Centre for Human Body Data Science
South China University of Technology

A Feature Learning Approach Based on Multimodal Human Body Data for Emotion Recognition

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Who Am I?

Ghanaian

Affective Computing

Emotion Recognition

Deep Learning

- PhD. Information and Communication Engineering.

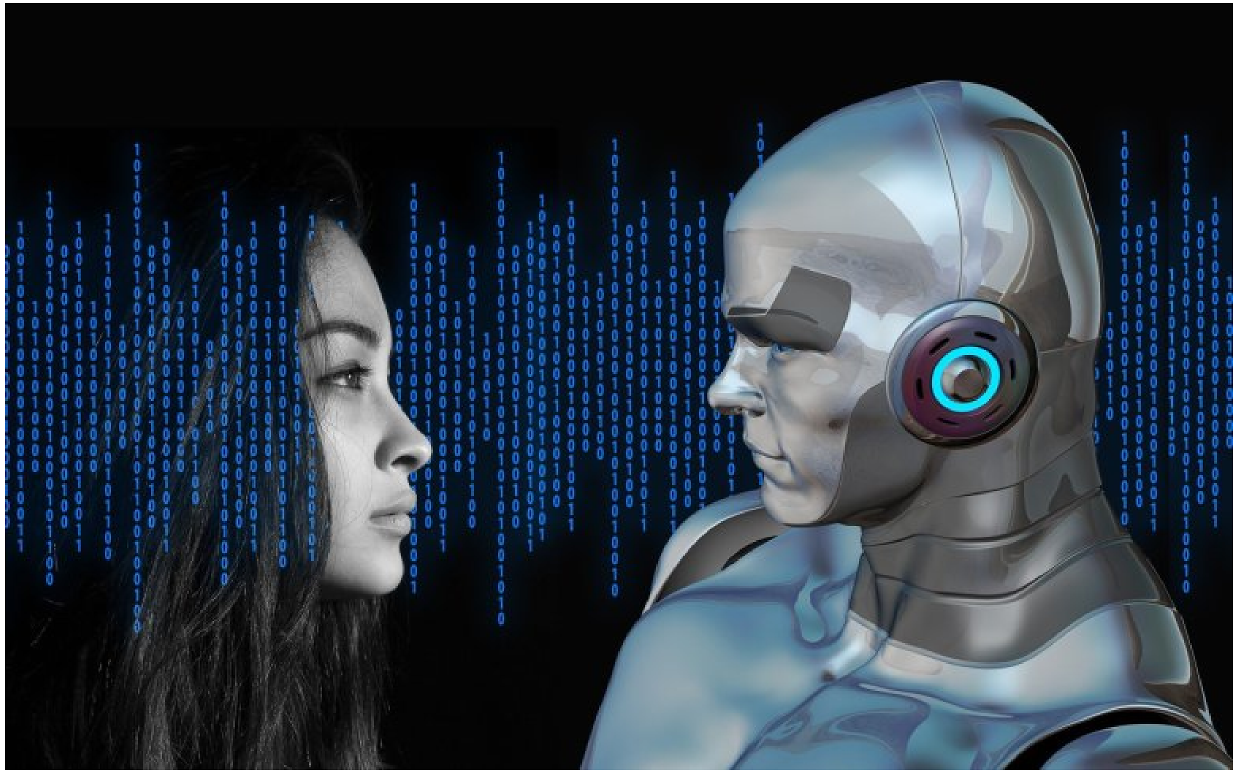
M.Eng. Information and Communication Engineering.

B.Eng. Computer Science and Technology.

Introduction

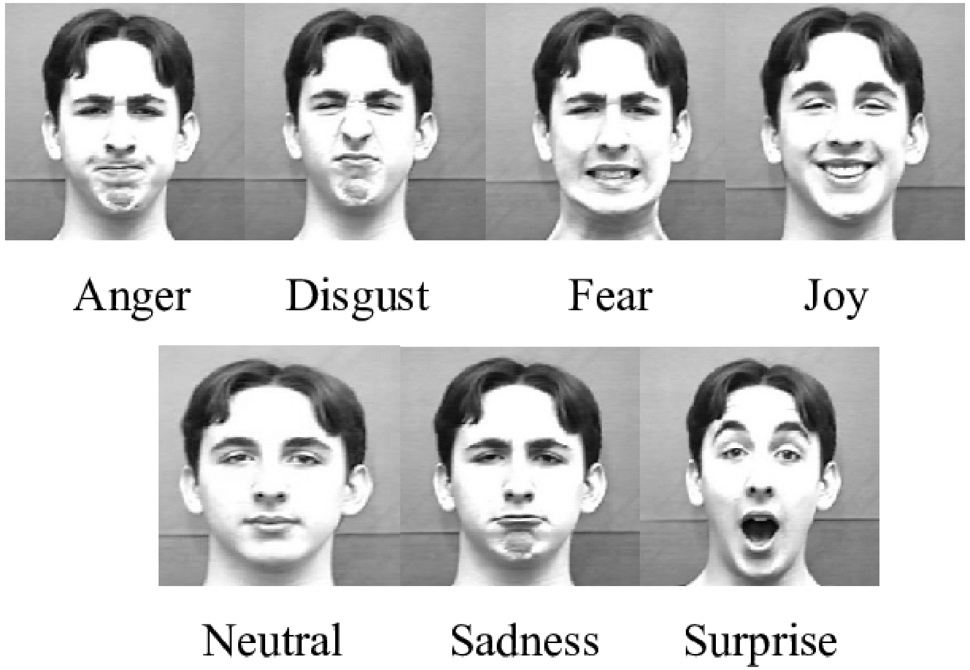
Affective Computing

- Human aspect of AI.
- Systems and devices that can recognize, interpret, process, and simulate human affect.

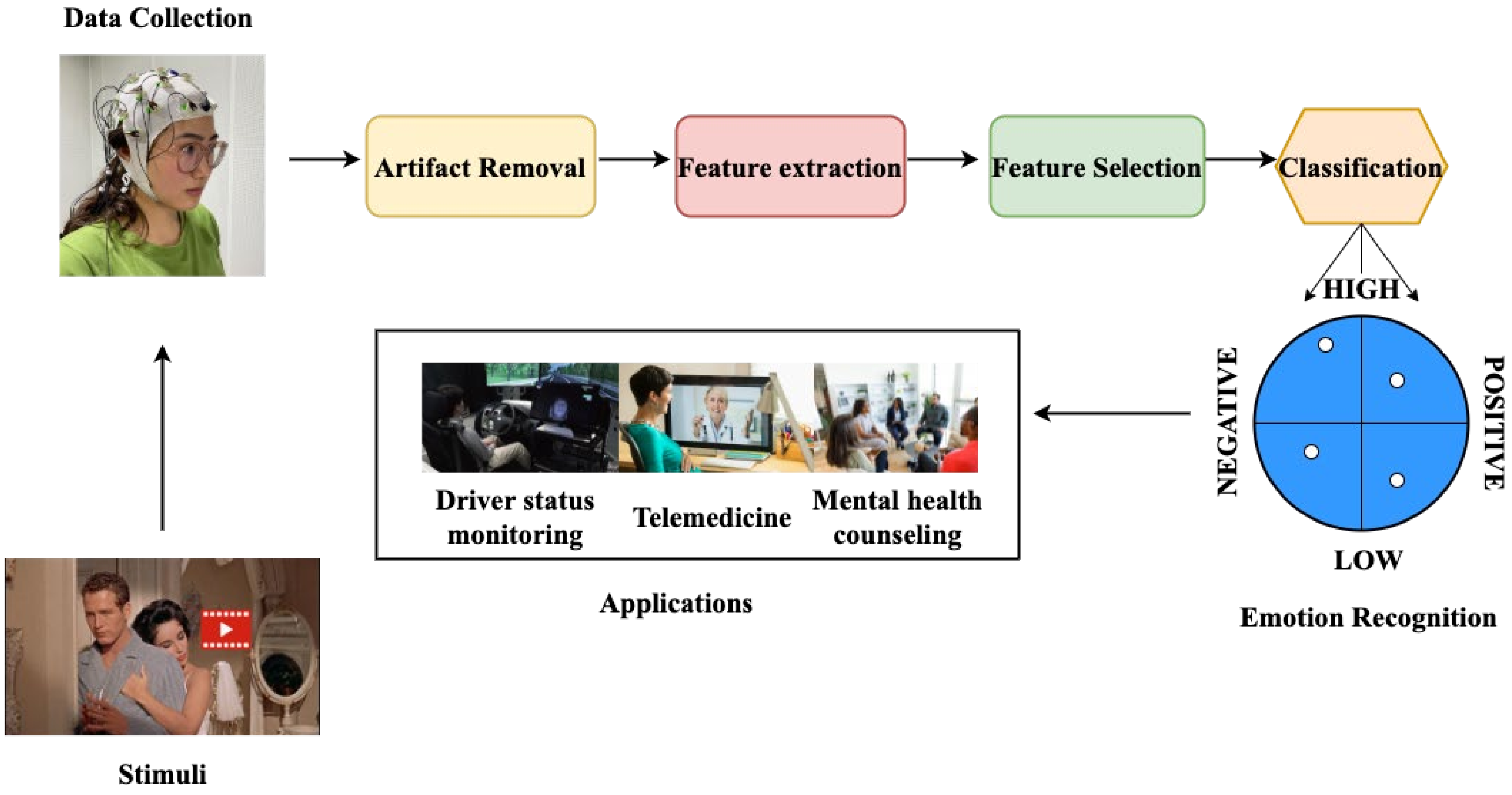


What are emotions?

- State of feeling;
- Physical and psychological changes;
- Thought and behavior.



Emotion Recognition



Fundamental modules of emotion recognition and its applications

Problem Statement

Problem Statement

- Which physiological signals are useful to distinguish between valence and arousal states?
- Can we build a model with strong representation ability to learn differences and similarities in feature nodes?
- Can we design an ensemble fusion paradigm that captures these relationships to improve multimodal performance?

Methodology

DEAP datasets

- Collected for analysis of human affective states.

Attributes

Part	**32 (16 M /16 F)**
Signals	EEG, GSR, RES, EMG (128 HZ)
Videos	40
Self-report	Valence, arousal
Rating scale	1-9

Two-Defined classes

Valence	**Arousal**	**Rating (r)**
Negative	High	$r \leq 4.5$
Positive	Low	$4.5 \leq r$

Three-Defined classes

Valence	**Arousal**	**Rating (r)**
Unpleasant	Calm	$1 \leq r \leq 3$
Neutral	Average	$4 \leq r \leq 6$
Pleasant	Excited	$7 \leq r \leq 9$

Emotional Keywords

Dimension	**Affective classes**	**Tagging**
Valence	Unpleasant Neutral Pleasant	Angry, sad, neutral, surprise, happy, amuse
Arousal	Calm Average Activated	Sad, Neutral, happy, amuse, surprise, angry

Features

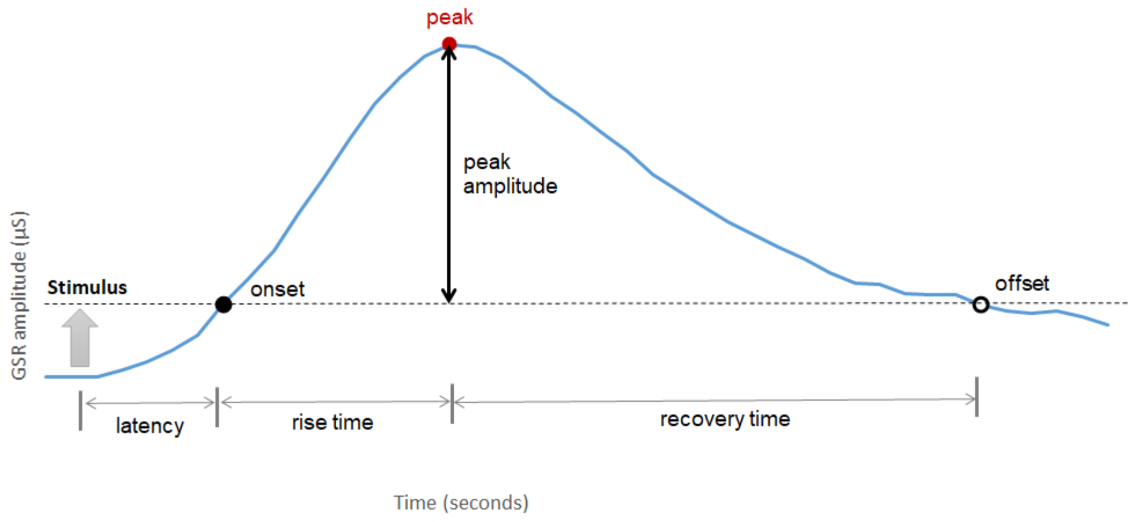
- Distinctive traits of signals.
- Require training on various models to perform classification.

Power spectral density;

Statistical moments;

Frequency;

Peaks.

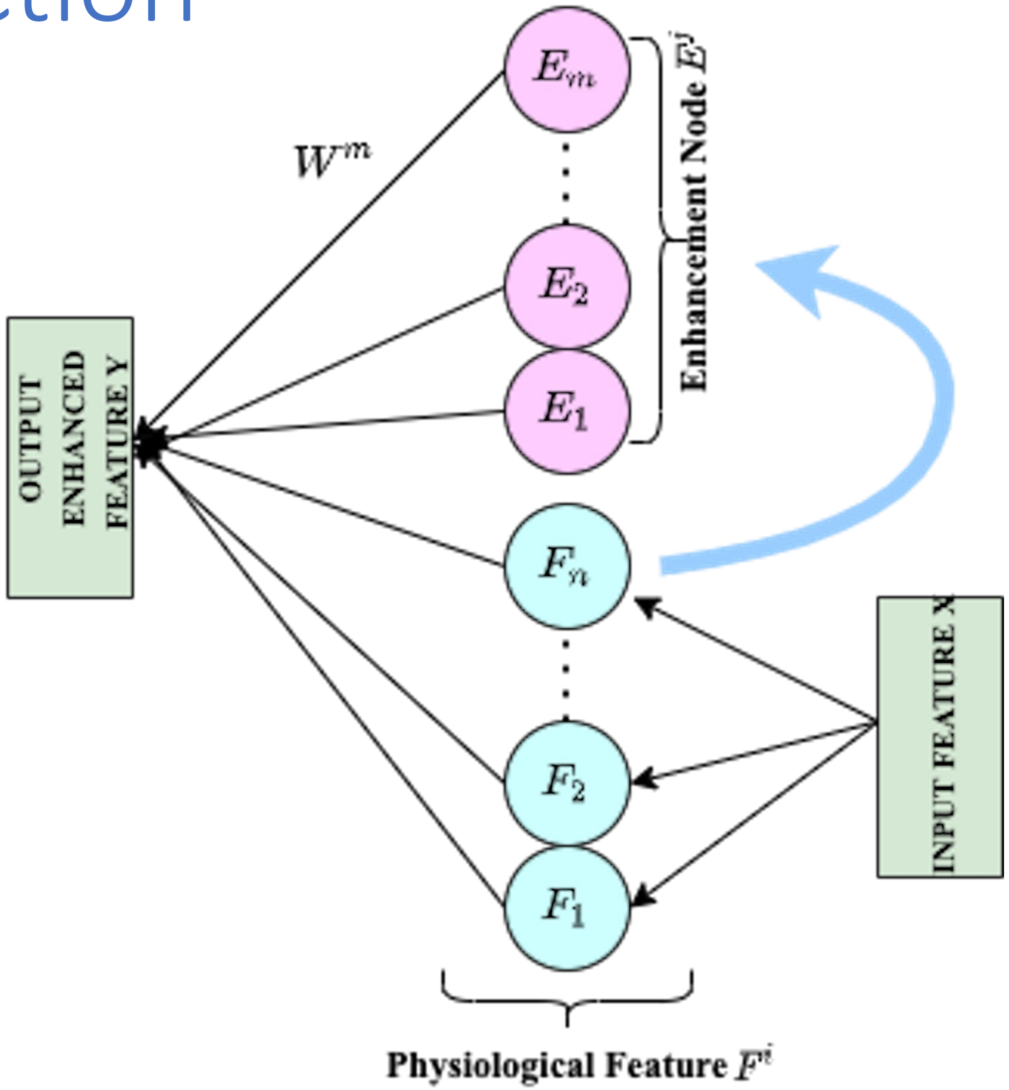


Ideal GSR signal with typically computed features

Hyper Enhanced Learning System (HELS)

- Let's assume input feature X, projected using $\phi_i(XW_{ei} + \beta_{ei})$, as the ith mapped physiological feature;
- First group, $F^i \equiv [F_1, F_2, \dots, F_i]$;
- Similarly for enhancement node, $\zeta_j\left(F^i W_{hj} + \beta_{hj}\right)$ is E_j;
- First group, $E^j \equiv \left[E_1, E_2, \dots, E_j\right]$;
- Obtain richer features.

HELS Construction



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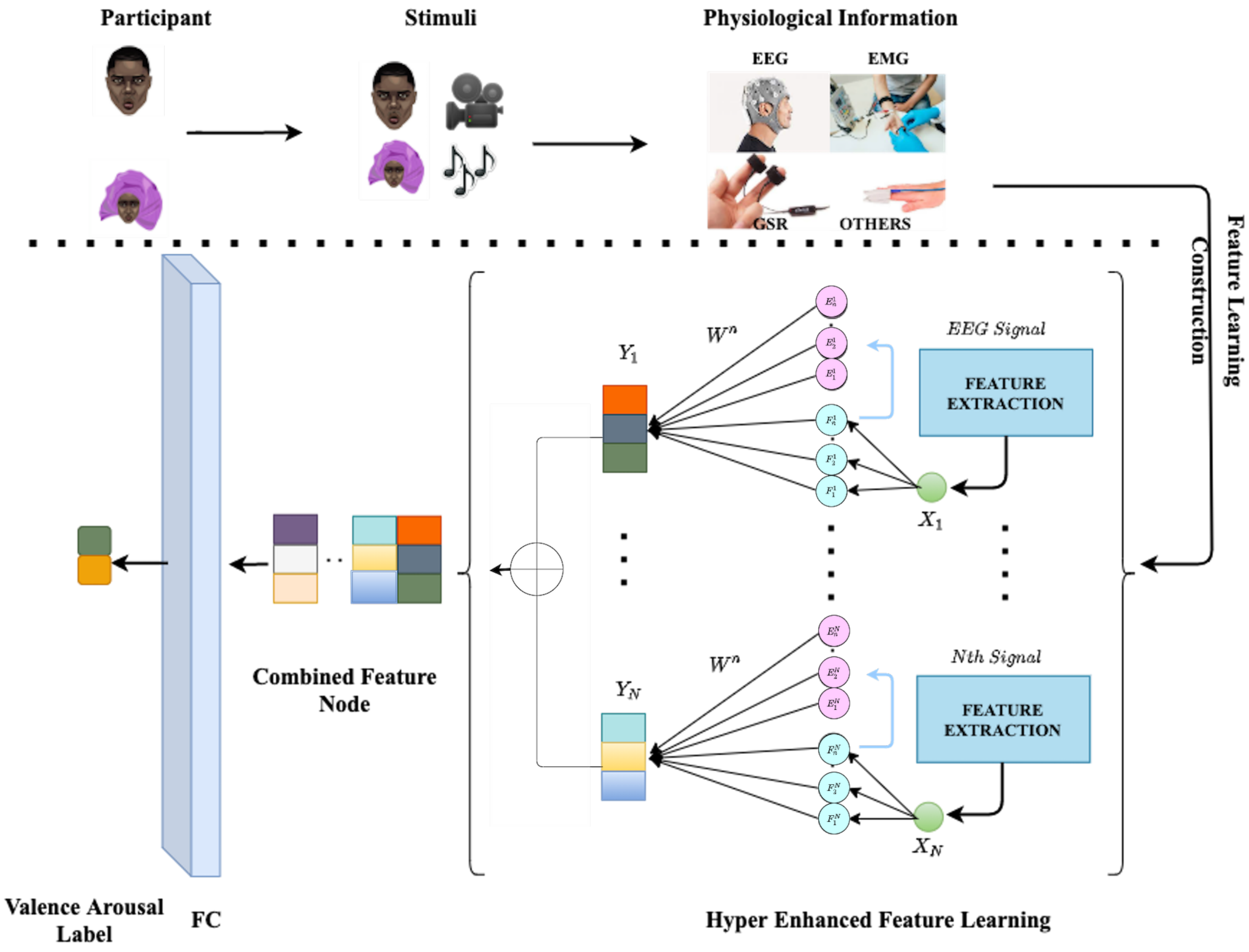
Overall framework



Experimental Results

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(Valence = V, Arousal = A)

(a) Two-Defined classes

Signals	V (%)	A (%)
EEG	70.1	72.2
GSR	73.3	75.6
RES	72.8	74.5
EMG	69.8	72.4
EMG+EEG	69.2	71.1
GSR+EEG	71.3	72.2
RES+EEG	68.7	70.2
GSR+EMG	68.8	70.3
RES+EMG	65.9	70.2
RES+GSR	69.4	70.9
GSR+EMG+EEG	71.3	71.4
RES+EMG+EEG	70.8	69.9
RES+GSR+EEG	71.0	71.2
RES+GSR+EMG	71.1	68.9
EEG+GSR+RES+EMG	**78.6**	**79.9**

(b) Three-Defined classes

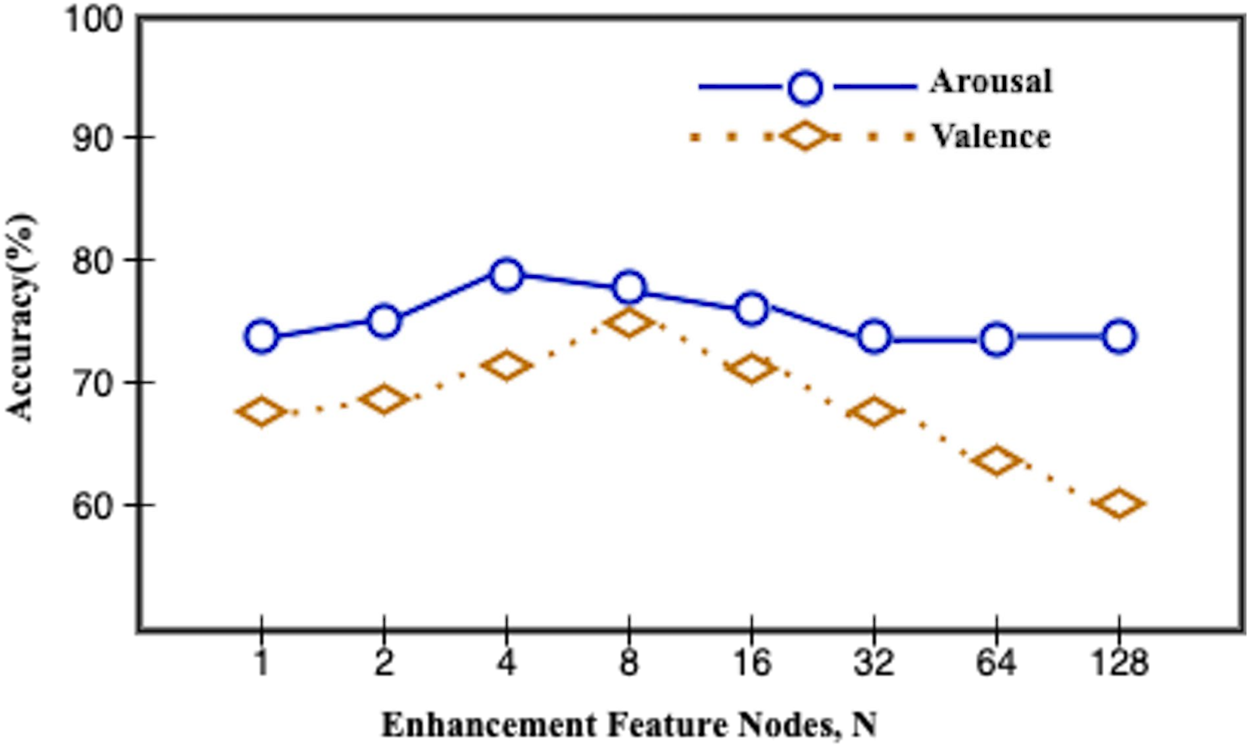
Signal	V (%)	A (%)
EEG	67.4	69.6
GSR	67.3	70.2
RES	68.4	69.7
EMG	66.6	68.0
EMG+EEG	66.2	68.5
GSR+EEG	67.4	70.1
RES+EEG	65.2	67.4
GSR+EMG	67.5	66.4
RES+EMG	67.9	65.3
RES+GSR	68.4	69.1
GSR+EMG+EEG	68.4	70.1
RES+EMG+EEG	67.1	69.8
RES+GSR+EEG	68.2	70.0
RES+GSR+EMG	69.1	69.9
EEG+GSR+RES+EMG	**69.7**	**71.9**

(c) Coded emotional keywords

Signal	V (%)	A (%)
EEG	68.1	70.6
GSR	69.2	72.9
RES	69.7	71.1
EMG	68.5	70.8
EMG+EEG	67.3	69.1
GSR+EEG	68.6	70.6
RES+EEG	66.2	68.1
GSR+EMG	69.7	68.4
RES+EMG	68.4	67.8
RES+GSR	69.2	66.6
GSR+EMG+EEG	69.2	71.3
RES+EMG+EEG	68.9	70.5
RES+GSR+EEG	69.0	71.1
RES+GSR+EMG	70.2	71.6
EEG+GSR+RES+EMG	**72.2**	**75.4**

Results

Influence of enhancement nodes on performance



Comparison with related works

Works	Valence %	Arousal %
Koelstra et al. [18]	62.7	57.0
Soleymani et al. [20]	57.0	52.3
Zhang et al. [11]	69.6	70.1
Luo et al. [3]	78.0	74.0
Ours	**78.6**	**79.9**

Summary

Summary

- Multimodal framework using physiological signals for accurate valence - arousal emotion recognition;
- Hyper-enhanced learning system that takes input as mapped features and generates random weight;
- Combining signals to validate emotional states of subjects;
- Obtained results are promising compared to related works.

Thank you and I may take your questions