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Contribution - Gradual Fine-Tuning for accurate Blood Glucose Level Prediction

DS applications and challenges in Medicine, Natural Sciences, and Engineering

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Abstract

For individuals with Type 1 diabetes (T1D) is of eminence importance to avoid hypo- and hyperglycemic events. The availability of long glucose time-series along with powerful AI methods allowed the development of glucose prediction algorithms. Nonetheless open issues remain such as prediction time-delays, amount of history needed, and how heterogeneous and sparse diabetes information affect the performance.

Materials and methods: In this study, we utilized data from 100 individuals with T1D provided by the Juvenile Diabetes Research Foundation. The dataset provides pump settings, sensor outputs (e.g. insulin-rates, continuous glucose monitoring-CGM) and conceptual information such as age, years of diabetes. To mitigate the adverse impact of large inter-patient variability, we propose a training scheme based on gradual fine-tuning. Initially, the novel AI-model is trained on all data and subsequently fine-tuned over groups with shared characteristics to individual patient-level. The individuals with T1D are assigned to groups based on similarity measures defined using glucose variability indices. For each individual, an ensemble of five dedicated sequence-to-sequence LSTM networks is used. The ensemble uses CGM data, bolus dose and meal intake as input and outputs blood glucose predictions 30 min ahead in time.

Results: As shown in Table 1 the root-mean-square-error (RMSE), mean-average-error (MAE), and time-lag used as performance measures for the various training schemes.

Table 1: Initially, we trained our network on the entire population and utilized that global parameter set as initialization for the fine-tuning per patient, the patient group training and the training on OhioT1DM data. Within each group, subsequent fine-tuning per patient was applied.

Training scheme		RMSE (mg/dL)	MAE (mg/dL)	Time-Lag (min.)
JDRF Dataset	CGM+insulin+carbohydrate intake from entire population	21.56	15.81	20.10
	As above by fine-tuned per patient	19.56	14.05	19.30
	CGM+insulin+carbohydrate intake per group of patients	19.59	13.98	19.60
	As above but fine-tuned per patient within the groups	**19.39**	**13.89**	**19.05**
OhioT1DM Dataset		18.19	12.98	15.00

Conclusion: There is evidence that high performing AI-based prediction models do not only depend on the algorithmic approach per se. The performance may increase by identifying groups of patients that share common hidden metabolic patterns.