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Optimal Feature Selection and Deep Learning Ensembles Method for Emotion Recognition From Human Brain EEG Sensors

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ABSTRACT Recent advancements in human–computer interaction research have led to the possibility of emotional communication via brain–computer interface systems for patients with neuropsychiatric disorders or disabilities. In this paper, we efficiently recognize emotional states by analyzing the features of electroencephalography (EEG) signals, which are generated from EEG sensors that noninvasively measure the electrical activity of neurons inside the human brain, and select the optimal combination of these features for recognition. In this paper, the scalp EEG data of 21 healthy subjects (12–14 years old) were recorded using a 14-channel EEG machine while the subjects watched images with four types of emotional stimuli (happy, calm, sad, or scared). After preprocessing, the Hjorth parameters (activity, mobility, and complexity) were used to measure the signal activity of the time series data. We selected the optimal EEG features using a balanced one-way ANOVA after calculating the Hjorth parameters for different frequency ranges. Features selected by this statistical method outperformed univariate and multivariate features. The optimal features were further processed for emotion classification using support vector machine, k-nearest neighbor, linear discriminant analysis, Naive Bayes, random forest, deep learning, and four ensembles methods (bagging, boosting, stacking, and voting). The results show that the proposed method substantially improves the emotion recognition rate with respect to the commonly used spectral power band method.

INDEX TERMS EEG pattern recognition, Hjorth parameter, EEG feature extraction, EEG emotion recognition.

I. INTRODUCTION

Qualitative metrics and assistive sensor technologies related to human–computer interaction (HCI) have become essential research topics in computer science [1], [2]. HCI-based multisensory and cloud-assisted technologies can play a key role in facilitating healthcare in smart cities [3]. The emergent interest in HCI for healthcare in smart cities has resulted in the further development of intelligent machines for providing services intended to improve the quality of life. These technologies can be used in health centers to help physicians and researchers treat a patient instantly. Moreover, it is also possible to develop a HCI-based cloud-assisted platform that can improve healthcare services in smart cities [4], [5].

In this paper, we focus on emotion recognition using human brain-activity sensors, which has many healthcare applications in smart cities for the treatment of patients with any kind of mental disorder. Emotional intelligence requires systems to be able to recognize and understand a user's emotions. With respect to affective computing, there has been a research trend toward estimating the emotions induced by watching visual stimuli in a variety of applications [6]–[8]. When a user watches visual stimuli, he or she may experience an emotional response based on his or her cognitive understanding and appraisal of the situation [9], [10]. Therefore, it is important to understand the human cognitive processes for a given situation and their association with emotion [11].

Thanks to the recent advancements in HCI research, emotional communication via brain computer interface (BCI) systems for patients with neuropsychiatric disorders or disabilities is now becoming possible [12]–[14]. The emotional response to a single stimulus may, in fact, be subjective. Various BCI emotion-related applications will become possible if we can distinguish different human emotions and the corresponding cognitive processes of the related stimuli through cortical neural recordings.

Recently, electroencephalography (EEG) has played a key role in BCI systems. EEG reflects the electrical activities of the brain and provides a subjective emotional response based on the subject's own experience [15]. Takahashi and Tsukaguchi [16] used EEG signal features to classify an emotional response to a video into joy, sadness, disgust, fear, or relaxation. They proposed an emotion recognition system using multimodal bipotential signals. Six statistical features were used for the emotion recognition and a support vector machine (SVM) was employed as the classifier. Koelstra and Patras [15] also used EEG signals to distinguish different emotions in response to music videos. They presented a multimodal approach that analyses both facial expressions and EEG signals to generate affective tags. They performed classification and regression in the valence–arousal space and presented results for both feature-level and decision-level fusion. However, both methods only achieved an acceptable accuracy. Alpha and beta frequency bands are commonly known to present prominent features in emotion-related EEG systems [17], [18]. However, the important features of EEG signal patterns within specific frequency bands vary slightly according to the condition of each subject. Furthermore, EEG signals, especially for emotion-related stimulus, may have event-dependent properties. We also need to analyze the variations for a signal feature in the time domain.

As mentioned above, the alpha and beta bands have been shown to contain useful features, and it is also known that the distribution of the power spectrum in brain wave patterns changes when the subject is stimulated by an emotional picture. Therefore, we studied different methods for EEG signal feature extraction in the time-frequency domains [19], including the fast Fourier transform (FFT) and auto-regression. Auto-regression analysis suffers from slow computation and is not always suitable for EEG analysis while the FFT is the least efficient of the considered methods because of its inability to process non-stationary signals [19].

Hjorth parameters are widely used for the time-frequency analysis of nonstationary signals [20]–[24], and the Hjorth parameters proposed in [25] are particularly useful because they can be used to extract discriminative information both in the time and frequency domains through simple computations [26]. We therefore employed this method to extract the features from the human-brain EEG sensors. This method was selected mainly because it offers the advantage of having a low computational cost relative to a conventional frequency analysis while providing results that can be easily interpreted.

To recognize the different emotional activities inside brain, we performed this study to find the optimal EEG features in the frequency and temporal domains. The proposed method employs the Hjorth parameters and performs a balanced one-way ANOVA on the extracted features set during the feature selection process. We select the optimal features for each subject by computing the Hjorth parameters for all channels at the specified frequency band. The optimal features were further processed for emotion classification using SVM and k-nearest neighbor (KNN), linear discriminant analysis (LDA), naive Bayes, random forest, deep-learning, bagging, boosting, stacking, and voting. The results show a higher recognition rate for the optimal feature selection, but not for all extracted features.

The study protocol was approved by the institutional review boards (IRBs) at Chonbuk National University (CBNU-IRB 2013-4). All participants provided IRB-approved written informed consent prior to study participation. The proposed method and experimental settings are presented in Section II. Section III contains the results and their discussion. Finally, the conclusion is presented in Section IV.

II. MATERIALS AND METHODS

The goal of this experiment was to extract the features of the various emotional states of subjects as they looked at different emotion-related pictures. We used the international affective picture system (IAPS) [27], [28] in this experiment. IAPS is a picture database that was specifically designed to perform emotion-related experiments with normative standards for arousal and valence [27], [29]. Emotional states are well defined in the arousal–valence model, which represents emotions using a two-dimensional model [28]. Presenting emotional pictures to subjects is a common way to evoke these states [30]–[33]. To ensure the emotions were distinct, four affective states were selected: low valence–low arousal (LV_LA), low valence–high arousal (LV_HA), high valence–high arousal (HV_HA), and high valence–low arousal (HV_LA) and represented through orange, purple, red and green bubbles, respectively. These categories were used to select 180 pictures (45 pictures $\times$ 4 states) from distinct groups along the arousal–valence axes of the IAPS database, as shown in Figure 1.

The EEG signals were recorded using the Emotiv-EPOC system [34]. This device has a maximum of 16 electrodes and collects 128 samples every second. We used 14 electrodes to record the neural activity of the brain. In addition, the common mode sense (CMS) active electrode and driven right leg (DRL) passive electrode were attached on the mastoid bone behind the ears to create an average reference channel (CMS/DRL). Tomography has shown that each brain region has a different simultaneous emotional response [35], so we decided to record all EEG channels. Figure 2 shows the electrode placements for the signals. The letters F, C, T, P, and O indicate the corresponding brain area, i.e., the frontal, central, temporal, posterior, and occipital lobes, respectively.

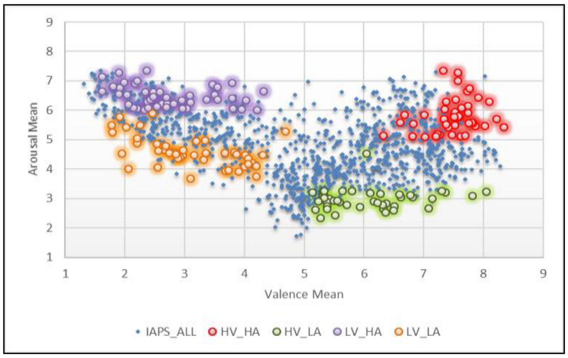

FIGURE 1. The scatter plot of International Affective Picture System (IAPS) images database, based on valence-arousal model.

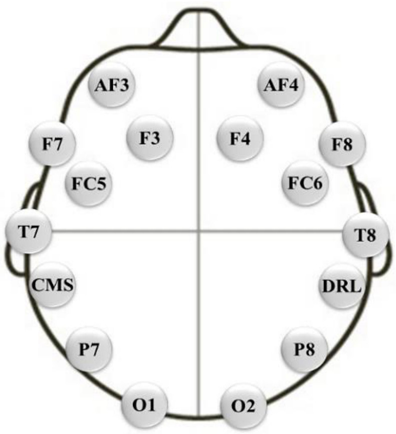

FIGURE 2. Emotiv-EPOC headset 16-channel placement. 14 channels were designed for detecting human brain signals with two reference channels located beside the ears. EEG channels were placed on basis of 10/20 electrode placement system.

Currently, EEG-based emotion research is in a preliminary stage. A total of 21 subjects (12 male and 9 female) participated in this experiment. All subjects were students at the same institute and were from 12 to 14 years old. The selected subjects were first informed of the purpose of our study and the experimental procedure. The subjects were then given a brief introduction and completed consent forms.

After the introduction, each individual subject was stimulated using the pictures. Simulation began with a fixation mark (cross) for 4 s in the exact center of screen to attract the attention of the subject. The designated emotion-related pictures were randomly presented for 1.5 s and followed with a blurred image for another 0.5 s. The blurred images were used to attenuate the emotional feeling or brain activity that had been generated by the previous stimulus so it would not affect the state stimulated by the next image. Figure 3 shows the timing diagram for this procedure, where the EEG signal recording of single session was 368 s long. This procedure was repeated twice for each subject.

After the recorded EEG data of each subject were verified, the EEG signals were preprocessed using the EEGLAB toolbox provided by SCCN Lab [36]. The main preprocessing steps consisted of artifact rejection [37], filtering [38], and epoch selection from the raw EEG data.

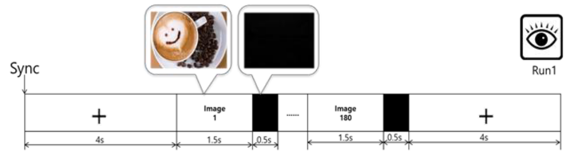

FIGURE 3. Timing diagram of emotional stimuli. Each subject saw the emotional stimuli using this timeline. Stimulus duration was 1.5 seconds, followed by 0.5 second of rest time with a black screen.

A. HJORTH PARAMETERS

Hjorth parameters are statistical functions that describe the characteristics of EEG signals in the time- and frequency-domains. The Hjorth parameters are also known as normalized slope descriptors (NSDs) and consist of activity, mobility, and complexity descriptors [25]. The descriptors can be computed according to the following equations [25], [39]:

$$Activity = \sigma_x^2 \tag{1}$$

$$Mobility = \sqrt{\frac{\sigma_d^2}{\sigma_x^2}} = \frac{\sigma_d}{\sigma_x} \tag{2}$$

$$Complexity = \sqrt{\frac{\frac{\sigma_{dd}^2}{\sigma_d^2}}{\frac{\sigma_d^2}{\sigma_x^2}}} = \frac{\frac{\sigma_{dd}}{\sigma_d}}{\frac{\sigma_d}{\sigma_x}} \tag{3}$$

where the variance in the EEG signal x is represented by σ_x^2, σ_x corresponds to the standard deviation of x, σ_d represents the standard deviation of the first derivative of x, and σ_{dd} represents the standard deviation of the second derivative of x.

Activity represents the signal activity and is a measure of the mean power, and mobility approximates the mean frequency. Complexity approximates the bandwidth of the signal. Because the computation of the Hjorth parameters is based on the variance of the signal, its computational cost is lower than that of other methods.

B. PROPOSED METHOD

When a subject sees emotional stimuli, the distribution of the power spectrum in the brain wave patterns changes. The power decreases in the alpha band but increases in the beta band. In contrast, the power spectrum converges on the alpha band when the subject is in a relaxed state [23]. The Hjorth parameters are also useful for differentiating the power spectra that are used as a feature vector.

Considering that different individuals have the same emotional reaction to the same situation with slightly different response patterns, each subject presented various physiological indications that highly correlated with each of the affected states. To improve the performance of emotion classification, we need to determine the individual EEG features that appear in event-related responses for all emotional states. To achieve this goal, it is essential to select a set of significant features. Therefore, we determined the optimal features for classification using a balanced one-way ANOVA method for a p-value < 0.05.

The EEG-based channels in the proposed method have the following form:

$$\mathfrak{T}(t) \in \mathbb{R}^k \tag{4}$$

where $\mathbb{R}^k$ denotes the vector of the time series of a single electrode t, k is number of time samples in $\mathfrak{T}(t)$, and $t = [1, 2, \ldots, 14]$. $\mathfrak{T}(t)$ represents the EEG dataset of each subject. Further,

$$EpochM\,(subject, \mathfrak{T}(t), ec) = extractEpoch^{21}_{t=1,subject=1}(subject, \mathfrak{T}(t)) \tag{5}$$

where, ec is an epoch counter that corresponds to 360 epochs of the four emotions for each $subject$. The method $extractEpoch$ returns the matrix $EpochM$ composed of all channel vectors $T(t)$ of length (stimulus time $\times$ sample rate).

Furthermore, the processed data is used for optimal feature extraction and selection. Three Hjorth parameters were calculated for five separate frequency bands. Matrix $EpochM$ was input to the classifier. The five frequency bands (n) were within the frequency range of 0.5–43 Hz. The five frequency filters $\delta, \theta, \alpha, \beta$, and γ, extract the frequency ranges 0.5–4Hz, 4–8 Hz, 8–13 Hz, 13–30 Hz, and 30–43 Hz, respectively. The duration of the extracted window consists of the first 1,500 ms of every epoch. All EEG signal patterns were obtained at the ith frequency filter and jth epoch. The function $computeHjorth$, which computes the Hjorth parameters (complexity, mobility and activity), is as follows.

$$AF_{fr}\,(subject, \mathfrak{T}(t), ec, hp3) = Hjorth^{5}_{fr=1}(EpochM). \tag{6}$$

Consider the case of a single subject, we compute the frequency band filtering by passing the raw signals of each epoch $EpochM(subject, T(t), ec)$ into the method $Hjorth$ in Eq. (6) to generate matrix AF, which is three times bigger than $EpochM$ (because of the Hjorth parameters) and contains every epoch ec of a given subject within five frequency bands fr. Matrix AF contains real numbers $\mathbb{R}$, i.e.,

$$AF \in \mathbb{R}^{ec360\times(t14\times fr5\times hp3+c1)}. \tag{7}$$

Here, ec_{360} represents the total number of epoch rows. The matrix columns consist of t_{14} (14 EEG channels), $fr5$ (five frequency bands), $hp3$ (three Hjorth parameters), and one attribute for emotion type, denoted as $c1$.

C. OPTIMAL FEATURE SELECTION

To select the optimal features in matrix AF, we computed a balanced one-way ANOVA on each feature vector fv in matrix AF for all subjects, separately. In this way, we can compare the means of the four emotional classes or groups in all epochs ec_{360} based on a single factor, which is fv. Each emotional class represents the independent computational result of corresponding Hjorth parameter hp under every frequency band fr and EEG-channel t.

Figures 4 and 5 show the differences among all emotional classes in both feature vectors of matrix AF after the ANOVA method is applied on two different feature vectors. Here, we can easily analyze the mean difference of each corresponding emotional class. These visual representations also ensure that there is discrimination between the selected emotional classes in same feature vector.

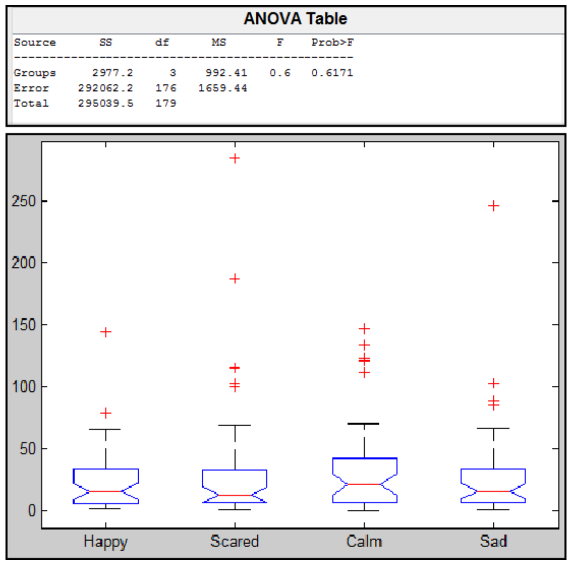

FIGURE 4. Sample from ANOVA analysis of feature vector where p-value $>$ 0.05.

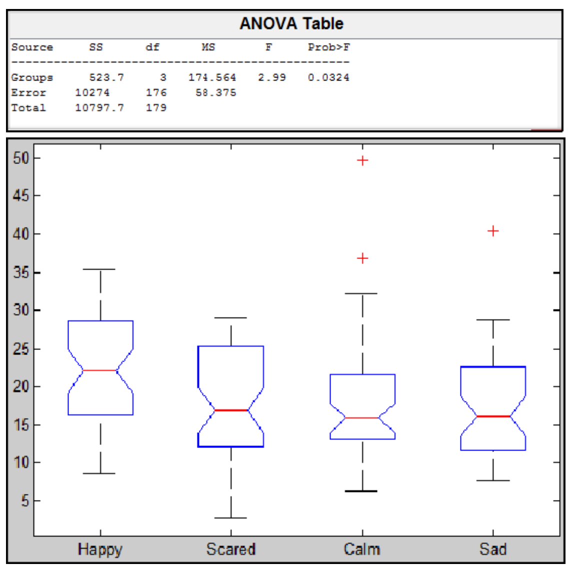

FIGURE 5. Sample from ANOVA analysis of feature vector where p-value $<$ 0.05.

Figures 4 and 5 present ANOVA results for two example feature vectors. These figures include the ANOVA table and box plot graph returned by MATLAB. The ANOVA

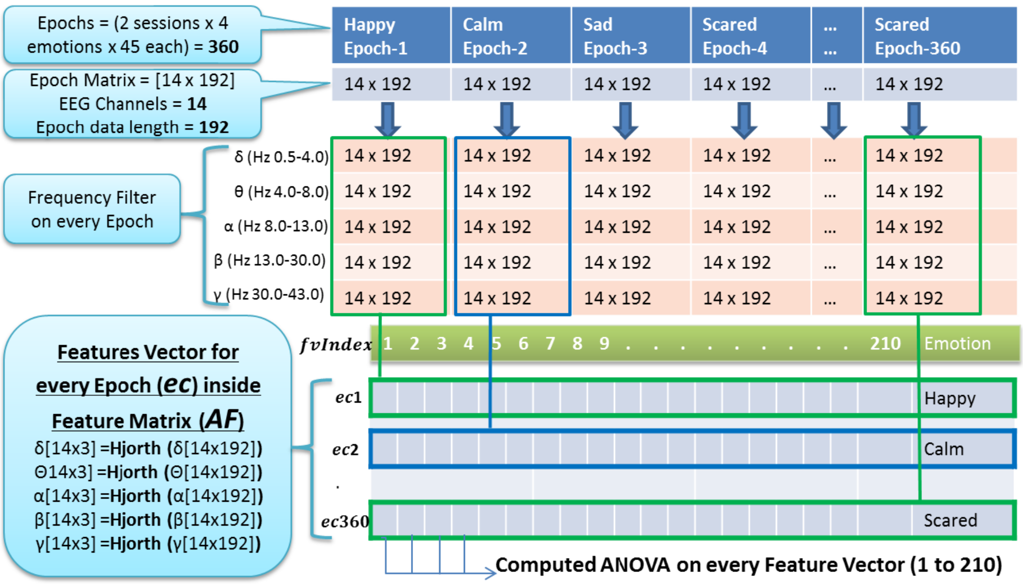

FIGURE 6. Self-explanatory feature extraction and selection process diagram.

table contains six columns: i) the source of the variability, ii) sum of squares (SS), iii) degrees of freedom (df), iv) mean squares (MS), which is the ratio SS/df, v) F-statistic, which is the ratio of the mean squares, and (vi) p-value, which is derived from F. In the box plot, each emotional class is represented as an individual box, the red central line of the box marks the median of the sample data, and the edges of the box are the 25th and 75th percentiles. The whiskers attached to both the top and bottom of the box show the extreme data points that are not considered to be outliers, and outliers are plotted individually by cross symbols [40].

In Figure 4, the p-value suggests the null hypothesis is valid, i.e., the means of all the emotion groups from the data in *fv* are either equal or not significantly different. This particular *fv* is hence not a candidate optimal feature vector and is removed from further emotion classification. However, Figure 5 shows that the p-value suggests rejection of the null hypothesis. It shows that there is a significant difference among the means of all emotional groups from the data in *fv*, and this *fv* is an optimal feature vector, as follows.

$$OF_{fv} = Opt\,(AF) \quad if\ \left(ANOVA1_{fvIndex=1}^{N}\left(AF_{fvIndex}\right)\right) < 0.05 \qquad (8)$$

where *Opt* returns the best optimal features and new matrix *OF* is the result.

The feature selection process is further explained in the self-explanatory Figure 6, the function *Hjorth* processed the input EEG epoch ***matrix*** after passing from each frequency filter ***fr***, and returns the three Hjorth parameters ***hp3*** for each channel ***t***, so it generates the feature matrix with all possible features for every epoch. Further, the optimal function *Opt*, which computes the best optimal features from matrix *AF*, which is defined in Eq. 8. Here, we applied the balanced-one-way ANOVA method to compute p-value < 0.05 on every feature vector $AF_{fvIndex}$. This method helps us to select all the feature vectors that satisfy the condition in Eq. 8.

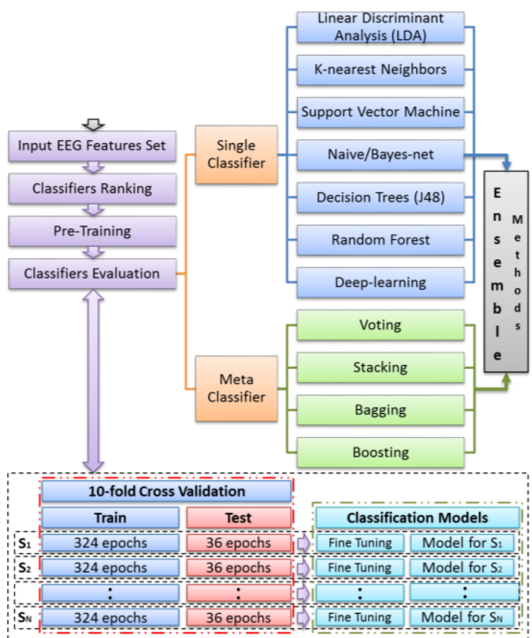

FIGURE 7. Emotion classification process diagram.

D. CLASSIFICATION PROCESS

The classifiers evaluations were performed on state-of-art server system with high specifications. This server is also loaded with four TITAN-X (Pascal) GPUs which helped us to perform a high-speed computation of deep networks. After the pre-processing was completed, we got the clean EEG signals, which were fed into the classification system as explained through Figure 7. This system explains about the flow of our emotion recognition experimental settings

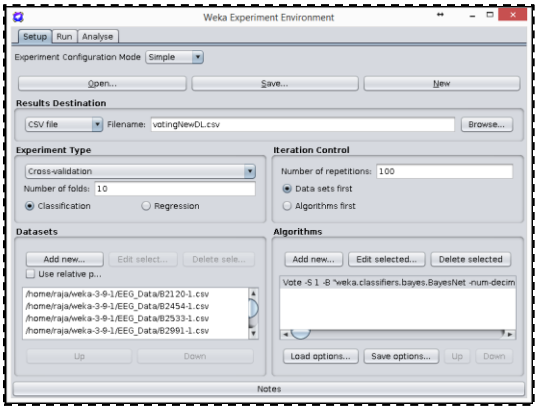

FIGURE 8. Experimental settings.

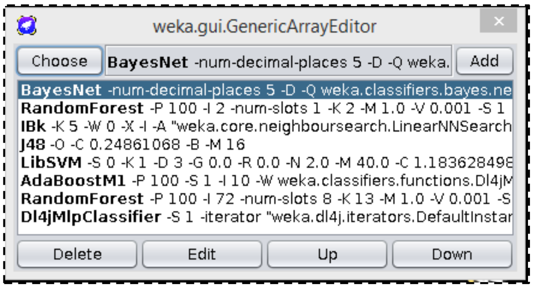

FIGURE 9. Top-ranked classifiers.

in detail. The optimal features were processed into the classification stack. This stack bundled with all well-known classifiers, such as LDA, KNN, SVM, naïve-Bayes, random-forest, deep-learning and ensemble methods. The classification process was performed using Waikato Environment for Knowledge Analysis (WEKA) software [41]. All selected classifiers were trained and tested over the group of four emotions. We used the default settings available in WEKA for both classifiers. Here, our selected feature extraction methods will be presented in next sections.

E. EEG FEATURES DATASETS

First, EEG based features sets from each subject goes to a system input. For the training of emotion recognition classifiers, we used two sessions of our EEG recording of each subject. It means, we have total of 360 epochs (2sessions x (4emotions x 45epochs)). In this way, we can double the dataset to build a classification model. So, classifiers were trained on total of 324 epochs and 36 epochs (total instances/epochs: 360) were used for validation test. Due to 10-fold cross validation, this step repeats 10 times with new combination of training and testing epochs of same dataset.

F. CLASSIFIERS RANKING

Next stage is classifier ranking, where our system had to rank top seven classifiers among well-known selected classifiers. The selected state-of-art classifiers with selected parameter options. These classifiers are included in WEKA

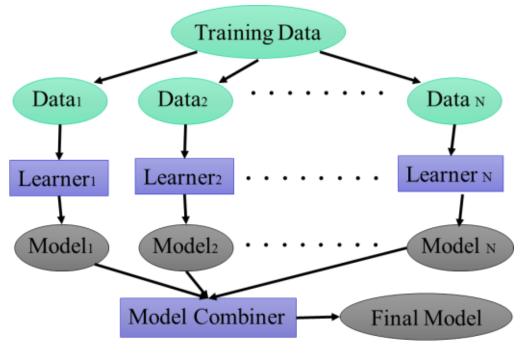

FIGURE 10. Mechanism of ensembles model building.

TABLE 1. Overall emotion recognition results.

Classifiers	All Features ($\mathcal{AF}$)	Optimal Features ($\mathcal{OF}$)
Bagging	45.5	70.5
Boosting	32.5	56.4
Deep Learning	50.1	**73.6**
J48	45.5	69.5
KNN	42.9	66.9
LDA	27.1	51.6
Naive Bayes	27.4	51.6
Rand-Forest	29.2	53.5
Stacking	45.9	70.0
SVM	32.5	54.3
Voting	**53.2**	**76.6**

machine learning system. The selection of top seven classifiers was based on Auto-Weka [42] library. This library provides us a wrapper interface to WEKA to find out the optimal solution for our dataset in terms of accuracy. Our ranking system should find out the top ranked classifiers based on the classification accuracy. After the ranking of classifiers, we were forwarded towards a pretraining of each of selected classifier on EEG features datasets from all subject together.

G. PRE-TRAINING

After selection of best classifiers, pre-training is a next step in this process. Pre-training is one of the challenging part, where it requires to find out the best parameters values and weights for each of top ranked classifier. In this step, we want to pretrain each classifier on whole data from all subject at once. We processed each classifier to compute the optimal weights, separately. The optimal configurations were computed for each classifier, separately. Later, classifiers evaluation was performed based on 10-fold cross validation.

TABLE 2. Analysis of current trends and our proposed methods.

Existing Methods	Description	EMO	Arousal/Valence %
Jirayucharoensak et al. (2014)	Deep learning network to find out the hidden features in EEG signals. Stacked auto encoder	2	46/50 %
Chanel et al. (2006)	Frequency domain features with Fisher Discriminant Analysis, Naive Bayes	2	72/x %
Khalili et al. (2008)	Linear Discriminant Analysis, K-Nearest Neighbor	3	61 .0 %
Horlings et al. (2008)	Frequency band power, cross-correlation between EEG band-power, peak frequency in alpha band and Hjorth parameters using SVM, 3-fold cross validation	5	37/32 %
Jenke et al. (2014)	ERP, Statistics of Signals, Higher Order Crossings, Band Power, Higher Order Spectra, Hilbert-Huang Spectrum, Discrete Wavelet Transform, Hjorth parameters, ReleifF, Univariate Effect-Size, min-Redundancy-Max-Relevance, Wilk-based Effect-Size, Roy-based Effect-Size	5	45 %
Yin et al. (2017)	Staked auto encoder, deep learning, ensemble methods	2	84/83 %
Atkinson et al. (2016)	Statistical features, band power for different frequencies, Hjorth parameters and fractal dimension for each channel. Statistical features included median, standard deviation, kurtosis coefficient; mRMR, GA-SVM	2	73/73 %
Proposed Methods	Hjorth parameters based Optimal feature selection, voting ensembles method includes top ranked classifiers such as deep-learning, naive-Bayes, LDA, KNN, SVM, and so on	4	76.6 %

H. CLASSIFIERS EVALUATION

As we mentioned earlier, emotion classification is subject dependent. Thus, we divided the epochs of each subject into training and test features datasets, separately. Considering the classifiers architecture that consists of pre-training and fine tuning, we used features datasets of all subjects for pre-training, and subject specific feature datasets for fine tuning of each subject as shown in Figure 7. Thus, the classification models were fine-tuned for each subject based on the initial weights in pre-training by their respective classifier. These models were further applied to features datasets from each subject for validation tests using 10-fold cross validation.

Our experiment employed two types of classification mechanisms, single classifiers and meta classifiers. In single classifier, only specific classifier was evaluated but meta classifiers were evaluated in combination of all top ranked classifiers. Here, we present the example of both classifiers settings in the following figures. In Figure 8, generic experimental setup was defined for all classifiers, but Figure 9 is showing the classification setting for ensembles methods such as voting, stacking, boosting, and bagging. Figure 8 shows four main components are mentioned *Experiment Type*, *Iteration Control*, *Datasets*, and *Algorithms*. In this experiment, we just need to change the classifiers types in *Algorithms* section. Figure 9 shows the configuration of meta-classifiers, where we can see a list of classifiers with their parameters. These classifiers are already pretrained with help of Auto-Weka libraries.

Further, ensembles methods were used in this paper such as Voting, Bagging, Boosting, and Stacking. By using of following Figure 10, we can easily understand the main purpose of ensembles methods. These methods learn multiple alternative definitions of a concept using different training data or different learning algorithms. At the end, model combiner function combines the final decisions of multiple definitions, e.g. using weighted majority voting.

III. RESULTS AND DISCUSSION

In the classification process, the dataset comprised 360 instances (2 sessions $\times$ 45 instances $\times$ 4 emotions) in total, where each instance corresponds to a single emotional class. Above, we described the possible feature sets proposed in this experiment, which can consist of a total of 210 features. However, the optimal feature set computed using Eq. (8)

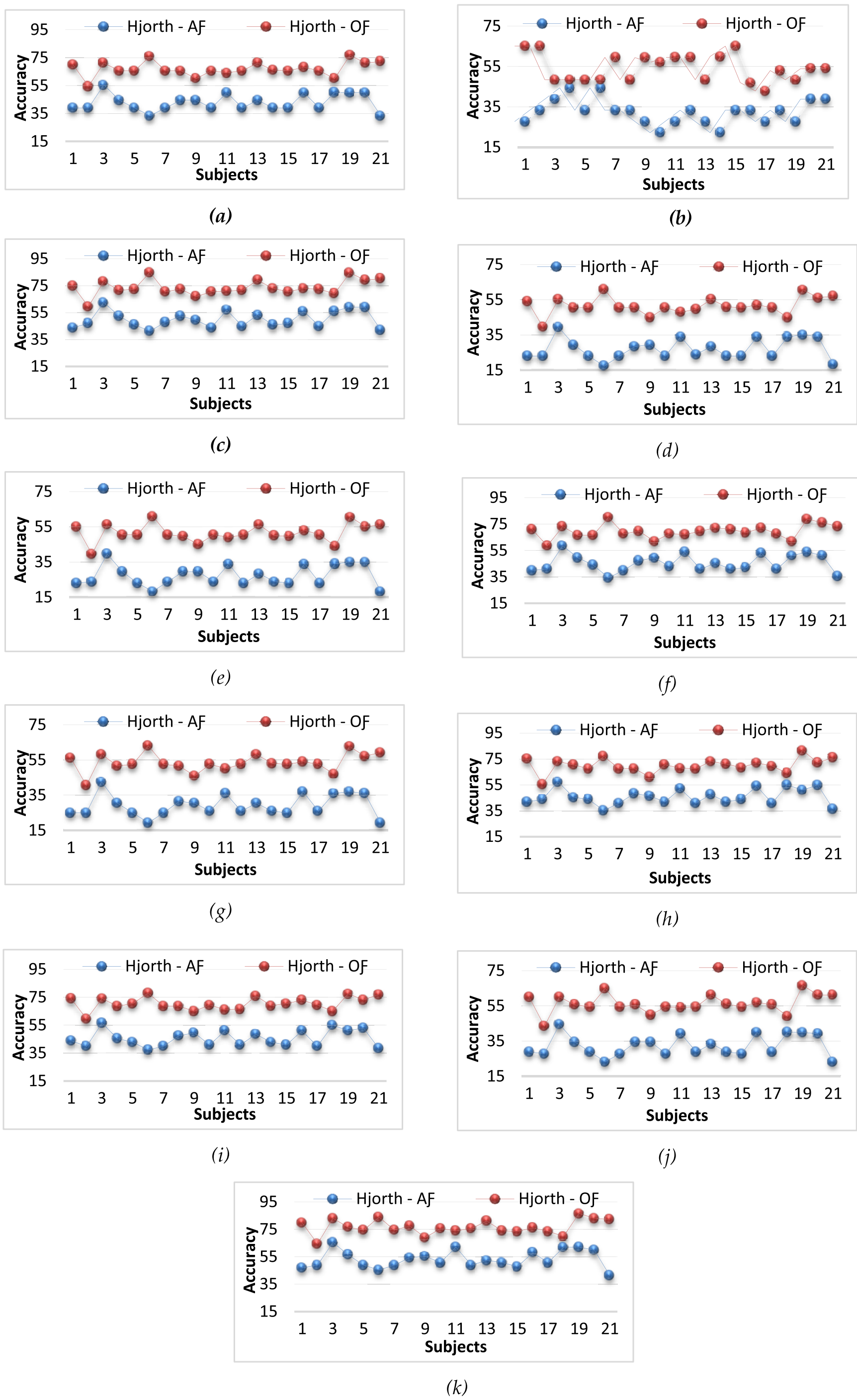

FIGURE 11. **Emotion recognition result with Hjorth parameters in case of all features and optional feature selection using KNN and SVM, separately. *(a) KNN. (b) SVM. (c) Deep learning. (d) LDA. (e) Naïve-Bayes. (f) J48 (Decision Tree). (g) Random Forest. (h) Stacking. (i) Bagging. (j) Boosting. (k) Voting.***

varies in size depending on the criterion set by the p-value. The emotion recognition was performed in WEKA [41] using 10-fold cross validation for each subject separately. Visualizations of the emotion classification are shown in Figure 11, which shows the overall emotion recognition accuracy of all subjects. The emotion recognition rate is presented on the y-axis with respect to each subject along the x-axis. The optimal feature selection method OF outperforms in all selected classifiers as presented through Figure 11. We employed a balanced one-way ANOVA method to select a set of optimal features that show a significantly better recognition rate and this optimal features set performs better than the other feature set consisting of all features AF. Using both methods with/without feature selection, recognition rates of all selected classifiers were obtained and presented in Table 1. The Hjorth-based features were tested with AF and OF, and the results show the highest average accuracy (76.62%) for OF for all selected approaches.

A very recent study based on deep learning [43], [44] showed some improvement in existing methods for two, three, and five emotional classes (low/high) in the arousal–valence domain. Other recent studies [24], [45], [46] have analyzed several methods in different experimental environments. We compared our proposed feature extraction and selection method with existing methods. Table 2 compares the emotion recognition performance of all the approaches based on the time domain, frequency domain, and power spectrum with our proposed method. This table lists the existing and proposed methods, number of emotions (EMO), and recognition rate in the arousal–valence domain.

The comparison with existing emotion recognition methods shows that our proposed method obtained a better accuracy rate with the minimum number of features. The Hjorth-based feature extraction with statistical feature selection (ANOVA p-value < 0.05) shows a significant improvement over existing methods. The proposed feature selection approach is shown to yield higher classification accuracy for the four selected emotions in the arousal−valence domain using the Voting ensembles method. To improve the accuracy of emotion recognition, Hjorth features along with the statistical optimal feature selection approach show good potential. This approach could increase the performance of emotion recognition using EEG brain signals.

IV. CONCLUSIONS

In this paper, we proposed an EEG feature extraction and selection method for emotion (happy, calm, sad, and scared) recognition. We employed Hjorth parameters in the frequency domain. To select the optimal feature set, we analyzed the extracted feature set using a balanced one-way ANOVA (p-value < 0.05) method. Furthermore, top ranked classifiers were used for the emotion classification using the optimal feature sets for each subject separately. Comparatively, the proposed method performs better than existing emotion recognition methods. The proposed feature selection method OF obtained the best emotion recognition rates of 76.6% for Voting ensembles method. Based on our results, we conclude that optimal feature selection is a good choice for enhancing the performance of EEG-based emotion recognition. To further improve emotion recognition performance, we need to explore additional feature combinations with more emotional classes in the arousal–valence domain.

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