AutoEncoder-based Detection of Insulin Pump Faults in Type 1 Diabetes Treatment

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INTRODUCTION

- Patients with T1D depend on lifelong insulin therapy to keep blood glucose (BG) levels within a healthy range.

- Technological advances, such as **CGM** and **insulin pumps (CSII)**, have improved T1D management by providing real-time glucose readings and automated insulin delivery.

- However, these devices are still prone to **malfunctions!**

INTRODUCTION

- **What is Insulin Pump Faults (IPFs)?**
  - IPFs = Malfunctions that stop or reduce insulin delivery without the patient being immediately aware.
  - **Examples:** Infusion set occlusions, kinks in the catheter, or hardware/ software errors that stop basal or bolus insulin delivery.

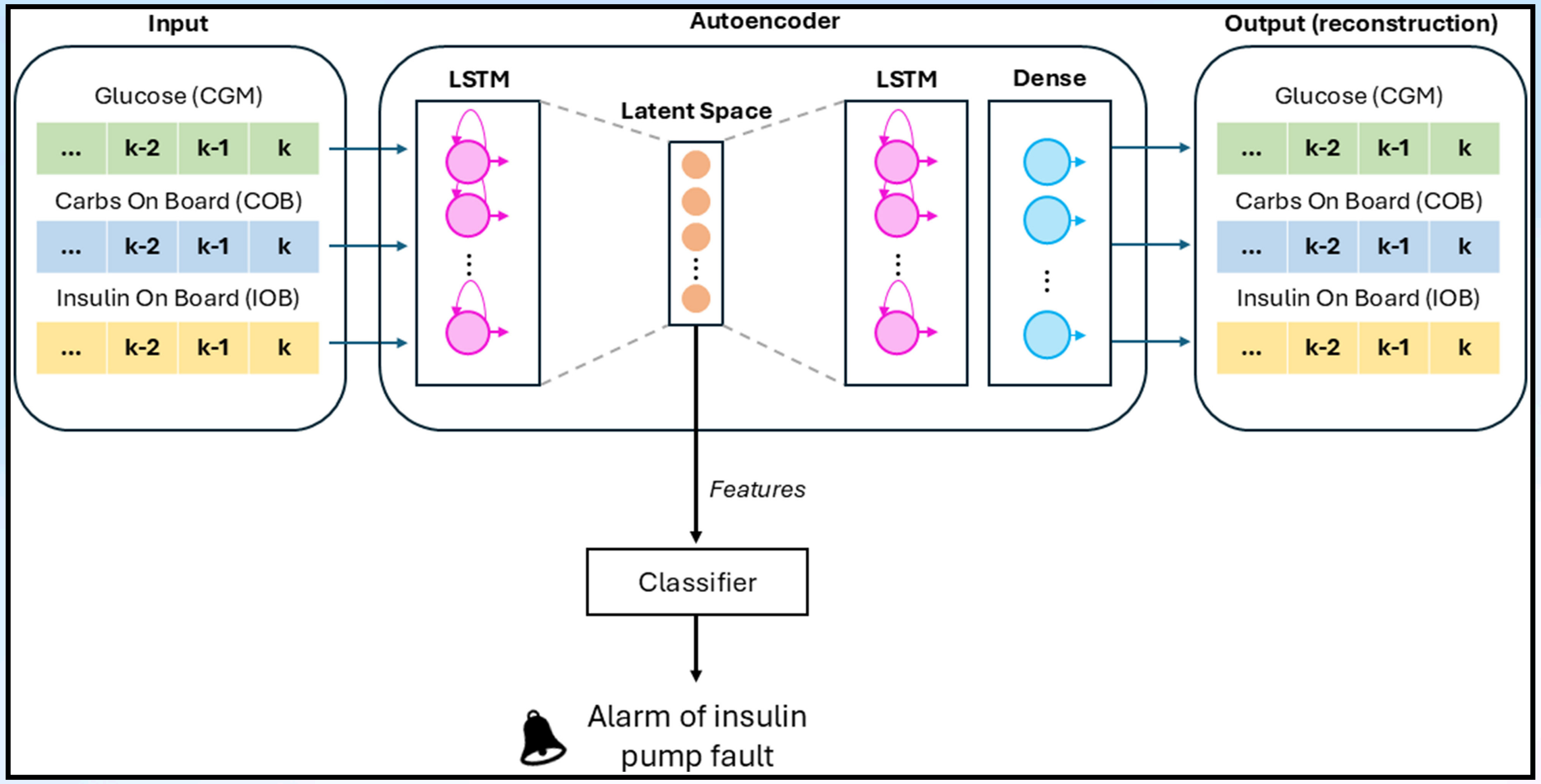
- **Why detecting IPFs is hard?**
  - Insulin effect is delayed (~45 min), so BG looks normal at first.
  - At night, faults are more dangerous since the patient is asleep.
  - Some pumps raise alarms, but many “silent occlusions” go undetected.

INTRODUCTION

- **Why detecting IPFs is important?**
  - Studies: 33–50% of patients experience undetected faults.
  - Detecting IPFs early is critical for safety and preventing long-term damage.
- **They addressed the problem of the real-time IPF detection by:**
  - Developing a deep learning approach
  - Based on a recurrent auto-encoder for the automatic feature extraction,
  - And a random forest classifier

METHODS

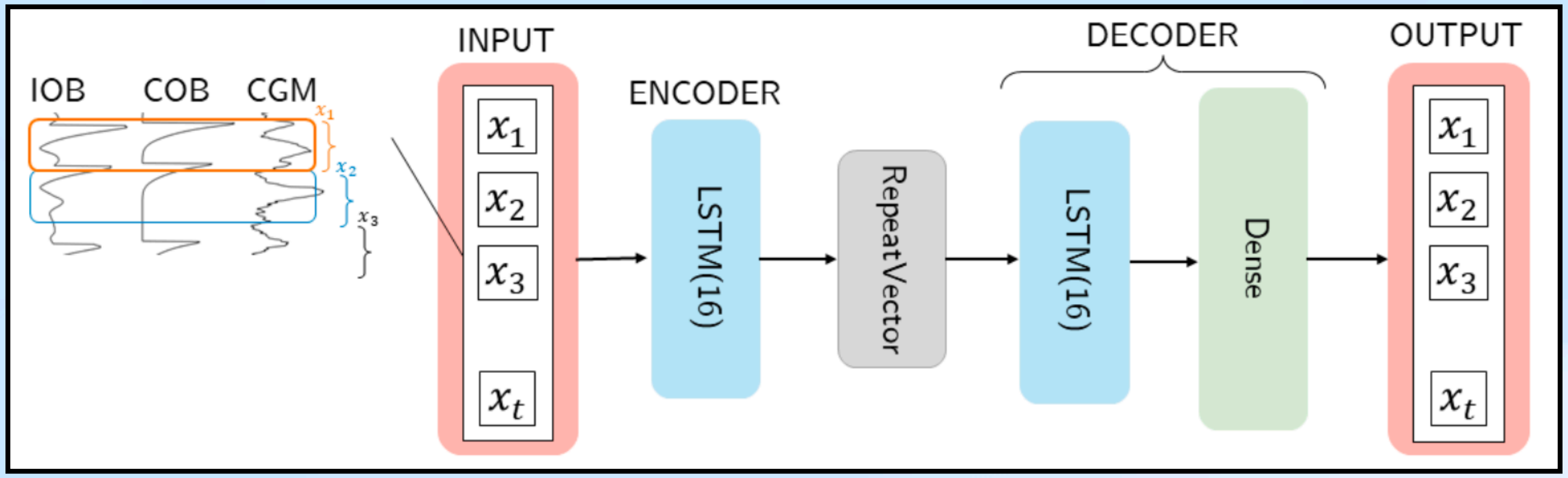
❖ Framework Overview



❖ Steps:

1. Data Preparation.
2. Feature Extraction with AE
3. Anomaly Detection with RF

AUTO-ENCODER

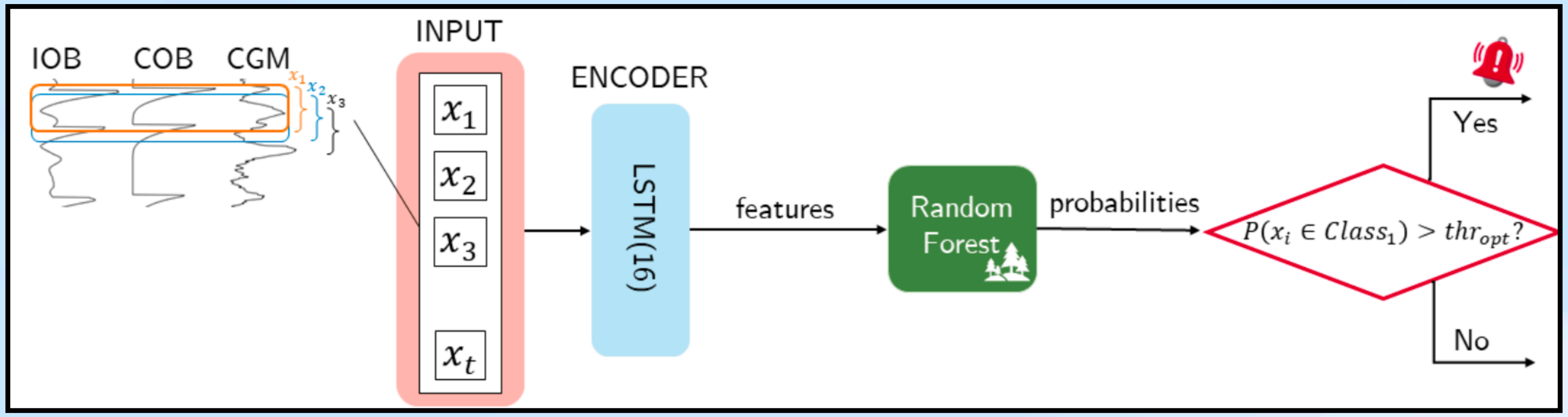


- Use an LSTM-based Auto-encoder (AE) to automatically extract meaningful, low-dimensional features from the multivariate time series.
- Learn normal patterns of glucose dynamics without manual feature design.
- The input of the encoder part is the sequence of CGM, IOB and COB defined as $X_t^{enc} = [x_{t-L+1}, x_{t-L+2}, \ldots, x_t] \in \mathbb{R}^{3\times L}$ where each vector at time t is $x_t = [CGM(t), IOB(t), COB(k)]$

AUTO-ENCODER

- **How it works?**
  - The AE is trained to reconstruct the input sequence as accurately as possible.
  - The encoder compresses the input sequence into a latent representation (16 features), which captures the essential dynamics.
- After training, the decoder is discarded, and the encoder is used as a feature extractor.

ANOMALY DETECTION



- Extracted features from the encoder are fed to a Random Forest (RF) to classify each sequence as normal or faulty.

- RF outputs probabilities for both classes and raises an **alert** if the fault probability exceeds a tuned threshold.

ANOMALY DETECTION

- The optimal threshold thr_{opt} minimizes:

$$J(thr) = \sqrt{\left(1 - Recall(thr)\right)^2 + \left(FP/day(thr)\right)^2}$$

- If the probability $\geq thr_{opt}$, the sample is classified as faulty.

- This threshold obtained during the training phase using a simple grid search.

DATASET

- ❖ **Simulator:** UVA/Padova T1D Simulator (FDA-accepted) — generates realistic BGL responses to insulin & carbs.
- ❖ Data: 2 synthetic datasets:
  - ✓ 100 subjects × 3 months.
  - ✓ Meals at random times with random carbs.
  - ✓ Basal insulin: MPC controller.
  - ✓ Bolus insulin: patient-estimated carbs.
  - ✓ Measurement every 5 minutes (CGM noise modeled)
  - ✓ Dataset 2: 1 nocturnal fault/month → simulated by stopping insulin delivery (basal & bolus) completely for 6 hours at night (midnight–6AM).

DATASET

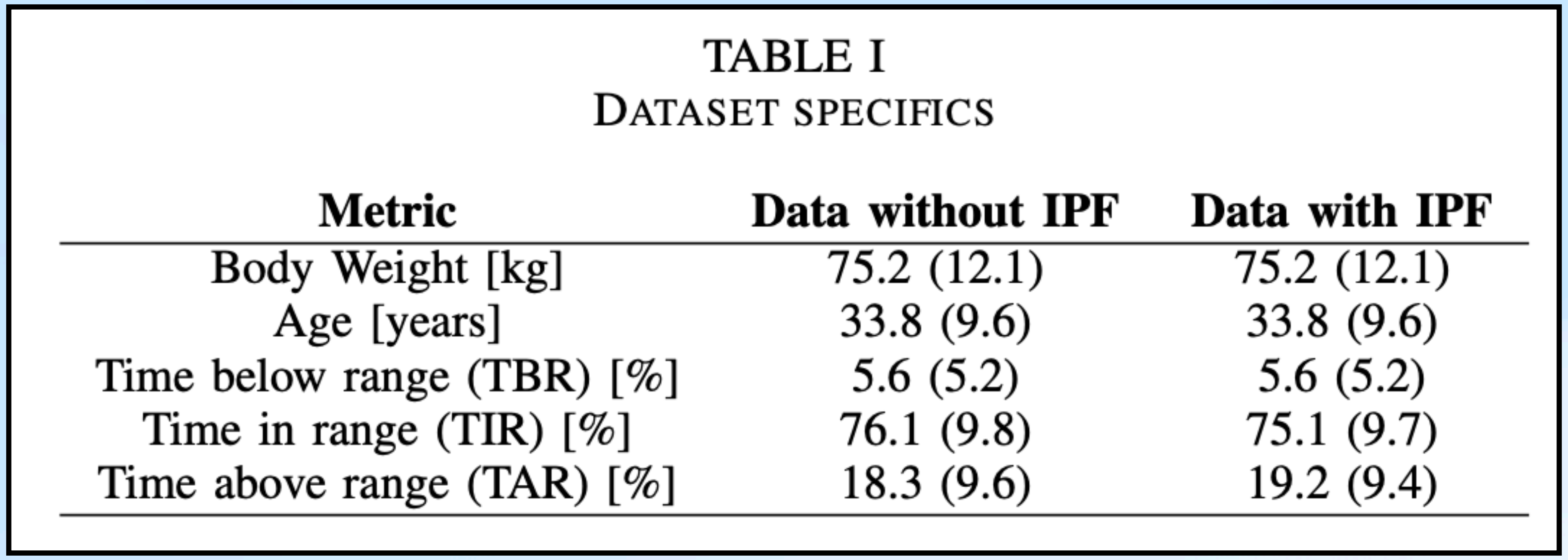


TABLE I
DATASET SPECIFICS

Metric	Data without IPF	Data with IPF
Body Weight [kg]	75.2 (12.1)	75.2 (12.1)
Age [years]	33.8 (9.6)	33.8 (9.6)
Time below range (TBR) [%]	5.6 (5.2)	5.6 (5.2)
Time in range (TIR) [%]	76.1 (9.8)	75.1 (9.7)
Time above range (TAR) [%]	18.3 (9.6)	19.2 (9.4)

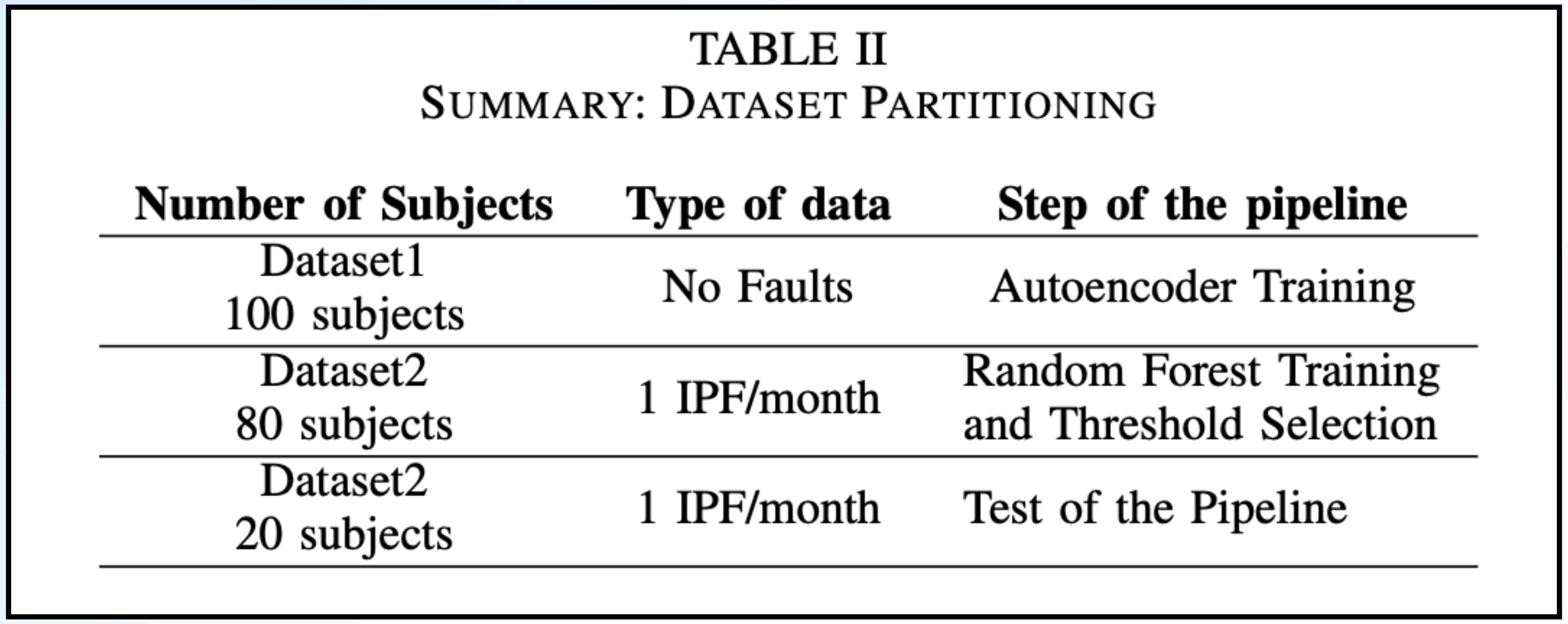


TABLE II
SUMMARY: DATASET PARTITIONING

Number of Subjects	Type of data	Step of the pipeline
Dataset1 100 subjects	No Faults	Autoencoder Training
Dataset2 80 subjects	1 IPF/month	Random Forest Training and Threshold Selection
Dataset2 20 subjects	1 IPF/month	Test of the Pipeline

EVALUATION CRITERIA

- **True Positive (TP):** Alarm during a fault.
- **False Negative (FN):** No alarm during a fault.
- **False Positive (FP):** Alarm without fault.
- **FP/day:** False positives per day.
- **Detection delay:** Time from fault start to alarm.
- **Recall (Sensitivity)**: $r = \dfrac{TP}{TP + FN}$

RESULTS

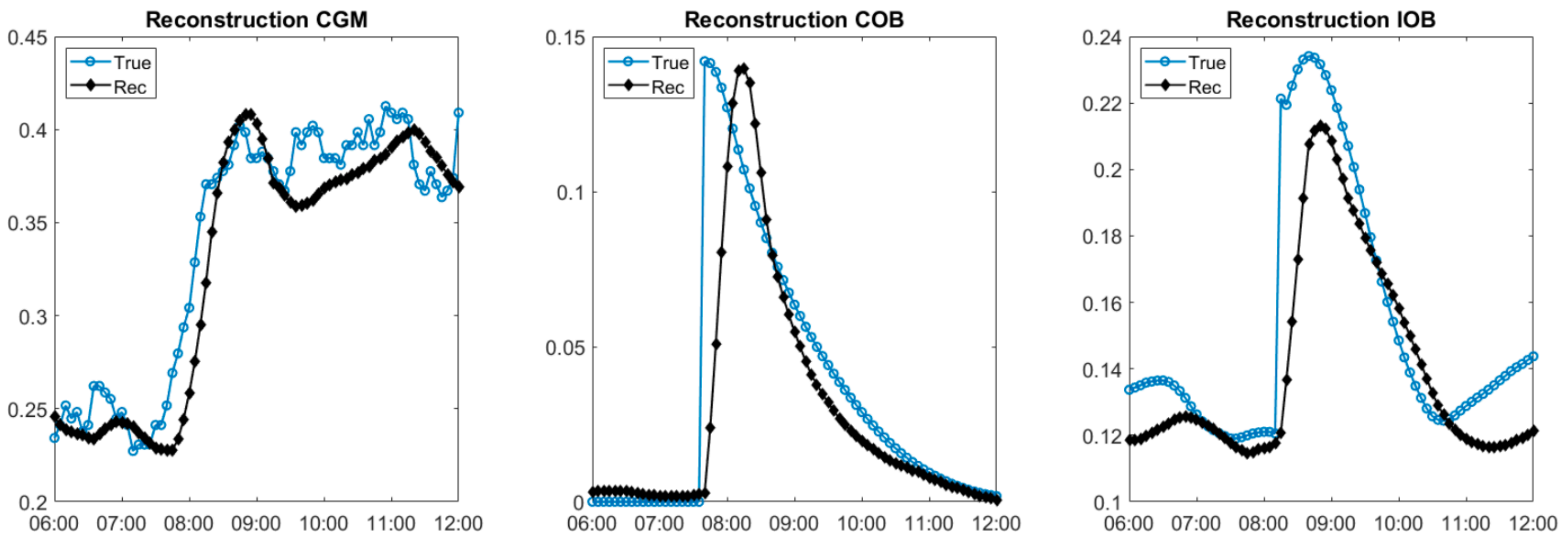


Fig. 2. Reconstruction of the inputs (CGM, COB and IOB respectively) on a training subject in absence of faults. The true signals are reported as blue solid line (circle markers), while the correspondent reconstructions are shown as linked black diamonds.

- Figure 2 reported the output of the AE where the reconstructed inputs are shown together with the original signals during 6 monitoring hours of a subject in the training set.

RESULTS

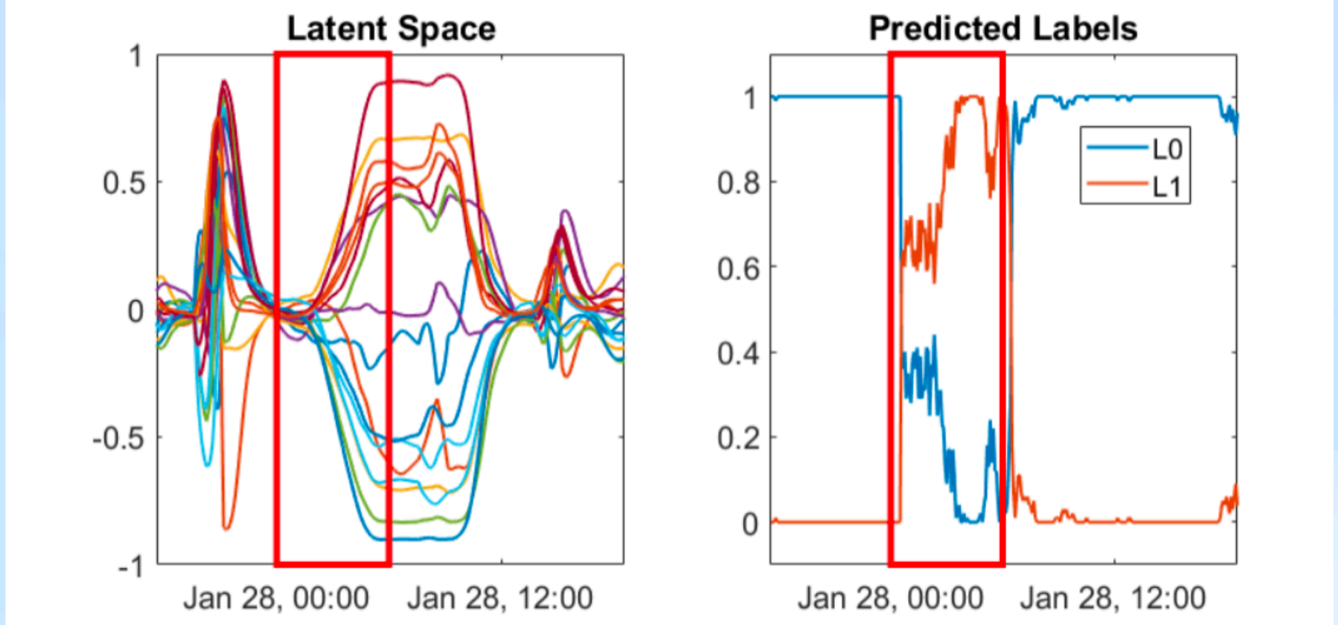


Fig. 3. In the left panel are reported the 16 features extracted with the encoder. The right panel shows the predicted probability computed by the Random Forest Classifier of belonging to that normal class ($L0$, in blue) or the anomalous one ($L1$, in orange). The red square indicates the occurrence of an insulin pump fault.

- The **left panel** shows the 16 latent features extracted by the encoder, which diverge sharply from normal patterns during a fault.

- The **right panel** shows the Random Forest's output probabilities, where the fault probability rises and crosses the threshold, triggering an alert.

RESULTS

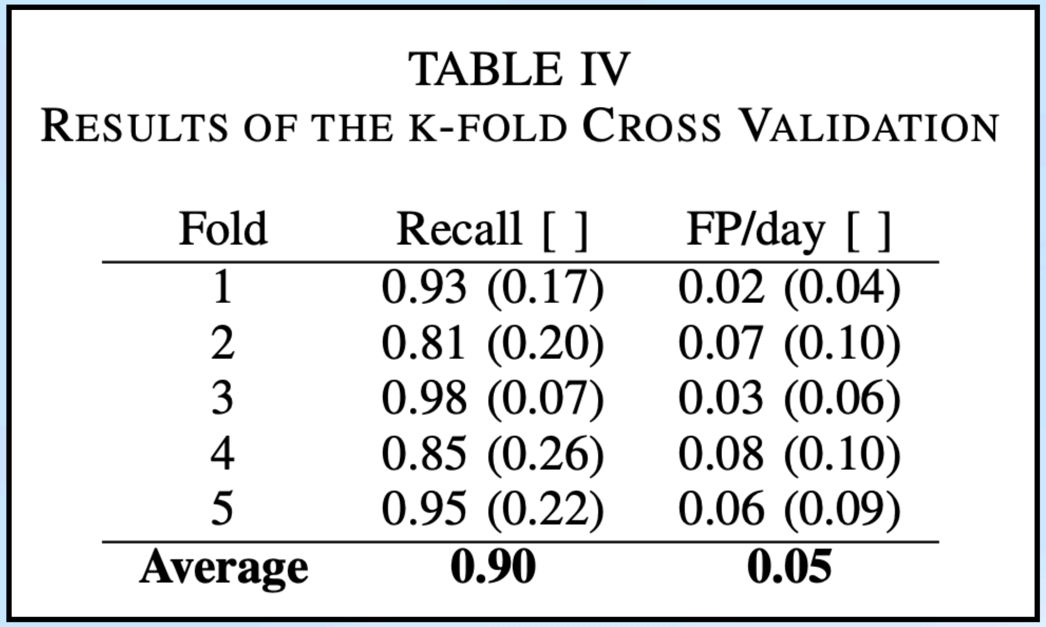


TABLE IV
RESULTS OF THE K-FOLD CROSS VALIDATION

Fold	Recall [ ]	FP/day [ ]
1	0.93 (0.17)	0.02 (0.04)
2	0.81 (0.20)	0.07 (0.10)
3	0.98 (0.07)	0.03 (0.06)
4	0.85 (0.26)	0.08 (0.10)
5	0.95 (0.22)	0.06 (0.09)
Average	**0.90**	**0.05**

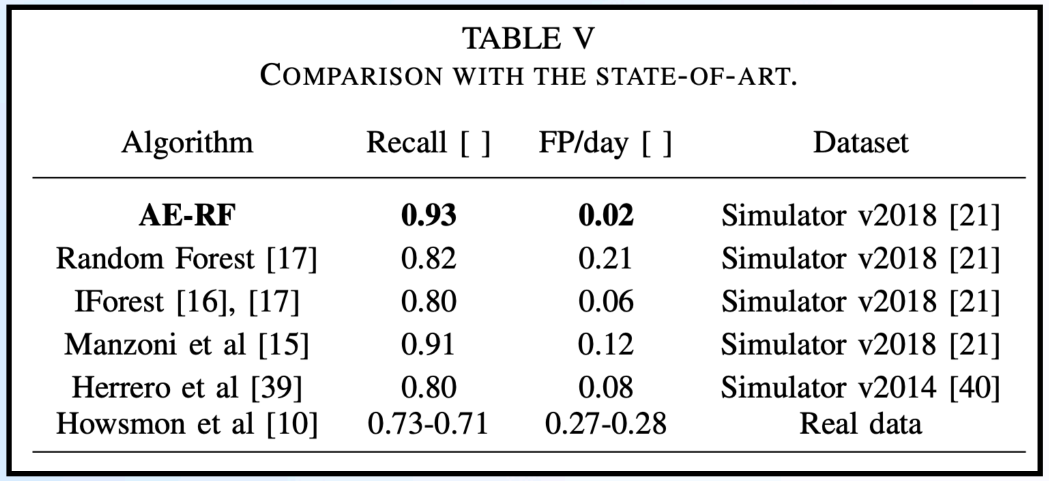


TABLE V
COMPARISON WITH THE STATE-OF-ART.

Algorithm	Recall [ ]	FP/day [ ]	Dataset
AE-RF	**0.93**	**0.02**	Simulator v2018 [21]
Random Forest [17]	0.82	0.21	Simulator v2018 [21]
IForest [16], [17]	0.80	0.06	Simulator v2018 [21]
Manzoni et al [15]	0.91	0.12	Simulator v2018 [21]
Herrero et al [39]	0.80	0.08	Simulator v2014 [40]
Howsmon et al [10]	0.73-0.71	0.27-0.28	Real data

- They employed **5-fold cross-validation**:
  - Dataset is **randomly partitioned** into 5 equally sized folds
  - Each fold is used as a test set once
  - The **remaining four folds** are used for training.
- This process is repeated 5 times, with each fold acting as the test set exactly once.
- Their approach is able to recognize the **90% of the IPF on average** while generating about 4 false alarms in 3 months.

RESULTS

- On average, **the algorithm detects a fault in ~220 minutes.**
- This delay is similar to clinical studies, where detection can take up to 4 hours.
- **In reality:**
  - If you have **accurate pump logs**, you can detect the fault **immediately** because the log shows “no insulin delivered.”
  - But if you only look at **blood glucose (BGL)**, you’ll notice the effect only **~2 hours later**, because insulin already in the body keeps working for a while.

Thank you for your attention