Blood Glucose Forecasting based on CGM data

Gustaw Żyngiel (s192673), Krystof Spiller (s200360), Veniamin Tzingizis (s192851)
in cooperation with Hedia - Mads Jakobsen
Deep Learning - DTU Compute
Technical University of Denmark

Introduction

This project is about forecasting blood glucose (BG) based on continuous (taken every 5 minutes) glucose monitoring (CGM) [1], exogenous insulin and carbohydrate (CHO) intake from meals. This 30 minute forecast is shown to the user who can then more easily regulate their BG levels and prevent hypo- (below 70 mg/dL) or hyper- (above 180 mg/dL) glycemic states.

Data & Tools

The team was given the *in vivo* Ohio T1D dataset [2] and a deep learning framework from Hedia which preprocesses the data, trains the model and evaluates the results. Part of the framework was a simple model with five dilated convolutional layers. The attempted models were inspired by this simple model (which is in turn based on [3]) and by an architecture presented in [4].

Workflow

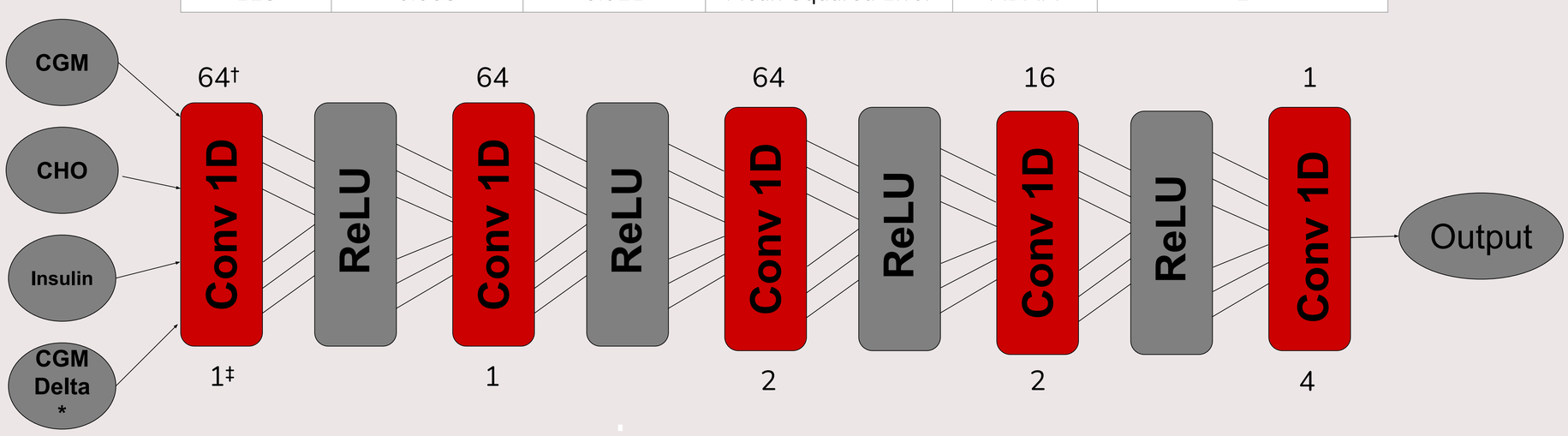
2 model design approaches
- Focused purely around CNNs
- Focused around LSTM usage

Experimenting with
- Different kernel sizes, paddings
- Dilation introduction
- Parameters optimization
- Usage of different optimizers

Results comparison
- Clarke [5]] error grids
- RMSE
- MARD
- Time lag

Model

Batch size	Learning rate	Weight decay	Loss criterion	Optimizer	Kernel size (all layers)
128	0.003	0.021	Mean Squared Error	ADAM	2



* Values above Conv1D blocks show number of hidden units
** Values below Conv1D blocks show the size of dilation
*** Preprocessed value, delta between the 5 minute CGM measurements

Modules		Parameters
1st Conv1d layer	weights	512
	bias	64
2nd Conv1d layer	weights	8192
	bias	64
3rd Conv1d layer	weights	8192
	bias	64
4th Conv1d layer	weights	2048
	bias	16
5th Conv1d layer	weights	32
	bias	1
Total sum		19185

Results

Model	RMSE	MARD	Time lag (min)	A+B	C+D+E
Hedia - Best	20.027	9.97%	20.45	99.57%	0.43%
Ours - Best Personalized	20.401	10.57%	20.41	97.85%	2.15%
Ours - Best Generalized	20.492	10.66%	20.49	97.83%	2.17%
GluNet* [3]	19.28	8.73%	8.03	-	-
CRNNfGP* [4]	21.07	-	-	-	-

*** These results are not directly comparable to other results in the table as they are taken from the papers where it is not described in detail how were these values obtained.**

Fig. 1: The results comparison between Hedia's top model, our model and research papers

Fig. 2: The plot presenting the actual (light blue) and predicted (dark blue) BGL measurements

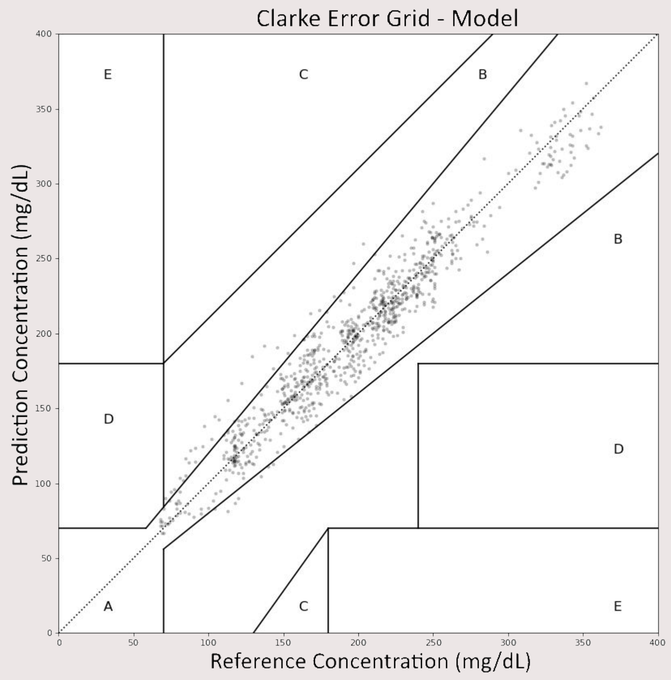


Fig. 3: Clarke Error Grid for our results

The models that are proposed are two, a generalized and a personalized. The generalized one is a model that is used for all case samples. On the other hand, the personalized one it's tuned for each individual case. Taking a look at the results, as expected the model that is tuned for each patient performs better than the generalized one.

For this application it is very important that the model can predict accurately the valleys and the hills because those are the danger zones for the patient. As shown from the results the personalized model outperforms the generalized one across the board. That would indicate that each patient has his own unique patterns and characteristics. A real world approach to this problem would be to use the generalized model on a patient for a period of time and after optimize it for that individual. A flexible strategy like this will ensure that any changes to behaviour/pattern in the future can be compensated and the model can be re-optimized for that individual.

Both models performed similarly with an average A+B value close to 98%. A+B ranges in the Park graphs are the ones that are clinically acceptable, with A being very good and B being good. Both models have 86% in the A region which is acceptable. For comparison the model from Hedia has 89%.

References

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