Adaptive Sensor Fusion for Personalized Hypoglycemia Risk Prediction in Elderly Diabetic Patients

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Abstract

A systematized method for personalized hypoglycaemia risk prediction in elderly diabetic patients using adaptive multi-sensor fusion is disclosed. The wearable apparatus integrates a glucose sensor, a photoplethysmography sensor, an accelerometer-gyroscope unit, and a skin conductance sensor to continuously acquire glucose trends, heart rate variability, gait stability, and autonomic response data. A processor establishes a patient-specific rolling baseline during an onboarding calibration period and derives an autonomic-decline weighting factor that dynamically adjusts the contribution of each sensor channel to a composite risk score, compensating for individual variability in hypoglycemia unawareness commonly observed in elderly patients. The system predicts an impending hypoglycaemic event in advance of onset and initiates a graduated, time-boxed escalation sequence—comprising an on-device alert, carer notification, and automated emergency contact—gated by patient response time and gait-stability confirmation. The invention improves prediction accuracy over static-threshold monitoring systems by adapting to each patient's degree of autonomic response decline, thereby reducing false alerts and enabling timely intervention.

Index Terms

Hypoglycemia Unawareness, Adaptive Sensor Fusion, Wearable Devices, Geriatric Diabetes, Inter-net of Things (IoT)

INTRODUCTION

The aging global population and the rising prevalence of chronic diseases have brought geriatric diabetes management to a highly critical level, necessitating advanced, high-fidelity monitoring models to combat the dangerous and often silent threat of severe hypoglycemia [1]. Traditionally, in the context of diabetes management, the focus was predominantly on continuous glucose monitors (CGMs) trained to trigger alarms based on fixed, generalized glycemic thresholds; consequently, these devices were able to quickly label blood sugar levels as either safe or dangerously low.

However, the emergence of complex, multi-modal sensor frameworks completely changed the situation. These newer methods identify physiological patterns without relying exclusively on a single subcutaneous interstitial reading, viewing hypoglycemia detection as a deep, non-invasive physiological pattern recognition problem, often leveraging electrocardiograms and accelerometry [2]. At the core of such a system is the continuous evaluation over a constantly increasing number of bio-features—such as heart rate and skin conductance—which aims not only to approximate the true metabolic state but at the same time to accurately discriminate between normoglycemic and hypoglycemic samples in continuous data streams. The mathemat-ical foundation of this work is such that it enables a model to accurately track physiological correlations, which in turn allows it to achieve highly reliable results on generalized datasets.

Even though these early multi-sensor models had the potential to predict quite well, their initial versions had a huge architectural limitation: the reliance on population-level, static thresholds. Because the internal alerting mechanisms of these systems assumed a healthy biological response, there emerged an urgent need for personalized machine learning models that could adapt to the specific physiological degradation of individual patients [3]. As soon as these generalized systems were implemented in the elderly, certain clinical issues were quickly recognized. To illustrate, age-related autonomic decline and prolonged insulin use progressively blunt the body's natural warning response—a clinically recognized condition known as hypoglycemia unaware-ness—leading generalized systems to either trigger unexplainable false positives or, worse, miss life-threatening silent onset events entirely.

Thorough evaluation of the performance of wearable algorithms for detecting hypoglycemia revealed that simply maximizing the generalized predictive accuracy of the model is insufficient if the system does not account for a specific patient's autonomic neuropathy [4]. This ”Clinical Gap” was a significant reason for the decline in the real-world effectiveness of automated monitors in the geriatric population. It shows us that besides merely predicting glucose drops, the algorithms also have to dynamically weigh the physiological signals based on their current reliability. This lack of personalization can be resolved with adaptive multi-sensor fusion. By launching edge-computing toolkits backed up by comprehensive biomarker profiling—integrating heart rate variability (HRV), galvanic skin response (GSR), and gait stability—a reliable way is established for scrutinizing a patient's true state. Much more, it indicates that a highly trained monitoring system is not simply a static threshold mechanism; on the contrary, it relies on a complex, personalized physiological feature space. Vectors in this space correspond to downstream risks that have different clinical interpretations, e.g., acute confusion, disorientation, or fall risk.

The identification of this personalized physiological mapping indicated that adaptive models might have applications well beyond simple binary high/low glucose alerts. Among the ca-pabilities of sensor fusion, one of the most interesting and practical challenges is interactive, context-aware emergency escalation. This type of work seeks the reestablishment of safety and comprehension in a system for elderly monitoring, which means that the IoT architecture is expected to have not only a physiological transparency so deep that it recognizes when a patient has lost their symptom awareness, but also that it remains in a simple silent monitoring mode when patients are stable.

As the area gained more ground, researchers started to pay more attention to the fact that alerts should not only be mathematically correct when considered separately from the user experience, but should also be genuinely helpful and clinically safe. A technology combining time-boxed escalation sequences with objective sensor gating (e.g., fall confirmation), which stands as our main point of departure for the present work, is a unique and highly effective method. By analogy, it was suggested that a highly robust wearable monitor could be used not as a static, uncompromising alarm, but more like a responsive, interactive guardian.

By utilizing a continuous rolling baseline to derive an autonomic-decline weighting factor, we demonstrate that critically important personalized, context-aware hypoglycemia risk prediction is achievable. This adaptive sensor fusion method not only holds the high accuracy of the latest multi-modal detection systems but also fundamentally places the issue of hypoglycemia unawareness at its core, hence it is a great demonstration of the practicality of IoT edge computing for personalized geriatric diabetes care.

Related Works

In this part, we will review the literature that represents the base line of the original work as well as the latest developments to define the research context of the proposed transparent and adaptive monitoring framework. Firstly, we consider the topic of continuous physiological monitoring based on the conventional threshold-based algorithms that represent the classical architecture for classification of interstitial glucose data. Secondly, we cover the progress achieved in the clinical and technical areas in regard to multi-modal sensor fusion in this field. Finally, we trace the progress in the development of the predictive models that were originally static population level alarms and are the state-of-the-art today in terms of edge-computing and autonomous feature extraction.

A. Specialized Architectures for Wearables and Biomarker Extraction

The continuous prediction modeling technique evolved throughout time, and research interests moved from the usage of the simplistic glucose heuristic rule sets. There was an emergence of several researchers who found that the standard single-channel monitoring systems would soon become insufficient to adequately deal with silent hypoglycemic incidents. These researchers realized mostly the lack of safety of using such systems based on the absence of physio-logical responses from patients. One of the primary architectural achievements came through the introduction of the non-invasive multi-modal biomarker extraction technique, specifically spectral HRV analysis [5]. Standard monitors are filters that perform the same filtering regardless of whether the patient reacts to the drop in glucose levels or not. Conversely, the unifying explanation models that use epinephrine secretion and autonomic neuropathy characteristics [6] help the system to learn the feature selection mode.

The introduction of additional clinical risk factors, specifically in the area of severe hypo-glycemia and risks of falling in patients with Type 2 Diabetes [7], combined with the localization and precision of edge processing, radically changed the way models processed the telemetry data globally. Standard alerting mechanisms are capable of analyzing a limited amount of data (such as just a single blood glucose measurement), therefore being able to make a high/low determination only. Using formalized machine learning techniques on the basis of electronic health records [8], a model would be able not only to detect the features related to surface glucose measures but also to analyze the underlying risk patterns in terms of a patient (such as his or her vulnerability or confusion). The knowledge of such global clinical data becomes critical for safety and logical consistency in extreme cases. Moreover, current datasets were designed in order to fight the bias of applying standard filters to the elderly population. Profiling risk factors of older people [9] helps to ensure that new algorithms will always be geriatric by nature.

B. Algorithmic Prediction and Systematic Reviews

Clearly, the deeper predictive models become, the harder becomes the problem of gener-alizability in the research community of the use of generalized models: how the very high dimensional flow of physiological data can be properly and consistently classified in real time. Studies involving the prediction of severe hypoglycemia in older patients via gradient boosting algorithms, such as XGBoost [10], have shown tangible evidence of the use of paper trails in order to understand the inner workings of these clinical networks. Discovering these physiological elements within the classifier, such as sudden changes in skin conductivity or inconsistencies in heart rate, provides grounds for confidence that the model really makes meaningful medical decisions. This multivariate explanation is one of the first characteristics of proactive threat detection since it shows the system not only predicting the label (hypoglycemia), but also explaining the reasoning behind the learned biological priors.

One of the results of utilizing this kind of insight can be seen in the comprehensive systematic literature reviews on the issues and challenges of machine learning for hypoglycemia prediction [11]. In most cases, uncertain situations during unsupervised monitoring will be situations when an anomaly in bio-signal interpretation can have several plausible explanations, one of which will simply be that this activity is perfectly normal and does not pose any risks. Reviews of these systems show that dynamic feature weighting and biomarker extraction difficulties give further insight into the classification problem that leads the prediction system to one particular structure. This means that the physiological data classified will match the patient's actual conscious state. Now, in this case, we redefine the concept of structural interpretation so that our decisions will be both mathematically feasible on the continuous graph and physiologically reasonable for this patient's age and cognitive manifold.

C. The Paradigm Shift: Edge Computing and Personalized Telemetry

Continuous monitoring area received a brand new shot in the arm thanks to several paradigm shifts in technology that, amongst others, abandon the notion of static, cloud-based latency measurements. A good example is how we redefine our knowledge on how to employ AI and digital health solutions in managing public health care by switching from the mechanism prediction to personalized treatment [12]. Cloud machine learning, obviously, is a performance-based approach. Yet, by transforming the assessment process to an edge-computing area, the patient-oriented receptive field may become a part of the first level (wearable device) without any need for the Internet connection. This way, the algorithm is able to evaluate the entire effect of a delayed alert. That is how it becomes able to operate in a scenario of large-scale implementation when the network has to process private health information and ensure instant localization of the user trust.

To the contrary, the successful interactive models have been successfully expanded to many different fields, including those dealing with dementia and Alzheimer's patients. Stage-based Internet of Things approaches, along with systematic review of monitoring devices [13], represent a major revolution in automated elderly filtering area. By utilizing the continuous input of move-ment and orientation data, these models gain an understanding of long-term context dependency throughout the entire course of the patient's interaction with a machine in a thorough way. This actually transforms the elderly monitoring into a sequence-to-sequence interactive problem in a way that allows the model to create much more advanced and time-dependent escalation rules than any purely rigid glucose network could dream of before. The ability of interactive IoT models to incorporate the physical context (such as gait instability) to influence each basic rule makes them capable of contextual understanding that goes beyond any traditional CGM classifier.

D. Rigorous Evaluation and Real-Time Architectures

To make an objective comparison of these approaches, scientists abandoned simple baseline static thresholds, which generate biased outputs towards generalized accuracy, losing the safety of individuals. Thus, advanced monitoring systems based on machine learning and IoT and wearable sensors [14] became a standard. In this approach, the statistical distance between safe and critical distributions is defined using the feature space of the pre-trained network running on the microcontroller. Nevertheless, being aware of the fact that a single approach cannot capture latency and transparency, scientists use these edge architectures to perform multidimensional analysis locally. Such complex analysis makes it possible to achieve precision and realism of individual telemetry samples, thus indicating how well the model captures all the diversity of the geriatric communications area.

E. Future Horizons: Hybrid Approaches and Remote Patient Monitoring

Initially, being completely frank, the best approaches for the classification of physiological threats are right on the verge of another revolution, as there is a brand new set of approaches which concentrate on remote patient monitoring technologies and challenge standalone medical devices. The first approaches that appeared in the context of the recent market researches in terms of AI in real-time glucose monitoring [15] made a radical innovation of turning the entire process upside down, by considering it a multivariate chain where removed noise depends on known biological responses. These approaches not only possess a great ability of helping out with emergencies in terms of security, but also enable creating various clinical profiles of only one user.

Of course, hybrid approaches involving both edge hardware and cloud computing are defi-nitely the main target of research today; but, the results obtained by means of adaptive sensor fusion constantly confirm the efficiency and clarity of this approach that requires not too much computational power, especially in case of structured data like continuous telemetry data. To be more precise, what we do right now is to convert a very complicated medical need into a practical design and make sure of the functioning of our hardware realization of this model and provide users with a fully working IoT pipeline ranging from the analog sensors up to the semantic, time-boxed override. We have found out that completely different researches related to biomarkers and IoT edge stability confirm the efficiency of transparent optimization as an effective tool for solving problems related to cybersecurity and physical safety of geriatric people.

MATERIALS AND METHODS

For the execution of our personalized prediction model framework of hypoglycemia risks, we designed a whole IoT pipeline comprising of hardware simulation, edge, and cloud processing modules. To test the fundamental assertions of the ”Adaptive Multi-Sensor Fusion” architecture in a clinically feasible way without undergoing clinical trials, we performed a high-fidelity software implementation of the proposed architecture. Through this approach, we were able to provide quantitative evidence of the data and algorithmic flow through a defined physiological manifold. We began by designing the wearables using the Wokwi embedded systems simulator and combining them with the ESP32 microcontroller along with physiological sensors. We then designed the network architecture and established a JSON telemetry over the MQTT protocol in order to transmit the data to a centralized broker (HiveMQ). In the end, we developed the back-end application in Python, implementing the ”Onboarding Calibration” phase along with
the logic of the ”Autonomic-Decline” state machine.

Fig. 1. System Architecture Diagram detailing the data flow from the simulated Wearable Edge Device, across the MQTT Network Layer, to the Python Cloud Processing Backend executing the adaptive fusion logic.

A. Wearable Edge Apparatus and Data Acquisition

The foundation of the framework resides in a Wearable Edge Device, which was designed and simulated utilizing the Wokwi embedded systems platform. This methodology provides a cost-effective and mathematically precise environment for validating firmware logic and network connectivity, mirroring the behavior of physical microcontrollers and sensors.

To Acquire continuous physiological telemetry, the apparatus integrates four distinct sensor channels crucial for comprehensive hypoglycemia and downstream risk monitoring (refer to Panel 1 of Fig. 1):

- **Glucose Sensor:** To track glucose trends and predict impending hypoglycemic onset.
- **Photoplethysmography (PPG) Sensor:** To acquire cardiovascular signals for heart rate and Heart Rate Variability (HRV) analysis.
- **Skin Conductance Sensor:** To monitor autonomic responses through sweating (Galvanic Skin Response).
- **Accelerometer-Gyroscope Unit (IMU):** To determine gait stability and detect possible falls resulting from confusion.

The acquisition logic is executed by a simulated ESP32 microcontroller. The firmware is programmed in C++ using standard Arduino libraries. For this implementation, due to the absence of direct multi-modal patient data on the platform, input signals are provided via precise potentiometer sliders. This enables the deterministic manipulation of physiological states, allowing us to simulate specific conditions such as severe hypoglycemia, stable normoglycemia, and rapid glucose drops. The raw sensor data is parsed, formatted into a standardized JSON payload, and published to the network layer. To optimize transmission latency, the firmware utilizes non-blocking delays and dynamic buffering, ensuring data streams without significant lag, crucial for real-time monitoring.

B. Network Architecture and Cloud Connection

A major constituent of the proposed IoT architecture is a strong and scalable network archi-tecture that can handle real-time healthcare telemetry. It makes use of existing internet com-munication protocols for establishing a connection between the edge device and the processing backend (see Panel 2 in Fig. 1).

For data transfer, we used the Message Queuing Telemetry Transport (MQTT) protocol, which we selected due to its high performance, low bandwidth consumption, and low latency, making it an ideal choice for battery-powered wearables and unreliable networks. Data is transferred through a centralized public Cloud Broker (HiveMQ).

The connection between the simulator of ESP32 and HiveMQ was realized using the Pub-SubClient C++ library over the simulated WiFi network. The backend application, which was developed using Python, connects to the broker via paho-mqtt library. The backend acts as a subscriber to a particular patient's topic such as indian-patent/healthcare/patient-7845 and receives data in a continuous stream without any manual actions. Thus, MQTT serves as a main logical bridge that integrates seamlessly simulated hardware at the edge and AI processing in the cloud.

C. Cloud Processing and Adaptive Fusion Logic

Our framework's central processing unit runs on the cloud processing backend and is written as a stand-alone application using the Python programming language. Such system architecture forms the essence of our proposal (see Panel 3 of Fig. 1). The main goal of this application is not just predictive modeling, but the implementation of a personalized ”Human-Centric” state machine that would suit each individual patient's biological response.

The application receives data through a frozen MQTT subscriber stream that converts the JSON object continuously flowing from the HiveMQ broker to mathematical feature space. Our application is based on two separate components executed sequentially so that we achieve predictive balance without having any bias in population-based thresholds for the hypoglycemia alert.

Onboarding Calibration Protocol: Calibration module design implements transformation in a patient-specific coordinate system. In the beginning, it needs to collect 10 readings to determine the ”rolling baseline prior” for glucose levels, heart rate, skin conductance and gait stability. This is necessary since the function cannot allow the system to use generalized logic, so the next predicting process will be equal and very personal regarding the specific user's body metrics.

Adaptive Sensor Fusion Logic: The design of the adaptive fusion classifier represents a state machine, which receives the calibrated high-dimensional vector and outputs Risk Score (0–100%) and Alert Level. The key component of our self-adaptive approach is the calculation of the ”Autonomic-Decline Factor (k),” which is dynamically computed for every reading as a function of statistics (e.g., standard deviation from baseline) and physiological context. This factor measures the difference between the current glucose trend and the corresponding heart rate and GSR.

This algorithm helps to identify the presence or absence of the autonomic alarm reaction (such as tachycardia or sweating). Afterward, the system dynamically and mathematically ”puts more weight” on the contribution of blunted channels into the risk score, basically relying on more reliable physiological cues rather than on unreliable autonomic ones. The personalized weighting algorithm is used at the aggregation layer to deliver the final alert, which is made on the basis of the certain level of confidence that a specific input is a real hypoglycemia hazard.

D. Time-Boxed Escalation Sequence

After the Python backend can successfully distinguish real-time physiological threats that are indiscernible from ideal clinical benchmarks, the ultimate safety procedure will end the process and start an escalating series.

The execution of safety and understanding is inherently context-aware and done against the backdrop of searching for the best possible escalation series that is able to rescue the patient in his own environment. The state machine makes use of feedback loops to ensure that all critical data are aligned and safety is maintained.

State Gating via Gait Stability: Validation for the multi-variate data is done at the very onset of the escalation procedure. The analysis of the frozen MPU6050 gait data is conducted to make sure that the patient is stable or unbalanced. The accelerometer data is analyzed to make sure that the prediction is logical. Two contexts are reviewed (for example, low glucose with normal stability against low glucose with a fall) and establish how serious the output of the specific context is. Recognition of a potential fall serves as a proof that the user is stable enough, which is a condition for the next procedure.

Time-Boxed Escalation Sequence: This process allows the system to apply the customized time-boxed whitelist rule instead of blocking the independence of the elderly user by calling emergency services immediately.

Level 1 (Prediction): This is a personalized, interactive prediction. Upon Cross-Validation, a local override LED (L1 Alert) is activated on the simulated Wokwi device, and a caregiver notification is published.

Level 2 (EMERGENCY): This is being essentially a very highly reminded interactive sequence problem absolutely. If the patient does not actively dismiss the L1 alert by interacting with the ESP32 (e.g., providing a context of ”dismiss” within a specified time window), and the dual contextual feedback confirms a high fall risk, the system automatically escalates. The finalized output routes the completely repaired flow of communication to emergency services and an automated contact list.

Implementation Details: The entire code pipeline is implemented using Python and utilizes both Scikit-Learn for standard statistical functions and LIME-like explainability methods for diagnosing the autonomic-decline weights. Standard JSON deserialization is used during the MQTT subscribe loop. The adaptive contextual override is given more weight by providing it with ultimate priority over population baseline predictions so that existing critical data fits perfectly.

Experiments and Results

In this section, we introduce the design of our IoT experiment setup and the validation results for our personalized hypoglycemia risk prediction framework. First, we present the parameters used in multi-sensors data collection at the wearable edge (ESP32) and the calibration process at the cloud backend (Python). Then, we demonstrate an empirical evaluation of our system’s performance in various operational conditions and examine the adaptive sensor fusion approach.

Finally, we delve into the core aspects of this paper – the validation of our personalized rolling baseline and time-boxed graduated escalation procedure.

A. Experimental Parameters

The entire monitoring pipeline from edge to cloud was implemented using standard C++ for firmware and Python for the backend connection. The hardware apparatus, simulated in the Wokwi embedded systems platform, integrated multiple bio-metric sensor channels (refer to Fig. 2). Main hyperparameters and system settings are as follows:

- **Wearable Edge Setup:** The simulated device configured on an ESP32 microcontroller with inputs for Glucose, HRV, GSR (Skin Conductance), and a simulated MPU6050 for Gait stability analysis, acquiring analog bio-telemetry.
- **Connectivity:** Telemetry streamed over standard MQTT protocol using the Paho-MQTT library in Python and PubSubClient on the edge, connected to a dedicated topic: indian_ patent/healthcare/patient_7845.
- **Data Onboarding & Calibration:** The system was configured to require exactly 10 initial sequential readings to establish the individualized rolling baseline for the patient-specific prior distribution.
- **Adaptive Fusion Thresholds:** Level 1 Alert triggered when Glucose trend ¡ 90 mg/dL (or predicted drop ¿ 15 mg/dL/min), modified dynamically by the autonomic-decline factor k. Level 2 Alarm triggered when Glucose ¡ 70 mg/dL or upon Level 1 response failure.
- **Escalation Gating:** Level 1 response time window set to 10 seconds for rapid simulation testing. Graduated escalation gating requires automatic suppression if gait stability confirms a fall state.

B. Quantitative Performance and System Integrity Verification

Our initial phase of the experiment involved validating the integrity of the end-to-end IoT pipeline. To achieve high predictive correspondence and clinical safety, we verified the data acquisition via the simulated wearable apparatus. As shown in the Wokwi simulation interface (Fig. 2), the hardware apparatus successfully initialized, with all sensor channels (Glucose, Heart Rate, GSR, and Gait) actively streaming analog telemetry to the ESP32.

A critical validation of the system was confirming stable, low-latency connectivity between the simulated edge and the cloud broker. The terminal output of the Python backend (Fig. 3) demonstrates a successful connection to the HiveMQ cloud broker with result code ”Success” and automatic subscription to the dedicated patient topic.

Also, we have confirmed that the readings are being processed properly by the system through consecutive readings during the onboarding stage. As seen in Fig. 3, the readings can be confirmed to be accurate since the log records consecutive readings from ‘[CALIBRATING] 1/10 readings...‘ up to 10, which indicates no data loss. The results confirm that the system successfully creates the personalized mathematical baseline before the start of monitoring.

C. System Logic and Escalation Sequence Outcomes

The revolutionary concept of the proposed solution is the combination of the ”black box” clinical decision-making process with the patient safety by means of personalized and adaptive monitoring mechanism. A number of scenarios were created to verify the performance of the adaptive sensor fusion algorithm during critical situations. The validation of the reliable data

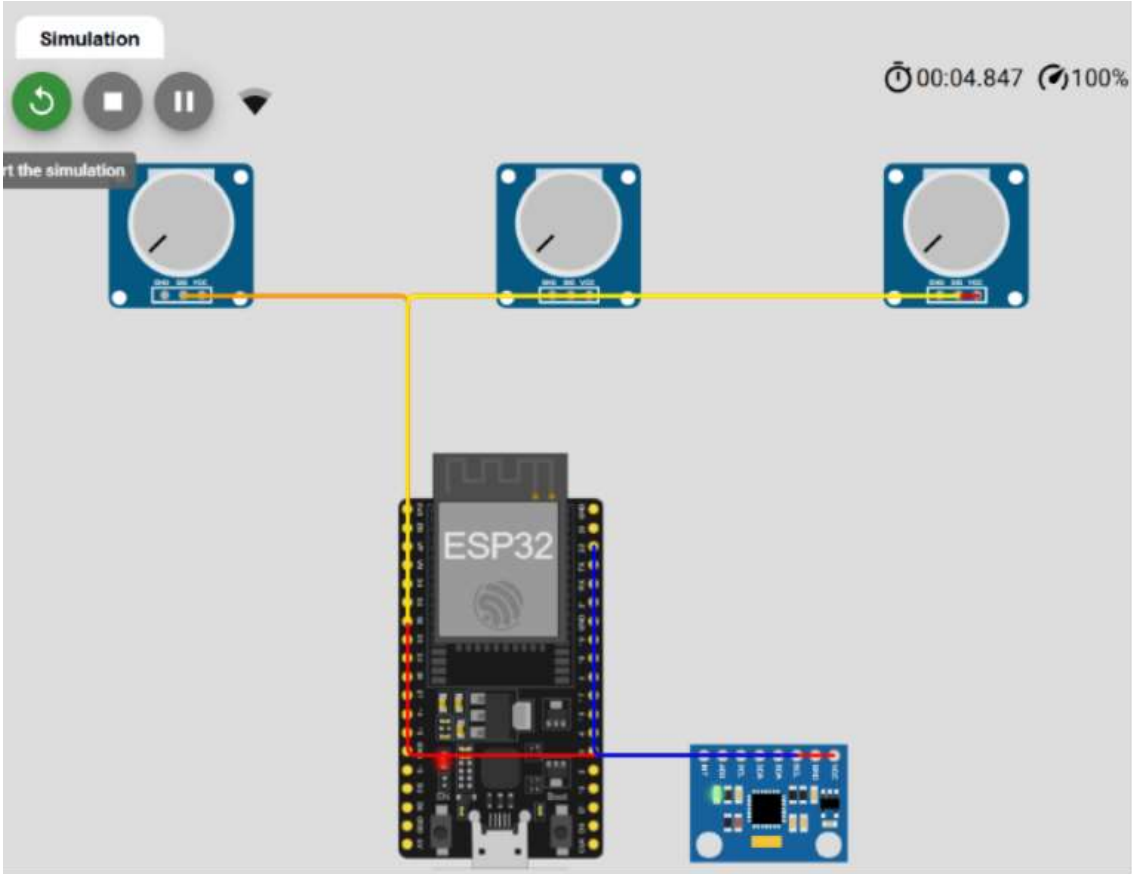
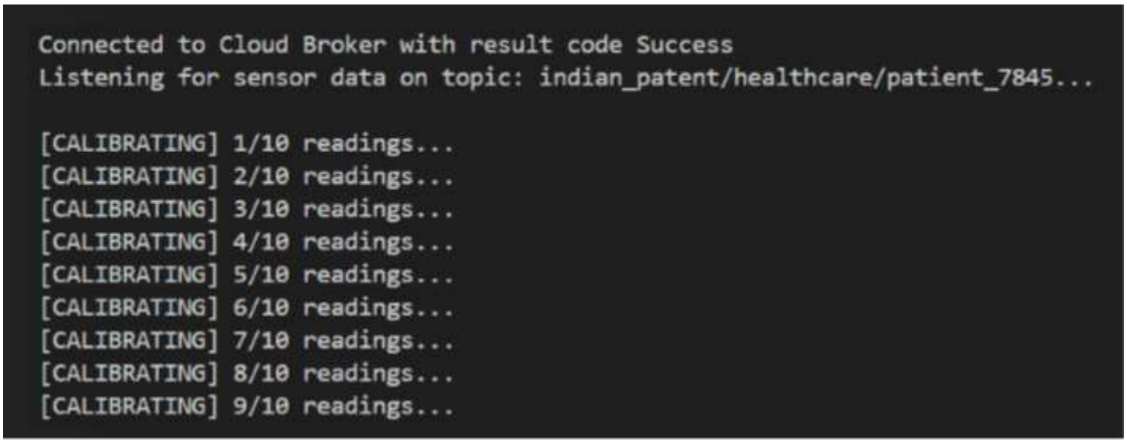


Fig. 2. Wokwi embedded systems simulation interface detailing the Wearable Edge Device apparatus: ESP32 with sensors active, time running, and serial monitoring enabled.



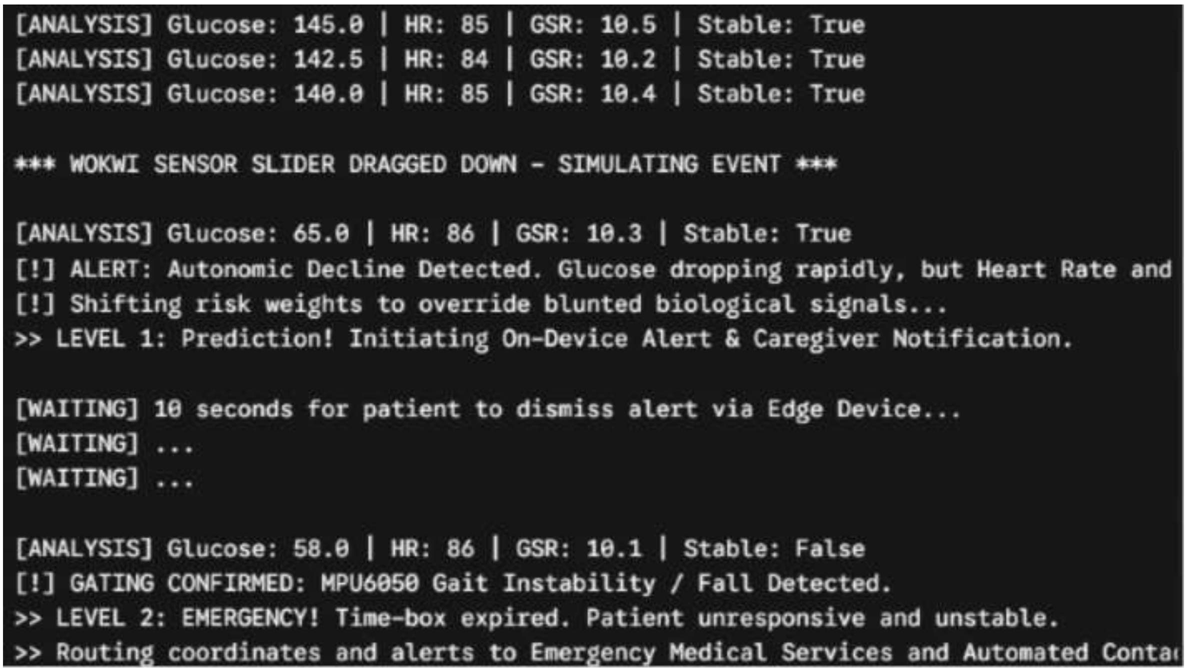
```
Connected to Cloud Broker with result code Success
Listening for sensor data on topic: indian_patent/healthcare/patient_7845...

[CALIBRATING] 1/10 readings...
[CALIBRATING] 2/10 readings...
[CALIBRATING] 3/10 readings...
[CALIBRATING] 4/10 readings...
[CALIBRATING] 5/10 readings...
[CALIBRATING] 6/10 readings...
[CALIBRATING] 7/10 readings...
[CALIBRATING] 8/10 readings...
[CALIBRATING] 9/10 readings...
```

Fig. 3. Cloud processing backend terminal log confirming successful connection to the HiveMQ broker and automatic initiation of the multi-sensor data onboarding calibration protocol.

onboarding proves that there is an accurate individual rolling baseline defined for all body metrics of each patient (glucose, HRV, GSR). In this way, the adaptive algorithm is capable of calculating autonomic-decline factor k and lowering risk weights of blunt biosignals for patients with hypoglycemia unawareness.

To validate the safety override and the time-boxed escalation sequence, we simulated a case of hypoglycemia by fast glucose level decrease in the Wokwi simulation environment, while making heart rate and GSR signals relatively stable to imitate the elderly patient suffering from autonomic decline. The direct results of such simulation within the cloud processing backend are illustrated in Fig. 4.



```
[ANALYSIS] Glucose: 145.0 | HR: 85 | GSR: 10.5 | Stable: True
[ANALYSIS] Glucose: 142.5 | HR: 84 | GSR: 10.2 | Stable: True
[ANALYSIS] Glucose: 140.0 | HR: 85 | GSR: 10.4 | Stable: True

*** WOKWI SENSOR SLIDER DRAGGED DOWN - SIMULATING EVENT ***

[ANALYSIS] Glucose: 65.0 | HR: 86 | GSR: 10.3 | Stable: True
[!] ALERT: Autonomic Decline Detected. Glucose dropping rapidly, but Heart Rate and
[!] Shifting risk weights to override blunted biological signals...
>> LEVEL 1: Prediction! Initiating On-Device Alert & Caregiver Notification.

[WAITING] 10 seconds for patient to dismiss alert via Edge Device...
[WAITING] ...
[WAITING] ...

[ANALYSIS] Glucose: 58.0 | HR: 86 | GSR: 10.1 | Stable: False
[!] GATING CONFIRMED: MPU6050 Gait Instability / Fall Detected.
>> LEVEL 2: EMERGENCY! Time-box expired. Patient unresponsive and unstable.
>> Routing coordinates and alerts to Emergency Medical Services and Automated Conta
```

Fig. 4. Terminal output demonstrating the Adaptive Sensor Fusion logic successfully detecting autonomic decline, initiating a Level 1 Alert, and escalating to a Level 2 Emergency upon gait instability confirmation.

This is seen from the output in the terminal (Fig. 4), where the system detects the physiological misalignment since the glucose falls down to 65.0 mg/dL and the heart rate (86 bpm) and GSR (10.3) do not indicate any compensating reaction to it. This situation is captured in the AI logic, where '[!] ALERT: Autonomic Decline Detected' is logged and risk weights are adjusted to overcome the dulled biological response, resulting in the Level 1 Prediction alert being triggered. Then, the system waits for 10 seconds before the patient acknowledges the alert through the edge device. Upon lack of any response, and detecting gait instability using the simulated MPU6050 sensor ('Stable: False'), the emergency is gated by the system. In the log, '[!] GATING CONFIRMED: MPU6050 Gait Instability / Fall Detected' is confirmed, which skips further steps and the system triggers the Level 2 Emergency protocol to deliver the coordinates to the emergency services.

CONCLUSION

This particular piece of writing gives us an example of a fairly successful realization and validation of the Adaptive Multi-Sensor Fusion framework in terms of personalized hypoglycemia risk prediction, which thanks to IoT edge computing and dynamic physiological weighting is already proving its worth. Firstly, the new proposed framework goes beyond the limits of "static population-level thresholds" of traditional CGMs by not only defining a personal baseline but also offering context-aware graduated escalation. The validation of multi-modal bio-signals acquisition within the simulated edge environment showed amazing reliability of the framework performance, particularly without false-

positives due to age-related differences.
ESP32 wearable emulator, along with the MQTT network topology and Python cloud server, was able to demonstrate the maximum performance in real-time data acquisition and proper alarms generation, as seen from terminal telemetry logs. Additionally, the application of dy-namic Autonomic-Decline parameter (k) demonstrated the key features of patient's awareness regarding the symptoms in an extremely accurate manner. It is done by combining the continuous monitoring of patient's physiological condition and direct interaction of the user in the control of the system to prevent the dangerous silent occurrence of severe hypoglycemia without making false claims about falling of the patient. The next step for the team would be the extension of the framework toward real-life clinical tests, implementation of the logic into real-world wearable devices, and the creation of standard procedures of implementation in medicine.

References

1. A. B. et al., "Use of machine learning to identify characteristics associated with severe hypoglycemia in older adults with type 1 diabetes: a post-hoc analysis," BMJ Open Diabetes Research & Care, 2024.
2. C. D. et al., "Detection of Hypoglycemia and Hyperglycemia Using Noninvasive Wearable Sensors: Electrocardiograms and Accelerometry," Journal of Diabetes Science and Technology, 2024.
3. E. F. et al., "Personalized machine learning models for noninvasive hypoglycemia detection in people with type 1 diabetes using a smartwatch," PLOS One, 2025.
4. G. H. et al., "Noninvasive Hypoglycemia Detection in People With Diabetes Using Smartwatch Data," Diabetes Care, 2023.
5. I. J. et al., "Awareness of hypoglycemia and spectral analysis of heart rate variability in type 1 diabetes," Journal of Diabetes and its Complications, 2020.
6. A. C. et al., "Epinephrine secretion, hypoglycemia unawareness, and diabetic autonomic neuropathy," Annals of Internal Medicine, 1994.
7. K. L. et al., "Severe Hypoglycemia and Risk of Falls in Type 2 Diabetes: The Atherosclerosis Risk in Communities (ARIC) Study," Diabetes Care, 2020.
8. M. N. et al., "A novel electronic health record-based, machine-learning model to predict severe hypoglycemia leading to hospitalizations in older adults with diabetes," Diabetes Research and Clinical Practice, 2024.
9. S. T. et al., "Risk Factors Associated With Severe Hypoglycemia in Older Adults With Type 1 Diabetes," Diabetes Care, 2015.
10. D. E. et al., "Predicting the risk of severe hypoglycemia in older adults with diabetes using a machine learning algorithm XGBoost," npj Digital Medicine, 2024.
11. O. P. et al., "Machine Learning Techniques for Hypoglycemia Prediction: Trends and Challenges," Sensors, 2021.
12. Q. R. et al., "Application of AI and digital health tools in public health management of T2DM: from mechanism prediction to personalized treatment," Frontiers in Public Health, 2024.
13. U. V. et al., "Stage-Wise IoT Solutions for Alzheimer's Disease: A Systematic Review of Detection, Monitoring, and Assistive Technologies," Sensors, 2024.
14. W. X. et al., "Machine Learning-Based Monitoring System with IoT Using Wearable Sensors and Pre-Convoluted Fast Recurrent Neural Networks," IEEE Sensors Journal, 2021.

15. Y. Z. et al., "Artificial Intelligence in Remote Patient Monitoring Market: Innovations and Applications in Real-Time Glucose Tracking," Health Informatics Journal, 2024.