Assessment of Video Game Player Proficiency Through the Brain Activity Analysis Using EEG Signals

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Context

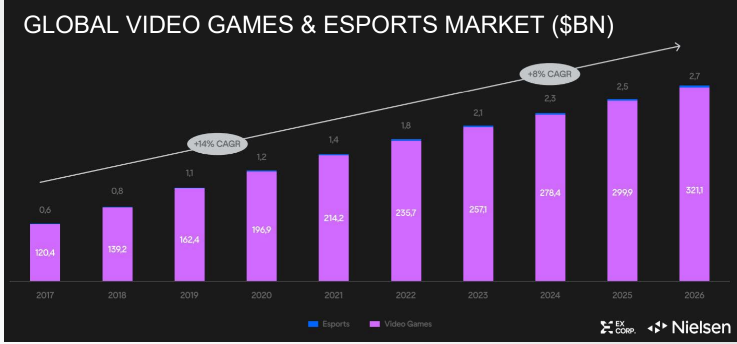
eSports (electronic sports) is organized competitive video gaming.

- **$278.4 BN** market revenue
- **3.42 BN** players*

CS 2 (Counter-Strike 2): a multiplayer tactical first-person shooter.

Motivation

- Expanding market and growth in gamers and audience
- A newly recognized sport discipline
- High availability and ease of retrieving data



Source: https://esportsinsider.com/2023/08/nielsen-ex-corp-competitive-gaming

Source: https://steamcharts.com/app/730

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*according to Nielsen report, https://esportsinsider.com/2023/08/nielsen-ex-corp-competitive-gaming

Literature review on EEG-based player analysis

Articles	Game (Game genre)	Object of study	EEG features used	Experimental protocol (N players, conditions recorded, tracking time)
Minchev et al. [1]	Project I.G.I (FPS)	reaction to game events (loss, win)	spectral	10 players, during game session
B. Meneses-Claudio & A. Roman-Gonzale [2]	DOTA 1 (MOBA)	player's proficiency	frequency	2 players, during game session
Anwar et al. [3]	TempleRunis (endless runner)	player's proficiency	temporal	20 players, during game session
Melentev et al. [4]	CS:GO (FPS)	player's proficiency and tiredness prediction	time-frequency	20 players, before and after game session
Smerdov et al. [5]	LoL (MOBA)	player's proficiency	time-frequency	10 players, during game session
Gostilovich et al. [6]	CS:GO (FPS)	player's winning prediction	temporal, time-frequency, spectral	24 players, visual search task, specific events

- **The in-depth analysis of the brain activity of players of different game levels based on EEG data recorded during game sessions in the tactical FPS game CSGO**

Aim:

To investigate differences in brain activity between players of different skill levels and to assess the impact of high game proficiency on brain activity patterns.

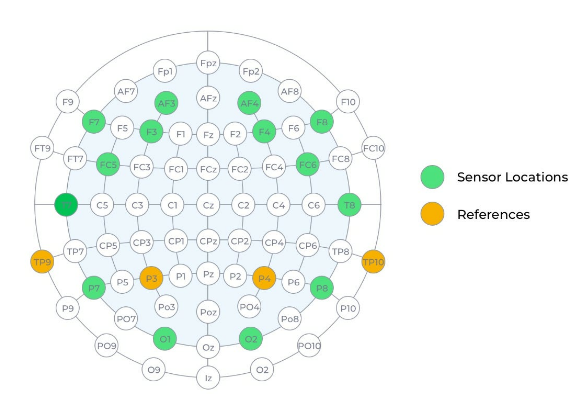
Objectives:

1. Build a dataset consisting of cleaned, filtered, and class-separated EEG signals.
2. Determine the distinctive patterns of brain activity for casual and professional players.
3. Develop a reliable baseline for player skill prediction.

Methodology

Data Description

- ➢ Experimental protocol
  - 17 subjects with different game experience
  - data collected during game sessions ~30-50 minutes
- ➢ EEG recordings



- the wireless EEG headset Emotiv Epoc+
- from 14 usable saline electrodes (10–20 system)
  AF3, F7, F3, FC5, T7, P7, O1, O2,
  P8, T8, FC6, F4, F8, AF4
  and 2 references on parietal sites (P3 and P4)
- automatically pre-filtered bands' power (uV^2 / Hz)
  for 5 diffrent frequency bands:
  - theta (4-8Hz)
  - alpha (8-12Hz)
  - betaL (low beta, 12-16Hz)
  - betaH (high beta, 16-25Hz)
  - gamma (25-45Hz)

Bandwidth: 0.16 – 43Hz, digital notch filters at 50Hz and 60Hz
Filtering: Built in digital 5th order Sinc filter

Methodology

Data Preprocessing

- resampling
- outlier removal (IQR based)
- temporal windowing (1-3 seconds + overlap)

Feature extraction

- time domain (per channel)
- channel-band based (from articles and custom)

Data analysis

- Dimension reduction (PCA)
- Feature selection (SelectKBest)
- Upsampling (SMOTE)
- Hyperparameter tuning with GridSearchCV
- LR,SVM,RF, KNN, MLP
  with 5-fold cross-validation

time domain features

Minimum	2nd Quartile (Median)
Maximum	3rd Quartile
Mean	Root mean square
Std	Decorrelation time
Hjorth parameters (complexity, mobility)	Peak-to-peak (PTP) amplitude
Skewness	Variance
Kurtosis	Entropy
1st Quartile	

channel-band based indexes

$$Valence_1 = \frac{\beta(F3)}{\alpha(F3)} - \frac{\beta(F4)}{\alpha(F4)}$$

$$Valence_2 = \ln[\alpha(F3)] - \ln[\alpha(F4)]$$

$$Valence_3 = \frac{\alpha(F4)}{\beta(F4)} - \frac{\alpha(F3)}{\beta(F3)}$$

frontal alpha asymmetry

$$AW_1 = \alpha(F4) - \alpha(F3)$$

$$AW_2 = \frac{\alpha(F4) - \alpha(F3)}{\alpha(F4) + \alpha(F3)}$$

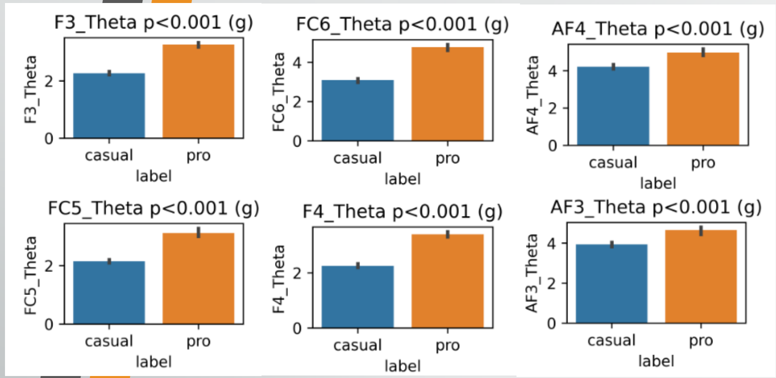
$$\text{Effort Index} = \frac{\theta(F4) - \theta(F3)}{\theta(F4) + \theta(F3)}$$

$$\text{Choice index} = \frac{log(AF3) - log(AF4)}{log(AF3) + log(AF4)}$$

Khondakar et al.[7]
Aldayel et. al. [8]

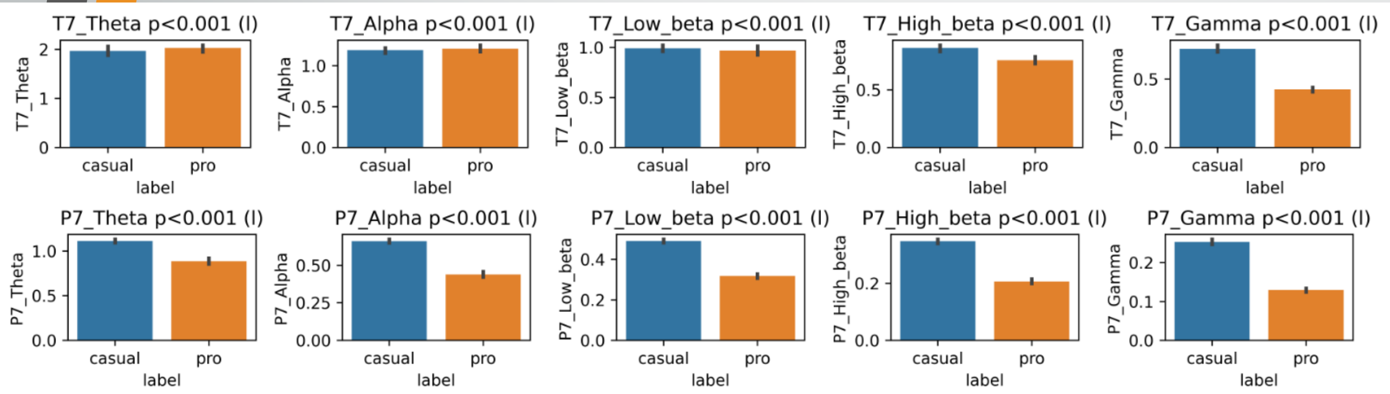
Results and Discussion

Insight from data and comparison with existing works



- Increased* Theta rhythm for professionals (align with [4] and [9])
  -> more focused on game

- values in temporal cortex (T7, P7, T8, P8) higher* for casual players (except for theta band)
  -> pro players are more focused in game and less distracted by side sounds compared to casual gamer, who are more entertained in game



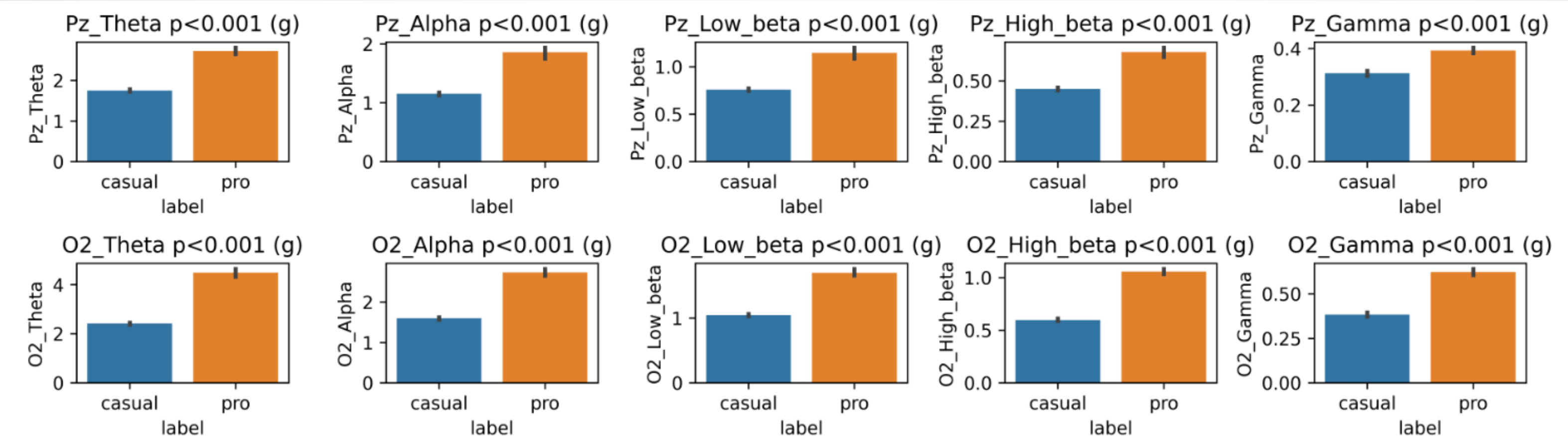
* Mann-Whitney stat test

Results and Discussion

Insight from data and comparison with existing works

- rhythms’ values in O2 channel higher* for professionals
  -> more intense processing visual information while playing

- rhythms’ values in Pz channel higher* for professionals
  -> more intense motor functions



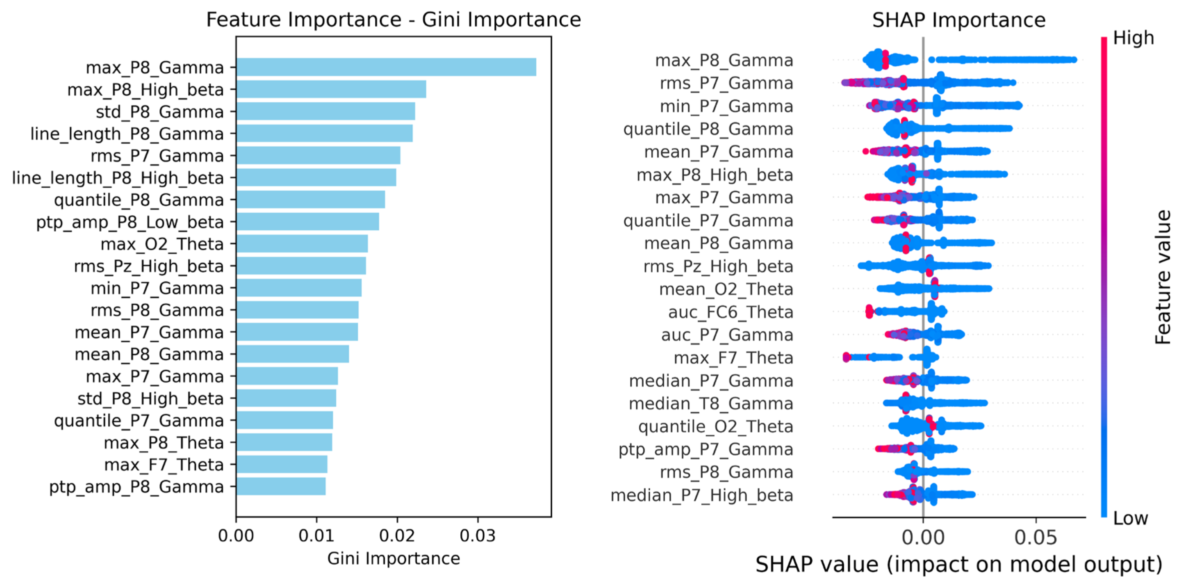
* Mann-Whitney stat test

Results and Discussion

The model results of players proficiency prediction based on time-domain features using 5-fold CV

Model	F1-score (weighted)	Accuracy
LR	0.971 ± 0.004	0.972
SVM	0.907 ± 0.008	0.906
KNN	0.726 ± 0.004	0.740
RF	0.972 ± 0.003	0.967
MLP	0.881 ± 0.009	0.879

Feature importance analysis for Random Forest



The main differences between groups lies in:

- **Gamma- and beta based features**
- **P7,P8 - channel based features** (temporal cortex)
- **O2 - channel based features** (occipital lobe)

Conclusion

1. Preprocessed EEG dataset was built.
2. The distinctive patterns of brain activity for casual and professional players was identified.
3. The reliable classifier for player skill prediction was developed.
4. The comparison with some relevant works was performed.

Future plan

- additional data cleaning
- add more features
- test other window sizes
- more thorough connectivity analysis

References

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THANK YOU
FOR ATTENTION!