A fuzzy-based IoMT intelligent data platform for enhanced glucose data interpretation and healthcare assistance

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***Abstract*—Diabetes has become one of the most relevant concerns of the century due to the large number of users who are affected by it. Devices that control blood glucose are very diverse and the user and the healthcare professionals in charge need to analyze their output to help them in the most agile way possible. In this proposal, an intelligent data platform based on IoMT devices is presented to retrieve data from diabetic patients in real time. This data is processed and summarized using generation of linguistic descriptions of time series (GLiDTS) techniques, together with Fuzzy Logic and the Computation with Words paradigm, to highlight the most relevant information for a full day. In the application layer of the platform, a web application is provided to visualize raw glucose data and summaries generated for each patient's Time series (TS) of glucose data. This service is intended to serve users as a help to understand their condition and health professionals to speed up the detection of possible problems or wrong habits in their patients using natural language (NL).**

***Index Terms*—Diabetes, Internet of medical things, Intelligent health platform, Linguistic summaries, Fuzzy logic, Computing with words**

I. Introduction

In recent decades, diabetes has emerged as a pervasive global health concern. The World Health Organization (WHO) defines diabetes as a chronic disease that arises either by the time the pancreas is not producing a sufficient amount of insulin or when the body is not able to manage it in an efficient manner [1]. This condition may lead people to experience hyperglycemia episodes, what refers to an uncontrolled increase of blood glucose, which is susceptible to derive in severe complications if not managed properly.

By 2021 [2], the International Diabetes Federation reported that approximately 537 million adults aged between 20 and 79 were dealing with this disease, a quantity representing 1 in 10 individuals in that age bracket. An estimation points out that the number of people affected will escalate to 643 million by 2030 and will reach 783 million by 2045. Europe has registered 61 million of diabetic adults, with an additional concern that around 36% of cases are still undiagnosed. Health expenditures linked to diabetes reached $189 billion in 2021 while 1.1 million of deaths were accounted for this illness.

History has underscored the profound correlation between the evolution of humanity and the advancement and application of science and technology. Today, technology finds application in an infinite number of fields, but one of the most important is undoubtedly the realm of medicine and healthcare.

Within this area, technological platforms [3] play a crucial role intending to facilitate not only governance, but also currently existing healthcare institutions' services. These platforms, well-known as intelligent data platforms, collect data and store it centrally, but also process it and extract relevant information in order to improve the quality of certain processes.

In order to achieve this, it is necessary to supply this type of platform with information that comes from the environment through devices that have multimodal sensors. These elements are interconnected and send data that is processed by decision systems; this technology is known as the Internet of Things (IoT). In the particular case of the healthcare context, there are a diverse number of devices capable of measuring physiological signals of patients such as heart rate [4], temperature [5], [6], blood pressure [5] and oxygen saturation [6], among others. These devices create a variant known as the Internet of Medical Things (IoMT). This technology presents a big number of opportunities [7] for the healthcare sector, including patient empowerment through a quality of life improvement

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and the development of personalized treatments, and even advancement in medical education.

In the particular case of diabetes, the last five years have seen a proliferation of devices to measure glucose in real time and continuously [8]. These sensors are invasive and, as opposed to traditional glucometers, measure glucose in the interstitial fluid that is produced by exchanges between tissue cells and blood.

Although these commercial sensors are able to connect to mobile devices and display the glucose data obtained, these sensors have not been integrated into technology platforms. Therefore, healthcare professionals are unable to access this information and provide personalized treatments. In addition, due to the large number of patients and the large amount of information that is continuously generated, it is necessary to develop systems capable of summarizing this knowledge and facilitate the work of healthcare professionals.

The generation of summaries [9] that allow us to extract the major meaning from the data obtained is one of the most important and complicated tasks today, especially in the field of health. Users and technical personnel need to obtain only those results that are of interest, omitting superfluous statements. The process of generating this information requires, on the one hand, an adequate representation of expert knowledge and, on the other hand, the generation of a clear, concise and useful message. For this purpose, the use of Fuzzy Logic [10], [11] and Computation with Words [12] techniques provide a framework where knowledge can be represented in a similar way to how the expert does it. Likewise, the management of data from IoT devices, where inaccuracy and/or loss of data is inherent, is necessary. Nonetheless, the construction of messages in NL from TS also requires the flexibility that is inherent to language and human perception.

Therefore, this proposal presents an intelligent platform based on IoMT and Fuzzy Logic with the following main contributions:

- Propose a centralized intelligent data platform to manage information on patients with diabetes.
- Provide this platform with a novel intelligent model to summarize a user's glycemia behavior over a full day, highlighting the most relevant episodes and using a language that is useful and close to the end-user.

This document is structured as follows: A review of the main technologies on which we have based this proposal is included in Section II. Next, an intelligent layered architecture based on IoMT is presented in Section III. The process of this architecture that generates linguistic summaries from data got from glucose devices are detailed in Section IV. Then, in Section V, the workflow among final users is presented together with the developed Web Application. Consecutively, limitations and future extensions for this proposal have been added in Section VI. Finally, Section VII exposes the conclusions obtained from this work.

II. Related works

In this section, a concise review of the related works is presented. For this purpose, this part is divided into the main elements of this research: the intelligent data platform and the summarizer model.

A. *Intelligent Data Platforms*

Nowadays, IoMT-based systems [13] are essential for the society of the future. Such systems are used in the literature to provide new healthcare services or improve existing ones. For example, Pelaez et al. [4] provides a methodology for cardiac rehabilitation that employs wearable devices to obtain heart rate. These systems present some challenges [14], such as safety, efficiency and a more end-user centered approach.

On the other hand, intelligent data platforms are emerging. These systems are characterised by integrating data sources, storing them and extracting knowledge through artificial intelligence models. The objective of this type of platform is to improve decision-making and procedures in an organization. In the literature there are several platforms of this type focused on different areas.

In the health field, some authors have proposed this type of intelligent data platform. Li et al. [15] define a platform titled Wiki-Health used to service a personal health coaching application. On the other hand, Denaxas et al. [16] propose a platform called CALIBER to develop and validate electronic health record phenotypes. Finally, Ortega-Calvo et al. [17] define a hospital platform to extract relevant information from historical patient data.

Although all these platforms differ in their architecture with different types of layers and connections, all of them converge on the source data layer. This layer is responsible for obtaining all the input data from the platform. However, none of the platforms indicate how they collect this input information. Therefore, it is difficult to apply it in a real environment.

In the literature, no intelligent data platforms have been found with the purpose of integrating glucose data of diabetic patients. Park et al. [18] propose a system for self-care of diabetic patients by monitoring insulin intake, sleep, diet and exercise. Also, traditional glucometers are used to measure blood glucose.

Compared to the reviewed works, a new intelligent data platform with automatic and pervasive data collection for any diabetic patient is proposed. Furthermore, it provides a set of modular layers allowing to easily scale the system and incorporate new devices and provide a user-friendly interface for the end-users: patients and healthcare professionals.

B. *Summarizer*

The enormous amount of data generated by different technologies, such as those obtained by IoT devices, has led to the urgent need to develop technologies that allow us to transmit only relevant information to the user. To do that, it is important to address the context or problem to be studied, for which we need an expert knowledge model to rely on. Moreover, the output of these systems must be adapted to the way in which the user accepts and understands the reality around them. Fuzzy logic [10], [19] has played a fundamental role in the modeling of these issues, since it allows to represent data and reason about them in a flexible way, close to how we humans do it. It has been illustrated by Alcalá and Alonso [20] that organize the different types of software developed using it, and by Soto et al. [21] that present a framework to be used in Fuzzy Logic applications. In particular, IoT architectures benefit from the properties modeled by fuzzy logic, allowing the representation of the implicit imprecision incorporated in the data provided, for example, by transmition failures, noise, etc. It can be seen in Rodriguez-Lozano et al. [22] and Mimbrera et al. [23] two proposals that built different platforms to establish a connection between both technologies.

The GLiDTS [9], through the use of Computation with Words and Fuzzy Logic techniques [12], [24] allow the most relevant results of the data obtained to be transmitted and highlighted with a simple text message. In this sense, there are many proposals that generate summaries from TS in the health area such as the one of Pelaez et al. [4] which creates summaries using protoforms based on users' heart rate streams to describe relevant indicators in rehabilitation sessions. Also, in the cardiology domain, Fontenla-Seco et al. [25] generate fuzzy temporal protoforms to generate NL summaries, and Harris et al. [26] generate summaries from personal data, obtained from personal monitoring devices, among others.

In the field of blood sugar analysis, there are plenty of works on time series analysis for the prediction of possible anomalous events. However, there are no previous studies to monitor this measurement with the only aim of describing the TS with words, i.e. to make easier for the non-expert users the reading of the data generated by these devices and to speed up data reading for health professionals.

III. Platform architecture design

This section introduces the architecture of the intelligent platform based on IoMT for people suffering from diabetes. In total, the system has been divided into seven perfectly distinguished layers. Subsequently, each layer is introduced.

A. Virtualizer Layer

At first, there is the virtualizer layer, a technology enabling the generation and administration of containers —discrete units that enable the execution of services and their associated dependencies—. All these applications share the host's core, ensuring lightweight and fluid operations, deriving in faster start-up times, a reduced resource consumption and a enhanced efficiency in their management. In the context of the present platform, the deployment of services associated with the Data Layer, Summarizer Layer, Transfer Layer and Application Layer, is allowed. Nonetheless, the latter mentioned layers are found interconnected through a virtual network.

B. Data Layer

This second layer establishes all aspects related to data persistence. In the pursuit of reaching a comprehensive data modeling, a relational database has been employed. The defined schema for this platform provides patient-related information primarily focusing on glucose levels (mg/dL) along with extra attributes regarding its treatment. In the latter instance, the purpose is to save information related to food intake, insulin administration or any other type of relevant healthcare-related event. In all cases, it is indispensable to store data timestamps.

Furthermore, the schema addresses a distinction that is made between patient and medical staff user types. In both instances, fundamental information and ciphered credentials are retained.

C. Summarizer Layer

In this layer, the process of constructing the summary in NL from the glucose data provided is performed. This summary has the main purpose of simplifying the TS interpretation while highlighting potential health problems, with special emphasis on episodes of hypoglycemia and hyperglycemia.

The generation this linguistic descriptions from TS requires the application of data-to-text techniques, that uses Fuzzy Logic and the Computing with Words paradigm. The resulting messages correspond to the relevant events that occurred in 24 hours. The whole process is detailed in Section IV.

D. Transfer Layer

The following layer is called the transfer layer. In this case, its purpose is to set a way of communication for data transfer. The element serving as a support to this layer is a RESTful API service. In total, a distinction of four operations can be made: information retrieval (GET), enrollment (POST), data modification (PUT) and elimination (DELETE).

This service communicates directly with the data layer allowing to manage the database, also establishing a connection with the summary layer aiming to generate a linguistic summarization of the requested days and providing the demanded information by the application layer that is presented in the following section.

This kind of service facilitates system scalability, as any type of application may make use of HTTP requests.

E. Application Layer

In this section, the application layer is defined, whose primary objective is to supply the designed intelligent diabetes platform with user applications for data consultation not only by patients on their own, but also on behalf of healthcare personnel.

Regarding this case, the system initially relies on a web application, which allows user identification within the platform by means of credentials that separate into two types of roles: the patient and the healthcare personnel. A patient accessing the platform is only able to see all associated data, whereas, the medical staff can consult the historical glucose data of all their patients. Aiming to carry out this task, the end-user is provided with graphs that reflect the evolution of glucose levels over the course of the day, as well as a linguistic summary.

F. Security Layer

The security layer bears the responsibility for the protection of all the other layers, primarily securing communication between the application and user layers.

Elements for simultaneous petitions and externally accessible ports limitations are incorporated within this layer. Additionally, the TLS protocol is employed to uphold secure connections.

At last, it is important to highlight that there is a realization of active and passive monitoring for a continuous assessment of the machine status, allowing the detection of potential issues, vulnerabilities and malware attacks ensuring a proactive approach to the system security.

G. Device Layer

The remaining layer corresponds to the one concerning the devices, assuming a significant role in the continuous glucose data acquisition from sensors in real time. These sensors are provided with Bluetooth (BLE) connection and Near Field Communication (NFC), whose purpose is to sample interstitial glucose levels from the user. To initiate this process, the sensor must be paired in advance with a mobile device via NFC connection, enabling the continuous sampling retrieval that is subsequently sent to the smartphone through the BLE connection.

All collected samples are transmitted through a third-party application named xDrip+. This application integrates with other types of more restricted systems such as Nightscout. Therefore, our RESTful API service (Transfer Layer) emulates the petition-level behavior implemented by Nightscout, not being necessary to develop proprietary applications for data collection.

With the purpose of sending all pertinent information, it is imperative to identify the patient in some way. Addressing this requirement, we assign the patient with a unique code upon registration in our platform.

All the described architecture is summarized in Figure 1.

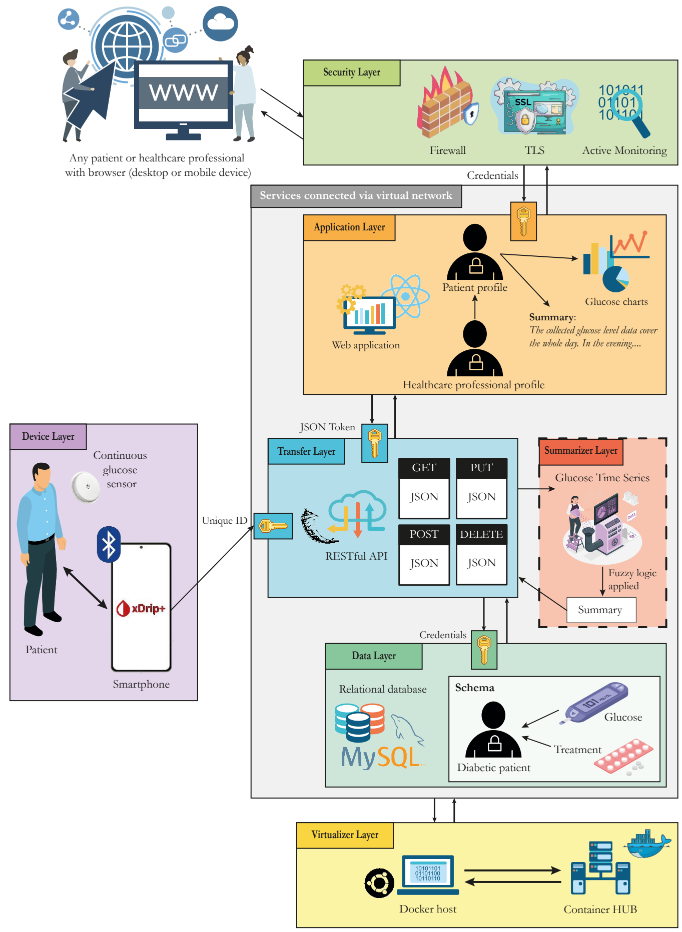

Fig. 1. Layered architecture of the intelligent platform based on IoMT

IV. Generation of Interpretable Summaries Using Fuzzy Logic

The process of generating linguistic summaries from glucose TS follows the methodology described by Marin et al. in [9], and Martinez-Cruz et al. in [27]. This process consists first in describing a knowledge model participated by experts in the health field, which allows us to identify the most relevant characteristics of this measure. To do this, Fuzzy Logic techniques are used to help us represent the different glucose measurements in the same way as humans do, i.e., where imprecision is inherent in the interpretation of the data. Next, the generation of summaries requires going through different stages. Preprocessing and segmentation of the TS is crucial to simplify the number of measurements processed while highlighting the most relevant values. A series of protoforms are then obtained from the modeled knowledge base that summarize in words the most outstanding values of the TS. Later, these protoforms are transformed into a linguistic description using NL. Let us look at this process in a more detailed way, exploring the role of fuzzy logic in it.

A. Knowledge Model using Fuzzy Logic

According to expert knowledge and International Diabetes Federation [2], [28], blood glucose ranges are categorized as normal, high and low. However, limits could be flexible, since a user does not go from normal to low or high levels by changing at one point. Likewise, this measurement also requires observation of the glucose trend, to observe abrupt changes that may raise an alarm in an user's health and the time of day when these measures have taken place. For this reason, Fuzzy Logic theory, defined by Zadeh [10], has been used to model the following fuzzy variables (summarizers) in Tables I, II and III by means of a set of values that define their associated membership functions.

These variables are used in a series of protoforms to describe and summarize glucose quantitative data in words [11]. The experts express the interest of associating any type of remarkable event to the time of the day in which it has taken place. In order to accomplish this objective, we are using the *Protoform Type 2 with qualifiers*: *"R Q A are S"*, where *A* is a fuzzy variable in the dataset *C*, *R* is the summarizer referring

Summarizer	Membership function
Very low	*z-shape*$(-\infty, -\infty, 54, 60)$
Low	*trapmf*$(54, 60, 75, 80)$
Medium	*trapmf*$(75, 80, 120, 130)$
High	*trapmf*$(120, 130, 160, 170)$
Very high	*s-shape*$(160, 170, \infty, \infty)$

TABLE I
SPECIFICATION OF SUMMARIZERS FOR GLUCOSE VALUES

Summarizer	Membership function
Sharply decreasing	*z-shape*$(-\infty, -\infty, -0.75, -0.5)$
Decreasing	*trapmf*$(-0.75, -0.5, -0.25, -0.1)$
Steady	*trapmf*$(-0.25, -0.1, 0.1, 0.25)$
Increasing	*trapmf*$(0.1, 0.25, 0.5, 0.75)$
Sharply increasing	*s-shape*$(0.5, 0.75, \infty, \infty)$

TABLE II
SPECIFICATION OF SUMMARIZERS FOR SLOPE OR TREND

to the day moment, S is the summarizer of glucose measure and Q is a quantifier (e.g. *At the morning many glucose levels are high*). The quantifiers used here are modeled using right shoulder membership functions as shown in Table IV.

This process includes the iteration over all collected samples comprised within the concrete day being evaluated pretending to obtain the protoforms that satisfy a predefined threshold of $\tau \geq 0.7$; every summarizer $s \in S$ is evaluated through a qualifier $r \in R$ and undergoes quantifier $q \in Q$ evaluation. The veracity and/or acceptance of the statements are deduced through the membership function that better describe data (set C) as reflected on Equation 1 which is based on Zadeh proposal [29]:

$$\tau(R\ Q\ A\ are\ S) = max\left(\mu_q\left(\frac{\sum_i(\mu_r \cap \mu_s)(c_i)}{\sum_i \mu_r(c_i)}\right)\right), \quad (1)$$

where $c_i \in C, \forall i \in \mathbb{N}, i \in [1, N]$, and $N = |C|$

Finally, the experts have also described the following relevant information regarding blood sugar measurements that are of fundamental interest in this data analysis:

Summarizer	Membership function
Night	*z-shape*$(-\infty, -\infty, 6am, 8am)$
Morning	*trapmf*$(6am, 8am, 12pm, 2pm)$
Afternoon	*trapmf*$(12pm, 2pm, 8pm, 10pm)$
End of day	*s-shape*$(8pm, 10pm, \infty, \infty)$
During the daytime	*s-shape*$(7am, 9am, \infty, \infty)$

TABLE III
SPECIFICATION OF SUMMARIZERS FOR PARTS OF THE DAY (IN HOURS)

Quantifier	Membership function
Few	*s-shape*$(10, 30, \infty, \infty)$
Many	*s-shape*$(40, 60, \infty, \infty)$
Most	*s-shape*$(60, 80, \infty, \infty)$
Almost all	*s-shape*$(80, 100, \infty, \infty)$

TABLE IV
SPECIFICATION OF QUANTIFIERS

- Hyperglycemia: When there are several high or very high blood sugar levels, modeled graphically as a peak, but this situation is prolonged in time (set of peaks).
- Hypoglycemia: When the situation changes relatively sharply from normal to low or very low values (graphically modeled as valleys).

The detection of these situations requires the analysis of the linguistic variables related to the glucose value, together with the slope value.

B. Linguistic summaries generation

The generation of linguistic summaries from glucose TS is illustrated in Figure 2. The first part of the process consists of the TS simplification which is performed after preprocessing the data taken from the sensors previously described in the architecture. Briefly, the preprocessing stage applies a moving average on the data collected every 5 minutes, due to the need to cover those situations of lack of data because of technical problems. This average will be applied over periods of less than 1 hour. The Ramer-Douglas-Peucker geometric algorithm [30] has been used as a mechanism to highlight the most relevant points of the glucose TS, just as humans do when interpreting any line graph. This algorithm, in turn, decomposes a TS into segments of different sizes, which are the ones we proceed to analyze semantically, using the knowledge base described above. The threshold set to select the granularity of the segments is established at 0.2 as discussed in [31].

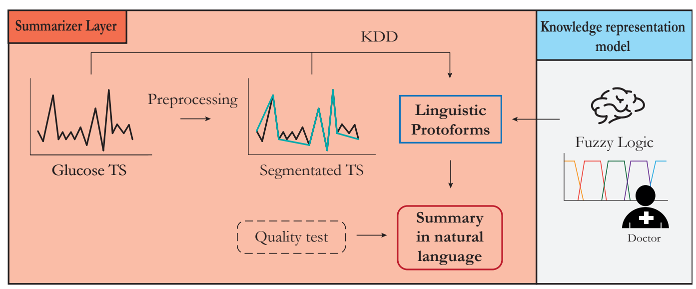

Fig. 2. Specification of the processes occuring within the Summarizer Layer

Segments are analyzed from two different points of view:

- as simple objects. Protoforms are obtained from the summarizers and quantifiers described above.
- as objects with a higher level of abstraction. Here the segments are grouped into longer segments, which have a geometric and semantic meaning. In this case, peaks and valleys are searched in the TS and new analysis on this expanded segment is performed.

The protoforms designed are described in Table V.

Once the TS has been analyzed, it is generated a message using a linguistic construction (example given in Figure 3) close to the profile of user it is intended for. In this case, a series of linguistic templates have been created whose instances allow the construction of the summary (see Table V for a further explanation of the variables):

- Collected glucose levels (GL) are between **[hour]** and **hour**.

TABLE V
PROTOFORMS DESCRIPTION

Protoform	Description
[quantifier] GL measures are **[gluc. level]** **[moment]**.] [A **[event]** of **[glucose level]** GL measure is detected at **[moment]**. GLs have been **[gluc. level]** during **[period]** with a **[slope]** trend.]	**gluc. level:** very low, low, medium, high, very high **quantifier:** few, many, most, almost all **moment:** at night, at the end of the day, during the whole day, in the morning, during the afternoon **event:** peak, hypoglycemia episode **slope:** sharply decreasing, decreasing, steady, increasing, sharply increasing **period:** time interval.

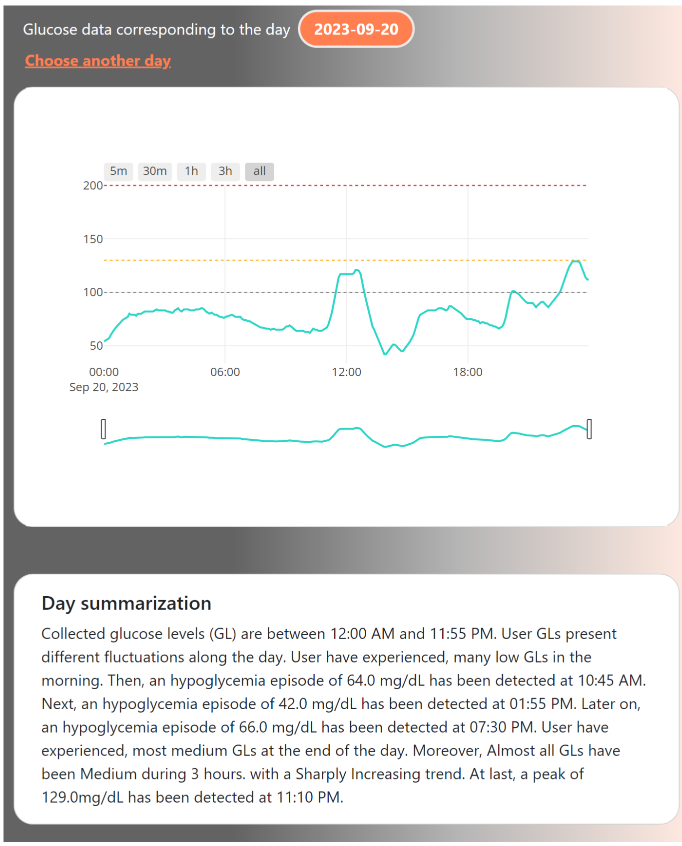

Fig. 3. View of a graph accompanied by its summarization in NL

- User has experienced **[quantifier] [gluc. level]** GLs **[moment]**.]/User GLs were normal during the day. /User GLs present different fluctuations along the day. **/[moment]**
- A **[event]** of **value** mg/dL has been detected at **hour**[.] /[, followed by a **[event]** of **value** mg/dL at **hour**[.] /[and lasted for **[period]** /[hours] /[minutes]. **/[quantifier]** GLs have been **[glucose level]** during **[period]** /[hours] /[minutes] with a **[slope]** trend.
- A set of **[event]** have appeared for around **[period]** /[hours] /[minutes] with a /[maximum] /[minimum] of **value** mg/dL at **hour**[.] /[An hyperglycemia episode with a maximum of **value** mg/dL has been registered at **hour** and lasted for **[period]** /[hours] /[minutes].]

Finally, a series of quality requirements established for the blood glucose domain are determined to check the usefulness of the summary obtained. Some of these quality requirements are[1]:

- TS descriptions go from the general to the particular.
- The summary should be as short as possible
- The results related to mean blood sugar measurements are not included in the summary due to their low interest.
- Actual time measurements are rounded to quarters, and time periods are approximated to the closest number of hours.
- Descriptions relating to very short periods (less than one hour) are ignored.
- Consecutive segments or sentences with the same values are merged.
- Connectors used are Next, Then, Moreover, Consecutively, Subsequently, Later on, and At last.

V. PLATFORM USER WORKFLOW

In this section, the workflow of the end-users in the intelligent data platform is defined. In this case, the system focuses on two types of users: patients and healthcare professionals.

A. Patients

The first end-user is the diabetic patient. The patient is the main actor and his workflow can be divided into two parts: web application and mobile application.

On the one hand, our proposal allows a web application to consult all historical glucose data. To use this service, the patient must first register. Once this is done, a URL (e.g. passphrase@hostname/api/v1) is provided, which is required to send data via the mobile application. Once logged in, the patient can view the daily glucose history as a line graph, as well as a NL summary of key events. It must be considered that by the time a diabetic is providing personal information, due regard should be given to their customary glucose levels. The aim of filling this fields in the registration form is to give a personalized summary based on the summarizers that best describe an individual's habitual glycemia fluctuations, which may differ from one to another.

On the other hand, our system is integrated with a third-party application entitled xDrip+[2]. Our system leverages Nightscout's integration with this application, due to the fact that the application layer implements exactly the same type of requests[3]. Once the sensor is configured and paired, it is possible to retrieve real-time glucose readings and attach treatment information at any time. All the data collected is automatically sent to our platform.

[1]For reasons of clarity we have included only a few of the most illustrative and relevant quality rules.

[2]https://github.com/NightscoutFoundation/xDrip

[3]https://github.com/cosm0naut/nightscout/blob/deploy/swagger.yaml

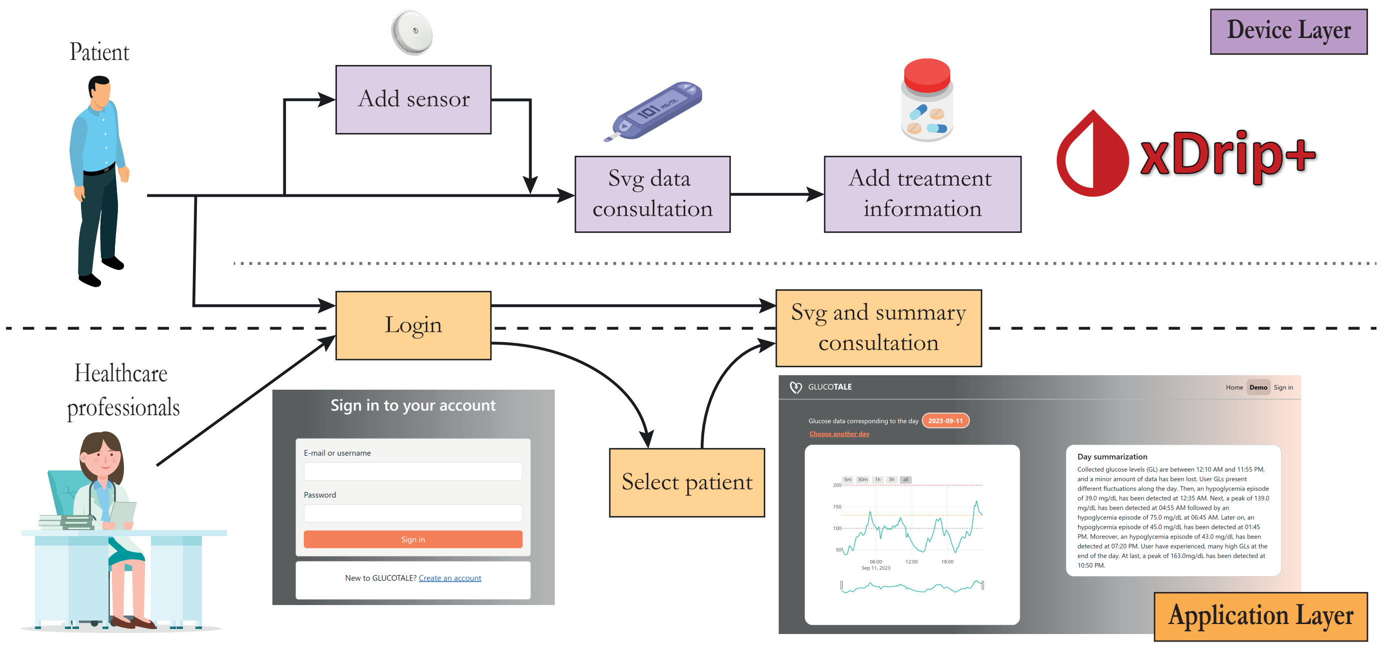

Fig. 4. Workflow on the intelligent data platform for each type of end-user

B. *Healthcare professionals*

Another end-user is the healthcare professional. In this case, the platform administrators provide access credentials to the web application. Through the interface, they can view all the glucose information and daily summaries of all their associated patients. This allows healthcare professionals to quickly assess the patient's health by focusing on hypoglycemic and hyperglycemic events, and to provide more personalized care to their patients.

An overview of the workflow for each of the end-users is shown below in Figure 4. A demonstration of the glucose data visualization that can be accessed by end-users is available on our Glucotale[4]. web application.

VI. Limitations and Future Research

As this research has begun to promote personalized assistance in diabetes patients throughout the use of a fuzzy-based web platform, yet it remains clear that its limitations and the needed future research in this topic must be addressed.

When handling data modeling, it is important to note that the developed algorithms are focused on knowledge extraction from collected data, either using implicit or explicit information considered of interest to the final users aiming to provide the most relevant information needed when interpreting the retrieved glucose values. In this way, system's parameters should be adjusted and configured according to every individual, as different diabetic patients may present different needs established by their medical staff. In our approach, thresholds used for data description have been determined according to the standard ones defined by WHO [32] pretending a general overview and understanding of our proposal (i.e. through the recognition of daily activities).

Equally, the generation of the linguistic summaries is limited to a day-by-day description, emerging the need for considering not only larger time periods for their summarization (including more types of quantifiers), but also other variables that may be of interest in the domain; in this way, integrating new heterogeneous data that allow us to assess the patient's state of health and lifestyle is a crucial advancement in future works.

Also, it is imperative to consider in this proposal a profound analysis of the user experience, usability and their betterment, plus enabling the inclusion of predictors for possible glucose values that may occur in a close future, based on past instances. Nonetheless, our proposal is found as an innovative application that comprehends actual and future needs of individuals suffering from diabetes.

Finally, at the device layer, it would be crucial to develop a mobile application to manage the raw glucose data directly, eliminating the need for third-party applications and to improve the communication security. Another option is to integrate a federated system that incorporates the summarization algorithm in this layer, so that only the summarized data is sent to the cloud.

VII. Conclusions

In this proposal, a new intelligent data platform based on IoMT devices and fuzzy logic has been presented. Its architecture is composed of a total of seven layers that allow the integration of diabetic patient data such as glucose and treatment. In the case of glucose, data is collected automatically through continuous glucose sensors that do not require direct patient interaction.

[4]https://asia.ujaen.es/glucotale

An important element of this platform is the summarization layer, which is responsible for summarizing glucose data. In order to perform this task, an application has been developed using Fuzzy Logic and Computation with Words techniques, which summarizes the data collected. This application is accessible to any diabetic patient who uses this type of device and creates a profile in it. Their measurements are stored in the system and summarized in NL on a daily basis at the user's request. This allows patients to check their glucose levels and healthcare professionals to assess the health of their patients, providing a key tool to be used in the context of diabetic populations.

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