis

2.1.1 Attention-based U-Net for robotic ultrasound system

U-Net is a well-established convolutional neural network architecture for image segmentation, particularly effective in biomedical imaging due to its encoder–decoder design and skip connections. The encoder–decoder design captures semantic context, while skip connections preserve spatial details, enabling U-Net to produce accurate, high-resolution image segmentations. Building upon this foundation, Jiang et al. introduce Optical Flow U-Net (OP-U-Net) [5], a novel extension tailored for real-time vessel segmentation in robotic ultrasound imaging under articulated motion. The key innovation of OP-U-Net is its integration of optical flow estimation into the U-Net structure, enabling the network to capture spatiotemporal continuity across sequential ultrasound frames. Optical Flow is the estimation of motion between two consecutive image frames. It describes how each pixel in one image moves to its position in the next, forming a vector field. It allows the model to recognize patterns of anatomical consistency even when the joint position or probe angle changes. OP-U-Net also incorporates a channel attention mechanism and a motion propagation module that fuses optical flow-derived features into the U-Net encoding path. This enhances the network's ability to identify vascular structures that may be faint, distorted, or temporarily occluded. As a result, OP-U-Net achieves superior segmentation accuracy and robustness compared to baseline models, especially in dynamic, motion-heavy ultrasound scenarios. This architecture is integral to the system's success in autonomously guiding an ultrasound probe to image target vessels using an MRI-derived anatomical atlas, bridging static planning with real-time adaptability.

2.1.2 Hybrid CNN framework for Skin cancer detection

Jitendra et al. developed a skin cancer detection system aiming to support clinical diagnosis by accurately classifying skin lesions, especially distinguishing between benign and malignant forms [6]. This model is a hybrid framework that combines machine learning and deep learning techniques for improved diagnostic precision. The deep learning component leverages CNNs to automatically extract semantic features from dermoscopic images, capturing complex lesion patterns. In parallel, the machine learning component utilizes handcrafted features such as Contourlet Transform and Local Binary Pattern Histograms, which emphasize texture and structural information. By integrating both automated and manual features, the ensemble model achieves enhanced accuracy and recall, surpassing individual model performance.

2.1.3 ML in Parkinson detection

Aditi Govindu and Sushila Palwe represents a stride in the application of telemedicine and machine learning for early-stage Parkinson's Disease detection [7]. By analyzing audio signals—specifically vowel phonations—using the MDVP dataset, the study proposes a non-invasive, remote diagnostic framework that caters especially to aging populations with limited mobility. Employing four machine learning models (Random Forest, SVM, Logistic Regression, and KNN). Through rigorous comparative analysis and intelligent dataset balancing and feature extraction (via PCA), the study underscores the potential of voice biomarkers as reliable indicators of PD, offering a scalable and cost-effective solution in global healthcare delivery. This achievement not only advances the computational diagnosis of neurodegenerative disorders but also exemplifies the integration of AI in personalized telehealth care.

2.2 Surgery

2.2.1 Machine learning for autonomous robotic vascular access

Vascular access is a critical procedure in clinical care but remains highly dependent on clinician expertise and is often challenging in pediatric or emergency settings. To address these limitations, Chen et al. invented a deep learning-based robotic guidance system for autonomous vascular access, representing a significant advancement in medical robotics [8]. This robot integrates a convolutional neural network (CNN) trained to detect and localize blood vessels in real-time ultrasound images with a robotic arm system capable of autonomous needle insertion. The CNN is trained on labelled ultrasound and NIR (Near-infrared spectroscopy) data to identify vascular targets, while real-time feedback is used to guide robotic motion. The system also includes a closed-loop visual serving controller that dynamically adjusts needle trajectory during insertion. Furthermore, the approach demonstrated robust performance across varying vessel depths and angles, showing potential for deployment in high-risk or underserved environments. This work represents a pivotal step toward autonomous, AI-driven clinical procedures that reduce operator variability and expand access to safe, effective vascular interventions.

2.2.2 Semantic segmentation of the instruments in the surgical console

Semantic segmentation of surgical instruments is essential in robot-assisted surgery for precise tool tracking and automation. Shvets et al. proposed specialized deep learning models that adapt and improve upon the standard U-Net architecture, it is called TernausNet [3]. TernausNet replaces U-Net's encoder with a pretrained VGG11/VGG16 network, leveraging transfer learning to significantly improve segmentation accuracy with limited medical data. This adaptation enhances feature extraction capabilities and reduces convergence time during training. Another model, LinkNet, utilizes a ResNet-based encoder-decoder architecture, designed for faster inference, making it suitable for real-time applications. The authors benchmarked these models on the MICCAI 2017 EndoVis dataset for both binary segmentation (tool vs. background) and multi-class segmentation (different tools and their parts), achieving state-of-the-art performance. These innovations led to substantial improvements in segmentation accuracy (e.g., TernausNet16 reaching a Jaccard index of 0.836 in binary segmentation) while maintaining computational efficiency, thus supporting real-time integration into surgical systems.

2.2.3 Deep learning for super-resolution in endomicroscopy

Probe-based confocal laser endomicroscopy (pCLE) has been essential in operating room because it is a method for live optical biopsies. However, the reliance of its hardware design on thousands of optical fibres fundamentally limits the image quality. Daniele R et al. proposed a novel synthetic data generation approach to training Deep Neural Networks (DNNs) to use it to generate a higher resolution image [9]. This innovation overcomes the lack of high-resolution (HR) training data by leveraging a video-registration algorithm to synthesize HR target images from sequential low-resolution (LR) video frames. These HR reconstructions are then paired with synthetically degraded LR images to train deep neural networks—eliminating the need for real HR pCLE data. This synthetic training pipeline significantly enhances the performance of DNN architectures, enabling accurate single-image super-resolution that previously required full video sequences. The effect of this innovation is substantial: it delivers improved image quality across multiple quantitative and qualitative metrics, including Mean Opinion Score, and demonstrates the feasibility of real-time optical biopsy enhancement using only individual pCLE frames. This breakthrough opens the door for clinical use of super-resolved pCLE imagery in environments where frame sequences are unavailable or real-time speed is essential.

2.3 Rehabilitation

2.3.1 Machine learning control of robotic knee

Robotic knee exoskeletons offer promise in rehabilitation by assisting human motor function, yet they are often constrained by the complexity of human-in-the-loop control and a lack of reliable adaptive learning mechanisms. Gao et al. proposed a novel Flexible Policy Iteration (FPI) framework to enable more stable and efficient reinforcement learning (RL) control of robotic knee systems during interaction with human users [4]. It enhances standard policy iteration by integrating experience replay and supplemental value functions, which allow the system to re-use past learning episodes and incorporate prior knowledge to accelerate convergence. In realistic simulations of human–robot knee control, exoskeleton equipped with FPI algorithm achieves smoother and more adaptive motion trajectories in response to human feedback. By reducing reliance on detailed biomechanical models, FPI enables stable robust, data-efficient adaptation in high-dimensional control environments, offering advancement toward intelligent and personalized robotic rehabilitation.

2.3.2 Smart wearable and ml-driven robotic hand for stroke rehabilitation

Stroke rehabilitation often requires precise, responsive systems that can interpret user intent and assist in motor function recovery. To address this, Yang et al. proposed an IoT-enabled stroke rehabilitation system that combines a smart wearable armband with machine learning algorithms and a 3D-printed dexterous robotic hand [10]. This innovation lies in the development of a lightweight, textile-integrated wearable device equipped with surface electromyography sensors that capture bio-potential signals from the forearm. These signals are pre-processed and wirelessly transmitted in real-time to a cloud-based ML model, which classifies up to nine distinct hand gestures. A critical innovation is the optimized feature selection algorithm, which improves classification accuracy while minimizing computational complexity. The system then maps these classified gestures to control signals for a robotic hand, enabling real-time gesture mimicry for functional hand training. This innovation provides a comfortable, responsive, and portable assistive system for stroke patients, enabling intensive and adaptive hand therapy outside traditional clinical settings. This approach facilitates early intervention and home-based rehabilitation,

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making recovery more accessible and effective.

3. Discussion

As shown above, ML has become essential to the advancement of intelligent medical robotics. However, while the methods demonstrate great progress, their clinical deployment is far from mature. These approaches face practical limitations that impact both their reliability in real-world settings and their broader applicability across diverse healthcare environments. This section critically discusses these challenges, ranging from technical limitations and interpretability to data privacy, and explores future directions, particularly focusing on the promise of AI-powered medical robots for home-based care.

3.1 . Challenges in diagnostic, surgical and rehabilitation robot

One challenge in diagnostic is the generalizability of ML-based robotic systems, which is facing diverted patient anatomies, clinical settings, and hardware configurations in diagnostic. Deep learning systems have demonstrated impressive performance in narrow diagnostic tasks but lack generalizability across diverse populations and real-world variability. Esteva et al. emphasized that AI models trained on limited datasets are prone to bias and often lack interpretability, posing serious risks when applied at scale in clinical settings [11].

In the surgical field, robotic systems promise enhanced precision and minimally invasive interventions. However, their deployment is constrained by high costs, limited surgeon training, and uneven global access. Reddy et al. outlined that despite the technological progress, robotic surgery adoption is hampered by a lack of large-scale outcome studies, resource disparities in low- and middle-income countries, and significant learning curves [12].

Rehabilitation robotics also face critical technical and clinical limitations. Yang et al. identified issues in wearable EMG-based systems, including sensitivity to electrode placement, signal noise, and user discomfort, which can degrade gesture recognition and long-term usability [13]. Moreover, their system's performance in controlled environments may not generalize well to real-world rehabilitation settings. In parallel, Gao et al. highlighted challenges in reinforcement learning (RL) control of robotic knees, such as data inefficiency, difficulty modelling human-robot dynamics, and lack of safety guarantees during real-time interactions [4]. These limitations underscore the need for more robust, adaptive, and patient-specific control strategies before clinical integration.

3.2 Challenges in interpretability and privacy

Beyond domain-specific issues, two overarching limitations also blocks the wide-ranged deployment of AI into medical robotics: interpretability, and data privacy.

Interpretability remains a major concern. Medical professionals should understand the rationale behind model decisions, especially when surgical or diagnostic choices are involved. Black-box deep learning models, while performant, lack intuitive outputs, limiting clinician trust. Explainable AI (XAI) tools like Grad-CAM and SHAP are being actively explored to address this issue [13]. Grad-CAM, for example, can highlight image regions that most influenced a decision, offering insights into why a segmentation or classification was made. Still, the clinical integration of these tools is minimal, and their interpretability remains indirect and non-intuitive for many end-users.

Meanwhile, data privacy and security pose major hurdles to collaborative AI development in healthcare. Traditional centralized training requires aggregating large volumes of patient data—a process that raises ethical, legal, and logistical concerns. Federated learning (FL) offers a compelling solution by allowing decentralized model training directly on local devices, without data leaving the hospital or patient's device. This technique enables institutions to collaboratively improve model performance while maintaining data confidentiality, a crucial benefit in high-sensitivity domains like surgical videos or personal rehabilitation metrics [14].

3.3 Future Prospects

Despite these challenges, emerging frameworks and technologies offer feasible paths forward. First, incorporating domain knowledge and expert systems can provide constraints that improve both interpretability and clinical safety. Integrating anatomical priors, known tissue characteristics, or procedural logic into model architectures helps reduce hallucinations and failure cases. Hybrid models that combine rule-based logic with deep learning, such as anatomy-aware U-Nets or reinforcement learners with kinematic constraints, represent a promising direction.

Second, XAI tools like SHAP and Grad-CAM need tighter integration into medical software interfaces. For surgical robots, real-time heatmaps showing which tissue region influenced a decision can enhance surgeon confidence and allow for human override. In diagnostics, saliency-based overlays on ultrasound or dermoscopic images could make ML outputs more understandable and auditable by clinicians [9].

Third, federated learning has the potential to revolutionize collaborative model development in healthcare. By decentralizing the training process, FL allows multiple clinics, hospitals, or even home-based devices to improve a shared model without exposing sensitive data. This is especially promising for rehabilitation and chronic condition monitoring, where longitudinal data collected from patients at home can significantly enrich models while preserving privacy [14].

4. Conclusion

This article has reviewed how machine learning empowers medical robots across diagnostics, surgery, and rehabilitation, fundamentally enhancing their intelligence, adaptability, and clinical value. From real-time image segmentation in robotic surgery to reinforcement learning-driven rehabilitation and AI-assisted home diagnostics, these innovations demonstrate the transformative role of AI in advancing precision medicine. The integration of ML enables robots to interpret complex data, adapt dynamically, and support clinicians in high-stakes decisions. However, challenges remain current systems face limitations in generalizability, interpretability, and data privacy, hindering widespread clinical adoption. Addressing these gaps will require robust regulatory frameworks, improved explainability tools, and decentralized training solutions such as federated learning. Despite these hurdles, the trajectory of development is clear—AI-powered medical robots are poised to reshape healthcare delivery, extending high-quality care from the operating room to the patient's home. Continued interdisciplinary collaboration will be key to ensuring these technologies are not only effective but also ethical and accessible.

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