Continuous Blood Glucose Prediction in Insulin dependent Type 1 Diabetics

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***Abstract*—In this project a deep learning model based on 1D convolutions is used to model blood glucose levels in Type 1 Diabetes patients using insulin. Using the D1NAMO dataset a model was constructed for predicting future blood sugar levels based on past blood sugars, insulin dosages and physical activity levels. It was found that absolute errors of approximately 0.7-1.2 mmol/l were achieved for prediction horizons of 30-60 minutes. However poor prediction accuracy was achieved after events that caused blood sugar to change drastically after the last time sample in the input. For comprehensive prediction it is hypothesised that an estimate of carbohydrate intake is also necessary.**

***Index Terms*—Type 1 Diabetes, Blood Glucose Prediction, Deep Neural Networks**

I. Introduction

In this report modeling for the prediction of future blood glucose (BG) levels based on measurements of an individual's current and past state will be tackled. Persons with Type 1 diabetes suffer from impaired pancreatic function which leads to a dearth of natural insulin in the blood. Under normal physiological function insulin acts to reduce the concentration of glucose in the blood stream. For individuals with Type 1 diabetes the lack of natural insulin is replaced by frequent injections of insulin analogs. Despite the availability of manufactured insulin effective management of Type 1 diabetes remains challenging for patients. The many aspects which affect blood glucose including carbohydrate intake, additional macro-nutrient intake, activity levels and of course insulin dosage and type must all be balanced to maintain blood sugars within the healthy range.

This has led diabetes management to develop towards being able to continuously monitor and correct for current blood sugar levels using continuous glucose monitoring (CGM) sensors which are constantly measuring glucose levels and relaying this information to devices such as smartphones, and insulin pumps which can infuse insulin into the blood stream in small incremental doses throughout the day. The inherent delay in insulin action (to correct for high blood sugar) and digestion of carbohydrates (to correct for low blood sugar) mean that having the ability to predict blood sugars 15-30 minutes in the future can be incredibly useful for patients.

In this report an attempt at modeling sugar levels in Type 1 diabetics is presented. The D1NAMO dataset [1] will be leveraged for training and testing the algorithm. This dataset includes glucose data from a CGM device sampled at 5 min intervals, insulin dosage (both fast insulin and long lasting), and very densely sampled data from various other sensors including accelerations (indicating body motion), heart rate meters and breath rate. These other sensors are also aggregated together into an "activity" metric by the supplier of the sensor suite.

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II. Modeling Approach

A. Data Pre-processing

Of significant importance in this modeling task is how the data is processed and presented to the model. The first point is the varying time density of the different data streams. To simplify the time series modeling task the data is remapped to a single consistent time sampling frequency. For this the 5 minute interval of the CGM measurements is used. The much more densely sampled physical activity data is averaged over 5 minute windows.

Including insulin dosage presents the opposite challenge in that the signals are incredibly sparse. Long lasting insulin is usually administered once a day and rapid insulin only administered at meal-time. To alleviate the sparsity of the insulin data channel the single dosages will be converted into an insulin action rate metric. This will be done by dividing the dosage by the action time of the insulin type and setting the insulin rate variable at each time sample equal to the sum of insulin action from all insulin doses taken within the relative time frame. For fast acting a 4 hour action window is used and for long lasting a 24 hour window is used [2]. In Figure 1 a sample from the data for a single patient can be seen.

The data is subdivided into individual patients but we further subdivided the data if any of the measurements was missing for a long interval (for example from taking off the CGM). When training and evaluating, input and output instances should be continuous and not spill into adjacent blocks i.e. the time between individual samples is constant.

B. Model Architecture

The model is structured such that its inputs and outputs consist of $N_{t,in}$ and $N_{t,out}$ time slices respectively. The input is of dimension $N_c \times N_{t,in}$ and the output of dimension $1 \times N_{t,out}$ where N_c is the number of measurement channels corresponding to insulin, activity and other measurements that may be included or omitted. We used 3 channels for the input corresponding to BG, insulin rate and activity.

The architecture used for the training consists of a series of 1-D Convolutional Layers followed by a small number of fully connected layers to convert the output from the last

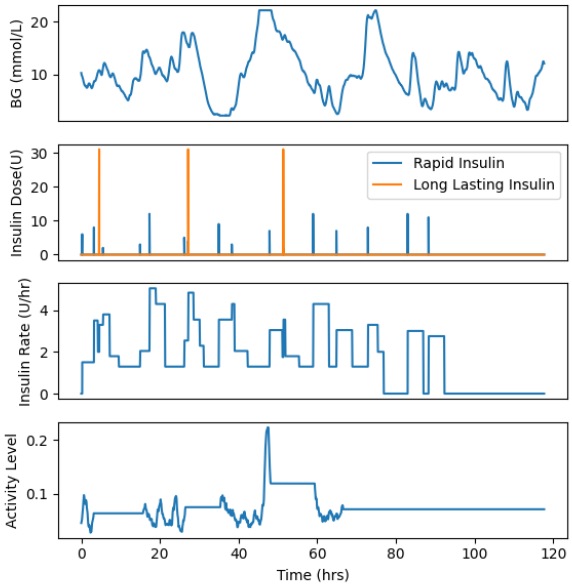

Fig. 1. Pre processed data from a single patient

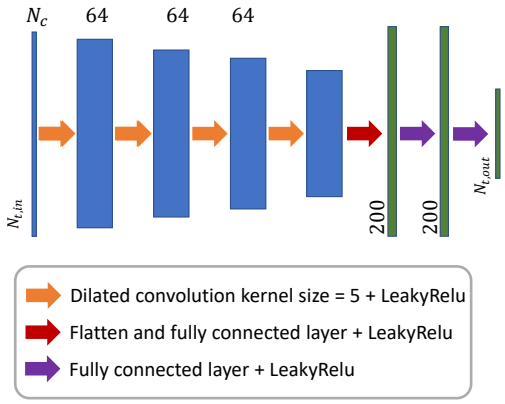

Fig. 2. Diagram of the network architecture used for the blood glucose prediction model.

convolutional layer to the appropriate output size. Leaky ReLU nonlinearities were used between layers. The full architecture can be seen in Fig. 2.

C. Training

The data is partitioned into training and evaluation sets. There are several ways that this could be done. Either a subset of the patients could be held out for evaluation. Otherwise slices of data from a random selection of patients could be removed and set aside for validation. This second option was chosen.

Furthermore when generating instances for training and evaluation random data segments with length $N_{t,in} + N_{t,out}$ were selected from a random data block.

For training the Adam [3] optimization algorithm was utilized. Furthermore, utilizing a learning rate of $\eta = 0.0005$

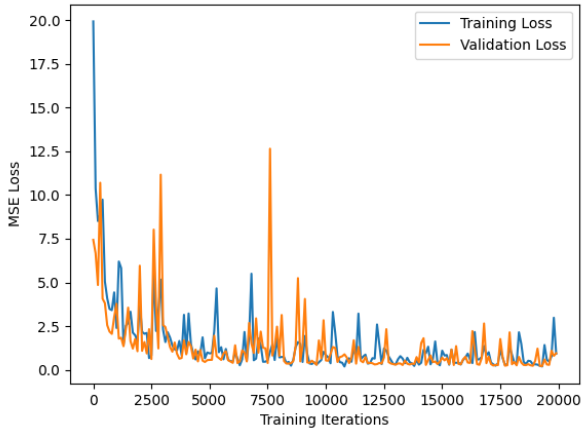

Fig. 3. Training and Validation Loss over the course of one training session.

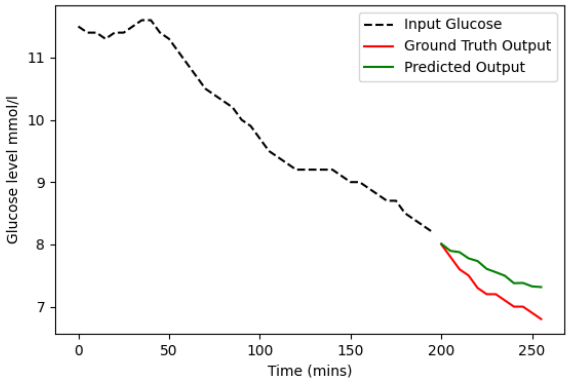

Fig. 4. An example predicted blood glucose for a 1 hour horizon.

it was found that 20000 iterations were sufficient for convergence. Mini-batches were not utilised.

III. Results

For a $N_{t,in} = 40$ and $N_{t,out} = 5$ (corresponding to 3.3 hours and 25 minutes) it was found that the Mean Squared error converged to a value of around 0.5 equating to an absolute error of 0.7 mmol/l. This is satisfactory for usage in a diabetes management setting where even commercial CGM equipment measurement accuracy is only guaranteed to about 5-10%. Furthermore, patient intervention usually take place when excursions exceed 1 mmol/l from the target range. Also it was found that extending the output size to have a time horizon of 1 hour increased to a still use-able error equivalent to approximately 1.2 mmol/l. An example predicted output can be seen in Figure 4.

Despite this positive mean accuracy the limitations to this approach are clearly evident in some sample predictions. For example see Fig. 5. Here there is a large increase directly after the time window of the input likely due to the ingestion of a fast acting carbohydrate. This illustrates a key limitation of the current model in that the input space is not complete

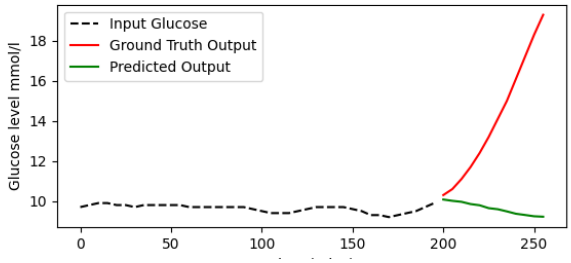

Fig. 5. Sample prediction where prediction does not match ground truth due to rapid change.

for the current task. Given the significant importance of food intake on blood sugar levels not having this information and without patients eating consistent repeatable meals it becomes largely impossible to predict blood sugars at the occurrence of such external disturbances.

IV. Conclusion and Future Work

In conclusion it was shown that predicting blood sugar using a deep learning approach was plausible and modeling could be used in conjunction with body mounted senors to predict future blood sugars in diabetic patients. Future investigation and development could focus on how to include estimates of carbohydrate intake into the model from either image data of food consumed or patient manual input.

References

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