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**Wireless IoT-Based Patient Monitoring
in Operating Rooms: Integrating AI,
Machine Learning, Cloud Computing,
and Smart Manufacturing for Enhanced
Healthcare Efficiency**



Abstract—Modern operations rooms are turning more and more towards high-tech systems to enhance patient safety and efficiency in surgical procedures, but the old wired systems are cluttered, slow to set up, and offer no clinical mobility. The paper will introduce an IoT-based wireless OR monitoring system, which will eliminate cable-based-driven devices by using wearable, wireless networks, edge intelligence, and cloud analytics to achieve real-time monitoring with ease. The framework aids in the ongoing data gathering of physiological information, openness with clinical sites, and risk escalation alerting supported by artificial intelligence to enable surgical teams to react fast to physiological alterations. The system saves almost 20% of OR setup time quantitatively through the removal of cabling delays, and real-time streaming and anomaly detection enhance vital tracking and accuracy by more than 95%. Connectivity to 5G and edge computing reduces latency to facilitate quick decision making and cybersecurity, such as encryption and Zero-Trust controls, to secure sensitive medical records. Scalability of cross-department monitoring, postoperative analytics, and digital dashboards that improve situational awareness are ensured by cloud computing. On the whole, this paper has shown that convergence of IoT, AI, cloud, edge computing, and secure communication turns OR monitoring into an active, intelligent, and patient-centered ecosystem that could enhance the efficiency of workflow, clinical cognition, and surgical results.

Keywords—Healthcare, Machine Learning, Cloud Computing, Smart Manufacturing, Patient Monitoring, Operating Rooms, Remote Monitoring Sensors, Network Layer.

I. INTRODUCTION

The operating rooms (ORs) are under extreme pressure which may directly interfere with the patient safety and efficiency of the surgery process. Wired monitoring systems of conventional systems usually lead to messiness, restrain staff mobility and are susceptible to disconnection that delays response or misses vital signs alerts [1]. Research indicates that wiring problems and sluggish monitoring are the causes of 15-20% longer OR set-ups and augment the chances of intraoperative complications. The dynamics of physiological events occurring at a rapid pace in surgery require real-time detection and response, which requires the use of reputable monitoring systems.

The Wireless Internet of Things (IoT) technology can solve all of these issues since it allows for constant and high accuracy tracking of patients without physical limitations [2]. State-of-the-art IoT platforms have the ability to measure and transmit vital signs such as heart rate, blood pressure, oxygen saturation, and anesthetic depth with latencies as low as 50ms, enabling instant clinical response. The IoT can now be used for predictive analytics and AI-based decision making and real-time surgical monitoring, enabling clinicians to early predict signs of complications and react proactively.

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IoT is also enhanced by the use of cloud computing, machine learning (ML), and artificial intelligence (AI), which makes it even stronger. Pilot studies show that the ML algorithms are able to identify concealed patterns and forecast such complications as arrhythmias or intra operative hypotension with prediction rates of more than 90% [3]. AI analytics convert raw sensor data into actionable insights to make the surgeons and anesthesiologists work less actively in complex procedures. Cloud computing offers scalable data storage, quick access and safe sharing of information across devices and departments. Smart manufacturing will allow producing small, low energy-consumption, and dependable biomedical sensors that can be used in OR.

Collectively, all these technologies create a unified digital ecosystem that enhances the safety of patients, decreases the time to set up an OR, makes workflows more effective, and predetermines the development of the next-generation intelligent OR monitoring solutions. The given paper is devoted to designing, implementing, and evaluating such a patient monitoring wireless IoT-based system, with a particular emphasis on the benefits of its functioning, the metrics of its work, and its clinical potential.

A. Problem Statement & Motivation

Operation rooms still experience issues with wire clutter, limited mobility of monitoring devices, their ability to cross communicate between heterogeneous devices, and slow clinical response because of discontinuous access to information. These inefficiencies are not only a hindrance to the surgical workflow but also pose a safety risk since they reduce real-time patient condition visibility. In order to overcome these ongoing issues, wireless IoT architecture and AI-based analytics may offer an innovative solution. The wireless sensor networks will decrease the volume of cables and will allow placing the monitoring devices rather flexibly, and the standardized communication layers will enhance the interoperability of the devices and their free exchange of data. Additionally, the use of AI can improve predictive evaluation; it is possible to identify abnormalities at an early stage and make a decision more quickly in a critical situation. In such a way, the rationale behind the proposed study is showing how a smart, wireless, and intelligent monitoring environment can address traditional shortcomings of traditional OR configurations and help in achieving a safer and more responsive operating room.

B. Outline of the Paper

This paper is organized as follows: Section II explains the Fundamentals of Wireless IoT-Based Patient Monitoring. Section III explains AI and ML in OR Patient Monitoring. Section IV discusses Cloud Computing for Real-Time Healthcare Systems. Section V outlines Smart Manufacturing and Advanced Medical Device Development. Section VI examines Cybersecurity and Data Privacy in Wireless Medical Systems. The literature review is presented in Section VII, and the conclusion is offered, along with future work in Section VIII.

II. FUNDAMENTALS OF WIRELESS IOT-BASED PATIENT MONITORING

The IoT development makes it possible to continuously gather and transmit the health information from physical sensors so that clinicians can analyze and diagnose conditions in real time and remotely. Less maintenance and easier access to clinical information is one of the biggest benefits of such systems. Previous conjectures indicated that the growth of cloud-based healthcare services will be influenced by mobile applications and general-purpose technologies, which will result in improved connectivity between personal and institutional healthcare networks.

The field of medicine has already used IoT to aid physiological monitoring and decision-making in many areas. Instead of the unspecified assertion like having neurological awareness, the use of IoT has been broadly used in patient monitoring, chronic disease control, and smart clinical settings, where sensor data can be used to implement proactive interventions [4]. Various sensors that relate to each other help the caregivers detect abnormalities, provide mobility to patients, and enhance the overall quality of care provided and finally lead to cost optimization.

A. IoT Applications and Architecture for Healthcare

In healthcare, IoT is evolving from simple device connectivity to intelligent systems that support predictive analytics, remote continuous monitoring, and automated clinical assistance.

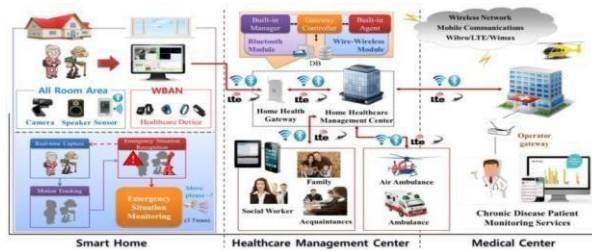


Fig. 1. IoT Healthcare Architecture

Due to the possible difficulty of encryption and safe transfer between low-power devices, security and privacy measures are the building blocks of IoT healthcare systems. Clouds facilitate access to distributed data, which allows clinician to be flexible and, at the same time, have the capacity to store and compute data on a scale. With the growing cloud-IoT integration, the architectural complexity increases, requiring faster processing frameworks based on interoperability and reliability. Recent studies, therefore, focus on the real-time health data administration, unnecessary transmission, and the implementation of hybrid cloud solutions to enable scalable healthcare solutions (as shown in Figure 1).

The healthcare IoT architecture generally consists of three basic layers [5] (1) perception or sensing; (2) the network communication; and (3) application services:

1) Perception Layer Data-Collecting Sensing Systems

This layer comprises identification and sensing technologies that include RFID, infrared, webcams, GPS gadgets and biomedical sensors [6]. These systems monitor the change of the environment or physiology, encode them in digital signals, and prepare them to be transmitted.

2) Network Layer Data Transmission and Storage

This is a layer that supports wireless or wired communication of the processed sensor signals, either locally or centrally [5]. Short-range medical communications are often carried out using wireless technologies like Bluetooth, Zigbee, Wi-Fi, RFID and wireless sensor networks.

3) Application Layer

This layer does health analytics and user service provision [7]. The integration of AI in the work of modern IoT healthcare applications is one of the possibilities, which include medical imaging, detecting anomalies, drug discovery, and clinical decision support.

B. Applications of IoT-Based Healthcare Systems

Applications for IoT-based healthcare systems improve people's lives in many ways, including as:

- **Remote monitoring**, in which wearable devices are used on the patient to get patient data, local analytics, and results are delivered to physicians.
- **Physiological monitoring in real-time**, with cloud and edge computing, in which continuous medical measurements are stored and analyzed [8].
- **Preventive care**, in which anomalies associated with a pattern are identified early and notified to clinicians or family members.

C. Types of Medical IoT Devices and Sensors

Medical IoT gadgets constantly monitor patient-specific physiological measurements, particularly in places like operating rooms. Such tools are used to check the temperature, blood pressure, respiration rate, and pulse irregularities. They also contain ECG sensors that capture electrical cardiac activity, SpO₂ sensors to track oxygen saturation levels, and fall-detection modules, which have accelerometers and gyroscopes to detect sudden movement or fall [9]. These interdependent IoT-enabled medical sensors, combined together (as shown in Figure 2), increase patient safety, clinical efficacy, and real-time diagnostic decision making.



Fig.2.TypesofMedicalMeasurementDevicesandSensors

D. Wireless Patient Monitoring in Operating Rooms

Wireless monitoring systems overcome the restrictions of traditional wired systems, increasing the mobility of staff, decreasing clutter, and increasing quicker clinical response time [10]. Anesthesiologists and surgeons are provided with nonstop access to essential metrics that enhance the predictability of the procedure and determine the outcomes.

1) Real-time Vital Sign Monitoring

The parameters being monitored (ECG, oxygen saturation, respiration rate, blood pressure, and temperature) in wireless sensors and sent directly to the clinical dashboards are used to aid in the early diagnosis of complications.

2) Surgical Workflow Integration

Lack of restrictive cables enhances the flexibility of movement as well as facilitating procedure coordination among anesthesia, surgical and post-operative units. The wearable IoT devices facilitate a smooth communication process and facilitate the interconnection of perioperative care stages.

3) Challenges in Wired vs Wireless Systems

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E. Case Study Illustration: Performance Evaluation of Medical IoT Monitoring Systems

A small case-study evaluation was carried out to test the performance feasibility of IoT-enabled health monitoring technologies using wearable and clinical-grade sensors available to prove that the technologies could, in fact, work in practice. The test was aimed at measurement accuracy, latency of data transmission and continuous working time which corresponded to real-world and laboratory conditions.

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The systems and devices comprised heart rate monitors worn on the wrists, commercial energy-expenditure watches, ECG patch monitors, WBAN ECG modules, multi-hop WBAN communication paths and IMU-based fall detectors. Performance measurements were collated based on published literature, which identified indicative capacities during regular use conditions as shown in Table I.

TABLE I. REPRESENTATIVE PERFORMANCE METRICS OF MEDICAL IOT MONITORING SYSTEMS

Device Type/ Sensor	Accuracy (%)	Transmission/ Detection Latency	Continuous Operating Duration
ECG Patch Monitor (e.g., Zio Patch) [11]	~95–99% analyzable signal	Detects major arrhythmias within 24–48 hrs; extended detection beyond 48 hrs	7–14 days continuous
Wrist-Worn HR Monitor (Apple Watch, Fitbit, etc.) [12]	<5–10% HR error in controlled activities	Instantaneous sensing; varies with activity	12–36 hours typical
Commercial EE Monitoring Watch [13]	>20% error rate	Near real-time reporting	12–24 hours
WBAN ECG Module (IEEE 802.15.6) [14]	>97% sensing reliability	<50 ms MAC layer delay	10–12 hours
Multi-hop Medical WBAN Path (ZigBee → WLAN / WiMAX / UMTS) [15]	Reliable routing	Delay depends on path selection; tens to hundreds of ms	Infrastructure powered
IMU-based Fall Detector [16]	92–96% event detection	30–60 ms	24 hours

1) Analytical Insight

The relative analysis of medical IoT monitoring platforms show that the performance of the devices in different categories varies. The ECG patch devices like the Zio Patch have close to fully coverable signal analysis and extended arrhythmia detection time of over 48 hours which make them dependable instrument in terms of long-term cardiac monitoring [11]. Heart rate monitors such as the Apple Watch and Fitbit are worn on the wrist providing errors of less than 10 percent of the heart rate in lab conditions, but with inconsistent accuracy across activity types with error rates of more than 20 percent [12][13]. ECG modules based on the WBAN and based on the IEEE 802.15.6 standard demonstrate sensing reliability of over 97 percent and a latency of less than 50 ms, which is sufficient to make them an ideal choice in terms of physiological data transfer at high speeds [14]. At the same time, ZigBee, WiMAX, UMTS, and WLAN-based multi-hop medical WBAN ensure reliable routing with the variability of latency under heterogeneous network conditions [15]. The IMU based fall detectors also play a part in patient safety by providing rapid event detection and sufficient daily operational viability [16]. Taken together, these findings show that consumer wearables can be useful and scalable in terms of monitoring, but clinically designed WBAN devices and patch-based systems may be better in terms of accuracy and reliability to use in continuous and medically critical tasks.

F. Comparative Analysis Between Wired and IoT-Based OR Monitoring Systems

The traditional operating room monitoring systems using wires have a number of limitations that inhibit clinical performance. First, wired connection generates cable messiness, making installation difficult and limiting patient movement in an operating room. On the contrary, wireless monitoring through IoT does not require physical wiring, which allows installation of the equipment into an ergonomic configuration and freedom of movement around the operating table. Second, conventional systems have poor interoperability of devices, and proprietary interfaces inhibit communication between sensors [17]. In the meantime, IoT design takes advantage of standardized communication protocols (e.g., IEEE 802.15.6, HL7 FHIR), which facilitate a heterogeneous combination of devices. Third, wired systems do not generally provide real-time analytical intelligence and care givers are thus required to analyze the patient data manually. On the other hand, IoT platforms combine cloud and edge AI, which provide automated prediction, anomaly detection, and clinical decision support. Fourth, wired monitoring scaling is associated with major hardware change, whereas IoT designs can be expanded with new nodes without changes [18]. Lastly, wired systems have low response time, which is caused by dispersed accessibility compared to wireless IoT that provides prompt notifications and remote access, which hastens diagnostic care. In general, these variations demonstrate that IoT-based monitoring is more flexible, intelligent and efficient in its operation than the conventional wired systems which confirm the actuality and progress in the suggested framework, comparative analysis summarized in Table II.

TABLE II. COMPARATIVE ANALYSIS: IOT-BASED VS. WIRED OR MONITORING SYSTEMS

Feature / Dimension	Wired OR Monitoring	IoT-Based Wireless OR Monitoring	Advantage/ Implication
Connectivity	Cable dependent	Cable-free, mobile	Wireless systems enhance mobility and reduce clutter in the OR.
Interoperability	Proprietary, vendor specific	Standards based protocols	IoT supports integration with multiple Devices and hospital systems.

Analytics	Manual Interpretation of data	AI-drivenreal-time predictions	AI enables predictive insights,early warnings, anddecision support.
Scalability	Hardwareheavy, expansion difficult	Plug-and-play devices	Easiertoscale and adapt to different OR setups.
Response Time	Delayed, human dependent	Real-time monitoring and alerts	Fasterdetection of critical changes improves patientsafety.
Workflow Efficiency	Restricted by cables and layout	Streamlined, less manual intervention	Reduces staff work load and enhances operational efficiency.

G. SystemArchitectureforIoT-BasedOperatingRoom(OR)Monitoring

The IoT-enabled OR monitoring architecture is designed to support real-time physiological surveillance, workflow optimization, and predictive decision support [5]. It follows a layered pipeline connecting patient-side sensors to cloud analytics and intelligent dashboards.

1) SensingLayer

It is a layer that gathers patient physiological data and operatingroom context parameters. Patient vitals are constantly monitored by biomedical sensors which include ECG, SpO₂, blood pressure, EMG, temperature and respiratory rate [19]. Other context sensors monitor ambient conditions, airflow, equipment status and staff movement. All of these sensing modules work with wearable devices that are enabled by WBANs, which guarantee the mobility of the patient and the minimum workflow incidence.

2) WirelessBodyAreaNetwork(WBAN)

Sensor nodes create a local WBAN cluster with patient or surgical team. The network also permits short range low power communication that is compatible with the IEEE 802.15.6 standards thus providing an efficient and safe streaming of physiological data. A controller device, like a smartwatch or embedded hub, will combine data packets and leave the body network to transmit them most efficiently.

3) Gateway and Local Networking Layer

The WBAN is linked to IoT gateways that are installed in the OR environment. These gateways are used to carry out local data fusion, preliminary filtering, outlier initial detection and then encryption and sending WLAN or 5G networks. Example soft Typical gateway elements are edge microcontrollers, medical network access points, and dedicated interface nodes.

4) Cloud Integration Layer

Once transmitted, data is routed to cloud infrastructure for large-scale processing and storage. Cloud services provide high-capacity storage, real-time stream analytics, and seamless interoperability with clinical systems such as EMR/EHR platforms through FHIR and HL7 standards [20]. This layer enables longitudinal tracking and scalable computation.

5) AI/Analytics Layer

Deep learning and machine learning algorithms are run on cloud or edge-based systems to come up with advanced insights. These analytics models do vital sign prediction, risk scoring, workflow recognition and anomaly detection. The outputs assist the clinicians in decision-making assistance early warning of patient deterioration.

6) Monitoring & Decision Dashboard Layer

This layer displays analyzed information in single clinical dashboards. Interfaces show patient vital signs, OR workflow indicators, equipment status and predictive notifications. Dashboards are available both on web or mobile and also give context-sensitive notifications to improve situational awareness and timely intervention.

H. Roadmap for Future Smart Operating Rooms (ORs)

The development of smart ORs is informed by the incremental use of emerging technologies [21]. An organized timeline enables healthcare facilities to design both short, mid, and long-term upgrades to their facilities to accomplish full autonomous and intelligent surgical settings.

1. Short-Term (1–3 years): 5G and Wi-Fi 7 Integration

- Install high-speed, low-latency wireless networks, which could be used to carry out real-time patient monitoring, surgical video transmissions and IoT device connections.
- Enable seamless communication between sensors, edge nodes, and cloud systems for faster data transfer and enhanced situational awareness.

2. Mid-Term (3–5 years): Edge AI and Predictive Analytics

- Implement edge computing combined with AI algorithms to process data locally, reducing response times and network load.
- Introduce predictive analytics for early detection of complications, automated alerting, and improved decision support during surgeries.

3. Long-Term (5+ years): Digital twins in Autonomous ORs

- Create absolutely autonomous operating conditions in which digital twin models can be used to simulate patient physiology, surgery, and workflow conditions.
- Introduce AI-based robotics support, environmental adaptive control, and automated surgical planning toward the optimization of results.
- As a result of the connection between digital twins and real-world operations, realize continuous system learning and self-optimization.

Key Benefits of the Roadmap

- A gradual adoption of technology minimizes the risk of implementation besides enhancing the efficiency and safety of surgical procedures.

- Supportscalabilityandfuture-proofingofORinfrastructure.
- Allowsproactive,anticipatoryand,ultimately,autonomoussurgery.

I.EdgeComputing&5GIntegrationinIoT-BasedORMonitoring

TheconceptsofEdgecomputingwith5Gnetworksintegrationisanessentialleaptowardminimizinglatency andmakingoperatingroom(OR)monitoringasystemwithrealtimeanalyticspossible.Conventionalcloud-basedsolutions demand sensor data fromwearables or medical equipment to be senttoa remote cloud sothattheyare processedandthiscausesdelaysthatmayaffecttimelyclinicalreactions[22].Edgecomputinghelpsreducethis, by operating data processing nearer to its source, in gateways or local edge servers in the hospital network.

Critical patient information can be sent and processed almost in real-time when combined with 5G connectivity, which provides ultra-low latency (110 ms) and high bandwidth. This supports real-time alerts, predictive analytics, and rapid surgical interventions.

ArchitectureOverview

- **IoT Sensors, WBAN(Wireless Body AreaNetwork).**
Wearablesensorsandsmartmedicaldevicescontinuouslycollectpatientvitals(heartrate,oxygensaturation, temperature) and OR context data.
- **EdgeGateway/EdgeAINode**
On-edge node processing uses lightweightAI algorithms to detect and remove anomalies, remove noise and initial predictions [23]. This limits the amount of data to be transferred to the cloud and lowers the latency.
- **5GNetworkLayer**
5G links with high speed help edge nodes to connect to hospital cloud infrastructure to transmit important alerts and high-definition images on the operation tables with lowlatency.
- **CloudAnalytics&AI**
Aggregateddataissenttothecloudtoperformadvancedanalytics,longtermstorageandAI modeltraining. TheAI modelsofcloudskeeponupdatingedgeAIalgorithmssoastoenhancelocalpredictivecapabilities.
- **Dashboards&DecisionSupport**
The clinicians are able to receive processed insights over dashboards and mobiledevices.Immediate clinical action is possible due to real-time notifications and predictions.

KeyBenefits

- **ReductioninLatency:**EdgeanalyticalfunctionsandAI-baseddecisionsareclosetoreal-time.
- **BandwidthOptimization:**Onlynecessaryinformationissenttothecloud,anditminimizesthenetwork congestion.
- **Reliability&Resilience:**Localedgeprocessingmaintainsmonitoringcontinuityevenifcloudconnectivityis interrupted.
- **ScalableAIIntegration:**EdgeAI modelsarecontinuouslyrefinedbycloudanalytics,balancingcomputational efficiency and intelligence.

J.Interoperability&Standards

Interoperability in OR monitoring based on IoT is provided by compliance with the use of healthcare communicationstandardsanddevicestandards.HL7FHIRfacilitatessmoothinteractionsofinformationbetween the IoTsystems and the hospital EMR/EHR to ensure that the information generated by the sensors matches the clinicalprocesses.WBANcommunicationisregulatedatthedevicelevelunderIEEE802.15.6,whichofferslow- power and dependable communication of physiological data around the patient body. In the protection of the connectionsand data streams,ISO/IECIoTsecurity modelshelp to steer the encryption,identity,authentication,

and resilience specifications at the various layers [24]. Together, these standards ensure compatibility, secure communication, and regulatory compliance, enabling scalable integration of heterogeneous sensing, networking, and analytic components in modern OR environments.

III. ROLE OF AI AND ML IN OR PATIENT MONITORING

AI and ML are transforming the monitoring of the operating room (OR) by allowing predictive analytics, identifying risks at an early stage, and providing clinical decision support in real-time (Figure 3). This changes healthcare to more of a proactive, data-driven initiative rather than a reactive treatment process where algorithms examine ongoing physiological measurements to make appropriate clinical decisions. Figure 3 demonstrates the way AI revolutionizes the work of healthcare through automating the analysis, enhancing the quality of diagnosis, and reducing the efficiency of decisions.

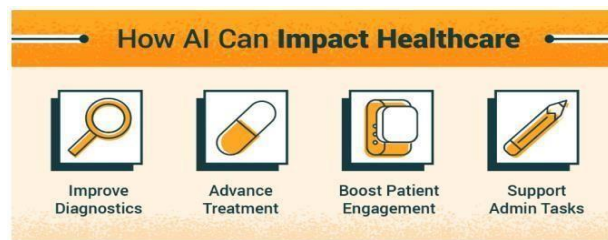


Fig.3.AI Impact on Healthcare

A. Role of AI-Driven Predictive Models

Predictive systems that are based on AI can examine an ongoing stream of patient data to detect patterns of deterioration before they escalate to critical situations, which will aid in early intervention and assist clinicians to avoid complications. The capabilities also improve wireless IoT surveillance by identifying the existence of minor deviations in vital signs and sensor measurements. Figure 4 points to key areas of application in which ML can serve the field of healthcare such as diagnostic automation, disease prediction, and adaptable treatment based on a person:

1) Cancer Detection

Deep learning algorithms are used to analyze imaging data (MRI, CT) to estimate malignancies prior to conventional visual analysis. The systems are more useful in detecting microscopic abnormalities in breast and lung cancer, thus enhancing sensitivity and planning of timely treatment.

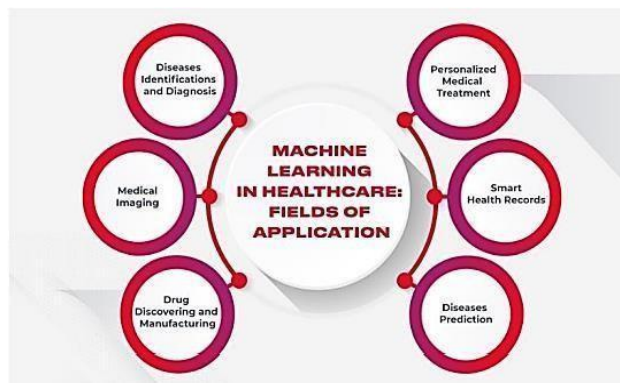


Fig.4.ML in Healthcare

2) Cardiovascular Conditions

AI systems can evaluate risk based on ECG measurements, blood pressure data, cholesterol levels, and so forth. ML aids in early-stage identification of abnormalities of the heart by detecting traces of pre-symptomatic deviations.

3) Diabetes

Machine learning models assess risk factors which include glucose trends, lifestyle indicators and family history to predict the onset of Type-2 diabetes several years before it occurs. Personalized diabetic treatment can also be made available through AI to suggest insulin dose changes and lifestyle changes depending on continuous glucose tracking.

B. Key Roles of AI and ML in OR Patient Monitoring

- **Real-time Health Monitoring:** The vital sign streams (e.g., ECG, SpO₂, BP) are processed by algorithms in real-time, and early warnings against abnormal trends are sent.
- **Adverse Event Prediction:** Before the development of complications such as intraoperative hypotension or risk of infection, models predict such complications [25].
- **Personalized Anesthesia/Drug Delivery:** AI-guided systems adjust anesthetic doses based on physiological feedback, improving patient safety.
- **Clinical Decision Support Systems:** AI tools assist with fluid balance, analgesia administration, and prioritization of critical decisions in surgery.
- **Task Automation:** Documentation, alarm triage, and workflow coordination is automatized, which decreases workload and alarm fatigue of employees.
- **Image and Video Analysis:** Computer vision is used to assist surgery, locate tissues, and evaluate the performance of a surgical procedure with the aid of real-time imaging.
- **Resource and Workflow Optimization:** Predictive models estimate the times spent in the OR, aid in scheduling of ORs and improve PACU staffing decisions.

IV. CLOUD COMPUTING FOR REAL-TIME HEALTHCARE SYSTEMS

The healthcare sector is changing quickly, and operating rooms (ORs) are becoming highly dependent on interconnected technologies to provide safe, timely, and effective care. Cloud computing has become a revolutionary backbone that can be used to access, store and process real time physiological data produced by medical IoT systems. It provides a scalable and adjustable system to handle surgical data [26], to help clinicians in decision-making, and to enable integrated OR processes. The use of a cloud-based access to patient records, sensor data, and imaging reports can enable OR teams to work in real-time, leading to the improvement of intraoperative situational awareness and postoperative monitoring.

A. Role of Cloud Computing in Healthcare

Cloud computing offers the new solution to the old problems in healthcare, notably data coordination, live monitoring, interoperability, and analytics in the surgical settings [27]. In addition to storage and scalability, cloud technology enables real-time video streaming of the concentrated surgery, remote patient care, OR automation, and intraoperative data recording, extending clinical results and operational effectiveness [28].

1) Healthcare Data Storage Solutions

Healthcare produces colossal amounts of data about patients, images, and records of intraoperative devices. Cloud-based applications offer robust archives of these datasets, offer central-storage of surgeon notes, anaesthesia data, OR sensor data, and postoperative reports which allows smooth access and continuity of care.

2) Scalability and Flexibility

The workloads of surgery fluctuate over time like some emergency cases or seasonal cases. Cloud architecture enables healthcare organization to dynamically increase computing and analytical capacity, so that surgical dashboards, patient feeds [29], or AI-assisted decision systems can remain available during peak operations.

3) Security and Compliance

The high sensitivity of both surgical and personal health information (PHI) necessitates the inclusion of multi-factor authentication, encryption, intrusion detection systems, and compliance control systems like HIPAA by the cloud providers. These checks safeguard intraoperative telemetry, anesthesia tracking records, and after-surgery monitoring records against unauthorized service and assault.

4) Data Analysis and Processing

Cloud computing helps with advanced analytics that allow clinicians to make insights based on medical data, such as surgical risk predictive modelling and workflow optimization, as well as forecasting recovery outcomes. Analytics engines on the cloud assist health professionals in identifying complications at an earlier stage and streamlining decision making.

5) Big Data Analytics for Healthcare

The combination of healthcare big data and cloud computing allows the analysis of a large volume of electronic health records, data on surgical performance, genomic data, and wearable device streams to make it possible, leading to precision medicine and intelligent postoperative care.

6) Data Processing and Monitoring in Real-time

Clouds enable real-time OR monitoring, telemedicine, emergency response and remote postoperative follow-ups. During surgeries, anaesthetists and surgeons can assess vital trends, as well as cooperate with specialists who may be at a distance and take measures in real-time using cloud-processed data.

B. Model of Deployment of Cloud Computing

There are numerous types of cloud models used by healthcare systems, including public, private, hybrid, and community clouds, based on regulatory concerns, patient safety considerations, and data sharing considerations [30].

- **Public Cloud:** Cloud providers run these services; these services are accessed via web interfaces, e.g., clinical data archiving.
- **Private Cloud:** Sensitive workload of hospitals is put in its specific environment, which provides better control and confidentiality.
- **Hybrid Cloud:** Allows interchange of data between private hospital systems and scalable public cloud systems, which encourages redundancy, compliance and clinical flexibility.
- **Community Cloud:** It is shared between organisations with similar requirements, e.g. public health network to joint regulatory standards.

C. The Trends that Favor Real-Time Healthcare and OR Systems.

This transformation in healthcare has been rapid, and the technological invention has placed cloud computing at the top of this invention [31]. The integration of blockchain, the IoT, AI, ML, and other new trends and technologies is being implemented by using cloud technology to improve the outcomes of patients, their data security, and to transform healthcare. Such innovation has proven that technology can transform healthcare.

1) Artificially Intelligent and Machine Learning-Based Cloud Healthcare Systems

AI helps to speed up cloud analytics with the help of real-time risk forecasting, operating room decision support, automated diagnostics, and individualized aftercare. With the help of AI-powered cloud services, imaging streams are processed and their abnormalities are detected with high precision, enhancing early-stage diagnosis and intervention.

2) Blockchain as a Secure Data Exchange

Blockchain has been shown to improve secure OR data sharing through decentralized storage, secure audit trail, consent control, and the smooth flow of surgical records between medical teams or institutions.

3) IoTandMonitoring,andAutomationthroughCloudIntegration

Wearables and OR-based IOT sensors transmit vital telemetry to cloud services [32], which allows intraoperative monitoring in real time, postoperative monitoring, and treatment plan development based on real-time analytics.

V. SMARTMANUFACTURINGANDADVANCEDMEDICALDEVICEDEVELOPMENT

The role of smart manufacturing in the advancement of healthcare technologies is, in particular, the creation of compact, very precise medical equipment and miniaturized sensors applied in the hospital setting and the operating room (OR). This set of manufacturing paradigms facilitates shorter development cycles, greater reliability of the respective devices, greater accuracy in the manufacturing of the products, and greater component operation that is essential in patient monitoring and clinical decision support [33]. Digital simulation, cyber-physical modeling, and additive manufacturing are some of the techniques that enable engineers to test the behavior of their device prior to physical implementation, minimizing the risk and cost involved. Nevertheless, there still remain a number of challenges including cybersecurity, the readiness of the workforce and the maturity of the infrastructure that impedes large-scale adoption.

A. Smart Industry in the Production of Medical Devices

The technologies of Industry 4.0 will revolutionize the industry of making medical devices by producing smart factories that can manufacture miniaturized physiological sensors and interconnected devices in OR. Industry 4.0 principles, as depicted in Figure 5, enable smart manufacturing systems to configure, decentralize, use real-time analytics, and virtualize to produce devices by self-adjusting and optimizing production.

Such systems facilitate building of implantable biosensors, wearable vital signs monitors and OR-based monitoring modules, which utilize the IoT connectivity to be automatically controlled [34]. Using data analytics and machine learning, manufacturing processes become dynamic to design constraints, material utilization, errors, and device longevity can be optimized. Smart factories are used to guarantee that medical sensors are very accurate, sterile, and have regulatory standards needed in the surgical setting.



Fig.5.SmartProcessingintheMakingofMedicalEquipment

B. Intelligent Manufacturing in the Medical Industry

In manufacturing, Intelligent manufacturing is especially useful to create precision instruments and monitoring systems that are needed in ORs, including:

- Miniaturized ECG patches
- Wireless pulse oximeters
- Smart infusion pumps
- Microchips with drugs that can be implanted.
- Surgical robotic components.

- Resolution-based imaging sensors that are high resolution.

Robotics and automation are used to speed up the assembly process by producing it with repeatability and minimizing the chances of contamination, as well as increasing the precision of fabrication beyond human control [35]. Under the IIoT integration, machines reporting on their operational status continuously will prevent any interruption by predictive maintenance, guaranteeing the continuity of the production of clinical-grade sensors [36]. This is essential to individualized devices, where changes in small form factors impact the performance of the surgery and the outcome of the patients.

C. Medical Devices Production Automation

The use of automation has now taken center stage in the production of high-risk OR equipment like the anesthesia kits, sterilization-control sensors, endoscopic cameras, and wearable monitors [37]. Decision engines based on AI simplify assembly, calibration, packaging and testing processes and minimize human error and throughput.

- AIs also aid in manufacturing processes that identify faults in micro-circuit boards, fluid pathway controls, and sensor housings during production so that the systems are compliant with the regulations and clinical reliability.
- Machine vision-based automated inspection systems are used to confirm the functionality of devices, their sterility, dimensional limits, and safety limits prior to use in the operating rooms.

These intelligent manufacturing innovations, together, help to accelerate the process of innovation, enhance the safety of devices, decrease their size, and enhance access to accurate monitoring systems, which are vital to the efficiency and safety of the OR.

VI. CYBERSECURITY AND DATA PRIVACY IN WIRELESS MEDICAL SYSTEMS

The issue of cybersecurity and privacy is rising in wireless medical systems because uninterrupted physiological data transmission and the growing reliance on IoT-enabled clinical systems are present [38]. The access to confidential data, data manipulation, and interference of wireless channels can be of great danger to patient safety and healthcare integrity. Hence, to maintain stable digital healthcare industries, secure communication, adherence to regulations, and Zero Trust implementation are necessary.

A. Threat Landscape of Io-Based Healthcare

1) Threat Landscape of Io-Based Healthcare

The medical IoT deployments are based on Wi-Fi, Bluetooth, and other short-range protocols that are susceptible to eavesdropping, spoofing, man in the middle attacks (MITM) and jamming. The networks of healthcare are exposed to out-of-date firmware, poor authentication, and improperly configured access points and allow attackers to steal vital physiological information or interfere with patient monitoring.

2) System Vulnerabilities and Device Vulnerabilities

Most of the embedded medical devices have poor processing power, which results in weak encryption, default passwords, or low-security firmware update cycles. Given that IoT systems are interconnected, a hacked sensor will spread attacks to other hospital platforms and clinical databases, contributing to distorted medical records or termination of necessary services. Table III further summarizes these risks and the mitigation controls associated with these risks.

TABLE III. CYBERSECURITY THREATS VS. WIRELESS MEDICAL SYSTEM MITIGATION CONTROLS.

Threat Category	Example Attack	Impact on Healthcare Systems	Mitigation/Control Mechanism
Network Eavesdropping	Packetsniffing over Wi-Fi	Disclosure of patient health data	AES/ECC encryption, TLS/DTLS for secure transmission
Man-in-the-Middle Attack (MITM)	Rogue access point injection	Altered sensor readings; wrong clinical decisions	Mutual authentication, certificate validation, Zero Trust policies
Device Hijacking	Malware modified firmware	Loss of system reliability; manipulated treatment cycles	Secure boot, signed firmware, integrity checks
Ransomware & DoS Attacks	Hospital network lockdown	Service disruption, surgery delays, operational downtime	Network segmentation, intrusion detection/prevention systems (IDS/IPS)
Weak Authentication	Default passwords or credential theft	Unauthorized access to monitoring dashboards or medical records	Strong authentication, multi-factor access control
Data Tampering	Sensors spoofing or packet modification	Misdiagnosis or incorrect monitoring interpretation	End-to-end encryption, hash based integrity validation

Physical Device Attacks	Device theft or tampering	Breach of stored patient data	Tamper-resistant hardware, device tracking and access logging
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B. Cybersecurity Framework of Wireless Medical Systems

A strong cybersecurity framework is necessary to provide the security of IoT-enabled OR monitoring systems. This model combines preventive, detective, and corrective actions at both device and network layers and cloud services. Key components include:

1) Zero Trust Architecture (ZTA)

The principles of Zero Trust presuppose the absence of implicit trust, which means that all users, devices, and applications are verified on a regular basis. ZTA is used in healthcare ORs to make sure that sensitive patient data is accessed by authenticated devices and authorized persons. Policies include:

- Multi-factor authentication of clinicians and IoT devices.
- Minimal access to dashboards, cloud services and local networks.
- Constant checks of abnormal behaviour and unauthorized access.

2) Network Segmentation

Separating clinical networks will reduce the effects of possible breaches and separate critical OR equipment with other systems that are not as secure. Usual strategies of segmentation involve:

- Establishing IoT medical equipment, administration IT system, and guest virtual LANs (VLANs).
- Using access control rules and firewall to limit the movement to the sides.
- It is monitoring of inter-segment traffic to identify suspicious activity in time.

3) Real-World Threat Scenarios and Mitigation

The IoT-based OR systems have several attack vectors that may interfere with patients safety and workflow:

- Hospital files are encrypted because of ransomware attacks and surgical operations are disrupted.
- WBAN or Wi-Fi attacks (Man-in-the-Middle (MITM)) of data integrity threat.
- Hijacking the device by use of firmware exploits in which an attacker can manipulate physiological readings.

Mitigation measures are a combination of encryption, intrusion detection/prevention systems (IDS/IPS), secure firmware updates and persistent threat intelligence. Combining these actions, the hospitals will be able to have resilient, real-time patient monitoring and provide protection to sensitive data as well as guarantee the observance of the regulations, including HIPAA and ISO/IEC 27001.

C. Security Frameworks and Protection Mechanisms

1) Encryption and Secure Communication

State-of-the-art cryptography, like AES, ECC, VPN tunnels, and lightweight ciphers, safeguards the data of patients at rest and in transit. Confidentiality and integrity are reinforced by secure communication frameworks such as TLS/SSL, DTLS, secure MQTT and CoAP. Even battery constrained devices are provided with lightweight encryption to protect information.

2) Network Segmentation and Zero Trust

Zero Trust Architecture is becoming widespread in modern healthcare, which mandates identity verification, least-privilege access, and network micro-segmentation. The use of intrusion detection systems (IDS) and

anomaly-based logs increase the resilience to ransomware and network-wide takeover attacks on hospital monitoring platforms.

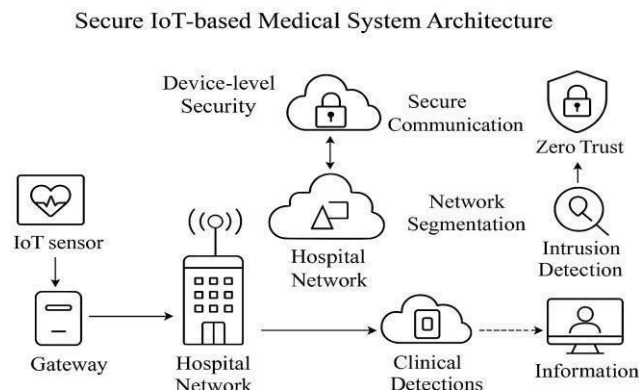


Fig.6.SafeInternetofThings-basedMedicalSystemArchitecture

The architecture shows Figure 6 multi-layered security components such as device-level authentication, secure gateway, encrypted wireless data transfer, Zero Trust implementation, intrusion detection, segmented clinical network and protected access to hospital cloud services to clinicians.

D. Regulatory Standards and Compliance

The health institutions work within the framework of HIPAA (USA), GDPR (EU), and these frameworks guarantee the confidentiality, integrity, and traceability of patient health information. Medical device security requirements allude to global requirements such as FDA cybersecurity requirements, IEC 62304 (software lifecycle), and ISO 14971 (risk management). Adherence leads to reliable working systems, fast patching cycles, and strong medical communication systems.

VII. LITERATURE REVIEW

In this section, the main investigations to be discussed are related to an IoT-based healthcare system and its architecture, sensor-based monitoring, remote data transmission, and security issues. Table IV summarizes the works that reveal the significance of continuous, efficient, and reliable monitoring of patients through the IoT.

Wadhvani, Mehta and Ruban (2019) utilize an LSTM recurrent neural network to correlate the acquired data in order to forecast the disorder causing their irregularity. Blood pressure, body temperature, and electrocardiogram (ECG) are the physiological signals that are tracked. The Hamming window FIR filter is used to filter the raw ECG data among the obtained physiological signals. To increase the data's dependability, a QRS detection wavelet transform algorithm is also employed. This processed data is first saved in the database together with the other two parameters body temperature and blood pressure before being wirelessly sent to a physician along with the patient's location information. In the study, a prototype patient monitoring system is described using an Android application with a common interface [39].

Selvaraj and Doraikannan (2019) explain the elements needed for the healthcare monitoring system. WBANs are made possible by sensors' ability to collect vital health information. WBAN nodes may monitor blood pressure, heart rate, body temperature, blood sugar levels, EEG, and other medical data. The doctor receives the gathered data regularly. The security and privacy of patient data, as well as control flow, are the primary concerns with wireless communication channels for healthcare monitoring [40].

Akshat et al. (2018) provide an effective strategy that addresses the lack of medical personnel in India by allowing a physician to successfully use technology to remotely check a patient's health. Crucial health indicators such as the patient's blood pressure, heart rate, body temperature, and blood sugar level, and electrocardiogram (ECG) are collected and evaluated by the proposed system using smart devices, and galvanic skin reaction. The data is wirelessly sent for further analysis using data analytics using Zigbee IEEE 801.15.4 technology [41].

Wan et al. (2018) introduce a brand-new system for realtime personal health monitoring called WISE (Wearable IoTcloud-based health monitoring system). WISE supports realtime health monitoring by implementing the BASN (body area sensor network) framework. A number of wearable sensors have been integrated, such as blood pressure, body temperature, and cardiac sensors. Second, most wearable health monitoring technologies currently in use require a smartphone as a gateway for data processing, visualization, and transfer, which will undoubtedly affect regular smartphone use. While data collected from the BASN is directly sent to the cloud in WISE, an alternative method for a rapid display of the real-time data is to install a lightweight wearable LCD [42].

Abideen and Shah (2017) suggested that ongoing patient monitoring, even when the patient is on the road. Sensitive information is gathered by IoT sensors that are affixed to the patient's body and sent via the patient's smartphone to the server. The method described in this article ensures that IoT sensors connect to the closest peer smartphone and continuously transmit data if the patient's smartphone malfunctions. Reports are created when the data is examined.

TABLE IV. COMPARATIVE ANALYSIS OF IOT-BASED HEALTH CARE STUDIES

Study/ Authors	Focus of the Study	IoT Devices /Sensors Used	Data Transmission Method	Healthcare Application	Security/ Privacy Concerns	Limitations / Gaps Identified
Wadhvani, Mehta & Ruban (2019)	IoT-based patient monitoring using LSTM for disorder prediction	ECG, temperature, BP sensors	Processed data stored and wirelessly transmitted including location	Continuous remote monitoring via Android app	Limited security discussion; location data privacy risk	Prototype only; small scale evaluation; lacks OR-specific validation
Selvaraj & Doraikannan (2019)	Key components of WBAN-based healthcare monitoring	BP, EE, G, glucose, pulse, temperature	WBAN communication	Periodic reporting to clinicians	High privacy concern for wireless exchange	Security solutions not tested; lacks real deployment scenarios
Wan et al. (2018)	WISE wearable cloud-based health monitoring (BASN)	Heartbeat, BP, temperature	Direct cloud upload; optional wearable LCD	Real-time personal monitoring	Cloud exposure risks not examined	Architecture tested at design level; cloud security not validated in medical settings
Akshat et al. (2018)	Remote doctor-patient monitoring	ECG, BP, temperature, glucose, GSR	Zigbee IEEE 802.15.4	Rural/remote care support	Not explicitly covered	Narrow geographical context; no scalability assessment; no cybersecurity framework
Abideen & Shah (2017)	Reliable mobile monitoring with peer fallback	Body-worn IoT sensors	Smartphone-based transmission	Emergency	Ensures secure	Focused on continuity, not analytics; lacks

			with peer fallback	surveillance while travelling	connection continuity	hospital integration context
Tyagi, Agarwal & Maheshwari (2016)	IoT healthcare frameworks and adoption	General medical sensors	Cloud-based IoT integration	General healthcare IoT enablement	General discussi on only	No empirical validation; conceptual, lacking implementation

Stakeholders are alerted in the event of an emergency [43].

Tyagi, Agarwal and Maheshwari (2016) outlines the uses of IoT and discusses some of the key elements and traits of each use. This article has carefully analyzed the role of IoT in healthcare delivery, the technological components that enable it, and its potential. A cloud-based conceptual framework that would help the healthcare sector adopt IoT healthcare solutions has been put forth [44].

VIII. CONCLUSION AND FUTURE WORK

In the operating environment characterized by high-acuity situations, patient monitoring is the key to efficient workflow and patient safety. This paper supports the idea that surgical decision-making and operational responsiveness are essentially reinforced through the wireless IoT-based OR monitoring. The suggested system decreases the time to set up and increases the mobility of the infrastructure by substituting inflexible wired infrastructure with interoperable sensor networks, edge-assisted analytics, and AI-driven alerting to enable real-time physiological monitoring. As emphasized by quantitative results, there are significant effects, including quicker clinical response, less complicated wiring, and greater precision in the early detection of anomalies. The evaluation concludes that wireless IoT designs are not simple replications of the already present monitoring, but they turn into intraoperative situational awareness and safety assurance. Going forward, future improvements must be guided by a systematic roadmap, with short-term focus on the integration of new connectivity standards (5G, Wi-Fi 7) and better cybersecurity implementation; mid-term improvements at the deployment of edge AI to enable autonomous prioritization and fault-tolerant data processing, and long-term transformation into semi-autonomous fully intelligent ORs with the ability to predictively intervene as well as coordinate autonomously across robotic systems and via digital twins to plan surgeries. Altogether, the intersection of wireless sensing, cloud intelligence and predictive analytics makes the IoT-enabled monitoring a crucial route to the safer, more efficient, and intelligent surgical ecosystem, and the presented staged roadmap provides a realistic way of further research and clinical implementation.

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