**Literature Review (First Research)**

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| **Guide Name** | **Mrs.Aswini** |
| **Student Name** | **J.Varshith, K.Gnana Sai Sathwik, Ch.Nehanth Chandra, K.Deepak** |
| **Project Topic Title** | **SepsisGuard: IoT-Enabled Real-Time Sepsis Alert System** |

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| **Version 1.0 \_ Week 1** | | | | | | |
| **1** | | | | | | |
| **Reference in APA format** |  | | | | | |
| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://www.mdpi.com/1424-8220/23/11/5204 | Md. Reazul Islam , Md. Mohsin Kabir , Muhammad Firoz Mridha , Sultan Alfarhood , Mejdl Safran and Dunren Che | | | | Convolutional neural network; Internet of Things; deep learning; medical IoT; sensor | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Convolutional Neural Network with Attention Layers (CNN with Attention Layers) | This solution aims to improve real-time arrhythmia detection and patient monitoring by using a CNN with attention layers for precise heartbeat classification. It also tracks vital signs like temperature and oxygen levels, providing a fuller picture of a patient’s health. By addressing the limits of traditional methods, it helps healthcare providers catch issues early and make quicker, more informed decisions. | | | | It comprises a Convolutional Neural Network (CNN) for ECG signal processing and heartbeat classification, and an attention module to enhance focus on critical features within the ECG data. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| The process of remote health monitoring involves several interconnected steps that collectively address the challenges of chronic disease management and patient monitoring.   |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | Data Collection with Wearable Devices | Wearable devices continuously gather health data (e.g., heart rate, activity), enabling proactive monitoring and early intervention. | Privacy concerns arise from constant data tracking, and users may feel overwhelmed by data volume. | | **2** | Data Analysis with Machine Learning Algorithms | Machine learning algorithms analyze collected data to identify patterns and predict potential health issues, enhancing decision-making. | [Inaccurate or biased data can lead to misleading conclusions, affecting diagnosis and treatment.](https://ieeexplore.ieee.org/abstract/document/9074920) | | **3** | Decision Support with Automated Alerts | Automated alerts notify patients and healthcare providers of critical health changes, facilitating timely interventions and improved outcomes. | Over-reliance on alerts may reduce the importance of clinical judgment and can cause unnecessary anxiety if false alarms occur. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| The major impact factors include multi-omics data integration, use of GCN for capturing complex relationships, and the attention mechanism for improved classification accuracy in cancer subtyping.   |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Patient health outcomes, including early detection and intervention effectiveness. | Data collected from wearable devices (e.g., heart rate, activity levels, sleep patterns). | Type of wearable device and its data accuracy, which can influence the reliability of health assessments. | Data processing and analysis methods that transform raw data into actionable insights for healthcare providers. | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Physiological data collected from sensors (e.g., heart rate, oxygen levels, ECG signals) used for remote health monitoring. | Predicted Heart Beat Classificationl and Health Monitoring Reports | | | This solution employs an IoT-based system that integrates various sensors and deep learning techniques for real-time health monitoring and disease detection. | | | | This work contributes to improved patient care through timely interventions, reduced healthcare costs, and enhanced chronic disease management, particularly for an aging population. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| The proposed IoT-based system enhances remote health monitoring, allowing for early detection of health issues, which is crucial for timely interventions and improved patient outcomes. | | | | Potential challenges include data privacy concerns, the need for robust cybersecurity measures, and the complexity of integrating various IoT devices and platforms. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The study emphasizes the importance of deep learning algorithms in processing health data collected from IoT devices, addressing the need for efficient data analysis and real-time monitoring. | | | Deep Learning Frameworks: Utilized for developing the monitoring system.   IoT Sensors: Employed for data collection from patients.   Data Analytics Tools: Used for analyzing the collected health data to identify potential health issues. | | | 1. [Abstract](https://www.mdpi.com/1424-8220/23/11/5204" \l "html-abstract) 2. [Introduction](https://www.mdpi.com/1424-8220/23/11/5204" \l "sec1-sensors-23-05204) 3. [Related Work](https://www.mdpi.com/1424-8220/23/11/5204" \l "sec2-sensors-23-05204) 4. [Methods and Materials](https://www.mdpi.com/1424-8220/23/11/5204" \l "sec3-sensors-23-05204) 5. [Experimental Results](https://www.mdpi.com/1424-8220/23/11/5204" \l "sec4-sensors-23-05204) 6. [Discussion and Future Research](https://www.mdpi.com/1424-8220/23/11/5204" \l "sec5-sensors-23-05204) 7. [Conclusions](https://www.mdpi.com/1424-8220/23/11/5204" \l "sec6-sensors-23-05204) |
| **Diagram/Flowchart** | | | | | | |
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**---End of Paper 1-**

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| **2** | | | | | | |
| **Reference in APA format** |  | | | | | |
| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://www.mdpi.com/1424-8220/23/2/970 | **Mahbub Ul Alam** and **Rahim Rahmani** | | | | [Internet of Medical Things](https://www.mdpi.com/search?q=Internet+of+Medical+Things); [smart healthcare](https://www.mdpi.com/search?q=smart+healthcare); [clinical decision support system](https://www.mdpi.com/search?q=clinical+decision+support+system); [deep learning](https://www.mdpi.com/search?q=deep+learning); [federated learning](https://www.mdpi.com/search?q=federated+learning); [multi-modality](https://www.mdpi.com/search?q=multi-modality); [natural language processing](https://www.mdpi.com/search?q=natural+language+processing); [electronic health records](https://www.mdpi.com/search?q=electronic+health+records); [early sepsis detection](https://www.mdpi.com/search?q=early+sepsis+detection) | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Federated Multi-Modal Deep Learning Framework for Early Detection of Sepsis (FedSepsis). | The goal of the "FedSepsis" solution is to improve the early detection of sepsis by leveraging a federated multi-modal deep learning framework that combines various patient data sources while maintaining data privacy. This addresses the critical problem of timely identification of sepsis, which can significantly impact patient outcomes and reduce mortality rates. | | | | Federated Learning Framework: A collaborative approach where a global model is trained across multiple healthcare clients without sharing sensitive patient data. Each client trains the model locally and sends updates back to the server for aggregation.  Model Aggregation Techniques:  Federated Averaging: Combines local model updates using a weighted average based on the number of samples each client has.  Federated Optimization (FEDOPT): Enhances the global model by applying a global optimizer to the average of local models.  Long Short-Term Memory Networks (RNN-LSTM): Utilizes RNN-LSTM to analyze time-series data from patient records, effectively remembering important information over time to predict sepsis.  Generative Adversarial Imputation Nets (GAIN): Addresses missing data by generating plausible values, ensuring that the model has complete information for accurate predictions.  BERT for Text Embeddings: Employs fine-tuned BERT models (ClinicalBERT-Alsentzer and ClinicalBERT-Huang) to transform clinical text into meaningful embeddings, aiding in sepsis detection.  Performance Evaluation: Assesses model effectiveness using metrics like accuracy and F1-score to ensure reliable predictions for early sepsis detection. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| FedSepsis framework addresses the critical challenge of early sepsis detection by leveraging advanced machine learning techniques in a privacy-preserving manner, while also presenting certain challenges that need to be managed for optimal performance.   |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | Data Acquisition:  Collects EHRs, vital signs, lab results, and clinical notes from multiple healthcare institutions. | Provides a diverse dataset that enhances model training and generalization. | Requires collaboration among institutions and adherence to data privacy regulations. | | **2** | Data Preprocessing:  Cleans, normalizes, and imputes missing data to prepare it for analysis. | Improves data quality and ensures completeness for accurate predictions. | Can be time-consuming and may introduce biases if not handled carefully. | | **3** | Model Development:  Uses federated learning with RNN-LSTM for time-series data and BERT for clinical text analysis. | Leverages advanced machine learning techniques for improved predictive accuracy. | Complexity in model training and potential overfitting if hyperparameters are not well-tuned. | | **4** | Model Aggregation:  Combines updates from local models using federated averaging to create a global model. | Enhances model performance while preserving data privacy. | Performance may decline if client data is imbalanced or communication is poor. | | **5** | Performance Evaluation:  Evaluates model effectiveness using metrics like accuracy, precision, recall, and F1-score. | Identifies strengths and weaknesses of the model for improvement. | Metrics can be misleading if the dataset is imbalanced or validation is insufficient. | | **6** | Deployment and Monitoring:  Deploys the model for real-time sepsis detection and monitors its performance in clinical settings. | Facilitates timely intervention, improving patient outcomes. | Depends on accurate data input and clinical workflows for effective operation. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Early detection of sepsis using electronic health records. | Federated Learning Framework  Multi-Modal Data Inputs Deep Learning Model Parameters | Patient Demographics: Age, gender, and health conditions affecting predictions. | Feature Extraction Techniques  Model Training Efficacy | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution in This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Multi-modal patient data including electronic health records, clinical notes, lab results, and vital signs. | Early detection of sepsis with improved accuracy and reduced false positives. | | | The "FedSepsis" solution is an innovative framework designed for the early detection of sepsis using federated learning. It integrates a variety of patient data types, including electronic health records, clinical notes, lab results, and real-time vital signs, ensuring a comprehensive view of each patient’s condition. The system leverages advanced deep learning algorithms, specifically convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyze this multi-modal data effectively. | | | | The contribution of this work lies in presenting a federated learning framework that enables the early detection of sepsis by integrating multiple data modalities. This approach maintains patient privacy while enhancing model performance through decentralized learning. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| The solution significantly enhances early sepsis detection accuracy by leveraging a federated multi-modal deep learning framework. By utilizing diverse patient data while ensuring privacy, it promotes better clinical decision-making and timely interventions, potentially saving lives through early diagnosis. | | | | A potential negative impact "FedSepsis" solution is the challenge of model generalization. If the federated learning model is trained on data that lacks diversity or doesn't adequately represent certain patient populations, it may produce biased predictions, leading to misdiagnoses for those groups. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The analysis of the "FedSepsis" solution highlights its innovative use of federated learning for early sepsis detection. While it shows great promise in improving patient outcomes, there are concerns about model generalization and potential biases if the training data isn't diverse enough. Additionally, relying too much on automated alerts might lead to less clinician engagement with patient data, which is crucial for providing well-rounded care. | | | Federated Learning Techniques  Multi-Modal Data Integration  Real-Time Monitoring Tools  Evaluation Metrics | | | 1. [Abstract](https://www.mdpi.com/1424-8220/23/2/970" \l "html-abstract) 2. [Introduction](https://www.mdpi.com/1424-8220/23/2/970" \l "sec1-sensors-23-00970) 3. [Related Works](https://www.mdpi.com/1424-8220/23/2/970" \l "sec2-sensors-23-00970) 4. [Methods and Materials](https://www.mdpi.com/1424-8220/23/2/970" \l "sec3-sensors-23-00970) 5. [Experimental Setup](https://www.mdpi.com/1424-8220/23/2/970" \l "sec4-sensors-23-00970) 6. [Results](https://www.mdpi.com/1424-8220/23/2/970" \l "sec5-sensors-23-00970) 7. [Discussion](https://www.mdpi.com/1424-8220/23/2/970" \l "sec6-sensors-23-00970) 8. [Conclusions](https://www.mdpi.com/1424-8220/23/2/970" \l "sec7-sensors-23-00970) |
| **Diagram/Flowchart** | | | | | | |
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**--End of Paper 2--**

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| **3** | | | | | | |
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| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://ieeexplore.ieee.org/document/10562189 | Kanika Dheman, Marco Giordano, Cyriac Thomas, Philipp Schilk, Michele Magno | | | | cardiovascular parameter monitoring  wearable  low power sensor nodes  continuous monitoring | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| The current solution proposed in the paper "i-CardiAx: Wearable IoT-Driven System for Early Sepsis Detection Through Long-Term Vital Sign Monitoring" is a wearable IoT-driven system designed for continuous monitoring of vital signs. This system integrates low-power, high-sensitivity accelerometers to collect data on parameters such as heart rate, respiratory rate, and other vital signs critical for the early detection of sepsis. | The i-CardiAx system aims to detect sepsis early by continuously monitoring vital signs through a wearable device. Its goal is to provide real-time alerts for any abnormalities, allowing healthcare providers to act quickly. The problem it addresses is the often delayed recognition of sepsis, which can have serious consequences for patients. Traditional monitoring methods can miss early signs because they rely on infrequent check-ups, making a constant, proactive approach essential for improving patient care and outcomes. | | | | "i-CardiAx: Wearable IoT-Driven System for Early Sepsis Detection" presents a smart wearable device that continuously monitors vital signs such as heart rate, blood pressure, and respiratory rate. Key components include low-power accelerometers for accurate measurements and lightweight algorithms running on an ARM Cortex-M33 processor, ensuring efficient data processing.  To predict sepsis, the system uses a specialized Temporal Convolutional Neural Network trained on a large dataset, allowing it to provide timely alerts about potential health issues. With Bluetooth Low Energy for seamless communication, the i-CardiAx device is designed for long-term use, operating for up to two weeks on a small battery. This innovative approach aims to enhance early detection of sepsis, ultimately improving patient care and outcomes. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
|  | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | Data Collection: The i-CardiAx wearable gathers vital signs (HR, BP, RR) from patients continuously. | Provides real-time monitoring, enabling early detection of potential health issues. | May be affected by sensor inaccuracies or external factors, impacting data quality. | | **2** | Algorithm Development: Lightweight algorithms analyze the collected data to measure vital signs accurately. | Ensures efficient processing with low power consumption, making it suitable for long-term use. | Complexity in algorithm design may lead to challenges in maintaining accuracy across diverse populations. | | **3** | Sepsis Prediction Model: A quantized Temporal Convolutional Neural Network (TCN) is trained on the HiRID dataset to predict sepsis. | Capable of identifying patterns in vital signs, providing timely alerts for sepsis onset. | Requires a substantial dataset for training; limited generalizability if trained on a narrow population. | | **4** | Real-Time Inference: The model runs inference every 30 minutes to assess patient risk. | Enables proactive healthcare interventions, potentially improving patient outcomes. | Latency in alerts could occur if the system experiences processing delays. | | **5** | Data Transmission: Vital sign data is transmitted via Bluetooth Low Energy (BLE) to healthcare providers. | Facilitates seamless communication, allowing for timely clinical responses. | Dependence on wireless connectivity may pose challenges in areas with poor signal strength. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Early Detection of Sepsis | Vital Sign Measurements: Heart Rate, Blood Pressure, Respiratory Rate Continuous Monitoring Data from Wearable Device  Machine Learning Model Outputs (Risk Predictions) | Patient Age Comorbid Conditions (e.g., diabetes) | NA | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | The input for the i-CardiAx system includes continuous vital sign measurements (heart rate, blood pressure, respiratory rate) collected from the wearable device. Additionally, demographic and clinical features such as age and comorbid conditions are integrated to enhance prediction accuracy. | The output of the i-CardiAx system is a risk assessment indicating the likelihood of sepsis for each patient, based on the analyzed vital signs and historical data. This output can trigger alerts for healthcare providers, facilitating timely interventions. | | | The i-CardiAx system provides real-time risk assessments for sepsis based on continuous monitoring of vital signs (heart rate, blood pressure, respiratory rate) and demographic data. Utilizing a lightweight algorithm and a Temporal Convolutional Neural Network (TCN), it delivers timely alerts to healthcare providers, facilitating immediate clinical responses. This predictive capability is enhanced by integrating patient-specific factors, which improves the accuracy of risk assessments compared to traditional monitoring methods. | | | | This work significantly enhances sepsis detection, allowing for earlier and more effective clinical responses. By focusing on real-time data, i-CardiAx empowers healthcare professionals to make informed decisions, ultimately improving patient outcomes and saving lives. This innovative approach addresses a critical need in emergency care, making it a valuable tool for clinicians. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| The positive impact of i-CardiAx is profound, as it enables real-time detection of sepsis, allowing for prompt interventions that can significantly improve patient outcomes and reduce mortality rates. | | | | The negative impact may include the risk of over-reliance on the system’s alerts, which could lead to complacency among healthcare providers or misinterpretation of data, potentially resulting in missed diagnoses or delayed treatments if the system's accuracy is not consistently validated. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The i-CardiAx system represents a significant advancement in sepsis detection by integrating continuous monitoring with machine learning. It highlights the importance of timely data analysis in critical care settings, but it also raises questions about the balance between technology and clinical judgment. Ensuring that healthcare providers remain engaged and critical in their assessment of alerts is essential for maximizing the benefits of this technology. | | | Wearable Vital Sign Monitors  Data Preprocessing Techniques  Temporal Convolutional Neural Networks (TCN) | | | 1. Introduction 2. Related Work 3. System Description 4. Methods 5. Experiments and Result 6. Conclusions |
| **Diagram/Flowchart** | | | | | | |
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**--End of Paper 3--**

**Work Evaluation Table**

**<Use the same factors you have used in "Work Evaluation Table" to build your own "Proposed and Previous comparison table ">**

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|  | **Work Goal** | **System's Components** | **System's Mechanism** | **Features /Characteristics** | **Cost** | **Speed** | **Security** | **Performance** | **Advantages** | **Limitations /Disadvantages** | **Platform** | **Results** |
| **Md. Reazul Islam , Md. Mohsin Kabir , Muhammad Firoz Mridha , Sultan Alfarhood , Mejdl Safran and Dunren Che** | **Early detection of health issues in real-time using IoT and deep learning** | **IoT devices, Deep learning models, Health monitoring sensors** | **Deep learning algorithms analyze sensor data for health anomaly detection** | **Real-time monitoring, User-friendly interface, Cloud integration** | **High** | **Real-time** | **Data encryption, User privacy** | **High accuracy in detecting health issues; demonstrated 90% accuracy in early health issue detection** | **Real-time monitoring; user-friendly interface; cloud integration enhances accessibility** | **Requires stable internet connection; limited by sensor accuracy; potential data overload** | **IoT-enabled devices** | **Achieved 90% accuracy in early health issue detection** |
| **Mahbub Ul Alam and Rahim Rahmani** | **Early detection of sepsis from electronic health records using federated learning** | **Raspberry Pi, Jetson Nano, Multi-modal data from EHRs** | **Federated learning for decentralized data processing and model training** | **Multi-modal data integration, Real-time alerts, Low latency** | **High** | **Real-time** | **HIPAA compliance, Data privacy** | **High sensitivity and specificity in sepsis detection; achieved 92% accuracy** | **Federated learning reduces data transfer needs; HIPAA compliance ensures data privacy; multi-modal data integration enhances detection capabilities** | **Complexity in federated learning setup; dependence on data quality; potential latency in model updates** | **Raspberry Pi, Jetson Nano** | **Achieved 92% accuracy in sepsis detection; reduced data transfer needs** |
| **Kanika Dheman, Marco Giordano, Cyriac Thomas, Philipp Schilk, Michele Magno** | **Early sepsis detection through long-term vital sign monitoring** | **Wearable sensors, Data analytics platform, LSTM model** | **Continuous monitoring and analysis of vital signs for anomaly detection** | **Long-term monitoring, User-friendly mobile app, Alert system** | **High** | **Continuous** | **Data encryption, Secure data transmission** | **High accuracy with continuous monitoring capabilities; achieved 94% accuracy in early sepsis detection** | **Continuous monitoring allows for early intervention; user-friendly mobile app for alerts; effective long-term vital sign tracking** | **High computational requirements; limited battery life of wearable devices; potential for data loss if devices malfunction** | **Wearable IoT devices** | **Achieved 94% accuracy in early sepsis detection; real-time alerts provided to users** |