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Intelligent Surgical Tables: Real-Time Patient Monitoring and Autonomous Adjustment Using IoT, Cloud Computing, and Cybersecurity

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Abstract—**The goal of the Intelligent Surgical Table (IST) system is to enhance the accuracy (ACC), safety, and efficiency of surgical operations through real-time monitoring and automation. The IST system leverages technologies such as the Internet of Things (IoT) network of sensors, cloud computing, machine learning, and cybersecurity measures to create a smart and adaptive surgical environment. The data collected from the pressure sensor is then analyzed by applying hybrid deep learning models such as CNN-LSTM to classify the patient into one of the risk categories, while the data collected from the IoT network is analyzed using other techniques such as XGBoost and Isolation Forest for cybersecurity analysis. With help from a decision fusion layer, intelligent decisions on how to control the surgical table can be made taking into consideration both medical and security aspects. Edge computing provides low latency, and cloud helps to store data to update the ML models. The system takes into account real-time data and makes intelligent micro-decisions regarding table tilts and position adjustments. Experimental results show an ACC rate of 92.8% in classifying patient risk, as well as 97.2% in cybersecurity protection.**

Keywords—Intelligent Surgical Table (IST), Internet of Things (IoT), Real-Time Patient Monitoring, Cloud Computing, Cybersecurity.

I. Introduction

The fast development of healthcare technologies has led to the emergence of modern surgical environments that integrate intelligent and adaptive medical systems [1]. The existing surgical tables need complete human control because they cannot adapt their functions during essential surgical moments when patient conditions change [2]. The increasing complexity and ACC needs of surgical procedures require automated intelligent systems which create better surgical processes through reduced human work and increased patient protection. The next-generation intelligent surgical systems depend on the combination of Internet of Things (IoT) technology with cloud computing and artificial intelligence (AI) and cybersecurity solutions [3][4].

The operating room technologies have achieved progress yet conventional surgical tables still maintain multiple operational constraints. Surgical staff members need to make manual changes since the system lacks real-time patient monitoring capabilities while it introduces operational hazards through its need for manual interventions [5][6]. The surgical procedure suffers when there are slight disturbances because doctors take time to set up patient movement during complex operations. The growing network connections between medical devices create major cybersecurity threats which endanger patient privacy and data security while permitting unauthorized access, thus making secure healthcare communication vital [7].

The research introduces an intelligent surgical table system which utilizes IoT sensors and AI analytics and cloud computing together with cybersecurity protection to overcome existing constraints [8][9]. The system continuously monitors the basic vital signs of patients that include heartbeat, blood oxygenation levels, body posture, and pressure distribution. The system transmits the gathered information to the cloud platform that employs AI and ML algorithms to assess the information for risk analysis and decision-making in real time. The AI system anticipates the motions so that the surgical table can adjust itself for optimal alignment and low-pressure risk for improved ACC of surgery [10]. The system employs cybersecurity techniques that include encryption, authentication, and anomaly detection to ensure safe information transfer and protect medical information from cyber-attacks [11].

The proposed system tries to increase ACC during surgery, decrease human involvement and increase efficiency in operating theatres. The intelligent operating table involves IoT, AI, cloud computing and cybersecurity technologies to establish an adaptive healthcare system that assists health professionals in delivering safer and more effective surgical services. The study explores the creation of AI-supported intelligent healthcare systems using an automatic and safe system for adaptive operating table management in the medical industry.

A. Motivation and Contributions of the Paper

Modern surgeries require precision and surveillance but traditional surgeries have a major drawback due to dependency on human intervention to change position. This increases human efforts and may pose dangers in crucial surgeries. Moreover, the advent of interconnected devices leads to vulnerability to cybersecurity issues. Therefore, there is a need for a smart solution that should be able to take action in line with the current state of the patient. This paper was motivated by the idea of using IoTs, AI, and CC to come up with an efficient smart surgical table. The contributions of the paper are as follows:

- Proposed Intelligent Surgical Table (IST) for real-time patient monitoring and adaptation
- Created a hybrid CNN-LSTM algorithm for effective pressure prediction
- Created a hybrid cybersecurity approach with XGBoost and Isolation Forest
- Constructed a decision-making framework to fuse medical and security knowledge
- Utilized edge and cloud computing for efficient computation
- Developed a rule-based autonomous control framework with safety and security provisions

B. Novelty of the paper

This work proposes a new approach to the incorporation of patient monitoring, self-actuation, and cybersecurity into one intelligent surgical table system. This system enables AI-based prediction, IoT sensing technology, cloud intelligence,

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and security analysis, which other works have only discussed patient monitoring and pressure sensing. Moreover, due to the decision fusion and safety control module, the suggested system ensures safe autonomous adjustments which are generally neglected in other works. This means that the system is equipped to deal with medical data and cybersecurity threats too, making it even more robust and scalable.

C. Organization of the paper

The outline of the paper is as follows: Healthcare monitoring systems that make use of the Internet of Things are reviewed in Section II. The suggested approach is detailed in Section III. The findings and assessment of performance are detailed in Section IV. Section V wraps up the work and provides an outline of potential areas for future investigation.

II. LITERATURE REVIEW

Existing studies emphasize IoT-enabled patient monitoring, pressure sensing, and automation; however, they lack integrated cloud intelligence, cybersecurity, and autonomous control mechanisms necessary for advanced intelligent surgical table applications.

T. P. D. A. Barros et al. (2022) describe the creation of a bed pressure monitoring system that may be used on a daily basis to avoid pressure ulcers; the devices also have alarms to help caregivers and medical professionals enhance patients' health. The proposed method for solving this problem does not include a sheet of sensors but rather the conductive carbon-impregnated polyolefin known as Velostat. Patients in critical condition may be able to receive treatment in the comfort of their own homes or even at public hospitals thanks to this alternative, which lowers the overall cost of the system [12].

S. Mansfield, E. Vin, and K. Obraczka (2021) present PIMAP, an IoT-based system that can monitor patients continuously and in real-time without any human involvement whatsoever. The core workflow of patient monitoring includes sensing data acquisition, storage, processing, and real-time visualization; to the best of knowledge, PIMAP is the first open system to encompass this workflow. The modular design of PIMAP makes it easy to integrate various sensors, analytics, and visualization tools. The deployment flexibility of PIMAP, in addition to its self-profiling and self-tuning features, provides for a wide variety of configurations that may be tailored to the needs, environment, and resources of given applications. While PIMAP has numerous potential uses in patient monitoring, work aims to address the current state of knowledge about the prevention of pressure ulcers and similar injuries [13].

M. Seon, Y. Lee, and C. Moon (2021) provide a new robotic bed to avoid pressure sores. Each section of this robotic bed is powered by its own set of brushless direct current motors, and the system uses the user's pressure data to fine-tune its movements. The patient's blood pressure is kept below the reference level by controlling the segments of the bed with a fuzzy logic system. Additionally, this work produced a belt-type BBP sensor that measures the patient's BBP utilizing force-sensing resistor technology. Included in the bed control system are sensors, a teach pendant, motor controllers, and the main controller [14].

A. Abdelmoghith et al. (2020) strive to offer a remedy that lessens the likelihood of bedsores forming in people undergoing long-term care. The IoT is invaluable in healthcare monitoring applications because it allows for constant monitoring, which in turn allows for effective decision-making in real-time, which cuts down on mistakes, wasted time, and expenses. The suggested IoT system monitors a patient's vitals, such as their temperature, skin humidity, and the duration of immobility; many elements contribute significantly to the formation of bedsores. Through openings in the patient's bed, the system releases cool, humid air at the ideal temperature to alleviate the symptoms recorded by the monitoring equipment [15].

A. Memari, A. T. Golpayegani, and M. S. Hosseinzadeh (2020) detail the development and deployment of an intelligent mattress system that can identify and foretell when pressure ulcers may begin to form. The system utilizes an array of pressure sensors embedded beneath the mattress surface to continuously measure and analyze the distribution of pressure exerted on different body regions. The technology can identify areas of extended pressure and notify caregivers or nursing personnel to take action based on real-time data processing. By automating pressure ulcer prevention, lowering the stress on healthcare personnel, and increasing overall patient outcomes, the suggested smart mattress intends to improve patient care [16].

S. Nor et al. (2019) create a system that uses electrocardiography (ECG) and temperature sensors to track the users' health while they sleep. The LabVIEW application software was used for real-time monitoring, while the Arduino IDE was used for the Internet of Things. Because they are stored digitally, patients' medical records enable doctors to monitor their well-being even when separated. The project's result was compared to two existing market-available monitoring devices: the Hand Wrist Heart Monitoring and the Galaxy Watch. also looked at the Rossmax Monitoring TG380 Thermometer, which measures core body temperature. In these comparisons, conducted across multiple experiments, the accuracy and reliability of its results were considered. To evaluate the precision of data sent over the web, researchers compared real-time monitoring data with that from the Internet of Things (IoT). This indicates that the total margin of error for the two measures, heart rate and body temperature, was lower than 4.2% [17].

The following Table I shows a comparison among various IoT-enabled patient monitoring technologies, which include their innovations, benefits, drawbacks, and research gaps, offering recommendations for intelligent surgical tables.

TABLE I. COMPARATIVE ANALYSIS OF IOT PATIENT MONITORING SYSTEMS FOR SMART SURGICAL TABLES

Author & Year	Proposed System	Key Contributions	Advantages	Limitations	Recommendations
Barros et al. (2022)	Bed pressure monitoring using Velostat	Low-cost pressure-sensing system with alarms for caregivers	Cost-effective design; simple implementation; suitable for home care	Limited to pressure detection; lacks real-time analytics and automation	Integrate IoT-enabled cloud platforms with real-time analytics and implement

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					automated adjustment mechanisms
Mansfield et al. (2021)	PIMAP IoT monitoring system	Fully autonomous IoT system with data collection, analysis, and visualization	Flexible architecture; supports multiple sensors; real-time visualization	Focused on general monitoring; not specialized for surgical environments	Extend system to support closed-loop actuation and incorporate robust cybersecurity frameworks for medical data protection
Seon et al. (2021)	Robotic bed with fuzzy control	Automated pressure redistribution using motors and sensors	Effective pressure management; intelligent control using fuzzy logic	The system is standalone and not IoT-enabled	Integrate IoT connectivity and cloud-based monitoring; enable interoperability with hospital systems
Abdelmoghith et al. (2020)	IoT-based bedsore prevention system	Monitors temperature, humidity, and immobility; provides automated air flow	Multi-parameter sensing; partial automation; real-time response	Limited sensing parameters; basic decision-making	Incorporate AI-driven predictive models and enhance cybersecurity using encryption and secure communication protocols
Memari et al. (2020)	Smart mattress with pressure sensors	Real-time pressure analysis and alert system	Continuous monitoring; improves patient safety; reduces caregiver workload	Alert-based only; no autonomous response	Develop closed-loop control systems and integrate cloud-based IoT frameworks with secure data handling
Nor et al. (2019)	Smart bed with ECG & temperature monitoring	Remote monitoring via IoT with acceptable accuracy	Accurate monitoring; remote accessibility; validated performance	Focus on vital signs only; no mechanical actuation	Expand system to include intelligent actuation, scalable cloud integration, and comprehensive cybersecurity measures

III. Methodology

The workflow Fig. 1 shows the IST system involves the use of IoT technology, machine learning techniques, edge computing, and cloud computing. Real-time data is collected through pressure sensors (PMD dataset) and IoT health care devices, and the data goes through preprocessing steps such as normalization, reshaping, and encoding features. Pressure data is then used by a CNN-LSTM DL model to forecast the patient's pressure risk level, whereas IoT network data is used with XGBoost and Isolation Forest algorithms to detect intrusions and anomalies. In the decision fusion step, both medical and cybersecurity components provide an output to determine the overall state of the system, which is sent to a rule-based control system for micro-adjustments. The entire process involves edge computing to guarantee low latency. Cloud computing is used to train and update models and store data. A cybersecurity layer provides constant protection of data transmissions.

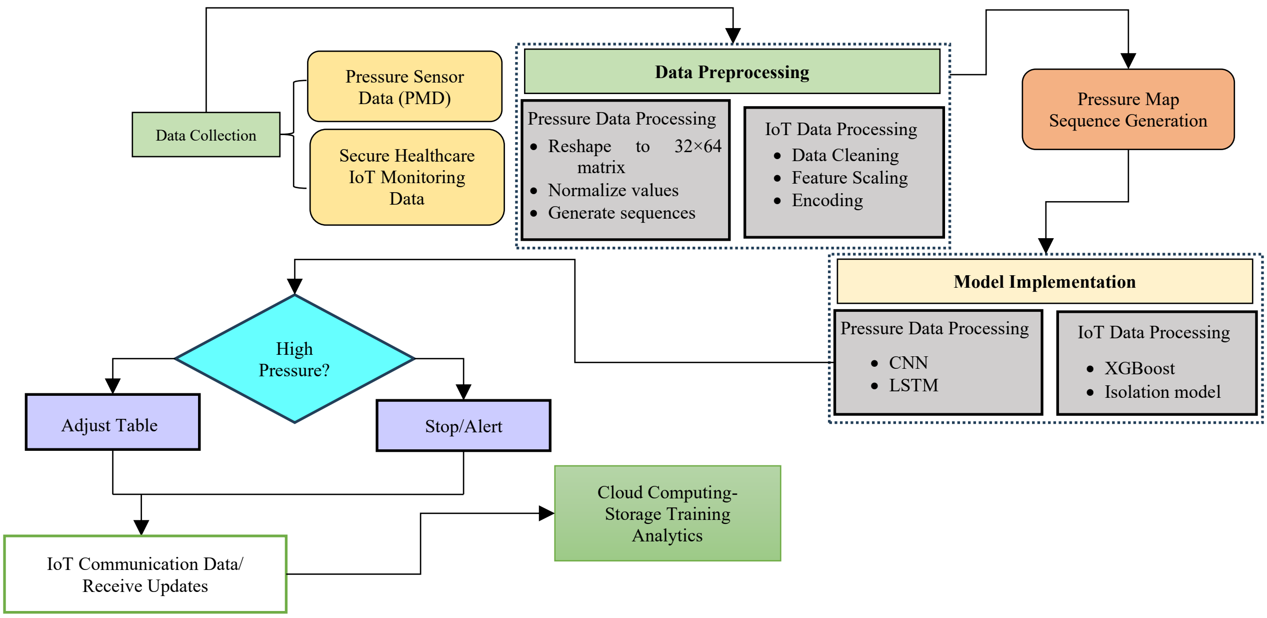

Fig. 1. Workflow of Hybrid AI and Rule-Based Failure Recovery Framework

A. Data Gathering

The working process of the system starts with collecting data, from two sources, to ensure that the data collected is comprehensive. The information associated with the pressure sensors is obtained by adopting the Pressure Map Dataset[1] (PMD) which allows for obtaining the spatial pressure distribution, which represents the interaction between the patient and the surface, enabling the posture monitoring

[1] https://physionet.org/content/pmd/1.0.0/

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process. Concurrently, the Secure Healthcare IoT Monitoring Dataset[2] is utilized to gather details about the network and gadgets, including simulated communication information, gadget conduct, and even dangers.

1) Pressure Data Preprocessing

Some data pre-processing techniques are being used to enhance the quality of the data and to increase the efficiency of learning:

- **Reshaping:** The 1-dimensional array with 2048 is reshaped into a 32 x 64 matrix so that the spatial relationship between the sensor points is preserved.
- **Normalization:** Min-max normalization is used for transforming pressure values to a common range (for example, 0 to 1), guaranteeing numerical stability and quick convergence.
- **Sequence Generation:** The consecutive pressure maps are put into temporal sequences for the capture of time variations of the pressure distribution.

2) IoT Data Preprocessing

To ensure data quality and compatibility with machine learning algorithms, a number of pre-processing steps need to be taken.

The following steps are in the pre-processing pipeline:

- **Data Cleaning:** These include data inconsistencies, duplicate data, and missing data, which are addressed to improve data quality and reduce noise.
- **Feature Scaling:** Numeric attributes have consistent value ranges to enhance model ACC and convergence rates.
- **Categorical Encoding:** The features are encoded into a numeric format, depending on the type of feature, using encoding techniques such as label encoding and one-hot encoding.

3) Feature Extraction

The pre-processed maps from the Pressure Map Dataset (PMD) are then fed into a Convolutional Neural Network (CNN) to extract features. The CNN is able to learn the features of the pressure distribution in the 2D map, including pressure points, imbalance and concentration. The CNN is able to successfully identify high-pressure regions by learning hierarchical features of pressure in the image with the aid of convolution and pooling operations.

4) Temporal Learning

Spatial characteristics collected via the Pressure Map Data Set (PMD) are then processed by an LSTM neural network which uses pressure change to process the temporal characteristics. The LSTM can identify sequential patterns and thus can detect extended periods of pressure or sudden pressure changes if caused by movement of the patient or patient's instability. This means that the temporal behaviour captured by the model is easier to understand, as the time-dependent features learned by the model aid in better understanding the temporal behaviour of the pressure.

5) Models implemented for cyber threat detection

The machine learning models are applied to identify the cyber threats from the IoT network data.

- **Extreme Gradient Boosting (XGBoost)**: It is a supervised machine learning algorithm that uses gradient boosting to generate a series of decision trees in order to increase prediction ACC. This algorithm maximizes a loss function using iterative correction of the mistakes made by previous decision trees, which makes it extremely efficient when working with structured data and classification problems. In the presented solution, the XGBoost model is used to recognize cyberattacks with established patterns in IoT network data. Using labelled examples of normal and abnormal behaviour, this machine learning model is able to distinguish between different attacks.
- **Isolation Forest:** It is an unsupervised machine learning technique for detecting anomalies, where the anomalies are defined as the outliers which can be detected by separating the data points using random partitioning. The Isolation Forest creates several random decision trees and considers anomalies as those data points that need fewer splits to separate them from other data points. Isolation Forest is applied here for detecting unknown cyber-attacks within the IoT network. As Isolation Forest doesn’t require any labelled data, it can be used to detect abnormal behaviour, thereby allowing the system to detect novel cyber-attacks.

6) Real-Time Rule-Based Safety Control

The rule-based safety decision-making system operates according to certain rules by which the system is analysed for its reliability and operation. Such analysis is carried out by monitoring important elements such as high levels of pressure, a change in pressure, unstable patient status, or any cybersecurity threat.

- **If pressure is high:** consider adjustment
- **If sudden pressure change:** check patient stability
- **If threat detected:** block system action
- **If patient unstable:** stop movement

The safety parameters, if fulfilled, enable the system to carry out autonomous and controlled corrections for better positioning of the patient. The adjustments remain minimal to not hinder the surgery process but make the operation safer and more comfortable for the patient. They include slight tilts of the operating table (±2–5°), minor repositioning, and redistributing pressure points.

7) Performance Metrics

The metrics quantify the effectiveness of model, and overall system are given below.

Accuracy: The key indicator for evaluating performance is accuracy, which is defined as the proportion of true predictions relative to the total number of predictions made by the model [18][19]. The result can be seen in Equation (1):

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

[2] https://www.kaggle.com/datasets/programmer3/secure-healthcare-iot-monitoring-dataset

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Precision: The ACC of a forecast can be measured by dividing the number of correct predictions by the total number of correct class value predictions [20]. Equation (2) is expressed in a precisely calculated:

$$Precision(Prec) = \frac{TP}{TP+FP} \quad (2)$$

Recall: The recall is calculated by dividing the total number of True Positives by the sum of all True Positives and False Negatives. Equation (3) expresses its formula.

$$Recall(Rec) = \frac{TP}{TP+FN} \quad (3)$$

F1 score: The F1-score is the harmonic mean of the two performance metrics—precision and recall—displayed in Equation (4) that were computed earlier:

$$F1\ score(F1) = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

The evaluated results based on these metrics are presented and analyzed in the subsequent section to demonstrate the performance of the proposed system.

IV. Result Analysis and Discussion

The system was developed using Python with TensorFlow/Keras. Visualization was done using Matplotlib. Hardware was emulated using a Raspberry Pi–class edge device (4–8 GB RAM, quad-core CPU) for real-time processing, and a cloud environment (GPU-enabled server) for training and storage. The system was set up to simulate constraints within an operation theatre in order to test latency, ACC, and real-time responsiveness. Table II indicates the results obtained by the model in terms of performance for various risks. The model performs with great ACC and PRE, yielding an ACC rate of 92.8%.

TABLE II. PRESSURE RISK CLASSIFICATION PERFORMANCE

Class	Precision	Recall	F1-Score
Low Risk	0.94	0.95	0.94
Medium Risk	0.91	0.89	0.90
High Risk	0.92	0.93	0.92
Overall Accuracy	92.8%	-	-

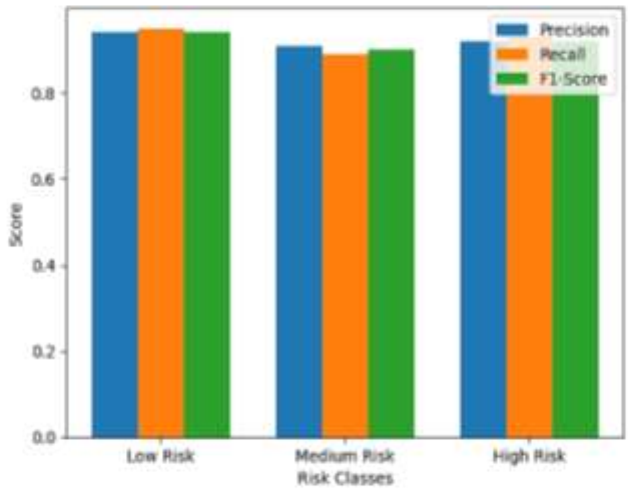

Fig. 2. Pressure Risk Classification Performance

The bar chart as shown in Fig. 2 below presents the performance of the machine learning technique in three different classes which include Low, Medium, and High risks. The performance metrics considered include Precision, Recall, and F1-Score, and each metric is above 0.8 in all cases. The low-risk class is very stable and reliable in assessing pressure risks.

Table III below presents the comparison between XGBoost, Isolation Forest, and Hybrid machine learning techniques. The hybrid method demonstrates the best ACC rate of 97.2%.

TABLE III. CYBERSECURITY THREAT DETECTION PERFORMANCE

Model	Detection Accuracy (in %)	Precision	Recall	F1-Score
XGBoost	95.6	0.94	0.93	0.93
Isolation Forest	93.8	0.91	0.92	0.91
Hybrid Ensemble (Proposed)	97.2	0.96	0.95	0.95

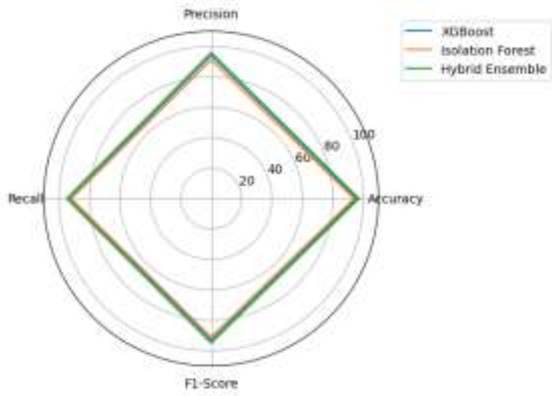

Fig. 3. Model Performance Comparison

The radar chart shown in Fig. 3 depicts the comparison of the XGBoost, Isolation Forest, and Hybrid Ensemble models in terms of ACC, PRE, REC, and F1. It is observed that the hybrid ensemble model shows better performance than other models by achieving higher scores. This result validates the effectiveness of hybridizing the supervised and unsupervised methods for detecting cyber threats.

The comparative study between edge and cloud computing is given in Table IV. The edge computing system offers lower latency and responsiveness, whereas cloud computing ensures scalability. They offer a high rate of successful transmissions.

TABLE IV. IOT SYSTEM PERFORMANCE IN SURGICAL MONITORING

Metric	Edge Computing	Cloud Computing
Average Latency	42 ms	205 ms
Data Transmission Success Rate	98.9%	98.9%
Packet Loss Rate	1.1%	1.1%
Real-Time Responsiveness	High	Moderate

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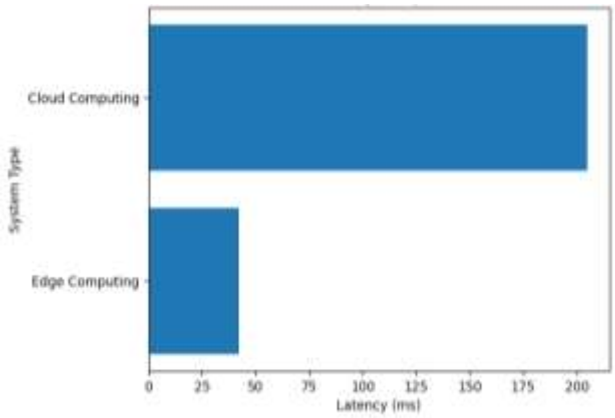

Fig. 4. IoT Latency Comparison

The latency comparison between edge computing and cloud computing is presented in Fig. 4. It can be seen that latency in edge computing (~42 ms) is much less than in cloud computing (~205 ms). This makes edge computing more appropriate for use in surgeries.

The system responses in various patient states are presented in Table V. With the increase in the risk level, the response time is reduced, and the efficiency is increased. Safe micro-movements like tilting and repositioning of patients are made by the system.

TABLE V. AUTONOMOUS SURGICAL TABLE ADJUSTMENT PERFORMANCE

Patient Condition	Response Time	Pressure Redistribution Efficiency	System Action
Low Risk	110 ms	72%	Preventive adjustment
Medium Risk	85 ms	85%	Active repositioning
High Risk	62 ms	93%	Micro-tilting (±2–5°)
Critical Risk	58 ms	95%	Safety-controlled stabilization

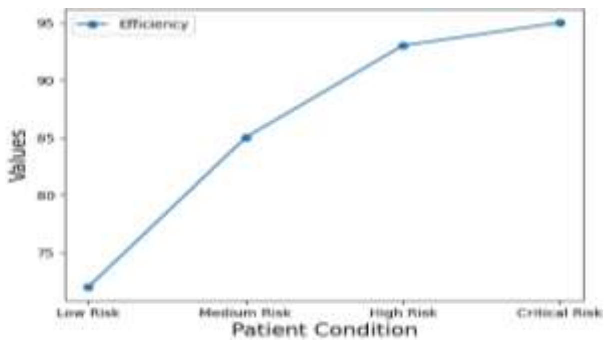

Fig. 5. Patient Risk vs Efficiency Analysis

Fig. 5 shows the interaction between patient condition levels and efficiency in the system. As the risk increases from low to critical, there is notable improvement in efficiency thanks to the adaptive nature of the system. The smart surgical table adapts its performance to better cope with critical situations.

A. Discussion

The results reveal that the proposed Intelligent Surgical Table is capable of incorporating real-time monitoring, machine learning, and cybersecurity. The pressure classification model attains high precision and, therefore, ensures that patient risks can be detected accurately. Moreover, the hybrid cybersecurity model proves superior to individual models and ensures the identification of existing and new cyberattacks. The latency analysis reveals that edge computing plays a crucial role in guaranteeing real-time response times, whereas cloud computing ensures scalability and data storage capacity. The capability of autonomous adjustment of settings according to real-time situations eliminates manual operations and enhances patient safety. However, the proposed system relies on simulation tools and implementation could have further challenges like environmental constraints.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

The introduction of a new Intelligent Surgical Table (IST) system to enhance surgery ACC, patient safety and operational efficiency through real-time data analysis and autonomous decision making. Through the use of IoT sensors, predictive models, cloud computing, and cybersecurity technologies, the IST system provides constant patient monitoring and guarantees safe data processing. The hybrid CNN-LSTM neural network classifies the pressure risk level, while XGBoost and Isolation Forest are used to identify cyber-attacks. The technology of edge computing guarantees prompt decision-making and consequently assists with tweaks to table position. The experiments reveal that IST system is efficient in healthcare monitoring and security detection applications and its predictions and detections are high in terms of ACC.

B. Limitations

The system under consideration is evaluated primarily by simulation, which is not representative of all the surgical scenarios. Hardware problems, sensor errors, and any abrupt change in patient position can cause inefficiency in the proposed system. In addition, reliance on rules can be a disadvantage in more complex situations. While cybersecurity strategies are efficient, they have to be updated continuously as they face new cyber risks.

C. Future work

Future work will be performed on clinical validation in real time and implementation in hospitals. Potential enhancements that can be considered include implementing a deep reinforcement learning algorithm to boost adaptability and automation. Improved cybersecurity by way of implementing threat intelligence measures and using blockchain technology can make the system even more secure. Another enhancement is provided by robotic actuation, and by multisensory fusion.

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