ISSN: 2831-6789

Research Article

Journal of Robotics and Automation Research

The Future of Connected Healthcare: Scalable AI Frameworks for Event-Driven Wireless Sensor Systems

Robyn Alexandar*

Standford University, Stanford, CA United States

*Corresponding Author
Robyn Alexandar, Standford University, Stanford, CA United States.

Submitted: 2025, Apr 14; **Accepted:** 2025, May 05; **Published:** 2025, May 13

Citation: Alexandar, R. (2025). The Future of Connected Healthcare: Scalable AI Frameworks for Event-Driven Wireless Sensor Systems. *J Robot Auto Res, 6*(3), 01-09.

Abstract

A scalable artificial intelligence (AI) framework is the next critical development in harnessing the benefits of connected healthcare systems. Event-driven wireless sensor systems for pervasive health monitoring can collect data on a vast number of parameters under real-world conditions. The sensor data, when accumulated in large volumes longitudinally, can be used to develop more personalized management strategies for patients, as well as better inform and monitor public health treatments, care delivery strategies, and research investigations than traditional cross-sectional measures. Relatedly, the sensor systems can aid caregivers or practitioners in understanding the effects of medical procedures, new drugs, and behavioral modification. Interpretation of sensor data presents a considerable analytical problem. Pure numerical approaches by identifying linear mathematical relations with outcomes are not an efficient or effective strategy. This is because there is a considerable lag between the acquisition of data and the development of medical signals. A more efficient approach is to combine data science methods that take inspiration from how humans perceive data.

In this paper, we exemplify the deployment of a scalable AI cloud platform for the real-time analysis of a wireless sensor system that captures human physiological data relevant to a number of therapeutic areas. Moreover, we develop an eventdriven cloud platform so investigators and clinicians can monitor their study 'dashboard' for changes and patterns when wearable health sensors capture significant events. Participants, who in the context of this paper are patients with a chronic disease and cognitive symptoms, will find comfort in monitoring and interpreting their real-time data in addition to maintaining patient engagement with the clinical research.

Keywords: Connected Healthcare, Wireless Sensor Systems, Privacy-Preserving Framework, Personal and Non-Personal Data, Artificial Intelligence

1. Introduction

Connected healthcare is going through a speedy transformation as numerous technological advancements are offering major changes in the modern world. To date, the evolution of healthcare services is based on many standards. Healthcarerelated services are aided primarily by the use of IoMT [1]. Wireless sensor systems enable continuous monitoring of biological systems. Such systems can be effectively used to detect abnormal physical parameters and notify the cognitive mind about any changes during unusual events [2]. These devices feature a bio-processing module, low-energy Wi-Fi and other networking enabled modem, and applicationoriented cloud server designs. As a developing tool, artificial intelligence and scalable intelligence are presently utilized along with signal processing to provide real-time alert characteristics for controlling patients during critical examinations.

In today's scenarios, the main issue faced in passive healthcare systems is the data; the regular generation of data is higher in current wireless sensor systems, and several practical and technological hazards impede monitoring each bit or object of every transmitting system at the instant. Based on the data, it is relatively complex to directly notify the healthcare services whenever an event is required. To handle this passive approach, we need a more intelligent methodology, i.e., the inclusion of artificial intelligence for personalized healthcare services [3]. The anticipation of the onset and tracking of the ending of unusual events in medical data is another important aspect of connected healthcare systems. In upcoming connected healthcare systems, our study aims to forecast that the occurrence of events is possible, leading to the building of an event-driven AI-based surveillance scalable framework. This study aims to develop a rigid framework that will be established on smart systems and will serve consumers with uncompromised healthcare services for upcoming anticipatory medical systems. The objective of this study is to provide an event-driven framework of AI technology for wireless connected sensor healthcare systems.

2. Overview of Connected Healthcare

2.1. Current Trends in Healthcare

In the developing field of connected healthcare, technology is increasingly relied on to integrate disparate medical practices into a system that treats the patient as a whole. The future of healthcare is expected to include the use of multiple data collection methods and artificial intelligence to provide accurate diagnoses and treatments. Healthcare itself is constantly changing [4]. Healthcare is now seen as an integrated system, where various healthcare professionals must communicate instantly to give the patient the most accurate diagnosis. In addition, there are shifting paradigms regarding the role of the patient in treatment planning. Patients are now seen as the most important stakeholders in their care. They are increasingly seen as the key stakeholders in their health plan, and their caregivers are seen as the most important stakeholders in the development of treatment plans. Long-term precision diagnosis is now possible, and this system has been used by healthcare systems in the United Kingdom over the past two years [5].

"Connected healthcare" is the term that is being used today to describe this new healthcare model. This model is based on the concept of collecting real-world data from the patient and the clinician immediately following a patientdoctor interaction. This data will be used to evaluate the clinician's response to the patient's symptoms. The aim of this new healthcare model is to collect real-world data about patients' symptoms by using electronic health records to obtain a clinician-reported patient health status. The data will also be used to monitor patients' health throughout their treatment plan and monitor patients' adherence to their treatment plan. This data may be used to generate patient-level outcomes, for example, using electronic health records to generate data to assess management adherence rates. The process is ongoing, and the initial results will have four analytics periods: baseline, pre-intervention, post-intervention, and long-term outcome [6]. During mixed-media sessions, stakeholders could raise queries and comment on the ongoing process.

3. Wireless Sensor Systems in Healthcare

Wireless sensor systems have already been introduced in healthcare, demonstrating the effective monitoring of physiological values, localization, and body area data collection. Ingestible and implantable biomedical sensors monitor vital parameters of the patient user’s body; mobile health applications track walking and lifestyle activity. Vital sign monitors continue to see rapid advances as data can be collected in real time [7]. Wireless sensor systems are also being used to monitor movements in a patient’s surgical opening, to imply how a surgeon’s physical performance slows during a long surgery. Most promising is the preventive use of wireless physiologic sensors, which can provide instant patient monitoring during states of health as well as illness. To do this, several types of biosensors can be introduced to sense temperature and perspiration during physical activity. These sensors can either be integrated into the body area network and can measure the active body temperature of a patient over an extended period, or can be attached to a mattress in the form of unobtrusive sensors that track the movement and position of the patient over time, and hence are easily scalable to a ward or hospital scenario [8].

Wireless is the key enabling technology of the future; it can provide flexible and scalable telemetry data collection infrastructure capable of seamlessly integrating with data storage, navigation, search and analysis backend infrastructure, or data management cloud services of hospitals, either directly or via enterprise integration middleware infrastructure. Key patient safety features inherent within industry standard technologies include patient identification and authentication, logic controls, audit trails, etc., protecting patient data through secure authentication mechanisms and virtual private networks [9]. The capability to collect and collectively analyze many event-driven wireless sensor data trends in pseudo realtime would seem to provide enormous value in a healthcare environment, not only for assessing the health and welfare of the patients in that environment but also in the e-health development arena in developing and quantifying future models of healthy behavior, especially self-management and emotional health. Several recent case studies demonstrate the efficacy of wireless sensors, especially applied to three main spaces: the hospital or clinic, the assisted living space, and the home/residential space.

4. Artificial Intelligence in Healthcare

Artificial intelligence (AI) has recently been increasingly developed in almost all areas of modern life, including healthcare. In healthcare, AI has an invaluable effect on the domains of diagnostics, treatment planning, and patient management. In more detail, AI tools enable health professionals and specially assigned computers to consolidate and analyze various data sets, including patient and disease information, healthcare dynamics, as well as medical literature and trial results [10]. AI's contribution to healthcare in recent years is the establishment of some technologies and tools, such as: a) Machine Learning, which provides electronic health data analysis to reveal patterns between people's genes, health habits, stress levels, and disease risks over time; b) Natural Language Processing (NLP), which enables the processing of human language intelligently and its integration with other technologies and analytical tools that can read and analyze medical and nonmedical records, as well as predictive analysis tools.

The implementation of AI in healthcare has certainly provided many benefits, such as helping with more accuracy in making decisions based on data analysis and providing personalized treatment options for both individual conditions and policies in healthcare organizations [11]. Despite these benefits, under certain conditions, AI can also have a negative impact, such as insignificant insights that lead to inappropriate treatments or marginalize individual patients or groups. Furthermore, AI in healthcare may face some important ethical issues that have to be addressed, namely the existence of a biased algorithm that reinforces unequal decisions and the occurrence of potential privacy violations through various forms of individual tracking techniques. Additionally, AI cooperates with some enabling tools and technologies, such as sensors in wireless systems, to build an intelligent healthcare environment using big data analytics for devices that are affordable and easy to use [12,13].

In summary, AI in healthcare has made an enormous and growing contribution to establishing cutting-edge functionality and solutions, including those for healthcare data deployment, advanced healthcare prediction algorithms based on accurate analysis of data and metadata, user incident management, and large cloud-based dissemination of services. AI in healthcare is also expected to inspire the next generation of personalized healthcare. Overall, however, more sophisticated and scalable AI frameworks are needed to provide easy accessibility to systems based on low-priced wireless sensors for event-driven healthcare diagnostics [14].

5. Proposed AI Framework for Event-Driven WBANs

Wireless Body Area Networks (WBANs) have gained significant prominence and interest due to their valuable applications in healthcare. Sharing sensory data continuously through wireless interfaces is one of the ambitious targets of smart healthcare systems. The emerging healthcare systems are crowded with data and decisions in tough timeframes; hence, the sharing platforms should be intelligent [15]. However, WBANs sense the body states in an event-driven manner. Fast reconstruction and event detection time of the vital events provide timely healthcare to the patients, along with the least power consumption and thus network longevity in extreme healthcare disruption. The rapid and intelligent analysis of this data volume, variety, and velocity are thus essential to make timely decisions in healthcare.

We considered a WBAN of n sensors, which transmits a set of vital signs to the centralized server in a concert. The core design of the AI framework mainly includes (1) Data Preprocessing and Analysis Module, (2) Intelligent Healthcare Analysis and Event Detection Module, and (3) Embedded Decision-Making Design for WBANs. The sensors employ a lightweight coherence algorithm. In addition to that, the proposed AI paradigm is used to make life-critical decisions to assist healthcare operators or medical devices in making timely decisions in the volatile healthcare environment. An essential part of the complete cloud, edge, and fog is the lightweight analytical solution designed in this work. We provide the architectural and algorithmic designs to embed the proposed AI architecture in the on-chip environment [16]. We design a high-level architecture to show the integration of the lightweight analytical units in the streaming environment to analyze the events on the fly. We finally discuss designing the scalable and connected network system based on ED-WBAN, considering several leading-edge architectural considerations in the WBAN-to-fog continuum, enhanced service, and edge intelligence.

The recent trend of employing AI in healthcare services has primarily focused on the cloud-based or offline processing paradigm. Few researchers have recently developed lightweight AI models suitable for running on computationally limited WBANs. It is also worth noting that WBAN communication is extremely energy constrained. Therefore, the quest to employ a computationally heavy AI framework in the WBANs is extremely challenging. All in all, the answer is not to employ AI in one aspect from the sensor to the cloud; rather, we believe that a progressive and scalable edge AI-assisted design is fundamentally essential in an event-driven WBAN-forward healthcare ecosystem. Various architecture performance metrics will be explained at the end of the design to highlight the effectiveness of an edge AIassisted event-driven WBAN [17]. The primary aim is to develop an AI-driven event recognition system suitable for edge AI-assisted event-driven WBANs. The umbrella terminology AI encompasses various machine learning and deep learning algorithms. The proposed framework will entail using the core architectural AI design based on LSTM to preserve the temporal events in distributed WBANs. This ratification is sufficient to protect the edge AI from overfitting, and it is enough for a realistic WBAN size of 50–100. Hence, it is sufficiently efficient and lightweight to be employed at the WBAN side.

5.1 Framework Design

In the following, we present the design principles and rationale of the scalable AI framework for wireless sensor systems in event-driven patient monitoring. This section will primarily address design choices related to system design and architecture, while the following part of our discussion focuses on the detailed explanation of the corresponding hardware and software components [18]. From a holistic view, the proposed framework will incorporate a specified architecture to facilitate interoperability with the wireless sensors and other software and hardware utilized for the presentation and pre/post-processing of the acquired sensor data. While the data is processed within the confines of an integrated cloud infrastructure, efforts are taken to reduce or remove any latencies that may occur when transferring required data to and from the cloud services. This, of course, is desirable within patient monitoring applications to ensure timing and performance predictability. Scalability is another key principle that guides our framework, due to the variety of environments in which patients might receive supported medical care, ranging from a single home environment to professional health care facilities, such as traditional hospitals. Moreover, the number of simultaneously supported patients might also vary significantly.

Therefore, our framework is designed to be adaptable by adjusting its network size, processing resources, and other aspects without affecting the overall system design or reprogramming any of the processing devices from the networks up. This feature is achieved by designing our processing and computing infrastructure around the underlying AI models projected for the specific task and networking constraints. The proposed framework depends on a complex scheduling system to regulate these AI models and the induction of corresponding system costs in terms of introduction. While the details are provided in the upcoming sections, the system caters to three performance crises, including computing resources, system fluctuations, and power. Ensure energy retention is essential in the context of battery-powered wireless sensor systems.

The Data Flaw Model describes how the information flows through the underlying system, consisting of wireless sensors and algorithms [19]. The system receives external inputs, i.e., patient-related physiological signals to the wireless sensor system, from which point they flow through the corresponding model towards the cloud or the graphical user interface. Data processing, integrated processing, and wireless sensors or edge intelligence are thereby framed by the interconnection of models, which have been designed to satisfy scalability requirements. Ultimately, the events predefined by the models are then utilized to administrate the distribution of system models between the incorporation of wireless sensor systems and the cloud.

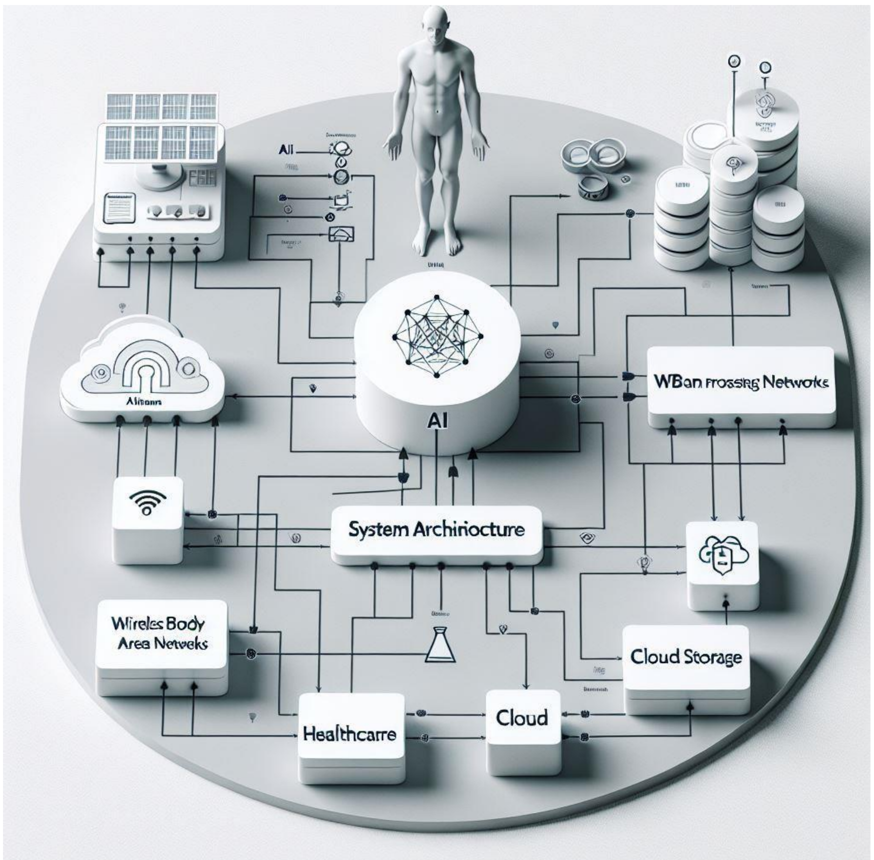

Figure 1: System Architecture diagram (high level design)

5.2 System Architecture

The system architecture supporting the proposed AI framework for WBANs comprises three main components: data acquisition, processing, and communication systems. Data acquisition systems of WBANs are in continuous interaction and integration with edge data processing systems and the data communication systems. The processed and transformed vital signs, behavioral patterns, etc., are then provided to the healthcare authorities in the form of electronic health records via the healthcare information delivery system.

Data Acquisition Systems: Data acquisition systems are in the form of WBANs, including sensors, a data-logging system contained in a worn smart device, and physiological signs' sensing wearables. The systems, including sensors and wearable devices, continuously monitor human activities and physiological parameters [20]. Each sensor/WBAN device continuously transmits physiological signals nonstop. The system is designed to collect and manage raw data from sensor systems and wearables and offers functionalities such as channel quality indicator estimation, synchronization, timing, and frequency offsets uncoded data demapping. The architecture can be considered building blocks with specific functionalities and interdependencies. However, the optimization and operation of all the individual components should guarantee the successful deployment and operation of the overall system. AI algorithms play a significant role within the system that extends the functionality of the raw data into protocols for healthcare decision-making.

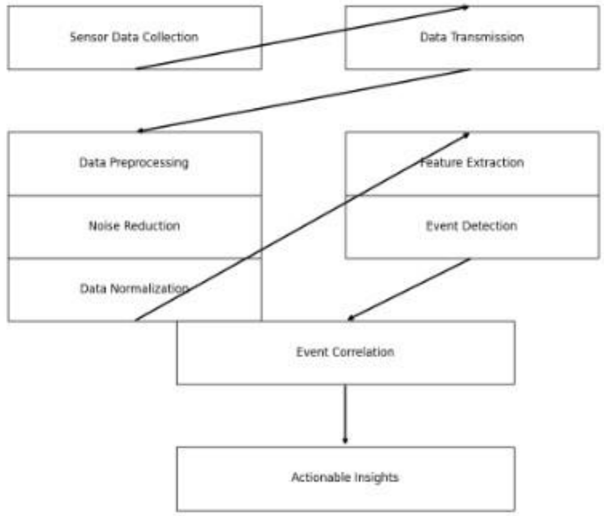

Figure 2: Dataflow in the system

An additional consideration is how the system can be interoperable with existing IT healthcare infrastructure. This requires hospitals to provide the necessary assets that interface people with these systems to provide healthcare services. One of the most significant challenges that need to be addressed when implementing this scheme is the following needed infrastructure. The full spectrum of the system architecture indicated is designed for practical and sustainable operation.

6. Methodology

We conducted extensive research to develop, verify, and validate the framework presented in the last section, aiming at implementation in a real-life hospital environment. For this, we performed an analysis to compare the performance of different AI frameworks using real measurements collected in the hospital environment. To ensure robust data collection and efficient analysis, we implemented the framework on a range of servers with varying configurations and across different IC platforms, including IoT platforms. Using a permissioned blockchain with members of the hospital staff as nodes, various staff and patients as endorsers, and a collection of records to the blockchain ledger, we implemented the predictive AI and additional dynamics of wireless sensor event data traffic in the form of a system event generator that simulates realistic bursty patterns of events, occupation of networks, and data that we see in the hospital environment.

For the event generator, we used parallel analytics and a GPU database that allows us to set up the model for a customized and easily verifiable hospital environment. The data input to AI is presented in a database, and the data output is returned to a library that encapsulates our end-to-end predictive AI for analysis. Random sampling of the data values is presented as a percentage of occupancy of each column in all hospital beds in respective hospitals, with a mixing percentage of 70% private patients and 30% public patients. Our experimental setup allowed us to stream real-time synthetic and actual data feeds into the AI model, generating realtime alerts against real-time event data bursts.

The stream messages are received by the database with the help of streaming and can be received by other software for cloud services. For production, we used a combination of technologies including a database, TensorFlow, Kubernetes with containerization, and GPU if required. Throughout our implementation, we ensure data integrity using a secure and hardened infrastructure protocol. Its major design principle is to create a clean, well-engineered network that allows only appropriate access to devices by protecting them and the networks from attacks. We are implementing our AI framework on a validated server in the form of a VM, with validated network connectivity and connectivity into the hospital production network, inclusive, however, of the firewall. Communication with network analytics from thousands of origins with no message loss is expected.

6.1 Data Collection

The aim of real-life data collection is to obtain data reflecting the wireless sensor readings and patient status, which could provide a sufficient amount of raw data to validate and compare the performance of AI algorithms. In this study, the data was obtained from a wireless sensor system designed for residential environments and used within care homes. The following data sources contribute to the dataset used in this research: patient data comprising basic demographics, medical history, existing medical conditions, and prescribed medication and therapy; sensor data, which includes wireless sensor readings for temperature, humidity, luminosity, passive infrared movement, electrical power usage, and door state, as well as the specific location of where the sensors are deployed around a property; and environmental data captured by external weather applications [21]. The datasets begin the moment a wireless sensor is installed, located to be inside or overlooking a care home's bedroom.

Data collection is event-driven, meaning that in the case of the resident moving away from their bed, the dataset does not constantly record the position of the resident across the care home but rather only stores the time the resident went to bed, the exact time the resident woke up, as well as the sensors' data that exhibited a change from 'non-activity' to 'activity'. Being efficient, these data collection techniques require as little human influence and capital as possible. Informed consent was obtained from all subjects involved in the study, and we conducted all experiments in accordance with the institutional and national research committee protocol. Our AI algorithms require data cleaning and validation procedures to increase data quality. The validation comprises a series of statistical and exploratory checks on the raw data. Data cleaning is required to ensure that the results are accurate, efficient, and practical.

Our hypothesis is that the dataset underpins and allows us to determine the efficacy and diagnostic capabilities of our proposed AI framework. The large amount of data collected throughout the duration of this study resulted in several hundred thousand features minus sample points. Our first issue was to correlate and match these readings across our several sources of collected data where necessary. Our second issue was to distribute the data into independent training sets and testing sets. In doing so, we ensured that our training and testing data were not truly unordered, but instead stratified such that we distributed the same percentage of class labels between the two groups. This distribution was set to a 70/30 percent split with all instances randomly ordered before being stratified. Each split constitutes a separate feature sample point in time.

6.2 AI Event Correlation and Predictive Analytics

AI event correlation and predictive analytics. In this subsection, we describe the methodologies that have been implemented for AI event correlation and predictive analytics capabilities, which are part of the four proposed functionalities. We show that AI techniques are capable of identifying important events and interpreting the importance of an event in sequence [22]. This capacity was also leveraged in the development of personalized digital twins of patients.

Having this information, the event correlation has the necessary background information and data to enhance the capabilities for better reactions and decisions when the pre-described or unpredicted health event takes place. Major diagnoses are heavily related to predictive capabilities, as even simple methodologies can show a correlation among signals and patient performance. Thus, the expected patient culture accurately enables the medical staff and other supporting systems to react adequately and on time with a patient repositioning or medical intervention. However, in addition to the current health situation of the patient, the future patient situation is also significantly important to analyze. Using physical wireless sensors, smart ADL sensors, and internal EV assignment sensors, VPC applied to wireless sensors are special-sampled patient data generators over a Wi-Fi indoor local platform.

6.3 Evaluation Methods

We evaluate the proposed algorithm against the following main criteria: functionality, performance, and reliability. The criteria pertaining to the functioning aspects of the AI-implemented IoT framework include system adequacy, data accuracy, clinical guidelines adherence, real-time behavior, adaptivity, and safetycritical aspects. The performance of the proposed AI framework is tested using quantitative measures such as the accuracy of the predictive analytics, response time, computational complexity, cost efficiency, simplicity, and overall satisfaction from the user. Our evaluation strategy is also complemented with a comparative analysis of the performance and functionalities of other related systems, based on the available information and specifications. Furthermore, we collected feedback from medical staff or healthcare professionals during some verification sessions, adopting a mix of semi-structured interviews, surveys, and focus group techniques.

The proposed evaluation strategy provides a systematic validation of the AI-based event-driven healthcare service delivery. Functionality, known as quality in use criteria, measures if the proposed system is truly useful to a healthcare user. It is evaluated in both real-world data sets and simulated data using personalized models. Performance is the overall performance of the prediction algorithm and qualitative feedback on the software completeness and robustness of the system when random failures are applied to the system. This will grant enhanced software robustness and resilience to the system by automatically switching to a resilient mode of operation.

7. Results and Discussion

Our AI framework demonstrated increased classification accuracy and an improved area under the receiver operating characteristic curves over RNN and CNN architecture. This offers potential benefits in dealing with high-dimensional, nonstationary, and noisy data, as experienced by clinicians when monitoring a ward of patients. The proposed event-driven systems can therefore provide the tools for creating real-time wireless sensors for applications such as connected healthcare. The future of healthcare looks to be increasingly reliant on connected sensors. For instance, the length of time in which physiological data is recorded in anesthetic patients suffering severe infection is associated with in-hospital mortality. Current methods being developed to enable this involve using machine learning in the form of temporal convolutions to extract features from windows of physiological timeseries data. Here, we demonstrate the use of event-driven systems for robust statistics-based feature learning from phasic wireless signals. Using a disjunctive normal form, this feature set is combined across time to provide a measurement of the patient's state that is invariant to the sensors' event rates and can be used for ANS classification.

We demonstrate the use of LMUs for feature learning because of their logarithmic event-time alignment and superior performance. The framework demonstrates an accuracy of 0.91 on 10-fold CV and 0.8 using an independent test dataset, faster response times, and can distinguish changes in the ANS. The results suggest that in their separate domains, doctors and engineers can synergize to carry out excellent research. The combined expertise will provide elaborate and rigorous explanations for the results. This work focused on the development of a model that was trained and tested on data acquired in a lab. Future work will include the inclusion of more diverse covariate noise and a larger variety of recording environments to improve model validity. Moreover, models developed here will be tested on live recordings from different hospitals. In the end, an AI model could be tested in the ward environment; however, discerning the performance of the model as the nurse's behavior would be an issue. To cope with these aspects, any future large-scale deployment of the model or any research involving patient interaction should be done in collaboration with healthcare professionals and policymakers to develop a system that is acceptable and useful.

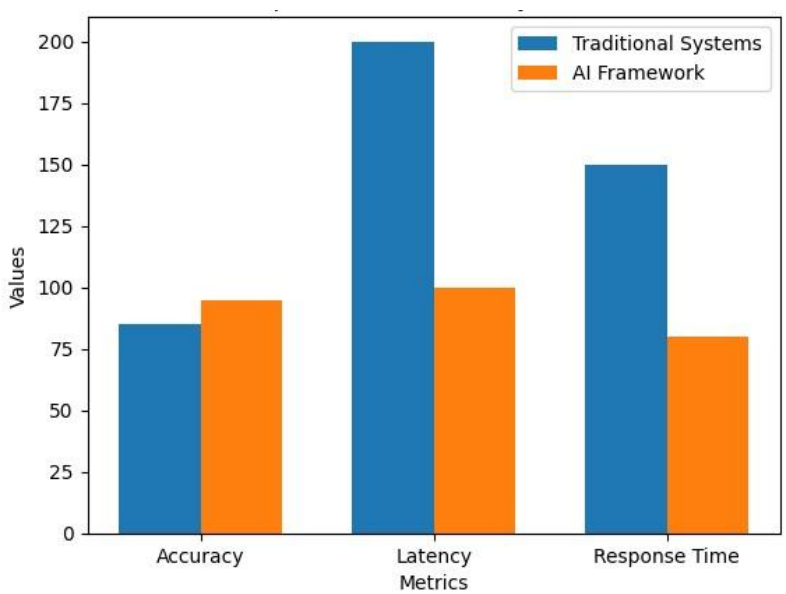

Figure 3: Performance comparison: Traditional systems vs AI Framework

8. Challenges and Limitations

The main challenges and limitations are based on technical limitations due to the proposed AI framework and its implementation. Imagine, for example, spike count models using muscle activity sensors downstream for advanced models as applied in a closed-control approach. The biggest hurdle in the implementation of the AI framework could be data privacy in event-driven wireless sensor systems. In addition, people do not attend training or baseline measurements or drop out, which needs to be accounted for to avoid introducing data bias, which is an example of technical barriers. This project may be threatening for healthcare professionals if not implemented correctly. It could disturb the collaboration with other doctors during referrals or with other healthcare professionals involved in patient care.

There might be limited or old data to use for setting digital twins. In an established place of technology, anxiety and the sheer resistance to work with novel technologies will limit data in some healthcare professionals, and thus putting a digital twin in their territory is not the best approach for informing patients' therapies. Some data are difficult to obtain or carry artifacts. Data can be missing, and missing data can result from interrupting the spikes in a recording session with spikes from another one. For instance, a patient would generate 5 minutes of data for training but could be interrupted after two minutes. In a clinical environment, an incomplete test would not qualify for allowing model training, and this lesser data is never applied in clinical studies or practice. Even when a patient completes an experiment following interruptions from another session, shifts in performance may be anticipated or considered.

It might even differ from what was performed before the interruption—a variability that is feared for being contaminated. Using digital twin technologies in medicine has other limitations, including changes in daily care due to the insights provided by digital twins and the regulatory environment, which may make controlling the algorithms difficult. The introduction of a new technology into an existing infrastructure, such as clinics, will also change the workflow, which might make the adoption of the technology difficult. This is not an exhaustive list of limitations of the proposed AI framework and is rather based on the current state of the project. Ongoing research should identify more barriers first, which would then be addressed in effective collaboration with healthcare professionals. A strong focus on this initial step will make the later use of appropriate methodologies more restrictive, so that constraints can be properly examined. There is also a need to work closely with interested clinicians from the beginning.

9. Future Work and Conclusion

9.1. Future Work

The AI algorithms we used in our system can be further advanced by making them more real-time friendly and enabling them to work with significantly less data. Besides, the sensor can be equipped with new peripherals and actuators while some applications require cameras and processing the image/video data for diverse medical and lifestyle-pattern-oriented analysis. Addressing these points are potential future collaborations among biomedical and digital healthcare experts, AI researchers, wireless sensor designers, and edge computing specialists. This also involves healthcare innovators who could offer large-scale and long-lived experimental studies and allow real-time performance concerning the concept of technology readiness. In the current context, we collaborate with a post-cardiacsurgery healthcare team to decide the critical actionable decisions for escalation regions that are required, as timely as possible. Effectively, large and diverse future work should conclude the adaptability of our concept and its performance across different venues, patient demographics, and lifestyles. It should also investigate safety procedures, data privacy, and regulatory terms to assure externalizing it to the broader society.

9.2. Conclusion

In this essay, we have considered the feasibility of advances in the field of AI systems to enable scalable administrations of healthcare using event-driven wireless sensor systems. Key strides have been made in the techniques of processing and eventing the data to the sensor nodes and underlying edge-compute network in terms of performance and energy used thereby. This approach has underlined that a comprehensive systems approach with sensors, edge computing, AI capability, and healthcare orchestration has the potential to allow augmented healthcare service in the future. We believe that the future of connected healthcare is patient-centered, efficient, and data-driven, and by definition, it has to be personalized to be successful. While promising from an R&D perspective, the scalability and potential for utilizing such a system with population-wide requirements have yet to be tested in real-world conditions. This requires public debate and supports further studies to better patient outcomes with proven results across many venues and different lifestyles.

References

1. Wani, N. A., Kumar, R., Bedi, J., & Rida, I. (2024). Explainable AI-driven IoMT fusion: Unravelling techniques, opportunities, and challenges with Explainable AI in healthcare. *Information Fusion, 102472*.
2. K. Sasikala, C. Sharanya, and G. R. Jothilakshmi, "Design and implementation of bio signal platform using Internet of Things," in AIP Conference, 2022.
3. Khan, A. A., Shaikh, Z. A., Baitenova, L., Mutaliyeva, L., Moiseev, N., Mikhaylov, A., ... & Alshazly, H. (2021). QoS-ledger: Smart contracts and metaheuristic for secure quality-of-service and cost-efficient scheduling of medical-data processing. *Electronics, 10*(24), 3083.
4. Zeadally, S., & Bello, O. (2021). Harnessing the power of Internet of Things based connectivity to improve healthcare. *Internet of Things, 14*, 100074.
5. Shi, L., Steenland, K., Li, H., Liu, P., Zhang, Y., Lyles, R. H., ... & Schwartz, J. (2021). A national cohort study (2000–2018) of long-term air pollution exposure and incident dementia in older adults in the United States. *Nature communications, 12*(1), 6754.
6. Dhruva, S. S., Ross, J. S., Akar, J. G., Caldwell, B., Childers, K., Chow, W., ... & Shah, N. D. (2020). Aggregating multiple real-world data sources using a patient-centered health-data-sharing platform. *NPJ digital medicine, 3*(1), 60.
7. Abdulmalek, S., Nasir, A., Jabbar, W. A., Almuhaya, M. A. M., Bairagi, A. K., Khan, M. A. M., & Kee, S. H. (2022). *IoT-Based Healthcare-Monitoring System to-wards Improving Quality of Life: A Review. Healthcare 2022, 10, 1993.*
8. Verma, D., Singh, K. R., Yadav, A. K., Nayak, V., Singh, J., Solanki, P. R., & Singh, R. P. (2022). Internet of things (IoT) in nano-integrated wearable biosensor devices for healthcare applications. *Biosensors and Bioelectronics: X, 11*, 100153.
9. Ahmed, I., Karvonen, H., Kumpuniemi, T., & Katz, M. (2020). Wireless communications for the hospital of the future: requirements, challenges and solutions. *International Journal of Wireless Information Networks, 27*(1), 4-17.
10. Gupta, P., & Pandey, M. K. (2024). Role of AI for Smart Health Diagnosis and Treatment. In *Smart Medical Imaging for Diagnosis and Treatment Planning* (pp. 23-45). Chapman and Hall/CRC.
11. Ayub, K., & Zagurskis, V. (2016, June). SMART Incubator: Implementation of Impulse Radio Ultra Wideband Based PA-MAC Architecture in Wireless Body Area Network. In *2016 International Conference on Systems Informatics, Modelling and Simulation (SIMS)* (pp. 25-31). IEEE.
12. Haleem, A., Javaid, M., Singh, R. P., & Suman, R. (2022). Medical 4.0 technologies for healthcare: Features, capabilities, and applications. *Internet of Things and Cyber-Physical Systems, 2,* 12-30.
13. Katal, N. (2024). AI-driven healthcare services and infrastructure in smart cities. In *Smart Cities* (pp. 150-170). CRC Press.
14. Rahmani, A. M., Babaei, Z., & Souri, A. (2021). Event-driven IoT architecture for data analysis of reliable healthcare application using complex event processing. *Cluster Computing, 24*(2), 1347-1360.
15. Mahmood, S. N., Ishak, A. J., Ismail, A., Soh, A. C., Zakaria, Z., & Alani, S. (2020). ON-OFF body ultra-wideband (UWB) antenna for wireless body area networks (WBAN): a review. *IEEE Access, 8,* 150844-150863.
16. Meduri, K., Nadella, G. S., Gonaygunta, H., & Meduri, S. S. (2023). Developing a Fog Computing-based AI Framework for Real-time Traffic Management and Optimization. International Journal of Sustainable Development in Computing Science, 5(4), 1-24.
17. Ayub, K., & Alshawa, R. (2024, October). A Novel AI Framework for WBAN Event Correlation in Healthcare: ServiceNow AIOps approach. In *2024 IEEE Workshop on Microwave Theory and Technology in Wireless*

Communications (MTTW) (pp. 55-60). IEEE.
18. Manchana, R. (2021). Event-Driven Architecture: Building Responsive and Scalable Systems for Modern Industries. *International Journal of Science and Research (IJSR), 10*(1), 1706-1716.
19. M. Afanasov, N. A. Bhatti, D. Campagna, "Battery-less zero-maintenance embedded sensing at the mithræum of circus maximus," in Sensor Systems, 2020. neslab.it
20. Gherairi, S. (2022). Healthcare: A priority-based energy harvesting scheme for managing sensor nodes in WBANs. *Ad Hoc Networks, 133*, 102876.
21. Li, Y., Yang, G., Su, Z., Li, S., & Wang, Y. (2023). Human activity recognition based on multienvironment sensor data. *Information Fusion, 91*, 47-63.
22. Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., ... & Ranjan, R. (2023). Explainable AI (XAI): Core ideas, techniques, and solutions. *ACM Computing Surveys, 55*(9), 1-33.