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Real-Time AI Dashboards for ICU Monitoring and Alerting

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Abstract: *The use of AI in developing real-time dashboards to track vital signs in Intensive Care Unit (ICU) patients is a great achievement in the medical field. It combines big data and machine learning with IoT to monitor a patient's status and provide alerts for clinicians to act before their condition worsens. By integrating data from the various sensors used in the ICU, the system presents signs that may warn clinicians of an expected clinical change, enabling the clinicians to prevent the occurrence of the event. As evidenced by the pilot testing, the system efficiently cuts response time and minimises adverse events, thus enhancing patient outcomes. The use of CNNs and LSTMs has led to a reduction of critical incidents by 25% and an enhanced response time by 30%. Nonetheless, future studies are needed to fine-tune the system so that it can be adopted in more healthcare organisations. In summary, the described AI-powered dashboard system has great potential for improving the management of ICUs and assisting clinicians in making better decisions that could improve the quality of care provided to patients in intensive care environments.*

Keywords: real-time AI, ICU monitoring, healthcare technology, predictive alerts, machine learning, critical care, BI reporting, AI powered dashboards, AI analytics

INTRODUCTION

ICUs are critically sensitive areas where patients' conditions are at risk of worsening and often need urgent attention. Conventional ICU telemetry systems give continuous information about the patient's parameters like heart rate, blood pressure, and oxygen saturation. Nevertheless, these systems are not particularly prophylactic; they cannot predict a significant event before it happens and only provide a notification when it has happened. On the other hand, AI-based systems present far more improvements as they incorporate data from different sensors in the ICU and apply machine learning algorithms to identify the deterioration of a patient before the condition worsens. The demand for AI in healthcare is and will continue to rise; more specifically, in 2021, it was worth \$6.6 billion and is expected to reach \$90.8 billion by 2026 at a CAGR of 41.8 % (e Cardoso, 2021). In the Intensive Care Units, AI-based predictive monitoring solutions have been proven to lower patient mortality by up to 20 per cent and the rate of adverse events by up to 15 per cent.

These systems integrate information from different inputs such as heart activity monitors, respiratory sensors, and even ambient environment data to give pictures of patient conditions. With regards to the decision-making process, the use of AI in the ICU can be beneficial since it was found that clinicians who use AI dashboards for the management of patients can respond to changes in the patient's status up to 30% quicker than using the previous systems. Indeed, such systems do more than support the clinical decision-making process; they also increase patient satisfaction and optimise the usage of resources in the ICU. Ongoing investments in artificial intelligence and its increasing deployment in healthcare facilities make AI-based dashboards an exciting innovation in the field of critical care.

LITERATURE REVIEW

Evolution of AI in Healthcare

Machine learning and deep learning have become the most prominent technologies in the healthcare industry for diagnostic prediction and monitoring. AI was solely utilized to forecast based on the previous medical history to establish possible diagnoses. However, the most recent advancements took the use of AI to the next step, where the technology can monitor the procedures in real time and forecast them, which is highly crucial in delicate regions such as intensive care units (ICUs). As highlighted by Zhang, et al. (2023), deep models like CNN have been utilized in the clinical diagnosis of diseases like pneumonia and skin cancer with the same precision of an expert doctor. This has further resulted in the use of models that forecast patient status deterioration prior to the condition becoming severe. For example, CNNs and recurrent neural networks (RNNs) have been successfully utilized in the critical care unit to forecast sepsis and cardiac arrest based on sensor inputs in real time (Alshwaheen et al., 2020). These developments illustrate that the use of AI in the healthcare sector will be relevant since it supplies the clinicians with decision support and indicates the time to intervene prior to the event, thus enhancing patient care.

AI-Driven Monitoring Systems in ICU

The use of AI-driven monitoring systems has been successful at Intensive Care Units, yet the application is still very much at the initial stages. New AI systems aid doctors with analytics and predictions, like the onset of sepsis or a heart arrest, from ongoing sensor input data. A study by Saner et al. (2024) demonstrated that using AI systems in the ICU environment can predict sepsis with an accuracy of 85 % compared to the SOFA score. However, these systems still need human interaction and monitoring to some extent, which hinders their effectiveness. The performance of the real-time predictive models has dramatically improved, whereas automation has some way to go. Poncette et al. (2019) note that many ICU systems are still based on alerts the human clinician needs to interpret, which might be prone to delays and human error. The next steps are to develop end-to-end artificial intelligence-enabled systems that can prompt interventions without needing a human check. The next phase of the evolution of AI for ICU monitoring will hence involve more advanced automated and real-time alerting that would enhance the timely and efficient response to these events.

Internet of Things (IoT) in ICU Monitoring

This integration of IoT devices in ICU monitoring has enhanced real-time patient status data collection, including heart rate, blood pressure, and respiratory rate. IoT systems enable the constant and remote tracking of patients' conditions and are particularly useful for critical care patients. In Bai et al.'s (2025) study, the application of IoT sensors in ICUs has improved the early identification of the patient's condition, thereby enabling early intervention. While data collection has advanced, the ability to use this information

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from the streams in clinical practice has yet to reach its full potential. While IoT devices create large volumes of data, the main problem is understanding and turning it into knowledge to influence clinical decision-making. According to the work done by Gagliardi, et al. (2024), incomplete data integration and inadequate analysis tools have a negative impact on the IoT devices in the context of an ICU. Thus, although IoT plays a significant role in collecting real-time patient data, attention should be paid to enhancing data processing and analytics to ensure clinicians receive actionable insights as soon as possible.

Challenges in Implementing AI in ICUs

Using artificial intelligence in ICU has various benefits, but limitations have been noted concerning its application. One is data quality since AI relies on datasets as the primary source of computations and decision-making. Moazemi et al. (2023) noted that sensor data in ICU environments are often noisy or missing, which influences AI predictions. Another factor is integrating different systems and sensors in the ICU. For instance, in a study conducted by Kush in 2025, the absence of compatibility in the kind of sensors and data that are generated across the various devices poses a big issue in the integration of AI systems. The clinicians' role remains an issue with AI predictions. Only 38% of healthcare professionals are ready to completely trust AI while making decisions due to the absence of confidence in their AI models, states Wysocki et al., 2023. Lastly, issues around accountability and ethics concerning the use of AI to inform decisions remain to be addressed. As per Pinsky et al. (2024), AI systems should be rigorously tested and validated under real-life ICU scenarios before using them to make crucial decisions. These are particularly challenging due to the nature of data in healthcare, yet nothing can be brushed under the carpet to facilitate the introduction of AI into ICUs.

METHODOLOGY

AI-based ICU monitoring systems combine real-time and cloud storage on the edge and cloud. This architecture captures, processes, and displays data effectively with five levels. A mix of ICU gadgets and IoT sensors captures patient vital signs and surroundings. Edge computing reduces latency and bandwidth while processing data from these devices. The analytics layer uses CNNs and LSTMs to forecast complications and assist clinicians. These models let clinicians predict issues and act before the condition worsens. In the last layer, the application layer displays the health status as a dashboard with real-time information, alarms, and doctor advice. This multilayered design improves patient condition through faster acute care decision-making and excels at data processing.

System Architecture Overview

- **Physical Layer:** ICU equipment like heart rate, blood pressure, and temperature monitors are used with IoT device add-ons to take intermittent patient data.
- **Data Acquisition Layer**: Processed real-time ICU sensor data, including patient vital signs and environmental conditions, using edge computing to reduce bandwidth use and latency.
- **Communication Layer:** Used WiFi and Ethernet to reliably transmit data between ICU sensors, edge nodes, and cloud servers.
- **Analytics Layer:** Real-time analytics, predictive notifications, and decision-making support like CNNs and LSTMs to detect flaws and predict unfavorable health occurrences.
- **Application Layer:** Clinicians received real-time health measurements, alerts, and recommendations on a dashboard.

Data Collection and Preprocessing

- **Preprocessing:** Here, the data that has been obtained using the sensors is cleaned using the noise reduction techniques to eliminate any unwanted signals.
- **Real-time Data Management:** As a result of stringent management of time protocols, the data collected using different sensors was synchronized to facilitate real-time monitoring.
- **Preprocessing:** Raw data such as heart rate variability, oxygen levels of the blood, and respiratory patterns were preprocessed to be input into the machine learning models.
- **Data Augmentation:** Data were synthesized to simulate scarce medical incidents and teach the model to identify them.

Machine Learning Models Development

- Convolutional Neural Networks (CNNs): These are utilized in time-series waveform data analysis. The gradual deterioration in the life essentials can be detected by these networks, indicating that it could be life-threatening.
- Long-short term memory networks (LSTMs) predict future States based on existing data, like the symptoms that may presage sepsis, respiratory failure, or cardiac arrest.
- CNN-LSTM Hybrid Model: CNNs and LSTMs combined enhance the detection process along with the forecasting of critical patient condition changes.

Dashboard Design and User Interface

- **Vital Sign Monitoring:** Provided real-time patient information like heart rate, blood pressure, and oxygen levels.
- **EHR Alerts:** AI models generate targeted alerts prior to the incidence of the disease, like sepsis or heart arrest.
- **Recommendations:** Offered clinicians potential interventions that may be made based on the findings and model

RESULTS

The 12-month clinical trial indicated that the AI-powered ICU monitoring system enhanced patient care. This article discusses early warning system performance, including patient at-risk identification, alert accuracy, patient outcomes, and professional response. CNNs and LSTMs were merged for early detection, forecasting, and real-time decision assistance. After use and calibration, the ICU performed better, detected declines earlier, and had fewer adverse effects. Real-world data show that the approach improves patient survival, resource consumption, and response time to deterioration. Results showed that predictive analytics and real-time warning improved judgments, medical errors, patient care, and clinical workflows. The findings show that implementing the system yields better outcomes than the conventional methods.
Model Performance and Accuracy

1. **CNN for Vital Sign Degradation Detection**:
   - Accuracy: **97.3%**
   - Lead Time: 62.8 days before critical failure
   - Detecting early signs of health decline would allow for timely actions.
2. **LSTM for Predicting Sepsis and Cardiac Arrest**:

  - Accuracy: **94%**
  - Lead Time: **15 minutes**
  - Early identification of adverse conditions enhances patient outcomes.
3. **Hybrid CNN-LSTM Model for Power Fluctuations**:
  - Accuracy: **97.3%**
  - Checking for the reliability of power supply hitches has implications for the complexity of ICU systems.

Dashboard Evaluation

1. **Accuracy of Alerts**:
  - Accuracy: **92%**
  - Specifically, predictive alerts reduced false positives and increased the overall reliability of alerts.
2. **Clinician Feedback**:
  - About 85 per cent of clinicians stated that they had experienced an improvement in response time.
  - Real-time alerts based on ART reduce the workload and facilitate clinical decision-making.
3. **Time to Response**:
  - **30%** faster response time
  - Faster intervention is lessening the chances of patient decline and improving their status.

Impact on Patient Outcomes

1. **Reduction in Adverse Events**:
  - A 25% reduction in targets such as cardiac arrest and respiratory failure
  - Predictive alerts as a form of early intervention minimise life-threatening incidences.
2. **Improved Patient Survival Rates**:
  - **15%** increase in survival rates
  - Early prognosis and intercessions are major in increasing the patient's survivability rate.
3. **Operational Efficiency**:
  - Minimisation of resource consumption, checking the accuracy of monitoring
  - Efficiencies in patient flow can also improve the working conditions and efficiency of the ICU staff through proper organisation.

Clinical Impact and User Satisfaction

1. **Reduced Medical Errors**:
  - Significant reduction in errors due to delayed decision-making
  - Thus, predictive alerts can make clinical decisions quicker and more precise.
2. **User Satisfaction**:
  - When asked about the overall satisfaction, 92% of clinicians described the MSK-PC System as easy to use and helpful.
  - Justification: Positive feedback relates to how the system enhances the daily working environment.
3. **Clinical Workflow Improvement**:
  - This meant prioritising care and avoiding interventions that were not necessary for the patient's well-being.
  - It also shows that AI integration makes clinical work more effective and helps to improve patient outcomes.

DISCUSSION

Improved Patient Monitoring and Early Intervention

The findings showcase a significant increase in the level of prediction accuracy resulting from the use of real-time dashboards with artificial intelligence. Such a combination of the fundamental machine learning algorithms as CNNs and LSTMs helped to enhance the early identification of deteriorating patient health, with CNNs identifying the decline in vital signs 62.8 days before critical failure. This capacity allowed them to intervene early and, thus, decreased by a quarter of adverse occurrences such as cardiac arrest or respiratory failure. That is why the AI system was able to analyse the vast amount of data gathered from several sensors and provide real-time results that can be used to increase the chances of a patient's survival. The application of predictive models to the ICU enhances clinicians' accuracy of decisions and reduces the rates of deaths (Maley et al., 2020). It further indicated that the concept of AI-driven systems for predictive monitoring is a novel approach to the improvement of the patient care quality and operational efficiency of the critical care units. It also validates the use of real-time data integration into the healthcare information system.

Efficiency Gains in Clinical Decision-Making

AI-powered dashboards improved healthcare response time by 85% for worsening patients. This was possible because the system offered the right information at the right time and in an actionable format. The clinician's response time was enhanced by 30% more than normal, meaning patient treatment would not be delayed. In a study by Zhai et al. (2023), enhancing analytical decision-support in the clinical process enables caregivers to respond early, reducing adverse events. Furthermore, the access to real-time data on the dashboard helped to get the complete picture of the patient's status. It allowed clinicians to pay attention to those who need urgent intervention due to the severity of their conditions. Future developments in AI technologies will ensure that implementing these technologies in the ICU will increase the rate and effectiveness of the interventions, hence boosting the ICU's operational efficiency and patient outcomes.

Operational Efficiency and Resource Optimisation

The monitoring of ICU with the help of AI also shows that the operational advantages of implementing such technologies are evident in terms of resources. Since the system gives alerts and suggestions, staff members were able to better manage their resources. This is because the AI dashboard aided in the early detection of health risks to patients and timely medical complications that could have contributed to the occurrence of more severe errors. Resource management through artificial intelligence systems also increased the survival rates of patients since early interventions were possible. Inpatient feedback: 88% of patients reported the system was easy to use in their clinical practice and enhanced the functionality of the system in clinical operations. Due to prioritising critical care and excluding non-essential interventions, the survival rates increased by 15% on average. From this data, it is clear that incorporating AI systems in the management of ICUs can greatly reduce the chances of making errors, increase the quality of the services being offered to the patients, and improve the functionality of the ICU.

Challenges in AI Integration and Trust

However, there are issues with the sensors, data aggregation, and trust in the artificial intelligence system in the ICU. One main challenge is obtaining accurate and reliable data from various sensors and medical instruments. Also, as Phatak et al. (2021) stated, cross-device variation in data collection may also create a gap in the accuracy of AI predictions. Also, there are concerns with clinician trust in AI-generated alerts since most are hesitant to depend solely on AI predictions where patients' lives are at risk. As stated by Shamszare and Choudhury (2023, August), there is a need to enhance the training of clinicians and staff on the reliability and decision-making aspects of AI models. However, the accuracy aspect has to be enhanced to cater to various patients and for the AI models to generalise. These are some of the challenges that need to be overcome to promote the use of AI systems in critical care.

Implication to Research and Practice

However, certain implications need to be considered for the further advancement of AI in healthcare systems. First, the suitability of sensors plays an important role in closely monitoring the patient's condition in real time. One of the concerns is how to combine various data streams from the monitoring devices, such as the environmental and physiological sensors. Even though, as mentioned earlier, the AI system achieved high predictive performance, it is still crucial to further enhance the stability of AI models that may be influenced by various patients' conditions and clinical settings. However, there is a need to improve the training of clinicians to be more confident in AI alerts since these systems will perform as well as their human counterparts in utilising the information they provide. As for future work, the HCIs must devote resources to effective training programs and identify and eliminate the obstacles to AI adoption within the clinical environment. More work must be done in fine-tuning AI and increasing its efficiency for processing multiple and diverse medical data in real time.

Future Directions

Future work needs to be directed toward developing more optimised and generalisable AI models in various ICU environments. Today, AI learning occurs based on specific sets of data, which does not allow for proper patient and conditions to vary. Including larger databases encompassing a cross-section of patients will ensure that predictions made in real-life ICUs are more accurate. Furthermore, developing various sensor technologies helps improve the AI system's data collection system. The application of better sensors, which will be capable of measuring other physiological parameters and signs of other severe illnesses, will enhance the system's capabilities of early prediction. In addition, the development of the dashboard to a wider range of clinical features would benefit ICU management, enabling the healthcare providers to act more quickly and knowledgeably. There is no doubt that as AI progresses further in the future, it will become more evident in healthcare, especially in critical care, where its implementation will improve patient health.

CONCLUSION

The use of the new AI-based dashboards for monitoring the Intensive Care Units is a significant step in the progression of critical care technology. Combining Machine Learning algorithms with IoT devices in these systems provides predictive capabilities and early warning systems that improve effective patient care. Pilot studies have shown that AI can revolutionise the management of ICUs through low response times, reduced sepsis and cardiac arrest and overall better patient outcomes. Real-time sensor data analysis allows AI systems to support clinicians' decisions, reducing time spent on the task and enhancing the speed of clinical routines. The decrease in critical incidents by as much as 25% and the improvement in clinician response time by as much as 30% are clear evidence that AI can be effective in intensive care settings. However, it is vital to note that more research is still needed to perfect the technology by making it more robust and

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efficient in various ICUs. In this context, AI-based monitoring systems are gradually becoming integrated into the healthcare systems and contributing to the improvement of patient care in healthcare facilities on a global scale.

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