Using EEG to Classify "Like" and "Dislike" Decisions From Visual Stimuli

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Abstract

Neuromarketing combines the field of neuroscience and marketing which analyzes the physiology of brain signals to gain intuition to better understand consumer behaviors. Using neuromarketing techniques, research can be done to analyze and predict the "Like" and "Dislike" Decisions within humans. Combing

The focus of this research will analyze how an image's saturation can alter human decision-making. Does the level of saturation change one's appeal? An example of this would be changing the saturation level on an image of food. A real-life application would be looking at online reviews or videos for a restaurant one has never tried. Do the saturations/colors presented in the image or videos impact one's choices? By understanding this relationship, it allows for the creation of helpful tools and applications to predict the trends seen in consumers. Allowing for learning of what appeals to consumers in order to design innovative products to solve user needs.

Utilizing a Brain computer interface (BCI), data can be collected from subjects to analyze their electroencephalogram (EEG). EEG waves undergo processing to analyze beta and alpha waves in relation to "Like" and "Dislike" decisions.

Hypothesis

If the subject views a stimuli of their liking, then the Alpha waves will go up and the Beta waves will go down and vice versa.

Methods

Equipment: BCI headset, gHIMAP amplifier, g.Sahara box, and MATLAB with SVN machine learning.

To research if the saturation of food impacted "Like" and "Dislike" decisions, a series of slides with foods of varying saturations was created. Subjects filled out a stimuli response form synced with the slides they were viewing. This gave way to distinguish which saturation was classified as a "Like" or "Dislike". On the form 1-3 is a "Dislike", 4-6 is neutral and 7-9 is a "Like". Data from the form is later analyzed in excel and compared with EEG data. Raw EEG data is collected as an hdf5 file which must be converted to a CSV using MATLAB. Finally, all files are ready to be analyzed and compared to yield results.

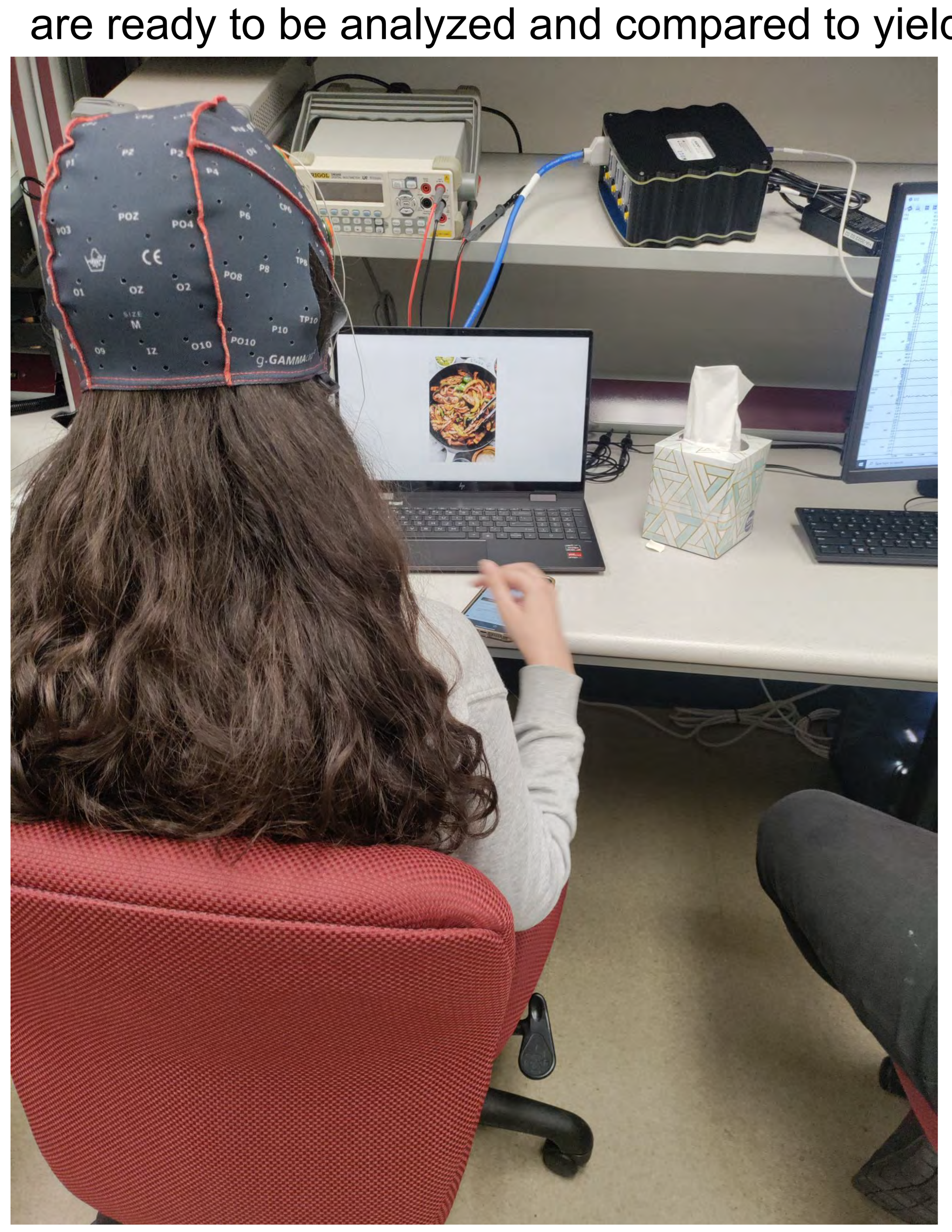
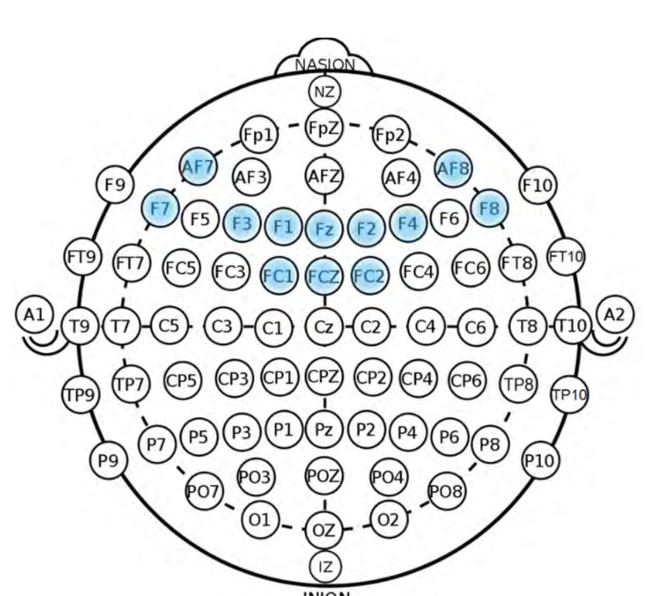


Figure 1: The experimental set up



F1	F2	F3	F4	F7	F8	FZ	FC1	FC2	FCz	AF7	AF8
1	2	3	4	5	6	7	8	9	10	11	12

Figure 2: In blue are the electrode positions on the scalp, below are the electrodes listed and the corresponding channels in order.

Results

The averages of Alpha and Beta values seemed to still reflect the hypothesis when the collected data was good. In some areas the data is inconsistent which could not be used to predict a result. Each subject was different and had varying alpha and beta averages making is helpful to compare per trial rather than all the data value together.

When the data was good it generally followed a few trends:

A high rating paired with a high alpha value: "Like"
A low rating paired with a low beta value: "Dislike"

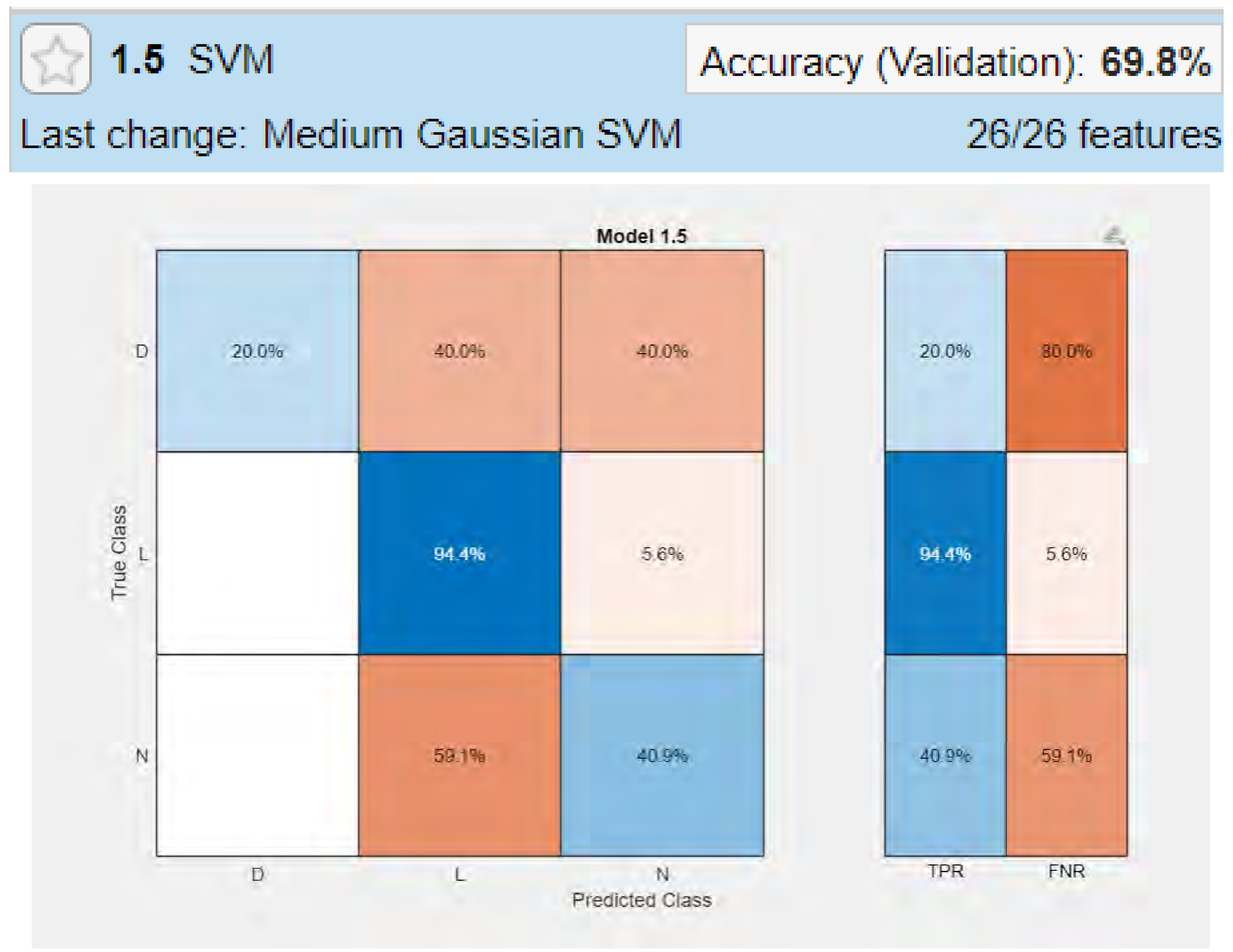
21947.2314	7	Good
5894.9471	5	Good
12392.5407	5	Good
8177.0499	6	Good
9727.1884	7	Good
77872.3820	5	Good
12286.9781	7	Good
75.8543	7	Good
36.0340	7	Bad
94.3156	6	Good
37.7655	6	Bad

Table 1: Left to right, average Alpha values, ranking of image from stimuli response form, classification of good or bad data

90.4459481	7	Good
65.60051355	7	Good
347.2672282	7	Good
170.2734848	6	Good
184.6485029	6	Good
445.6368281	6	Good
184.1793427	8	Good
1604.793215	8	Bad
2568.285461	8	Bad
2154.386383	9	Good

Table 2: Left to right, average Beta values, ranking of image from stimuli response form, classification of good or bad data

To further classify the data, a machine learning model (SVN) was used to run more tests. The rankings from the stimuli response form were used as classes in SVM as such: 1-3 (dislike), 4-6 (neutral), and 7-9 (like). SVM predicted accurate results 69.8 percent of the time.



Accurately Predicted: Dislikes 20%, Likes 94.4%, Neutral 40.9% (blue diagonal is accurate)

SVM did not incorrectly predict any dislikes which is a good result. Although some "Like" and "Neutral" were thought to be "Dislikes".

SVM showed a higher correlation of distinguishing liked data which represents an increase in Alpha waves. Decrease of Beta waves for "Dislikes" were hard to distinguish.

Conclusion

When comparing the averages of Alpha and Beta to the rankings from the stimuli response form, there were some inconsistencies. The variation from subject to subject created unique sets per subjects. Any movement or interference of the wires could also cause inconsistences. The subject's mental state such as agreeability, patience and hunger also can impact results. Hunger is important to note because when one is hungry any food is appealing. Additionally, some subjects had a hard time differentiating the change in saturations within images, thus using the same rating for all trials. Despite the variation and inconsistencies good data was able to reflect the hypothesis of Alpha increasing when stimuli represented "Like" and Beta decreasing when stimuli represented "Dislike".

The SVM model did sufficiently but still could be improved and yield more accurate results.

Many factors impact "Like" or "Dislike" decisions the research could be improved by having more trials and testing on more subjects. It would also be beneficial to standardize the trials to present with even less bias.

Future Work

In the future this experiment could be applied to many areas outside of food. An example could be how the consumer makes decisions when shopping. This would be an application to products and goods individuals may be inclined to. Another factor to look at besides saturation could be lighting, hue, contrast, image quality and more. Could the addition of audio stimuli impact one's "Like" or "Dislike" decision when it comes to a product, good or service? To streamline this experiment even more the exploration of real time EEG data collection and procession could yield very interesting results, though there may be some ethical concerns.

Humans make decisions daily beyond "Like" or "Dislike" understanding our thought processes helps create better products and applications to meet the needs of consumers in all areas.

References

M. Ramirez, M. A. Khalil, J. Can and K. George, "Classification of "Like" and "Dislike" Decisions From EEG and fNIRS Signals Using a LSTM Based Deep Learning Network," *2022 IEEE World AI IoT Congress (AIIoT)*, 2022, pp. 252-255, doi: 10.1109/AIIoT54504.2022.9817329.

S. Kaheh, M. Ramirez and K. George, "Using Concurrent fNIRS and EEG Measurements to Study Consumer's Preference," 2021 IEEE 12th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), 2021, pp. 0305-0310, doi: 10.1109/IEMCON53756.2021.9623092.

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Acknowledgements

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Alternate Text

Rachel Wang

CSUF- Project Raise

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Figure 3: A representation of a machine learning model that was used for the experiment.

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