From Wearable Data to Computational Notebooks: Towards an AI-assisted T1DM Data Analysis Pipeline

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Motivations and Goals

- Managing Type 1 Diabetes Mellitus (T1DM) in pediatric patients presents significant challenges, particularly in monitoring and treatment.
- A major obstacle is the integration of data from diverse medical sources to form a holistic understanding of a patients' conditions
- The high volume and complexity of data generated by technologies like insulin pumps and wearable monitors can overwhelm healthcare providers
- Our research investigates whether it is feasible to design a personalized assistant that supports doctors in interpreting heterogeneous data streams from various wearable devices

Our case-study

- Data acquisition performed during a pediatric diabetes summer camp organized by the Istituto Giannina Gaslini[1]
- Participants were supervised by medical staff and wore two types of devices:
    - Tandem insulin pumps with continuous glucose monitor (CGM) communicating with the Glooko platform
    - Comftech's Howdy Senior sensorized garments which measure multiple physiological parameters such as heart rate variability, ECG, respiration rate, stress/movement index

- The goal was to monitor the physiological and metabolic responses of five pediatric patients with T1DM during daily physical activities.

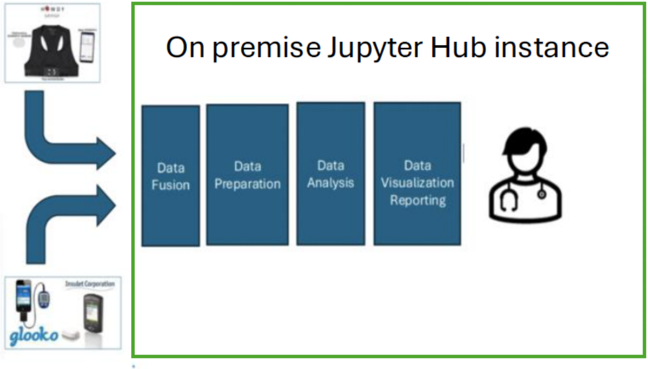
[1] A new data collection campaign with 15 patients started this week in Sarzana

Architecture

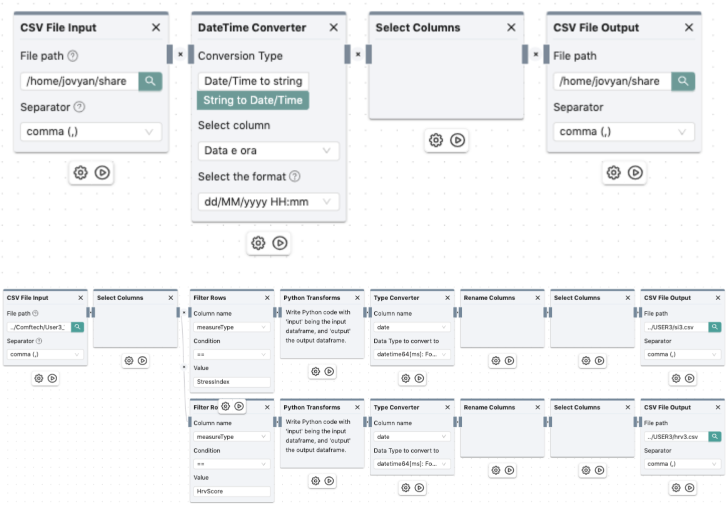
- We adopted Python-based Jupyter Hub framework as a central platform for acquiring, processing, and analyzing wearable data in a secure environment. This approach enables collaboration among researchers and clinicians while ensuring that sensitive health data remains within institutional boundaries.

- Our JupyterHub instance is deployed on a virtual machine hosted by the joint laboratory of the Gaslini Pediatric Hospital and our university.
- The system integrates data initially stored on proprietary cloud platforms managed by the device manufacturers.

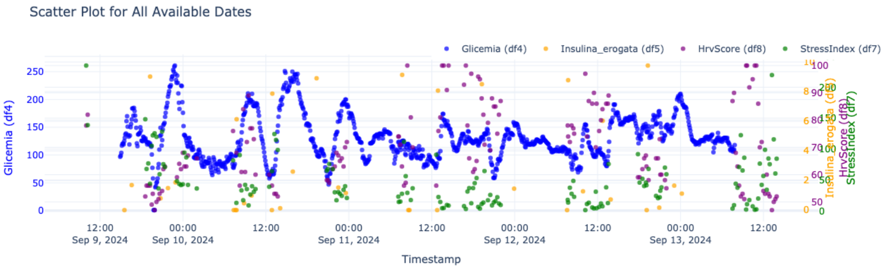
Architecture and Methodology



Data Preparation: Amphi Workflows

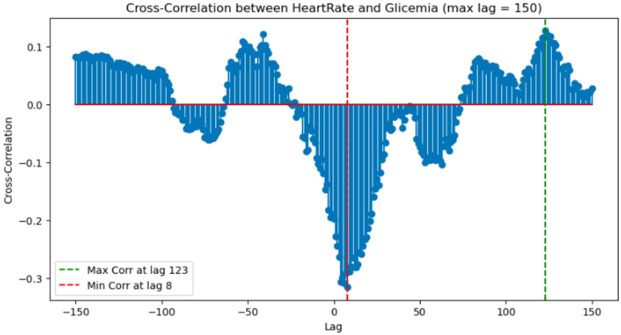


Data Fusion and Visualization



Explorative data analysis: Cross-correlation

- Among other analyses, we studied the cross-correlation between heart rate and glycemia over a range of time lags
- The goal was to identify time lags for highest positive and negative correlations to validate doctor's hypothesis on the effect of movement on glycemic level

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Maximum positive correlation at lag: 123
Maximum negative correlation at lag: 8
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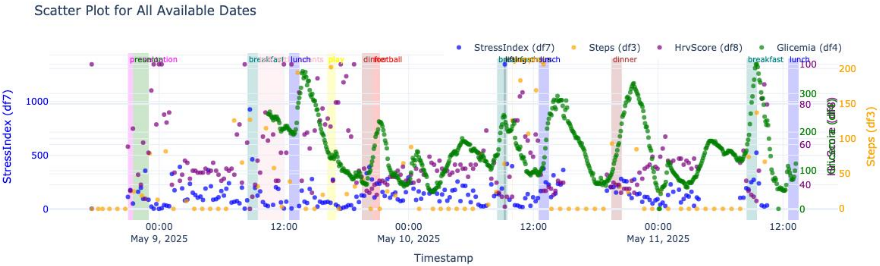
Explorative data analysis: Cross-correlation

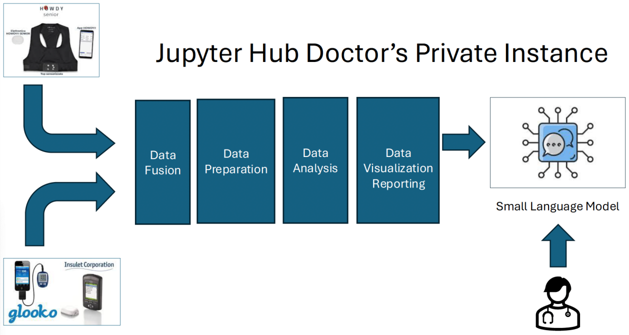
- The stress index demonstrates a strong negative correlation with glycemia (-0.72), suggesting that increased stress levels are associated with lower glycemia, potentially due to metabolic changes or increased energy expenditure under stress.
- Breathing frequency correlates positively with insulin delivery (0.59), possibly reflecting an association between metabolic demands and respiration. However, its correlation with stress is weak and negative (-0.17), suggesting that stress levels do not directly influence respiratory rate in a significant way.

- We are combining raw data with contextual information, e.g., categorization data related to physical activity



Towards an AI-assistant

- We experimented the use of local Large Language Models to support data interpretation as a possibile additional support for doctors, e.g., reports in natural language



Towards an AI-assistant

- We use the LangChain framework and Python libraries for extracting the knowledge based from patients' reports
- The knowledge base consisted on the provided biometric data.
- We created a ChromaDB vector database to generate a retriever to generate contexts associated to the questions
- During system prompting, additional contextual information was given, e.g., category for glycemic values
- We tested the resulting pipeline using a list of questions with ground truth provided by experts
- We also compared with AI services such as Google LM

Conclusions

- Exploratory study to design a pipeline for data fusion, processing and analysis in the context of a collaboration with the T1DM experts of the Gaslini Hospital supported by the benefit company ComfTech
- We are collecting more data, e.g. data collection campaign with 15 patients (this week!)
- We are considering data centric architectures such as Kafka and Spark to cope with large datasets
- We started a new collaboration with the Universitat de Girona to apply deep learning to predict the effect of movement analysis
- We need to improve the AI-assistant component extending the knowledge base and considering more complex queries posed by doctors