

Detection of physical activity using machine learning methods

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Abstract—In the case of diabetes mellitus physical activity does have a high effect on the glycemic state of the patients. This is especially regarding the patients with Type 1 diabetes mellitus, who need external insulin administration in their daily life. Nevertheless, physical activity – as one source of stress – is underrepresented in the decisions of patients and medical staff and in the decisions of the available automated glucose regulatory devices. The goal of the study was to build up a simulation framework for data generation and to assess which machine learning solution can be the most accurate in the identification of physical activity.

Index Terms—Machine Learning, Diabetes Mellitus, Physical Activity

I. INTRODUCTION

Diabetes mellitus (DM) is a chronic metabolic disease affecting millions of people worldwide. DM is connected to the insulin hormone. Insulin is the key protein which facilitates the entering of glucose molecules from blood plasma into several types of body cells. Hence, the blood glucose level decreases while the cells are able to use glucose as source of energy. In case of Type 1 DM (T1DM) the body is not able to produce insulin internally and the patients have to have external insulin administration. In case of Type 2 (T2DM) the body produces insulin, but often the effect of the hormone is not sufficient in terms of decreasing the blood glucose level [1].

One of the key components of the treatment for diabetics with T1DM is doing physical activity on a daily regimen which completes the external insulin administration and diabetic diet [2]. The stress caused by physical activity opens specific non-insulin dependent pathways in the cell-wall through which glucose is able to enter into the cells [3]. Thus, planned physical activity – beside its many positive effects – can help to regulate the blood glucose level and to increase the activity and effectiveness of the metabolic system. Due to this, the amount of externally administered insulin can be decreased if the physical activity is the organic part of the treatment [4].

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Nevertheless, not scheduled physical activity can be dangerous as well. If it is not considered by the diabetic patient during the calculation of necessary insulin amount, it can lead to overdosing of insulin which may lead to hypoglycemia [5]. Hypoglycemia is a dangerous condition for healthy people and even more risky for diabetics. The long-term hypoglycemic condition may cause ketoacidic conditions and lead to even coma or death over time. Thus, there is unquestionable need to consider the effect of physical activity in the daily life and especially if the treatment is semi-automatic, for example in case of insulin pump usage [6]. In the latter situation, the regulatory algorithms ought to take the scheduled and not scheduled physical activity into account. It is generally known that the physical activity causes the drop of the blood glucose level and increase of metabolic activity, with a certain time delay [7]. Namely, after the recognition of some sort of sports we still have time to intervene in to changing glycemic state. Still, after the recognition of the activity the algorithms should be prepared for the appearance of the already mentioned consequences. This is one of the biggest unsolved challenge in the research community, namely, to find ways which are satisfyingly capable to recognize and consider the unscheduled physical activity.

The capability of machine learning based models to recognize patterns is not questionable and it has proven in many applications related to biomedical engineering [8]–[11]. In case of diabetes treatment their also proven their usefulness [12]–[15].

In this study, we aimed to develop a machine learning application which is able to recognize physical activity using only available information about the patient. We did not categorize the type of the activity, only the recognition of its presence was the goal, however. Due to the lack of massive patient data we developed a platform by using the extended Jacobs T1DM simulator [16] for massive data generation. Our goal was to make our solution as realistic as possible in this proof-of-concept phase in order to be easily implementable and testable in case of real patient data.

The paper is structured as follows. First, we introduce the data generation platform, the determining properties of the generated data and the selected features. After, we detail the applied machine learning resources and methods. That comes the introduction and interpretation of our results which is followed by our conclusions and the directions of our future

work.

II. MATERIALS AND METHODS

A. Applied dataset

The primary goal of the study was to identify what machine learning algorithms are the most beneficial to be used for the detection of physical activity using only blood glucose measurements. In this study, we apply synthetic data generated by an extended version of the Jacobs T1DM simulator [17]. The simulator employs the Cambridge-model, however, it contains embedded physical activity submodel, which is an extension compared to the one presented in [18]. We applied the single hormone virtual patient population, where the simulator expects the insulin as control input only. The simulator provides 20 virtual patients with T1DM identified and validated based on a 3.5-day outpatient Artificial Pancreas (AP) study [17]. The simulator is open source, originally published on Github (https://github.com/petejacobs/T1D_VPP). In order to make the data generation part more realistic, we completed the simulator with Continuous Glucose Monitoring System (CGMS) model from [19].

The simulator is easy to parametrize with respect to carbohydrate (CHO) and insulin intake. We applied the following regimens by using randomization regarding time instances and amounts of CHO intake:

- The times of meal consumption randomly varied between -30 minutes and +90 minutes with respect to prescribed times. The default time instances in the simulator were: breakfast at 6 am, lunch at 12 pm and dinner at 6 pm.
- The amount of breakfast was set 35 ± 10 [g].
- The amount at lunch varied between 79 ± 10 [g]
- The amount at dinner varied between 117 ± 10 [g].
- The duration of physical activity varied between 30 minutes to 90 minutes.
- The blood glucose level at the beginning of the day varied between 160 ± 20 [mg/dL].

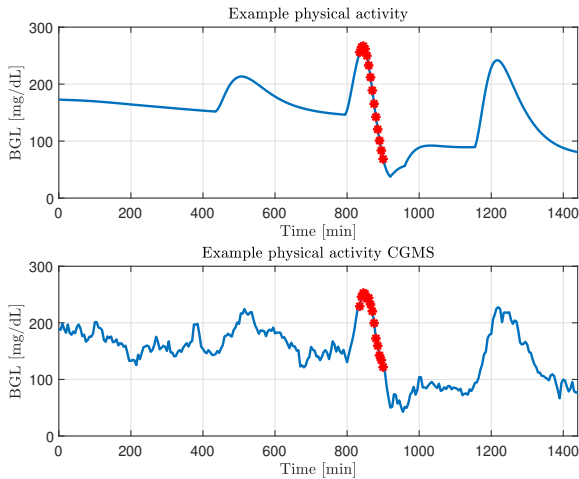


Fig. 1. Jacobs simulator model output indicating the physical activity with the red section on figure, without CGMS (top) and with CGMS (bottom)

The application of the CGMS model modifies the "pure" BG output value of the simulator - an example is given in Fig 1. We applied a realistic sampling time, namely, the blood glucose level was measured (simulated) by the CGM sensor every five minutes.

The synthetic data generation process were the following.

We have randomly selected 13 virtual patients from the available 20. During the data generation we did not change the parameters of the selected virtual patients.

For each patient, the simulation covered 640 days, not as a single very long simulation, but each day separately as a 24-hour simulation. Every day contained 288 sample points. We used a sliding window of 15 sample points to extract features. Samples within the sliding window were indexed from 0 to 14. Thus we extracted 274 data rows per day. Each sliding window was divided into three smaller inclusive windows of five consecutive sample in each, having indexes 0 to 4, 5 to 9, and 10 to 14, respectively. From each sliding window we extracted 32 features. The ground truth of the dataset are listed in the following:

- The patient's body weight w ;
- End-to-end blood glucose level change d defined as

$$d = bg(14) - bg(0) \quad (1)$$

- The blood glucose level variation between consecutive sampled points, or in other words the first order differences of blood glucose levels, defined as

$$dp(i) = bg(i + 1) - bg(i) \quad (2)$$

for any $i = 0 \dots 13$;

- End-to-end blood glucose level change in all inclusive sliding windows, defined as

$$dpp(i) = bg(5i + 4) - bg(5i) \quad (3)$$

for any $i = 0 \dots 2$;

- Second order changes of the blood glucose level, computed from 3 consecutive samples with the formula

$$\begin{aligned} ap(i) &= dp(i + 1) - dp(i) \\ &= bg(i + 2) - 2 \times bg(i + 1) + bg(i) \end{aligned} \quad (4)$$

for any $i = 0 \dots 12$;

- The decision dc , which is used as ground truth throughout this study.

The whole data set contains 2,279,680 entities. 95% of these represent measurements with no activity (0) and 5% with activity (1). Because of this strong imbalance we can say this is a so-called anomaly detection problem in machine learning.

B. Outcome of the prediction

The goal of this study is to evaluate the accuracy and effectiveness of various machine learning algorithms, when they are applied to predict the physical activity of patients. The outcome if the classification for each feature vector is binary, with the following two possibilities:

- 0 – No physical activity is currently performed by the patient.
- 1 – Physical activity is currently performed by the patient.

Some of the machine learning models (e.g. multi-layer perceptrons) involved in this study to predict the probability of physical activity ($p \in [0, 1]$). In these cases a threshold is applied to the predicted probability, so that it can be interpreted in binary mode. Other models (e.g. decision tree) provide binary output directly. Such models do not need threshold, as their output is either 0 or 1.

C. Tested machine learning models

This study involves eight different machine learning algorithms, some of them in multiple versions due to their parameter settings, totally resulting in 13 models. These models and their descriptions, together with their unique ID are presented below.

- *Logistic Regression* [20], with maximum 1000 iterations, and L2-type penalty (LogReg);
- *AdaBoost Classifier* (Ada) [21] with maximum 50 trees;
- *DecisionTree Classifier* (DecTree) [22], [23] with unlimited tree depth and all decisions allowed to use any one of the features;
- *Gaussian Naive Bayes* (Gauss) [24];
- *K-Nearest Neighbors Classifier* (KNN) [25] using $k - d$ tree implementation [26] and $k = 5$;
- *Support Vector Machines* [27] with 1000 iterations in five kernel variants: radial basis function kernel (SVM1), sigmoid kernel (SVM2), 3rd degree polynomial kernel (SVM3), 5th degree polynomial kernel (SMV4) and 10th degree polynomial kernel (SVM5);
- *Random Forest* [28], [29] with 100 trees (RF);
- *Multi-Layer Perceptron Networks* [30] with four hidden layers of sizes 100, 150, 100, and 50, respectively, maximum 1000 iterations, and three variants of activation functions: logistic (MLP1), ReLU (MLP2), and tanh (MLP3).

To implement these classification models, we used Python v2.7 programming language [31] and the Scikit package [32].

The total amount of available data was split into two sets, as follows: 75% of the feature vectors were randomly selected into the train data set, while the remaining 25% were assigned as evaluation (test) data. Feature vectors in the train data set were shuffled, so that two consecutive vectors are not likely to come from the same patient and simulation day.

For those classification algorithm, which are able to predict probabilities, the best threshold was established at the end of the training. The trained classifiers were applied to predict the presence or absence of physical activity for all feature vectors of the test data set. Statistical benchmarks, those presented in the next subsection, were established for each algorithm. Further on, the ROC curve were drawn and the AUC values computed to evaluate the overall accuracy of the algorithms.

D. Performance evaluation

The performance evaluation of each model relies on the count of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). The following metrics were applied:

- Accuracy (ACC) represents the rate of correct decisions, defined as

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} , \quad (5)$$

- Recall, also known as sensitivity or true positive rate (TPR), is defined as

$$TPR = \frac{TP}{TP + FN} , \quad (6)$$

- Specificity, also known as true negative rate (TNR), is defined as

$$TNR = \frac{TN}{TN + FP} , \quad (7)$$

- Precision, also known as positive prediction value (PPV), is defined as

$$PPV = \frac{TP}{TP + FP} , \quad (8)$$

- False positive rate (FPR), is defined as

$$FPR = \frac{FP}{TN + FP} , \quad (9)$$

- F_1 -score (F_1), also known as Dice score, is defined as

$$F_1 = \frac{2 \cdot TPR \cdot TNR}{TPR + TNR} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} . \quad (10)$$

III. RESULTS AND DISCUSSION

Table I presents the confusion matrix for all tested classification models. Values presented in this table are normalized in each row. The classification can be called successful if the rate of both true positives and true negatives are high, typically above 0.8. Only the RF model achieved higher rate than 0.9 of both TP and TN, while KNN, AdaBoost, Decision Tree and all tested multi-layer perceptron models scored at both normalized indicators above 0.8. The three SVM models that used polynomial kernel apparently predicted the opposite.

Figure 2 presents the ROC curves of all classification models, while Figure 3 indicates the Area Under Curve (AUC) metric values, all values except those below 0.75. These two figures suggest that the Random Forest model performed the best, having AUC value of 0.98. However, knowing that an AUC above 0.8 can be considered as an excellent classification [33], KNN and all three MLP models, AdaBoost, and Decision Tree also produced acceptable classification.

Table II presents the accuracy indicator metrics values for all tested classification models, highlighting the best value in each column. The better the classification the higher the indicator value in all cases except FPR. Although SVM5 apparently achieved perfect TNR and FPR, it cannot be highlighted as best achieved value because it predicted negative for every

TABLE I
NORMALIZED CONFUSION MATRIX OBTAINED BY THE USE OF VARIOUS CLASSIFICATION METHODS

		Predicted value	
		0	1
0	LogReg	: 0.779	LogReg : 0.221
	Ada	: 0.833	Ada : 0.167
	KNN	: 0.980	KNN : 0.020
	DecTree	: 0.991	DecTree : 0.009
	Gauss	: 0.789	Gauss : 0.211
	SVM1	: 0.717	SVM1 : 0.283
	SVM2	: 0.743	SVM2 : 0.257
	SVM3	: 0.327	SVM3 : 0.673
	SVM4	: 0.311	SVM4 : 0.689
	SVM5	: 1.000	SVM5 : 0.000
	RF	: 0.961	RF : 0.039
	MLP1	: 0.864	MLP1 : 0.136
MLP2	: 0.863	MLP2 : 0.137	
MLP3	: 0.848	MLP3 : 0.152	
1	LogReg	: 0.221	LogReg : 0.779
	Ada	: 0.167	Ada : 0.833
	KNN	: 0.101	KNN : 0.898
	DecTree	: 0.166	DecTree : 0.834
	Gauss	: 0.211	Gauss : 0.789
	SVM1	: 0.284	SVM1 : 0.716
	SVM2	: 0.257	SVM2 : 0.743
	SVM3	: 0.673	SVM3 : 0.327
	SVM4	: 0.689	SVM4 : 0.311
	SVM5	: 1.000	SVM5 : 0.000
	RF	: 0.073	RF : 0.927
	MLP1	: 0.136	MLP1 : 0.864
MLP2	: 0.137	MLP2 : 0.863	
MLP3	: 0.152	MLP3 : 0.848	

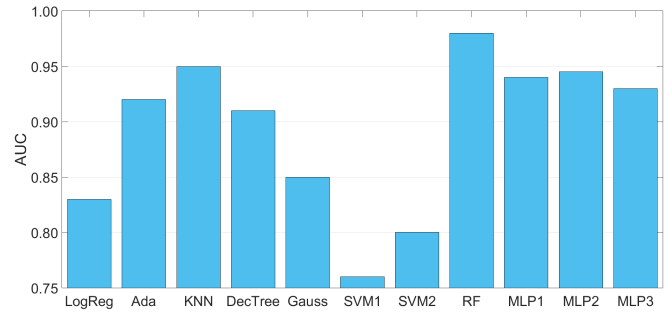


Fig. 3. AUC values obtained by various classification models

TABLE II
OBTAINED ACCURACY INDICATOR METRICS VALUES FOR ALL CLASSIFICATION MODELS

Classifier	PPV	TPR	F_1	TNR	FPR	ACC
LogReg	0.149	0.778	0.250	0.778	0.222	0.778
Ada	0.198	0.832	0.320	0.832	0.168	0.832
KNN	0.688	0.899	0.779	0.980	0.020	0.976
DecTree	0.813	0.833	0.823	0.990	0.010	0.983
Gauss	0.157	0.789	0.261	0.789	0.211	0.789
MLP1	0.239	0.863	0.374	0.863	0.137	0.863
MLP2	0.237	0.862	0.372	0.862	0.138	0.862
MLP3	0.217	0.848	0.346	0.848	0.152	0.848
RF	0.537	0.926	0.680	0.960	0.040	0.959
SMV1	0.111	0.716	0.193	0.716	0.284	0.716
SVM2	0.125	0.742	0.215	0.742	0.258	0.742
SVM3	0.024	0.326	0.044	0.326	0.674	0.326
SVM4	0.022	0.310	0.041	0.310	0.690	0.310
SVM5	0.000	0.000	0.000	1.000	0.000	0.953

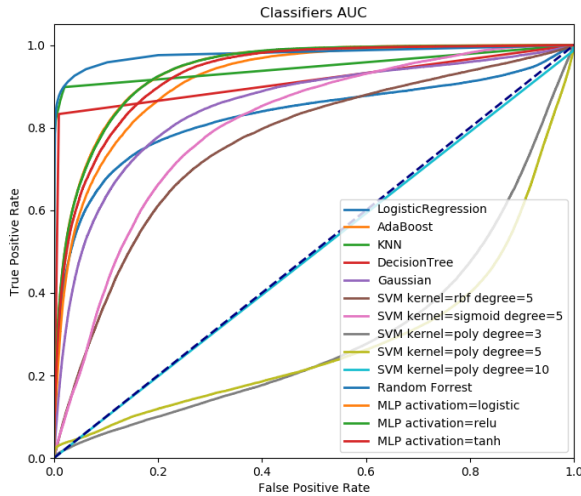


Fig. 2. ROC curve of models

tested feature vector. According to the results, DecTree has the most highlighted best values, while Random Forest has the highest Recall value. KNN is the model that also has acceptable values at all indicators. All others predicted too many false positives, which is best visible in the column of PPV values that penalizes false positives. Classifiers with finest outcome are those which have high values in both recall

(TPR) and positive PPV, namely, the Decision Tree, KNN, and Random Forest. The same benchmark is indicated by the F_1 -score column, which equally penalizes false positives and false negatives, and gives the highest values to the same three classification models.

To establish a unique ranking of the employed classification models, it is necessary to inspect those benchmark values, which penalize both kinds of mistaken decisions, namely false positives and false negatives. Recall (TPR) and specificity (TNR) together are able to characterize the accuracy of the classification performance, while the F_1 -score, which is the harmonic mean of TPR and TNR, unifies these two benchmarks into a single score. Having a high recall value is necessary for an accurate classification, because the rare positive cases need to be identified with a high probability. In case of a serious imbalance between actual positive and negative cases, it is good to have a TNR value very close to 1 (e.g. like DecTree and KNN in Table II), otherwise the number of false positives is too high. The high number of false positives in Table II is best reflected by the PPV benchmarks, which penalize true positives but discriminates more strongly than the TNR value. The last column of Table II reflects the rate of correct decisions also called overall accuracy (ACC), which in case of such imbalanced data (approx. 95% negatives and 5% positives), may lead to anomaly or mistaken conclusions. In this order, the ACC value is quite high for the

SVM5 classifier, which in fact predicts negative for all test data.

Based on the above criteria, we can assert that the three best classifiers for the given problem are the *Decision Tree*, *K-Nearest Neighbors* and *Random Forest*, which scored high at those benchmarks that penalize all mistaken decisions.

IV. CONCLUSIONS AND FUTURE WORK

This paper introduced a machine learning based framework for the detection of physical activity, using features extracted from blood glucose samples taken at five minutes intervals. Several classification models were involved in the study using various parameter settings. The statistical evaluation revealed that three of the tested models, namely the KNN, the Decision Tree and the Random Forest are the most suitable for the given problem, while several others can be made suitable but they need an extra mechanism to avoid the most part of the false positives. This sort of difficulty is quite common in classification problems where the amount of positives and negatives is imbalanced.

Future work will include collecting data from real patients and using them to validate classification algorithms that would detect physical activity. Further on, the developed model will be integrated into Apple watch and android mobile application, which will receive data from sensors, transmit the data to a database, and will make predictions, having the possibility to notify the doctor if the patient seems to be in bad condition.

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