Machine Learning Models for Blood Glucose Prediction in Diabetes Management

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Introduction
An estimated 382 million people in the world have diabetes, including 29.1 million Americans. From 5 to 10% of these people have type 1 diabetes (T1D), the most severe kind. In T1D, the pancreas fails to produce insulin, an essential hormone needed to convert food into energy. Therefore, T1D patients depend upon external supplies of insulin to live. T1D can not, at present, be prevented or cured; however, it can be treated and effectively managed.

The key to diabetes management is blood glucose control. Good blood glucose control can help delay or prevent serious long-term complications, as shown in Figure 1. Achieving and maintaining good blood glucose control is a difficult task for patients, who must continuously monitor their blood glucose levels and daily activities. It is a difficult task for physicians, who must review large quantities of blood glucose and life event data, looking for problems and making therapeutic adjustments to correct them.

Blood Glucose Prediction with Physiological Models and SVRs
Predicting blood glucose problems before they occur would give patients time to intervene and prevent these problems. This would not only improve overall blood glucose control, but would also enhance patient safety. The most important application is to predict hypoglycemia, or low blood glucose levels, which, if not promptly treated, can lead to seizures, coma, or death. Predicting hypoglycemia 30 minutes in advance would allow sufficient time to decrease insulin infusion and/or alert the patient to eat something to bring blood glucose levels back up to normal.

In our approach, a generic physiological model is used to generate informative features for a Support Vector Regression (SVR) model that is trained on patient specific data. The physiological model characterizes the overall dynamics into three compartments: meal absorption dynamics, insulin dynamics, and glucose dynamics. The parameters of the physiological model are tuned to match published data and feedback from the doctors. To account for the noise inherent in the data, state transition equations underlying the continuous dynamic model are incorporated in an extended Kalman filter.

Figure 2 shows the overall blood glucose prediction process. A continuous dynamical system implementing the set of physiological equations is run in prediction mode for 30 and 60 minutes. Physiological model predictions are then used as features for an SVR model that is trained on the two weeks of data preceding the test point. Furthermore, an ARIMA model is trained on the same data and its predictions are used as additional features. All models are trained to minimize Root Mean Square (RMS) error. SVR predictions are made at 30 and 60 minute intervals and compared to known outcomes and to physicians predictions.

Current Challenges: Modeling the Dawn Phenomenon and Predicting Hypoglycemia
Blood glucose levels during sleep can be difficult to predict due to the dawn phenomenon, a natural rise in blood glucose in the early morning caused by hormonal changes in the body. We modeled the dawn phenomenon through features that consider a linear growth of the BGL, starting at 4 hours of sleep and lasting for either 2 or 4 hours. The resulting SVM models were observed to improve BGL prediction in regions in which the patient is asleep. When compared with the original SVM model, these features led to relative error reductions of 10.5% and 6.1%, for 30 minute and 60 minute prediction, respectively.

Hypoglycemic events are the times when the patient’s blood glucose level is below the safe level of 70 mg/dl. When evaluated on predicting hypoglycemic events 30 minutes in advance, the SVR system was able to predict 45% of the true events. Although the corresponding precision is currently just 44%, most false positives are in near hypoglycemic regions (below 80 mg/dl). Work continues to improve hypoglycemic prediction performance.

The SmartHealth Lab
In the SmartHealth Lab, we are building Artificial Intelligence tools to help patients with type 1 diabetes on insulin pump therapy achieve and maintain good blood glucose control. Our current work focuses on new methods for blood glucose level prediction. Accurately predicting blood glucose levels (BGL) 30 to 60 minutes in advance would enable or facilitate applications of direct benefit to patients, including: alerts to warn of impending problems; decision support for taking actions to prevent impending problems; and “what if” analysis to project the effects of lifestyle choices on blood glucose levels. This work strives to improve the overall health and quality of life for people with type 1 diabetes. The SmartHealth Lab was established to support this work, promote additional smart health research, and help attract more women to careers in computer science.

Future Work: Using Physiological Sensors
Patients have been providing life event data via cell phones, but this is burdensome and error prone. We plan to exploit signals indicative of patient activity from heart rate monitors, accelerometers, and sensors that detect temperature, heat flux, and galvanic skin response. If successful, this would improve prediction performance, while reducing data entry burden on the patient.

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References