On the characterization of glucose data through HAR: An integrated IoMT architecture

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Abstract. Diabetes mellitus, particularly type 1 diabetes, requires continuous monitoring of blood glucose levels and a careful interpretation of the contextual factors that influence them, such as physical activity, food intake, and environmental conditions. In this work, we propose a Internet of Medical Things (IoMT) architecture that integrates a continuous glucose monitor (CGM), a wristband, and ambient sensors deployed in a domestic environment, all orchestrated through a low-cost edge node. The collected multimodal data are cleaned, fused, and segmented into sliding windows from which a set of motion-related features is extracted. A fuzzy logic layer transforms these features into linguistic labels, enabling the inference of four daily activities performed by the monitored individual (resting, eating, exercising and tooth brushing) by means of an interpretable rule base. The activity context is then combined with glucose-state, time-of-day, and quantity summarizers to produce protoforms that describe the patient's behaviour in natural language. Preliminary results show that the proposed pipeline is able to characterize glucose data through activity recognition in a transparent way, providing a basis for future interpretable monitoring platforms for patients with type 1 diabetes.

Keywords: Internet of Medical Things · Continuous glucose monitoring · Human activity recognition · Fuzzy logic · Type 1 diabetes · Time series description · Computing with words.

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1 Introduction

The rise in life expectancy observed in societies over the last decades has been accompanied by an increase in the prevalence of chronic diseases [12]. In Spain, more than half of the adult population lives with at least one chronic condition [11]. Diabetes mellitus is among the most common of these conditions: in 2023, 8.7% of the Spanish population older than 15 years was diabetic. Diabetes is caused by a deficient production of insulin or by a defective response of the cells to it, which leads to an abnormal accumulation of glucose in the blood. In type 1 diabetes, the pancreatic cells responsible for insulin production are damaged by an autoimmune process, so external insulin administration becomes mandatory [10]. Proper disease management relies on a delicate balance among insulin dose, food intake, and physical activity, complemented by an awareness of environmental and behavioural factors that may worsen the risks associated with the disease [3].

In this scenario, the Internet of Medical Things (IoMT) has emerged as a key enabler for continuous, personalized, and remote monitoring of chronic patients. In the domain of diabetes, continuous glucose monitoring (CGM) devices, which periodically sample interstitial glucose levels, are paradigmatic examples of IoMT technologies. These devices provide rich time series that can be exploited by data-driven techniques to infer behavioural patterns and anticipate adverse glycemic events [20].

Despite the widespread adoption of CGM technologies, most current diabetes-management solutions remain focused on isolated glycemic metrics and time-in-range indicators. However, glucose dynamics are strongly influenced by behavioural and contextual factors such as physical activity, sleep quality, stress, daily routines, and environmental conditions, all of which may modulate insulin sensitivity and contribute to hypoglycemic or hyperglycemic events in real-life scenarios [2, 15]. Recent studies suggest that CGM systems may encourage positive behavioural changes related to physical activity and diet, although the available evidence is still heterogeneous and limited in real-world environments where behavioural and contextual variables are jointly analysed [14]. Furthermore, emerging digital-health approaches integrating wearable sensing and behavioural analysis have demonstrated the potential of combining multimodal data sources to improve metabolic monitoring and personalized healthcare [18, 1].

In this context, raw glucose values alone are insufficient to fully characterize the state of the patient. The same glucose measurement may have very different clinical implications depending on the patient activity. Therefore, glucose readings should be interpreted together with contextual information, ideally acquired in a non-intrusive manner without requiring explicit user interaction. Human Activity Recognition (HAR) offers a promising solution for capturing such contextual information automatically. Nevertheless, designing HAR models that generalize across subjects remains challenging due to the high inter-individual variability in movement patterns and the need for interpretability in healthcare-oriented applications [7].

This work hypothesizes that an IoMT architecture combining a CGM device, a wristband, and ambient sensors, together with an interpretable fuzzy-logic layer, can characterize the glucose dynamics of a patient with type 1 diabetes by associating glucose readings with both daily activities and temporal context. The main contributions of this paper are threefold: (i) the design of an IoMT architecture that integrates heterogeneous sensing devices through an MQTT-based edge node; (ii) a multimodal preprocessing pipeline for cleaning, synchronizing, and windowing heterogeneous sensor streams; and (iii) an interpretable HAR module that combines feature extraction and fuzzy rules to generate linguistic summaries linking glucose values to patient activities and daily routines.

The remainder of this paper is organized as follows. Section 2 reviews related work on IoMT-based healthcare systems, smart healthcare platforms, HAR techniques, and fuzzy-logic applications in medicine. Section 3 presents the proposed architecture, the preprocessing methodology, and the activity-recognition module. Section 4 discusses the obtained results and their implications. Finally, Section 5 summarizes the main conclusions and outlines future research directions.

2 Related Works

2.1 IoMT-based monitoring architectures

Recent research has increasingly focused on IoMT-based architectures for chronic disease management and remote patient monitoring. Zeshan et al. [19] propose an ontology-driven intelligent healthcare framework that combines IoT sensing and semantic reasoning to support remote monitoring and decision making. Similarly, Subha et al. [16] present an Internet of Medical Things (IoMT) architecture for remote healthcare supervision using wearable devices and cloud services, emphasizing scalability and real-time monitoring capabilities. These approaches demonstrate the growing interest in integrating heterogeneous sensing technologies into healthcare-oriented IoMT ecosystems. In this regard, Thorat et al. [17] discuss how smart bracelets, fitness trackers, and medical-grade devices can be integrated into IoT platforms for continuous patient monitoring. Díaz-Jiménez et al. [5] propose a methodology for deploying sensor-based adherence platforms in multi-patient home environments, addressing the lack of standardized approaches for clinical integration. Chand et al. [4] describe an AI-enabled telemedicine platform with Clinical Decision Support Systems integrated into a web interface, combining electronic health records with intelligent triage mechanisms.

Within diabetes management, Zhu et al. [21] propose a wearable-based framework combining continuous glucose monitoring, insulin bolus information, and physical-activity data to support self-management in type 1 diabetes through deep-learning models. Ontiveros Neri et al. [13] present an integral diabetes-management system that integrates CGM, heart rate, body temperature, blood pressure, and geolocation data using recurrent neural networks for early-warning generation. Although these systems integrate heterogeneous physiological information, they remain mainly focused on glucose prediction and monitoring tasks,

without explicitly incorporating Human Activity Recognition (HAR) mechanisms capable of contextualizing glucose behaviour through interpretable daily-activity modelling.

2.2 Fuzzy logic and interpretability in healthcare

In healthcare applications, interpretability is essential because clinical decisions often require transparent reasoning mechanisms. In previous work, Gaitán-Guerrero et al. [7] transformed continuous glucose monitoring (CGM) time series into interpretable linguistic summaries capable of describing glucose states, temporal trends, time-of-day periods, and quantified glucose patterns through fuzzy logic. Similarly, Healey et al. [8] explored the use of Large Language Models (LLMs) to analyse CGM signals and automatically generate textual interpretations of glucose behaviour. Both approaches improve the interpretability of glucose monitoring by transforming numerical glucose values into human-readable narratives. However, they remain centered on glucose data analysis itself and do not integrate contextual behavioural information derived from HAR.

2.3 Identified gap

The reviewed literature demonstrates significant advances in IoMT-based healthcare systems. However, most approaches remain limited in at least one of the following aspects: (i) integration of heterogeneous contextual sensors beyond glucose monitoring, (ii) interpretable reasoning mechanisms suitable for healthcare environments and (iii) automatic generation of human-readable contextual summaries. Consequently, this work addresses these gaps by proposing an IoMT architecture that combines CGM devices, wearable devices, and ambient sensing with an interpretable fuzzy-logic HAR module capable of generating contextual linguistic summaries associated with patient glucose dynamics.

3 Methods

This section describes the proposed IoMT architecture, the preprocessing and characterization pipeline applied to the multimodal data, and the fuzzy-logic-based HAR module.

3.1 Architecture of the System

The architecture is built around a low-cost edge node (a Raspberry Pi 4 Model B) that hosts all the services required for data acquisition, message routing, and persistence. An overview of the architecture is shown in Fig. 1.

When the edge node boots, three core services are launched automatically. The first one is **EMQX**, an MQTT broker that acts as the messaging backbone between the data sources and the storage layer. MQTT is a lightweight publish/subscribe protocol widely adopted in IoT and chosen here for its low overhead and reliable delivery semantics. The second service is **Zigbee2MQTT**,

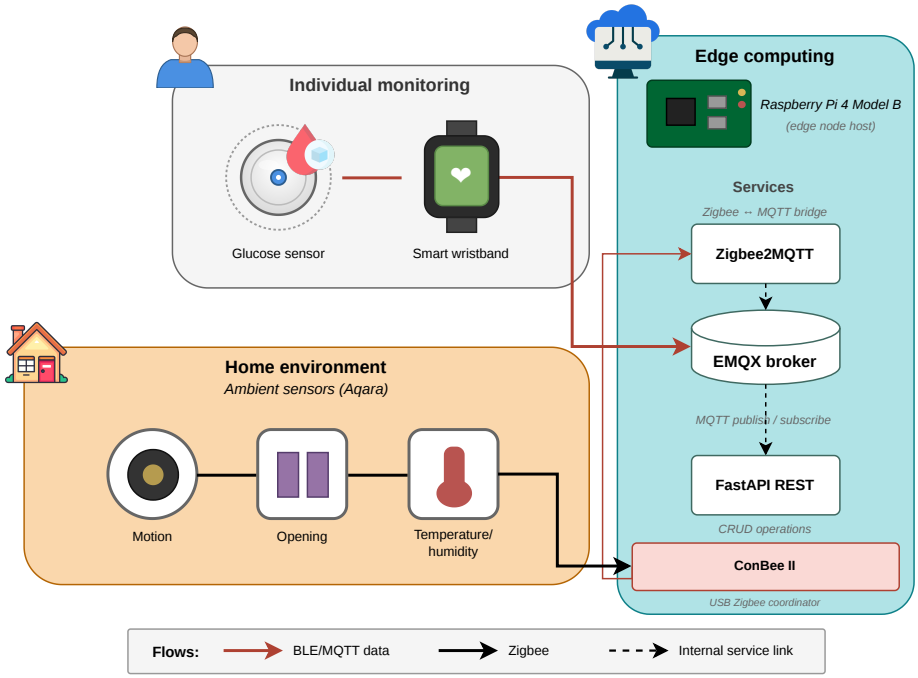


Fig. 1. Complete architecture of the proposed IoMT system.

which, together with a ConBee II USB stick acting as Zigbee coordinator, integrates the Aqara environmental sensors (motion, door/window, and temperature) into the MQTT bus. The third service is a **FastAPI** REST layer that exposes CRUD operations and ad-hoc endpoints used both by the data pipeline and by the visualization platform; it connects directly to a **MongoDB** for long-term storage.

Three data sources feed the broker. The CGM sensor connects via Bluetooth Low Energy (BLE) to its proprietary application; the edge node queries that application's servers, converts the readings to JSON formatting, and publishes them under the corresponding topic. A smart wristband is paired with a dedicated Android application developed in Android Studio that reads heart-rate, pedometer, gyroscope, and accelerometer values and publishes each new sample on the watch topic. Finally, the Aqara devices publish through Zigbee2MQTT. To keep the heterogeneous payloads consistent, all messages are normalized into a common JSON document that includes the household identifier, the sensor name, the main reading and a timestamp.

3.2 Data Preprocessing and Characterization

IoT pipelines generate large amounts of data, and a significant fraction of them are redundant. For example, the CGM application is polled every second even

though it only updates the interstitial glucose value every few minutes, so successive records frequently carry identical values. To reduce this redundancy, a daily cleaning task is executed at midnight on the edge node. The task retrieves the raw records of the day, keeps a backup copy, and traverses the records sensor by sensor, storing a new entry only when the reading differs from the last accepted value for that sensor.

After cleaning, accelerometer and gyroscope streams are merged using the `merge_asof` function from Pandas with a 1-second tolerance, so that samples acquired at slightly different timestamps are paired into a single record that contains the three axes of each inertial sensor. This step is crucial for the feature extraction stage, where both sources are needed simultaneously.

The merged stream is then segmented into overlapping windows. Disjoint windows can split a meaningful event, which would degrade the recognition of short activities, so sliding windows are used instead [9]. The window size has been set to 5 minutes with a 50-second slide, which is a compromise between short activities such as tooth brushing (with a duration around 2 minutes) and long activities such as exercising. With this configuration, a 2-minute pattern can appear in up to four consecutive windows, increasing the robustness of the subsequent inference.

For each window, a feature vector is computed. Five features have been selected following an exploratory data analysis: the variance of the accelerometer (σ^2_{ac}, "`ac_std`"), the variance and the maximum of the gyroscope ("`giro_std`" and "`giro_max`"), the angle between the average motion vectors of the first and the second half of the window (see Eq. 1), and the energy of motion. The angle is obtained from the cosine formula applied to the partial mean vectors of the accelerometer, as defined in Eq. 2.

$$\mathbf{v}_{\text{init}} = \frac{2}{n}\sum_{i=1}^{n/2}\mathbf{ac}_i, \qquad \mathbf{v}_{\text{end}} = \frac{2}{n}\sum_{i=n/2+1}^{n}\mathbf{ac}_i, \tag{1}$$

$$\theta = \arccos\left(\frac{\mathbf{v}_{\text{init}} \cdot \mathbf{v}_{\text{end}}}{\|\mathbf{v}_{\text{init}}\|\,\|\mathbf{v}_{\text{end}}\|}\right) \cdot \frac{180}{\pi}. \tag{2}$$

The energy of motion, used to discriminate between resting and active windows, is computed as the sum of the accelerometer and gyroscope variances:

$$E_{\text{mov}} = \sigma^2_{ac} + \sigma^2_{\text{giro}}. \tag{3}$$

Combining the variance of the accelerometer with E_{mov} allows the system to infer whether the user is moving and how intense that movement is, while the gyroscope features complement this information with rotational cues. Sudden changes in the angle of motion are also useful to distinguish between smooth activities and those that involve abrupt turns.

3.3 Human Activity Recognition

Once the feature vector is available, an interpretable HAR module is applied. We follow a fuzzy-logic approach due to its capability to provide transparent,

interpretable and linguistically meaningful rules, which is especially valuable in clinical contexts where the patient and the healthcare professional must understand why a given activity has been inferred.

Fuzzy labels over motion features. The trapezoid parameters of each linguistic label have been obtained from an exploratory data analysis carried out over the wristband streams, which revealed clearly distinct patterns for each target activity. For each motion feature, a set of trapezoidal membership functions $trapmf(a, b, c, d)$ is defined. The accelerometer variance *ac_std* uses three labels: *low* $= (0, 0, 0.05, 0.2)$, *medium* $= (0.1, 0.25, 0.4, 0.55)$, and *high* $= (0.45, 0.6, 5, 5)$; *giro_std* uses *low* $= (0, 0, 0.5, 2)$, *medium* $= (1, 3, 5, 7)$, and *high* $= (6, 9, 100, 100)$; and *giro_max* uses *low* $= (0, 0, 2, 8)$, *medium* $= (5, 10, 20, 30)$, and *high* $= (25, 40, 500, 500)$. The angle uses four labels so that a *very low* category can capture essentially linear movements: *very low* $= (0, 0, 5, 15)$, *low* $= (10, 20, 35, 50)$, *medium* $= (40, 60, 90, 120)$, and *high* $= (110, 140, 180, 180)$. Finally, the energy of motion E_{mov} uses five labels to cover from resting to intense exercise: *very low* $= (0, 0, 0.05, 0.2)$, *low* $= (0.1, 0.25, 0.5, 1)$, *medium* $= (0.8, 1.5, 3, 5)$, *high* $= (4, 7, 12, 20)$, and *very high* $= (18, 30, 500, 500)$.

Fuzzy summarizers over glucose and time. In parallel, three additional fuzzy summarizers are applied to the glucose stream, all of them adopting the membership function definitions proposed by Gaitán-Guerrero et al. [7]. The first one classifies each glucose reading into five clinical ranges (*very low*, *low*, *normal*, *high*, and *very high*) defined according to the American Diabetes Association guidelines [6]. The second summarizer attaches a meal-time label (*before*, *at the beginning*, *half an hour after*, *one hour after*, *two hours after*) to each measurement so that the glucose values can be interpreted with respect to the closest recognized activity. A third summarizer assigns the reading to one of five daily intakes (*breakfast*, *mid-morning*, *lunch*, *afternoon snack*, *dinner*) over the 24-hour cycle. Finally, a quantifier (*few*, *some*, *half*, *many*, *most*) measures the percentage of records that fall into each range.

Rule-based inference of the activity. For each window, the fuzzified motion features are combined through a fuzzy classifier whose rule base targets four activities of daily living: resting, eating, exercising, and tooth brushing. The complete rule base is detailed in Section 4.1. The rules adopt a Disjunctive Normal Form structure, in which each rule's antecedent may include an OR operator connecting alternative linguistic labels of the same feature; this choice allows a single rule to cover the full range of membership values compatible with a given activity without artificially splitting it into multiple rules. The rules were derived from an exploratory analysis of labelled wristband data. The minimum T-norm is used to aggregate the conjunctive antecedents within each rule, and the maximum T-conorm resolves the disjunction when several labels of the same feature are compatible with the same activity. The wristband is intentionally treated as the core sensing source so that the recognition pipeline remains functional regardless of the patient's location: as long as the device is worn, the system can

infer the activity even when the patient is away from home. The ambient sensors act as optional enrichment cues that disambiguate or reinforce the rule output when the patient is at home, but they are never strictly required for an activity to be inferred.

Linguistic protoforms. The output of the system is a set of protoforms that summarize CGM behaviour in natural language by combining the temporal qualifier, the recognized activity, the quantifier, and the glucose-state summarizer. Each protoform follows the structure [R A, Q S], where R denotes the temporal label provided by the summarization process (e.g. *half an hour after*), A represents the activity inferred by the fuzzy rule base (e.g. *eating*), Q corresponds to the linguistic quantifier (e.g. *most*), and S indicates the linguistic glucose state (e.g. *high*). Consequently, the protoforms may generate statements such as *"half an hour after eating, most glucose levels were high"*, summarizing in natural language both the activity context and the associated glucose dynamics.

4 Results and Discussion

This section reports the experimental findings obtained over a two-week monitoring campaign, which corresponds to the wear time of a single sensor of the CGM device used in the study. The discussion is organized in two blocks. First, the empirical evidence supporting each fuzzy rule is summarized through the aggregated fuzzy quantification of every motion feature per activity. Second, the resulting linguistic protoforms are analyzed to illustrate how the proposed pipeline characterizes glucose dynamics through the recognized activity context.

4.1 Empirical validation of the rule base

For every monitoring day, the fuzzy summarization module described in Section 3.3 produced quantified linguistic statements of the form "Q records of feature F are *label*", where Q is one of *few*, *some*, *many*, or *most*, and the truth value attached to each statement [7] reflects the degree to which it holds over the windows assigned to that activity. The resulting rule base is presented in Table 1.

Table 1. Fuzzy rules derived from the exploratory data analysis for the classification of four daily activities. "–" indicates that the feature is not used by the rule.

Rule	`ac_std`	`giro_std`	`angle`	E_{mov}	**Activity**
R1	Low	Low	Very low	Very low	Resting
R2	Low/Medium	–	Very low/Low/Medium	Low/Medium	Eating
R3	High	Medium	–	High	Exercising
R4	High	High	–	Very high	Tooth brushing

The empirical evidence supporting each rule can be characterized by the strictest quantifier whose truth value remained above 0.7 during the monitoring period. Quantifier strictness increases from *few* to *most*, so a high-strictness quantifier with a substantial truth value indicates that the corresponding linguistic statement holds for most of the windows of that activity. For *resting* (R1), every feature is described by its lowest label (L or VL) under the *most* quantifier with a truth value of 0.77, confirming that the wristband consistently reports near-zero motion. For *eating* (R2), the low motion pattern is captured by `ac_std`, `giro_max`, and the angle under the *some* quantifier with truth values close to 1.00, while `giro_std` and E_{mov} remain low under *many* with values around 0.72, matching the slow, rhythmic hand-to-mouth pattern modelled by R2. For *exercising* (R3), the *high* membership of `ac_std` and `giro_std` reaches values of 0.87 and 0.79 under *some*, while E_{mov} saturates at 1.00 under *few* in its *very high* label, clearly justifying the high-energy antecedents of the rule. Finally, for *tooth brushing* (R4), the *high* `ac_std` label is activated at 0.94 under *some* and `giro_max` reaches 0.99 under *most*, confirming the characteristic combination of intense local motion and rotational components. The fact that the same window can satisfy several labels with non-zero membership is consistent with the philosophy of fuzzy logic: the linguistic summary with the strongest cumulative truth value is selected for the protoform layer.

4.2 Linguistic characterization of glucose dynamics

Once the rule base in Table 1 infers the activity associated with each window, the qualifier, quantifier, and glucose-state summarizers described in Section 3.3 are combined into $[R\ A,\ Q\ S]$ protoforms. Only protoforms whose truth value exceeds a configurable threshold are retained as natural-language summaries of the monitoring period. Examples include *"before eating, most glucose levels are low"* (0.72), *"half an hour after eating, many glucose levels are normal"* (1.00), and *"one hour after lunch, most glucose levels are normal"* (1.00). These summaries associate a specific activity context with the corresponding glucose behaviour. Fig. 2 illustrates this transformation for one of these eating sessions: the upper panel shows the motion features used by rule R2, with the records satisfying the rule antecedents highlighted, while the lower panel tracks the glucose response across the time windows that feed the protoform layer.

From a clinical perspective, the most relevant protoforms describe the transition around meals. Before lunch and dinner, the dominant summary is *most low* (0.72), reflecting the pre-prandial glucose decrease that triggers corrective insulin bolus administration in the monitored patient. In the following periods, half an hour and one hour after eating, the summaries consistently evolve towards *many normal* or *most normal* (1.00), indicating a successful return to the target glucose range after insulin administration. This pattern is clearly visible in Fig. 2, where the glucose curve crosses from the *low* band before the meal into the *normal* band during the *half an hour after* and *one hour after* windows. Activities such as exercising, tooth brushing, and resting remain predominantly associated with *most normal*, while overnight resting periods occasionally exhibit

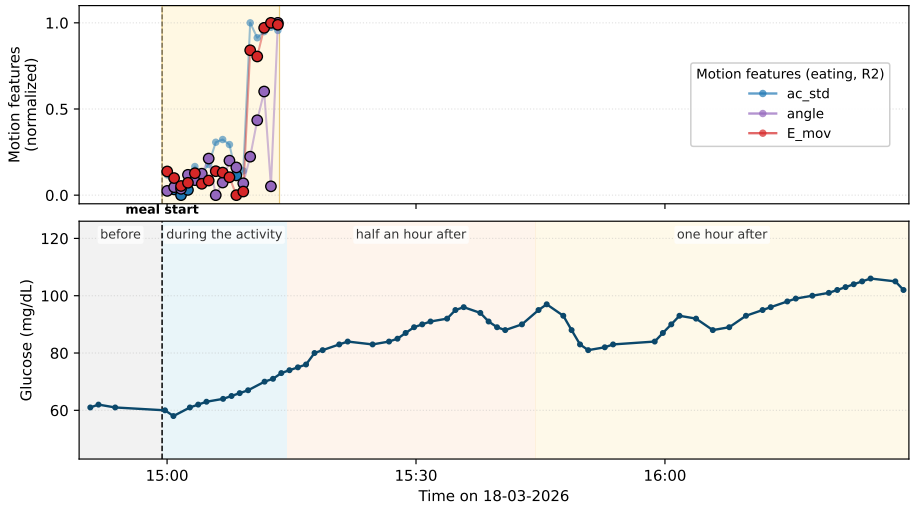


Fig. 2. Eating session on 18-03-2026: motion features fired by rule R2 (top panel, with markers highlighted when their dominant fuzzy label satisfies an antecedent of R2) and glucose evolution across the temporal windows used by the protoform layer (bottom panel). Both panels share the time axis, so the watch records during the meal and the glucose dynamics that follow are aligned vertically.

many low, which is consistent with the known risk of nocturnal hypoglycemia in type 1 diabetes.

Overall, these results illustrate how the proposed IoMT architecture transforms raw CGM and inertial data into interpretable narratives capable of linking daily activities with glucose responses in real-life scenarios.

5 Conclusions and Future Works

This paper has presented an IoMT architecture for the contextual characterization of glucose dynamics in type 1 diabetes through HAR and interpretable fuzzy reasoning. The proposed framework integrates heterogeneous sensing devices, including a continuous glucose monitor, a smart wristband, and ambient sensors, within a low-cost edge-computing infrastructure based on MQTT communication and multimodal data fusion. From the acquired sensor streams, motion-related features are extracted and processed through an interpretable fuzzy-rule system capable of inferring daily activities and associating them with glucose behaviour.

The proposed approach goes beyond conventional glucose-monitoring systems by incorporating contextual information derived from patient activities and daily routines. In this regard, the combination of HAR and fuzzy linguistic modelling enables the generation of human-readable summaries that facilitate

the interpretation of glucose dynamics in real-life conditions. Overall, the presented architecture demonstrates the feasibility of combining IoMT technologies, wearable sensing, and interpretable reasoning mechanisms into a unified framework for contextual diabetes monitoring.

Future work will focus on extending the HAR module using data from a larger cohort of patients with type 1 diabetes in order to refine personalized activity rules that capture inter-patient variability, incorporate additional contextual variables, and exploit the protoform layer to generate early alerts from atypical combinations of activities and glucose states. The clinical usefulness of the generated linguistic summaries will also be evaluated in real-world scenarios involving patients and healthcare professionals.

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