GLOW-ENV: A Dual-Data IoE-Based Approach for Integrating Glucose and Environmental Data into a Diabetes Recommendation System

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Abstract: This paper introduces GLOW-ENV, an intelligent Internet of Everything (IoE)-driven mobile application designed with the objective of integrating real-time glucose monitoring data and environmental metrics to enhance diabetes care and management. The proposed IoE ecosystem integrates a continuous glucose monitoring with a personalized Artificial Intelligence model designed to predict glycemic fluctuations in a near-future. Additionally, GLOW-ENV integrates a rule-based recommendation system to dynamically adapt its suggestions based on contextual glucose and environmental data. This framework advances personalized diabetes care, contributing to their progression and well-being offering valuable insights and improving decision-making.

1 INTRODUCTION

Diabetes diagnosis has emerged in recent decades, positioning it as a global concern within societies in general, due to the profound risk factors that are derived from it. According to the International Diabetes Federation (IDF), this disease is medically defined as a chronic condition that appears by the time the pancreas is no longer capable of producing insulin or when the body is unable to manage it in a proper manner (International Diabetes Federation, 2024). Essentially, there are three main different ways in which diabetes can be classified. First, type 1 diabetes is the condition of the disease that might be developed at any time while requiring insulin supply to guarantee patients' survival. Type 2 diabetes is the one that is more often diagnosed in adults, accounting for nearly 90% of all diabetes cases. Last but not least, gestational diabetes appears by the time high glycemia values are registered during pregnancy, whose consequences might be reflected on both, the mother and child. In any form, statistics are critical; the IDF has reported that there are around 537 million adults that

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are currently suffering from diabetes –3 in 4 adults live in low- and middle-income countries–, a number that is expected to rise in the upcoming years.

In parallel, the society has witnessed an impressive flow of information generated through the utilization of technologies such as the Internet of Things (IoT), as characterized by the capacity of characterizing different phenomena that can be monitored. Additionally, the reduction in the cost of devices and storage components has paved the way to a social panorama of massive interconnection, with a growing use of the IoT technology that often goes unnoticed in the environment. Many different and diverse fields have taken advantage of this paradigm. Specifically, in the healthcare realm, sensors are acquiring a notable importance in human beings' safeguarding and care. The information retrieved by this sort of systems is of high value and risk, not only for the need to ensure data privacy and safety, but also for the thorough treatment of the information, with the objective of not comprising the health state or the well-being of the patients involved. Different applications are being developed and some are cited next: hospital bed occupancy for accelerating the process of taking patients from the emergency room to an inpatient unit (Affleck et al., 2013), vital signs monitoring to prevent future complications (Chakraborty et al., 2020), or activity recognition approaches like (Schmitter-Edgecombe et al., 2024), (Lupión et al., 2020) and (López Ruiz et al., 2024). Beyond this, the intersection of people, processes, data and things is named after the Internet of Everything (IoE), materializing by the time real-time data coming from different and diverse sensors is processed to aid "automated and people-based processes" (Bradley et al., 2013).

In the domain of diabetes, commonly used devices refer to traditional glucometers. This instruments consists of a the device, a lancet with a needle, and a test strip. Therefore, the objective is to measure capillary blood glucose carrying out a tap over the patient's finger, extracting a drop of blood, placing it on the test strip to measure the level of glucose using the device. This process is characterized to be harmful, while necessitating the repetition of it many different times to be able to fully observed glycemic dynamics. As a consequence, technological advancements have paved the way for developing continuous glucose monitoring sensors. These devices are capable of solving the problem of the traditional ones, by their application over the patient skin to sample the glucose level from the interstitial fluid. This measurement is performed through the utilization of a filament from which an enzymatic reaction takes place to generate the glucose value. An example of this sensor is the Freestyle Libre 3 device (Abbott, 2022), which has been observed to be used widely in the diabetic population, or other similar versions.

Beyond this, glucose monitoring has allowed researchers to further investigate in glucose fluctuations, in a attempt to better understand patients' dynamics, rather than assuming only those factors that are directly associated to a patient's daily life (e.g.: physical effort, insulin administration or food intake). In these sense, different approaches evolve the study evaluation of the correlation between weather and environmental factors on people suffering from, or in the risk of, type 1 diabetes, type 2 diabetes or gestational diabetes. The main purpose of these proposals is to potentially determine how external factors varies blood glucose concentration, or even how the body performs when being exposed to certain contextual circumstances. According to type 1 diabetes, (Chiacchiaretta et al., 2024) determine that there is negative correlation between temperature and blood glucose levels, being even more pronounced in extreme heat conditions; a seasonal variation is observed deriving in stating that glycemia is more likely to be stable in hotter months with an increased risk of hypoglycemia, while showing higher variability during colder months, being the latter correlated to a higher risk of hyperglycemia. These findings are also attested by (Vodrahalli et al., 2023) and (Richardson et al., 2020) in the case of type 2 diabetes patients. The findings sustain that these patients are also affected by environmental factors like temperature and air quality, showing that high temperatures enhance glucose absorption while air pollution might worse glucose metabolism under certain conditions, by increasing insulin resistance (Vallianou et al., 2021). Gestational diabetes and environmental risk factors are addressed in (Preston et al., 2020) or (Elshahidi, 2019), where it is highlighted how elevated ambient temperatures are associated with increased odds of this condition. Taken together, these works acclaim the need for developing a decision support system that continuously inform diabetic patients about the ambient exposure they might experienced, together with the possible actions to take to prevent potential consequences.

Alongside these advancements, healthcare information technology systems are essential to provide personalized care and attention over the monitored patients Consequently, different approaches have been developed to continuously monitor glucose. (Murakami et al., 2006) proposes the development of a system capable of being implemented in cardiac patients in the intensive care unit, establishing a client-server architecture. (Helal et al., 2009) propose the design of a smart home-based platform to monitor, analyze and even alter patient behaviors, improving healthcare efficiency through IoT devices. To the best of our knowledge, there is no technological platform that supply diabetic populations with a monitoring tool that suggest actionable behavior based on glucose and ambient data. Nonetheless, these valuable digital tools are the premises of the main contributions of this work:

1. Definition of an IoE-based real-time monitoring architecture for information data retrieval of patients' glycemia and environmental conditions.
2. Construction of a simplified artificial neural network model to predict glucose values in a near-future, being tailored to a concrete patient.
3. Establishment of a predefined rule-based recommendation system integrating IoT devices data to enhanced diabetic patients' quality of life.

The rest of this paper is organized as follows. Section 2 describes the designed architecture, together with the procedures associated to it, a step-by-step description of the system developed. While Section 3 briefly evolves the interaction between the end-user and the graphical interface of the monitoring framework in the form of a mobile application, Section 4 contemplates the limitations of it and the future directions that may apply. Finally, Section 5 includes the concluding remarks of this proposal.

2 IoE ECOSYSTEM ARCHITECTURE DESIGN

This section is dedicated to the specification of all interconnected components of the IoE architecture developed. All of comprised elements come to the rescue after reviewing the different approaches and findings found in the literature. Therefore, the proposed system aims to promote the development of a recommendation system for diabetic patients based on environmental and continuous glucose monitoring data, both in real-time, providing a clear and straightforward response based on the observed phenomena.

In this regard, this work first contemplates the definition of a connection schema between a proprietary server and the sensor for continuously monitor glucose values. This process derives in the implementation of a RESTful API service that allows different operations for further treatment of the collected data (Section 2.1). With the purpose of not only providing the diabetic patient with an application capable of graphing the observed glucose values, our system opts for the utilization of these measures to generate an Artificial Neural Network capable of predicting expected measures in a close future (Section 2.2). In parallel, due to the different relationships established in scientific research between glycemia dynamics and environmental conditions, another connection is established with an external API for this data retrieval (Section 2.3). Ultimately, the developed application gather all the knowledge obtained by processing the raw data for establishing the recommendation that should be communicated to the patient (Section 2.4). The whole architecture is illustrated in Figure 1.

Listing 1: Example of JSON formatted message from the glucose sensor.

```
{
  "_id": "6739cee3978132dfc8bca30a",
  "timestamp": "1731841763741",
  "sgv": 75,
  "type": "sgv",
  "utcOffset": 60
}
```

2.1 Device Layer and Operational Workflow of the RESTful API

This layer concerns the glucose values sampling from an IoT glucose sensor, acquiring a significant role in providing a real-time solution in the domain handled in this work. Recently commercialized sensors consist of a filament or electrode for being placed subcutaneously, typically, on the upper arm of the patient. These devices measure interstitial glucose, which differs from capillary glucose only in terms of a slight delay during glycemia fluctuations; the system's architecture of this work is tested with the utilization of the Freestyle Libre 3 sensor (Abbott, 2022). To perform the sampling, Bluetooth Low Energy (BLE) and Near Field Communication technologies are needed, together with a third-party application named xDrip+ and a smartphone.

In detail, the process is initiated by the time the sensor is paired with a mobile device via NFC connection, allowing for the interstitial glucose values collection once the BLE connection becomes active. Next, data transmission for its storage and processing is performed by the xDrip+ application. The latter allows for the implementation of a proprietary RESTful API Service, enabling request-level procedures without establishing a dependency on other more restricted services that do not provide multi-patient monitoring.

The data is provided in JSON-formatted messages (see Listing 1), mainly containing the timestamp and

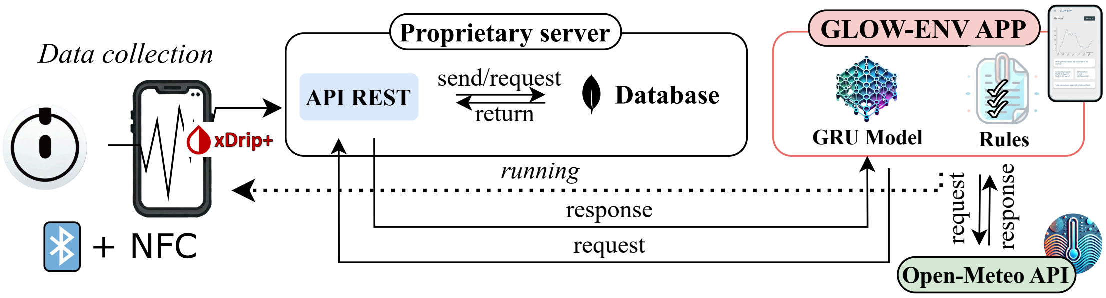

Figure 1: Description of the proposed system architecture.

the glucose value in mg/dL. The API service directly communicates with the smartphone for data sampling (GET) and the database (POST, GET) for persistent storage and data consultation, being the latter mainly used for its transfer to the application layer.

2.2 Artificial Neural Network for the Prediction of Glucose Values

The storage of the samples in the database have allowed for the obtaining of a large dataset comprehending glucose values for a single patient in a time interval of 405 days[1]. At first, the validation of the dataset in terms of validity and diversity is performed through the computation of linguistic protoforms; different linguistic labels are defined to clearly observe how different patterns and features appear along the dataset. As a consequence, distinct membership functions are defined for the linguistic labels associated to temporal day intervals (see Table 1), glucose values (see Table 2; values are specified according to the WHO (World Health Organization, 2024)), and quantifiers (see Table 3). This procedure takes advantage of the Fuzzy Logic (Zadeh and Aliev, 2018) theory.

Table 1: Specification of the different linguistic labels for temporal day intervals (in hours).

Day interval labels	Membership Function
At night	*z-shape*$(-\infty, -\infty, 6, 8)$
In the morning	*trapmf*$(6, 8, 12, 2)$
In the afternoon	*trapmf*$(12, 2, 8, 10)$
At the end of day	*s-shape*$(8, 10, \infty, \infty)$
During the daytime	*s-shape*$(7, 9, \infty, \infty)$

The different linguistic labels permit the creation of type 2 protoforms in the form R (day interval label) Q (quantifier) *glucose values are* S (glucose label). The activation of the protoform within the analyzed time series comes from Equation 1 as specified

[1]This dataset is available in https://zenodo.org/records/10713570

Table 2: Specification of the different linguistic labels for glucose registered values.

Glucose label	Membership Function
Low	*z-shape*$(-\infty, -\infty, 75, 80)$
Medium	*trapmf*$(75, 80, 125, 140)$
High	*s-shape*$(125, 140, \infty, \infty)$

Table 3: Specification of linguistic labels for quantifiers.

Quantifier label	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*$(80, 100, \infty, \infty)$

in (Zadeh and Aliev, 2018) (note that μ represent the distinct membership functions).

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

where c_i corresponds to the evaluated instance of the dataset and $*$ denotes minimum.

As a result, it has been observed that nearly the 92% of all possible protoforms are activated, ensuring the diversity of the individuals in the dataset. At this point, it must be highlighted that a 15% of the time series are excluded from the dataset in order to test the final generated outputs within the system, also based on protoform activation and pattern identification as attested by (Martinez-Cruz et al., 2021) or (Peláez-Aguilera et al., 2019).

The selected model to predict glucose values in a close future is a recurrent neural network, particularly, a Gated Recurrent Unit (GRU), due to its capacity to combine an update and a reset gate to control the flow of information. This kind of neural networks necessitate fewer parameters, being simpler and faster to train than other models. Additionally, as glucose time series data may exhibit rapid fluctuations according to different activities (e.g.: food ingestion, insulin supply, weather conditions and/or physical activity), a GRU architecture can effectively capture without the need of a more complex one. Furthermore, the consideration of the final model to be intended for mobile devices, derives in efficiency as a key feature to look up a this stage. Then, the proposed recurrent neural network is established in Algorithm 1.

Algorithm 1: GRU Model for Glucose Time Series Forecasting.

Data: $\mathbf{X} = \{x_1, x_2, \ldots, x_T\}$: Time series
Result: $\hat{y}_t$: Predicted glucose values
Parameters: Window size w, GRU units u_1, u_2, dropout rate p, learning rate α;

$$\mathbf{X}_t = \{x_t, x_{t+1}, \ldots, x_{t+w-1}\}, \quad y_t = x_{t+w}$$
$$\mathbf{X}_{\text{train}}, \mathbf{X}_{\text{val}}, \mathbf{X}_{\text{test}} \quad \text{with ratios } r, s, t$$
$$\mathbf{h}_t = \text{GRU}(\mathbf{X}_t, u_1), \quad \mathbf{h}_t \in \mathbb{R}^{u_1}$$
$$\mathbf{h}'_t = \text{GRU}(\mathbf{h}_t, u_2), \quad \mathbf{h}'_t \in \mathbb{R}^{u_2}$$
$$\mathbf{h}''_t = \text{Dropout}(\mathbf{h}'_t, p)$$
$$\hat{y}_t = \text{Dense}(\mathbf{h}''_t)$$
$$\mathit{optimizer}(\alpha)$$
$$\text{Loss function: } \mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$
$$\text{Minimize: } \min_\theta \mathbb{E}_{(\mathbf{X}_{\text{train}}, y_{\text{train}})}[\mathcal{L}]$$
$$\text{Validation loss: } \mathcal{L}_{\text{val}} = \mathbb{E}_{(\mathbf{X}_{\text{val}}, y_{\text{val}})}[\mathcal{L}]$$
$$\text{Test loss: } \mathcal{L}_{\text{test}} = \mathbb{E}_{(\mathbf{X}_{\text{test}}, y_{\text{test}})}[\mathcal{L}]$$

Firstly, the hyperparameters are defined in terms of the number of samples used for prediction (window size), the dropout rate for reducing overfitting by randomly deactivating a fraction of neurons during training, and the learning rate to control the convergence while avoiding local optima; the GRU units correspond to the number of neurons in the first, the second and successive layers within the network. After that, the dataset is split into three subsets, which refer to the training (70%), validation (15%) and test (15%) datasets, respectively. The model then starts to be constructed by the definition of the first GRU layer, used to transform the input data to capture temporal dependencies within it; the second one performs a further processing with a reduced dimensionality, to extract deeper temporal dynamics in data. Finally, a dropout layer is employed to prevent overfitting by deactivating some neurons prior to the final prediction of the glucose values. In this process, the Amam Optimizer is employed alongside the loss function, the minimization of the loss function, and the validation loss function to optimize the model parameters during training.

As a result, the designed GRU model is expected to estimate glucose values in a close future, by quantifying and labeling them according to the membership functions provided in Tables 1–2–3, with the objective of providing a clear message to the patient showing the expected values to happen.

An experimental process have been carried out to determine the specifications of the final model. Concretely, this work implements the GRU model incorporating two layers with 64 and 32 units, respectively, followed by a dropout layer with a rate of 40% to mitigate overfitting. The Adam optimizer is applied with an initial learning rate of 0.001, and the mean squared error (MSE) is selected as the loss function. The training process runs for a maximum of 35 epochs with early stopping set to a patience of 10 epochs and a learning rate reduction factor of 0.5 when improvements are no longer seen.

The final model setup results of training demonstrate a substantial reduction in both the training and validation losses over the 35 epochs, highlighting the GRU model's ability to effectively learn temporal dependencies and patterns in the dataset. The training loss began at 8384.49 and steadily decreased to 366.72 by the final epoch, while the validation loss showed a similar trend, reducing from 8303.06 to 239.60. Both metrics are stable after approximately 20 epochs. An output example is graphically shown in Figure 2 for the prediction of one hour values, as each sample is expected every 5 minutes.

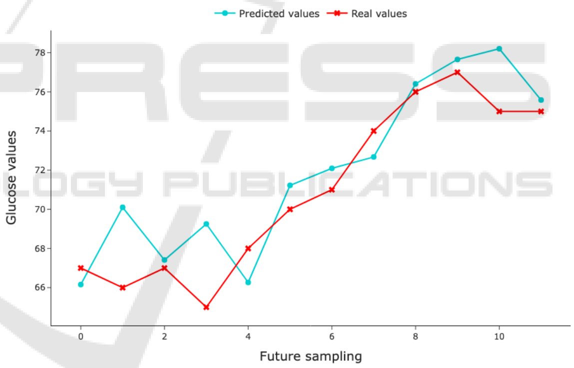

Figure 2: GRU model performance in predicting glucose values.

The results reveal how the model can effectively capture the general trend of the future values. Even though notable deviations may occur, it must be clarified that further improvement of the model is not considered necessary as the expected and real values are established within the same label (Table 2), thereby not necessitating higher complexity.

2.3 Environmental Data Collection

In this section, the environmental data corresponding to the temperature and the air quality is collected. As the nature of these phenomena reveals little variation in their recordings in a near future, the data utilized is the one that is present in the moment when the request

Listing 2: Example of JSON Response from Open-Meteo.


```
{
    "latitude": 40.4375,
    "longitude": -3.6875,
    "timezone": "GMT",
    "hourly_units": {
        "temperature_2m": "degC",
        "pm10": "mu-g/m^3",
        "pm2_5": "mu-g/m^3"
    },
    "hourly": {
        "time": [
            "2024-11-03T00:00"
        ],
        "temperature_2m": [
            16.3
        ]
    }
}
```


is made, in contrary to what happens with glycemia, due to its fast fluctuation according to both, internal and external factors of the patient.

To achieve this, the Open-Meteo API (Open-Meteo, 2024a) has been selected for the real-time environmental data retrieval. This API provides access to different environmental phenomena, including weather and air quality, providing the users the capability to request both, historical and real-time data, making it an ideal choice for this study, as being provided for non-commercial use, including the utilization of the service for public research (Open-Meteo, 2024b). For a better understanding of outdoor conditions on behalf of diabetic patients, as specified in the literature review, Open-Meteo API incorporates the metrics of temperature, PM10 and PM2.5 (the latter ones corresponding to air-suspended particles), which influence in patient health, if being exposed for a considerable amount of time. The data collection process involves constructing requests with different parameters. In our case, the utilized ones are related to the geographic coordinates of the patient (latitude and longitude) the date and the metrics of interest. These requests return structured JSON responses, detailing hourly values for the chosen variables. A sample response is presented below:

From this output, the metrics data is filtered to focus on the recordings that allows a real-time response. For air quality, PM10 and PM2.5 values are analyzed to determine the category (i.e.: “good”, “fair”, “unhealth” or “extreme”) based on established thresholds (Sloss and Smith, 2000). On the other hand, temperature is represented as low, normal or high. At last, all metrics together, i.e. glucose levels, air particles and temperature, derives in the generation of a rule-based recommendation system.

2.4 Application Layer

This layer may be consider the core of the system, responsible for performing the execution of the neural network model and the rule-based recommendation system. In detail, the application located in the patient’s smartphone is capable of connecting to the RESTful API service developed for glucose values retrieval, serving as an input for the prediction model that is stored locally. This last decision has been made considering that each patient, due to the simple designed of the network, could be provided with a tailored model, reducing server dependency and saturation in a context of multi-patient monitoring. Alongside this connection, the application is also able to request environmental data from the proposed API service. Through the combination of these components, the application layer dynamically adapts its glucose predictions and personalized recommendations, aiming to ensure context-aware guidance for users.

According to the application view (see Figure 3), it can be observed how the patient is capable of observing the collected glucose values in real-time, being able to interact with his/her glycemic dynamics. Followed by the graphical representation of the raw data, a message is provided to the patient, based on the results thrown by the GRU model for a near-future prediction of 1 hour, which are subsequently processed through fuzzy labeling and quantification. Next, the air quality and temperature data is shown, both in a quantitative and a qualitative manner, to make it easier and faster to understand. Based on all the information gathered, a final message is given to the diabetic patient as a recommendation, according to the literature review and expert knowledge.

3 USER WORKFLOW

In this section, the interaction of the user with the whole system’s architecture is addressed.

On the one hand, the patient must request access to the API service for glucose sampling. Therefore, he/she can be provided with an URL that is necessary for sending the data via the mobile application (xDrip+). Right after the patient has performed the connection between the mobile device and the glucose sensor, all the data collected is sent to the server automatically, allowing for data consultation and retrieval through the proprietary API.

On the other hand, once the GLOW-ENV application is also running on the patient’s device, as an user, the person will be able to check the collected glucose values and, the summarization of the expected one in

Figure 3: Dashboard of the designed mobile application.

the future. At this point, the patient could type manually his/her current location for environmental data consultation, being provided with a recommendation message at last (see Figure 3).

4 LIMITATIONS AND FUTURE RESEARCH

Since this research aims to enhance the care of diabetic patients by promoting personalized, context-based guidelines through API requests for data retrieval, fuzzy labeling and tailored Artificial Intelligence models, it is evident that addressing the limitations and future research in this topics is essential.

Regarding the API petitions, the real-time recommendation system could incorporate location and date parameters specification, thereby enabling patients to perform a historical data analysis for a better understanding of past events. Additionally, the automation of the latter mentioned parameters could improve the system by incorporating an automatic alert functionality. Ending up with this point, it is considered interesting to perform a data mining procedure to discover new relationships between glycemia and environmental conditions.

Noticeably, the architecture heavily relies on third-party API services for glucose data sampling and environmental conditions retrieval, creating a dependency that may introduce potential challenges due to restrictions imposed by the external providers; exploring alternatives to reduce dependency on them is a must in the future.

Lastly, future research could focus on developing a federated system that integrates a more complex model on the server side to improve glucose value predictions, since the current system already incorporates local personalized models. Therefore, this betterment could improve the accuracy of the predictions, which may be required by the time the patient monitoring integrates personal activities recordings (f.i.: food ingestion, physical activity or medicine intake).

5 CONCLUSIONS

In this proposal, a new intelligent IoE-based mobile application designed for glucose and environmental data fusion is presented, with the objective of enhancing diabetes care, management and prevention.

The system's architecture holds a sophisticated interconnection of different devices and servers, facilitating the collection, processing, and analysis of distinct data streams. Glucose sampling does not require direct patient interaction as being performed automatically, while the environmental data will not be available prior to the specification of the parameters on patients' behalf. However, the combination of continuous glucose monitoring data with environmental metrics, both in real-time, provides a context-aware approach throughout the utilization of tailored predictions and actionable insights.

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