NOVEL AI-BASED ALGORITHM TO DETECT AND RECONSTRUCT MEAL REAL TIME USING CGM DATA

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BACKGROUND AND AIMS

Self-management tools for insulin requiring patients are gaining considerable interest with the advent of smartphone applications, CGM systems, insulin pumps and connected insulin pens.

In those systems, the meal management remains a major issue. Patients still need to input manually the information regarding each meal in terms of carbohydrate intakes in a dedicated controller or smartphone application so that the system can provide relevant recommendations, and manual inputs lead to incomplete or missing data. Having clean meal data with correct amount of carbohydrates and timing, is key, otherwise the system may rely on inaccurate information.

Hence, it would be highly valuable to dispose of a real-time meal detection and reconstruction algorithm so that the system does not have to rely on manual inputs. Hillo has been working on a novel AI-based real-time meal detection algorithm based on CGM data.

MATERIALS AND METHODS

The meal detection algorithm was built and tested using a data set from the CDDIAB observational study **[A]**. 30 days of real-life data from 14 patients including CGM readings, self-reported carbohydrates (CHO) intakes and insulin injection data.

Sample Characteristics	
Group Size	n = 14
M / F	6 (43%) / 8 (57%)
Age (years)	51 ± 15
HbA1c (%)	7.09 ± 0.82

Table 1: Characteristics [M ± SD, n (%)]

We have opted for a global approach where we gathered data from all but one patient to train model. This approach aims to evaluate the feasibility of an inter-patient meal detection algorithm. Performances are assessed on test data set from the remaining patient. The process is repeated for each patient and averaged.

The data set is characterized as a series of observations: a binary classification {meal; no meal} for all timestamps where a CGM value is provided and if at least one hour of past signal is available.

For training only, all observations in the range of $[t_{meal}\,; t_{meal} + \delta]$ are removed from the learning steps to exclude data where meal has no effect yet. δ is used as a trade-off between precision and sensitivity. It has been determined during cross-validation and set to 15 min.

We define the detection time range (DTR) as the period given to the model to detect a meal after it occured in observations. A meal detected outside DTR is considered as a false positive.

In order to get metrics easily interpretable, some rules are applied to the test set to group observations:

- If we have several consecutive true positive detections inside DTR, only the one that comes first is kept so as not to record a true positive several times for the same observed meal.
- If we have several consecutive false negative detections inside DTR, only the one with the highest probability of a meal is kept so as not to record a false positive several times for the same observed meal.

To evaluate the model, precision and sensitivity are computed with other metrics:

- f1: the harmonic mean of the precision and the sensitivity. It represents the best trade-off between precision and sensitivity as they can have inversely proportional effects.
- AUC: the area under ROC curve which gives the ability of the algorithm to classify properly. The ROC curve is created by plotting sensitivity against the false positive rate at various thresholds
- MDT: the mean detection time the algorithm needs to detect a meal after it occurred

RESULTS AND DISCUSSIONS

Results					
DTR (min)	AUC (%)	Precision	Sensitivity	f1	MDT (min)
60	91.5 ± 2.7	0.59 ± 0.09	0.63 ± 0.09	0.60 ± 0.06	25.6 ± 4.2
45	88.7 ± 3.4	0.57 ± 0.11	0.57 ± 0.10	0.56 ± 0.07	22.6 ± 3.2

Table 2: Mean performances for DTR = 45 and 60 min [M ± SD]

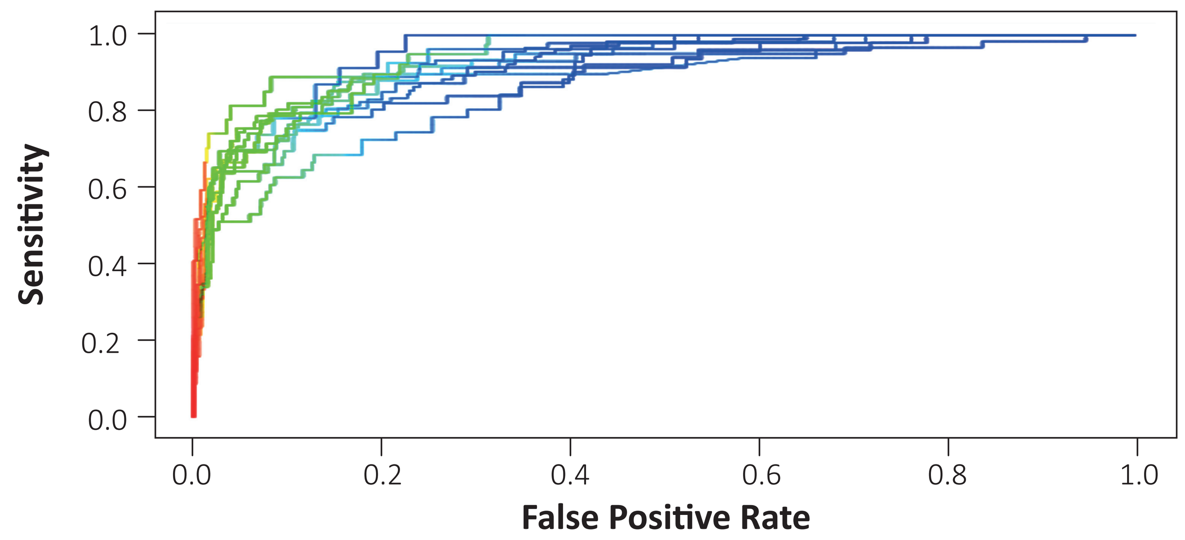

Figure 1: ROC Curve for DTR = 60 min

Preliminary work shows the feasibility of a meal detection system based only on real-life CGM data with very promising results, which could be improved using a more accurate data-set. Indeed, missing or inaccurate meal inputs in the test data set introduce biases in the evaluation of false positives:

- Some meals are not reported by patients. If the algorithm detects such a meal, it is considered as a false positive.
- Some timestamps are innacurate. If the algorithm detects a meal before it occured, it is considered as a false positive.

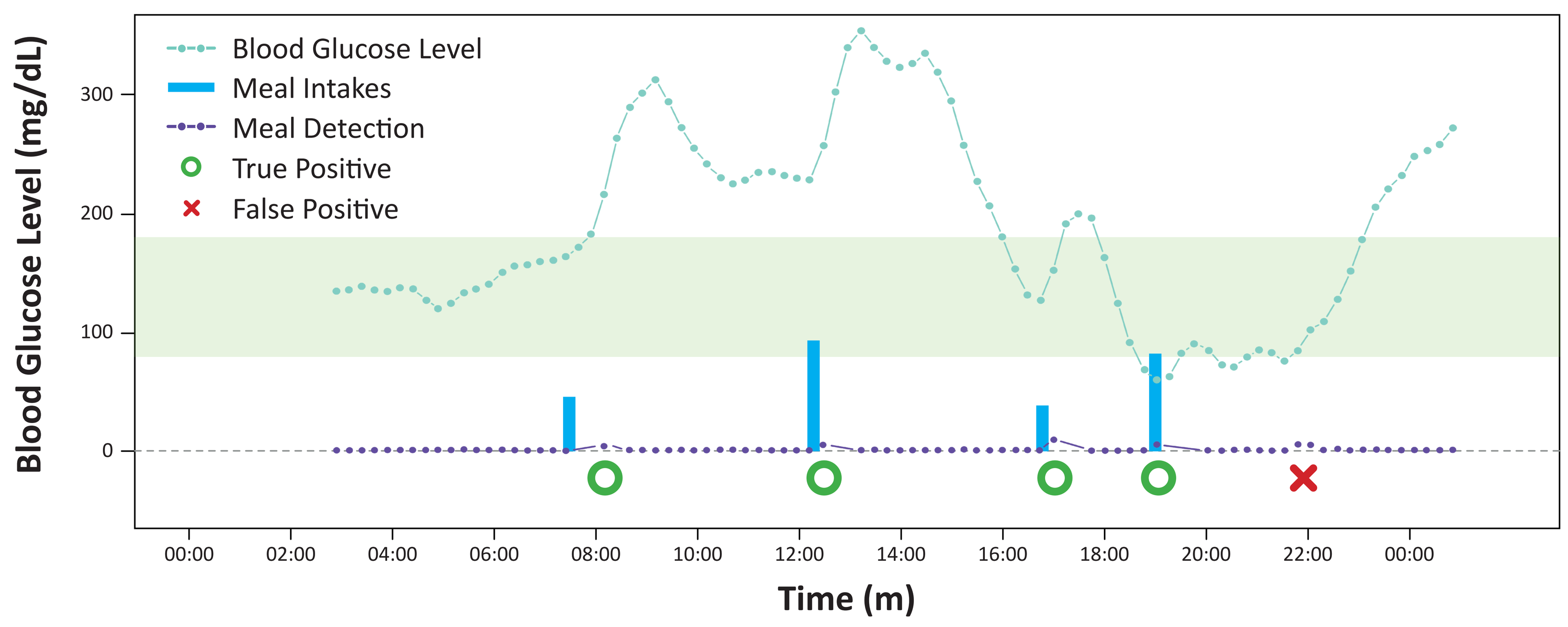

Figure 2: Example of meal detection

CONCLUSION

A meal detection algorithm based only on CGM signal can improve and streamline meal management in any decision support tools or diabetes management platforms and systems.

We have demonstrated promising results, but the lack of fully accurate data prevents any definitive conclusion on the performance of such a system. Having a clean dataset available would allow to have definitive insight on the performance of the proposed approach.

Such data set could also be used to evaluate a meal reconstruction algorithm (estimation of CHO amount), which is currently under development by Hillo.

REFERENCES

[A] S. Bidet, N. Caleca, E. Renard, T. Camalon, L. De La Brosse, M. Rehn, O. Diouri and J. Place. First assessment of the performance of a personalized machine learning approach to predicting blood glucose levels in patients with Type 1 diabetes: The CDDIAB study. *ATTD 2019.*