

Traditional Machine Learning approach for Emotion Recognition Challenge

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Overview

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- Dataset of "video-based 7 Korean emotional expression database" and baseline system were developed by Chonnam National University Research Foundation Laboratory (Basic Laboratory for Artificial Sensory Intelligence).
- Performs the task of classification of Emotion into 4 labels of Arousal-Valence space, namely:
 - HAHV: High Arousal, High Valence.
 - HALV: High Arousal, Low Valence.
 - LALV: Low Arousal, Low Valence.
 - LAHV: Low Arousal, High Valence.



Dataset

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Baseline system's preprocess stage extracts the following features from EEG, EDA and BVP signals for train, val and test.

- EEG (294 features): mean, std, power frequency, wavelet coefficient, energy, spectral entropy, kurtosis, hjroth complexity, peak-to-peak, katz fractal dimension, power spectral density.
- EDA (5 features): 5 statistical features using *PyTEAP* package. mean, std, peaks per second, mean amplitude, mean rise_time.
- BVP (17 features): Preprocessed of raw recording. 17 statistical features using *PyTEAP* package.
- Personality (5 features): Extraversion, Neuroticism, Conscienceousness, Agreeableness and Openness.
- Total 321 features. Train set: 690 samples; Test set: 522 samples.



Learning Strategy

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- Mainly approaches: Traditional machine learning
- Different features concatenation methods
- Hyper parameter + cross validation, filtering and average pooling.

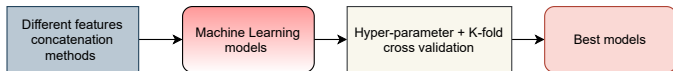


Figure: Learning strategy



Study Pipeline

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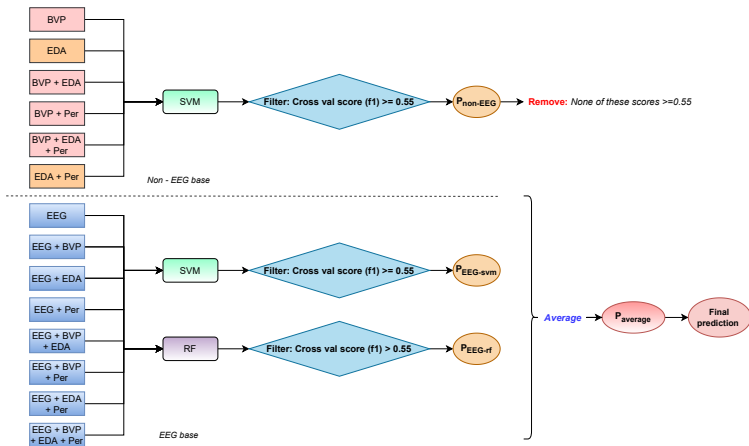


Figure: Study pipeline



Study Pipeline

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Table: All concatenation methods's cross validation scores

Model		Cross val score (f1)	
		SVM	
non-EEG base	BVP	0.449	
	EDA	0.426	
	BVP + EDA	0.461	
	BVP + EDA + Per	0.478	
	BVP + Per	0.478	
	EDA + Per	0.455	
EEG base		SVM	RF
	EEG	0.603	0.571
	EEG + BVP	0.589	0.568
	EEG + EDA	0.602	0.576
	EEG + Per	0.61	0.577
	EEG + BVP + EDA	0.591	0.569
	EEG + BVP + Per	0.593	0.572
	EEG + EDA + Per	0.613	0.569
	EEG + BVP + EDA + Per	0.593	0.577



Experimental and Result

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■ Evaluation metric: Mean F1-Score:

$$F_1 = \frac{2}{\frac{1}{\text{recall}} + \frac{1}{\text{precision}}} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (1)$$
$$= \frac{tp}{tp + \frac{1}{2}(fp + fn)}$$

Table: Experimental and Result

Approach	Private Score	Public Score	Note
Proposed (average all, svm + rf)	0.67013	0.68376	submitted, average all prediction with cross_val >0.55 (rf), >= 0.55 (svm)
SVM (EEG + BVP + EDA + Per)	0.67361	0.67521	non-submitted, highest of private test
SVM + SMOTE	0.66666	0.67521	submitted, SMOTE: Synthetic Minority Oversampling Technique for imbalance dataset
SVM (EEG)	0.66319	0.6923	submitted, highest of public test
TabNet	0.65625	0.68376	non-submitted, TabNet: Attentive Interpretable Tabular Learning. Suitable for tabular data
SVM + PCA	0.65277	0.66666	non-submitted
BaseLine	-	0.55902	baseline



Conclusion

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- The proposed approaches shows the good performance on the private testing set.
- Machine learning approaches could handle data shifting problem well.



Thank you!