Politecnico di Bari

SISINF LAB

Predicting Human Emotions using EEG-based Brain computer Interface and Interpretable Machine Learning

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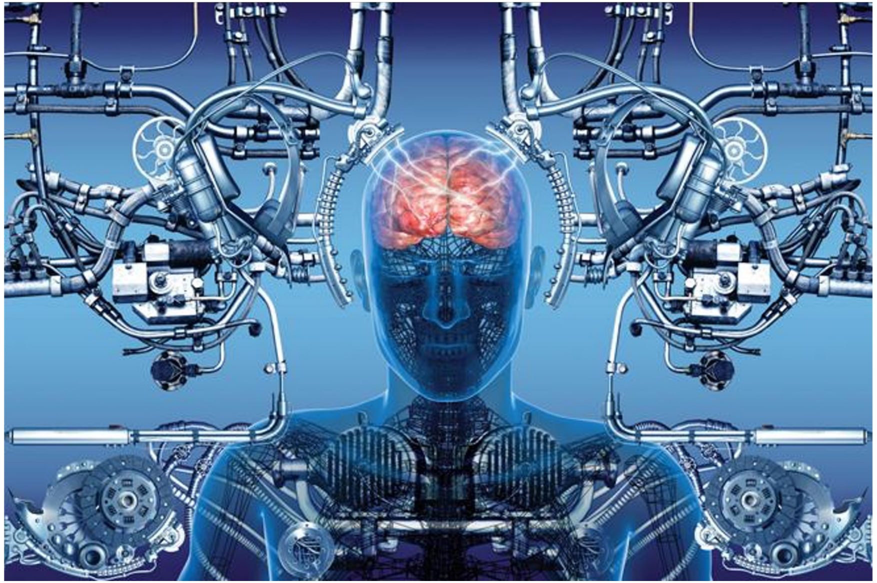
DIPARTIMENTO DI INGEGNERIA ELETTRICA E DELL'INFORMAZIONE

Research Framework

The availability of low-cost devices to capture brain signals as input for systems that identify the relationship between emotions and electroencephalographic (EEG) changes has accelerated research.

These devices are called brain-computer interfaces (BCIs).



EEG is a technique for studying electrical brain signals.

Research Framework

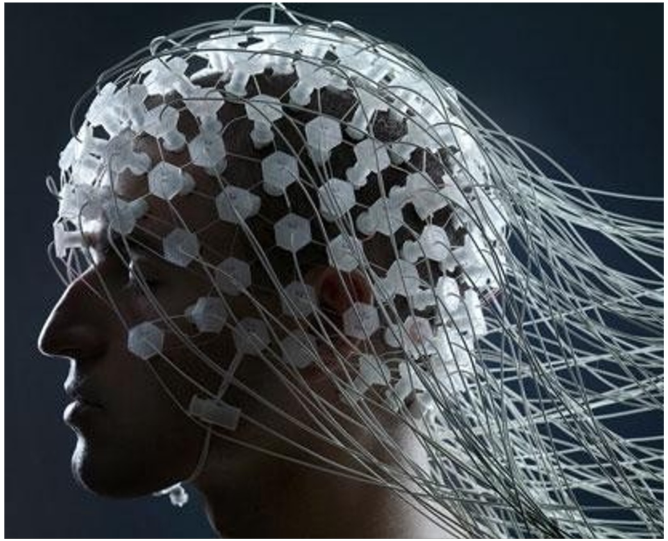
Contextualization

Detection of:

- ***Valence***: emotional polarity;
- ***Arousal***: state of emotional excitement;
- ***Dominance***: level of emotion control.

Detect the current **emotional state** of the user wearing the **BCI device**.

Our work presents a prototype of an **EEG-based emotion recognizer** that provides the user's emotional state exploitable as **bio-feedback**.

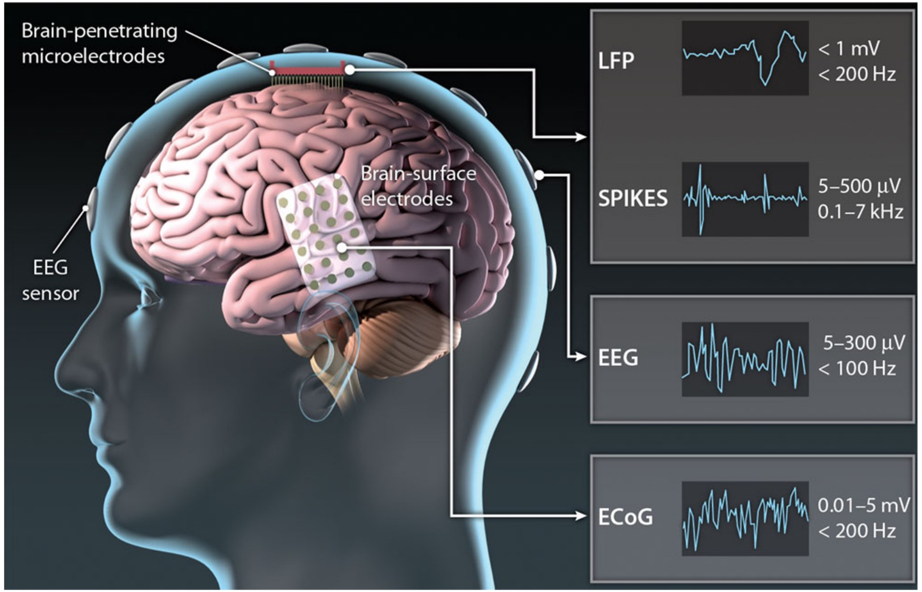


Research Framework

BCI - Brain Computer Interfaces

The proposed framework is based on a Deep Learning architecture because in the current state of the art, Deep Learning techniques have been found to provide the most efficient techniques for EEG analysis.

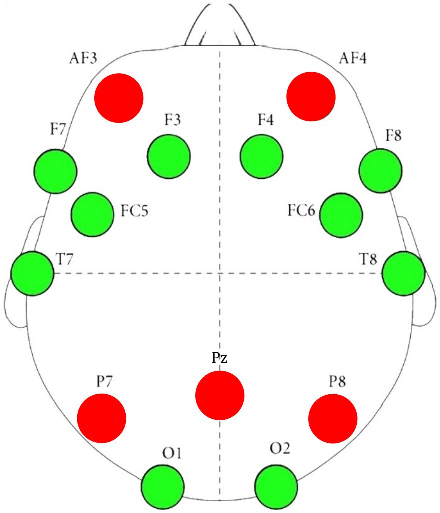
- Our prototype is a regression-based emotion recognition system that can detect the user's emotional state in a bio-feedback mode.
- An explainable AI analysis was performed on the trained model.
- Our prototype can be used in clinical trials.



MATERIAL AND METHODS

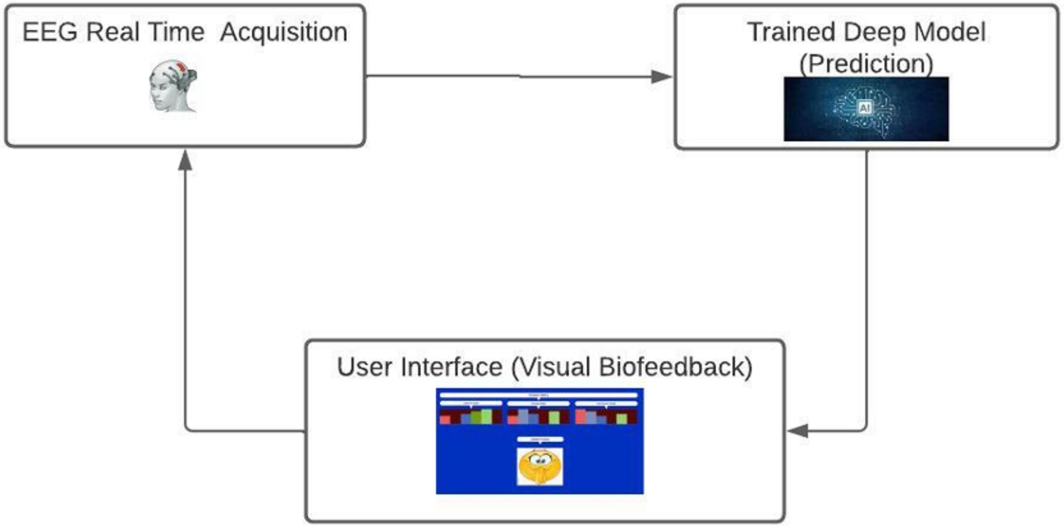
Device Description

Emotive Insight 5 electrodes



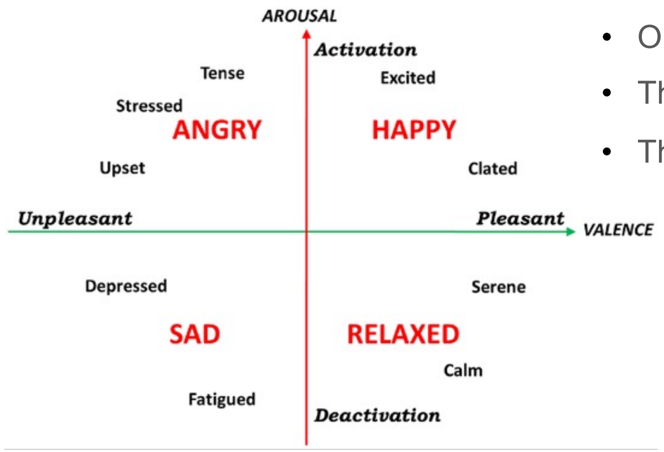
- **Sampling frequency**: 128Hz in output;
- **Electrodes used**: AF3, AF4, P7, P8, Pz (Reference electrode) ;
- **Output rate**: 128 Hz;

SYSTEM ARCHITECTURE PROPOSED



MATERIAL AND METHODS

Russel’s Diagram



- In the arousal-valence coordinate system, there are four categories of emotions.
- On the left we have the negative emotions and on the right the positive ones.
- The Valence axis represents positive and negative emotions
- The Arousal axis represents the cortex deactivation and activation.

Valence	Arousal	Global Emotion
>2.5	>2.5	Happy
>2.5	<2.5	Relaxed
<2.5	<2.5	Sad
<2.5	>2.5	Angry

MATERIAL AND METHODS

Dataset and Preprocessing

Dreamer dataset

- Composed of 23 users' EEG signals during emotional induction.
- The emotional elicitation protocol was deployed using audio-video clips.
- 18 video clips listed in nine basic emotions.
- Each user had to watch all the video clips ranging in length from 65 to 393 seconds.
- Users were asked to complete a self-assessment questionnaire based on a 5-point Likert scale for Valence, Arousal and Dominance.

MATERIAL AND METHODS

Dataset and Preprocessing

Preprocessing steps

- All trials with corresponding labels were selected, with a total of 414 samples. Each trial consists of signals from the EEG channels of the Emotive device and the corresponding Valence, Arousal and Dominance values.
- The first preprocessing step was to remove the DC offset using a script suggested by the helmet manufacturer.
- Afterwards, the data format was made compatible with the MNE framework to adjust the position of the headset electrodes according to the standard 10-20.
- A notch filter calibrated to the cutoff frequency of 50hz was used to remove noise due to the commercial electric current.

MATERIAL AND METHODS

Dataset and Preprocessing

- The trial was normalized in the frequency range 1-40Hz.
- Epochs of length equal to 1 second were created from the continuous EEG signal.
- Independent component analysis (ICA), was used to remove all noisy epochs and for the identification of EEG signal components.
- All artifacts in the signal were correctly removed.
- Identification and interpolation of defective channels and epochs were performed using pyprep framework[1]
- Epochs exceeding a certain noise threshold are removed and not interpolated.
- Finally, the continuous EEG signal is reconstructed by merging all the various preprocessed epochs.

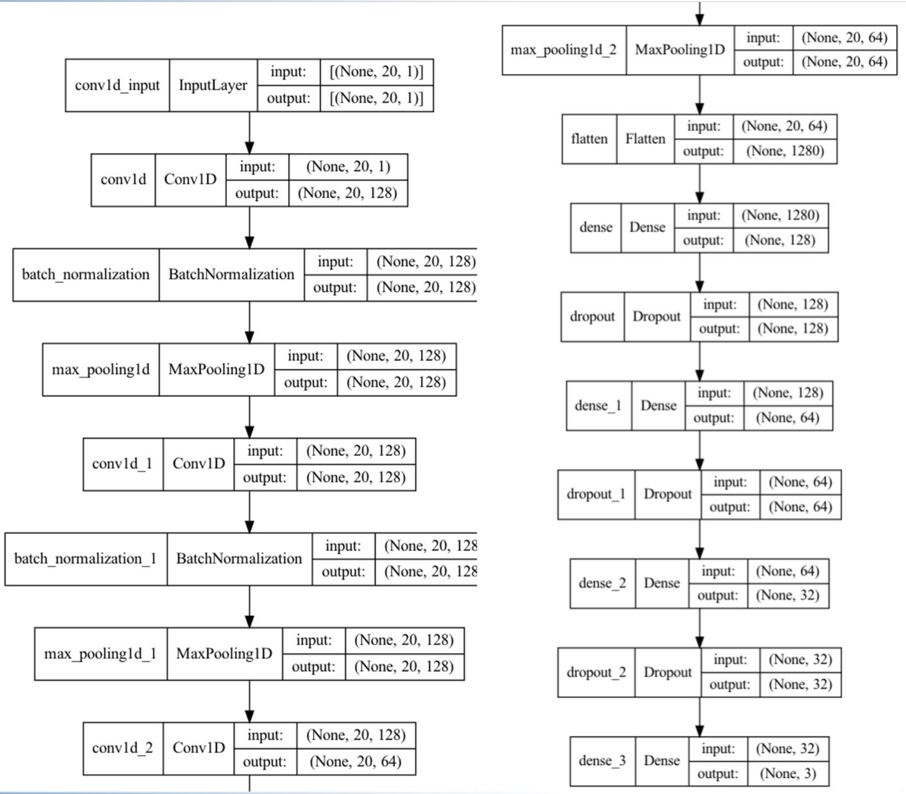
PROPOSED APPROACH

Deep Learning Model Description

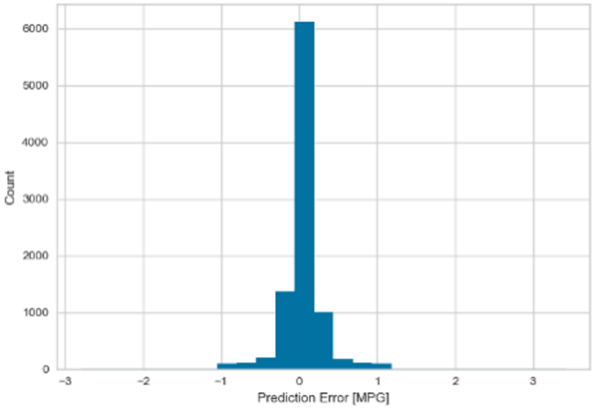
Splitting: 80-20 to train and test and 75-25 from train to obtain validation sub-dataset.

Configuration:

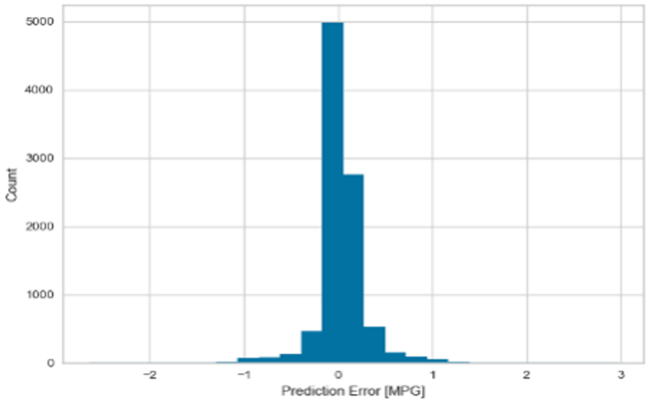
- Normalization with MinMax scaler
- 1D CNN Layers
- 3 convolutional layers (128x2 and 1x64 neurons)
- BatchNormalization
- MaxPooling-1D for extraction of most important features
- kernel_size = 3
- Activation Function = Relu
- Flatten Operation
- Dense Layer whit: 4 layer = input 128 – 128 - 32 – 3 out



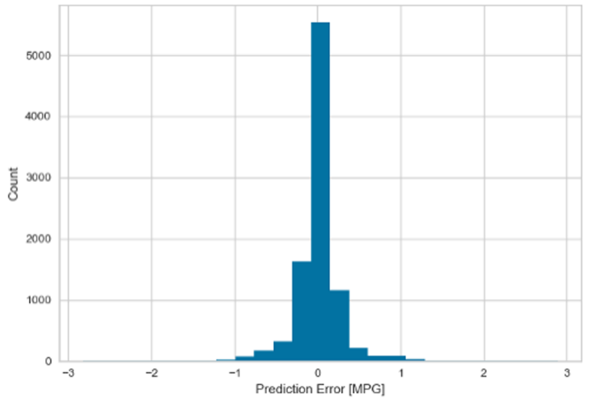
PROPOSED APPROACH
Experimental Results



Valence Error Distribution



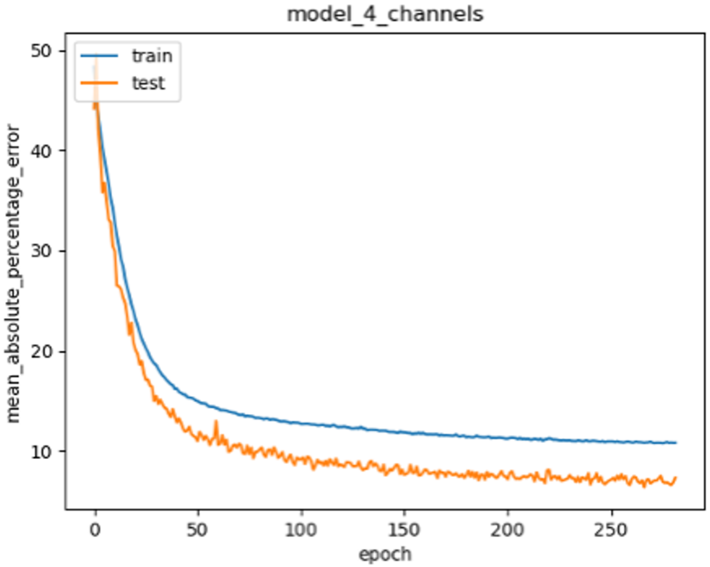
Arousal Error Distribution



Dominance Error Distribution

PROPOSED APPROACH
Experimental Results

Accuracy: **R2** = 0.93
Mean Absolute Error (**MAE**) = 0.08
Mean Absolute Percentage Error (**MAPE**) = 0.07

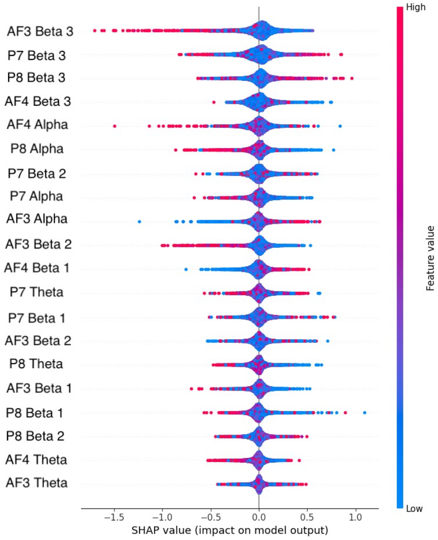


Loss - Mean Absolute Percent Error

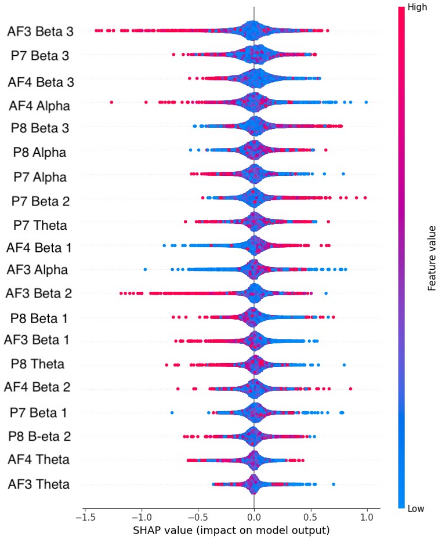
PROPOSED APPROACH

Explanation results

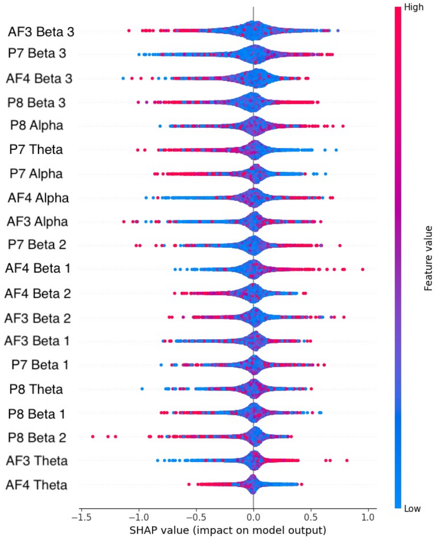
Arousal



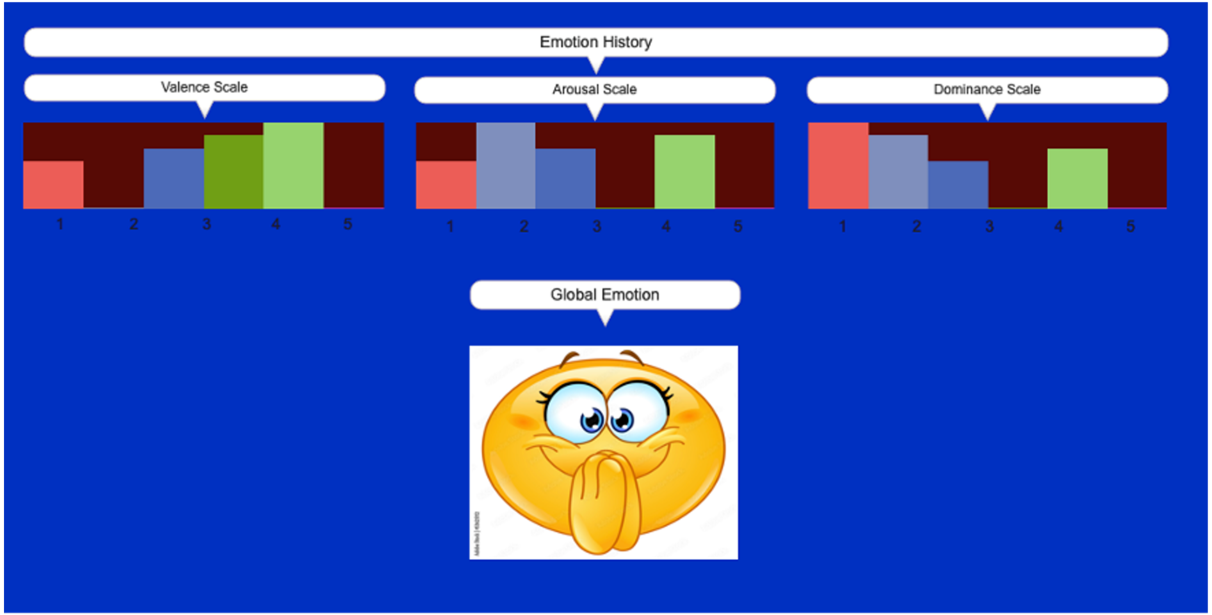
Dominance

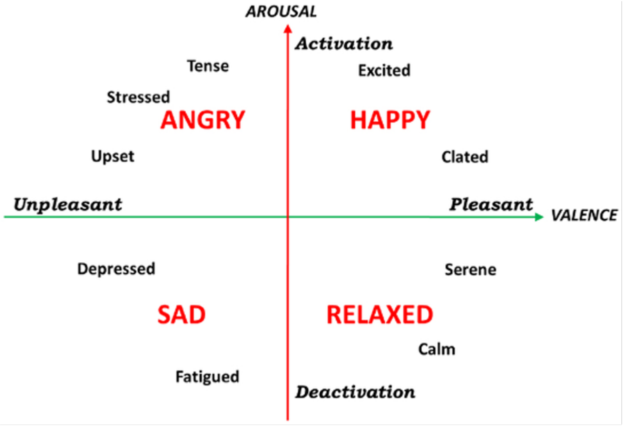


Valence



USER INTERFACE





Schematization of the Russel’s Circumplex Emotion Model

Discussion and Conclusion

- Developed a prototype of emotional bio-feedback based on EEG signals that can recognize human emotions.
- Trained a deep neural network to classify valence, arousal, and dominance levels.
- Classifying human emotions dynamically through the CNN-1D.
- Evaluate feature contributions during the prediction by exploiting shapley values

Provide a real-time multimedia helpful stimulus as a feedback system for both the user and the clinician.

Validating this prototype on a more extensive test sample

Thank you for your attention

Please do not hesitate to contact me for further discussion:
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