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RESEARCH ARTICLE

# Improving the accuracy of EEG emotion recognition by combining valence lateralization and ensemble learning with tuning parameters

**Evi Septiana Pane**[1,3] · **Adhi Dharma Wibawa**[1,2] · **Mauridhi Hery Purnomo**[1,2]

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**Abstract**

For emotion recognition using EEG signals, the challenge is improving accuracy. This study proposes strategies that concentrate on incorporating emotion lateralization and ensemble learning approach to enhance the accuracy of EEG-based emotion recognition. In this paper, we obtained EEG signals from an EEG-based public emotion dataset with four classes (i.e. happy, sad, angry and relaxed). The EEG signal is acquired from pair asymmetry channels from left and right hemispheres. EEG features were extracted using a hybrid features extraction from three domains, namely time, frequency and wavelet. To demonstrate the lateralization, we performed a set of four experimental scenarios, i.e. without lateralization, right-/left-dominance lateralization, valence lateralization and others lateralization. For emotion classification, we use random forest (RF), which is known as the best classifier in ensemble learning. Tuning parameters in the RF model were done by grid search optimization. As a comparison of RF, we employed two prevalent algorithms in EEG, namely SVM and LDA. Emotion classification accuracy increased significantly from without lateralization to the valence lateralization using three pairs of asymmetry channel, i.e. T7–T8, C3–C4 and O1–O2. For the classification, the RF method provides the highest accuracy of 75.6% compared to SVM of 69.8% and LDA of 60.4%. In addition, the features of energy–entropy from wavelet are important for EEG emotion recognition. This study yields a significant performance improvement of EEG-based emotion recognition by the valence emotion lateralization. It indicates that happy and relaxed emotions are dominant in the left hemisphere, while angry and sad emotions are better recognized from the right hemisphere.

**Keywords** Emotional recognition · Brain signals · Lateralization · Brain asymmetry · Random forest

## Introduction

Emotions greatly affect the human health condition, and emotions even affect the immune level (Koh 1998) and longevity (Pressman and Cohen 2005). This happens because emotions can affect the way our body reacts to a particular situation. For instance, as reported by Brosschot and Thayer (2003), negative emotions experienced continuously can increase blood pressure in the heart and can decrease the resistance of the body (Berk et al. 2001). Therefore, emotion recognition becomes important for monitoring individual health, especially in elderly health monitoring, because negative emotion reaction in elderly is vulnerable for their health. Therefore, an integrated of e-healthcare solutions that can provide to the elderly its global health status and monitor their emotions state is needed to perform for advance elderly care (Pires et al. 2015). If the emotion recognition is performed accurately and routinely monitored, special treatments can be developed to improve an elderly negative

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✉ Evi Septiana Pane
evi.pane15@mhs.ee.its.ac.id; pyrena.eve@gmail.com

Adhi Dharma Wibawa
adhiosa@te.its.ac.id; wibawa.adhi@yahoo.co.id

Mauridhi Hery Purnomo
hery@ee.its.ac.id

1 Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Building B and AJ, Raya ITS, Surabaya 60111, Indonesia

2 Department of Computer Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia

3 Industrial Training and Education of Surabaya, Ministry of Industry, Surabaya, Indonesia

emotional response. Castillo et al. (2016) initiate the architecture of software that intends to perform an automatic emotion recognition and regulation for elderly support. The software aims to enhance the quality of life of the elderly who live at home through the monitoring of emotion states.

Emotion recognition based on physiological measures has been done previously by several researchers using multimodal data, including ECG (Wibawa et al. 2016) and EEG (Bos 2006). Compared to ECG, EEG sensors have several advantages one of which is the real-time response. Koelstra et al. (2012) show that EEG has a significant correlation with the emotional video stimulus provided by personal assessment. EEG is known to be more reliable due to its unbiased assessment compared to other external appearance such as face, voice, galvanic skin response (GSR) (Koelstra et al. 2012). This is because EEG signals are generated by the limbic system which is part of the primordial brain tissue and responsible for emotional management (Bhatti et al. 2016).

Emotions recognition using EEG signals is one of the most challenging tasks to do. Since the EEG signal contains lots of noise and artefacts due to small movement of subject during measurement. Another thing is the low accuracy of emotion classification. This issue has attracted many researchers to propose algorithms and approaches for better performance of EEG emotion recognition. One of the proposed approaches that are rarely found on EEG emotion recognition studies is the use of emotional lateralization and investigation of classification algorithms. Emotional lateralization is the tendency of each hemisphere to process certain emotions. A better understanding in lateralization concept will have an impact on effective EEG signal measurement techniques, especially in the context of emotional recognition. Besides the use of powerful features, the right choice of classification algorithm has an impact on enhancing prediction results during the classification. Therefore, in this study we address two strategies to improve the accuracy of EEG emotion recognition. First, we proved the lateralization effect on increasing emotion recognition accuracy from EEG signal. Second, we proposed the ensemble learning approach, RF, for improving classification performance on EEG emotion recognition.

Related to the emotional lateralization in brain, there are two major theories, namely the right-hemisphere dominance of emotions and valence lateralization (Demaree et al. 2005). The right-hemisphere theory exhibits that the right hemisphere is predominant over the left hemisphere for all forms of emotional judgement. The valence lateralization hypotheses state that emotional valence affects hemispheric asymmetry for emotions perception. Both of those theories have been acknowledged by empirical studies using several modalities, including neuroimaging and EEG. The earlier study of lateralization for emotions perception and expression in brain was proposed by Ahern and Schwartz (1985). They utilize EEG spectral analysis to differentiate positive and negative emotions. According to their study, the negative emotions were found dominant in the right hemisphere and the positive emotions in the left hemisphere. Those findings are consistent with the present study by Schmidt and Trainor (2001). They examine the pattern of EEG movement to distinguish emotions by musical composition stimuli. Their research showed that the pattern of emotions lateralization was found relative to right-frontal hemisphere for fear and sad musical excerpts, while greater relation to left-frontal hemisphere for happy and joyful musical piece. A recent study by Altenmüller et al. (2002) revealed a form of brain activation patterns while listening to several musical genres. EEG activation has emerged widespread in the respective frontal–temporal area with a significant lateralization effect. The positive emotions are indicated by an escalation in a left-temporal hemisphere activation, while negative emotions have appeared in the right-frontal and right-temporal hemisphere area.

From various emotional lateralization schemes already discovered, we found no article has used the lateralization concept to improve the accuracy of emotional recognition through EEG signals. In addition, from the two prevalent theories in lateralization, there is currently no widely accepted schema of emotion lateralization to effectively improve the accuracy of EEG-based emotion recognition. By finding an appropriate emotional lateralization scheme on each hemisphere, we expect a significant improvement on the accuracy of EEG-based emotional recognition. Therefore, this study attempts to prove that the concept of lateralization can be used to enhance the accuracy of emotional recognition through EEG signals. A series of experiments were conducted by including the emotional lateralization concept based on two prevalent theories of emotional processing in the brain.

The interest of many researchers in the field of brain–computer interface (BCIs) in studying emotions through EEG signals is constrained by the low-accuracy problem of emotional recognition. In a study undertaken by Liu et al. (2011), accuracy problem is one of the challenges in the problems in recognizing the emotions from EEG signals. To address the problem, a study by Jenke et al. (2014) reviewed various methods used at the feature extraction stage in emotional recognition from EEGs based on 63 articles. Jenke's preliminary findings suggest that features extracted from three domains, frequency, wavelet and time, are able to work well as features of EEG signals to improve the emotion recognition accuracy. Meanwhile, according to (Bhatti et al. 2016) the combination of the three-domain features above can improve the accuracy of emotion recognition performance. Therefore, we propose a hybrid feature extraction method which combines the time-domain features, power spectral density (PSD) from frequency domain and discrete wavelet transform (DWT). Moreover, we further note the information about the most remarkable features among the existing features.

In addition to feature extraction, enhancing the classification accuracy can be performed by exploring the use of classification methods. A large number of studies in EEG-based emotional classification use SVM algorithms (Atkinson and Campos 2016; Bhatti et al. 2016; Lin et al. 2010; Zhang et al. 2016a). Other studies utilize k-NN (Bhatti et al. 2016; Mohammadi et al. 2016) and LDA (Wang et al. 2014). A different classifier was introduced by Li et al. (2017); they proposed the hierarchical convolution neural network algorithm by extracting differential entropy features from short-term Fourier transform on beta and gamma frequency band. Nevertheless, all previous classifier methods are single-model classification. In fact, using a combination of more than one classification models such as ensemble learning will improve the accuracy of classification results. Therefore, this paper proposes an ensemble learning approach that can improve classification results by incorporating two or more classification models. In particular, we use the random forest (RF) algorithm which is known as the leading method in the ensemble family. This approach allows for better prediction than a single classification model. Although RF has been widely used in the field of bioinformatics (Qi 2012), to our knowledge, this paper is the first to propose the classification of emotional recognition through EEG with RF implementation. RF has several characteristics that may be suitable for EEG datasets, such as the ability to handle large numbers of input variables from EEG datasets and the ability to manage continuous variables (Breiman 2001). To compare the RF performance accuracy, we also employ LDA and SVM, since both algorithms commonly use the methods to classify EEG signals in cases of emotional recognition in previous studies.

To summarize, there are two objectives stated in this study: first is to prove the impact of the emotional lateralization concept to improve the accuracy of emotional recognition; second is to validate the accuracy of the ensemble learning method by tuning parameters in classifying the emotions from EEG signal. In the first goal, we try to prove the appropriate emotional lateralization scheme from asymmetric channel pairs in the brain that enhance the accuracy of emotion recognition. Meanwhile, on the second purpose, the proposed classification method uses ensemble learning, in this case RF, known as the most accurate classifier in various fields of study (Bernard et al. 2012). Therefore, the contributions of this research are the following:

1. Providing an empirical evidence about the effect of valence lateralization to improve EEG emotion recognition accuracy
2. Proving the feasibility of using the ensemble learning method with a parameter tuning to improve the accuracy of emotional recognition.

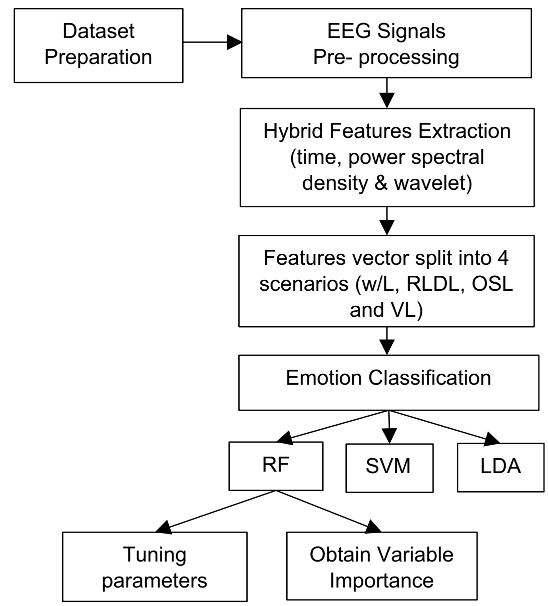



**Fig. 1** Proposed method of EEG-based emotion recognition

## Materials and methods

We propose an approach for EEG-based emotion recognition that aimed at improving classification accuracy through lateralization concepts and ensemble learning with tuning parameters. Figure 1 illustrates the steps of the proposed method sequence.

### Materials

In this study, we obtain the data from EEG recording on public DEAP emotion dataset (Koelstra et al. 2012).[1] This dataset includes 32 participants as the subject. Each subject watched 40 emotion stimulated video clips with a duration of one minute.

Table 1 summarizes the questionnaire response and video rating by the subjects after the experiment. Most of the subjects were young adults who had normal vision correction and right-handedness tendencies. The EEG capturing equipment utilized bio-semi-acquisition system with 32 channel locations over the scalp. The sampling rate (*fs*) of the raw EEG signal is 128 Hz. Eye blinking is removed using a blind source separation technique and a bandpass

[1] http://www.eecs.qmul.ac.uk/mmv/datasets/deap/index.html.

**Table 1** Summary of subjects answer to questionnaire and SAM rating

| Parameters | Detail information |
|---|---|
| Age (years) | 27.18 ± 1.4 |
| Gender (male/female) | 17/15 |
| Vision | Normal (14); corrected to normal (15); acceptable uncorrected (2); blank (1) |
| Handedness (right/left) | 31/1 |
| Arousal rating (scale 1–9) | 5.16 ± 2.02 |
| Valence rating (scale 1–9) | 5.25 ± 2.13 |

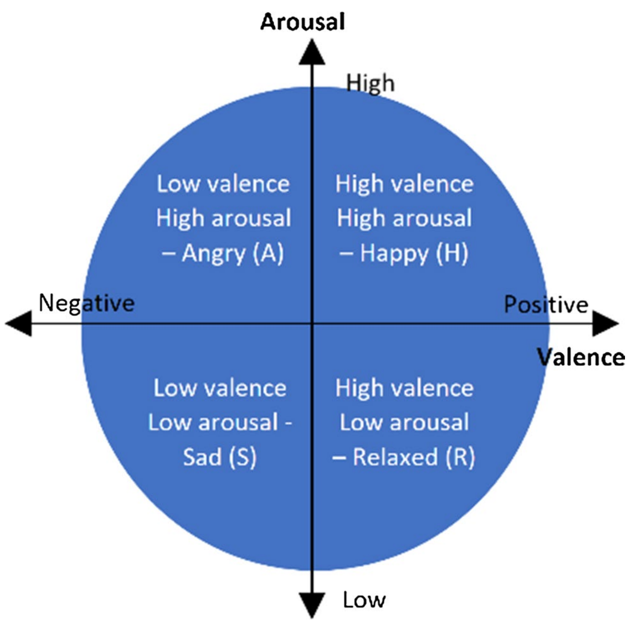



**Fig. 2** Arousal–valence model of emotion as target class of emotions

frequency filter of 4–45 Hz. For emotional recognition purposes, we target four emotional classes according to the arousal–valence emotional model. The emotional label is derived from the rating scores in the participant questionnaire. Each participant was given a questionnaire rating to measure their emotional responses after viewing each video. Participants evaluate the video stimuli using arousal/valence dimension rating which range from 1 to 9. Next, we mapped the valence and arousal scales into two parts of each dimension according to the Self-Assessment Manikin (SAM) (Bradley and Lang 1994). The rating values of arousal and valence 1–5 are mapped to low arousal/valence and 6–9 for high arousal/valence. Thus, the model of arousal and valence is divided into four quadrants or categories shown in Fig. 2. The four classes of emotion are happy (H), angry (A), sad (S) and relaxed (R) each class in sequence are 458, 296, 266 and 260.

## Methods

### EEG signal preprocessing

Each EEG record contains a 63 s length of data, consisting of 60-s stimuli recording and 3-s baseline. According to the study in the window size selection on DEAP dataset (Candra et al. 2015), the active segment size for emotions recognition lies between 3 and 12 s. With *fs* 128 Hz, consequently a 9-s data with 1152 data points was used for analysis. We applied the Chebyshev II bandpass filter to obtain the EEG of beta frequency band (12–30 Hz) which indicates the awake condition of subjects during stimulation recording. A related study shows that EEG of beta bands has significantly appeared during the awake condition, which is suitable for emotion recognition (Mohammadi et al. 2016; Zhang et al. 2016b). This also shown in our previous study (Pane et al. 2017) that features of beta frequency bands obtained the best classification accuracy compared to the features from alpha and gamma frequency bands. Moreover, a study by (Zheng and Lu 2015) suggests that features of energy from beta bands have specific neural pattern related to positive and negative emotions with the same type of video clips stimuli. Thus, in this study, we only extracted the features from the beta frequency band.

As suggested in the previous studies (Mohammadi et al. 2016; Zheng and Lu 2015; Lin et al. 2010), selecting asymmetrical channels from EEG scalp has provided better classification accuracy of emotion recognition. Thus, we obtained EEG from several pairs of asymmetry channel. Throughout the whole channels in EEG dataset, we have chosen 6 pairs of asymmetric channels, namely T7–T8 (temporal), F7–F8 (frontal), O1–O2 (occipital), C3–C4 (central), Cp5–Cp6 (centro-parietal) and P7–P8 (parietal). We selected only channels which have a strong correlation with audio and video stimuli, T7–T8, O1–O2 (Purves 2004) besides channels that have been widely used for emotion recognition such as F7–F8, C3–C4 (Mohammadi et al. 2016; Zhang et al. 2016b). For using Cp5–Cp6 and P7–P8 channels, we explain that in the ERP study (event-related potential) for emotion recognition using LPP (late positive potential), centro-parietal and parietal lobe were known to be relevant for emotional valence and processing (Olofsson et al. 2008).

In this experiment, we also observe the best combination from five possible pair combination of asymmetry channels according to each channels functional implication towards the video music stimulation. We limited the combination from 2, 3 to 4 pair asymmetry channels, such as CpP, TO, TCpP, TCO and TFCO that shown in Fig. 3.

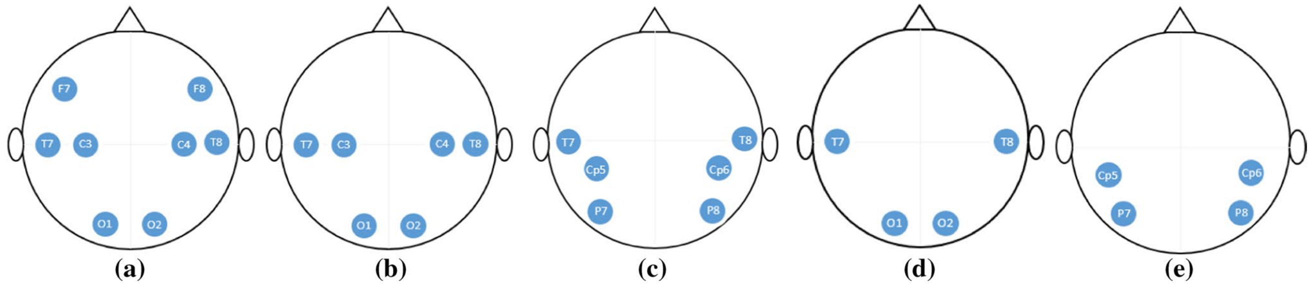



**Fig. 3** Channels pair location. **a** TFCO, **b** TCO, **c** TCpP, **d** TO and **e** CpP

### Hybrid features extraction

Even though many studies in EEG proposed band power feature extraction from frequency domain, the accuracy obtained from emotion classification was not quite significant (Jenke et al. 2014; Pane et al. 2017). Meanwhile, a study in emotion recognition from EEG signal believes that the combination of time, frequency and time–frequency-domain features is decent for identification of emotion characteristics (Bhatti et al. 2016). Therefore, in this paper we extracted the hybrid features that consist of time, frequency (PSD) and time–frequency (wavelet)-domain features extraction method for emotion recognition.

The time-domain feature extraction method covers statistical features (Atkinson and Campos 2016; Diykh et al. 2016), Hjorth parameters (Hjorth 1970), and fractal dimension (Higuchi 1988; Liu et al. 2011). We extracted several descriptive features in the statistic, including signal average, band power, standard deviation, kurtosis, skewness and zero-crossing number. In addition to previous work (Atkinson and Campos 2016), we also extracted the maximum peak. The peak is considered to be a maximum when the peak's value is larger than two times of its standard deviation.

The frequency-domain features are used in many BCI studies. Besides short-term Fourier transform and fast Fourier transform, the estimation of power spectral density (PSD) applying Welch's method (Jenke et al. 2014) can be used as an alternative method. The PSD deals with the distribution of spectral energy that would be discovered per unit time, since the total energy of such a signal on the whole duration usually is infinite. Thus, the average power $P$ of a signal $X(t)$ on the entire time is given by:

$$P = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} |X(t)|^2 \mathrm{d}t \tag{1}$$

From the PSD signals, we construct a new set of features including Hjorth parameters, statistical features and fractal dimension.

Several studies of EEG-based emotion recognition used discrete wavelet transform (DWT) decomposition due to its low cost of computation time (Bhatti et al. 2016; Mohammadi et al. 2016; Wang et al. 2014). In this paper, we present the Daubechies 4 (db4) with 3-level decomposition to separate the EEG into alpha, beta and gamma frequency bands. We choose this wavelet function because its character is near-optimal time–frequency location. From each frequency band of signals decomposition, we extracted three features, those are:

1. Detail coefficient. The detail coefficient we used is one-dimensional wavelet analysis function. It extracts the detail coefficients 1-D at each level from the decomposition structure.
2. The energy entropy. Entropy is the expected value of the information carried by each vector $x$. Both of the log energy and Shannon's energy definition are calculated. Both energy and entropy are given as:

$$E(x) = \sum_i \log(x_i^2) \tag{2}$$

$$H(x) = -\sum_{i=0}^{N-1} x_i^2 \log x_i^2 \tag{3}$$

3. The average of Teager–Kaiser energy operator (TKEO). The TKEO can be considered as a nonlinear measure of energy, taking into account both the frequency and the amplitude of the signals. It was first proposed in (Kaiser, 1990) and is defined as:

$$\psi\left(x_n\right) = x_n^2 - x_{n+1} \cdot x_{n-1} \tag{4}$$

where $n$ denotes the index of the input vector. Then, the mean of TKEO vector for each decomposition level is taken as a feature in the time–frequency-domain features.

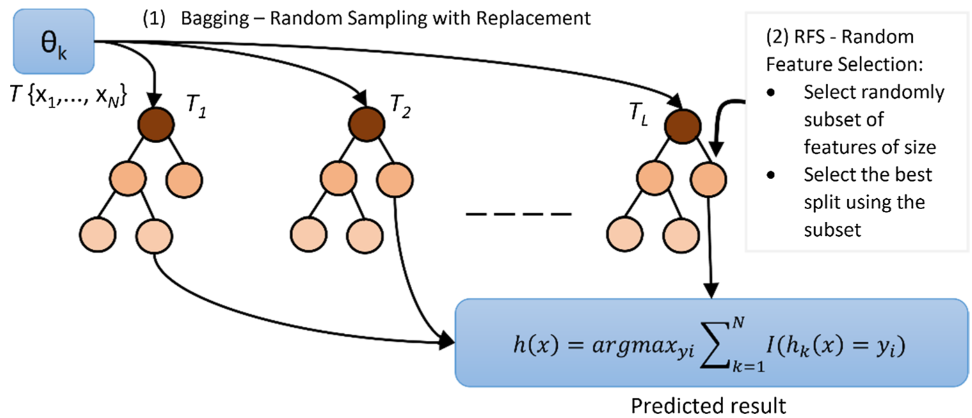



**Fig. 4** Illustration of how random forest algorithm works with two basic principles, bagging and RFS

### Ensemble learning approach

The ensemble learning approach is made by combining many predictors to classify instances. In this study, we employed prominent algorithm in classifier ensemble, which is random forest (RF). The primary learners in RF are decision trees. A random forest is a tree-structured-based classifier, which is given as:

$$\{h_k = h(x, \theta_k),\ k = 1, \ldots, N\} \quad (5)$$

Thus, each tree gives a vote for typical class appear in instances $x$ (Breiman 2001).

The fundamental principle of RF methods is using Bootstrap aggregating (bagging) and random features selection (RFS) as shown in Fig. 4. The randomness is injected by growing each tree through both principles. Bagging employs $N$ classifier by generating additional data in the training process. Random sampling technique produces the additional data with substitution from initial dataset. In this way, some observations may be reiterated in each new training dataset. However, any instances have equal probability to be appended in a new dataset. Meanwhile, RFS technique works by randomly choosing $k$ features among $M$ of features in the dataset. Then, it built the best splitting rule-based from these features. As for the prediction, aggregation of $N$ resulting classifier was used. The error measured in RF called out-of-bag (OOB) error. The RF model can handle a large number of input features, such as EEG data without a prior feature selection process. It can be used for giving an estimate of which features are important for classification. The Mean Decrease in Gini (MDG) is used as measures for feature importance. The MDG is a parameter of how each feature contributes to the homogeneity of the leaves and nodes in the resulting random forest model. A high number of MDG means that a particular variable has excellent contribution in classifying the data into the designated classes.

## Experiment setup

### Experiment scenarios

The experimental scenarios in this paper aim to classify four classes of emotions using four groups of lateralization scenarios: without lateralization (w/L), right/left-dominance lateralization (RLDL), valence lateralization (VL), and other schemes of lateralization (OSL). The experiment scenarios design is presented in Fig. 5. The w/L scenario was commonly used by studies in EEG emotion recognition (Mohammadi et al. 2016; Zheng and Lu 2015; Lin et al. 2010). It obtained the EEG signals of all emotions from both hemispheres. The RLDL idea comes from the right-hemisphere lateralization of emotion which obtained the EEG signal of all emotions from the right hemisphere (Borod et al. 1988; Schwartz et al. 1975), while the left lateralization was the opposite of the right-hemisphere lateralization. Many studies have shown empirical evidence for the right-hemisphere lateralization through the investigation using neuroimaging and physiological signals (Alves et al. 2008). The VL scenario was inspired by valence lateralization (Davidson et al. 1979; Demaree et al. 2005). This scenario suggests that the stimuli of valence affect the pattern of hemispheric dominance. The right hemisphere is prominent for processing negative emotions, whereas the left hemisphere is superior in response to positive emotions. Meanwhile, the OSL is another scheme of lateralization which was also taken into account in the investigation. In order to get consistent finding, several numbers of pair asymmetry channels were carried out.

### Testing and performance measure

For efficacy measure of performance, we calculate classification accuracy. The performance accuracy is given as:

$$\text{Accuracy (\%)} = \frac{\text{Number of correct predicted samples}}{\text{Total samples}} \quad (6)$$

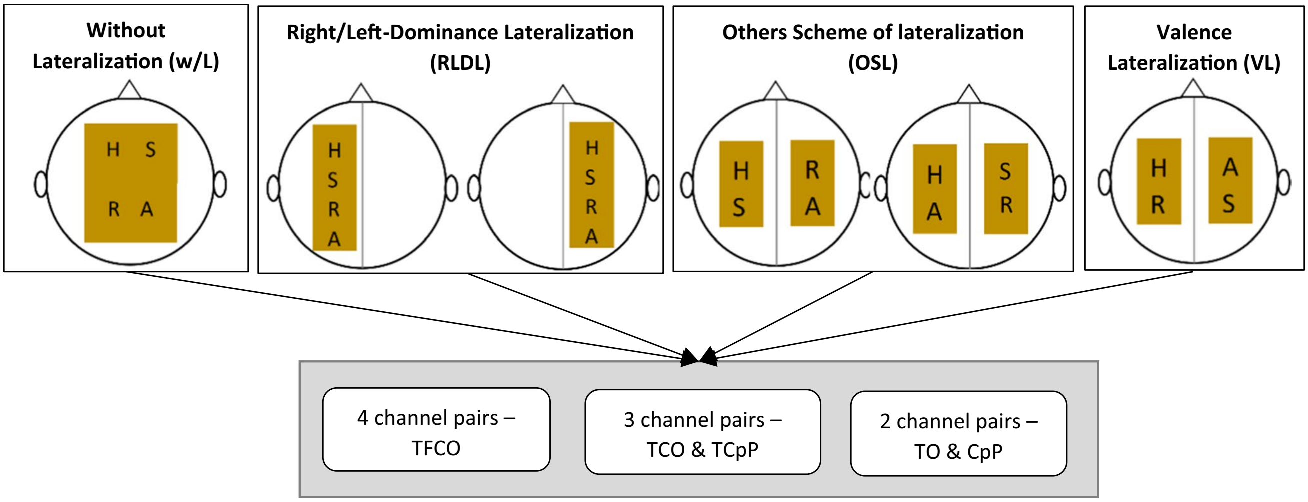



**Fig. 5** Experiment scenarios design

For RF method, we optimize the number of tree (ntree) and the number of splitting variable (mtry). Both of the variables are optimized using grid search technique. The ntree value is ranging from 100 to 500 trees, and the mtry value starts from $\sqrt{\sum f}$, where $f$ is the number of features in the dataset. Consequently, the tuning grid for mtry parameter is around those numbers. Parameters tuning is carried constructing classifier model. Variable importance of RF results is obtained by calculating the best 10 MDG number of features in the data. This variable importance indicates which features are more reliable for emotion recognition task from the EEG signals. To compare RF performance, we compared it with SVM polynomial kernel and LDA classifier.

We conducted classification with cross-validation technique as a testing option to evaluate the proposed method. We employ $k$-fold validation for divide training and testing data into $k$ group of smaller datasets randomly ($k=10$). The first part of the data serves as the training, while the remaining is the testing. This procedure is iterated $k$ times. The average result from complete fold classification is given as the final accuracy.

## Results and discussion

To demonstrate the effect of emotion lateralization and the RF method on improving the accuracy of emotion recognition from EEG, we have performed experiment with several scenarios as described in "Experiment scenarios" section. Systematic evaluation has been carried out with the published EEG emotion dataset. This section summarizes the findings from the experiments.

### Varying emotional lateralization scenarios

We compare the accuracy from all scenarios using five pairs of different asymmetry channels from EEG. The comparison of RF classification accuracies results between all scenarios is presented in Fig. 6. Apparently, from Fig. 6 we noticed that the accuracies from average pair asymmetry channels of w/L scenario (mean 47.98%) to the RLDL scenario (mean 46.11%) are slightly decreasing. This indicates that the use of both hemispheres (w/L scenario from left to right hemisphere) is still promising for classifying emotion. In detail from RLDL scenarios results, it is shown that EEG signal obtained from left hemisphere (mean 44.3%) is slightly better to recognize emotion rather than right hemisphere (mean 47.92%) for emotion recognition. This finding is against the right-hemisphere lateralization model. However, an investigation by Wager et al. (2003) supports our conclusion. Wager et al. (2003) were unable to prove the right-hemisphere lateralization model during the experiment from neuroimaging data, while the accuracies from w/L to OSL (mean 61.59%) and VL (mean 65.34%) are significantly increasing.

From the result shown in Fig. 6, we have seen that the proposed VL performance from all pair channels shows the best average accuracy of 65.34%. These findings support our hypothesis which use the strategy of asymmetry pair of channels with the valence lateralization schemes to improve performance. From detail observation in VL accuracies results, we can see that HRAS scenario obtain the best accuracy from all pair of asymmetry channels which included in the experiment. This HRAS result reveals that left hemisphere is better to recognize happy and relaxed emotion, while the right hemisphere is much of sad and angry emotion. These combinations of findings were consistent with previous

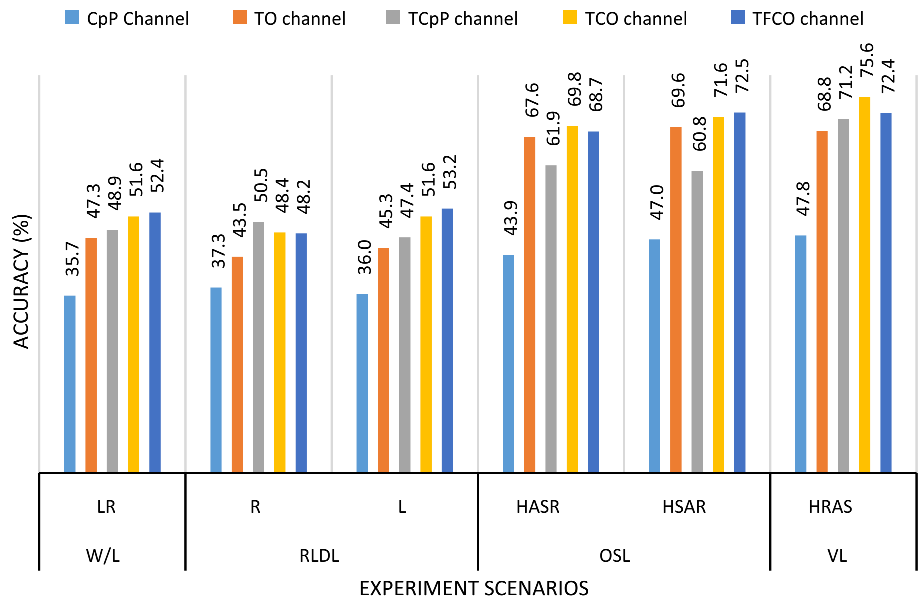



**Fig. 6** Performance accuracies from all scenarios obtained using RF classifier

theories by (Schmidt and Trainor 2001). Moreover, earlier studies by Altenmüller et al. (2002) found that emotions processed during listening to musical excerpts are significantly affected by lateralization effect. Altenmuller et al. found that brain activity increases in the left-temporal hemisphere for positive emotions, while negative emotions appear through an increased activity in the right-frontal–temporal area. It is evident from our experiments that the right and left hemisphere of the brain is functioning differently that confirms well with the valence lateralization theory. Indeed, our proposed VL combination of emotions gives an improvement in classification accuracy rather than only using one/two hemisphere for all emotion.

From Fig. 6 we also observe the performance accuracy among five pair of asymmetry channels. The more numbers of asymmetry pairs channel involved appear to have an impact on obtaining better accuracy. Related to the pairs of channels involved, the best pair asymmetry channels performance in all scenarios was the TCO combination, while the worst accuracy of pair asymmetry channel in entire scenarios was the CpP combination. This result was in contrast with the suggestion of many studies of EEG emotion recognition using LPP analysis (Olofsson et al. 2008). This is mainly because the features extraction method we used in this study was different from event-related potential (ERP) analysis implemented by Olofsson et al. In particular, the LPP used a time-locked EEG to an observable event in millisecond resolution that was around 300–700 ms (Ibanez et al. 2012). Meanwhile, in this study, we took continuous EEG recording signals in a second resolution.

Between the five pair asymmetry channels used in the experiment, the T7–T8 channels show a high contribution towards accuracies. It is shown by the increase in accuracies from the combination of CpP to the TCpP and the highest accuracy obtained from TCO channels. This evidence proved that the T7–T8 pair asymmetry channel is reliable for the emotion processing regarding the response to the music stimuli. These findings also confirm well with the related study of electrode selection for EEG emotion recognition in the same dataset performed by (Zhang et al. 2016a).

Furthermore, from the TCO combination result we also proved that the O1–O2 channels playing an important role related to the response of visual sensory from seeing the videos clip. Indeed, our result was supported by earlier findings of the best electrode for EEG emotion recognition in the same DEAP dataset (Özerdem and Polat 2017; Zhang et al. 2016a). Obviously, from the TCO combination, the C3–C4 channels were also contributing in improving classification accuracy. This is caused by the obvious activity of beta bands in central lobe region such as C3–C4 (Zhang et al. 2016b). In the previous study that used the same dataset by (Zhang et al. 2016b), they only use the F4 and C3 channel for the EEG-based emotion recognition.

To further support our HRAS findings, we compared the plot results of the k-means clustering from HR and HS class from TCO channels of VL scenario. We employ two best features according to MDG values information after classification, such as log entropy in gamma band (le1_bo1) and log entropy in alpha band (le3_bo1) from the occipital channel. The results are shown in Fig. 7. As can be seen in Fig. 7a, the sample data in HS class of emotions are well separated that indicates the happy and sad emotions are not homogeny, and the data variance is diverse. Meanwhile, in Fig. 7b, the sample data from HR class of emotion are not clearly separated, which denotes that happy and relaxed emotions are homogeny and the data variance is not too diverse.

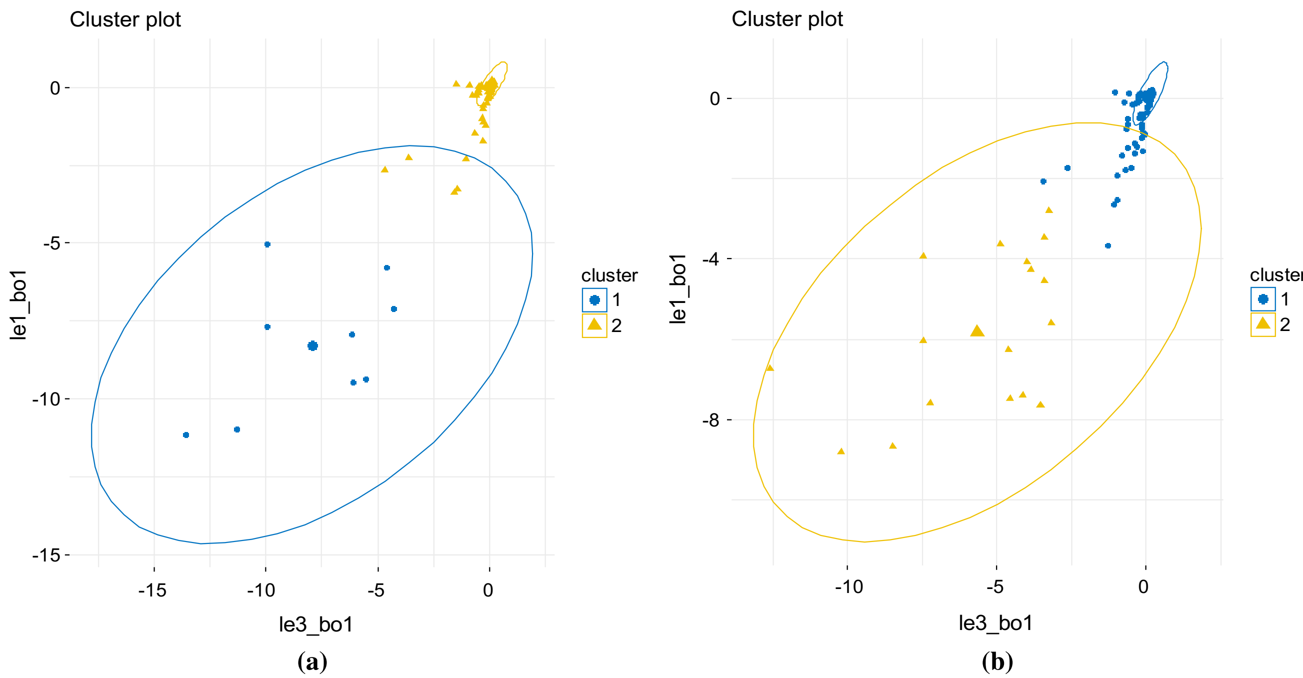



**Fig. 7** Cluster plot results of two important variables obtained from: **a** HS emotions and **b** HR emotions

## Emotion classification results

The classification results are obtained from SVM, LDA and RF classifier utilizing output from features extraction process. The feature extraction yields 10 variables of statistical features, 9 variables of PSD features and 12 variables of DWT features (4 variable X 3 level/band decomposition). In total, there are 31 attributes per each channel used as feature vector input to the classifier. The graphic plots of accuracy obtained from TCO channels are given in Fig. 8. From Fig. 8, it is visually shown that RF method (the yellow colour bar graphic) could improve the accuracy of emotion recognition compared to other classifiers. The RF model yields the best performance for each scenario. The average increased accuracy from all scenarios with RF compared to SVM is 11.4% and 12.1% against LDA. The improvement effect of RF also shows a consistent trend from all scenarios. Therefore, we can conclude that the RF model is working well for improving EEG emotion recognition.

In addition to Fig. 8, Table 2 shows multiple results from another number of pairs channel. From accuracies report in 3, we can observe from the entire number of pairs channel that the RF outperformed SVM and LDA. The best accuracy from all experiment is from VL-HRAS scenario which obtained from TCO pairs channel using RF classifier (75.6%). Accordingly, the RF model can enhance the accuracy of EEG emotion recognition in a varying number of channel pairs. The accuracies are increasing as the number of channels used in the experiments is also larger.

## Tuning parameters and variable importance

We further observe the capability of RF classification model from VL-HRAS scenario taken from TCO channel pairs. In RF model, two parameters need to be tuned—ntree and mtry. We optimized these parameters in order to seek the optimal number of tree in the ensemble and the splitting variable in each tree. The first parameter of tuning is ntree number. The tuning of ntree ranges from 100 to 500 trees. Figure 9a shows tuning results for ntree setting. In Fig. 9a, we can see that the OOB error curve is decreasing when it reaches ntree = 100 and then becomes stable until ntree = 500. Therefore, the optimal ntree number for

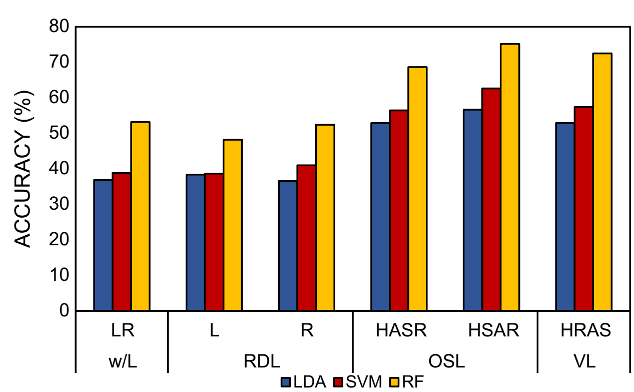
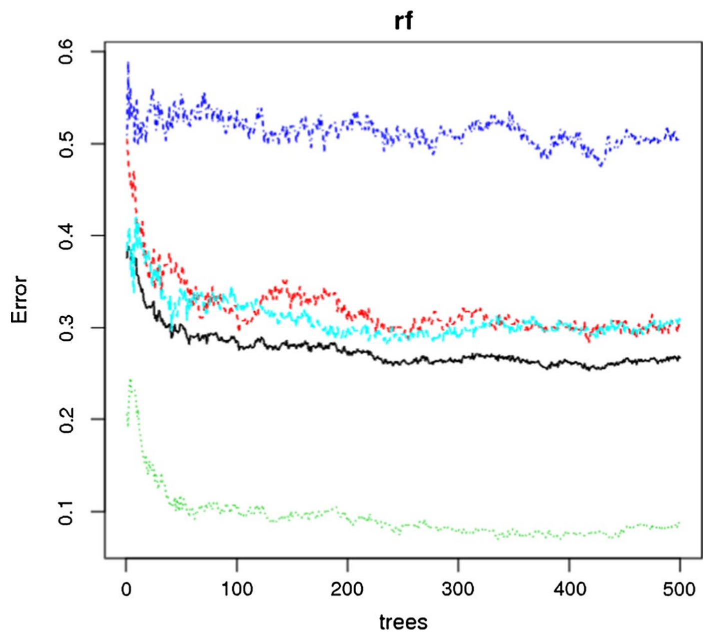



**Fig. 8** Comparison of performance accuracies among three compared classifiers obtained from TCO pairs channel

**Table 2** Multiple results of classification accuracies (%) from each scenario in all number of pair asymmetry channels

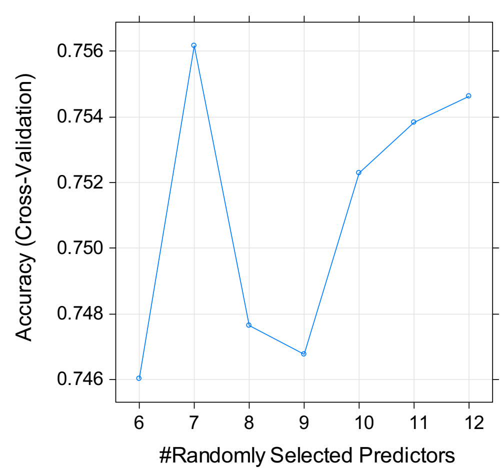
| Scenarios | | Pair channels | Accuracy (%) RF | SVM | LDA | Scenarios | | Pairs channel | Accuracy (%) RF | SVM | LDA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| RLDL | L | TFCO | 53.2 | 38.9 | 38.2 | OSL | HSAR | TFCO | 72.5 | 57.4 | 58.9 |
| | | TCO | 51.6 | 37.5 | 38.4 | | | TCO | 71.6 | 59.1 | 56.7 |
| | | TO | 45.3 | 36.2 | 37.9 | | | TO | 69.6 | 58.6 | 56.8 |
| | | TCpP | 47.4 | 36.1 | 32.7 | | | TCpP | 60.8 | 57.8 | 54.3 |
| | | CpP | 36.0 | 35.7 | 32.6 | | | CpP | 47.0 | 36.2 | 35.2 |
| | R | TFCO | 48.2 | 38.7 | 33.9 | | HASR | TFCO | 68.7 | 56.5 | 55.2 |
| | | TCO | 48.4 | 38.8 | 36.6 | | | TCO | 69.8 | 55.7 | 52.9 |
| | | TO | 43.5 | 38.4 | 35.4 | | | TO | 67.6 | 56.8 | 53.8 |
| | | TCpP | 50.5 | 37.6 | 35.0 | | | TCpP | 61.9 | 57.0 | 55.9 |
| | | CpP | 37.3 | 36.0 | 32.9 | | | CpP | 43.9 | 36.2 | 31.9 |
| w/L | LR | TFCO | 52.4 | 41.0 | 37.8 | VL | HRAS | TFCO | 72.4 | 62.6 | 64.7 |
| | | TCO | 51.6 | 41.0 | 36.9 | | | TCO | *75.6* | 69.8 | 60.4 |
| | | TO | 47.3 | 41.7 | 37.4 | | | TO | 68.8 | 58.4 | 64.5 |
| | | TCpP | 48.9 | 37.8 | 34.5 | | | TCpP | 71.2 | 58.6 | 63.4 |
| | | CpP | 35.7 | 35.2 | 32.3 | | | CpP | 47.8 | 36.0 | 35.6 |




(a)

| Class | Class error | Graph Color |
|---|---|---|
| Angry | 0.3358 | |
| Happy | 0.0593 | |
| Relax | 0.5242 | |
| Sad | 0.2251 | |
| OOB estimates error 25.21% | | |

(b)




(c)

**Fig. 9** **a** The tuning results of ntree parameter; **b** confusion matrix results from the RF classification; **c** the tuning results of *mtry* parameter

RF model is 500. From the confusion matrix presented in Fig. 9b, it indicates that among the four target classes of emotion, sad emotion reaches the highest predicted error, while happy emotion achieves the lowest error in RF classification model. These findings are confirmed well with the previous result by Zheng (2017).

The second parameter is mtry values. The mtry *values* are ranging around the square root of total variable in data.

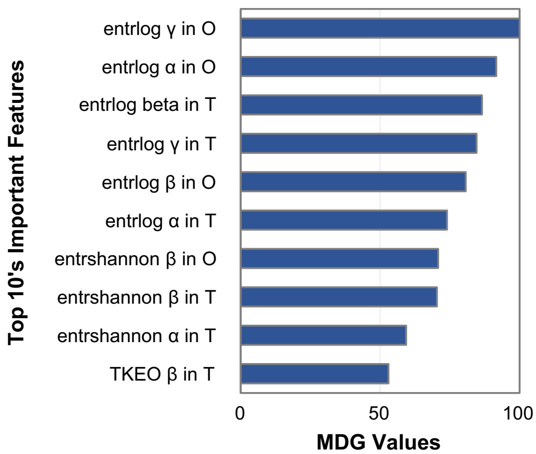



**Fig. 10** Top ten important features of MDG plot from RF model

The total number of features in HRAS-TCO channels is 93 variables. Hence, the mtry varies between $9 \pm 3$. The accuracy was used as measure of mtry parameter. From the resampling results across tuning parameters of mtry value, the optimal accuracy is yielded when mtry = 7 (accuracy of 75.6%), while the minimum accuracy yields 74.6% with mtry = 6. Figure 9c plots the accuracy obtained from the tune grid search for a range of mtry values with the highest accuracy reached when the mtry = 7.

One of the advantages of RF classifier is the ability to identify the variable importance of the whole tree in the forest. As a result, we plot the variable (feature) importance information overall features used in the data. The MDG number is used as feature importance measure. The MDG is a measure of how each feature contributes to the homogeneity of the leaves and nodes in the resulting random forest model. A high number of MDG means that a particular variable has a high contribution in classifying the data into the designated classes. In Fig. 10, we plot the top 10 important features over 93 features (VL-HRAS scenario taken from TCO channels).

According to the result shown in Fig. 10, among hybrid features extraction domain, features derived from wavelet show superiority over the other domains. Specifically, the log and Shannon energy entropy from the occipital and temporal area have a certain contribution to the performance of emotion recognition. The variable importance resulted from the RF model was in accordance with findings by (Petrantonakis and Hadjileontiadis 2010), which note that wavelet features accuracy is slightly higher than statistic features. The important features information could be beneficial for emotion classification task from EEG. Notably, for emotion classification which aimed at healthcare application, in healthcare application, the clinicians required more interpretable reason behind the classification process (Kononenko 2001).

In order to show the comparison of our proposed method results with the previous work in the same dataset, we present Table 3. Compared to other emotion recognition systems, our methodology is advantageous since it reports higher accuracy with the fewer number of channels. Consequently, the less amount of channels in emotion recognition will reduce the time setup for EEG headset and features extraction process (Liu et al. 2011).

As seen in Table 3, the ensemble learning approach (RF) works better than the previously known algorithm for EEG-based emotion recognition, SVM. This is caused by multiple models used in classification process, i.e. numbers of decision tree model as an ensemble model. Besides, the characteristic of RF support for handling EEG signals usually has a large-size data. It includes a large number of channels and high-frequency sampling rate. Despite the highest accuracy reports by Mohammadi et al. (2016), our proposed method was capable of classifying more class of emotions. Unlike our wrapper feature selection method, studies by Atkinson and Campos (2016) and Zhang et al. (2016a) proposed filter categories of feature selection methods which are independent of learning algorithm. Moreover, the number of channels used in Atkinson and Campos (2016) and Zhang et al. (2016a) was relatively too much for the EEG emotion recognition systems.

**Table 3** Comparison with previous studies in DEAP dataset

| Authors | Classifier | Number of channels | Classification target | Performance (accuracy in %) |
|---|---|---|---|---|
| Mohammadi et al. (2016) | SVM | 10 | Binary class | 86.7 |
| Atkinson and Campos (2016) | SVM | 14 | Multiclass | 73.1 |
| Zhang et al. (2016a) | SVM | 19 | Multiclass | $59.1 \pm 11$ |
| Our method | RF | 6 | Multiclass | 75.6 |
| | SVM | 6 | Multiclass | 69.8 |

## Conclusion

The experimental results of this study conclude that the emotional combinations obtained with the valence lateralization theory contribute to improving the accuracy of classification performance. The best emotion recognition accuracies are from the valence lateralization scenario. It reveals that left hemisphere is better to recognize happy and relaxed emotion, while the right hemisphere is much concerned with sad and angry emotion. These results are well confirmed with previous valence lateralization theory. Meanwhile, for the right-/left-dominance lateralization scenario, we were unable to prove the dominance of emotion from the right hemispheres. Although these findings contradict the theory of right-dominance lateralization, our findings are supported by several previous studies which were not aligned with the right-dominance lateralization.

Comparison of RF performance with SVM and LDA shows that RF yields the highest accuracy of 75.6% from the HRAS scheme in TCO channel. In addition, RF also achieves the best accuracy compared to SVM and LDA for several experimental scenarios. Therefore, we can conclude that RF method has been proven to improve classification performance on EEG-based emotion recognition. Furthermore, it is evident from the experiment that the number of pairs channel affects performance accuracy. The best asymmetry pairs channel during the investigation is located in T7–T8, C3–C4 and O1–O2 asymmetric channels. Regarding the plot of important variables with MDG measures, features extracted from wavelet which include log energy–entropy and Shannon entropy are notable as emotional features. As for the tuning parameters of the RF model, the best accuracy was obtained from the RF model with a minimum tree number of 500 and the depth of each tree is equal to 7.

For further research we are interested in investigating specific area in each hemisphere of the brain for specific emotions. Knowing certain region in the brain related to particular emotions will enhance the ability to recognize emotions accurately. The features selection techniques of random forest algorithm could be improved to address these issues.

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### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical approval** This article does not contain any studies with human participants performed by any of the authors. The data being used in this article is the public dataset which can be accessed online and also cited as one of the references.

**Informed consent** Informed consent was obtained from all individual participants included in the study performed by the dataset creator, not the author of these articles.

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