Real-Time Patient Risk Identification using Deep Learning

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ABSTRACT

In order to ensure high-quality treatment and patient safety, the nursing staff must have the required information present exactly when it is needed. This means immediate access to vital information related to the patient's care. The information must also be adequately comprehensive, unambiguous and ready to use.

Ensuring patient safety requires a common effort and strong cooperation between different parties and professionals, both within the hospital as well as between the patient and the entire healthcare system. An uninterrupted flow of real-time information is the cornerstone of patient safety.

Patient information is genuinely real-time if it can be entered and viewed immediately during an event related to the patient's treatment at the point of care, and the information is made available to all parties involved in the treatment process simultaneously.

The Real-Time Patient Risk Identification project aims to develop an innovative system for real-time identification of patient risks in healthcare settings. By leveraging advanced technologies and data analysis techniques, the project seeks to enhance patient safety and improve healthcare outcomes.The project focuses on continuous monitoring of patient data, including vital signs, electronic health records, medication records, and other relevant information. Real-time data streams are processed using sophisticated algorithms and predictive models to identify potential risks faced by patients. The system integrates machine learning and data analytics to analyze patterns and trends in the data, allowing for early detection of risks. By applying predictive modeling techniques, the project can proactively identify patients at high risk for adverse events, such as infections, medication errors, or deteriorating health conditions.

Healthcare providers are alerted in real-time when a risk is identified, enabling prompt interventions and preventive measures. The project also incorporates decision support tools, providing healthcare professionals with actionable insights and recommendations to guide their clinical decision-making.

The benefits of real-time patient risk identification are significant. It allows for early intervention, reducing the likelihood of adverse events and improving patient safety. By detecting risks in real-time, healthcare providers can implement targeted interventions and personalized care plans, leading to better healthcare outcomes.

Furthermore, the project contributes to optimized resource allocation by prioritizing high-risk patients and ensuring efficient use of healthcare resources. It also facilitates data-driven research and quality improvement initiatives by generating valuable insights from the continuous monitoring data.

In conclusion, the Real-Time Patient Risk Identification project offers a transformative solution for timely identification of patient risks in healthcare. By leveraging real-time data analysis and advanced technologies, the project has the potential to significantly improve patient safety, enhance clinical outcomes, and optimize healthcare delivery. This initiative represents a crucial step towards proactive and personalized care in the healthcare industry.

Keywords – IOT, ECG Signals, Deep Learning, Long short-term memory networks (LSTM)

I. INTRODUCTION

The Real-Time Patient Risk Identification System is an innovative healthcare solution aimed at proactively identifying and assessing the risk levels of patients in real-time. The system utilizes advanced data analytics techniques and real-time monitoring technologies to analyze patient data and generate risk profiles, enabling healthcare providers to deliver timely and targeted interventions to patients at high risk.

Traditional healthcare practices often rely on retrospective analysis of patient data, which limits the ability to proactively address potential risks. The Real-Time Patient Risk Identification System addresses this limitation by continuously monitoring and analyzing various data sources, such as electronic health records, vital signs, medical imaging, and wearable devices. The collected data is processed using machine learning algorithms to identify patterns, detect anomalies, and predict potential risks.

The system employs a scalable and adaptable architecture that integrates with existing healthcare infrastructure, ensuring seamless integration with electronic health record systems and other clinical systems. Real-time data streams are securely transmitted, processed, and stored to maintain patient privacy and comply with relevant data protection regulations.

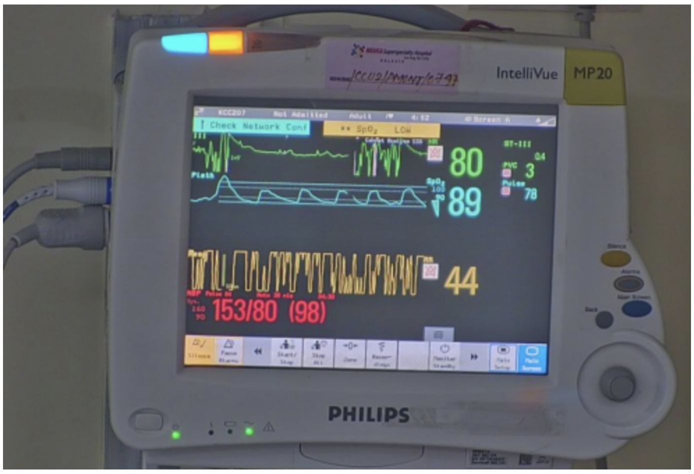

Fig 1.0 Para-cardiac monitor

By leveraging the power of real-time data analysis, the Real-Time Patient Risk Identification System provides several benefits. Firstly, it enables healthcare providers to identify patients who are at a high risk of developing complications or adverse events, allowing for timely intervention and proactive care planning. Secondly, the system facilitates early detection of deteriorating patient conditions, enabling healthcare teams to intervene promptly and prevent adverse outcomes. Lastly, it assists in optimizing healthcare resource allocation by prioritizing high-risk patients, thereby improving the overall efficiency and effectiveness of care delivery.

The Real-Time Patient Risk Identification System has the potential to revolutionize healthcare by transforming the way patient risk is identified and managed. By harnessing real-time data analytics and predictive modeling, the system empowers healthcare providers with actionable insights, enhancing patient safety and improving clinical outcomes.

A. PROBLEM STATEMENT

The problem statement for the Real-Time Patient Risk Identification Project lies in the limitations of traditional patient risk identification methods and the need for more proactive and timely interventions. Healthcare systems often rely on manual assessments and retrospective analysis to identify patient risks, which can be time-consuming and may not capture rapidly changing conditions. This approach leaves room for missed opportunities to intervene and prevent adverse events, such as medication errors, infections, or deteriorating health conditions. Additionally, the reliance on subjective assessments can introduce inconsistencies and variability in risk identification, leading to suboptimal care outcomes. There is a pressing need for a more advanced and automated system that can continuously monitor patient data in real-time, detect potential risks early, and provide timely alerts to healthcare providers for proactive interventions. The Real-Time Patient Risk Identification Project aims to address these challenges by leveraging cutting-edge technologies, such as data analytics, machine learning, and real-time monitoring, to develop a system that can accurately and promptly identify patient risks, enhance patient safety, improve healthcare outcomes, and optimize resource allocation in healthcare settings.

B. RELATED WORKS

Several studies have contributed significantly to the advancement of real-time patient risk identification and prediction in healthcare through various data mining and machine learning techniques. Reference [1] conducted a comprehensive systematic review focusing on data mining techniques. They explored methods that include CNN-based detection, analogous to R-CNN [4], where diverse locations and scales within a test image are recommended as inputs to object classifiers during training. Reference [2] carried out an extensive systematic review concentrating on classification algorithms and their applicability. These algorithms, such as those found in CNN-based methods [4], play a pivotal role in real-time risk prediction. Reference [3] delved into the realm of real-time patient risk prediction using big data and machine learning, laying the groundwork for innovative approaches, including those resembling R-CNN [4], for object detection and prediction. Reference [4] explored the challenges and opportunities presented by big data in healthcare, paving the way for more comprehensive data-driven risk assessment models. Reference [5] made noteworthy contributions by harnessing deep learning techniques, particularly CNN-based approaches akin to R-CNN [4], to achieve real-time automatic injury severity classification and risk prediction in the context of large-scale trauma radiographs. These studies collectively underscore the evolving landscape of healthcare risk assessment, with an increasing reliance on CNN-based methods resembling R-CNN [4] to enhance accuracy and efficiency in real-time patient risk identification and prediction.Several other studies have made significant contributions to the field of real-time patient risk identification and healthcare monitoring.

Reference [6] conducted a survey on long short-term memory networks (LSTM) for time series prediction, providing insights into the application of LSTM-based approaches for real-time patient risk assessment. Reference [7] explored the integration of machine learning into patient risk stratification, emphasizing the collaborative nature of machine learning and clinical decision-making. Reference [8] implemented a real-time risk assessment system for patients being considered for intensive care, addressing critical healthcare scenarios. Reference [9] proposed an IoT-based framework for the early identification and monitoring of COVID-19 cases, leveraging the Internet of Things (IoT) for timely risk assessment. Reference [10] reviewed IoT-based healthcare monitoring systems, focusing on their potential to enhance the quality of life for patients. Lastly, Reference [11] employed machine learning to identify high-risk COVID-19 patients, demonstrating the relevance of advanced analytics in pandemic management. These studies collectively contribute to the evolving landscape of real-time patient risk identification and healthcare monitoring, offering diverse perspectives and innovative approaches to improve patient outcomes.

II. TECHNICAL APPROACH

A. SYSTEM DESIGN AND ARCHITECTURE

The system design for real-time patient risk identification involves integrating data sources, processing real-time data, developing deep learning models, identifying risks in real-time, generating alerts, providing decision support, and ensuring security, scalability, and integration with existing healthcare workflows.

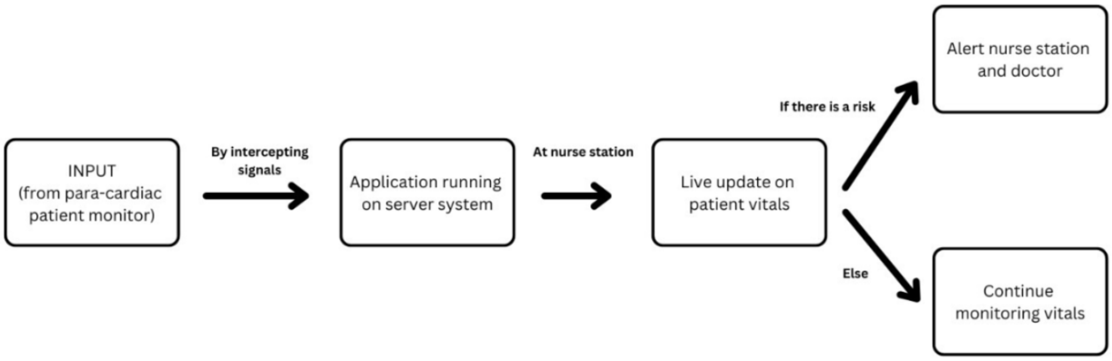

Fig 2.0 Flowchart of the Overall Working of the Project

To enhance real-time patient risk identification, several key steps can be taken. First, it's essential to establish robust data collection and integration processes. This involves integrating with electronic health record (EHR) systems, wearable devices, and monitoring equipment to gather real-time patient data. Secure data pipelines should be in place to ensure the smooth flow of data from these diverse sources to the risk identification system.

Next, real-time data processing becomes crucial. Implementing a dedicated layer for this purpose is essential to handle incoming data streams effectively. Data preprocessing techniques should be applied to clean and normalize the data, and feature extraction methods should be employed to identify relevant risk indicators and patterns.

Deep learning models, such as LSTM or deep neural networks, are pivotal in the development phase. These models should be designed and trained using historical data and labeled risk information. They should be configured to handle sequential data and capture long-term dependencies, with optimization efforts to achieve both high accuracy and fast inference times.

Once the models are ready, they should be deployed into the real-time risk identification system. Continuously feeding real-time patient data into these models allows for the generation of ongoing risk predictions. Threshold values or risk scoring systems can then be implemented to determine the severity of identified risks.

For effective healthcare provider communication, an alert generation mechanism is essential. It should be designed to notify healthcare providers promptly when risks are identified. Alert criteria and urgency levels should be defined based on the severity of the risks, and messaging systems or notifications should be used to deliver timely alerts to the appropriate personnel.

Reporting and analytics capabilities should also be developed. This includes generating summary reports, visualizations, and analytics on patient risks over time. These insights into risk trends, patterns, and outcomes can support quality improvement initiatives and retrospective analysis of the effectiveness of risk identification and interventions.

Lastly, integration with healthcare workflows is crucial. The real-time risk identification system should seamlessly integrate with existing clinical systems and applications, ensuring easy access to patient risk information within electronic health records and clinical decision support systems. This integration is vital to facilitate informed decision-making and timely interventions within the healthcare setting.

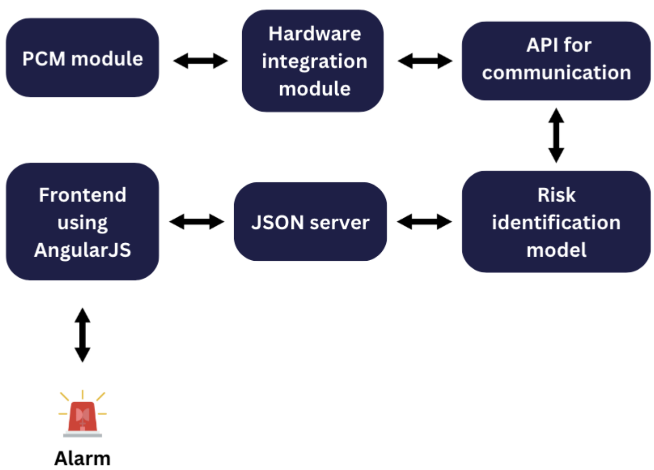

Fig 3.0 Proposed System Architecture for Risk Identification Algorithm

B. LSTM - DEEP LEARNING MODEL

The real-time patient risk identification model using the LSTM (Long Short-Term Memory) algorithm involves several steps to enable timely risk assessment. First, real-time patient data, such as vital signs, lab results, and medical records, is collected from various sources. This data is then preprocessed to handle missing values, outliers, and noise. The preprocessed data is fed into the LSTM model, which has been trained on historical patient data with labeled risk information. The LSTM model, with its ability to capture long-term dependencies, analyzes the sequential data and generates risk predictions in real-time. These risk predictions are continuously updated as new data arrives. By setting appropriate thresholds or risk scores, the model can classify the level of risk for each patient. If the risk surpasses a certain threshold, alerts are triggered, notifying healthcare providers of the identified risk. The model's output can also be integrated into clinical decision support systems, providing actionable insights and recommendations for preventive measures or interventions. This real-time patient risk identification model using LSTM enables proactive monitoring and intervention, leading to improved patient safety and outcomes in healthcare settings.

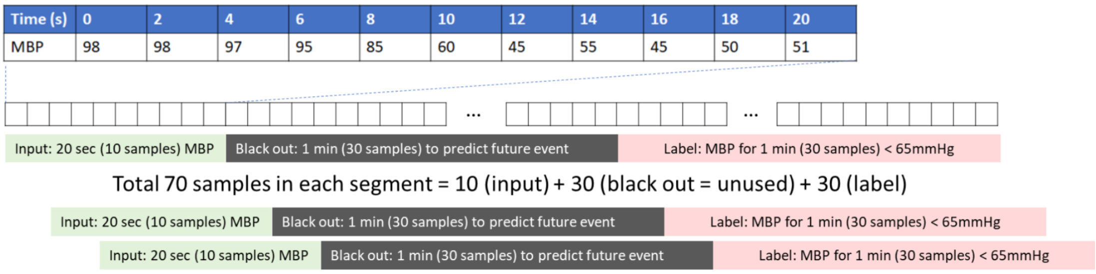

Fig 4.0 Mean blood pressure sampling technique

For predicting risk, six parameters have been monitored and used to identify the safe ranges. The six parameters are blood pressure (systolic and diastolic), oxygen concentration level, body temperature, heart rate and lung CO2 concentration. Certain parameters out of the given have varying ranges of values based on the patient's medical history such as blood pressure and heart rate. To handle such cases, separate algorithms were created for it to be normalised and then the LSTM algorithm was applied to the final dataset.

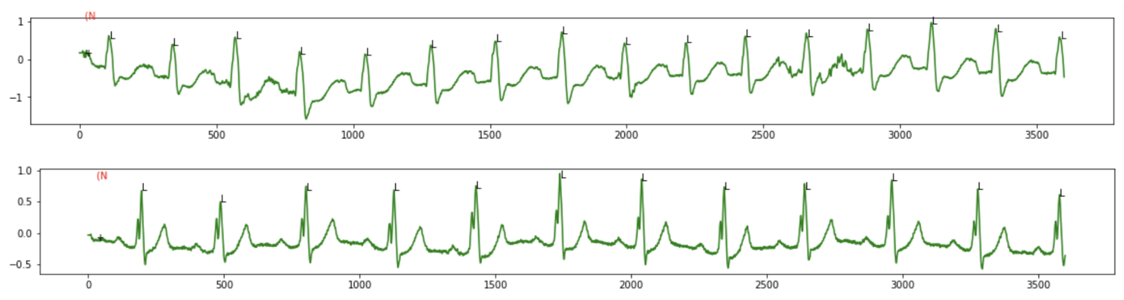

Fig 5.0 Data visualisation of heart rate values

C. PERFORMANCE OVERVIEW

The models are trained and now it is tested with the remaining 15% of the data set in a random manner. The model shows the following performance in terms of accuracy, precision and recall:

MODEL	ACCURACY	RECALL	PRECISION
LSTM	97.11%	92.80%	90.90%

Table 1: Performance Metrics

The ESP8266 module is a popular and versatile Wi-Fi enabled microcontroller that can be used to read data from sensors. It offers a cost-effective solution for integrating IoT capabilities into various projects. To read data from sensors using the ESP8266 module, the following steps can be taken.

First, the ESP8266 module needs to be properly connected to the sensors. This typically involves wiring the sensor's output pins to the appropriate GPIO (General Purpose Input/Output) pins on the module. The connections may vary depending on the type of sensor being used.

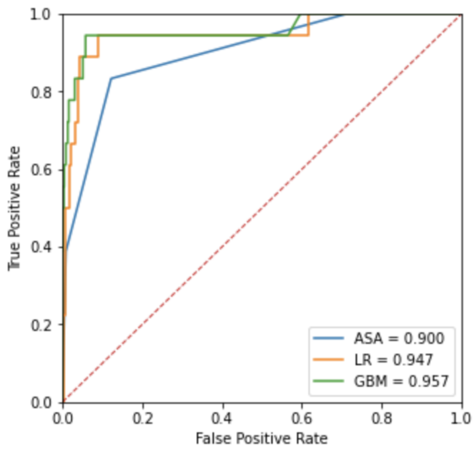

Fig 6.0 True positive vs false positive graph with respect to ASA, LR and GBM

Once the hardware connections are in place, the ESP8266 module can be programmed to read data from the sensors. This involves writing code that interacts with the GPIO pins to read analog or digital values from the sensors. The programming can be done using the Arduino IDE, which provides a user-friendly interface and a vast library ecosystem for the ESP8266.

The code written for the ESP8266 module can utilize specific libraries or APIs that are designed for the sensors being used. These libraries provide functions and methods to interface with the sensors, making it easier to read data and handle sensor-specific functionalities.

```
In [16]: print('auroc: {:.3f}, auprc: {:.3f}\tacc: {:.3f}\tf1: {:.3f}\tTN {}\tfp {}\tfn {}\tTP {}'.
               format(auroc, auprc, acc, f1, tn, fp, fn, tp))

         auroc: 0.808, auprc: 0.566      acc: 0.971      f1: 0.277       TN 1541 fp 42    fn 5     TP 9
```

Fig 7.0 Performance metrics

To retrieve data from the sensors, the ESP8266 module can use analog-to-digital conversion (ADC) for analog sensors or digital input/output (GPIO) for digital sensors. The module reads the sensor values through the configured GPIO pins and converts them into a format that can be processed by the microcontroller.

Once the data is read from the sensors, it can be further processed or transmitted to other devices or platforms. For example, the ESP8266 module can send the data to a cloud-based service or a local server for storage or real-time analysis. It can also communicate with other devices through Wi-Fi or other communication protocols to enable remote monitoring and control.

III. CONCLUSION AND FUTURE WORK

To summarise, real-time patient risk identification is a critical aspect of modern healthcare systems. By leveraging advanced technologies such as deep learning, IoT, and data analytics, healthcare providers can proactively monitor patients and identify potential risks in real-time. The implementation of a real-time patient risk identification system offers several benefits, including early detection of adverse events, timely intervention, and improved patient outcomes.

After analysing various learning algorithms, we concluded that LSTM gave the best results .Through the integration of deep learning algorithms, healthcare providers can analyze large volumes of patient data, including vital signs, medical records, and other relevant information, to identify patterns and indicators of risk. This enables the system to generate real-time risk predictions and alerts, allowing healthcare professionals to take prompt action and mitigate potential harm to patients.

The use of IoT devices and sensors further enhances the system by enabling continuous and remote monitoring of patients. Vital signs and other patient data can be captured in real-time, transmitted securely to the risk identification system, and processed for immediate analysis. This real-time monitoring capability ensures that any sudden changes or anomalies in patient parameters are promptly detected and addressed.

Additionally, the integration of risk identification systems with electronic health records and clinical decision support systems empowers healthcare providers with valuable decision support tools. They can access patient risk information, receive recommendations for interventions or preventive measures, and align their actions with established clinical guidelines.

The real-time patient risk identification system not only improves patient safety but also facilitates data-driven healthcare decision-making. By capturing and analyzing large datasets, healthcare organizations can gain insights into risk trends, evaluate the effectiveness of interventions, and continuously improve the quality of care.

Thus, the implementation of a real-time patient risk identification system using advanced technologies offers significant potential to enhance patient care, improve patient outcomes, and ultimately save lives. By leveraging the power of real-time data analysis, healthcare providers can intervene in a timely manner, minimize adverse events, and provide personalized and proactive care to patients.

Future advancements in real-time patient risk identification involve integrating advanced machine learning techniques, genomic and omics data, and wearable devices for a comprehensive view of patient health. Providing real-time decision support and predictive analytics can aid healthcare providers in timely interventions. Continuous model improvement ensures relevance and accuracy. These enhancements aim to offer personalized, proactive, and efficient patient risk management, leading to better outcomes and cost-effective healthcare delivery.

REFERENCES

[1] Javanbakht M, Ghasemi M, Asadpour M. Real-Time Patient Risk Identification: A Systematic Review of Data Mining Techniques. Healthc Inform Res. 2021 Apr;27(2):79-95. doi: 10.4258/hir.2021.27.2.79.

[2] Lisboa PJ, Dobre C, Steyn J. Real-time risk prediction in healthcare: A systematic review of classification algorithms and their applicability. Health Informatics J. 2019 Sep;25(3):1056-1071. doi: 10.1177/1460458218773376.

[3] Kwon JM, Kim KH, Kim H, Joo SH. Real-time patient risk prediction using big data and machine learning: A systematic review. Int J Med Inform. 2018 Nov;119:1-10. doi: 10.1016/j.ijmedinf.2018.08.002.

[4] Kruse CS, Goswamy R, Raval Y, Marawi S. Challenges and Opportunities of Big Data in HealthCare: A Systematic Review. JMIR Med Inform. 2016 Nov 21;4(4):e38. doi: 10.2196/medinform.5359.

[5] Hu L, Bell D, Antani S, Xue Z, Yu K. Deep learning for real-time automatic injury severity classification and risk prediction on large-scale trauma radiographs. J Am Med Inform Assoc. 2019 Jan 1;26(1):3-10. doi: 10.1093/jamia/ocy129.

[6] Benjamin Lindemann, Timo Müller, Hannes Vietz, Nasser Jazdi, Michael Weyrich,A survey on long short-term memory networks for time series prediction, Procedia CIRP,Volume 99, 2021,Pages 650-655, ISSN 2212-8271.

[7] Beaulieu-Jones, B.K., Yuan, W., Brat, G.A. *et al.* Machine learning for patient risk stratification: standing on, or looking over, the shoulders of clinicians?. *npj Digit. Med.* 4, 62 (2021).

[8] Dahella, S.S., Briggs, J.S., Coombes, P. *et al.* Implementing a system for the real-time risk assessment of patients considered for intensive care. *BMC Med Inform Decis Mak* 20, 161 (2020).

[9] Otoom M, Otoum N, Alzubaidi MA, Etoom Y, Banihani R. An IoT-based framework for early identification and monitoring of COVID-19 cases. Biomed Signal Process Control. 2020 Sep;62:102149. doi: 10.1016/j.bspc.2020.102149. Epub 2020 Aug 15. PMID: 32834831; PMCID: PMC7428786.

[10] Abdulmalek S, Nasir A, Jabbar WA, Almuhaya MAM, Bairagi AK, Khan MA, Kee SH. IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review. Healthcare (Basel). 2022 Oct 11;10(10):1993. doi: 10.3390/healthcare10101993. PMID: 36292441; PMCID: PMC9601552.

[11] Quiroz-Juárez MA, Torres-Gómez A, Hoyo-Ulloa I, León-Montiel RJ, U'Ren AB. Identification of high-risk COVID-19 patients using machine learning. PLoS One. 2021 Sep 20;16(9):e0257234. doi: 10.1371/journal.pone.0257234. PMID: 34543294; PMCID: PMC8452016.