

# Comparing Neural Network Methods to Predict Hypoglycemic Events

Tom Kirsh

November 7, 2022

## Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
<b>2</b>	<b>Methods</b>	<b>2</b>
2.1	Data Processing . . . . .	2
2.2	Predictive Modeling . . . . .	2
2.2.1	MLP . . . . .	3
2.2.2	RNN . . . . .	3
2.2.3	LSTM . . . . .	3
2.3	Anomaly Detection . . . . .	3
2.3.1	Autoencoder . . . . .	3
2.3.2	One-Class SVM . . . . .	3
<b>3</b>	<b>Results</b>	<b>3</b>
<b>4</b>	<b>Discussion</b>	<b>3</b>
<b>5</b>	<b>Conclusion</b>	<b>3</b>

## Abstract

Abstract is written at the end.

# 1 Introduction

Continuous Glucose Measurement Systems (CGMS) measure blood glucose levels by... These are prevalent in ... CGMS is typically used in people with Type I diabetes [source].

## 2 Methods

The data was collected using two CGM sensors attached to each participants' arms [cite Lisa's study]. Over a period of 16 weeks, participants' glucose measurements were collected from both sensors. Participants were randomly given a double-blinded CGM system, meaning they couldn't see their glucose measurements, or a blinded/unblinded CGM system. Out of the 40 participants, 22 were classified as high risk for hypoglycemic events, and indeed had multiple hypoglycemic events. We excluded 4 participants that had  $<10$  events and used 18 participants' data. Hypoglycemic events are defined as glucose levels  $<54$  mg/dL measured by both CGM sensors at the same time lasting  $\geq 15$  minutes.

### 2.1 Data Processing

Over the measurement time period, both sensors did not measure glucose simultaneously. There were periods where either the left or right sensor measured, neither sensor measured, and both sensors measured. Even when both sensors measured, there were small delays in time between the left and right sensors' measurements. To synchronize the left and right glucose measurements, only the times that both sensors were measuring were kept. To handle the small time delays ( $<15$  minutes), linear interpolation was used to map the measurements to a single time array [cite for linear interpolation] [cite for justification in signal processing] [cite in other CGM use?].

After the left and right sensors were interpolated, missing values were imputed using last-operation-carried-forward (LOCF) [cite]. The time series were transformed to into a Toeplitz matrix [cite]. During modeling, some sequences were padded with NaN values at the beginning of the signals and were not imputed with LOCF. During modeling, these values were mean-imputed.

Models were run on three different datasets of glucose measurements made from the left sensor, the right sensor, and both sensors.

## 2.2 Predictive Modeling

Multiple types of neural networks are compared to evaluate their performance, training time, and computational power to

### 2.2.1 MLP

The most basic neural network consists of an input layer, a hidden layer, and an output layer. Feedforward networks have been shown to have good classification predictions [cite] and thus we used different variations to mdoel on. Hyperparameters trained on were the number of layers (what makes it a "deep" network), the number of nodes in each layer, the learning rate, and the dropout rate.

### 2.2.2 RNN

The equations for Recurrent Neural Networks come from signal processing in electrical engineering. The state system... Time delay is intrinsic to the system and that determines the dynamics.

$$\vec{s}[n] = W_s \vec{s}[n-1] + W_r \vec{r}[n-1] + W_x \vec{x}[n] + \vec{\theta}_s \quad (1)$$

... This leads to the standard equations of RNNs.

$$\vec{s}[n] = W_r \vec{r}[n-1] + W_x \vec{x}[n] + \vec{\theta}_s \quad (2)$$

where  $W_r$  is the weight matrix for the previous state and  $W_x$  is the weight matrix for the input data.

$$\vec{r}[n] = G(\vec{s}[n]) \quad (3)$$

where the inputs into the RNN are  $\vec{x}[n]$ .

### **2.2.3 LSTM**

## **2.3 Anomaly Detection**

### **2.3.1 Autoencoder**

### **2.3.2 One-Class SVM**

## **3 Results**

## **4 Discussion**

## **5 Conclusion**