

Evaluating classifiers for Emotion Recognition using EEG

Ahmad Tauseef Sohaib, Shah Nawaz Qureshi, Johan Hagelbäck, Olle Hilborn, Petar Jerčić *

Blekinge Institute of Technology, Karlskrona, Sweden

Abstract. There are several ways of recording psychophysiology data from humans, for example Galvanic Skin Response (GSR), Electromyography (EMG), Electrocardiogram (ECG) and Electroencephalography (EEG). In this paper we focus on emotion detection using EEG. Various machine learning techniques can be used on the recorded EEG data to classify emotional states. K-Nearest Neighbor (KNN), Bayesian Network (BN), Artificial Neural Network (ANN) and Support Vector Machine (SVM) are some machine learning techniques that previously have been used to classify EEG data in various experiments. Five different machine learning techniques were evaluated in this paper, classifying EEG data associated with specific affective/emotional states. The emotions were elicited in the subjects using pictures from the International Affective Picture System (IAPS) database. The raw EEG data were processed to remove artifacts and a number of features were selected as input to the classifiers. The results showed that it is difficult to train a classifier to be accurate over large datasets (15 subjects) but KNN and SVM with the proposed features were reasonably accurate over smaller datasets (5 subjects) identifying the emotional states with an accuracy up to 77.78%.

1 Introduction

Humans interacting with computer applications are a part of everyday life. Similarly, emotions are a vital and constantly present part in everyday life of humans and can provide many possibilities in enhancing the interaction with computers e.g. affective interaction for disabled or people in stressful environments. As technology and the understanding of emotions are advancing, there are growing opportunities for automatic emotion recognition systems. There is much successful research on emotion recognition using text, speech, facial expressions or gestures as stimuli[1]. In this paper we focus on recognition of emotions from Electroencephalogram (EEG) signals, since this technique have the benefit of being more passive and less intrusive for the human than facial expressions or vocal intonation. The need and importance of the automatic emotion recognition from EEG signals has grown with increasing role of brain computer interface applications and development of new forms of human-centric and human-driven interaction with digital media. The asymmetry among left and right brain hemispheres are the major areas where the emotion signals can be captured[2]. According to a model

* Contact email: johan.hagelback@bth.se

developed by Davidson et al., the two core dimensions -arousal and valence- are related to asymmetric behavior of emotions. A judgment about a state as positive or negative lies under valence whereas the level of excitement (calmness, excitement) lies under arousal[3].

Human machine interaction on the base of physiological signals has been greatly investigated by previous and recent research. Of particular interest are systems that can make interpretations about psychological states based upon physiological data. Linear classifiers[4–6] are considered to be the most appropriate classification technology due to their simplicity, speed and interpretability. However, non-linear classifiers are considered to be the most appropriate when it comes to signal features and cognitive state[7, 8].

Sequential Floating Forward Search and Fisher Projection methods are used by Picard et al. to classify eight basic emotions with 81% accuracy[9]. Lisetti and Noasoz used Marquardt Back Propagation, Discriminant Function Analysis and K-Nearest Neighbor to distinguish between six emotions and acquired classification accuracy between 71% and 83%[10]. Conati argued that probabilistic models can be developed using a methodology provided which uses various body expressions of the user, personality of user and context of the interaction[11]. Mental workload has been evaluated using Artificial Neural Networks providing mean classification accuracies of 85%, 82% and 86% for the baseline, low task difficulty and high task difficulty states respectively[12]. Fisher developed an emotion-recognizer based on Support Vector Machines which provided accuracies of 78.4% and 61.8%, 41.7% for recognition of three, four and five emotion categories respectively[4]. According to Rani et al., if the same physiological data is used then Support Vector Machines with a classification accuracy of 85.81% perform the best, closely followed by the Regression Tree at 83.5%, K-Nearest Neighbor at 75.16% and Bayesian Network at 74.03%. Performance of K-Nearest Neighbor and Bayesian Network algorithms can be improved using informative features. Support Vector Machine shows 33.3% and 25% accuracy for three and four emotion categories respectively when it comes to physiological signal databases acquired from ten to hundreds of users[13]. For more research on emotions and EEG see for example [14–19].

It is difficult to compare the results between different studies due to different experiment environments, preprocessing techniques, feature selection etc.. However, studies have shown that various factors such as preprocessing and classification techniques can strongly affect the results in terms of accuracy. Even if several methods have successfully been used to develop affect recognizers from physiological indices, it is still important to select an appropriate method in each study for the classification of EEG data to attain uniformity in various aspects of emotion selection, data collection, data processing, feature extraction, base lining, and data formatting procedures.

Several machine learning techniques have been used for classifying EEG data. Some common ones that previously have been used for EEG data associated with affective/emotional states are K-Nearest Neighbor (KNN), Regression Tree (RT), Bayesian Network (BNT), Support Vector Machine (SVM) and Artificial Neural Network (ANN).

According to an extensive survey carried out by Rani et al. KNN is one of the most widely used techniques for classifying EEG data associated with specific affective/emotional states[13]. Yu et al. found that KNN was the most effective classifier

in classifying emotion sickness from EEG data[20]. Parvin et al. claims that KNN's ability of dealing with discriminant analysis of difficult probability densities makes it very effective for classifying EEG data[21]. According to Downey and Russell, RT is largely used in medical fields to, for example, classify EEG data[22]. Brown et al. also mentions the wide use of RT for classifying EEG data[23]. BN was used with success by Matas et al. for classifying varying emotional states[24]. In their survey, Rani et al. strongly supports SVM and recommend it for accurately classifying EEG data[13]. This claim is also supported by Chen and Hou[25]. According to experiment results by Yu et al. and Huang et al., SVM provides effective and promising results for classifying EEG data[20, 26]. In a study by Tangermann et al. the authors claim that SVM can show a high level of agreement on EEG data classification[27]. In a study by Ho and Sasaki ANN could accurately classify EEG data and they claim it is especially useful when a small number of electrodes are used[28]. Chen and Hou claims that ANN is an effective technique to classify EEG data due to its ability to handle noisy data efficiently[25].

These five techniques were found to be used in most of the empirical studies we have found and were considered to be suitable for the classification of EEG data associated with specific affective/emotional states based on the achieved classification accuracy. KNN and SVM seemed to be the most common ones among the classifiers with the highest attained accuracy where our interest was to achieve high accuracy over large datasets/participants.

2 Experiments

The goal of the experiments was to classify the various emotional states in subjects as they look on different pictures that are inducing strong emotions. The International Affective Picture System (IAPS) was used for this purpose. IAPS is a general picture database especially designed for experiments in emotions with normative values for valence, arousal, and dominance[29]. In these experiments we used the 2-dimensional emotional model with valence and arousal.

A total of 20 subjects (15 men and 5 women) participated in the experiment. All subjects were students of Blekinge Institute of Technology, Sweden, and aged from 21 to 35 years. The subjects were from different cultural background, nationalities and field of studies.

The EEG signals were captured from left and right frontal, central, anterior temporal and parietal regions (F3, F4, C3, C4, T3, T4, P3, P4 positions according to the 10-20 system and referenced to Cz)[30]. Based on these findings, the experiment was executed as described by Davidson et al.[3] and AlZoubi et al.[31]:

- An appropriate interface was applied for the automated projection of the IAPS emotion-related pictures.
- To compensate opening/closing of eyes 30 seconds gap was maintained before starting the experiments.
- 30 IAPS pictures (6 pictures for each emotion cluster as neutral, positive arousing/calm, negative arousing/calm) were displayed randomly for the duration of 5 seconds with a gap of a black screen between 5-12 seconds. The purpose of the

black screen duration was to reset the emotional state of subjects offering them the time to relax having no emotional content. A cross shape projection was displayed for 3 seconds before each picture to attract the attention of the subject. This process was repeated for each picture.

- A subject may feel an emotion which differs from the one expected. Therefore each subject was asked to rate his/her emotion on a Self-Assessment Manikin (SAM)[29]. Each subject rated their level of emotion on a 2D arousal and valence scale.
- Two recording sessions for 25 to 35 trials having 5 pictures, displaying each picture for 2.5 seconds were completed.
- During the whole process, subjects were directed to stay quiet and still (to realize and observe the emotion instead of mimic the facial expression) with as few eye blinks as possible to get rid of other artifacts (e.g., facial muscles).
- Fp1, Fp2, C3, C4, F3, and F4 positions were used to attain the EEG signals according to 10-20 system and all of the electrodes were referenced to Cz.

During the experiments, EEG data for each subject was recorded using BioSemi ActiveTwo System with a sampling rate of 2048Hz and stored in BioSemi Data Format (BDF) using ActiView BioSemi acquisition software. Each subject took approximately 20 minutes individually to complete an experiment.

The subjects were screened to select EEG data for data analysis and processing. The screening was based on SAM; subjects with low valence and arousal rating were rejected. The reason for screening was to select the most valuable data and remove the rest to get reliable results. The screening left 15 subjects out of 20. Screening was further applied to EEG data of 15 subjects to select the signal duration which fulfill the aimed emotion based on SAM. The idea behind this was to screen out and separate the data for each emotion. For example the signal for positive arousal were screened from the rest of the emotions and so on. EDF Browser¹ (a tool for reading and processing sensor data) was used to reduce the signals individually for the required duration. While reducing the signals, the first and last second had been eliminated from the total duration of five second stimulus presentations. This was in order to narrow down to exactly required data. The reason for this step was to focus on valuable data and filtering out the extra. Because when a picture is displayed, it takes some time for the brain to react to new stimuli and therefore the first second is usually noisy. Similarly, after looking at a picture stimulus for a while the brain goes into a relaxed state and does not react in the same activation as initially; therefore the last second was removed as well. This process was completed for pictures with positive, negative and neutral arousal as well as for positive, negative and neutral valence.

The screened data was preprocessed using EEGLAB Toolbox² for MATLAB. Epoch and Event info were extracted, the data was pruned and baseline removed. Finally, Independent Component Analysis (ICA) was performed on the data[32]. Preprocessing data with these various techniques helps to remove the artifacts such as eye blinking etc. This also make it easier to extract features from the signals.

¹ <http://www.teuniz.net/edfbrowser>

² <http://sccn.ucsd.edu/eeglab>

Feature selection is one of the key challenges in affective computing due to phenomena of person stereotype[13]. This is because different individuals express the same emotion with different characteristic response patterns for the same situations. Each subject involved in the experiment was having diverse physiological indices that showed high correlation with each affective state. The same finding has been observed by Chen and Hou[25] and is explained by Rani et al.[33]. From the obtained EEG data, it was observed that physiological features were highly correlated with the state of arousal among two subjects. According to Rani et al., a feature can be considered significant and selected as an input to a classifier if absolute correlation is greater for physiological features among subjects[33]. Based on these findings, it was observed that the accuracy improved for some techniques (i.e. KNN, BNT and ANN) when highly correlated features were used, while it degraded for the others (i.e. RT and SVM). Chen and Hou point out that selection of highly correlated features helps to exclude the less important features for affective state and hence improve the results[25].

The preprocessed data was further processed to get the real values for the signals using EEGLAB Toolbox for MATLAB. Based on findings by AlZoubi et al. the four features *minimum value*, *maximum value*, *mean value* and *standard deviation* were extracted from each signal in order to further process the data[31].

The raw EEG data is processed to extract the selected features. Different signal processing techniques are available for this purpose such as Fourier transform, wavelet transform, thresholding, and peak detection. The values obtained were formatted in Attribute-Relation File Format (ARFF), which is an acceptable file format for the data-mining tool WEKA³. The values obtained are used as instances in the ARFF file with a binary class value as negative and positive arousal/valence. Each feature value (min value, max value, mean value and standard deviation) for each electrode is a separate attribute in each instance in the ARFF file. Six electrodes were used making the total number of attributes 24 (plus the class value). A separate dataset was created for each subject, as well as a combined dataset with data from all subjects.

Each dataset were classified using machine learning techniques available in WEKA. During the classification, the classifier was trained to classify negative or positive arousal/valence values as correctly classified whereas neutral values as incorrectly classified. The techniques used had all the default parameter values as implemented in WEKA. In all experiments 10 fold cross validation were used.

Figure 1 shows the complete process of capturing, processing and classifying the EEG data in the conducted experiments. The results from classifying the EEG data for all 15 subjects are presented in Table 1 and Figure 2. The highest accuracy was obtained with SVM (56.10%) closely followed by KNN, RT and BT (52.44%). The three latter all had the same accuracy indicating that they at least in this case discriminate the data in a similar way. The result are not very promising indicating that there can still be noise in the processed data, or that the selected features are not representative for all subjects which can be a problem as pointed out by Rani et al.[13]. As comparison a random guess would give an accuracy of 33% since three possible emotional states (positive or negative valence/arousal and neutral) are used.

³ <http://www.cs.waikato.ac.nz/ml/weka>

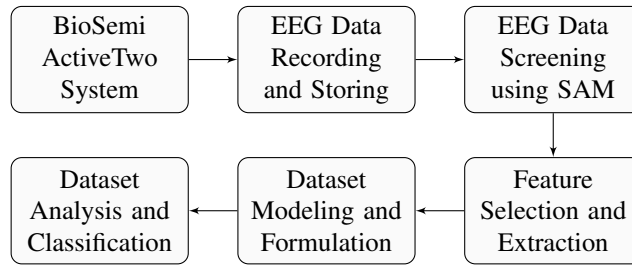


Fig. 1. The process for capturing, processing and classifying the EEG data.

Table 1. Results from classifying EEG data for all subjects.

Technique	Accuracy
K-Nearest Neighbor	52.44%
Regression Tree	52.44%
Bayesian Network	52.44%
Support Vector Machine	56.10%
Artificial Neural Networks	48.78%
Random guess	33.33%

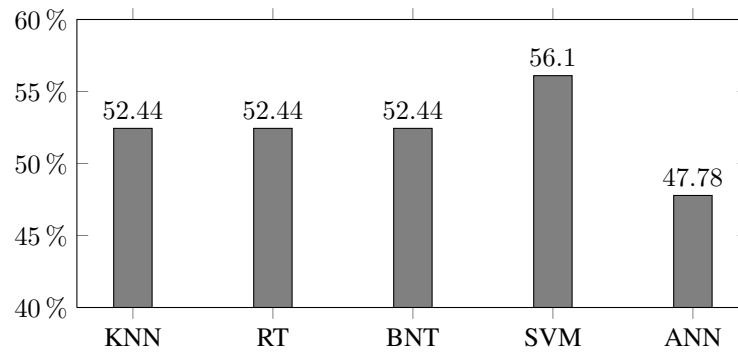


Fig. 2. Results from classifying EEG data for all subjects.

To see if there could be problems with the generality of the selected features we divided the dataset into three subsets each with data from five subjects. The subsets were split in a semi-random fashion. The first five subjects was put in Dataset 1, the next five in Dataset 2 and the last five in Dataset 3. The results are shown in Table 2 and Figure 3. They show that all classifiers except RT had difficulties classifying Dataset 3. RT had problems classifying both Dataset 2 and 3. In this experiment SVM are still

the best classifier followed by KNN. It is interesting that KNN, RT and BN all had the same accuracy when classifying the full dataset, but in this case RT and BN are well behind KNN. The best results (over 70% accuracy topping at 77.78%) are in line with the accuracy of other related experiments (see for example [2]).

Table 2. Results from classifying datasets of five subjects each.

Technique	Dataset 1	Dataset 2	Dataset 3	Average
K-Nearest Neighbor	70.37%	66.67%	51.35%	62.80%
Regression Tree	62.96%	44.44%	45.95%	51.12%
Bayesian Network	59.26%	55.44%	48.65%	54.45%
Support Vector Machine	77.78%	70.27%	51.35%	66.47%
Artificial Neural Networks	70.37%	61.11%	43.24%	58.24%
Random guess		33.33%		

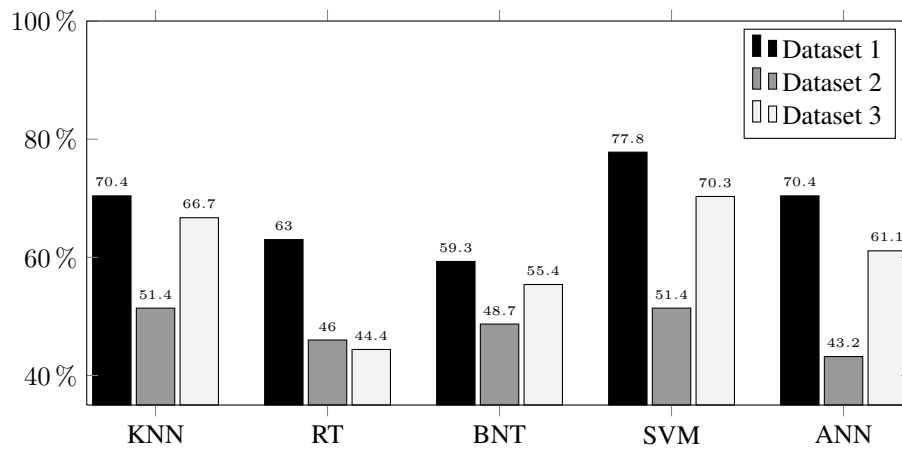


Fig. 3. Results from classifying datasets of five subjects each.

In the last experiment we used datasets containing of only a single subject. This was done for the first three subjects. The results are shown in Table 2 and Figure 4. In this experiment KNN was the most accurate classifier with 83.33% accuracy for Subject 3. It is interesting to see that SVM was only able to get 50.00% accuracy on the same subject. BN showed very large differences with 72.72% accuracy for Subject 2 and only 36.36% for Subject 1.

Table 3. Results from classifying datasets of single subjects.

Technique	Subject 1	Subject 2	Subject 3
K-Nearest Neighbor	54.54%	72.72%	83.33%
Regression Tree	36.36%	54.54%	50.00%
Bayesian Network	36.36%	72.72%	66.66%
Support Vector Machine	45.45%	45.45%	50.00%
Artificial Neural Networks	45.45%	45.45%	50.00%
Random guess		33.33%	

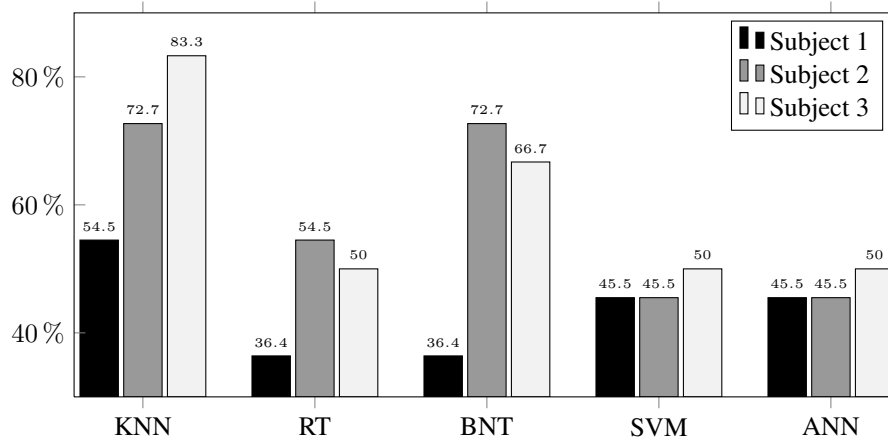


Fig. 4. Results from classifying datasets of single subjects.

3 Discussion and Future Work

The main purpose of our experiments was to evaluate different machine learning techniques for classifying EEG data. From our results we can conclude that it is not trivial to process and classify data to be accurate over a large number of subjects. The results from all 15 participants was in the best case 56.10%. When dividing the subset into three parts with five subjects each the accuracy rose to 77.78%. In both cases SVM was the best classifier with KNN slightly behind. The results from classifying data from single subjects showed an accuracy of 83.33% for KNN. Interesting is that SVM only showed an accuracy of 50.00% on single subjects.

As Rani et al. discusses the feature selection is a key challenge in affective computing due to phenomena of person stereotype[13]. This is probably the reason why the accuracy in our experiments greatly increased on smaller datasets. It is difficult to find features that are generally working well over a large number of subjects. Another reason is that EEG data is noisy and diverse and is often very difficult to work with. There

is also the possibility that the IAPS pictures did not induce strong enough emotions on some subjects making it difficult to classify some emotional states.

Based on the results we cannot say which classifier that generally is the best, but KNN and SVM seems to be good choices regardless of the size of the datasets.

In the future we would be interested in using more features and different combinations of them to see how it affects the accuracy over many subjects. It would also be interesting to observe if more subjects in the experiment would have any positive or negative impact on the results, as the amount of data for the classifier increases. In this experiments we used a binary class value for the classifiers (negative or positive valence/arousal) and an unknown as neutral valence/arousal. It could have impact on the results if we use three separate classes with neutral valence/arousal as its own class value instead.

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