WeDea: A New EEG-Based Framework for Emotion Recognition

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***Abstract*—With the development of sensing technologies and machine learning, techniques that can identify emotions and inner states of a human through physiological signals, known as electroencephalography (EEG), have been actively developed and applied to various domains, such as automobiles, robotics, healthcare, and customer-support services. Thus, the demand for acquiring and analyzing EEG signals in real-time is increasing. In this paper, we aimed to acquire a new EEG dataset based on the discrete emotion theory, termed as *WeDea* (*W*ireless-based *e*eg *D*ata for *e*motion *a*nalysis), and propose a new combination for *WeDea* analysis. For the collected *WeDea* dataset, we used video clips as emotional stimulants that were selected by 15 volunteers. Consequently, *WeDea* is a multi-way dataset measured while 30 subjects are watching the selected 79 video clips under five different emotional states using a convenient portable headset device. Furthermore, we designed a framework for recognizing human emotional state using this new database. The practical results for different types of emotions have proven that *WeDea* is a promising resource for emotion analysis and can be applied to the field of neuroscience.**

***Index Terms*—Electroencephalography, emotion recognition, wireless devices, artifact removal, feature extraction, deep learning.**

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I. Introduction

EMOTION plays a critical role in perception, recognition, reasonable decision-making, and social interactions of human beings. With the recently increased interest in emotion recognition in various fields, including human–computer interaction (HCI) and robotics, interaction modeling between humans and computers has been studied extensively using the emotional state of users [1]. Human emotions are expressed through facial expressions, voice tones, and physiological signals, such as heart rate and EEG signals. However, as people can intentionally manipulate their voices or facial expressions, many researchers typically tend to analyze human emotions based on physiological signals that cannot be controlled intentionally. Among the various physiological signals, the EEG signal represents the activities of the human brain in real time; it is the most frequently used physiological signal for analyzing human emotions because it can directly reflect any changes in the emotional state of humans [2].

A brain signal represents an electrical flow that occurs in the signal transfer between cranial nerves, and acts as an important indicator for measuring the status of brain activity. EEG refers to a technology that amplifies and records the signals coming from the electrodes attached to the participant's head [3]. It has been used in affective computing, which identifies participants' emotions by analyzing and classifying the EEG data recorded under various situations. EEG can also be applied in various other domains, such as brain–computer interfaces (BCIs), psychotherapy, user custom service, and architecture design, for recognizing the feelings and emotions of the user [4], [5]. In addition, in neuroscience and psychology fields, psychological stability, mental health state, and grasping the subjective psychological states of participants using EEG, have been actively studied [6].

Recently, with the growing importance of brain diseases and mental health, many new EEG-based products are being commercialized, including the use of miniaturized neuro-imaging technology in the global wearable brain healthcare market. For emotion recognition research based on EEG signals, small wearable devices that enable simplified EEG monitoring, such as Mindwave [7], Muse [8], and EPOC+[9] have been developed. A typical example of this is a type of wireless headset that attaches brain sensors to measure the perception activities of the brain and conveys the related information. In other words, it measures EEG signals through a headset and transmits the measured data to a computer via a wireless communication module in a bluetooth environment. The ultimate objectives of such wearable devices are to measure and analyze EEG data in real time, which are used not only in brain disease treatment but also in other domains such as automobiles, national military defense, education, and entertainment.

In this paper, we measured a new EEG dataset according to participants' emotional states using a wireless portable EEG piece of equipment and proposed a new combination of frameworks for real-time emotion recognition and analysis. *W*ireless-based **e**eg *D*ata for *e*motion *a*nalysis (*WeDea*) were collected for studying basic emotions, such as happiness, sadness, rage, disgust, and fear, regardless of racial and cultural differences, based on the discrete emotion approach method [10]. The newly combined emotion recognition framework eliminated noise and artifacts occurring during the EEG measurement and extracted the features according to each emotional state. Then, we validated the reliability of the emotion-based EEG data by performing classification learning according to the emotional state of the participant using the extracted features. The contributions of this paper are as follows:

- **New approach-based EEG data:** we recorded the emotion-related EEG data based on discrete emotion theory to conduct real-time emotion recognition research. The discrete emotion-based EEG data is highly effective for "basic emotion analysis" because it is analyzable in the emotional state separately.
- **Usefulness of new data:** *WeDea* distinguishes the emotional state using the self-reported experience (perceived) method, simple to administer without requiring expert knowledge in terms of scoring and analyzing. Therefore, *WeDea* is easily usable in pattern detection, recognition, and prediction of emotion based on the "basic emotion" analysis.
- **Efficient framework:** for real-time analysis of the new emotion-related EEG data, the framework consisting of a new combination is composed with preprocessing by wavelet-independent component analysis (wICA), feature extraction using wavelet packet transform (WPT), and a classification learning phase using long short-term memory (LSTM). The proposed framework provides good performance.

The rest of this paper is organized as follows. Section II describes the studies related to emotion recognition, and Section III describes the experimental procedure in detail. Section IV illustrates the experimental evaluation of the emotion recognition framework that consists of preprocessing, feature extraction, and classification phases. Section V discusses the new *WeDea* dataset for emotion recognition. Finally, Section VI presents the conclusions of the study.

II. Related Works

EEG signals are collected using wireless or wired measurement equipment. The technique used to identify a user's emotion by analyzing the recorded EEG data has drawn considerable attention from researchers. Because these EEG signals contain significantly complicated vibrational patterns, the analysis of raw EEG data may be highly inefficient. Therefore, emotion recognition using EEG data is performed using the following three main steps: pre-processing, feature extraction, and classification of the cognitive process.

A. EEG Dataset

For emotion recognition, voice, facial expressions, and physiological signals, such as EEG signals, have been widely used [11]. However, emotion recognition through voices or facial expressions is difficult if the participants do not disclose their emotions intentionally. In contrast, physiological signals, such as EEG, electrocardiogram (ECG), body temperature, and skin conductance, are more objective because they cannot be controlled intentionally [12]. Of these, EEG exhibits the highest correlation with emotions [13]. Therefore, various EEG data have been used to conduct EEG-based emotion recognition research.

Using an EEG-measuring instrument with 32 channels, Koelstra *et al.* [14] recorded DEAP data at a 128 Hz sampling rate with 32 volunteers who were asked to watch 40 video clips for eliciting their emotional states according to the valence-arousal model. Zheng and Lu [15] instructed 15 participants (7 men and 8 women) to watch 15 Chinese video clips (positive, neutral, and negative emotions) of 4 m each, and recorded their EEG signals using 62 channels for each clip. Their SEED EEG data were sampled at 200 Hz, and filtered using a bandpass frequency filter, ranging from 0 to 75 Hz. Soleymani *et al.* [16] recorded a multimodal MAHNOB-HCI dataset comprising face videos, audio signals, eye gaze data, and physiological signals associated with the peripheral/central nervous system. This dataset was recorded from 27 participants (11 men and 16 women) using 20 emotional video clips.

The abovementioned datasets were recorded using wired-based EEG measurement devices such as Biosemi Active Two or Neuroscan, which have been the most frequently used public datasets in emotion recognition studies. The wired-based devices for measuring EEG are composed of many electrodes. The higher the number of electrodes used in measurement devices, the more time is required to set up the EEG device, and the greater the effect on the comfort level of users who wear the device [11]. Also, the number of electrodes in the measurement devices produces the features to be processed the number of features depends on the number of electrodes. In this respect, the number of electrodes should be minimal. However, most of the EEG datasets were recorded using expensive wired devices with a large number of electrodes.

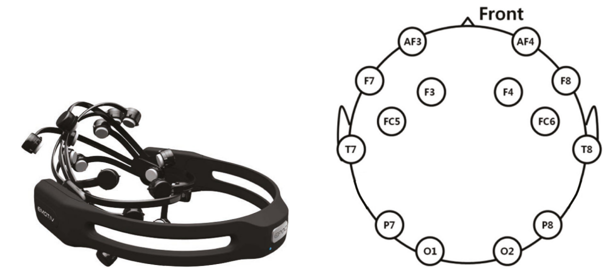
Recently, for recording EEG data more inexpensively and under comfortable conditions, wireless EEG-measuring devices have been used. Shahabi and Moghimi [17] recorded EEG data using a wireless Emotive EPOC+ device composed of 14 channels from 19 non-musicians who listened to the classical and Iranian music for 60 s. These data were recorded at a sampling rate of 128 Hz, and the emotional states were labelled as joyful, melancholic, and neutral. Katsigiannis and Ramzan [18] recorded data from 23 subjects using a portable wireless EEG device with 14 channels and a sampling rate of 128 Hz. For recording the DREAMER dataset, they used 18 video clips to stimulate subjects' emotions, where the length of each clip varied from 65 to 393 seconds. For labeling, the participants self-rated their arousal, valence, or dominance on a scale of 1 to 5. These data have been used as representative data in wireless EEG-based emotion recognition research. Besides, using wireless EEG devices, Arnau-Gonzalez *et al.* [19] presented BED data for facilitating research on the influence of emotions on EEG-based biometric tasks, and Lim *et al.* [20] provided the STEW EEG data covering multitasking mental workload activity induced by a single-session simultaneous capacity. For measuring EEG signals, the above studies used wireless devices which are portable and easy to wear. Small and wireless EEG devices minimize the movement of electrodes wires, this is a major source of electromagnetic interference and electrode displacement which significantly degrades the EEG signal quality [21].

B. EEG-Based Emotion Recognition

1) Pre-Processing: As data reliability of physiological signals is determined from the signal-to-noise ratio, a better noise detection method results in higher reliability and better accuracy. In general, EEG signals are measured by attaching sensors to the scalp. However, during the process, noises or various artifacts, typically including eye movement, muscular movement, heartbeat, sweat, and tongue movement, get mixed with the signals [22]. Completely eliminating these noises and artifacts is impossible; However, they can be minimized using principal component analysis (PCA), regression analysis, adaptive filtering, independent component analysis (ICA), and wavelet transform (WT) techniques [22]. Of these, PCA can eliminate noises by considering the adaptive threshold value; however, it also eliminates the signals that have no direct relevance with the actual noises of the EEG signals [23]. In addition, adaptive filtering and regression analysis require reference signals, such as electrooculography or ECG, which become a source of artifacts [24].

2) Feature Extraction: Feature extraction is conducted to extract only critical features that can differentiate between emotional states. To extract features from EEG signals, Yohanes *et al.* [25] extracted the energy components of a discrete wavelet transform (DWT) coefficient containing time information, and then eliminated redundant information using PCA. Zabidi *et al.* [26] extracted the features of an EEG signal through short-time Fourier transform (STFT) using a non-overlapping Hamming window. Lan *et al.* proposed the stable features selection method using the Intra-class correlation coefficient often used in EEG stability studies [27], and a combination of fractal dimension and statistical features [28].

Other important methods for feature extraction in emotion recognition include power spectral density (PSD) [11], statistical methods (SM) [29], differential entropy (DE) [30][31], fractal dimension (FD) [32], and WPT [33].



(a) Headset (b) Location of the channels

Fig. 1. EMOTIV EPOC+. (a) 14-channel wireless EEG headset and (b) EEG electrode placement in the 10-20 system for EEG recording.

3) Classification: The final step in the emotion recognition process is classification and recognition, which distinguishes between emotional states using the extracted features. Li *et al.* [34] classified the emotional states into positive, neutral, and negative categories using hierarchical convolutional neural networks (CNNs). Soroush *et al.* [35] applied three well-known classifiers, namely multilayer perceptron (MLP), K-nearest neighbor (K-NN), and support vector machine (SVM) to enhance emotion recognition. Lin [36] proposed a machine learning strategy, called the robust PCA, to develop a personalized cross-day emotion classification model. However, recently, deep learning methods that guarantee higher performance than existing machine learning methods for the classification of emotional states have been proposed [37].

III. Experiment Protocol

A. Data Collection

In this paper, we used the wireless Emotiv EPOC+ (Fig. 1(a)) for collecting emotion-based EEG data; Emotiv EPOC+ is a portable, high-resolution, multi-channel EEG monitoring device. The wireless Emotiv EPOC+, as shown in Fig. 1(b), is made up of the AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 channels, based on 10–20 international systems. We recorded the raw EEG data using these 14 channels of Emotiv EPOC+ at a sampling rate of 256 Hz. Stimuli are necessary to elicit an emotion before measuring an emotion-based EEG signals. Most emotion recognition studies have used images, music, or movies as a stimulus [38]. Similarly, we selected video clips to measure EEG data using both visual and auditory stimuli. Regarding the video clips used in our experiments, only clips which could be easily understood and audiovisual empathized were chosen using emotion-related keyword searches on YouTube. We collected 210 video clips according to five emotion categories, namely happiness, sadness, rage, fear and disgust, based on the discrete emotion theory [10]. The most well-known core emotions on the discrete emotion are happiness, surprise, sadness, anger, disgust, contempt, and fear. These discrete theory-based emotions are very useful in basic emotion recognition research, as these emotional responses biologically decide the expression and recognition of all people regardless of their different ethnic and cultural backgrounds.

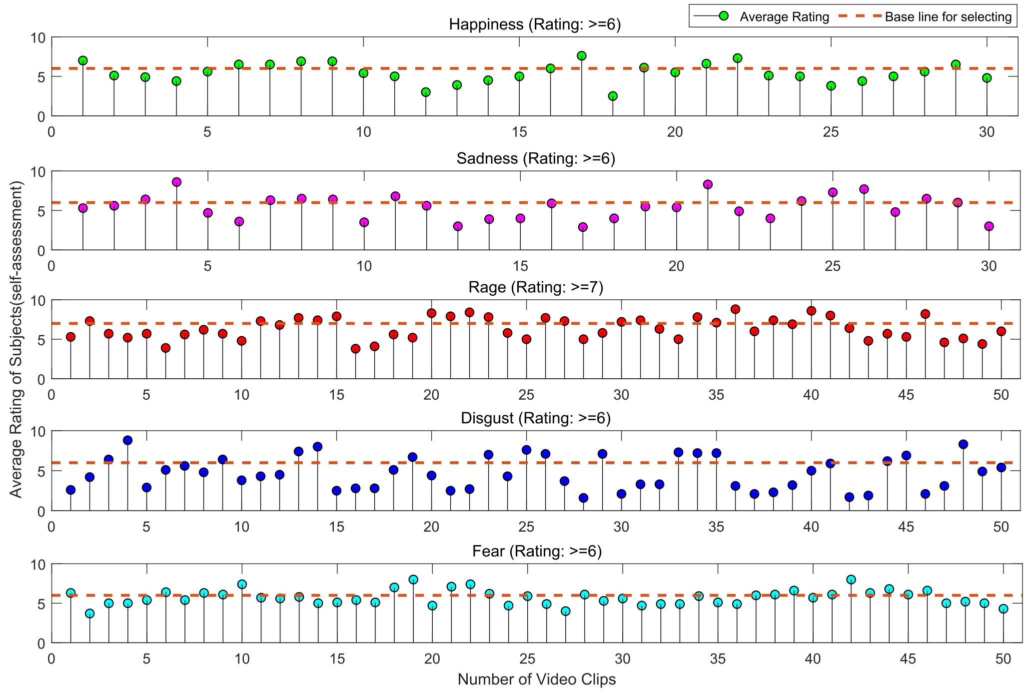


Fig. 2. Selected video clips according to the average ratings of the volunteers.

To be used as stimuli for the emotion-based EEG data measurements, we found areas to best induce each emotion from the collected 210 videos and edited them as 3-minute length video clips. However, the collected and edited 210 video clips are highly subjective because they were chosen by a few researchers. Therefore, to consider the objectivity of emotion-induced stimuli, we conducted a screening process using 15-volunteers. To select the video clips used for measuring EEG signals, one volunteer devoted at least three more days (210 trials *3 m / 60=10.5 h) to watch the all collected video clips (happiness:30, sadness: 30, rage: 50, fear: 50, and disgust: 50). Every volunteer watched each video clip and self-recorded the score according to their emotional states on a scale of 1 to 10. That is, we used the self-report measurement method to record the level of the emotion. The self-report is a method most widely used to record emotional states, and is based on the self-reported (perceived) emotion of the participant, and not on behavioral or physiological emotional information. The advantage of the self-report measurement mainly involves the ability to measure a range of discrete emotions. Also, the self-report measurement is straightforward to administer, and does not require expert knowledge in terms of scoring and analysis [39].

As shown in Fig. 2, we chose video clips with average ratings of 6 or above based on the self-report scores that could distinctly invoke the emotions of each individual. The video clips related to the overall rage emotion showed higher average ratings than those related to other emotions; thus, the selection criterion was set to an average rating of ≥ 7. In this paper, we measured the EEG data according to five emotions states such as happiness (joy), sadness, rage (anger), disgust, and fear among core emotions of discrete emotion using the selected video clips as the stimulus. Fig. 3 shows the experimental scene where the EEG signals were recorded while the video clips were observed. We showed the selected videos related to each emotion (happiness: 11, sadness: 12, rage: 20, fear: 20, and disgust: 16) to 52 new participants (excluding the fifteen volunteers), and recorded their EEG data.

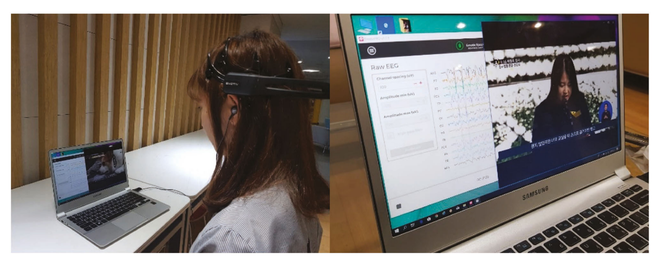


Fig. 3. Experimental scene.

The experiment protocol for EEG data measurement consisted of a 1 m relaxation time period before watching the 3 m video clips, and then another 1 m relaxation time period after the video. That is, we measured the EEG signals of the participants for a total five m. The total measuring period per participant varied from 1 week to 1 mo (one participant: 79 trials*5 m / 60=6.5 h). Whole participants rated themselves (1 to 10) with respect to their emotional states after watching the videos. From the 52 participants, we excluded the participants that include inordinately missing value problems, or who refused to look at the collected video clips according to the emotional state such as the fear or disgust. That is, we used 30 participants' data that EEG data was normally measured according to the five emotional states and used as the experiment data. 30 participants' data recorded mostly the average score 6 and more on the emotion score through the self-reporting

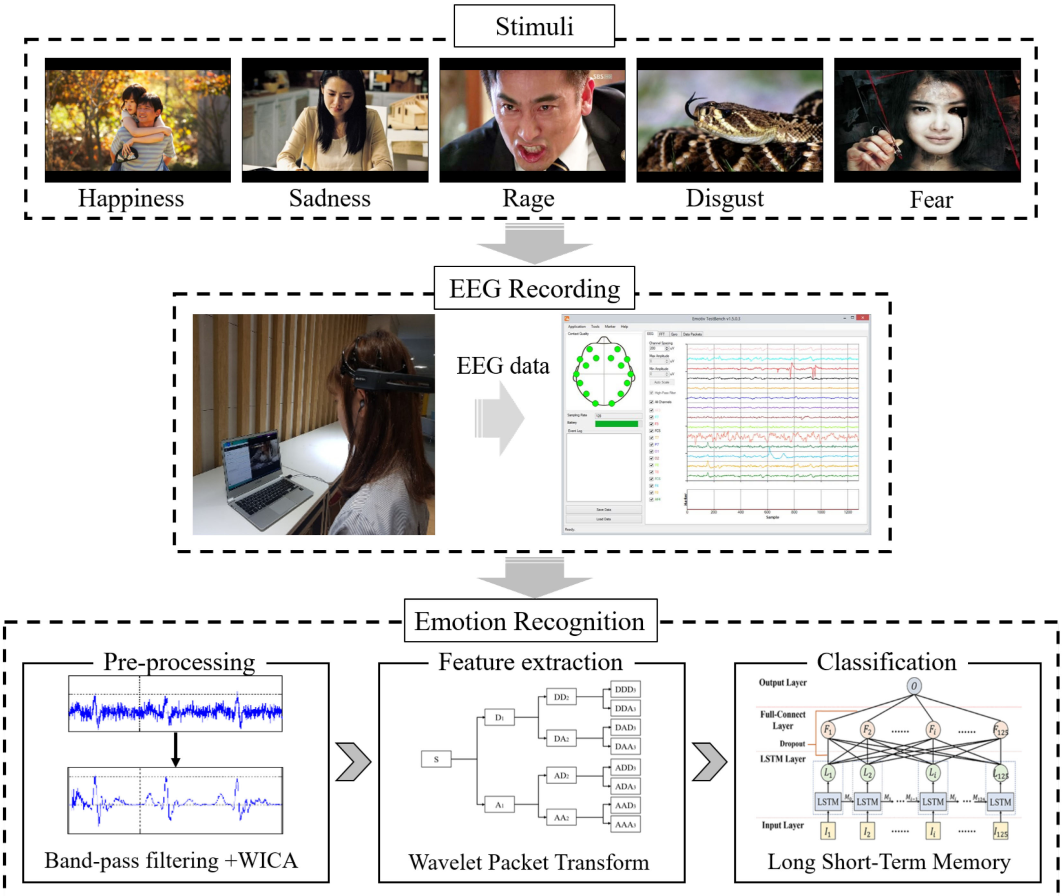


Fig. 4. New EEG data-based framework for emotion recognition.

TABLE I
DETAILS OF COLLECTED EMOTION EEG DATA

Experiment Information	
Number of video-clips	79
Video-clip duration	180 s
Number of participants	30 (male:18, female: 12)
Age of participants (years)	19−32(Mean=23.4, STD=3.23)
Types of emotions	happiness, sadness, rage, disgust, fear
EEG measuring equipment	Wireless Emotiv EPOC+
Number of channels	14
Sampling rate	256Hz

method (30 subjects $\times$ 79 trials $\times$ 14 channels $\times$ 300 s). Table I provides details of the collected EEG data. *WeDea* can be accessed from https://drive.google.com/drive/folders/1uPOx2Mf63kPcnnx7Azw4A8Zp5dapI_3h?usp=sharing ”https://WeDea-DataSet.com”.

B. EEG-Based Emotion Recognition Framework

In this paper, we measured discrete emotions-based EEG data using wireless devices and designed a reliable framework for emotion recognition. The framework comprises preprocessing by wICA, feature extraction using WPT, and a classification phase using an LSTM classifier, as shown in Fig. 4.

1) Pre-Processing: Most contamination factors, such as noise, can be prevented in advance by creating an appropriate experimental environment when data are measured. However, the artifacts produced by uncontrollable physical activities, such as blinking of the eyes or heartbeats, should be eliminated during the preprocessing step after the EEG recordings [22]. Therefore, we performed band-pass filtering on the measured raw EEG data within the frequency bandwidth of 0.5−30 Hz using a wireless EEG-measuring device. Because it was impossible to remove all artifacts or noise with filtering alone, we also applied wICA [40], which exhibited excellent artifact removal performance in preprocessing for emotion recognition. wICA is a combination of wavelet analysis and ICA. WT is used to simultaneously represent the time and frequency components of a signal whose frequency varies with time [41]. The basic WT function is represented by $\psi_{a,b}(t) = 1/\sqrt{a}\psi(t-b/a)$, where a is the scaling parameter, and b is the translation parameter. These WTs can be used to remove the artifacts contained within a signal, based on a spectral separation between the original signal and artifact. However, this technique must be applied to a single channel only. ICA is a signal processing method that separates a blind source, and has been used to isolate the source signal S from the obtained signals X, which are mixed with various unknown signals [22], as $X = AS$. A is a mixing matrix. Unlike wavelet analysis, fundamental ICA can only be applied in a multi-channel data. wICA is a combination of these two technologies. In other words, wavelet components obtained from each channel are used as an ICA input, and then, the source signal without artifacts is obtained by conducting ICA.

2) Feature Extraction: The extraction of EEG features is a process that robustly discover the underlying discriminative features with respect to each emotion. Consequently, the classification and recognition on such data can be facilitated. The extracted features are utilized for learning in the classification and recognition processes, which distinguishes the emotional states. We used WPT for extracting features that could distinguish among the emotional states from the newly collected EEG data. WPT is a generalized technique of DWT [25] that transforms the time domain in a signal into frequency domain at each level. WPT can decompose both approximation coefficients capturing low frequency information associated with the scaling function and detail coefficients capturing high-frequency information associated with wavelet function. Thus, it generates 2^n wavelet components at the n-level. In other words, WPT can provide a more accurate frequency resolution by decomposing into the subrange on both low and high frequencies. Moreover, it can obtain many more features of a signal than DWT. WP can be indicated as $\psi^i_{j,k}(t)$ as in Eq. (1).

$$\psi^i_{j,k}(t) = 2^{-\frac{j}{2}}\psi^i(2^{-j}t - k) \tag{1}$$

where i is a modulation parameter, j is a dilation parameter, and k means a translation parameter, $i = 1, 2, \ldots, j_n$. n indicates the decomposition level in the wavelet packet tree. WP coefficient $C^i_{j,k}$ corresponding to a signal $S(t)$ can be represented using Eq. (2).

$$C^i_{j,k} = \int_{-\infty}^{\infty} S(t)\psi^i_{j,k}(t)dt \tag{2}$$

In this case, if the WP coefficient satisfies the orthogonality condition, then the WP component of the given signal from the specific node can be obtained by Eq.(3).

$$S^i_j(t) = \sum_{k=-\infty}^{\infty} C^i_{j,k}\psi^i_{j,k}(t)dt \tag{3}$$

WPT is comprised of a low-pass filter(LPF) and a high-pass filter(HPF). A wavelet packet is a linear combination of wavelets, whose coefficient in a linear combination and is calculated as a recursive algorithm generating the wavelet packet coefficient. WPT can have a wavelet packet with more than one basis function on a given scale, and is formed as a complete tree basis through the repetition of all LPFs and HPFs. In this paper, we used WPT for time representation (upper level) for a signal and a better frequency resolution (lower level), in order to extract EEG data features according to the emotional states.

3) Classification: Recently, an increasing amount of research has been conducted for recognizing user emotions through deep learning, as it is actively utilized in various fields with gradually improving performance. LSTMs are frequently used for data that exhibit temporal characteristics; and this model can solve the vanishing gradient problem of a recurrent neural network (RNN) [42]. Herein, we applied an LSTM classifier in the classification phase of our designed framework for recognizing the emotional states via EEG signals [37]. LSTMs are structures that adds a cell state to the hidden state of an RNN, and is comprised of a forget, input, and output gate. Cells contain information corresponding to each time-point and decide which information to memorize and which to forget as they pass each gate. Each gate and cell is defined as shown in Eq. (4).

$$\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)\\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)\\
\tilde{C}_t &= tanh(W_c \cdot [h_{t-1}, x_t] + b_c)\\
C_t &= f_i \odot C_t + i_t \odot \tilde{C}_t\\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)\\
h_t &= o_t \odot tanh(C_t)
\end{aligned} \tag{4}$$

where σ is the sigmoid activation function, and $\odot$ is element-wise product between the vectors. f, i, o, and C are the forget gate, input gate, output gate, and memory cell vector, respectively. $tanh$ is a hyperbolic tangent activation funcion. W_f, W_i, W_c, and W_o are the weight matrices, and b_f, b_i, b_c, and b_o are the bias vectors. The hidden layer, h, is is free from the gradient vanishing problem by maintaining the previous and current time-step information without a loss. This is because it is consistently updated by the memory cell. LSTMs exhibit a recursive characteristic and are more accurate than the traditional RNN because they can compute what should be memorized and forgotten while repeating the functions. We used an LSTM network for classification learning according to the emotional states. The LSTM classifier comprises two layers, where the hidden units are set up as 125 and 100, respectively. The dropout layer is set as 0.5. We used the Adam optimizer in Training Options for the LSTM classifier, with a gradient threshold of 1 and the maximum number of epochs as 50.

IV. Experimental Results

In this paper, we collected a new EEG dataset, called *WeDea*, which can also be used for emotion recognition. In addition, we designed an emotion recognition framework to validate the new EEG dataset. Our framework for emotion recognition comprises the following steps: preprocessing for removing noise and artifacts, feature extraction to distinguish between emotional states, and classification for evaluating emotion recognition performance.

A. Removing Noise and Artifact

We used filtering to remove noise using a bandpass filter with a bandwidth of 0.5-30 Hz for the raw EEG data. In addition, we used wICA to eliminate the artifacts. To verify the wICA method which was used for removing the noise and artifacts in the preprocessing phase of the newly combined framework in this paper, we measured and compared the signal-to-noise ratio, (SNR) according to each method. Table II shows the SNR result of five subjects that were randomly selected. For the experiment, we randomly chose the five subjects from the dataset, and we also chose one trial in per emotional states in among 79 trials

TABLE II
SNR Comparison With wICA (Band-Pass Filter + wICA) and the Other Methods Such as Filtering (Band-Pass Filter) and ICA (band-Pass Filter + ICA)

Emotinal state	1-subject Filtering	1-subject ICA	1-subject wICA	2-subject Filtering	2-subject ICA	2-subject wICA	3-subject Filtering	3-subject ICA	3-subject wICA	4-subject Filtering	4-subject ICA	4-subject wICA	5-subject Filtering	5-subject ICA	5-subject wICA
Happiness	13.93	13.54	16.69	10.00	10.01	16.55	15.02	16.22	17.62	14.79	14.85	16.43	14.21	14.29	16.18
Sadness	13.42	13.85	16.15	11.37	11.75	16.63	10.63	10.26	14.19	13.38	13.36	15.74	14.71	15.12	16.55
Rage	7.86	9.87	9.35	10.92	10.36	15.81	13.00	12.87	17.47	12.25	12.47	17.76	10.53	10.27	16.52
Fear	11.13	9.95	10.36	13.91	13.92	16.53	11.02	10.94	14.21	13.59	13.69	17.64	14.86	14.84	16.64
Disgust	12.28	12.29	16.40	9.18	9.18	6.92	13.52	13.30	15.64	12.72	12.94	16.75	15.03	15.49	17.15
Average	11.72	11.90	**13.79**	11.07	11.04	**14.49**	12.64	12.72	**15.83**	13.34	13.46	**16.86**	13.87	14.00	**16.61**

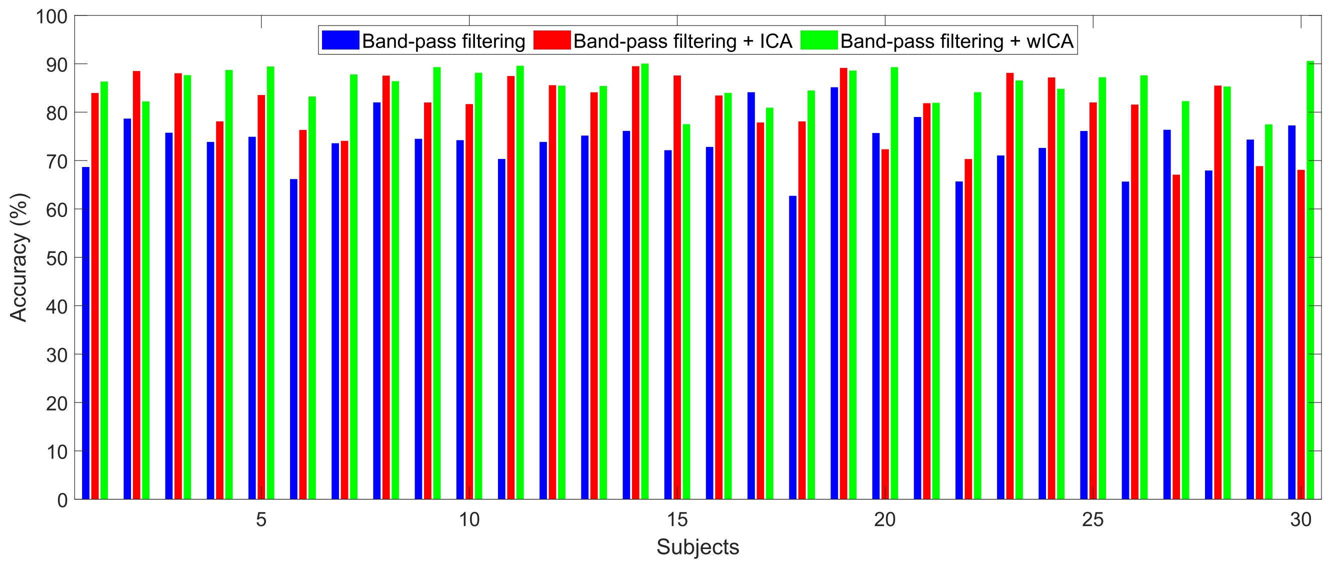


Fig. 5. Classification accuracy of the pre-processed dataset.

for each selected subject. Then we computed the SNR for each channel from a trial according to the band-pass filtering, filtering with ICA, and filtering with wICA. Noting the results, as shown in Table II, SNR is highly displayed in order filtering, filtering with ICA, and filtering with wICA on every subject. Therefore, our method for preprocessing can be said to remove much more noise and artifacts than the existing methods since wICA has higher SNR on average. To support these claims, we evaluated the classification accuracy according to the emotional states using data in which the artifacts were eliminated.

Fig. 5 shows the results of the classification accuracy experiments conducted using the data from which the noise and artifacts were removed with a band-pass filter, as well as by ICA and wICA. We used all the data, without feature extraction, for classification learning and measured the classification accuracy through 10-fold cross-validation using the RBF kernel-based multi-class SVM classifier. The 10-fold cross-validation technique was used in order to verify classification performance on each subject data. Each subject used 79 datasets classified into five emotion classes (size of experiment data: 79 trial $\times$ 14 channels $\times$ time(s)). For measuring the classification accuracy by the 10-fold cross-validation, 79 trials for each subject randomly split into ten groups (ex. Training vs. Testing: happiness-10:1, sadness-11:1, rage-18:2, fear-18:2, disgust-14:2). At each step of the cross-validation, one group was used for testing, and the other nine groups used for training the classifier (only, one group included all five-emotional states). We repeated ten times until every K-fold (K=10) served as the test set and recorded the average of recorded scores in this process.

In Fig. 5, the blue bar indicates the classification accuracy of the data with band-pass filtering, and the red and green bars indicate the classification accuracies of the data pre-processed for ICA and wICA, respectively. The classification accuracy of wICA was 8% higher than that of ICA; additionally, an improvement of approximately 12% was noted in the average accuracy obtained by applying only band-pass filtering (Fig. 5). These results indicate that the emotion-based raw *WeDea* dataset included noise or artifacts, and that better results are generated when using the preprocessed data with the artifacts removed. If the data collected for emotion analysis include considerable noise or artifacts, it may result in incorrect classification or recognition of emotions. Therefore, we enhanced the performance of emotion classification by including a preprocessing step, which eliminated the noise and artifacts prior to actual analysis.

To validate the availability of the collected EEG data, we compared the classification results using the DREAMER EEG dataset [18], described in Subsection A of section II. DREAMER data, which are very similar to our data, were recorded using the wireless Emotiv EPOC+ device, and raw data was used without preprocessing. Therefore, we conducted preprocessing using the same method as that used for *WeDea* data. For a

TABLE III
COMPARISON OF THE CLASSIFICATION ACCURACY RATE: DREAMER VS *WEDEA* (%)

Database Name	No. of subject	Band-pass filter	Band-pass filter + ICA	Band-pass filter + wICA
WeDea	1	68.6	83.9	86.3
	2	78.6	88.5	82.2
	3	75.7	88.0	87.6
	4	73.8	78.1	88.7
	5	74.9	83.5	89.4
	6	66.1	76.3	83.2
	7	73.5	74.1	87.8
	8	82.0	87.5	86.4
	9	74.4	82.0	89.3
	10	74.2	81.6	88.1
	Average	74.2	82.3	86.9
DREAMER	1	60.9	70.6	68.1
	2	58.6	67.8	69.8
	3	62.4	62.3	77.8
	5	57.7	57.2	66.1
	11	63.3	75.5	74.3
	14	61.2	63.2	71.9
	16	72.1	66.7	69.2
	18	68.0	69.0	65.1
	21	53.4	66.8	69.0
	23	65.2	61.7	70.0
	Average	62.3	66.1	70.1

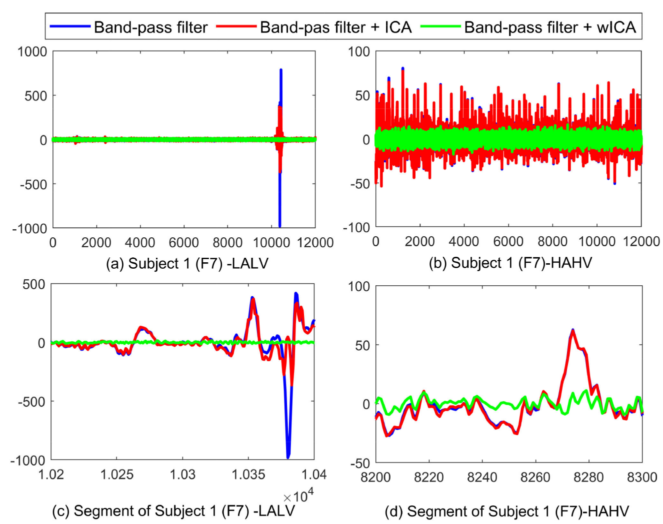


Fig. 6. Pre-processed DREAMER data.

comparative analysis in the experiment, we compared the following four classes based on the rating values for arousal and valence: low-arousal low-valence (LALV), low-arousal high-valence (LAHV), high-arousal low-valence (HALV), and high-arousal high-valence (HAHV). The conditions "low is ≤ 2, high is ≥ 4" was applied in label classification to clearly distinguish the emotion states.

Fig. 6 shows parts of the preprocessed DREAMER data. Fig. 6(a) and (b) shows the signals measured at the F7 sensor position on subject 1, corresponding to LALV and HAHV classes, respectively. Fig. 6(c) displays part of the signals shown in (a), and Fig. 6(d) shows a part of the HAHV signal shown in (b). The signal patterns of the original filtered data and the signals preprocessed using ICA were similar(Fig. 6(c)). In contrast, the signal preprocessed using wICA, unlike the filtered signal, appeared to be flat. The filtered signal was similar to the signal preprocessed using ICA (Fig. 6(d)). In the case of using wICA, the signal had a smaller amplitude than that in the two cases. Therefore, the artifacts in DREAMER were better eliminated through wICA.

We conducted band-pass filtering on the DREAMER raw EEG data and used the data preprocessed using ICA and wICA for the classification experiments. We utilized only the datasets that corresponded to the label classification conditions among the subjects. The size of DREAMER for classification learning was 18 trial-n $\times$ 14 channels $\times$ time (s) per subject. Here, n denotes the number of datasets that do not meet required conditions. Therefore, we used 10 subjects that included all four classes according to the label classification conditions of the experiments. Table III shows the classification accuracy rates for *WeDea* and DREAMER databases. *WeDea* exhibited 74.2% accuracy, on average, when applying only band-pass filtering, and 82.3% and 86.9%, respectively, after eliminating artifacts using ICA and wICA. DREAMER showed approximately a 8% and 4% improvement in results, respectively, when applying wICA to the filtered data as compared to the case of applying only a band-pass filter and ICA to the filtered data. These results show that better performance can be achieved when using input data for classification learning after removing noise and artifacts using band-pass filtering and wICA.

B. Feature Extraction

On the emotion recognition framework, we used WPT as the feature extraction method. We extracted the features using PSD [11] and STFT [26], which are the most frequently used methods in EEG-based emotion recognition research, and compared their performances by measuring their classification accuracies. For these experiments, we used the three EEG emotion datasets (as described in Section II. A-mentioned). For the DEAP data [14], we used the preprocessed EEG Matlab files of the 32 subjects, while in the case of SEED data [15], we used

TABLE IV
DATA DESCRIPTION FOR EXPERIMENTS

Data Name	No. of Subjects	No. of Class	No. of Data	No. of Total Data
WeDea	30	5	10 trials /per subject in each class	50 trials /per subject
DREAMER	23	4	Low $\leq$2, High $\geq$4 (rating values: 1 $\sim$ 5)	18 trial-n /per subject
DEAP	32	4	Low $\leq$3, High $\geq$7 (rating values: 1 $\sim$ 9)	40 trial-n /per subject
SEED	15	3	10 trials /per subject in each class	30 trials /per subject

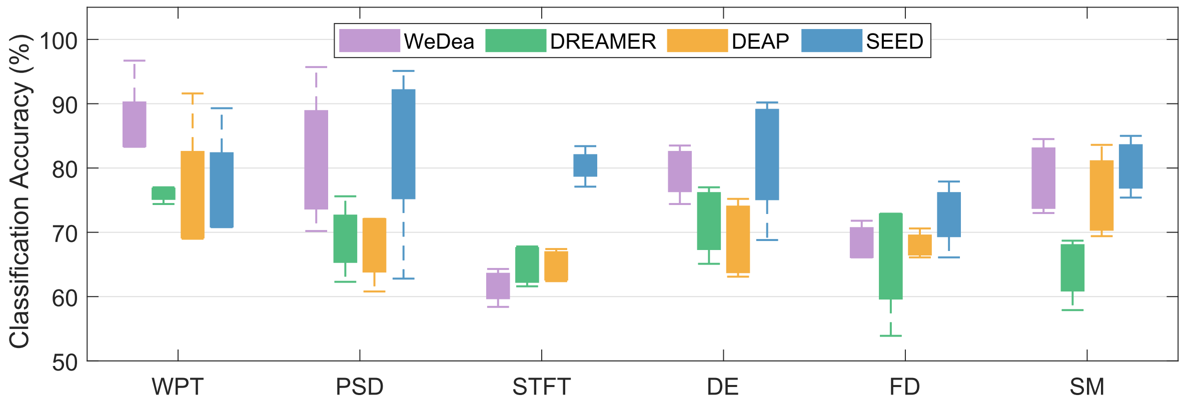


Fig. 7. Average classification accuracy according to the feature extraction methods.

the files of 15 subjects. DREAMER [18] used the same data set as Table III, and *WeDea* randomly selected 10 trials from each subject according to the emotional states in considering the class imbalance problem in the classification step. That is, WeDea used the selected fifty trials for each subject.

We used the "pwelch" Matlab function for extracting features with PSD. In this function, we set the window length as 10 s for all channels and bands, with 50% overlapping between the sections per sample. For example, in the case of *WeDea*, we recorded data using 14 channels, and obtained 56 features (4 bands $\times$ 14 channels) per sample by reference to [43]. For the other dataset, we set the window length to 10 seconds, similar to that in *WeDea* (i.e., window lengths of DEAP: 1280, SEED: 2000, DREAMER: 1280). We applied STFT with the "spectrogram" Matlab function and a Hamming window of 10 seconds, with 50% overlapping between sections. We also applied the WPT tree [33] for feature extraction using the overlapping windowing approach. This method used a window length of 10 s with 5 s increments, and assumed seven decomposition levels. For instance, a trial of happiness data being 3 m in length was re-composed as 14 channels $\times$ 10 s $\times$ 35 samples by segmenting through the sliding window. Then, WPT extracted features set with a 35 $\times$ 3570 size by obtaining 255 features per channel from the 7 decomposition levels from the 35 samples that are segmented. For more a diverse comparison among feature extraction methods, we also used DE to construct features in five frequency bands such as delta, theta, alpha, beta, and gamma and we extracted the features by calculating the FD. In addition, SM extracted six statistical features from each channel as on [29]. In summary, for the four EEG databases, as shown in Table IV, we extracted features by applying six feature extraction methods (WPT, PSD, STFT, DE, FD, and SM) to the preprocessed EEG data; those extracted features were used as input data for the classification.

Fig. 7 shows the classification accuracy results obtained using the features extracted through the six above feature extraction methods. We used a multi-class SVM classifier for measuring the classification accuracy. In the case of the *WeDea*, when we used the STFT method for extracting the features, the classification accuracy exhibited the lowest classification accuracy compared to the other datasets. However, *WeDea* showed a higher accuracy than DEAP and DREAMER when used with other methods such as PSD, DE, FD, and SM but a lower accuracy compared to SEED. When the WPT method was used for extracting the feature, *WeDea* exhibited the highest classification rate (Fig. 7) among all datasets. *WeDea* data showed an average classification accuracy of 86% when extracting features using WPT, and an average of 81% and 61% accuracies when using PSD and STFT, respectively. In addition, *WeDea* produced the average 79.4%, 68.4%, and 78.4% classification accuracy when used DE, FD, and SM methods. While *WeDea* showed a relatively lower accuracy rate for most methods than those of SEED, the mean accuracy rate of *WeDea* was similar or higher than those of other data. Thus, our *WeDea* dataset appears to be sufficiently valuable in emotion recognition research, and has a similar performance to the published conventional data for emotion recognition. In addition, feature extraction using WPT may be an appropriate approach in our framework for *WeDea* data analysis, demonstrating improved classification rates.

C. Classification

For classification learning, we used the LSTM, which uses the extracted features as input data [37]. We measured and compared the classification accuracies obtained with 10-fold cross-validation conducted using LSTM and multi-SVM classifiers. The data used for the experiments were the same as mentioned in Table IV. The features extracted by WPT were used as the

TABLE V
CLASSIFICATION ACCURACY COMPARISON WITH SUBJECT-DEPENDENT VS. -INDEPENDENT

No.Subject	Subject -dependent	Subject -independent	No.Subject	Subject -dependent	Subject -independent	No.Subject	Subject -dependent	Subject -independent
1	86.8	79.6	11	88.3	91.8	21	90.0	87.0
2	93.2	89.3	12	91.9	88.7	22	94.7	90.7
3	88.4	89.7	13	96.0	89.3	23	91.2	92.9
4	92.6	91.6	14	93.5	92.1	24	88.9	86.3
5	96.1	82.1	15	87.7	84.4	25	90.5	89.9
6	96.2	87.8	16	86.7	88.9	26	93.8	90.7
7	95.3	86.5	17	86.0	86.3	27	92.3	88.9
8	85.1	81.6	18	90.0	89.1	28	95.7	96.0
9	94.5	83.8	19	90.5	83.9	29	90.0	87.9
10	84.9	87.0	20	91.2	80.1	30	88.2	86.6
Average(STD)	91.3(±4.55)	85.9(±3.95)	Average(STD)	90.1(±3.13)	87.4(±3.76)	Average(STD)	91.5(±2.51)	89.6(±3.06)

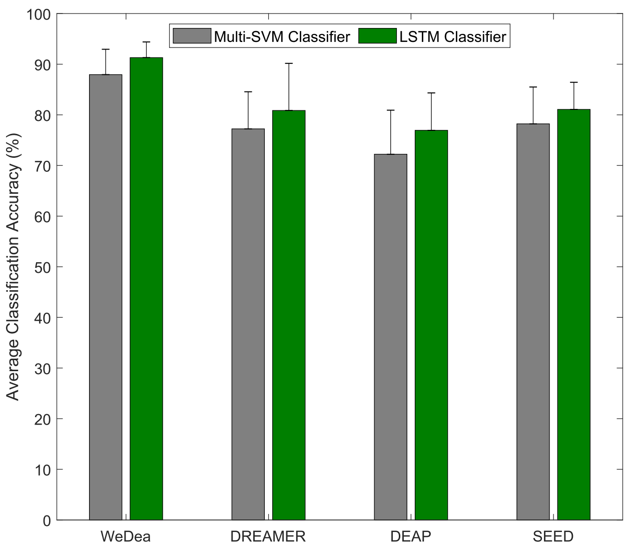


Fig. 8. Average classification accuracy comparison: Multi-SVM vs LSTM classifier.

input data for the multi-SVM and LSTM classifiers. Fig. 8 shows the classification accuracy measured using the two classifiers. *WeDea* showed an average classification accuracy of 87.94% (± 5.01) when using the multi-SVM classifier and 91.3% (± 3.1) when using the LSTM classifier. In case of the DREAMER dataset measured using wireless EPOC+ devices, similar to the *WeDea* dataset, the average classification accuracies obtained using multi-SVM and LSTM were 77.23% (±7.33) and 80.86% (±9.31), respectively. Additionally, the accuacies of the multi-SVM and LSTM classifiers were 72.22% (±8.7) and 76.94% (±7.39) for the DEAP dataset and 78.22% (±7.27) and 81.07% (±5.36) for the SEED dataset, respectively. Thus, the LSTM classifier showed a 4% improvement in the result compared to the multi-SVM classifier in the classification phase of the designed framework for emotion recognition. Moreover, the LSTM classifier also showed an improvement of 3−4% in the classification accuracy for the DREAMER, DEAP, and SEED datasets. When using the multi-SVM classifier, *WeDea* exhibited a 10.7%, 15.7%, and 9.7% improvement in the classification accuracy compared to the DREAMER, DEAP, and SEED datasets. In the case of the LSTM classifier, our dataset indicated a 10.4%, 14.3%, and 10.2% improvement in accuracies, respectively. Thus, *WeDea* can be confirmed experimentally as beneficial to emotion recognition research. Moreover, the newly combined framework exhibits suitable performance for analyzing not only the existing EEG dataset but also *WeDea*.

To verify the effectiveness of our newly combined framework for emotion recognition, we performed subject-independent classification using the leave-one-subject-out cross validation [44], and compared it with the subject-dependent method using 10-fold cross validation on one subject's data. In the case of the subject-independent method, one subject dataset was used as testing data and the remaining subject datasets were used as the training dataset of the LSTM classifier. In addition, we recorded the classification accuracy of each subject used as testing data. Table V showed the classification accuracy measured by subject-dependent and -independent. Following the results of Table V, the subject-independent method from the leave-one-subject-out cross validation showed approximately 3% lower performances than the subject-dependent method. Through these experimental results, it can be noted that our framework does not suffer from the problem of overfitting. That is, our framework worked well on the testing data. Thus, we can confirm that the newly combined framework is suitable for EEG-based emotion recognition research.

V. DISCUSSION

EEG is a physiological signal that cannot be controlled intentionally. It is used for studying not only emotion recognition but also various other domains including seizures, epilepsy, headaches, brain tumors, sleep disorders, brain death, rehabilitation, and security [3], [45], [46]. The greatest advantage of EEG is its capability to monitor human brain activities in real time at the millisecond level (one thousandth of a second). In this paper, we collected EEG data that could directly reflect a change in the emotional state of a human. Unlike the existing open data, which are mostly measured using wired devices, *WeDea* datasets are recorded using a wireless headset device. Wireless EEG measurement devices are low-cost, noninvasive, and portable. Thus, they are highlighted as the next-generation neuroscience technology devices that can be applied to the study of real-time brain activity. We used these wireless EEG measurement devices for recording EEG signals related to emotions. These devices are relatively less expensive than wired devices, and reduce the setting time required for measurement. In addition, they collect data continuously without cut-off in real time.

We used video clips as the stimulus for eliciting emotions when measuring EEG signals using wireless devices. EEG data were recorded while watching the pre-selected video clips according to each emotional state, namely happiness, sadness, rage, disgust, and fear. We distinguished between these emotions through the discrete emotion approach method [10]. This approach is a useful way to study basic emotions regardless of ethnic and cultural backgrounds. On the other hand, a dimensional emotion model which refers to the Valence-Arousal-Dominance model is most commonly used in emotion data collection; and is an approach to express with the point within the continuous space that is defined by two or three dimensions without distinction of the discrete emotion. This approach can be used to express a wide range of emotional states. However, this cannot easily distinguish emotions which share the same values of arousal and valence, such as anger and fear [47]. In addition, it is unintuitive and may require special training for labeling each emotion [48]. Therefore, our emotion EEG dataset that was collected based on the discrete emotion approach may be used in the functional analysis research part of psychological and behavioral, evolutionarily derived, as well as ‘basic,’ emotion research.

Numerous artifacts are added during the capturing stage, owing to the nature of EEG signals. Artifacts are electrical waveforms that appear during EEG recording along with the EEG waveforms. For instance, during an EEG recording, various independent source signals, such as noises caused by ocular movement (ocular artifacts), brain activity, and scalp muscle movement (EMG activity) and impacts caused by a change in the electrode attachment position (mechanical electrode displacement), get mixed [22]. As these artifacts hinder EEG analysis, preprocessing is required to eliminate them. ICA or WT allows the elimination of artifacts using only EEG data without any reference signal. ICA shows excellent performance in terms of eliminating artifacts; however, some EEG data are lost when eliminating the independent components containing artifacts, because the actual EEG signals and artifacts are not completely separated. To address these issues, a method for automatically detecting the components having artifacts among the independent components [49] and the wICA method, which compensates for the disadvantage of ICA through a combination with the existing WT, have been proposed. In this paper, we employed wICA to eliminate the artifacts from EEG data. Moreover, EEG data in which the artifacts have been eliminated using wICA show better performance than those processed using ICA.

The goal of the EEG analysis step is to suggest an EEG data analysis model that can assess the participants’ emotional states. Eventually, an analysis model should be able to assess the user’s emotions by just recording the EEG data. Previous studies have mainly used observational methods; However, with recent developments in computer technology, studies applying deep learning technology are being actively conducted in the emotion recognition field to perceive user emotions. Unlike conventional artificial neural network technology, deep learning technology demonstrates a potential application for treating various unstructured data using LSTMs for time-series data analysis, and CNNs for visual and perceptual data with multiple hidden layers [50]. As EEG data involve significant amounts of data inculding properties such as being non-stationary and having non-linearity, the deep learning model is likely to be more appropriate than the machine learning model. Therefore, we used the RNN-based LSTM classifier for classification learning of the designed emotion recognition framework. We could verify the usability of the newly collected EEG data through the newly combined emotion recognition framework.

VI. Conclusion and Future Work

With the recent development in AI technology, significant efforts have been made to infuse human emotions into AI. The studies on expressing the emotions perceived from humans through AI technology have been conducted in various domains, including rehabilitation, BCI, genome-wide applications, and healthcare services. Although different forms of data, such as facial expressions, voices, and gestures, are used to recognize human emotions, EEG data have been increasingly used in single- or multi-modal forms. In this paper, we collected EEG data according to the emotional states in real-time as inspired by the fundamental research to express emotions using AI technology. This is achieved by recognizing human emotions. Further, we designed a newly combined emotion recognition framework to analyze and recognize the collected emotion data. We used a wireless EEG measurement device and collected multi-way EEG data from 30 participants according to the five categories of emotional stimuli based on the discrete emotion approach method. Furthermore, to allow *WeDea* to be utilized in various emotion recognition studies, we validated the reliability and utility of the *WeDea* dataset using the designed framework with the following three steps: pre-processing, feature extraction, and classification. *WeDea* demonstrated a higher emotion classification accuracy than the existing datasets. In future, we intend to conduct a broader emotion recognition study in combination with other physiological signals using the extended deep learning technology.

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