A Machine Learning Approach to EEG-Based Emotion Recognition

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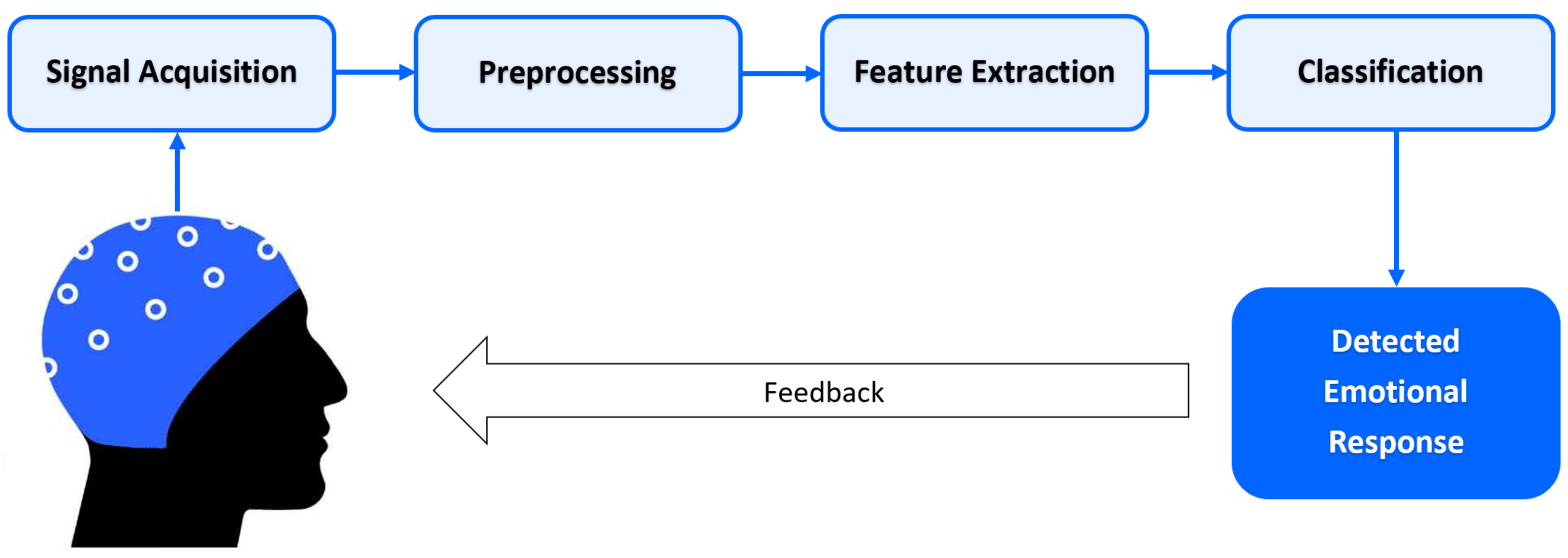
Introduction

In recent years, emotion classification using electroencephalography (EEG) has attracted much attention with the rapid development of machine learning techniques and various applications of brain-computer interfacing such as prosthetics for communication disorders, therapy for mood disorders, interactive games.

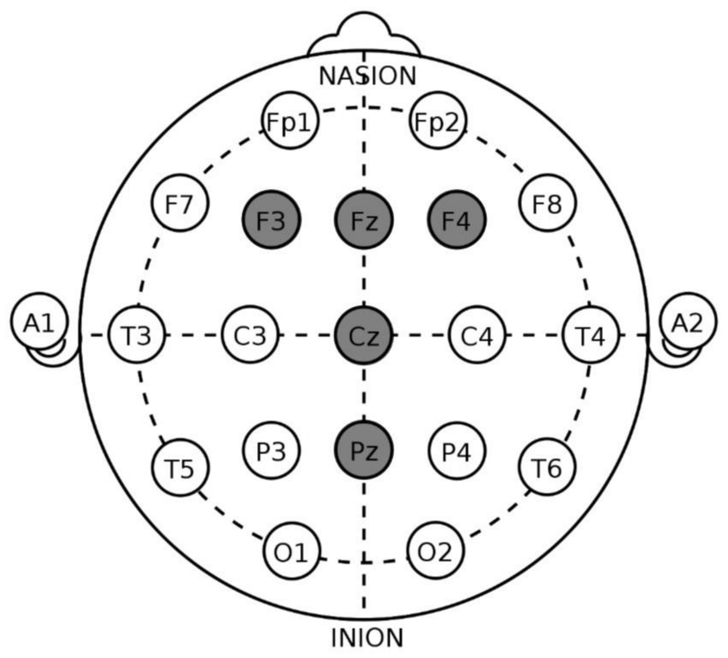
In this study, we attempted to classify a user's emotional state by creating a general model for emotion recognition using a large dataset of EEG responses to happy and fearful videos. We compared discrete and dimensional emotion models, assessed various popular feature extraction methods, evaluated the efficacy of feature selection algorithms, and examined the performance of 2 classification algorithms.

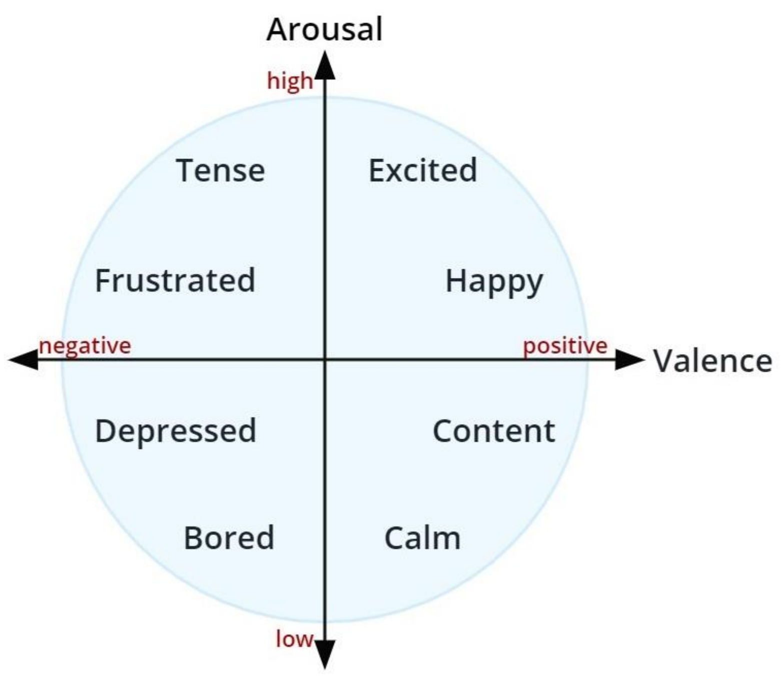
Methods



The EEG dataset used was recorded from a previous study of responses to emotional videos, conducted at the LIVELab in McMaster University. EEG data of 116 participants were acquired across two sessions using 5 electrodes.

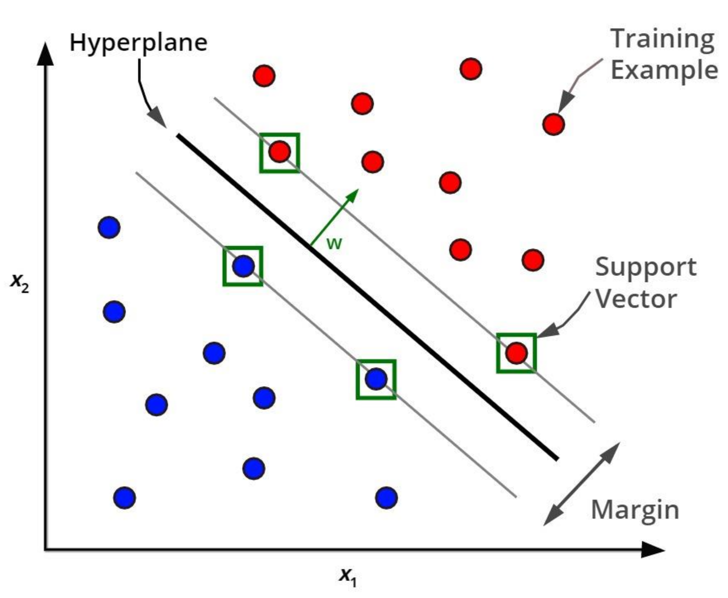
Two main emotion models were tested for classification: discrete and dimensional emotion models. The discrete emotion model attempts to classify between fearful and happy emotional responses while the dimensional emotion model attempts to classify emotions on a 2D valence-arousal plane.

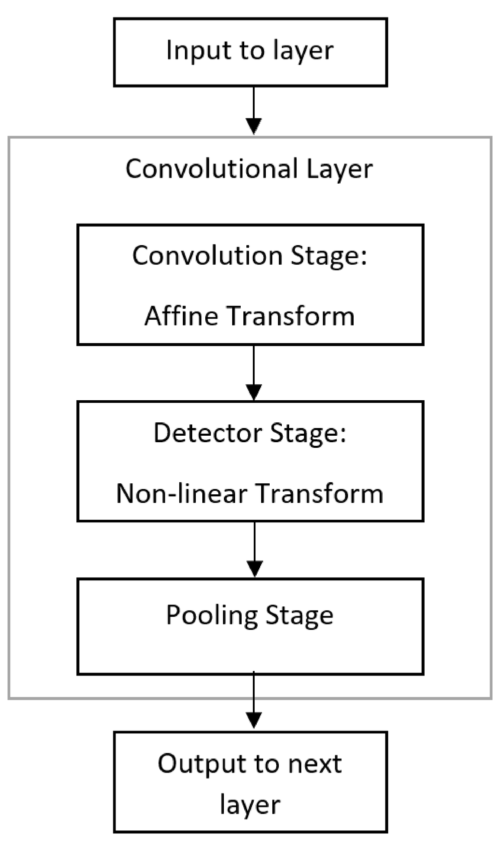




The features extracted for the task of classifying emotional EEG responses include spectral features, hemispheric asymmetries in power in particular frequency bands, cross-electrode coherence at particular frequencies, and higher order spectral features. Spectral features consist of the power spectral density and cross-power spectra density at individual electrodes, while higher order spectral features consist of bispectrum and bicoherence measures at individual electrodes. Feature selection was performed using the minimum Redundancy Maximum Relevance (mRMR) feature selection method.

The two machine learning algorithms used in this study are Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). A parameter search was conducted to find the ideal algorithm parameters for each model.

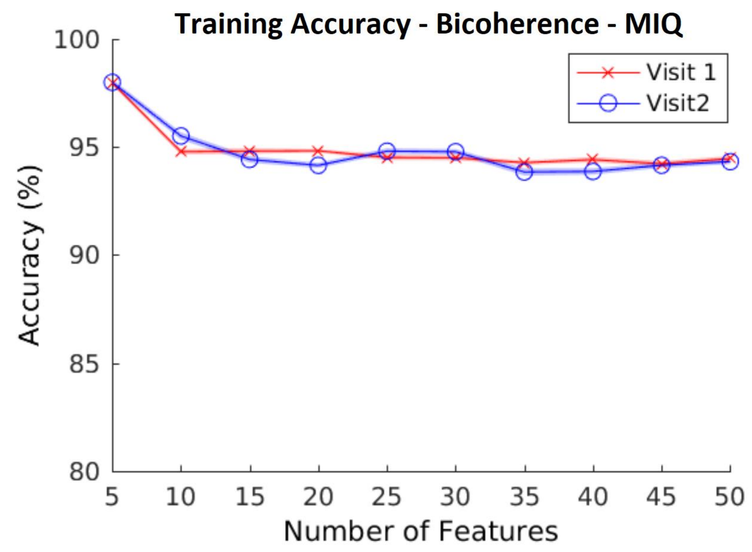


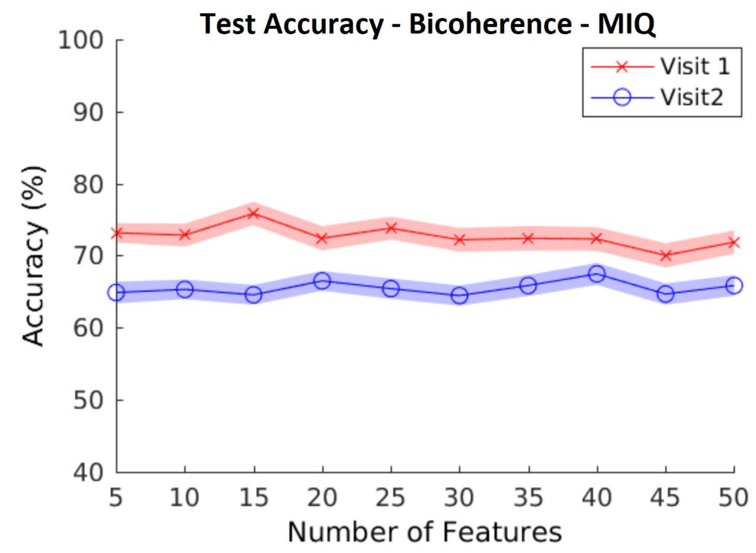


Results

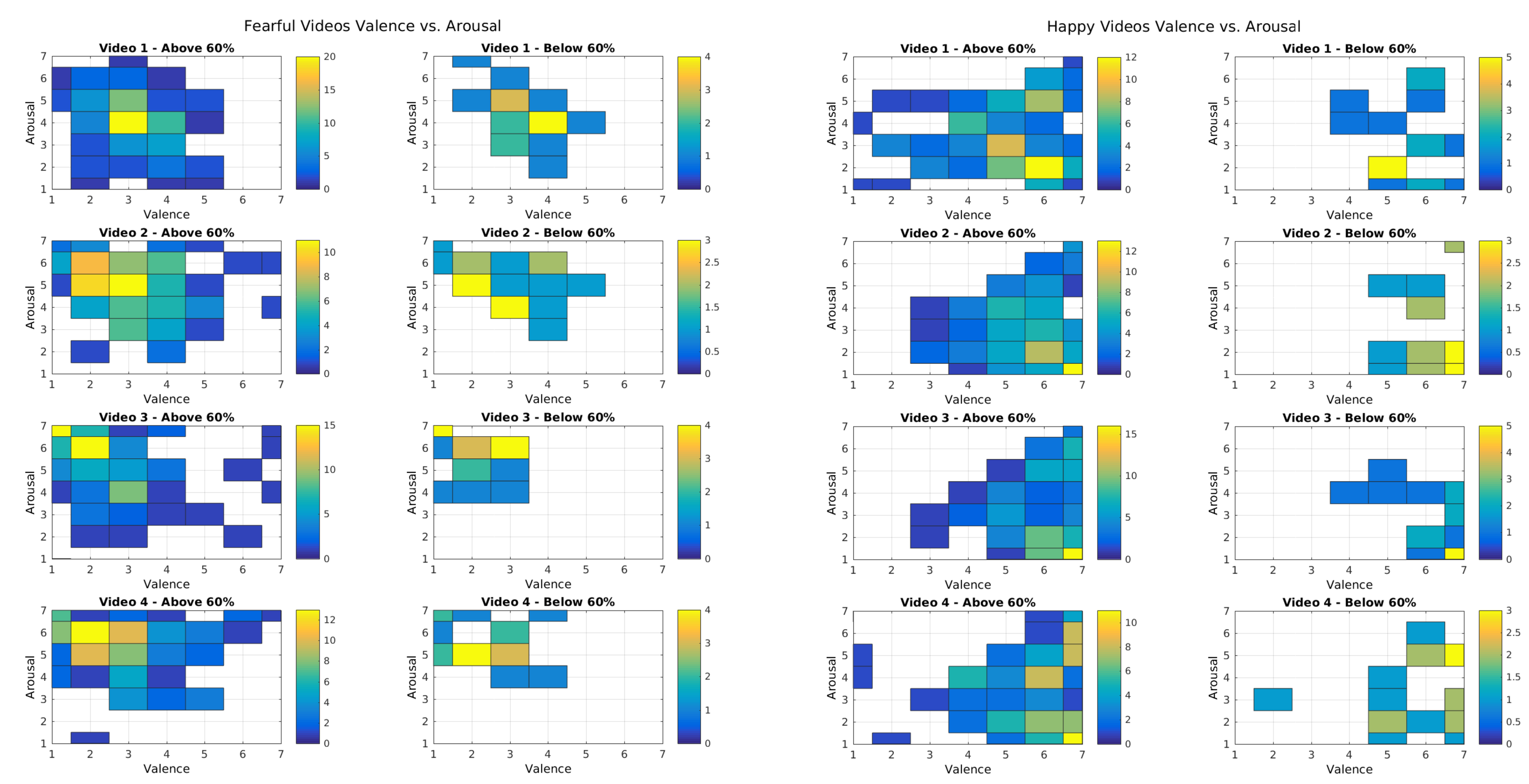
From our experimental results, we have found that a model trained using bicoherence features with feature selection and an SVM classifier outperforms other methods. The best average classification accuracy of 75.86% was obtained with LOSO cross-validation for determining between fearful and happy emotional responses which outperformed the valence and arousal emotion models.

	Visit 1		Visit 2	
Feature Set	Mean Training Accuracy	Mean Testing Accuracy	Mean Training Accuracy	Mean Testing Accuracy
BIC	94.60	**73.01**	94.65	**65.13**
FAA	99.37	57.71	98.53	63.65
PSD	92.08	64.35	91.75	59.02
RMS	99.83	65.18	99.52	64.24





In addition, we found that it is possible to obtain an increased classification accuracy of 78.57 when training on the subset classifiable participants. Moreover, we were able to achieve an accuracy of 72.71% and 67.13% for participant-dependent and between-session models, respectively.



	Visit 1		Visit 2	
Model	Mean Training Accuracy	Mean Testing Accuracy	Mean Training Accuracy	Mean Testing Accuracy
Classifiable	95.87	**78.57**	97.17	72.12
Non-Classifiable	94.69	59.03	96.43	56.25
All Participants	94.82	75.86	94.43	67.46

Conclusion

We found that overall performance was similar to comparable previous work. Studies that outperformed our model were found to either have included 32 or more EEG channels or consisted of about one forth the number of participants or fewer. Potential improvement of classification accuracy on this our dataset may be achieved with the addition of better artifact rejection methods (e.g. filter-bank artifact rejection), various feature extraction methods (e.g. fractal dimension or differential entropy), feature smoothing (e.g. linear dynamical systems), or other classification methods (e.g. graph-regularized extreme learning machine).

References

Barrett, L. F., Mesquita, B., Ochsner, K. N., and Gross, J. J. (2007). The Experience of Emotion. Annual Review of Psychology, 58(1), 373{403. ISBN: 0066-4308.
Cristianini, N. and Shawe-Taylor, J. (2000). An Introduction to Support Vector Ma- chines: And Other Kernel-based Learning Methods. Cambridge University Press, New York, NY, USA.
Dhindsa, K. and Becker, S. (2017). Emotional reaction recognition from EEG. 2017 International Workshop on Pattern Recognition in Neuroimaging, PRNI 2017. Citation Key: Dhindsa2017 ISBN: 9781538631591.
Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep Learning. MIT Press.
Peng, H., Long, F., and Ding, C. (2005). Feature selection based on mutual information: Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy. IEEE Trans. on Pattern Analysis and Machine Intelligence, 27(8), 1226{1238. arXiv: f Citation Key: Peng2005 ISBN: 0162-8828.
Sigl, J. C. and Chamoun, N. G. (1994). An introduction to bispectral analysis for the electroencephalogram. Journal of Clinical Monitoring, 10(6), 392{404. Citation Key: Sigl1994 ISBN: 0748-1977 (Print)nr0748-1977 (Linking).
Soleymani, M., Lichtenauer, J., Pun, T., and Pantic, M. (2012). A multimodal database for affect recognition and implicit tagging. IEEE Transactions on Affective Computing, 3(1), 42{55. ISBN: 1949-3045.