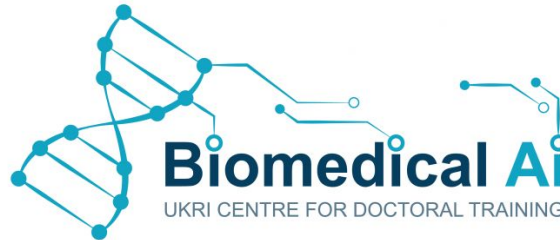


# Neural Networks and Self-Supervised Learning nei disturbi affettivi

Filippo Corponi  
MD, MSc, PhD Student in Biomedical AI

*april*



# A new paradigm?

Present



Some months later...



# A new paradigm?

Present



?

Some months later...



# A new paradigm?

Present

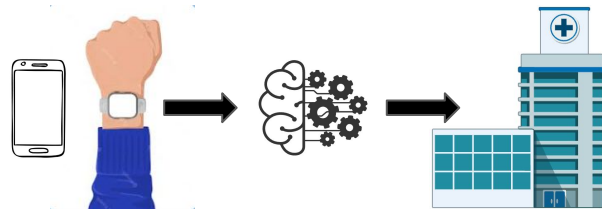


?

Some months later...



Future

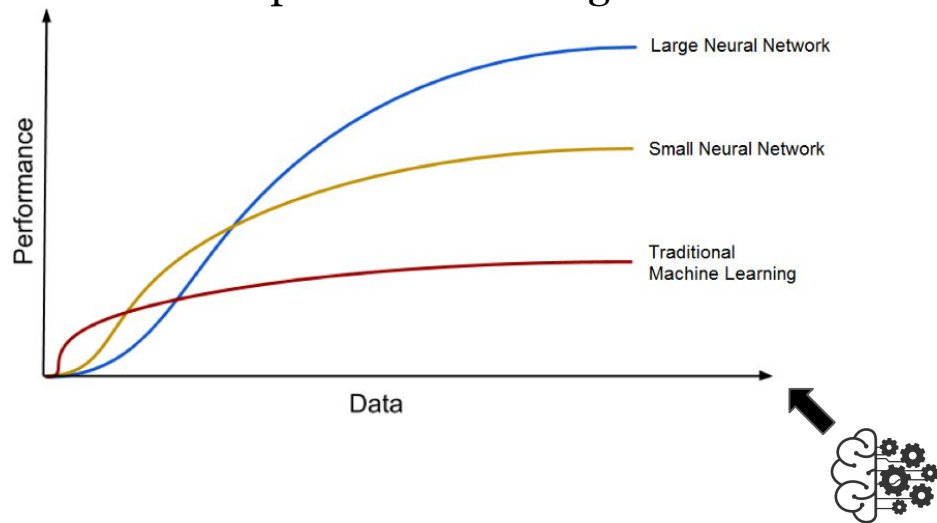


Monitoring / Early interventions



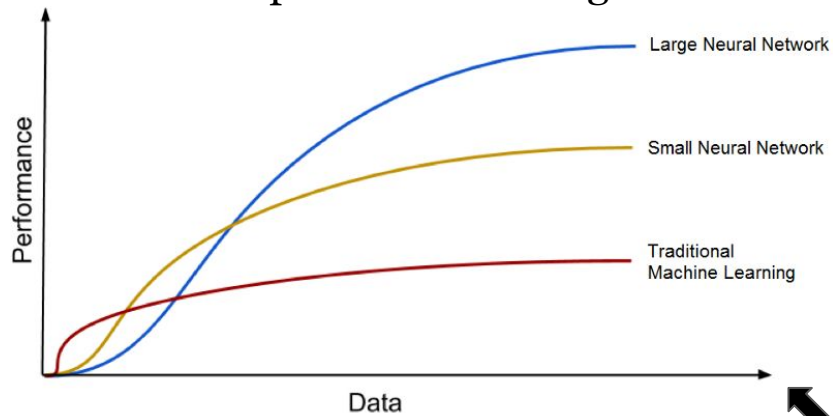
# Challenge

## Supervised Learning



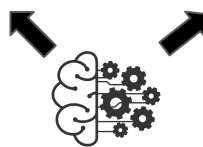
# Challenge

## Supervised Learning



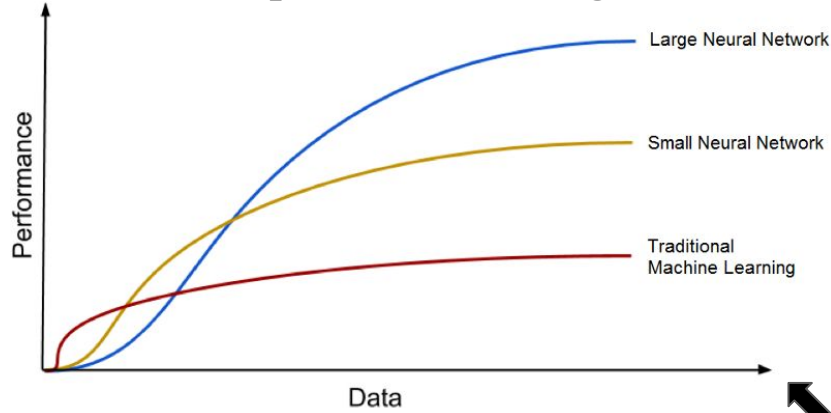
Labelling data is very resource-intensive

↪ psychiatrist assessment



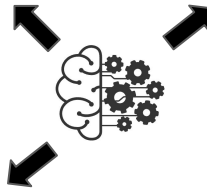
# Challenge

## Supervised Learning



Labelling data is very resource-intensive

↳ psychiatrist assessment

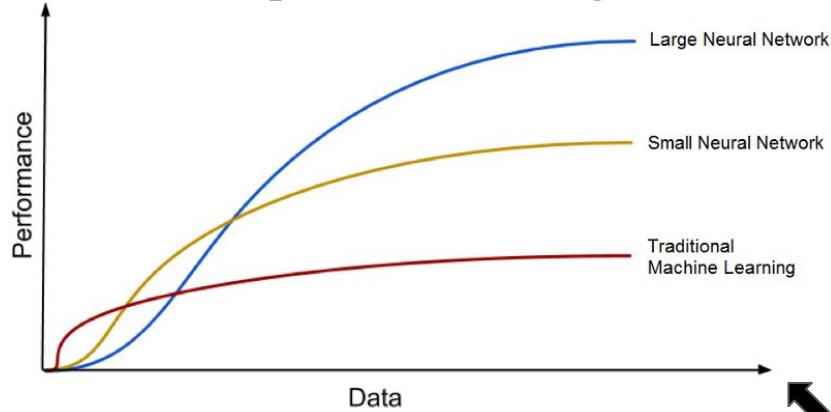


Unlabelled data is easier to source

↳ data not collected for other purposes

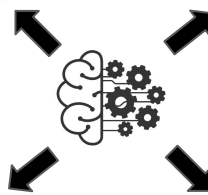
# Challenge

## Supervised Learning



Labelling data is very resource-intensive

↳ psychiatrist assessment



Unlabelled data is easier to source

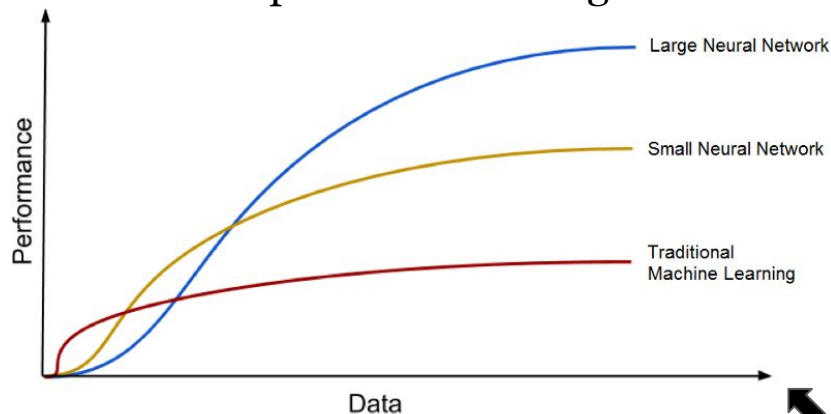
↳ data not collected for other purposes

Is it possible to learn from unlabelled data something useful towards our goals?



# Challenge

## Supervised Learning



Labelling data is very resource-intensive

↳ psychiatrist assessment

Unlabelled data is easier to source

↳ data not collected for other purposes

Is it possible to learn from unlabelled data something useful towards our goals?

↓  
Self-Supervised Learning

# **Mood Disorders**

Global prevalence: depression 4.4%, bipolar disorder 2.4%

# Mood Disorders

Global prevalence: depression 4.4%, bipolar disorder 2.4%

Depression is the second leading cause of chronic disease burden

(Years Lived with Disability)

# Mood Disorders

Global prevalence: depression 4.4%, bipolar disorder 2.4%

Depression is the second leading cause of chronic disease burden

(Years Lived with Disability)

Population-level economic burden: £6.43 billion

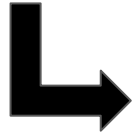
(UK-based estimate for 2018-2019)

# Mood Disorders

Relapsing remitting course

# Mood Disorders

Relapsing remitting course

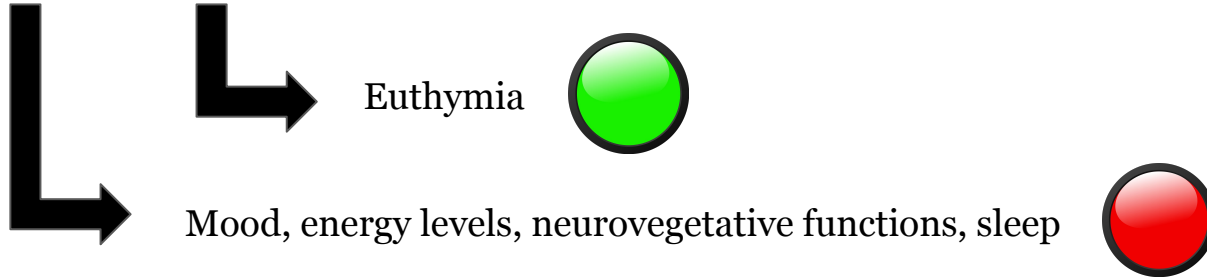


Euthymia



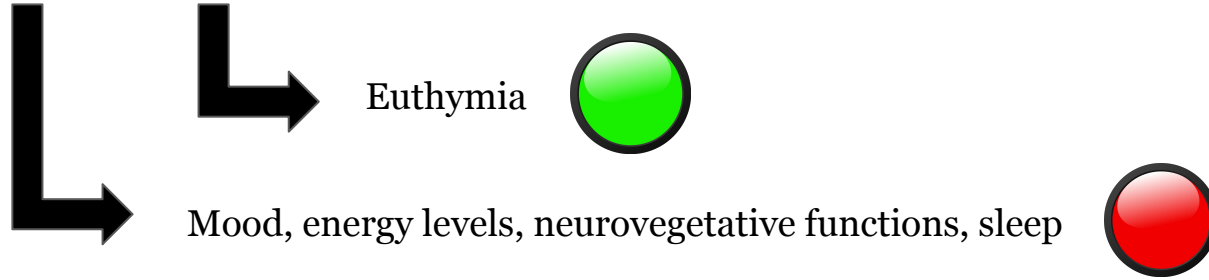
# Mood Disorders

Relapsing remitting course



# Mood Disorders

Relapsing remitting course



Binary classification as the simplest yet useful scenario



# Personal Sensing

Mood disorders' symptoms translate into changes in physiological parameters

# Personal Sensing

Mood disorders' symptoms translate into changes in physiological parameters

Wearable technology and AI

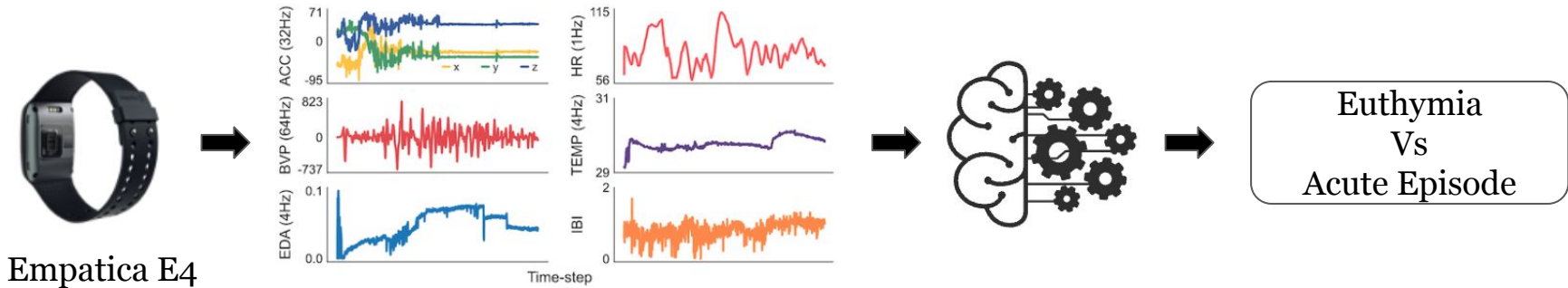
↳ near-continuous, passive, ecological monitoring ➡ early interventions

# Personal Sensing

Mood disorders' symptoms translate into changes in physiological parameters

Wearable technology and AI

↳ near-continuous, passive, ecological monitoring ➡ early interventions



# Motivation

Annotation\* is resource-intensive

\*Annotation: mood state of the person wearing the device as given by a specialist

# Motivation

Annotation\* is resource-intensive



Studies have limited sample size (dozens)

\*Annotation: mood state of the person wearing the device as given by a specialist

# Motivation

Annotation\* is resource-intensive



Studies have limited sample size (dozens)

Several unlabelled open access datasets

\*Annotation: mood state of the person wearing the device as given by a specialist

# Motivation

Annotation\* is resource-intensive



Studies have limited sample size (dozens)



Self-supervised Learning

Several unlabelled open access datasets



\*Annotation: mood state of the person wearing the device as given by a specialist

# Self-Supervised Learning

Pre-train model with **unlabelled data** on **surrogate task**

Step 1



# Self-Supervised Learning

Pre-train model with **unlabelled data** on **surrogate task**

Step 1

↓  
→ Model learns about the data

# Self-Supervised Learning

Pre-train model with **unlabelled data** on **surrogate task**

Step 1



Model learns about the data

Fine-tune model on **target task** with **labelled data**

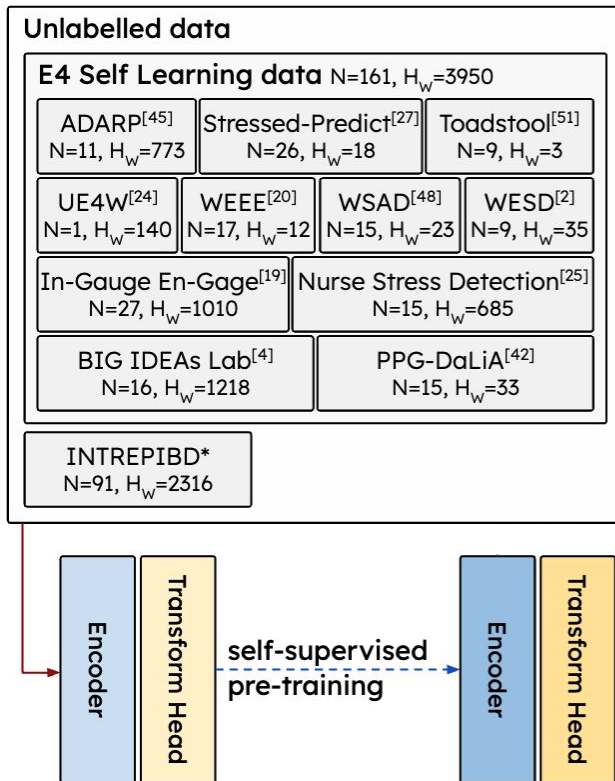
Step 2

# E4 Self Learning

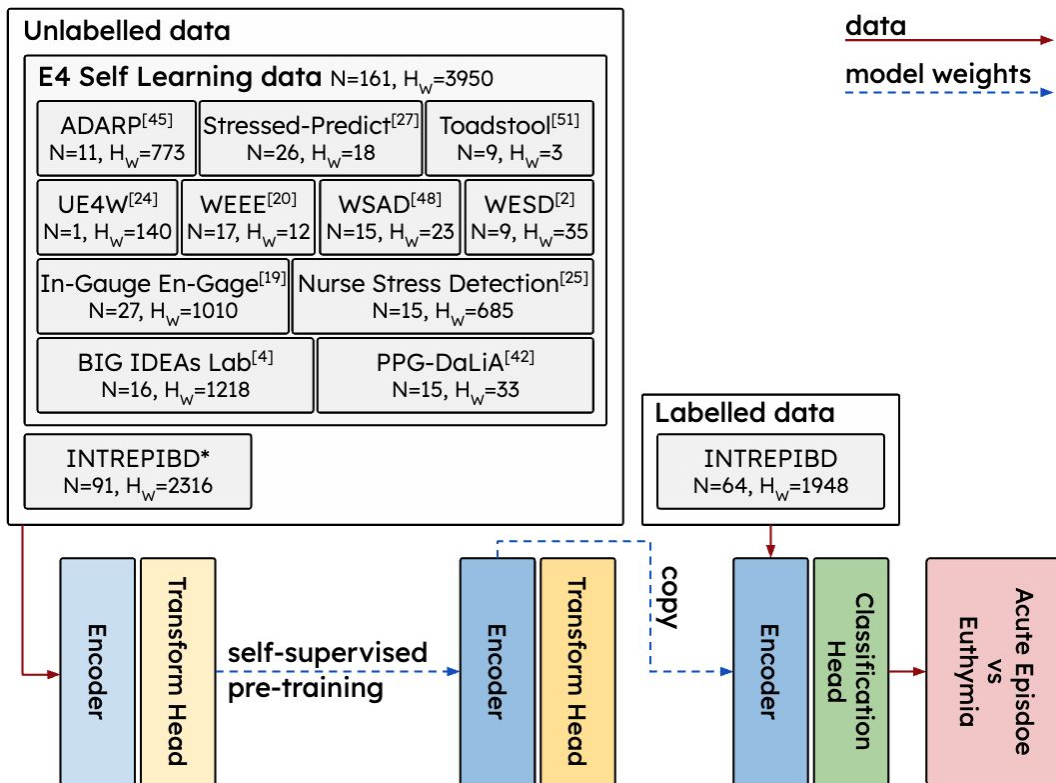
Unlabelled data			
E4 Self Learning data N=161, H <sub>w</sub> =3950			
ADARP <sup>[45]</sup> N=11, H <sub>w</sub> =773	Stressed-Predict <sup>[27]</sup> N=26, H <sub>w</sub> =18	Toadstool <sup>[51]</sup> N=9, H <sub>w</sub> =3	
UE4W <sup>[24]</sup> N=1, H <sub>w</sub> =140	WEEE <sup>[20]</sup> N=17, H <sub>w</sub> =12	WSAD <sup>[48]</sup> N=15, H <sub>w</sub> =23	WESD <sup>[2]</sup> N=9, H <sub>w</sub> =35
In-Gauge En-Gage <sup>[19]</sup> N=27, H <sub>w</sub> =1010		Nurse Stress Detection <sup>[25]</sup> N=15, H <sub>w</sub> =685	
BIG IDEAs Lab <sup>[4]</sup> N=16, H <sub>w</sub> =1218		PPG-DaLiA <sup>[42]</sup> N=15, H <sub>w</sub> =33	
INTREPIBD* N=91, H <sub>w</sub> =2316			



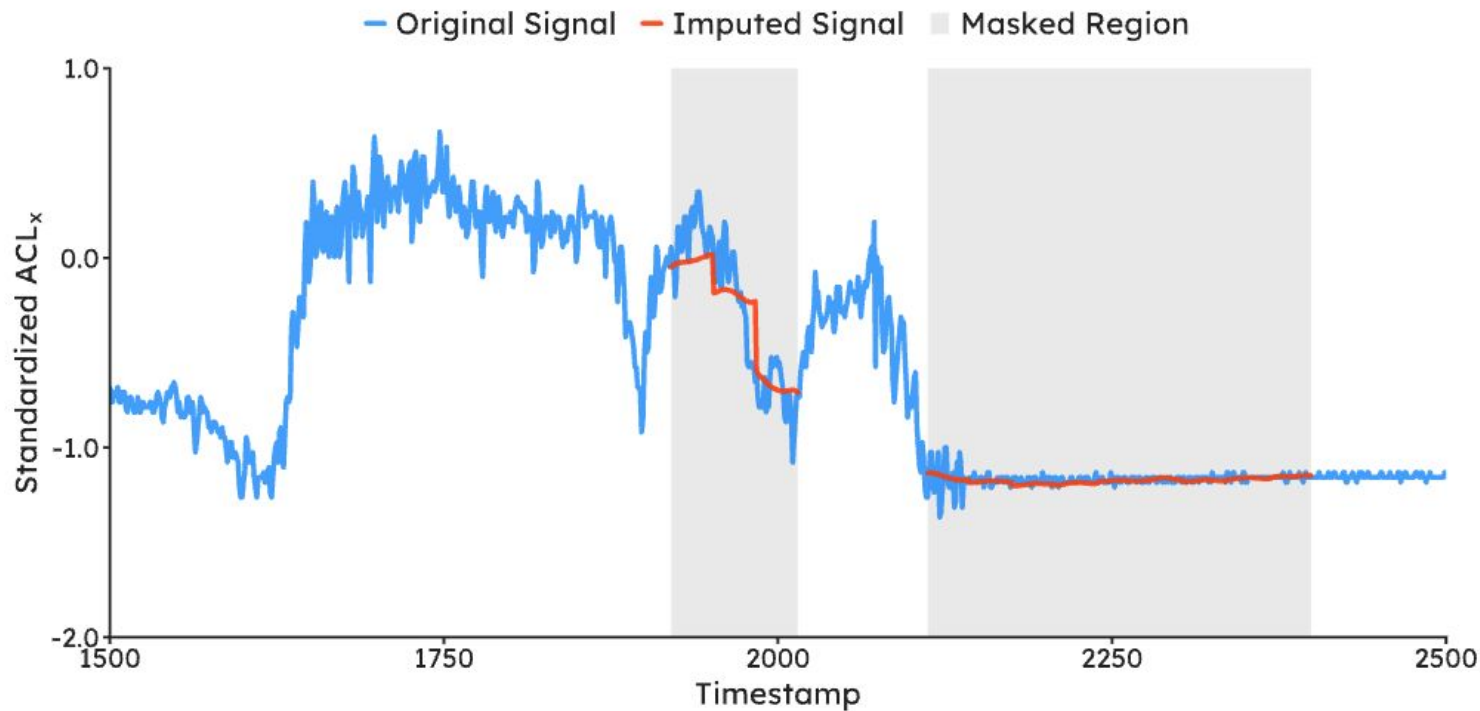
# Analyses Pipeline



# Analyses Pipeline

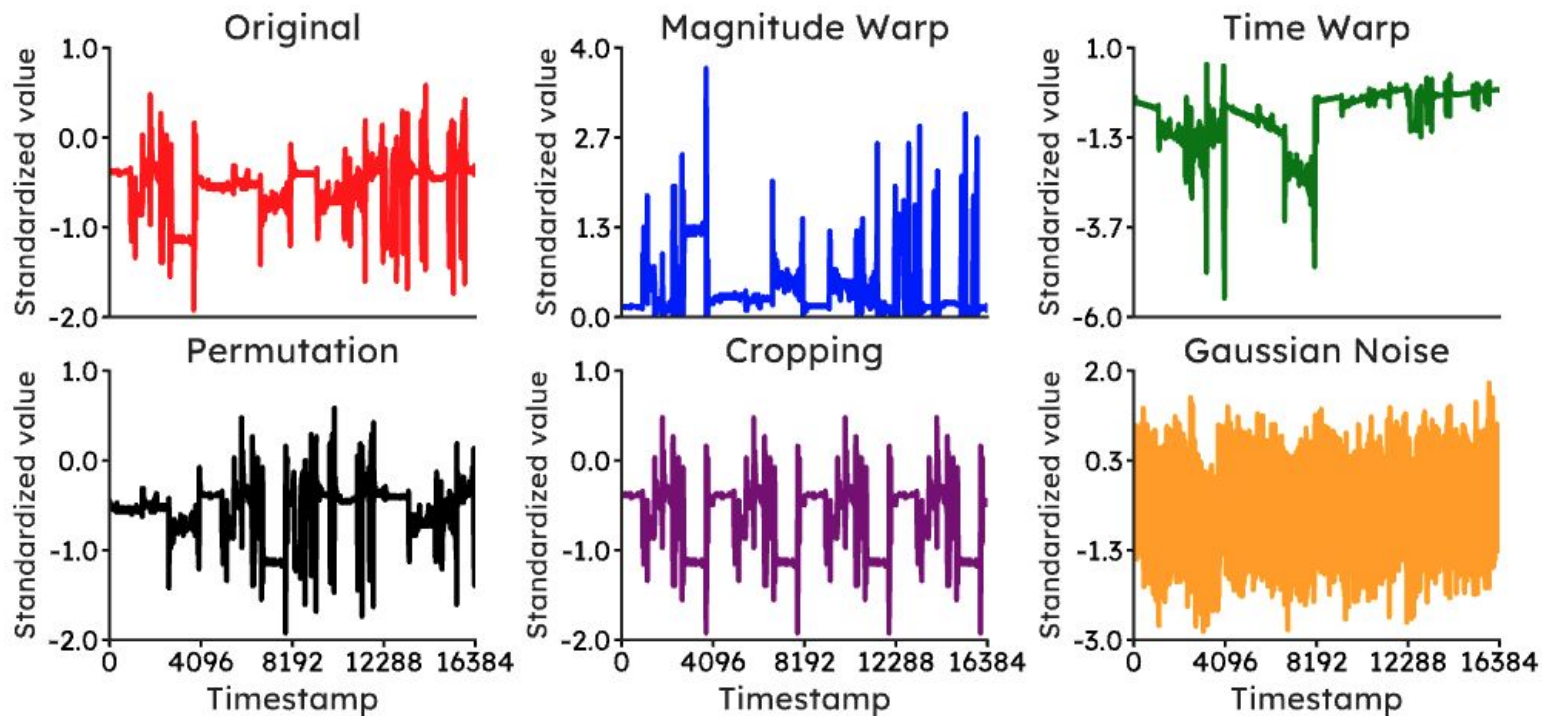


# Surrogate Tasks



Masked Prediction

# Surrogate Tasks



Transformation Prediction

# INTREPIBD Cohort

	AGE	FEMALES	DIAGNOSIS	HDRS	YMRS
	MEAN (STD)	N (PERCENTAGE)		MEAN (STD)	MEAN (STD)
<b>EUTHYMIA</b>	47.22 (16.06)	14 (43.75%)	BD (N=26)	2.93 (1.73)	1.3 (1.61)
<b>N=32</b>			MDD (N=6)	3.14 (1.95)	0.29 (0.76)
<b>ACUTE EPISODE</b>	50.56 (13.05)	15 (46.88%)	MDE-BD (N=9)	20.22 (6.34)	2.56 (3.94)
<b>N=32</b>			MDE-MDD (N=7)	25.14 (4.78)	1.86 (2.41)
			ME (N=14)	5.67 (4.37)	20.13 (6.28)
			MX (N=2)	16 (4.24)	13.5 (4.95)

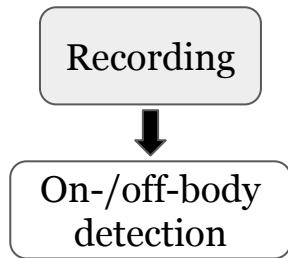
Target task dataset



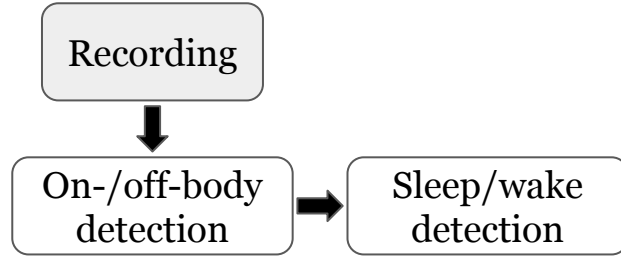
# Pre-processing

Recording

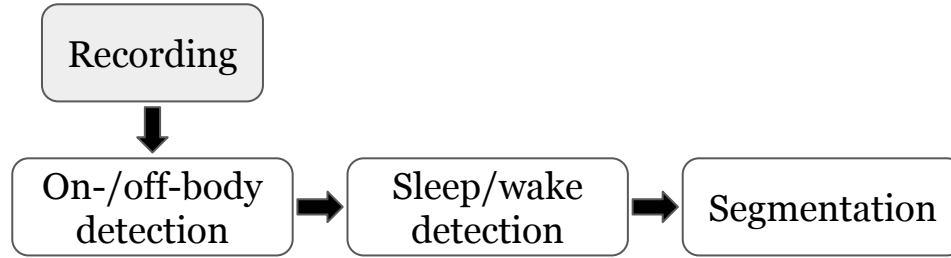
# Pre-processing



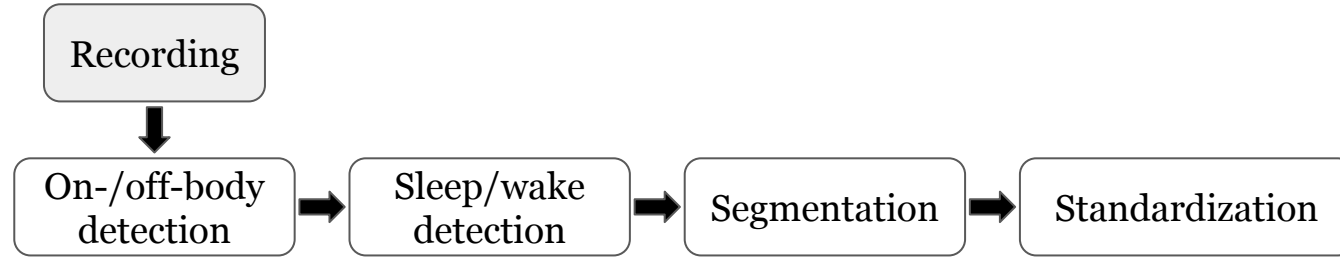
# Pre-processing



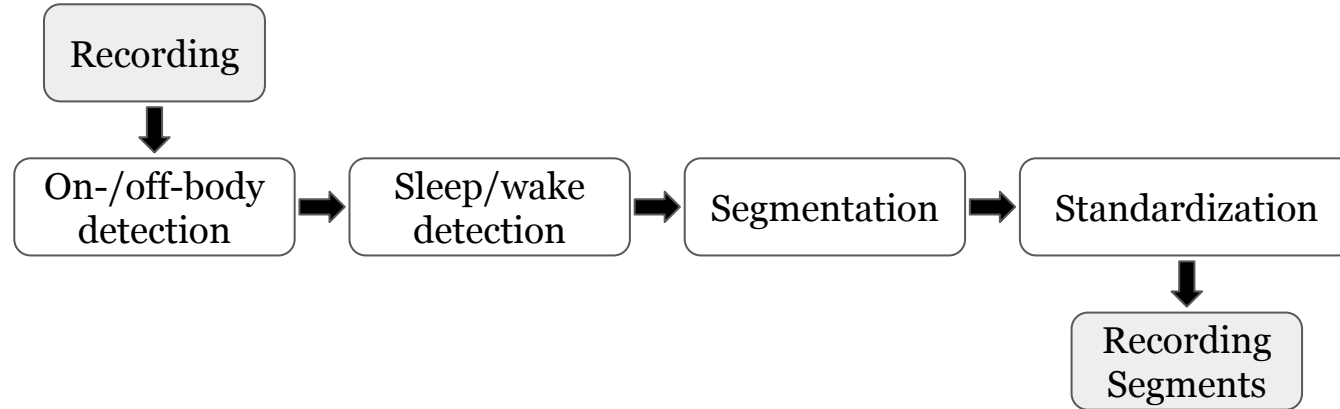
# Pre-processing



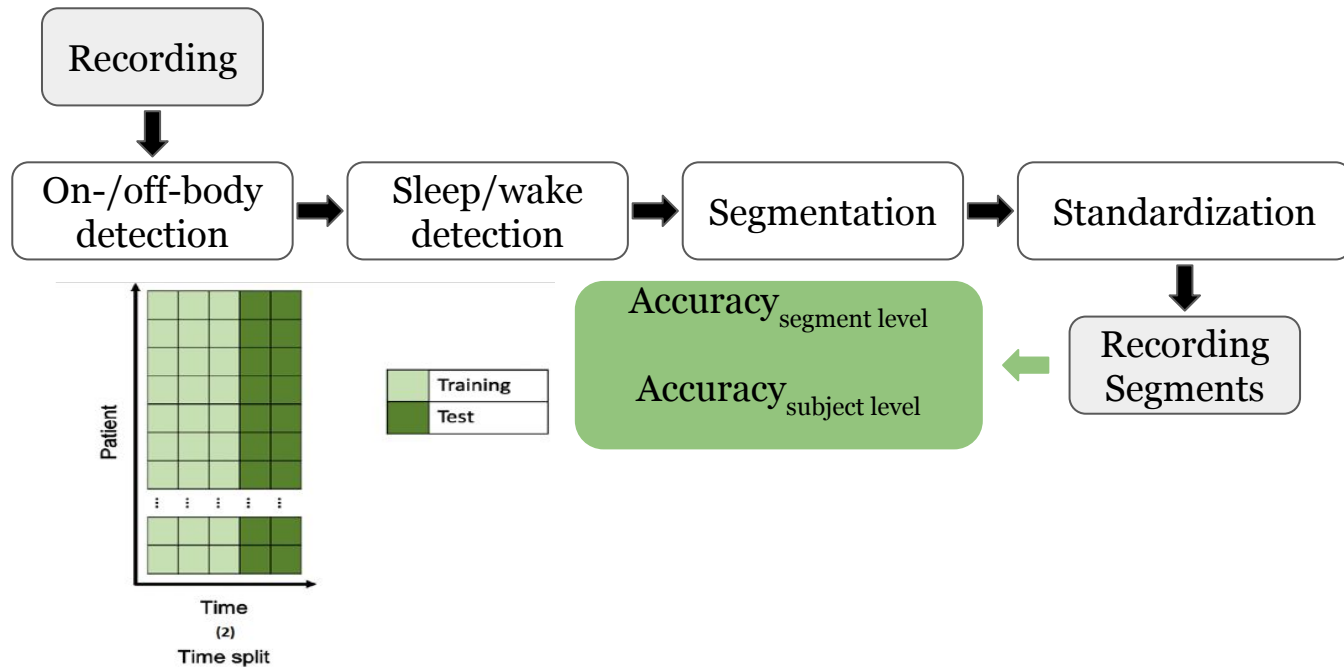
# Pre-processing



# Pre-processing

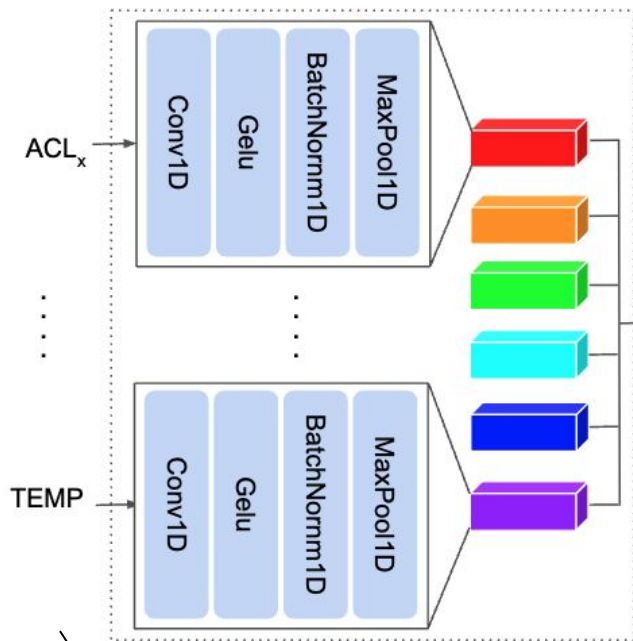


# Pre-processing

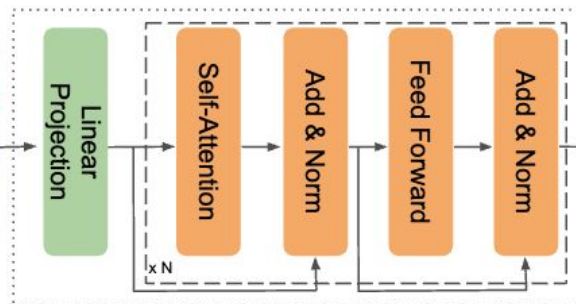


# E4mer

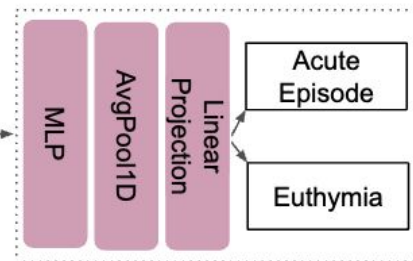
## Channel Embeddings



## Representation Module



## Classification Head



Encoder



# Results

MODEL	ACC		PRECISION		RECALL		$F_1$ SCORE		AUROC		
	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	
SL	XGBOOST	72.02	82.81	71.33	83	72.11	81.1	71.72	82.03	72.44	83.17

XGBoost: traditional machine learning with extracted features

# Results

MODEL		ACC		PRECISION		RECALL		$F_1$ SCORE		AUROC	
		SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT
SL	XGBOOST	72.02	82.81	71.33	83	72.11	81.1	71.72	82.03	72.44	83.17
	E4MER	75.35	81.25	73.46	80.55	75.34	82.14	74.39	81.33	75.68	82.22

XGBoost and a modern deep learning pipeline perform on a similar level

# Results

MODEL		ACC		PRECISION		RECALL		$F_1$ SCORE		AUROC	
		SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT
SL	XGBOOST	72.02	82.81	71.33	83	72.11	81.1	71.72	82.03	72.44	83.17
	E4MER	75.35	81.25	73.46	80.55	75.34	82.14	74.39	81.33	75.68	82.22
SSL	MP (LR)	77.53	87.50	78.34	88.6	77.41	88	77.87	88.3	78.02	89.2
	MP (FT)	<b>81.23</b>	<b>90.63</b>	<b>80.91</b>	<b>90.11</b>	<b>82.00</b>	<b>92.87</b>	<b>81.45</b>	<b>91.47</b>	<b>82.02</b>	<b>93.11</b>

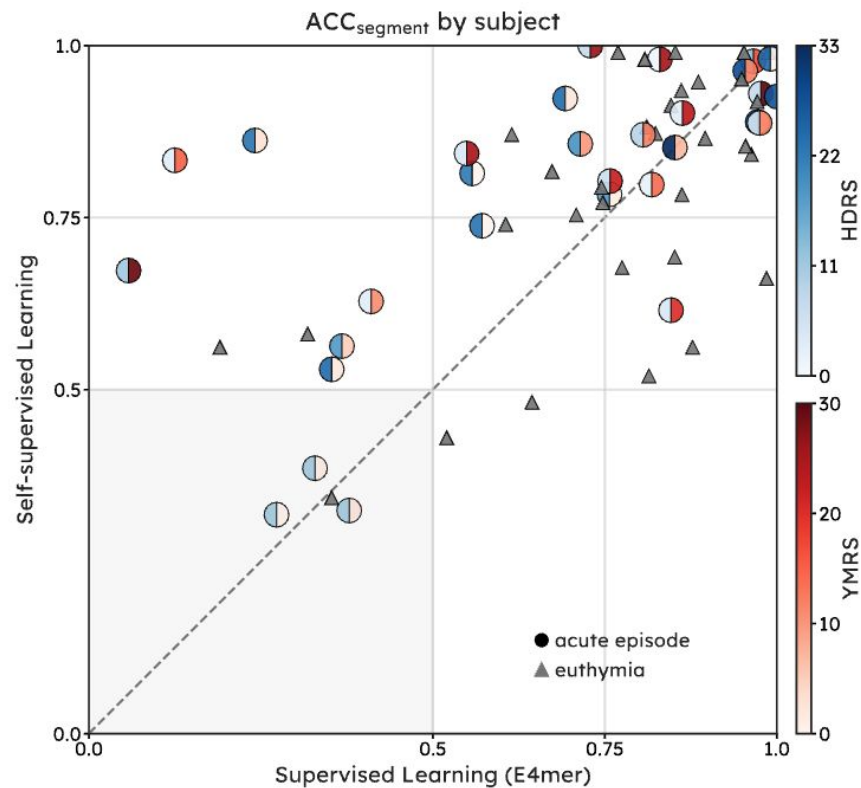
Self-supervised learning confidently outperforms baselines on all metrics

# Results

MODEL		ACC		PRECISION		RECALL		$F_1$ SCORE		AUROC	
		SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT	SEGMENT	SUBJECT
SL	XGBOOST	72.02	82.81	71.33	83	72.11	81.1	71.72	82.03	72.44	83.17
	E4MER	75.35	81.25	73.46	80.55	75.34	82.14	74.39	81.33	75.68	82.22
SSL	MP (LR)	77.53	87.50	78.34	88.6	77.41	88	77.87	88.3	78.02	89.2
	MP (FT)	<b>81.23</b>	<b>90.63</b>	<b>80.91</b>	<b>90.11</b>	<b>82.00</b>	<b>92.87</b>	<b>81.45</b>	<b>91.47</b>	<b>82.02</b>	<b>93.11</b>
	TP (LR)	71.16	81.25	72.12	82.44	72.01	82.31	72.06	82.37	71.89	84.12
	TP (FT)	75.69	84.38	75.41	82.11	74.79	83.90	75.10	X 83	75.21	84.32

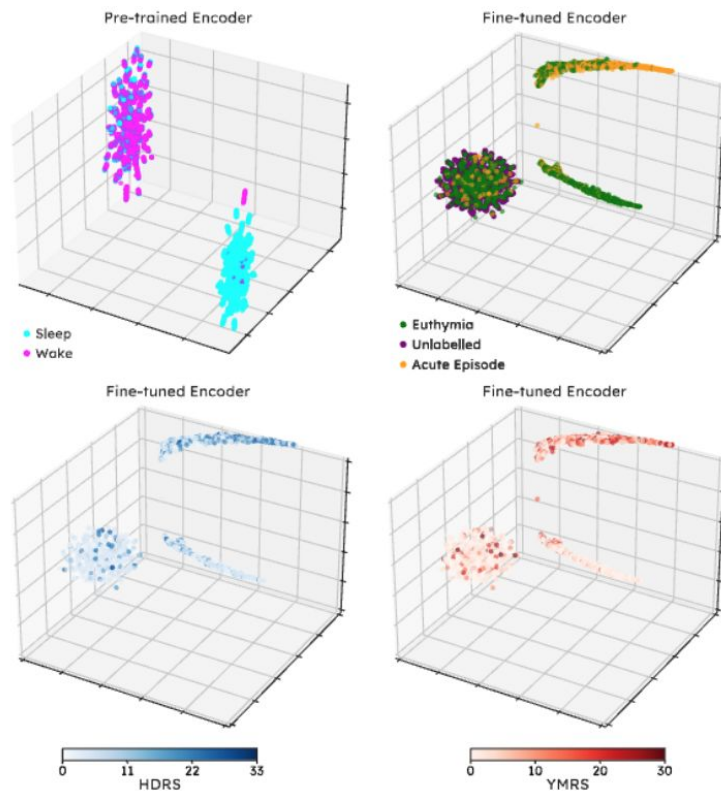
Surrogate task makes a difference

# Results



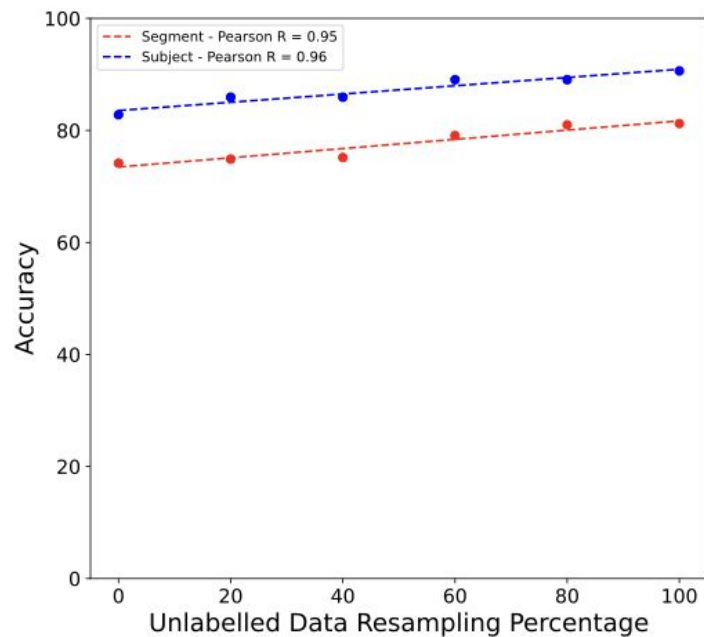
# Results

## Embeddings



# Results

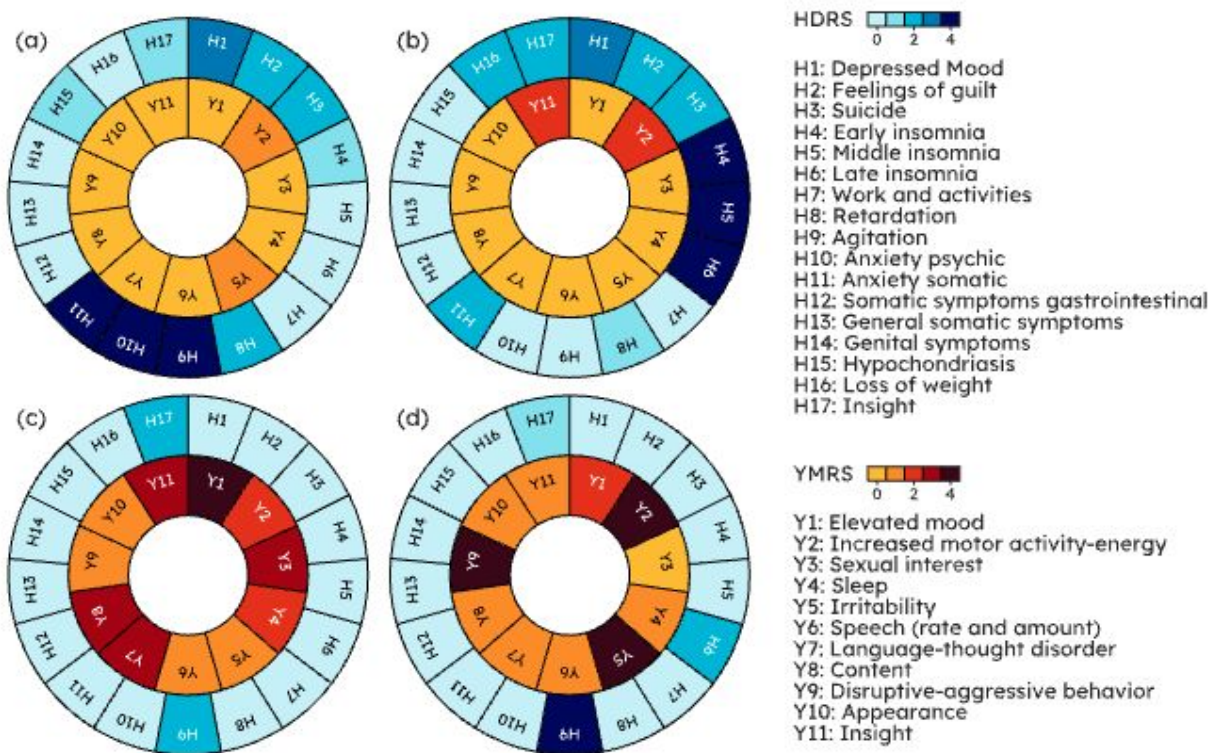
## Ablation analysis



**Is euthymia vs acute episode the whole story?**



# Is euthymia vs acute episode the whole story?



# Challenges

Mood disorders are highly heterogeneous

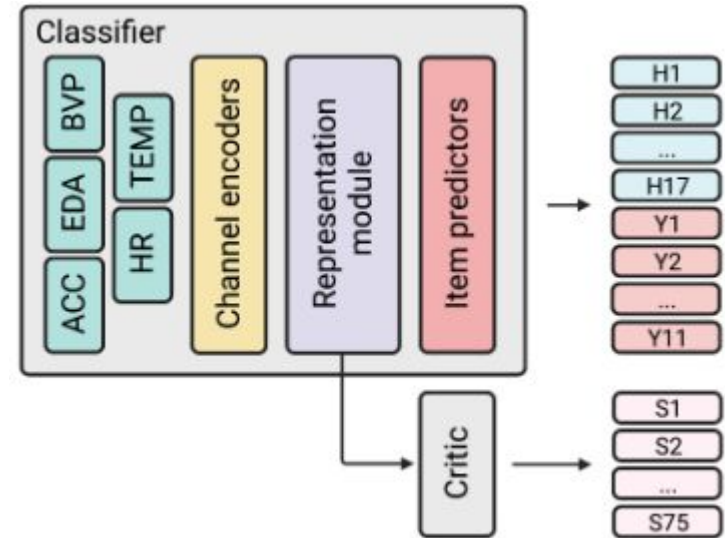
# Challenges

Mood disorders are highly heterogeneous → Generalization  
across subjects and within subject

# Challenges

Mood disorders are highly heterogeneous ➡

Generalization  
across subjects and within subject



# Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy

# Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy



More variability in the signal down to physiological rather than illness-related factors

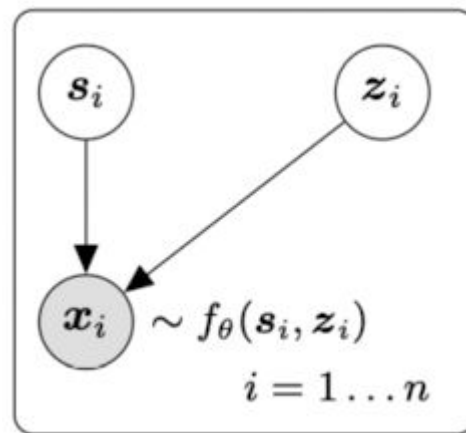
# Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy



More variability in the signal down to physiological rather than illness-related factors



# Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy

Optimal windowing



# Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy

Optimal windowing

Explainability

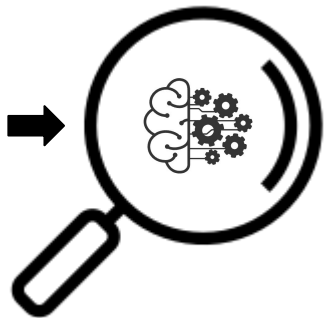
# Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy

Optimal windowing

Explainability



# Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy

Optimal windowing

Explainability

Action policy and uncertainty