



Artificial Intelligence improving life of type 1 diabetes

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November 25, 2019

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Abstract—The recent increased availability of insulin pumps and continuous glucose monitors (CGM) created a new focus in current research: the development of a close-loop system that would become the perfect artificial pancreas. So far, there are some community projects that try to achieve this goal. If our hypothesis is supported, then artificial intelligence could solve this problem once and for all. Artificial intelligence could help the patient maintain the blood glucose level as stable as possible, while requiring little to no interaction from the user. Such a closed-loop system may improve the quality of life for the patient and prevent the long-term side effects of diabetes.

Keywords—artificial intelligence; type 1 diabetes; blood glucose; artificial pancreas; closed-loop; LSTM; linear regression;

I. INTRODUCTION

Type 1 diabetes (T1D) is a condition in which the pancreas of the patient produces little to no insulin - the hormone needed to allow glucose (sugar) to enter cells and produce energy[4]. Therefore, type 1 diabetics need to receive an additional intake of insulin in order to bring the level of their blood glucose (BG) to an optimal value of 80 to 120 mg/dl. One of the daily challenges of patients is to normalize and maintain constant this level of glucose in their blood. To achieve this, the patients must balance the number of carbohydrates that they eat, a potential abnormal level of BG, the additional insulin that they receive and all the physical and mental activities that they perform.

To help the patients face this challenge, researchers developed several devices like the insulin pump and the continuous glucose monitor. In 1963, the first prototype of an insulin pump was built and, later in the 1990's, the first insulin pump was released to the public. As far as continuous glucose monitors are concerned, FDA approved the first such system in 1999. In 2013, the first artificial pancreas was ready for tests but it is still far from being ready to be released on the market

To create the desired closed-loop system, that would act like an artificial pancreas, we need an insulin pump and a CGM in order for the AI algorithm to be able to work properly.

Safety must be the main concern of a closed-loop system. The loop will take the input data from the sensor, predict the trend for the next period of time and then command the

needed action to the insulin pump. However, CGMs are not perfect yet and might thus be erroneous (the compression of the sensor or its potential approach to the end of a life cycle could cause unprecise readings). Therefore, the prediction of the AI algorithm cannot entirely rely on a single reading. Knowing that modern CGMs provide a new value from a new reading every five minutes, the system should evaluate its old prediction based on the new data - update it if necessary or even go as far as canceling the old plan if it is no longer valid and create a new one. If the system cannot run properly with the current information, it must also have a fallback option and use a known good setting (usually the normal rate) or let the user take the wheel.

One of the existent prototypes of closed-loop systems is the Open Artificial Pancreas System (<https://openaps.org>), an open, transparent effort to create a safe and effective basic artificial pancreas using predefined fixed mathematical formulas. We aim at obtaining better results than this reference design using AI algorithms.

Our algorithm running in a closed-loop makes it more difficult to have all the relevant data, like food intake or future plans for sport or sleep. Thus, the nature of our data is very similar to that from the stock market. In the case of the stock market, artificial intelligence has already claimed its rightful place: algorithms like ARIMA, Prophet or Long Short-Term Memory produce good results for stocks prediction. This encourages us to work on developing AI algorithms to help type 1 diabetics.

We want to create a linked system consisting of short individual algorithms which can obtain information about the various changes happening in the patient body and which should be able to communicate and react accordingly to these changes.

The workload is divided in two parts:

- 1) The first algorithm predicts the blood glucose level for the next period of time, considering the values from the CGM and the trend of the readings.
- 2) The second algorithm receives as input the values predicted from the first algorithm. If these values are outside the normal range, it will try to bring the BG level back to normal using the patient's history as reference (the algorithm should consider the current

health condition of the patient and only the past data from the same time of the day as the wanted prediction).

II. METHODS

The Dexcom G6 continuous glucose monitor sensor reads the blood glucose level every 5 minutes - around 288 times per day. This continuous data is used to predict future values and, thus, to help prevent a potential drift from the target values. The prediction of a hyperglycemia or a hypoglycemia would help the patient take actions to avoid it before it occurs.

Various algorithms were tested for prediction, like classical statistical methods. These were able to successfully predict blood glucose for a period of 30 to 60 minutes. Machine learning is currently used for real-time learning. Bunescu et al. [1] proposed to use the support vector regression (SVR) for predicting blood glucose levels, by taking as input daily events, like insulin boluses and food intake; deep convolutional neural networks are also used with better results than classical shallow network. We use a recurrent neural network (RNN) fed with both glucose and insulin information. The model using RNN outperformed the autoregressive model using glucose information. However, the main disadvantage in using classical RNNs is the limited capacity to learn long-term dependencies. The problem is caused by the vanishing or exploding gradient.

To work around this problem, recent algorithms like LSTM use forget gates and memory cells. The memory cells allow to improve prediction confidence by combining the memories and the new input data; also, the neurons that work like forget gate mark the information from the past epoch that must remain in the network. LSTM based neural networks have shown good results for time series prediction, and have been applied to predict stock prices, sea surface temperatures and highway trajectories. LSTM can learn much faster than other networks and solves complex tasks that have never been solved before by recurrent network algorithms. By incorporating bidirectional structure, each cell of LSTM is enabled to access the context from the both past and future directions. A deep bidirectional LSTM (Bi-LSTM) structure was used in the past.

Using a good prediction, the second algorithm evaluates the situation and outputs the required action for keeping the blood glucose in the target range.

The second algorithm will have as input data the following features: current blood glucose level, predicted blood glucose level, trend of blood glucose, active insulin, current basal rate and the history of past relevant events.

As you may see, the non-linear and dynamic relation between the inputs is dependent to the patient and the time of day, so it is perfect for an artificial neural network like the one in [3].

III. THE ALGORITHM

Our approach will use one LSTM layer with 6 units followed by four fully connected layers. The last layer, the output layer, is made of one unit dense layer. We intend to use epochs of 25 iterations each.

The data used is from the last three months of my CGM creating an individual model. The synthetic set contains data from the Padova Type 1 Diabetes Simulator. Cross validation splits of 66/33 were used to prevent over-fitting the data during pre-train phase and also for the train phases.

For the evaluation and ranking of our solution we will measure the time lag and the root mean error which will give a better view of our performance. For comparison we will use ARIMA and SVR as competitors. A similar study concluded that the LSTM method can simultaneously decrease RMSE and Time Lag, while CC and Fit are both increased.

IV. CONCLUSION

The flexibility of the machine learning algorithms makes them the ideal candidate for solving the problem in question about finding the perfect balance in which a type 1 diabetic must live every day.

In the future work of this study, the data from the patient's CGM is sent in the Cloud, where the model is retrained every week and only the decision is computed on the user's phone, avoiding the need for a dedicated device and to be able to run even when offline.

A solution to the problem will save a lot of time for every user and also prevent dangerous situations such when the events are happening during sleep and thus the user is unaware of what is going on. Also, the users of other closed-loop systems have reported a smaller HbA1C average which may lower the long-term risks of diabetes.

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