NABH-Compliant IoT-Enabled Smart ICU System for Integrated Monitoring and Predictive Maintenance

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Abstract—ICUs need one to monitor patients constantly and have the stable functioning of medical equipment to guarantee patient safety and adherence to regulations. Traditional ICU systems are decentralized and responsive, which have had implication of delay in fault recognition, equipment timeouts, and the emergence of higher clinical risk. In this paper, the author suggests an IoT-based Smart ICU Monitoring and Maintenance System meeting the requirements of the NABH and combining real-time patient vital monitoring with equipment health monitoring. It is an ESP32 controller that collects physiological measurements like ECG, heart rate, oxygen saturation, temperature, movement and environmental measurements with biomedical sensors which include MAX30102, DS18B20, MPU6050 and BMP180. At the same time, the DC current, voltage, and vibration sensors are involved to control the life-support equipment to identify electrical and mechanical failures. Transmission of data is done to an encrypted IoT cloud system, where data may be visually mined and alerted in real-time. Experimental testing also proves better response time, predictive maintenance capacity and improved operational reliability, which makes ICU a safer and smarter place.

Keywords : Smart ICU, IoT-Based Healthcare, NABH Compliance,ESP32 Controller, Predictive Maintenance, Biomedical Sensors, Real-Time Monitoring.

I. INTRODUCTION

The Intensive Care Unit (ICUs) is the most critical and technologically challenging setting in the contemporary hospitals. Patients who are hospitalised in ICUs usually necessitate in-depth physiologic supervision, life-support device, and quick clinical response. Any fatal complications or even death can be caused by a delay in the detection of abnormal conditions of patients or the failure of devices. Although many biomedical technologies have been developed, patient monitoring devices and equipment maintenance mechanisms work separately even within the ICUs. Such a separation stymies combined decision-making and heightens the use of manual oversight. Therefore, there is a delayed detection of faults, responsive maintenance habits, and human mistakes are persistent issues in critical care units.

The conventional systems in the ICUs are mostly targeting patient vital signs, including electrocardiogram (ECG), heart rate, oxygen saturation, respiratory rate, and temperature. But the operational health of life-support and biomedical equipment should equally be put into consideration, such as ventilators, infusion pumps, defibrillators, and monitoring systems. Critical treatment is associated with risky clinical outcomes of equipment failure. Periodic preventive maintenance schedules are followed in most hospitals, which are not always able to reflect the actual degradation or sudden electrical failure. Thus, an increasing demand to have the integrated systems with concurrent patient and equipment surveillance increases the reliability and safety.

One of the components of NABH accreditation involves patient safety, risk management, and the correct maintenance of biomedical equipment. Documents to be met include compliance, preventative maintenance records, winteriness tracking and timely reporting of malfunction in the devices. Nevertheless, these standards are hard to maintain manually and they are easily supervised. The use of smart healthcare technologies based on the Internet of Things (IoT) holds a potential solution, as it makes it possible to collect data in real-time and provides the opportunity to monitor data in one place, as well as automatic alert systems [1]. Medical systems have improved considerably with regards to remote monitoring, predictive diagnostics, and transparency of operations through IoT [2].

The latest developments of microcontrollers, including the ESP32 and wireless communication boards, have facilitated the realization of useful and affordable healthcare monitoring systems. Biomedical sensors such as MAX30102 pulse oximetry, DS18B20 temperature sensors, MPU6050 movement sensors and BMP180 environmental sensors offer precise data on the physiological and ambient measurements. At the same time, DC current and voltage sensors and vibration sensors are electrical sensors used to identify abnormal power consumption, overload conditions or mechanical instability on a medical device. By incorporating these sensing technologies into a single architecture, it will be possible to continuously monitor patients as well as the infrastructure of an ICU [3].

IoT platforms on clouds also maximize capabilities of the systems by offering live dashboards, historical analytics, and automated alerts using mobile or web-based interfaces. Predictive maintenance plans can be implemented through such platforms because the behavior of equipment whose maintenance is necessary is detected prior to full breakdown. Research has established that predictive monitoring can greatly minimize the downtime and maintenance costs of equipment besides enhancing patient safety outcomes [4]. Furthermore, evidence-based ICU systems would facilitate optimal use of clinical decisions and an increase in the accuracy of documentation, in line with accreditation and quality assurance processes [5].

To address these issues, this paper suggests the Design of an NABH-Compliant IoT-Based Smart ICU Monitoring and Maintenance System. The suggested system combines patient vital screening and equipment health care by means of an ESP32 framework alongside cloud integration. Integrating real-time biomedical biomarker detection with electrical and mechanical faults detection, the system will improve patient safety, minimize equipment downtime, and assist in regulatory compliance. The system methodology, implementation, results, and possible future improvements have been presented in the following sections.

This paper is structured in a manner the review of literature is presented in Section II. Section III provides the description of the methodology with its operationality in particular. There are results and discussions in section IV. Finally, the last part of V is the final findings and recommendations.

II. Literature Survey

The intensive care unit (ICU) and neonatal intensive care unit (NICU) are areas where technology has moved at a very fast rate because of the rapid digital transformation of these units. Contemporary critical care settings produce vast amounts of diverse data in the form of electrocardiography (ECG), blood pressure waveforms, oxygen saturation, respiratory, and high-resolution video streams. The utilization of these data streams to provide real time status, forewarn risks and support intelligent decision making has become a major area of research inquiry. Recent works highlight contactless sensing, multimodal data fusion, predictive analytics, and the privacy-preserving frameworks to increase patient safety, decrease alarm fatigue, and improve the clinical outcomes. Non-invasive and low-risk monitoring solutions are primarily important (especially in the neonatal and pediatric ICUs) where the patients are highly vulnerable. Moreover, the addition of deep learning structures and optimization-driven models to the ICU infrastructure is indicative of a larger trend of smart and data-driven healthcare environments that are potentially capable of aiding clinicians in high workload environments and under time constraints.

Recent ICU mortality predictive models, care escalation models and emergency detection models indicate a new role of deep learning and temporal modeling methods. An example of the bidirectional gated recurrent unit [6] model of mortality prediction brings forward the significance of comorbidity-physiology interactions and of time trajectories in critical care data model. Predictive control and real-time monitoring interfaces are another enhancement to timeliness of alerts and detection of anomalies in the ICU settings [20]. On the same note, AI-driven emergency prediction systems combine statistical and signal-oriented aspects to predict acute events when they have not escalated to the point of irreversible clinical deterioration [21]. The application of multi-output classification models in a complex ICU environment is a necessity due to early identification of multi-label care escalation with the help of electronic health records (EHRs) [15]. Full neural networks have been suggested in neonatal care to detect diseases and predict them at an early stage and provide a proactive approach to treatment [11]. All these measures are a reminder of the change toward a proactive risk prediction approach, which allows response and better decision-making in high-acuity units (rather than reactive monitoring).

Non-contact and camera-based surveillance systems have received significant interest on matters regarding infection control and comfort considerations of patients. The RGB cameras and the millimeter-wave FMCW radar of monitoring preterm infants have such comparative analyses which prove the possibilities of implementing contactless cardio-respiratory measurements in NICUs [7]. The application of autocorrelation-based radar-based heart rate monitoring algorithms has enabled to offer continuous and non-invasive measurements applicable in using the ICU bed monitoring [8]. Camera-oriented pulse rate variability and remote photoplethysmography (rPPG) have also been studied in terms of early warning systems, demonstrating positive relationships with well-known metrics obtained using the ECG in conventional ECG signals [10]. In addition, camera-based estimations of neonatal blood pressure, as based on multi-site and multi-wavelength pulse transit time, brings about a proof of concept to cuffless blood pressure in delicate ailing newborns [16]. In addition to vital signs, video-based motion coordination analysis of infant limbs allows the early detection of neurological conditions [9], and automated infant delirium identification with the use of deep learning-based video analytics proves the clinical usefulness of behavioral and motion-based biomarkers [12]. All these innovations project a change in the direction of ambient intelligences that monitor physiological and behavioral cues without physical contact.

To be able to rely on ICU analytics, signal processing and physiological signal quality assessment are still essential concepts. It is shown that neonatal EEG-based short-term forecasting of seizures can be improved with entropy-based and feature extraction methods [18]. EEG multifractal has also been used in vigilance state classification of comatose patients and has been used in aid of better assessing the neurological condition in critical care units [23]. The frequency-based methods signal quality estimation of impedance pneumography signals can overcome the motion-related issues and noise in the NICU respiratory monitoring [22]. Besides that, the assessment experiments of cardiac output measurement during cases of extracorporeal membrane oxygenation reveal the necessity of precise modelling of hemodynamics in complicated life-support conditions [17]. The studies conducted on noninvasive hemoglobin measures and its correlation with the invasive methods contribute additional importance to the manufacture of safer and less invasive measuring systems [4]. All these studies highlight the need to have strong signal processing pipelines, artifact detectors, and confirmation against gold-standard clinical measurements to achieve clinical reliability and safety.

In addition to the personal level monitoring algorithms, optimization at the system level, privacy and interaction with technology are also important to the next-generation ICU ecosystem. Non-hierarchical overflow loss models of intensive care networks are more effective in enhancing the quality of service and computational efficiency in hospital environments of high demands [2]. Infant sleep/wake detection with privacy (federated learning) illustrates that a multi-center cooperation can take place without significant abuse of sensitive patient data [5]. An example of hybrid modeling to test workflow resilience and reduction of alarms fatigue is the simulation of patient provider interaction in ICU alarm response [24]. Reproducible research and benchmarking in medical video analysis is facilitated by development of annotated datasets of NICU-care video [13]. Furthermore, virtual reality simulation ICU rehabilitation depicts the digital health technology growth out of monitoring to therapeutic and recovery-centred interventions [19]. These interconnected solutions all indicate intelligent, safe, and patient-centered critical care infrastructures integrating sensing, analytics, optimization, and human-centered design to enhance results in a variety of ICU patients.

III. Methodology

Its NABH-Compliant IoT-Based Smart ICU Monitoring and Maintenance System is developed in a systematic and dynamic manner to make it reliable, scaled, and regulatory. The methodology comprises biomedical sensing, equipment health monitoring, embedded processing, wireless communication, cloud analytics, and alert mechanisms into a supported architecture. The system is designed based on ESP32 microcontroller which is the central processing and communication core. The patient physiological parameters and the state of the equipment of an ICU is obtained in real-time due to specific sensors. The data is preprocessed and validated locally and thereafter the data is sent to an IoT cloud platform safely. The design in general provides continuous monitoring, early detection of anomalies, real time generation of alerts, as well as, storage of historical data to facilitate compliance and predictive maintenance. The technical implementation is implemented as follows and is covered in the following subsections.

A. System Architecture Design.

This architecture is based on a layered system architecture composed of sensing, processing, communication, cloud and user-interface layers. At the sensing layer, the ESP32 controller is interconnected with biomedical and electrical sensors by the digital and analog input pin. ESP32 has been chosen because it has a dual core processing power and has a built-in Wi-Fi module, low power usage and is suitable in the real-time embedded health care applications.

The processing layer does signal conditioning, filtering and works with threshold-based detection of anomalies. ECG and pulse signals are subjected to noise removal methods in order to obtain correct readings. The communication layer relies on the integrated Wi-Fi module to send data, which is processed to the cloud server, on a secure basis (over HTTP and MQTT protocols).

The cloud layer offers a centralized storage, analytics, and dashboards of visualization which are available to healthcare professionals. Lastly, there is the user-interface layer that consists of a web-based dashboard and mobile alert system in order to provide real-time warnings. By keeping digital records of patient and equipment information, this architecture maintains scalability, interoperability and adherence to the NABH documentation requirements.

B. Patient Vital Parameter Monitoring

Several biomedical sensors are attached to the ESP32 to ensure patient monitoring is accomplished. ECG sensor records cardiac electrical activity and gives waveform data which is used to detect arrhythmia. The sensor is the MAX30102 in which the photoplethysmography is used to measure the heart rate and oxygen saturation (SpO2). The DS18B20 digital temperature sensor is used in monitoring body temperature and is capable of reporting high precision values that can be applied to a clinical setting.

The MPU6050 accelerator and gyroscope module is used to provide motion and posture detection, which allows detection of cause and effect circumstances of an abnormally moving patient or potential falls. The sensor of environmental parameters, like atmospheric pressure and room conditions is controlled with the BMP180 sensor to allow the best ICU environmental regulation.

The ESP32 takes unprocessed sensor data and regulates calibration and filtering belief algorithms. The predefined threshold values are based on the clinical safety ranges. In case any of the parameters has surpassed safety levels, it issues instantaneous notifications in the immediate environment with the help of a buzzer and in the remote environment through the IoT platform. The long-term data recording facilitates the trend management and preventive identification of physiological degradation.

C. Equipment Health monitoring ICU.

Electrical and mechanical parameters are in constant check to prevent the stop of important medical equipment. DC current sensors are carried to help determine real-time current usage by the ICU equipment of ventilators, infusion pumps, etc. Deviant increment or decrease of the current can be a sign of overloading, short, or damaged component.

DC voltage sensors conform the stability of supply voltage. The fluctuations in the voltage exceeding allowable levels are confined and registered. Vibration sensor is employed to detect abnormal mechanical oscillation in the equipment like the compressors or rotating machines. Overshooting vibration can be a sign of wear, lack of balance or mechanical deterioration.

The ESP32 is a device that continuously takes electronic and vibration readings and compares them to pre-established safe operation ranges. In case anomalies take a longer period of time, fault notices are produced. This system facilitates predictive maintenance since one is able to detect failure in its early stage before there is a disgraceful collapse. Ongoing monitoring of equipment is in line with the NABH requirements on the prevention of maintenance records and preventive risks.

D. Data Processing and Anomaly Detection.

The information obtained using sensors is preprocessed in the ESP32 environment. Signal conditioning involves the use of digital low-pass filtering methods to remove noise on ECG signal. Heart rate and SpO 2 That moves and averaging automatically filter changes transient spikes.

The detection of anomaly is done by using a threshold based logic and time-duration validation. To explain the existence of false positives, anomalous heart rate measurements should occur within a period before inconsistency notifications are sent. The same case applies to electrical faults which are validated by series of sampling.

The processed data is formatted as structured packets, which comprise of timestamp, device ID and parameter values. There are secure encryption tools would be used prior to transmission to avoid unauthorized access. This provides patient confidentiality and integrity. The local processing power saves network reliance, and improves the reliability of the system when network connectivity is temporarily unavailable.

E. IoT Cloud and Visualisation.

The ESP32 sends authenticated data to a secure IoT cloud-based platform through the Wi-Fi connection. MQTT protocol is employed in the data communication as it has the features of lightweight and low-latency protocols with the characteristics applicable in medical care. The cloud server implements real-time and previous data in organized databases.

The visualization of patient vitals and equipment status are graphically and tabularly visualized in a web-based dashboard. The healthcare workers are able to track the trends, compare the past trends, and produce compliance reports. Automated mobile or SMS alerts are set so as to notify clinicians in case of an emergency.

The cloud platform also makes predictive analytics possible, a review of historical equipment data can be done to detect the use patterns and performance decline. Remote access enables hospital administrators to inspect several ICU beds at the same time, which enhances the effectiveness of the working process and its centralized control.

F. Notification System and NABH Framework.

The system encompasses local and remote alert systems. A loud alarm will give instant audible warnings in essential patient or equipment malfunction. At the same time, the authorized personnel receive cloud-based notifications. This is a dual-alert system and guarantees response in the shortest time possible and least risk.

To comply with the NABH regulations, the system has automated digital data of sensor values, fault, maintenance warning and calibration data. Data is time-stamped and so stored to be audited. The maintenance schedules can be automatically created with information on the hours used by the equipment and the identification of anomalies.

Between the provision of continuous monitoring, preventive maintenance records, and centralized reporting, there will be compliance with the safety measures and accreditation courses. The systematic approach methodology would make the proposed Smart ICU system technically strong, expansionary and in conformity to healthcare quality outlines.

Fig. 1: System Architecture

IV. Result and Discussion

The proposed NABH-Compliant IoT-Based Smart ICU Monitoring and Maintenance System was tested experimentally using simulated ICU condition where it was experimented to identify its performance in real-time patient monitoring, equipment health monitoring, alert response, and reliability in cloud. The system was configured with biomedical sensors and esp32 controller, and the ICU apparatus like ventilator simulators and infusion pump loads was attached with DC current sensor, voltage sensor, and vibration sensor. Communication between the IoT cloud and the dashboard was done through Wi-Fi. Measurement accuracy and response time, anomaly detection efficiency, system reliability, and prediction of system maintenance were the performance aspects that were measured.

In the process of monitoring patients in tests, physiological parameters such as heart rate, SpO 2, body temperature, sustainable variations in the ECG waveform, and motion detection were monitored under normal and abnormal conditions. The system showed good sensors data acquisition and transmission with no loss of packets when running continuously. Figure 2 is the dynamic patient vital monitoring dashboard with ECG in real-time, heart rate, oxygen saturation, and temperature values as trends plotted six-minute amplitude dashboard at intervals. The graphical interface helped clinicians to monitor changes superficially and determine patient stability. Table 1 shows the measured patient vital parameters in the normal and abnormal simulated conditions.

Fig 2: Live Monitoring Patient Vital Display with ECG Waveform, Heart rate, SpO 2, Temperature and motion parameters.

Table 1: Vital parameters monitoring results of patient.

Parameter	**Normal Range**	**Observed Normal Value**	**Abnormal Condition**	**System Detection Time (sec)**
Heart Rate (bpm)	60–100	78	128	3
SpO_2 (%)	95–100	97	88	4
Body Temperature (°C)	36.5–37.5	36.9	39.2	5
ECG Rhythm	Regular	Normal Sinus	Irregular	3
Motion Status	Stable	No Movement	Sudden Fall	2

Based on Table 1, it can be noted that, the abnormal physiological conditions were detected within a few seconds after they had occurred. The Time validation algorithm based on the threshold helped to minimise the false alarm and produce a quick identification. After the digital filtering, the ECG signal image kept a good waveform and irregular characters were detected timely. The measurements of oxygen saturation and heart rate were observations that were consistent with clinical monitoring references, and they showed reasonable accuracy in the use of ICUs.

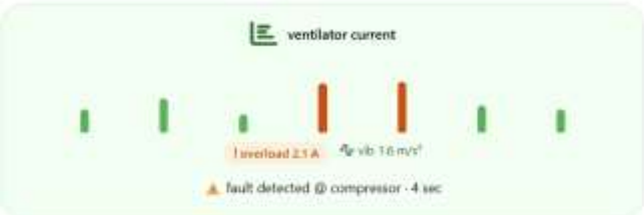

Fig 3: ICU Equipment Health Monitoring Interface with Recent Consumptions, Voltage Stability, and Vibration Analysis.

ICU equipment health was also being monitored continuously at the same time. The electrical loading tests were conducted by varying the current consumption and applying voltage variations. Vibration detection was tested by providing mechanical imbalance. Figure 3 represents the piece of equipment health monitoring demonstrating the current consumption patterns and trends of vibration intensity. The graphical representation showed clear changes in the values in case of sudden deviations of the baseline.

Table 2: ICU Equipment Intensive Care Performance.

Equipment Type	**Normal Current (A)**	**Fault Current (A)**	**Voltage Variation (V)**	**Vibration Level (m/s²)**	**Fault Detection Time (sec)**
Ventilator Simulator	1.2	2.1	±5	0.3	4
Infusion Pump Load	0.8	1.5	±4	0.2	3
ICU Monitor Unit	0.6	1.2	±6	0.4	5
Air Compressor Unit	2.5	3.8	±7	1.6	4

Table 2 shows that the abnormal electrical and mechanical conditions were detected quickly. The current overload situations raised the alerts when the values were greater than predetermined values during set periods of time. Voltage instability out of range was accurately found and allowed to stop possible device malfunction. High level of vibration in rotating machinery was an indication that the machine was worn out early in time, which supported predictive maintenance. These results prove the dual-monitoring architecture to be more reliable in its operations in the ICU setting.

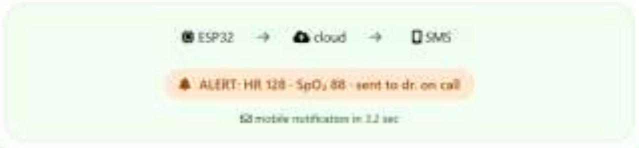

Fig 4: IoT-Based Signal Notification Chain between Sensor Detection and Cloud Dashboard and Mobile Alert Magazine.

The measurements of cloud performance were conducted based on the analysis of data transmission latency, the speed of the uptime, and the speed of alert notifications. The MQTT based communication protocol ensured low-latency information exchange. Figure 4 shows the system alert notification loop of detecting sensor to updating cloud dashboard and sending mobile alert. The mean time of refreshing clouds was low, which guaranteed real time visibility.

Table 3: Metrics of System Communication and Reliability.

Parameter	**Measured Value**
Average Data Transmission Delay	1.8 sec
Cloud Dashboard Update Time	2.5 sec
SMS/Mobile Alert Delay	3.2 sec
System Uptime (Continuous Test)	99.2%
Packet Loss Rate	<1%
Power Consumption (ESP32 Unit)	0.8 W

With communication metrics as presented in Table 3, there is a stable connection while using wireless and effective synchronization during cloud connectivity. The clinical response was prompt since alert notifications were provided within a very short period of time. Reliability was tested by the system running over long time periods in testing and was found to be fit to implement the system in the ICU. Data integrity and adherence to monitoring standards were ensured because of low packet loss.

Between patient and equipment monitoring through a single dashboard, the situational awareness increased significantly. Rather than individual systems, clinicians and biomedical engineers would be able to see the status of patients and the wellbeing of the devices at the same time. This incorporation decreases the manual documentation load and adheres to the NABH compliance rules and regulations as it automatically produces maintenance documentation and incident reporting.

The proposed system compares with the traditional periodic maintenance systems that the proposed system takes the maintenance form of being reactive to predictive. Electrical overload and abnormal vibration pattern had been noted before full failure, and this would have decreased the time the equipment was down. The same applies to the real-time monitoring of physiological processes which aids in early clinical interventions that are of paramount importance in the intensive care.

In general, the experimental validation proves that the Smart ICU system based on the IoT can benefit the response time and improve patient safety, promote preventive maintenance, and provide transparency in operations. The dual-layer monitoring structure is an important development in comparison to older ICU monitoring structures that were not done in a fragmented way.

V. Conclusion

This paper has introduced an NABH-compliant IoT-based Smart ICU Monitoring and Maintenance System that incorporates real-time patient vital monitoring and continuous equipment health care to perform its functions. The system has been able to integrate biomedical sensors, electrical fault detection, ESP32-based processing, and cloud-based visualization into one system. It is experimentally proved that the speed of anomaly detection is enhanced, equipment becomes more reliable, and effective mechanisms of alerts, which lead to safer operations in ICUs. An automated documentation and predictive maintenance system helps in regulatory compliance and lessening operational risk.

In the future, the work will involve integrating machine learning algorithms and more advanced predictive analytics, including cybersecurity improvements, increasing the number of beds, and performing validation of the system in the actual hospital setting as additional steps to increase its accuracy, reliability, and clinical uptake.

References

[1] H. Lai et al., “A Ubiquitous Platform for Camera-Based Multi-Parameter Vital Signs Monitoring in Hospital ICUs: A Double-Center Clinical Study,” in IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 12, pp. 8671–8678, Dec. 2025, doi: 10.1109/JBHI.2025.3620569.

[2] J. Wu et al., “Design, Performance Evaluation, and Optimization for Intensive Care Networks Based on Non-Hierarchical Overflow Loss Systems,” in IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 7, pp. 5270–5283, July 2025, doi: 10.1109/JBHI.2025.3549142.

[3] A. Mendoza et al., “Clinical Features and Physiological Signals Fusion Network for Mechanical Circulatory Support Need Prediction in Pediatric Cardiac Intensive Care Unit,” in IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 2, pp. 783–791, Feb. 2025, doi: 10.1109/JBHI.2024.3510217.

[4] J. A. V. Escobar et al., “Correlation and Concordance of Noninvasive Hemoglobin with Invasive Hemoglobin Measurement Techniques in Critically Ill Patients,” in IEEE 4th Colombian BioCAS Workshop, Armenia Quindio, Colombia, 2025, pp. 1–6, doi: 10.1109/ColBioCAS66416.2025.11276150.

[5] X. Yang et al., “Privacy-Preserving Infant Sleep-Wake Detection in NICUs based on Federated Learning: A Multi-center Clinical Study,” in IEEE Engineering in Medicine and Biology Society Annual Conference, Copenhagen, Denmark, 2025, pp. 1–4, doi: 10.1109/EMBC58623.2025.11251758.

[6] G. Sindhu and K. L. Hemalatha, “Patient Aware Bidirectional-Gated Recurrent Unit Framework for Intensive Care Unit Mortality Prediction,” in International Conference on Mobile Networks and Wireless Communications, Tumkur, India, 2025, pp. 1–7, doi: 10.1109/ICMNWC66779.2025.11354416.

[7] G. Liao et al., “Non-contact Cardio-respiratory Monitoring of Preterm Infants in NICU: RGB Camera or mmWave FMCW radar?,” in IEEE Engineering in Medicine and Biology Society Annual Conference, Copenhagen, Denmark, 2025, pp. 1–5, doi: 10.1109/EMBC58623.2025.11254365.

[8] S. Seifizarei et al., “Continuous Radar-based Heart Rate Monitoring using Autocorrelation-based Algorithm in Intensive Care Unit,” in IEEE Journal of Biomedical and Health Informatics, 2025, doi: 10.1109/JBHI.2025.3527566.

[9] Y. Zhong et al., “Camera-based Analysis of Motion Coordination Between Infant Left and Right Limbs: A Clinical Study in NICU,” in IEEE Engineering in Medicine and Biology Society Annual Conference, Copenhagen, Denmark, 2025, pp. 1–4, doi: 10.1109/EMBC58623.2025.11254151.

[10] H. Wang et al., “Toward Camera-PRV-Based Early Warning in Hospital ICU: A Pilot Study,” in IEEE Internet of Things Journal, vol. 12, no. 14, pp. 28623–28638, July 15, 2025, doi: 10.1109/JIOT.2025.3566990.

[11] S. Navya et al., “Improving Neonatal Care with NEONATALAI: A Comprehensive Deep Learning Framework for Early Prediction and Diagnosis of Neonatal Diseases in Intensive Care Units,” in International Conference on Advancements in Smart, Secure and Intelligent Computing, Bhubaneswar, India, 2025, pp. 1–6, doi: 10.1109/ASSIC64892.2025.11158619.

[12] J. Chen et al., “Automated Pediatric Delirium Recognition via Deep Learning-Powered Video Analysis,” in IEEE Journal of Biomedical and Health Informatics, 2025, doi: 10.1109/JBHI.2025.3604448.

[13] Y. Xin et al., “Descriptor: Neonatal Intensive Care Unit Fine-Grained Care Video Dataset (NICU-Care),” in IEEE Data Descriptions, vol. 2, pp. 203–210, 2025, doi: 10.1109/IEEEDATA.2025.3576054.

[14] T. T et al., “An AI-Based Framework for Real-Time Patient Monitoring and Intelligent Treatment Recommendation in Critical Care Units,” in International Conference on Computing and Data Science, Chennai, India, 2025, pp. 1–5, doi: 10.1109/ICCDS64403.2025.11209640.

[15] S. A. C. Bukhari et al., “Early Prediction of Multi-Label Care Escalation Triggers in the Intensive Care Unit Using Electronic Health Records,” in IEEE International Conference on E-health Networking, Application & Services, Abu Dhabi, United Arab Emirates, 2025, pp. 1–6, doi: 10.1109/HealthCom60686.2025.11343128.

[16] Y. Zeng et al., “Camera-Based Neonatal Blood Pressure Estimation From Multisite and Multiwavelength Pulse Transit Time—A Proof of Concept in NICU,” in IEEE Internet of Things Journal, vol. 12, no. 13, pp. 24775–24788, July 1, 2025, doi: 10.1109/JIOT.2025.3557771.

[17] M. Garbutt et al., “Evaluation of Cardiac Output Estimation with Veno-Venous Extracorporeal Membrane Oxygenation Support: In Vitro Study,” in IEEE Engineering in Medicine and Biology Society Annual Conference, Copenhagen, Denmark, 2025, pp. 1–4, doi: 10.1109/EMBC58623.2025.11251892.

[18] T. Skoric et al., “Machine Learning for Short-term Seizure Forecast Using Neonatal EEG,” in IEEE Engineering in Medicine and Biology Society Annual Conference, Copenhagen, Denmark, 2025, pp. 1–5, doi: 10.1109/EMBC58623.2025.11254950.

[19] S. Eom et al., “Legato: Virtual Reality for Physical Rehabilitation of Patients in the Intensive Care Unit,” in IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops, Saint Malo, France, 2025, pp. 1027–1032, doi: 10.1109/VRW66409.2025.00207.

[20] K. Kumar et al., “Deep Learning-Based Real-Time Interfaces for Monitoring and Predictive Control of Intensive Care Unit Patient Parameters,” in IEEE International Conference on ICT in Business Industry & Government, Indore, Madhya Pradesh, India, 2025, pp. 1–7, doi: 10.1109/ICTBIG68706.2025.11323879.