The channels with the highest accuracy are shown in Figure 4.

Table 5. The most successful packets, channels and accuracy rates detected by the Coiflet 1 wavelet of eyes close measurement signals

1st Packet	2nd Packet	Channel	Accuracy (%)
64	95	F3	77.50
64	93	F3	77.00
67	81	T7	76.00
84	120	F4	76.00
101	117	FC5	76.00

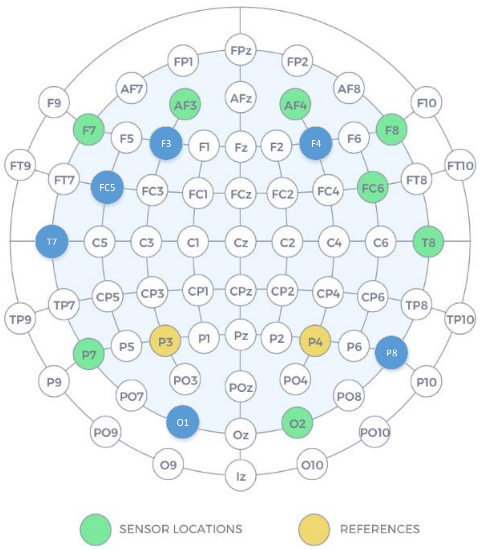

Figure 4. The most successful channels according to the measurement results

IV. Discussion and Conclusion

A database created by EEG records in hungry and full cases was used from 20 healthy male participants under appropriate environmental conditions. The low pass, high pass, and notch filters were applied to the EEG signals and the pretreatment stage was completed by removing noise. In the classification phase of WPT package energy rates, 120 packages and 14 different channels were used as LDA inputs, and 5 channels and packages with the highest accuracy were determined. When we examine the eyes, the Coiflet 1 wavelength is 18 (8.5-9 Hz) and 53. (26-26.5 Hz) Packages and P8 channel in classification based on open measurement; Daubechies 4 wavelengths and 64th (31.5-32 Hz) and 95th (47-47.5 Hz) packages distinguished with the highest accuracy in classification based on eyes closed measurement. When analyzed by channel, it was observed that the most effective channels were P8, F3, F4, FC5, T7, O1.

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