THE 2ND E-PREVENTION CHALLENGE: PSYCHOTIC AND NON-PSYCHOTIC RELAPSE DETECTION USING WEARABLE-BASED DIGITAL PHENOTYPING

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ABSTRACT

The 2nd e-Prevention challenge[1] aims to foster innovative research in the prediction and identification of mental health relapses by analyzing and processing the digital phenotype of patients within the psychotic spectrum. The challenge offers participants access to extensive, continuous recordings of raw biosignals from wearable sensors such as accelerometers, gyroscopes, and heart rate monitors integrated into smartwatches. Participants are tasked with utilizing the provided data to develop digital phenotypes that accurately capture behavioral patterns and traits in patients. The evaluation focus on two main objectives: first, the detection of non-psychotic relapses, and second, the detection of psychotic relapses.

Index Terms— relapse detection, psychotic disorder, biometrics, smartwatch

1. INTRODUCTION

For over six decades, research in neurobiology and neurophysiology has sought to unravel the mysteries of psychotic disorders such as bipolar disorder and schizophrenia. However, understanding their etiology remains challenging, hindering the development of effective biomarkers [1] for tracking these disorders. Early detection and symptom management are critical for better patient outcomes.

The advent of wearable technologies, such as smartwatches and fitness trackers, has birthed the interdisciplinary field of digital phenotyping [2]. This field quantifies human traits and behaviors, aiding in health monitoring and predictive analytics in areas like emotional well-being and physical activity. While the lack of public, diverse datasets remains an important hurdle, wearables promise beneficial shifts from hospital care to proactive, tailored mental health care.

The first e-Prevention Challenge [3], hosted at ICASSP 2023, showcased the potential of digital phenotyping in modeling microbehavior and predicting progression of psychotic illnesses. Participants achieved high accuracy in user identification, offering insights for discovering indications of psychotic relapses [4]. The second track saw participants producing promising results employing deep unsupervised methods for detecting psychotic relapses. All these directions contributed significantly to detect relapses, emphasizing the necessity for further research and improvements in outcomes.

Building on this momentum, the 2nd e-Prevention Challenge further advances the field by providing participants with raw data, long-term temporal information, and patient demographics while respecting privacy guidelines. The challenge focuses on two tasks: detecting relapses in patients with and without psychotic symptoms. Participants are required to address the challenges using unsupervised methods, treating them as anomaly detection tasks. This approach aligns with the data scarcity during relapse states, facilitating early detection of signs in mental health patients.

2. THE E-PREVENTION PROJECT AND DATASET

During the course of the e-Prevention project [5], a total of 60 people (37 patients on the psychotic spectrum and 23 healthy controls) were recruited at UMHRI in Greece. Participants were provided with a Samsung Gear S3 smartwatch that monitored the user's linear and angular acceleration, heart rate and RR intervals (time between successive heartbeats), sleeping schedule, and steps. This information was continuously collected from the patients for a monitoring period of up to 2.5 years. During the study, the clinicians annotated patients' relapse periods according to their monthly assessments and communication with the attending physician or the family. The resulting dataset [5] is one of the largest of its kind, comprising approximately $20,000$ human-days of data from all participants.

3. CHALLENGE TRACKS & BASELINES

A relapse is defined as a clear clinical deterioration of patients with the reappearance of psychotic symptoms (delusional ideas, hallucinations) or with the occurrence of manic, depressive, or mixed episodes **with or without the presence of psychotic symptoms**.

In the context of this challenge, participants are tasked with detecting two types of relapses in patients: **1) non-psychotic relapses**, which are relapses without psychotic symptoms, and 2) **psychotic relapses**. For this purpose, two carefully curated stratified subsets were sampled from the patient subgroup of the ePrevention dataset, considering the occurrences of both non-psychotic and psychotic relapses. The challenge for participants in both tracks is to apply unsupervised methods to these data, treating the task as an anomaly detection problem. As such, the training set contains only data from stable patient states, while the validation/testing sets include both stable and relapsing states. The statistics of the final datasets for both tracks can be seen in Table 1.

In both tracks, daily patient state evaluations are conducted. Due to the task's nature, the final metrics comprise the average PR-AUC and ROC-AUC scores, calculated across daily predictions.

	# Patients	# Days Per Patients		
		Train	Val	Test
Track 1	9	187±22	86±13 (28±13)	89±18 (37±16)
Track 2	8	195±33	82±26 (28±26)	78±23 (29±14)

Table 1. Data statistics of the two tracks. Numbers in parentheses denote relapse days.

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[1]`https://robotics.ntua.gr/icassp2024-eprevention-spgc/`

	Method	PR-AUC	ROC-AUC	AVG
Track 1	SRPOL [8]	0.620	0.711	0.666
	MagCIL [9]	0.642	0.651	0.646
	Jackalope [10]	0.574	0.595	0.584
	Baseline	0.485	0.560	0.523
	Random Chance	0.430	0.500	0.465
Track 2	Jackalope [10]	0.444	0.563	0.504
	CHI-EIHW [11]	0.493	0.505	0.499
	SCRB-LUL [12]	0.424	0.569	0.496
	Baseline	0.412	0.548	0.480
	Random Chance	0.347	0.500	0.424

Table 2. Final and baseline results for both tracks.

3.1. Baselines

For constructing the baselines[2] we follow the concept around [4, 6] which assigns anomaly scores based on the misclassification rate of a network trained to predict user identity. First, in the preprocessing stage, we extract the following features from the raw data using short-time analysis with a window length of 5 minutes: the mean, the standard deviation, and the root mean square of the RR-interval waveform, the mean of the heart rate waveform, the norm of the accelerometer signal, and the high-frequency power of the RR-interval waveform extracted using the Lomb-Scargle periodogram. Additionally, for each extracted sample, we incorporate the corresponding time of the day using cosine and sine functions [7]. Subsequently, we train a Transformer Encoder [7] that, given an input sequence of length L samples from a single day, predicts the identity of the participant. In order to perform the relapse detection task in an unsupervised way (anomaly detection), we extract features from the training set using the penultimate layer of the trained Transformer Encoder and train an Elliptic Envelope outlier detector on these features. At validation/test time the outlier detector is used to score features extracted from multiple windows for each day in the val/test dataset, the scores are averaged per day and then the average score is used as an anomaly score. Baseline results are presented in Table 2.

4. CHALLENGE RESULTS

A total of 21 teams actively participated, with 8 teams submitting solutions for both tasks. In Table 2, we present the results of the top 3 performing teams for both Tracks. It is important to note that the leading solutions universally rely on Transformer architectures augmented with effective outlier detection mechanisms.

In the first track, the SRPOL team [8] achieved the best performance by focusing exclusively on nighttime data, employing Soft Dynamic Time Warping, and utilizing Nearest Neighbor Ensembles. The MagCIL team [9] applied a vision transformer model for representation learning from augmented features and created a hybrid outlier based on either a one-class SVM or a simple Gaussian model. Jackalope [10], which achieved top-3 in both tracks, employed an identification technique to predict the time of day for each recording, using that to reveal changes in patients' routines.

In the second track, Jackalope combined their system with multi-layer perceptron heads, yielding the best detection results. There results highlighted that during many relapse days greater errors occurred, especially during nighttime. At second-place, CHI-EIHW [11] developed three separate autoencoders for heart rate, sleep, and acceleration data. Then, they computed Elliptic Envelopes and prototypical representations for each patient, yielding a distance-likelihood for a segment to be included in a relapse day. Finally, SRCB-LUL [12] trained a transformer encoder for patient identification, employing two losses: a cross-entropy loss and a prototype loss. They subsequently fed Elliptic Envelop outliers to reveal the outlier days in the dataset.

[2] https://github.com/filby89/spgc-eprevention-icassp2024/

5. CONCLUSIONS

In this paper, we have introduced the 2nd e-Prevention challenge, which is centered on the detection of relapses in patients with psychotic disorders using long-term, continuous data recorded from commercial smartwatches. We believe that this challenge is an important step towards advancing research on mental health monitoring through digital means, ultimately resulting into early prediction of mental health relapses.

6. REFERENCES

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