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Relapse Prediction from Long-Term Wearable Data using Self-Supervised Learning and Survival Analysis

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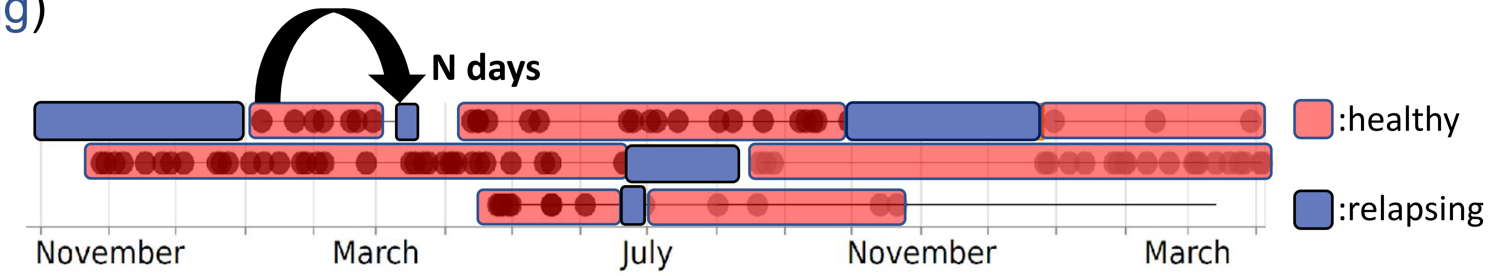
Other approaches

Classification:
- Data Imbalance (since relapses are rare)
- End-to-end limitations:
  - require labels during training
  - cannot handle additional unlabeled data, from patients whose **relapse status is unknown**

Anomaly Detection:
- Can use data from unlabeled patients
  - leveraging the existing oversupply of unlabeled data
  - learning **better representations**

Both:
- Don't provide information on the **proximity** of a user to relapse:
  - The system will detect anomaly or relapsing date only when they have already happened

Regression:
- Label = difference in days between the current date and the beginning of the relapse
- Loss of the information that the lighter colored dots provide for at least t event-free periods (right censoring)



Contribution - Motivation

- Combination of **Self Supervised Learning** and **Survival Analysis**
- Long-term data: *e-Prevention project* [1]
- **Self-Supervised pretraining:** representations from fully unlabeled, long-term, continuous recordings of biometric signals (commercial smartwatches)
  - Monitoring training procedure: **proxy Person IDentification** task
- **Learned representations** → **Downstream Survival Analysis** task → predict relapses on the data subset containing relapse labels
  - can handle right censoring, i.e., samples with no relapses in their future
- Combined with **handcrafted features:** (e.g., # of previous episodes) → promising results

[1] A. Zlatintsi et al., "E-Prevention: Advanced Support System for Monitoring and Relapse Prevention in Patients with Psychotic Disorders Analyzing Long-Term Multimodal Data from Wearables and Video Captures", *Sensors*, vol. 22, no. 19, Oct. 2022

e-Prevention project: http://eprevention.gr

Dataset I

Raw data:

- **38 patients**
  - 3-axis linear acceleration and angular velocity (sampled at 20 Hz)
  - heart beats per minute, and RR-intervals (sampled at 5 Hz)
- Ground truth relapse labels based on expert clinician assessments
  - **20 patients** had **one** or **more** relapses of varying duration and severity (**37 total relapsing incidents**)

Data Preprocessing:

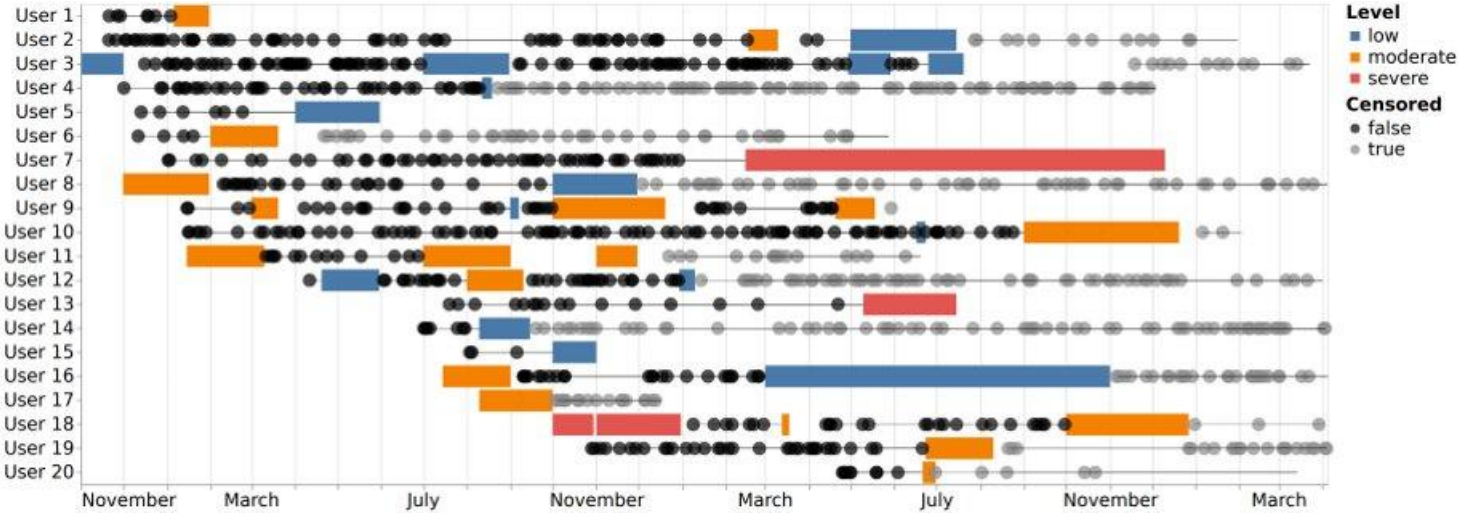
- **Excluded** data points:
  - outside the sensors' limit values
  - identical consecutive RR intervals
  - RR-intervals > 2000 ms or < 300 ms
- Linear interpolation, kept 1-hour recordings, where the heart rate sequence summed up to at least 54 min
- Applied 1-minute moving average filter (low-pass filtering → noise reduction)
- **Match** patients' daily activities with the time of day they occurred → $x_{\sin} = \sin\left(\frac{2 \cdot \pi \cdot \text{hour}}{24}\right)$ and $x_{\cos} = \cos\left(\frac{2 \cdot \pi \cdot \text{hour}}{24}\right)$

Dataset II

Dataset construction:

- **Three datasets**: consecutive measurements of **4, 8, and 12-hours**
- **Each dot**: 10-dimensional time series (preprocessed kinetic and physiological data + sinusoidal encoding)

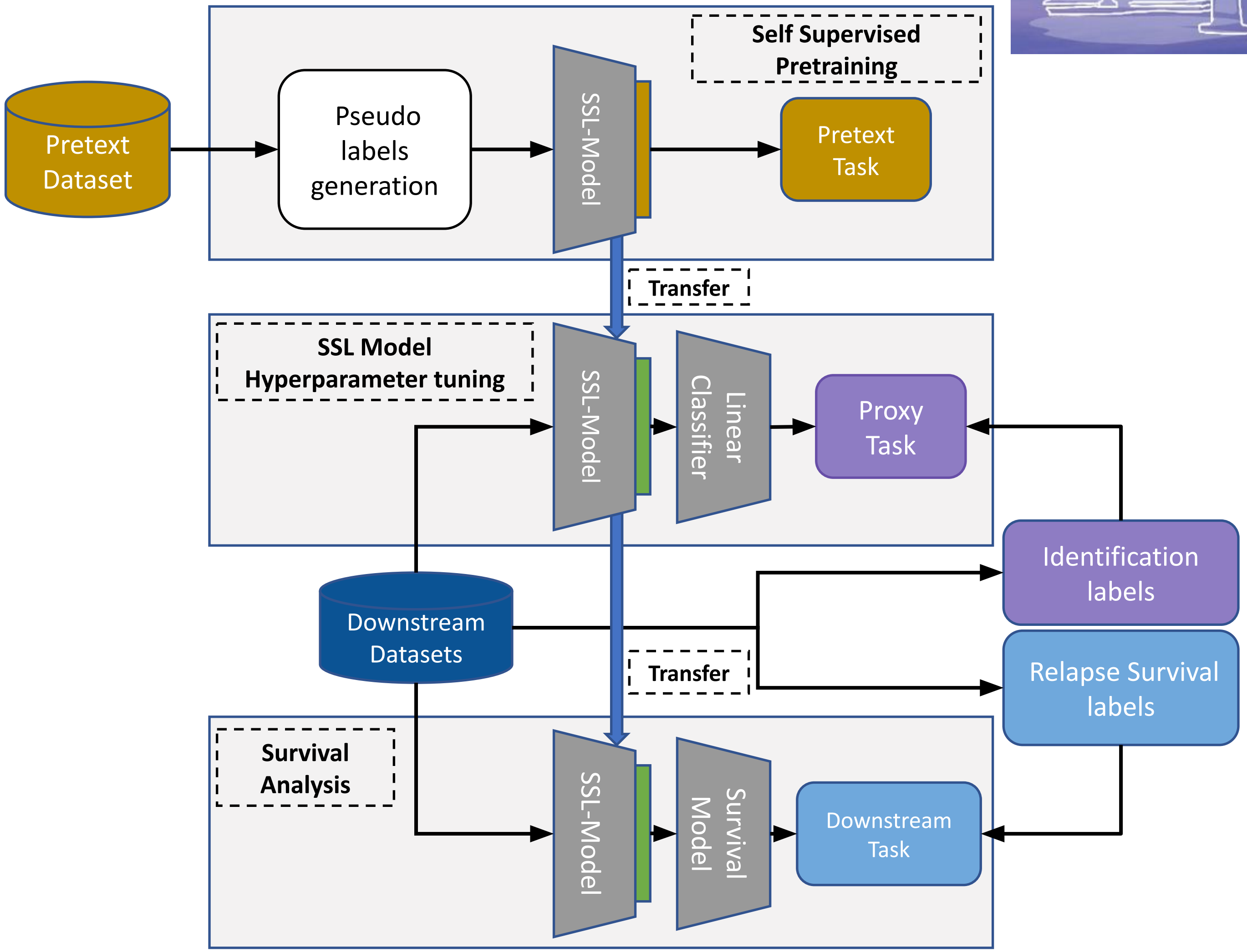
- **Pretext Datasets:** All **38 patients** with sample durations of **4, 8, and 12** non overlapping hours
- **Downstream Datasets:** Subsets of the Pretext datasets (only the **20 patients** with known relapses)



*We mark in **black** the days with an episode to their right, while in **gray**, otherwise. We also color the severity level of each episode differently, as shown in the legend.*

Methodology

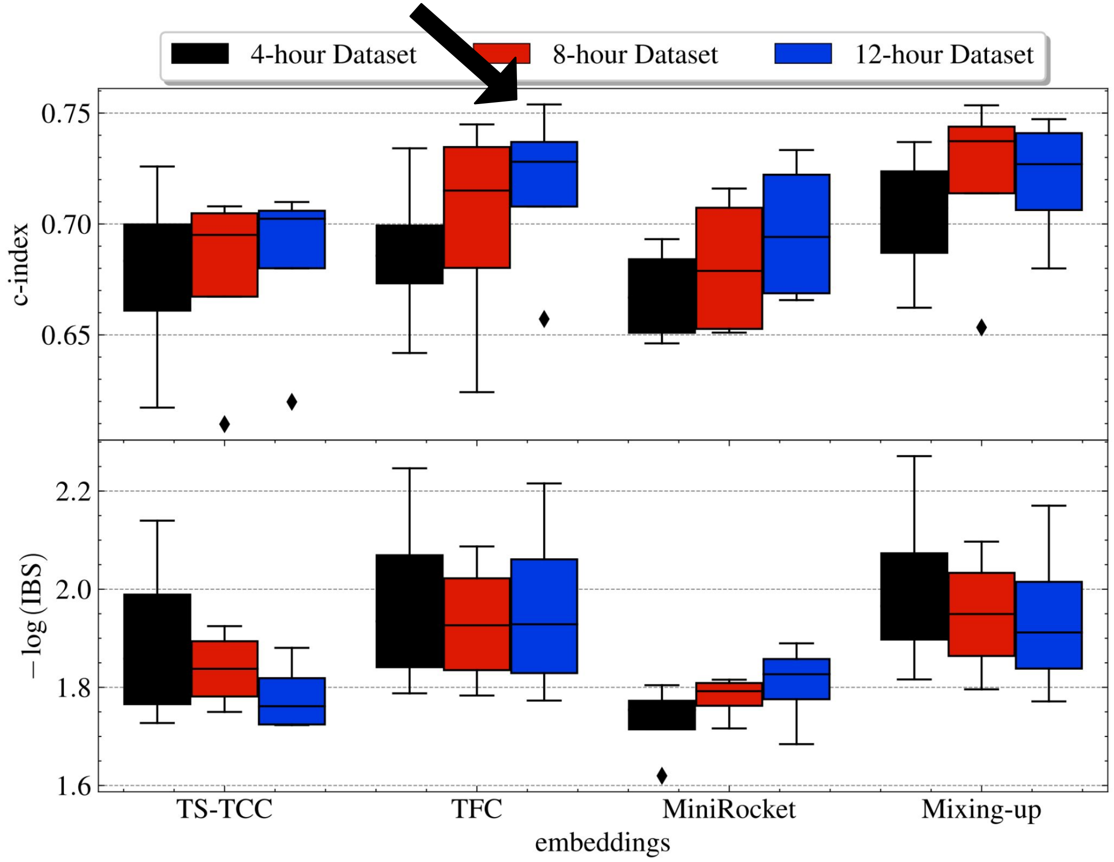
1. **Pretrain** 3-SSL frameworks on the **Pretext dataset**: Mixing-Up [1], TS-TCC [2] and TFC [3]
2. **Tune** embedding size and augmentation hyperparameters using **User IDentification as a proxy task** (linear classifier upon the learned representations)
3. Use Tuned+Pretrained and **MiniRocket** [4] (baseline) representations on **downstream dataset** using 4 survival-regression models: Conditional Survival Forest [5], Extremely Randomized Survival Trees [6], Neural MTLR [7] and DeepSurv [8]
4. **Evaluate** using C-index, Brier-Score (−log(IBS))



[1] K. Wickstrøm et al., Pattern Recognition Letters, 2022.
[2] E. Eldele et al., in Proc. IJCAI 2021.
[3] X. Zhang et al, in Proc. NeurIPS 2022.
[4] C. W. Tan et al., CoRR, vol.abs/2102.00457, 2021.
[5] N. Wright et al, Statistics in Medicine, 2017.
[6] P. Geurts et al., Machine Learning, 2006.
[7] S. Fotso, CoRR, vol. abs/1801.05512, 2018.
[8] J. L. Katzman et al., BMC Medical Research Methodology, 2018.

Embeddings Comparison

- Different deviations from stable behavior,
  - Concatenation of the one-hot-encoded user-ID with the embeddings
- 60/40% train/test ratio, train 4 survival models on top of the pretrained embeddings



Results:

- **SSL-based** embeddings generally outperform the Minirocket baseline
- **TFC embeddings** obtain the best results on the 12-hour dataset (using DeepSurv model):

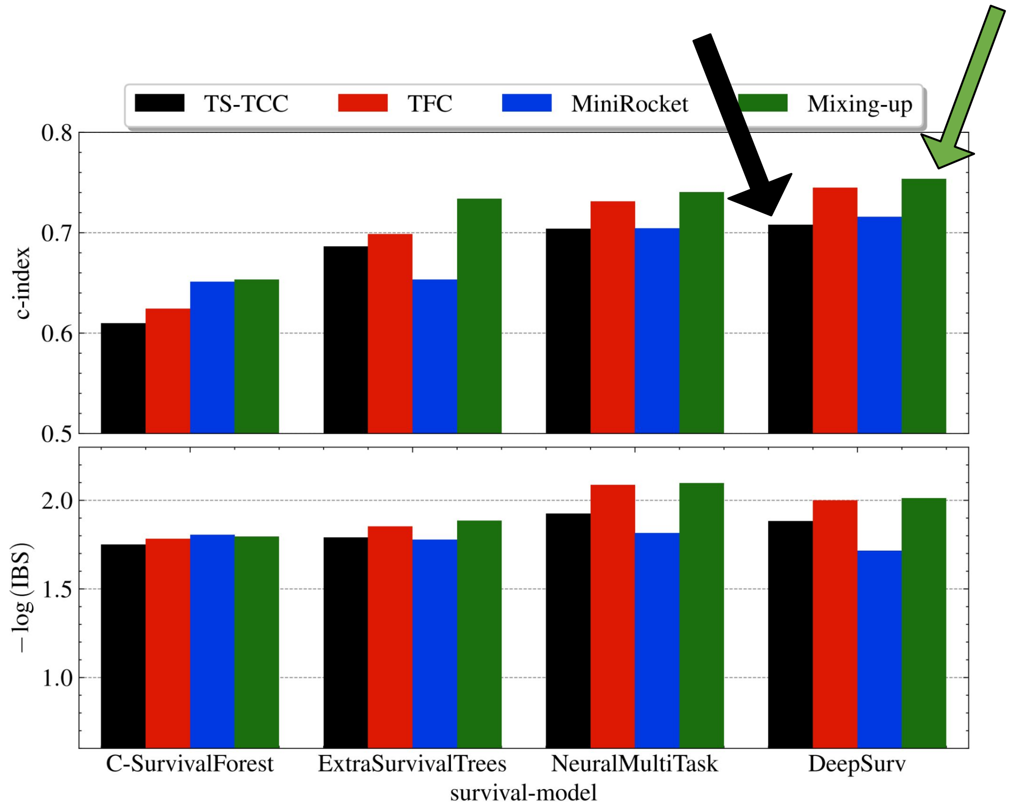
  C-index = 0.754 and **−log(IBS) = 2.012**

- **8-hour** and **12-hour**: better discrimination (higher C-index)
- **4-hour**: better calibration (higher −log(IBS))

Survival Model Comparison

We chose the **8-hour** dataset (highest C-index)

- The two deep-learning based methods:
    - **Neural MTLR** and **DeepSurv** have more capacity and thus obtain **better results**
- In terms of the pretrained embeddings and for the **DeepSurv** survival model that yields the best results
    - **TS-TCC** gives the worst results with C-index = 0.708
    - **Mixing-up** the best with C-index = 0.753



Feature importance and static features

Static features (st): associate users with similar characteristics

Features that change only after an event occurs:

- number of **previous episodes** (p ep)
- the **severity level of the last episode** (ll)
- whether the **last relapse was psychotic or depressive** (ps)

(+): included (−): excluded	C-index rel. change (%)	− log (IBS) rel. change (%)
− user's-ID	-23.74	-19.24
− heart rate	-1.66	-1.30
− hour-of-day	-1.15	-0.01
− accelerometer	-0.03	+0.22
− gyroscope	+1.94	+0.14
+ st	-1.39	-2.67
+ ps, p_ep, ll	+9.56	+14.17
+ st, ps, p_ep, ll	+11.60	+15.90

Feature importance framework:

- Pretrain models from scratch, **drop/add one feature at a time**
- **Decrease** in the model's score → **model depends on that feature**

Results:

- **Model focuses on:** user-ID, heart-rate, and hour-of-day alignment, and **less on kinetic sensors**
- Performance improvement when **removing the gyroscope data**
- Performance drops when we **solely add the static features**
- When **(st)** is combined with **information on past events**, we obtain the **best results**, with:
  - **C-index = 0.841** and **−log(IBS) = 2.329**

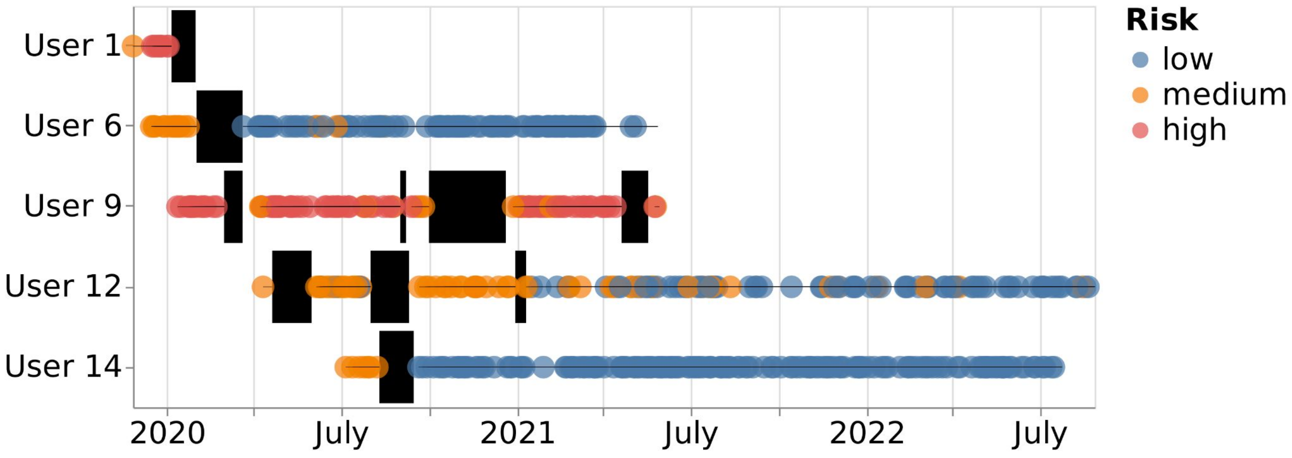
Results

Threshold the predicted risk scores into three categories: low, medium, and high

- User 1 has only a few pre-relapse samples and only **one relapse**
- Users 9 and 12 have many relapses
- Users 6 and 14 have **one** relapse and stay **event-free** for much time

Observations:

- low risk for patients who indeed stay risk free
- high or medium risks before the actual events



Conclusions

Combination of Self Supervised Learning and Survival Analysis for relapse prediction:

- Utilization of a large amount of unlabeled kinetic and physiological data through **Self Supervised Learning** ⟶ Useful intermediate representations
- Prediction of the time until the next relapse event through **Survival Analysis**

Promising results:

- SSL Representations > Minirocket Representations
- Static attributes that describe the past course of the patient's condition

Future work:

- **Fuse** wearable's data with other modalities: vision and/or audio
- Use available **control data**

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For more information and project results, visit https://eprevention.gr

e-Prevention
Advanced Support System for Treatment Monitoring and Relapse Prevention in Patients

European Union
European Regional Development Fund

EPAnEK 2014-2020
OPERATIONAL PROGRAMME
COMPETITIVENESS
ENTREPRENEURSHIP
INNOVATION

ΕΣΠΑ
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