

Objective

This research will test the application of deep learning algorithms on the prediction of blood glucose (BG) levels in people living with diabetes. BG levels are a time-series of sensor readings from continuous glucose monitoring (CGM) systems. The ability to predict these readings can aid in health outcomes. This research will test a series of model types (RNN, LSTM, GRU), tune hyperparameters, and build additional data features, in attempts to create an accurate forecast and framework for this prediction challenge.

Background

CGM is a technology that people with diabetes use in managing their condition. CGM includes body-worn sensor that takes BG readings every 5 minutes. This data is shared with assistant devices and show current BG readings. Deep Learning algorithms can be used to create predictions on this time-series data to aid in the management of this condition. Such applications include - adjusting insulin delivery in real-time and help to alert people that may be falling outside of their target range. Deep learning algorithms are well suited for work in this field as they have further flexibility to be enhanced with data sources and create accurate personalized information.

Methodology:

Data: Sourced from the [Jaeb Center for Health Research](#) (8.4m observations across 153 patients) the data was processed using a process designed to ensure complete time-series and structure for repeated random sampling. This could be used for other datasets.

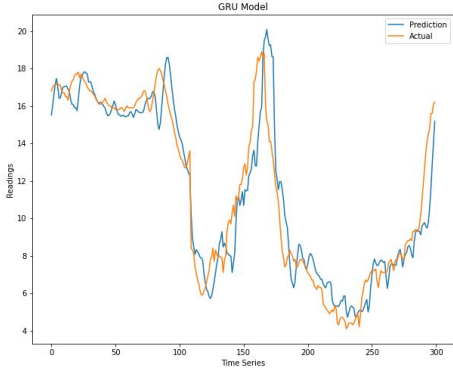
EDA: Focused on client specific analysis (mean, variance) and the overall quantity and length of time-series.

Experiments: To forecast the response variable MMOL/L BG experiments focused on model development (RNN, LSTM, GRU, CNN) hyperparameter tuning, feature engineering, data smoothing, and model personalization

Results:

Best model performance was after a grid search for optimized hyperparameters. The Simple RNN trained faster and the GRU obtained best accuracy by RMSE.

Model	Training Time (seconds)	Best Test RMSE (MMOL/L)	Mean Test RMSE (MMOL/L)
Simple RNN	50.2	1.320	1.960
GRU	88.4	1.184	1.690



Conclusions:

The gated recurrent network (GRU) and Simple RNN were both efficient to train and consistently provided best RMSE. The GRU has more RMSE consistency in cross validation. Future work should focus on further improvements for the GRU in personalization (single model for single client) and leverage the GRU to create signal of when a client will be out of range. Feature engineering should further be explored for data that is outside the core dataset of time / value / and patient.