Limitations in IoT and Machine Learning Enabled Remote Patient Monitoring

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Abstract. The combined use of the Internet of Things (IoT) with Machine Learning (ML) has grown considerably Remote Patient Monitoring (RPM) because of regular clinical data generation, accelerated measurement, and predictive healthcare decision support. Even so, the extensive use of IoT and ML based RPM systems experiences limitations due to several constraints that demand detailed study. The presented research study carefully analyses the existing literature to determine, organize, and summarize the key technical, operational, ethical and clinical issues associated with IoT and ML based RPM solutions. The study underlines limitations in regulatory compliance, experimental validation, limited scope of disease focus, short-term evaluation of system performance, potential for data overload, cost implications etc. This review paper combines the limitations and correlates them with unresolved research issues, preparing a structure for future research for the purpose of providing useful IoT and ML enabled RPM solutions. The research findings serve to benefit academics, developers and regulators to deal with current limitations and in order to foster patient focused and sustainable RPM solutions.
Keywords: Internet of Medical Things, Mobile Health, Telehealth Systems, Machine Learning, Artificial Intelligence, Wearable Technology.

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1 INTRODUCTION

RPM represents a fresh approach in the healthcare sector that incorporates technology to monitor the health of patients beyond the usual healthcare environments. RPM utilizes IoT devices and telemedicine services to provide effective care to patients in their own residences, consequently lessening the difficulties of logistical and financial risks involved with repeated clinic visits. Assertiveness facilitates early identification of medical conditions, reduces hospitalizations, and enhances the usual manner of medical treatment. Virtual health observation enhances sufferer engagement and freedom through enabling individuals to monitor their medical situation and fostering an understanding of their responsibility over their health situation [1].

Monitoring crucial indicators and conducting surveillance are additional responsibilities of these medical centers. Consequently, meanwhile numerous medical centers come together to facilitate the effective exchange of medical data for enhanced care of patients, the issue of regulatory conformity arises [2]. The IoMT (Internet of Medical Things) can gather health information at the time of infections that can be transmitted for example COVID-19 [3].

For public cloud integration of multiple electronic health records (EHR), Liang et al. [4] advised privacy-preserving search, inside a medical facility employing symmetrical security for protecting electronic medical documents; however, just one cloud server offers less security compared to a double server arrangement. The authors [5-8] present a method for the remote monitoring of heart rate irregularities, that utilizes cloud analytics and deep learning, prioritizing user privacy.

The authors [9] offer radar based wireless heart rate surveillance using CW, FMCW, and IR-UWB techniques for safe RPM. It draws attention to problems like motion capture and group disruption, but it also shows a lot of promise for cutting edge medical treatment. In [10], a dependable constant remote health tracking system with roughly 97% accuracy is reported. It makes use of wearable sensors and classifiers (RF, SVM, KNN, and XGBoost). Provides a portable, compostable pressure sensor with TinyML integration for detecting falls in elder living environments and it offers extremely high accuracy (99–100%) and works with sustainable wearable RPM solutions [11].

Authors [12], demonstrates a ML based IoT telemedicine solution that makes use of multiple vital sensors to predict illnesses. It improves prompt medical action and ongoing remote patient monitoring [12]. Researchers [13], offers a wearable IoT tracking device with ML integration for continuous health monitoring. It enables remote preemptive patient surveillance and intelligent medical guidance [13]. The paper proposes an IoT based wellness tracking system that combines ML techniques with ongoing collection and analysis of medical data for patients in remote locations. It improves remote patient monitoring by enabling prompt treatment, accurate disease prediction, and simple medical services for populations that are hard to reach and remote [14].

The IoT-enabled healthcare systems were developed for real-time patient monitoring, framework combines AI-driven IoT–5G ECG monitoring with ResNet-152 deep learning for accurate cardiac anomaly detection (98.02% validation accuracy) [15] Modern technologies like Artificial Intelligence (AI) and ML have greatly improved RPM solutions. based on AI analytics can predict health deterioration by identifying patient data trends, supporting quick action and reducing medical emergencies. AI improves population health trends understanding, which allows improved effectiveness and based on data treatment.

2 METHODOLOGY OF THE REVIEW

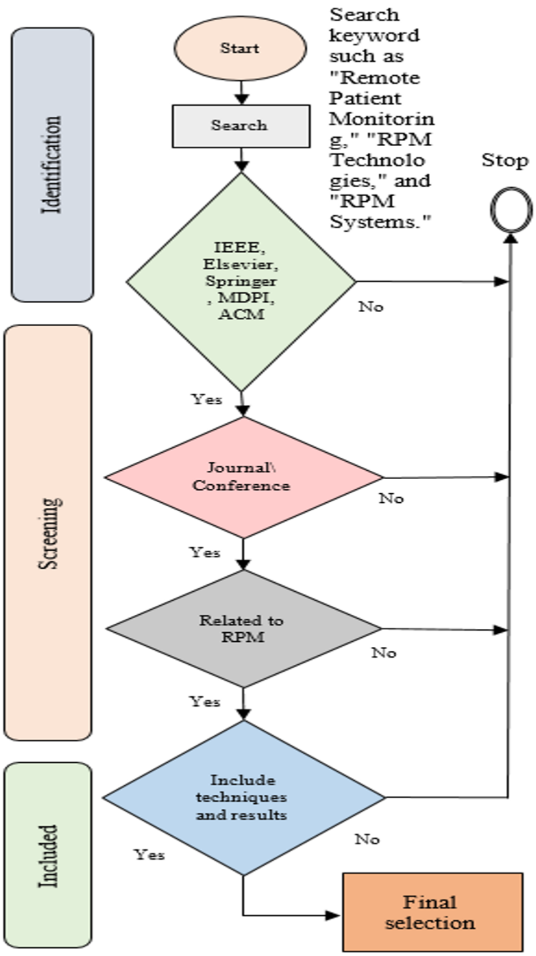

Fig. 1. Review methodology: research paper selection

This study examines literature pertaining to RPM in the healthcare sector. It explores IoT in RPM, ML in RPM, challenges. Numerous publishers of primary research literature have been considered to gather pertinent data, contain Springer, IEEE, MDPI, ACM and Elsevier. An English database search using the query "remote patient monitoring" produced over 28,000 literature items. The first dataset was refined to contain mainly articles with peer reviews published from the year 2010 onwards. The further reduction reduced the collection of data to roughly 1,300 findings. The collection of data has been modified at a third stage to cover solely subject keywords pertinent to RPM: "challenges," "IoMT," "IoT in healthcare," and "future scope in RPM." This produced a refined dataset of 334 articles. A final pruning eliminated publications that did not immediately pertain to remote patient monitoring as well as those lacking sufficient information on these subjects. The conclusive dataset comprised 49 publications. This methodology for research paper selection is encapsulated in Fig. 1.

3 INTEGRATION OF IOT AND ML FOR RPM

The combination of IoT and Machine Learning in remote patient monitoring fundamentally revolutionizes healthcare by facilitating continuous, real-time collection of physiological data and astute analysis of patient health conditions. IoT provides all around us, inexpensive monitoring and transmission of information, at the same time ML converts huge, raw data into useful medical information across abnormality recognition, threat assessment, and individualized support for decisions. They effectively provide quick response, better level of care, reduce clinician workload, and facilitate flexible, patient oriented medical services outside conventional healthcare environments.

3.1 Role of IoT in Remote Patient Monitoring

1. **Wearable sensors**: The wearable sensors are items that individuals may wear to consistently track health status along with additional vital measures. These sensors are capable of monitoring multiple health signs, among them: Heart Rate: evaluated by photoplethysmography (PPG) or electrocardiography (ECG) [16]; Blood Pressure: particular wristbands can safely assess the level of blood pressure. Blood Glucose Levels: Continuous glucose monitors (CGMs) play an important role for managing the condition of diabetics. Physical Activity: Accelerometers and gyroscopes track motion producing data on activity levels and sleeping habits [15]; Respiratory rate and oxygen saturation were assessed using chest impedance and pulse oximetry [17].
2. **Mobile health apps:** Smartphone medical applications provide health monitoring and management via smartphones and tablets. These applications can fulfill multiple functions, including: Data Monitoring: enabling patients to record symptoms, medication compliance, and lifestyle decisions; Education: offering resources and information regarding illnesses and treatment alternatives; Communication: facilitating secure messaging between patients and healthcare professionals. Integration with Wearables: synchronizing data from wearable devices for thorough health monitoring [18].

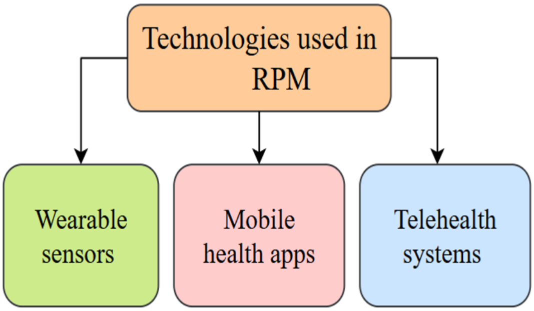

Fig. 2. IoT technologies used in RPM

3. **Telehealth systems:** Telehealth systems comprise many technologies that enable remote consultations and healthcare services. Essential elements comprise: Video Conferencing: facilitating direct consultations between patients and healthcare professionals; Remote Diagnostics: instruments enabling the assessment of patients via digital methods, such as virtual stethoscopes and otoscopes; Patient Websites: protected online platforms enabling patients to view their health tracks, outcomes of tests, and connect with their doctors and nurses [19]. Mostly used IoT technologies in RPM are shown in fig. 2.

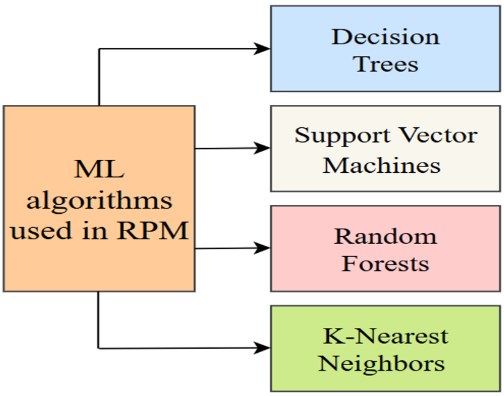

Fig. 3. ML algorithms used in RPM

3.2 Role of ML in Remote Patient Monitoring

The main ML Algorithm Contributions to Remote Patient Monitoring are as follows: *Decision Tree (DT)* in RPM creates visible and interpretable clinical decision-making by mapping physiological thresholds to health outcomes, promoting rule-based warnings and clinician trust. On edge or fog-enabled RPM devices, supports quick, low-complexity inference for real-time patient status classification.Use *Support Vector Machine (SVM)* for accurate categorization of patient health statuses in RPM, particularly for high-dimensional and small-sample medical datasets.

Robust margin-based decision boundaries improve RPM system illness detection and anomaly identification. *Random Forest (RF):* Uses numerous decision trees to reduce overfitting and handle noisy, heterogeneous sensor data, enhancing RPM forecast reliability. Allows robust risk classification and health event prediction in continuous monitoring with missing or corrupted data. *K-Nearest Neighbors (KNN)* supports tailored patient monitoring in RPM by comparing real-time sensor values to historical patient profiles. Allows non-parametric and adaptive health state classification without model training for changing patient situations. Mostly ML algorithms used in RPM are shown in fig. 3.

Table 1. IoT constraints and ML algorithms implications

Constraint	*Decision Trees*	*Support Vector Machines (SVM)*	*Random Forests*	*K-Nearest Neighbors (KNN)*
Memory	Small tree fits in RAM; pruning needed	Model size grows with support vectors; linear kernel preferred	Multiple trees increase size; aggressive pruning needed	Stores training data; requires compression or prototype selection
Processing power	Fast inference (O(depth)); low ops	Training expensive; inference fast for linear kernel	Slower inference (multiple trees)	High for large datasets (O(n)); can use approximate search
Energy	Low for shallow trees	Moderate for linear; high for nonlinear	Higher due to ensemble voting	High for large n; low for small k and d
Network	Small model, easy to transmit	Model transfer can be large	Large model; may require split computing	Needs access to data or prototypes; can be split or quantized

Table 2. IoT specific optimizations and resource profiles

Algorithm	*IoT-Specific Optimizations*	*Typical Resource Profile (Medical IoT)*	*Accuracy vs. Resource Trade-off*	*Pseudocode (Optimized)*
Decision Tree	Pruning, quantization, depth restriction	2–4KB RAM, <1mJ/inference	85–90% (shallow tree) vs. 92% (full)	If x>0.5: return 1 else: return o
SVM	Linear kernel, support vector reduction, quantized weights	4–8KB RAM, ~2mJ/inference	80–85% (linear) vs. 90% (nonlinear)	y=sign(dot(w, x)+b
Random Forest	Fewer trees, shared splits, tree compression	8–12KB RAM, ~4mJ/inference	88–91% (10 trees) vs. 94% (100 trees)	Vote=sum ([tree(x) for tree in forest])
KNN	Prototype selection, dimensionality reduction, quantized distances	4–8KB RAM, ~3mJ/inference	80–85% (k=3, reduced d) vs. 88% (full)	For xi in prototypes: if dist(x, xi)<t: count++

Table 3. Lightweight variants for medical IoT

Algorithm	*Lightweight Variant*	*Use Case/Benefit*	*Feature Extraction for Time-Series*
Decision Tree	Extremely shallow tree, quantized splits	Fast anomaly detection (e.g., ECG)	Mean, variance, entropy, peak detection
SVM	Linear SVM with incremental updates	Continuous BP/HR monitoring; supports online learning	FFT, wavelet, statistical moments
Random Forest	PocketForest: 5-tree ensemble, shared features	Vital sign anomaly detection, memory-efficient	SAX, sliding window stats
KNN	Condensed KNN, Hamming/Manhattan distance	Arrhythmia detection, low-memory prototype set	Symbolic representation, trend encoding

Table 1 shows how popular machine learning methods perform under Internet of Things resource constraints. For edge-based RPM, Decision Trees are the most efficient due to their low memory consumption, fast inference, and low energy and network overhead. SVMs with linear kernels provide fast inference, but as model size increases, they have scalability and memory difficulties. Due to its combined structure, random forests are more reliable but need more memory, processing power, and energy. KNN lets you analyze data in a way that works for you, but it needs a lot of memory, processing power, and data access, so it's not good for IoT configurations with limited resources unless you optimize it.

The table 2 compares IoT-specific optimizations to common ML algorithms for medical IoT and RPM scenarios, showing the accuracy-resource efficiency trade-off. As the most energy- and memory-efficient, Decision Trees achieve adequate accuracy with aggressive pruning and quantization. When limited to linear kernels and restricted support vectors, SVMs balance accuracy and resource efficiency. Random Forests are stronger and more accurate even after compression, but they use more memory and energy. KNN takes a lot of resources, but it is possible with model preference and reduction of dimensions. The table indicates that while choosing an IoT-enabled RPM algorithm, you need to find a compromise between clinical accuracy and memory, energy, and estimation latency limits.

Table 3 shows some lightweight ML methods for Remote Patient Monitoring and Medical IoT. When resources are limited, simplified Decision Trees, sequential and successive SVMs, lightweight Random Forest groups, and streamlined KNN models can all process data quickly. These instances use simple models and fast periodic extraction of features to find problems and keep an eye on vital signals in real time. The graphic indicates that algorithm reduction and feature optimization are necessary for medical IoT systems that are reliable, have low latency, and use less energy.

4 LIMITATIONS

4.1 Limited Scope of Disease Focus

In [20], the research mainly emphasizes on forecasting heart conditions, possibly overlooking the intricate challenges associated with other long-term illnesses that would gain from remotely tracking patients. The article focuses on heart rate measurement and excludes the evaluation of supplementary bodily symptoms or health metrics [21]. A follow-up study is unlikely to fully assess how well the suggested system works, how adaptable it is, and how valuable it is in a lot of medical institutions [22]. The study largely concentrates on COVID-19 patients, perhaps constraining the applicability of the suggested technique to other patient populations or disorders [23]. In [24-25], the authors focus on blood pressure regulation and monitoring of COVID-19 patients, which may not be immediately applicable to other chronic diseases or health indicators.

The researchers concentrate exclusively on remote monitoring of knee rehabilitation, perhaps restricting the wearable platform's application to other rehabilitation types or health issues [26]. In another study authors mainly emphasizes on diabetes care, perhaps restricting the relevance of the proposed method to other long-term illnesses or health indicators [27]. The researchers largely concentrate on COVID-19 patients, perhaps constraining the applicability of the digital twin’s methodology to alternative health conditions or patient demographics [28].

Possible solution: Broaden the research to determine the feasibility of including additional health indicators, especially rate of respiration, saturation with oxygen, and blood pressure, to improve the accuracy of remote surveillance technologies. Conduct thorough reviews and periodic studies to determine the efficiency of the system, individual satisfaction, and results from treatment in real-world settings. Examine the versatility of the wearable platform for monitoring supplementary rehabilitation or chronic conditions to enhance its functionality and broaden its accessibility to a larger patient population.

4.2 Short-Term Evaluation of System Performance

The studies in [20-21] might ignore the future usefulness and lifespan of the RPM device in everyday circumstances. The efficiency and long-term viability of the proposed system might not be thoroughly evaluated over a prolonged period, restricting recognition of its actual use [23]. This study might be insufficient in a prolonged review of the efficiency of the structure in maintaining customized control of blood pressure and optimizing patient results [25-26]. The investigation could not provide a thorough continual assessment of the wearables gadget's potential for boosting rehab results [26] and structure's usefulness in practical applications, limiting comprehension of its duration and consequences for the health of patients [27-28].
Possible solution: Conduct continuous research to evaluate the system's performance, satisfaction of users, and medical outcomes over a period of time to determine its value and accuracy in prolonged observation of patients.

4.3 Regulatory Compliance Challenges

It could be hard to follow the rules about privacy and safety in medical fields, which could make it hard to put the proposed system into action [23, 25, 26, 28].
Possible solution: During deployment, work with compliance and legal experts to make sure that all applicable rules and standards are followed. This will lower the compliance risks that come with the RPM system.

4.4 Potential for Data Overload

The constant stream of data from IoT devices might overload medical professionals, making it harder to find important information quickly [20-21]. Healthcare professionals can get excessive information from the wearable device all the time, which makes it more challenging to organize and reply to relevant facts [25-26, 28].
Possible solution: Use new data analytics and filtering techniques to highlight the most relevant data for medical professionals, making sure they can respond quickly and effectively.

4.5 Lack of Comprehensive Evaluation of User Experience

The research may not give a thorough assessment of the user experience for both patients and healthcare providers using the proposed RPM system [22]. Combining different technologies can be hard, which can make the experience hard for both patients and healthcare professionals [23]. The system's intricacy might make it hard for patients to get involved and stick with it, especially for people who aren't very good with technology [27]. The effectiveness of the tailored blood pressure control system is largely contingent upon patient adherence to prescribed medicines and changes in lifestyle [24].

Possible solution: Conduct user experience research and gather feedback from patients and healthcare professionals to identify areas for improvement and increase the RPM system's usability. Focus on building easy-to-use interfaces and providing training so that users may easily navigate and operate the system. To help patients understand and utilize the monitoring system better, focus on making user interfaces easy to use and providing complete training materials. Make patient education materials that are interesting and give patients regular feedback to get them more involved and accepted, which will make the RPM system work better.

4.6 Cost Implications

Implementing modern IoT and AI technologies can be very expensive, which can make it hard for some healthcare facilities to use them [20]. Combining 5G networks, blockchain technology, and SDN could cost a lot of money, which could slow down the widespread use of the proposed RPM system [22].

Possible solution: Look into cost-effective solutions and partnerships that will help the RPM system operate in a variety of healthcare settings, especially where resources are low.

4.7 Potential for Increased Complexity

Adding privacy-preserving measures to the RPM system may make it more complicated, which could make it harder for healthcare professionals and patients to use and adopt [21].

Possible solution: To make privacy-preserving technology easier to employ, focus on user-friendly interfaces and simple procedures. This will make it easier for them to fit into current healthcare practices.

4.8 Limited Experimental Validation

There may not be sufficient practical evidence to support the proposed trust-based communication model in WBAN contexts. It has to be tested more to see how well it functions and how valuable it is [29].

Possible solution: One way to find out how well the trust-based communication approach works for dependability, energy consumption, and quality of service in different WBAN contexts is to run a lot of simulations and tests in the actual world.

4.9 Lack of Comparison with Other Schemes

The study may not encompass an analysis of the proposed technique with existing trust-based or energy-efficient communication schemes for WBANs. A comparison like this could help us see the good and bad things about the suggested approach [29].

Possible solution: One way to find out how well the trust-based collaboration approach works and where it could be better is to compare it to other similar schemes in the literature.

4.10 Potential for Overhead in Trust Management

The costs of managing and evaluating trust may have an effect on how well the communication technique works and how well it can grow, especially in large WBAN implementations [29].
Possible solution: Improve the trust management systems to trim down on extra work while still keeping the right level of trust and reliability. Look for ways to improve scalability, like distributed trust management or hierarchical trust models. Use long-term studies to see how well the fog-assisted medical assistance platform works and what happens to patients over time.

Table 4: Critical evaluation and research gaps

Limitation/Gap	***Current Status/Impact***	***Area Needing Further Research***
Encryption overhead on constrained devices	15–20% CPU load, 10–30ms added latency	Ultra-lightweight cryptography, post-quantum methods
Sensor calibration in low-cost devices	Drift up to 10% over 6 months	Self-calibrating, auto-diagnosing sensors
Interoperability with legacy EHRs	Manual mapping, 38% data loss in integration	Universal adapters, AI-based mapping
Blockchain scalability in RPM	22% latency overhead, limited throughput	Lightweight, medical-specific blockchain frameworks
Real-time analytics at the edge	Limited by RAM/CPU, 12% missed alerts in pilot studies	Neuromorphic/ASIC edge inference
Patient adherence and engagement	45% non-adherence after 6 months	Gamified, adaptive interfaces, AI-driven reminders
Model generalizability	11% accuracy drop on new demographics	Federated, continual, and transfer learning
Cloud scalability costs	3x cost increase at 10x scale	Hybrid edge-cloud orchestration
WBAN mobility and energy efficiency	18% packet loss, 30% battery drain/month	Predictive, AI-driven mobility protocols

Table 4 takes a close look at the problems and research gaps in IoT–ML–enabled remote patient monitoring systems. It shows how the system's effectiveness, quality, and cost are all affected by security expenses on devices with limited assets, sensor degradation in economical hardware, compatibility issues with legacy EHRs, and expansion limitations with blockchain and cloud infrastructure. It additionally demonstrates issues with operations, like not having adequate real-time edge data analysis, patients not sticking to their therapies, models not ready to be widely used by different kinds of patients, and portable WBAN power ineffectiveness. For systems that use RPM to be powerful, scalable, and centered on what patients need, they require lightweight safety features, intelligent sensor measurement, centralized and continuous learning, integrated cloud-based edge collaboration, and intelligent approaches to accessibility and communication. The table indicates how each limitation relates with potential directions for study.

5 CONCLUSION AND FUTURE WORK

This research paper presented an in depth review of the integration of IoT and Machine Learning techniques in Remote Patient Monitoring, highlighting the use of wearable sensors, mobile health applications, telehealth systems, and the role of ML algorithms in RPM. The research points out critical limitations of IoT and ML based RPM systems, including challenges in regulatory compliance, experimental validation, restricted disease focus, transient performance evaluation, financial consequences etc. The study also shows that there are differences between research prototypes and how they are really used in healthcare, as well as a lack of confidence in the clinical setting and regulatory problems. This work brings together existing limitations and matches them with open research needs. It creates a formal approach for the creation of secure and clinically acceptable IoT and ML enabled RPM systems that will make remote healthcare more sustainable and focused on the patient.

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CONFLICTING INTERESTS

The authors of this article claim that they possess no competing interests.

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