Application of Bayesian Networks for classifying Cognitive load signals

ỨNG DỤNG BAYESIAN NETWORK ĐỂ PHÂN LOẠI TÍN HIỆU NHẬN THỨC

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INTRODUCTION

Problems definition:

- **Input:** Physiological data from wearable devices
- **Output:** Bayesian network infers and classifies cognitive states

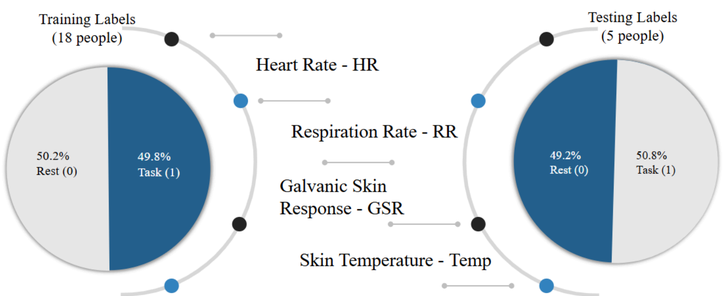
Challenge:

- Cognitive load is a latent state – it cannot be measured directly.
- Physiological signals (GSR, HR, Temp, RR) are indirect indicators.

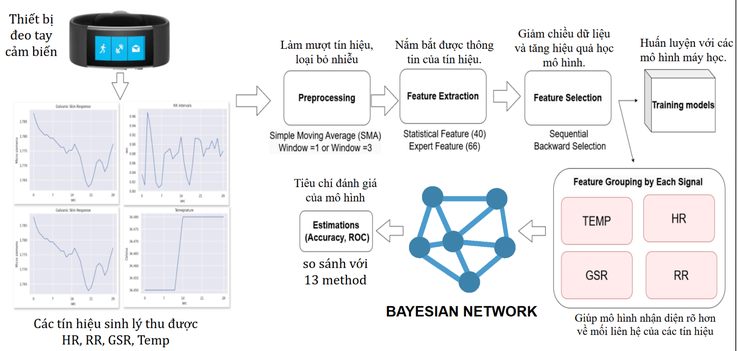
Thesis Goal: Analyze physiological signals and model their causal relationship with cognitive load using Bayesian Networks

DATASETS

- Quantity: 825 samples from 23 participants. 632 samples (training set) and 193 samples (test set).
- Data source: UbiComp2020
  https://colab.research.google.com/drive/1TcGrzhtlb6XdIE33l5cnedPeaPlyNrNE?usp=sharing



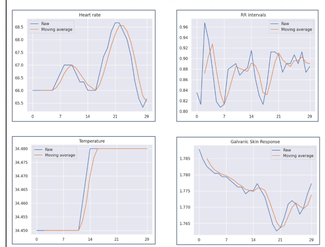
PROPOSED METHOD



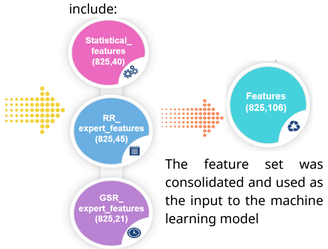
Overview of Cognitive Load Classification using Bayesian Network

1 Preprocessing & Feature Extraction

Raw (unsmoothed) physiological signals (blue) and smoothed physiological signals (orange)



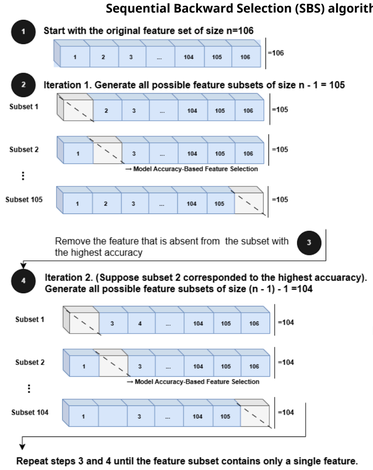
Feature groups extracted from physiological data include:



The feature set was consolidated and used as the input to the machine learning model

2 Feature Selection & Training Models

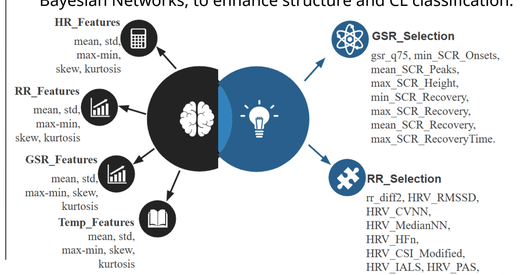
Sequential Backward Selection (SBS) algorithm



Using the SBS algorithm to select the optimal feature set that yields the highest model accuracy

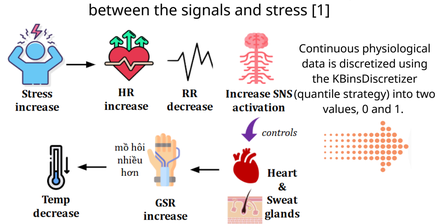
3 Feature Grouping By Each Signals

Combine statistical and selected features, organized by signal in Bayesian Networks, to enhance structure and CL classification.



4 Analyze the relationship between physiological signals

A 2021 research analyzed the relationship between the signals and stress [1]



Continuous physiological data is discretized using the KBinsDiscretizer (quantile strategy) into two values, 0 and 1.

Rest
1 HR↓
0 RR↑
1 GSR↓
0 Temp↑

Task
0 HR↑
1 RR↓
0 GSR↑
1 Temp↓

EXPERIMENTS

Experiment 1: Identify the model with the highest performance. Evaluate and compare models to find the one with the optimal feature set based on accuracy.

Experiment 2: Identify the nodes and edges. Group features by signal type and assess the impact of adding feature groups to the model.

Experiment 3: Examine the influence of observed variables on the target variable. Identify which physiological signals have the strongest effect on cognitive load

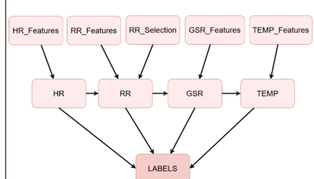
Experiment 1: Identify the model with the highest performance

Experimental results of 10 models with SMA = 0

Model	Features	Accuracy	ROC
SVM	52	0.6788	0.69
XGB	85	0.7098	0.71
LR	11	0.7098	0.73
RF	**21**	**0.7565**	**0.73**
MLP(SKLearn)	25	0.6943	0.71
MLP(Keras)	11	0.5751	0.50
E7GB	24	0.7306	0.75
WGLR	31	0.7306	0.74
ESVM	16	0.7047	0.68
CNN	106	0.6010	0.61
RNN	106	0.6528	0.67

A total of 21 important features were selected using the Random Forest model. The features are categorized based on signal type as follows:

- GSR: 8 features
- RR: 11 features
- Temp: 2 features
- HR: 0 features



The Bayesian Network model uses groups of input signals to predict Task/Rest state

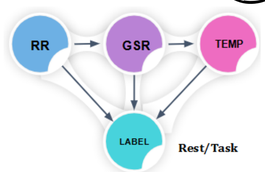
Experiment 2: Identify the nodes and edges

Experiments using different combinations of physiological features

Signal groups (number of features)	Accuracy
• HR(5): HR_Features • RR(5): RR_Features • GSR(5): GSR_Features • Temp(5): Temp_Features	0.6269
• HR(5): HR_Features • RR(5): RR_Features • GSR(13): GSR_Features, GSR_Selection • Temp(5): Temp_Features	0.6269
• **HR(5): HR_Features** • **RR(16): RR_Features, RR_Selection** • **GSR(5): GSR_Features** • **Temp(5): Temp_Features**	**0.6425**
• HR(5): HR_Features • RR(16): RR_Features, RR_Selection • GSR(13): GSR_Features, GSR_Selection • Temp(5): Temp_Features	0.5907

Experiment 3: Examine the influence of observed variables on the target variable

Signal impact table (exhaustive search) in Bayesian Task/Rest model

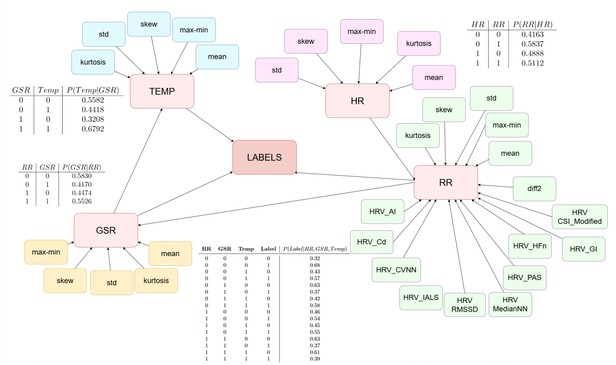


RR (HRV), GSR, and Skin Temperature all have clear physiological associations with stress

Case	Signals Influencing The Label	Accuracy
1	HR	0.5544
2	RR	0.6010
3	GSR	0.5803
4	Temp	0.4819
5	HR-RR	0.6010
6	HR-GSR	0.5699
7	HR-Temp	0.5544
8	RR-GSR	0.6010
9	RR-Temp	0.6010
10	GSR-Temp	0.5803
11	HR-RR-GSR	0.6062
12	HR-RR-Temp	0.5803
13	HR-GSR-Temp	0.5544
14	**RR-GSR-Temp**	**0.6580**
15	HR-RR-GSR-Temp	0.6425

RESULTS

COGNITIVE LOAD BAYESIAN NETWORK



SOTA results of participating teams in the UBiComp 2020 challenge

Method	Proposed Classifier	Accuracy
I	Ensemble of 7 Gradient boosting decision trees	0.694
II	Support vector machine	0.679
III	Ensemble of support vector machine	0.674
IV	**Logistic regression**	**0.663**
V	**Random Forest**	**0.653**
VI	Weighted sum of individualized and global logistic regression models	0.653
VII	Multilayer perceptron	0.648
VIII	Logistic regression	0.648
IX	Support vector machine	0.627
X	XGBoost Classifier	0.580
XI	Convolutional neural network...	0.560
XII	Recurrent neural network	0.554
XIII	Logistic regression	0.503
Our team	**Bayesian Networks**	**0.658**

Submitting paper "A Multiscale Approach for Inferring Cognitive Load from the CogLoad Physiological Dataset" ICCIES2025 - *International Conference On Computational Intelligence In Engineering Science 2025*