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Arousal and Valence Classification Model Based on Long Short-Term Memory and DEAP Data for Mental Healthcare Management

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Objectives: Both the valence and arousal components of affect are important considerations when managing mental healthcare because they are associated with affective and physiological responses. Research on arousal and valence analysis, which uses images, texts, and physiological signals that employ deep learning, is actively underway; research investigating how to improve the recognition rate is needed. The goal of this research was to design a deep learning framework and model to classify arousal and valence, indicating positive and negative degrees of emotion as high or low. **Methods:** The proposed arousal and valence classification model to analyze the affective state was tested using data from 40 channels provided by a dataset for emotion analysis using electrocardiography (EEG), physiological, and video signals (the DEAP dataset). Experiments were based on 10 selected featured central and peripheral nervous system data points, using long short-term memory (LSTM) as a deep learning method. **Results:** The arousal and valence were classified and visualized on a two-dimensional coordinate plane. Profiles were designed depending on the number of hidden layers, nodes, and hyperparameters according to the error rate. The experimental results show an arousal and valence classification model accuracy of 74.65 and 78%, respectively. The proposed model performed better than previous other models. **Conclusions:** The proposed model appears to be effective in analyzing arousal and valence; specifically, it is expected that affective analysis using physiological signals based on LSTM will be possible without manual feature extraction. In a future study, the classification model will be adopted in mental healthcare management systems.

Keywords: Arousal and Valence Analysis, Supervised Machine Learning, Classification, Machine Learning, DEAP Dataset

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I. Introduction

Recent advances in artificial intelligence technologies, such as deep learning, have resulted in the rapid development of the field, and hence in new research opportunities [1,2]. While the support of stable mental healthcare needs to be considered, the focus is on automated mental state detection, which is a complex phenomenon with both affective and physiological responses. Although regulation of emotion is a difficult concept, arousal and valence recognition studies have been undertaken to provide an understanding of affective experiences using physiological signals, such as such as electrocardiography (ECG), photoplethysmography (PPG), and electroencephalography (EEG) [3-5]. In addition, some studies about early mental stress detection using physiological signals have been performed in the mental healthcare domain [6-9]. On the other hand, with significant advances in machine learning technologies, such as deep learning, artificial intelligence methods can be applied to improve the efficiency of emotion recognition. Recently, deep learning methods have been applied in the processing of physiological signals, such as EEG and skin resistance. The results were comparable to those of conventional methods [10-12]. In this study, a dataset for emotion analysis obtained from an EEG, physiological, and video signals database (DEAP) was used to conduct an emotion classification experiment to validate the efficacy of the deep learning-based approach. The database is the largest, most comprehensive physiological signal emotion dataset publicly available. The goal of this study was to design an LTSM-based emotion classification model using EEG, galvanic skin response (GSR), and PPG signal data that can classify arousal (which indicates strength of emotion) and valence (which indicates positive and negative degree of emotion) as high or low. The DEAP dataset provides data for 10 channels—namely, for 8 EEG channels as well as single channels of GSR and PPG—to analyze emotional states. Then the accuracy of the emotion analysis presented in this paper is assessed by comparing it with the previous studies of Wang and Shang [11], which classifies emotions based on the deep belief network (DBN), which conducts learning by probabilistic judgment using signals of four channels as input data in the DEAP dataset from the central nervous system.

The remainder of this paper is organized as follows. In Section II, a brief overview of both emotion recognition and deep learning for emotion recognition is provided. The experimental design aspects of long short-term memory (LSTM)-based emotion recognition using physiological signals are discussed in Section II. The simulated and experimental schemes and their results are described in Section III. Finally, the conclusions are summarized in Section IV.

1. Emotion Recognition Using Physiological Signals

As previously mentioned, methods for emotion detection using physiological signals have been extensively investigated and have provided encouraging results where the affective states are directly related to changes in bodily signals [13,14]. For the central nervous system (CNS), EEG is a useful technique to study emotion variance. The brain's response to various stimuli is usually measured by dividing the EEG signals into different frequency rhythms, namely, delta (0.5–4 Hz), theta (4–8 Hz), beta (16–32 Hz), and gamma (32 Hz and above). These band waves are omnipresent in various parts of the brain [15]. In addition, among peripheral systems, autonomic nervous system (ANS) activity is considered a major component of an emotional response because the physiological signals based on ANS activity are very descriptive and easy to measure [13-15]. Pulse waves result from periodic pulsations in the blood volume, and are measured by the changes in optical absorption that they induce [16-19]. Changes in the amplitudes of PPG signals are related to the level of tension in an individual. GSR signals can be an indicator of the autonomic activity of physiological arousal, which varies with the moisture level of the skin.

Emotion refers to the human being's complex emotional state that is changed by external factors [20,21]. Russell [22] classified human emotions into two dimensions: arousal represents the strength of emotions in the degree of arousal and relaxation, while valence represents the degree of positivity and negativity.

Among the many emotion models, we adopted Russell's model [22], where the two dimensions are represented by a vertical arousal and a horizontal valence axes.

2. Long Short–Term Memory

Deep learning in neural networks comprises decomposition of networks into multiple layers of processing with the aim of learning multiple levels of abstraction [5]. LSTM is one of the deformation models of an RNN that is used to overcome its long-term dependency problem. LSTM is particularly useful for sequential data, such as time series data [23]. LSTM solves the long-term dependency by installing three gates, which are used for input and output of the memory space; these are the input gate, forget gate, and output gate. Each of the three gates determines how much of the input value will be reflected, how much of the current value is to

be forgotten, and whether or not to display the calculation up to present [24].

II. Methods

This section describes the data used in the experiment, the model, and the experimental method.

The first step in mapping physiological signals to emotions is to extract some features from raw signal data—for instance, analyzing the heart rate variability (HRV), which is equivalent to the response of the nervous system of the physiological signal with R-R intervals. These features are usually hand-engineered using task-dependent techniques developed by domain experts [13,25-27] and selected by experts or feature selection algorithms. However, in this study, we overcame these disadvantages by adopting the LSTM model, which allows automatic feature selection through the learning and training process.

1. DEAP Dataset

DEAP is a multimodal dataset for the analysis of human affective states [12]. The EEG and peripheral physiological signals (down sampled to 128 Hz), including the horizon-

tal electrooculogram (hEOG), vertical electrooculogram (vEOG), zygomaticus major electromyogram (zEMG), trapezius major electromyogram (tEMG), GSR, respiration belt data, plethysmogram, and body temperature, of 32 subjects were recorded as each subject watched 40 one-minute long videos. The subjects rated the levels as continuous values of arousal, valence, liking, dominance, and familiarity. The structure of the DEAP dataset is shown in Table 1 and Figure 1. Figure 1 shows a small part of the DEAP dataset used as the input data. Also, Figure 1 shows the input data consisting of 10 channels' physiological signals.

As a reference [13,14], we selected a PPG signal, a GSR signal, and 8-channel EEG signals of the frontal lobe (Fp1, Fp2, F3, F4) that are responsible for the high level of cognitive, emotional, and mental functions; temporal lobes (T7, T8) responsible for the auditory area; and the occipital lobes (P3, P4) responsible for the auditory area of the 32-channel EEG signals. Only data with a length of 60 seconds (128 Hz × 60), excluding the initial 3 seconds (128 Hz × 3) corresponding to the baseline of the total data length of each signal (128 Hz × 63 seconds), were used in the experiment. For each subject, arousal and valence were evaluated in successive values from 1 to 9. A result of less than 5 was set to 0, while a result

Table 1. Structure of the DEAP dataset

Array name	Array shape	Array contents
Data	40 × 40 × 8064	(Video/trial) × channels × data (128 Hz × 63 seconds)
Labels	40 × 4	(Video/trial) × label (valence, arousal, dominance, liking)

Fp1	F3	T7	P3	Fp2	F4	T8	P4	GSR	PPG
4.05213	1.186079	-5.44357	-10.4073	4.857162	3.189637	4.648617	1.054497	768.1206	8121.618
2.89121	4.616423	-3.20577	-10.1641	2.203179	2.300912	0.62529	0.467882	781.6041	8078.161
-1.77959	0.803399	-1.75188	-1.60698	-1.26365	-0.65972	0.550914	3.29879	781.6041	8065.466
-5.25212	-3.67648	-2.04754	8.119572	-2.81377	-4.46894	-1.08954	2.60621	781.6041	8058.63
-5.62955	-3.47551	-4.63037	12.31872	-3.54799	-5.16084	-2.23369	0.231172	781.6041	8084.509
-6.37942	-5.53004	-8.21402	14.81967	-7.64755	-7.65665	-0.06239	3.320026	804.0788	8116.735
-9.92225	-9.49132	-4.18526	17.59535	-14.6222	-13.8737	0.282822	6.394621	804.0788	8156.285
-12.4696	-10.8892	4.101281	16.11077	-17.4386	-14.2321	-1.02791	5.635635	804.0788	8180.21
-9.2785	-11.5728	3.153199	8.49204	-12.0733	-8.37377	1.255629	6.679653	804.0788	8209.507
-2.49855	-7.0968	1.24402	-1.07338	-2.82668	-3.2931	3.273171	4.552266	822.0604	8219.272
3.195885	3.123256	5.380645	-5.88175	3.320102	1.226062	0.218824	-4.71942	822.0604	8199.741
7.580071	8.17537	4.51097	-7.14519	5.599446	5.938737	-2.36672	-9.59114	822.0604	8188.999
9.900878	7.351236	2.899671	-11.2141	7.901676	9.87181	-0.25498	-6.41601	826.5561	8130.895
7.677811	5.545824	3.615565	-13.9587	9.504421	11.9963	3.83636	-1.77141	840.0438	8073.767
4.362218	3.423386	-2.76782	-11.1732	8.950643	10.90118	6.617993	1.645685	840.0438	7993.69
4.087202	5.793422	-5.24705	-8.03428	8.350068	9.315508	4.159485	0.125744	840.0438	7877.481
3.785664	9.214996	0.846918	-3.70092	5.627974	7.484697	-2.53273	-4.58255	840.0438	7769.084
2.326476	5.896564	1.391672	2.297874	1.061998	3.521014	-6.77026	-5.78613	858.0288	7662.152
2.895657	3.567366	3.044579	3.031916	2.24546	3.153532	-9.34783	-7.12208	858.0288	7525.435
2.282499	4.202702	7.344363	2.291296	6.307759	5.369069	-11.3573	-8.61496	858.0288	7362.84
-1.18311	-1.02986	-1.24071	5.206078	3.675173	1.440075	-6.06919	-2.31928	858.0288	7205.616

Figure 1. Example of the DEAP dataset.

greater than or equal to 5 was set to 1 and used as output data (labels). The input and output data were stored as separate files, each of which was divided into 40 files for each participant. The total number of files was 1,280 (participant

× video). Of the 1,280 experimental data files, 1,024 files (representing 80% of the total data, from the 1st to the 32nd participants' 40-channel signal files) were used to train the model, and 256 files (representing 20% of the data, from the
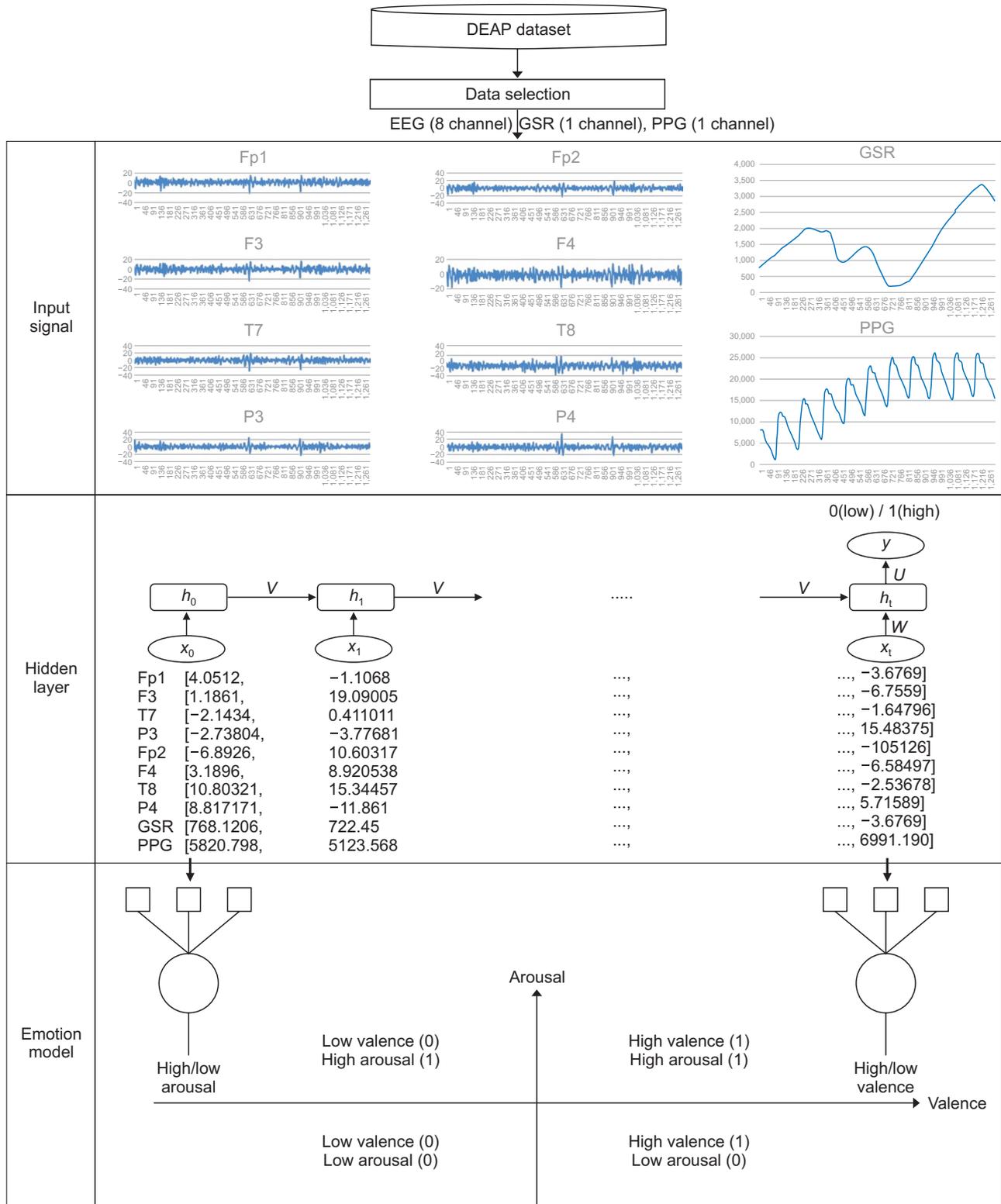

Figure 2. Long short-term memory (LSTM) model for emotion classification.

33rd to the 40th participants' 40-channel signal files) were used to evaluate the performance of the model.

2. LSTM–Based Emotion Classification Model

The structure of the proposed LSTM-based emotion classification model using the central nervous system signals and autonomic nervous system signal is shown in Figure 2. In the hidden layer of Figure 2, $x_0, x_1, \cdots, x_t$ represent the 8 EEG signals of the central nervous system, the autonomic nervous system GSR signal, and the PPG signal, which are physiological signals of 10 channels used as input data. The state values $h_0, h_1, \cdots, h_t$ of the hidden layer, determined from the input data, are those in which the result of the previous signal affects the current signal. In addition, a forget gate ($\cdot$) was installed between the hidden layer nodes to determine how much of the current value should be forgotten. The output value y is communicated only once at the end, since the degrees of arousal and valence are classified into two categories of low and high. Therefore, weights W, V and U are calculated for each physiological signal with sequence and output values of low or high that are generated. The output data of the proposed emotion classification model was the result of evaluating the degree of arousal and valence between 1 and 9 in the DEAP dataset. Since the performance of the model depends on the numbers of layers and nodes and the hyperparameters, we evaluated its accuracy by varying each parameter. Accuracy is a measure of how precise the model is based on the evaluation criteria. The ratio of prediction—true positive (TP) and true negative (TN)—is expressed as accuracy (%). We tried to improve the performance of the proposed emotion classification model. The experiments were conducted using Deeplearning4j written for Java and Scala in a Window 10 environment. We installed CUDA 8.0 to use the GPU, and managed the project library by installing the build automation tool Apache Maven [27].

III. Results

1. The Designed LSTM Model

The accuracy results of the arousal and valence classification models, according to the hyperparameter setting values applied to the LSTM, are shown in Tables 1 and 2, respectively. We modified the hyperparameter more than 30 times based on the setup method that can give the best learning result. Thus, only the top four results from each hyperparameter are shown in Tables 2 and 3.

Settings 1, 2 and 3 in Table 2 show the process of setting the hyperparameter value of the arousal classification model, and the numbers of layers and nodes. Settings 3 and 4 are part of the process of setting the hyperparameters with a fixed number of layers and nodes. The accuracy of the model differs according to the value of the forget gate bias. If the learning rate is too low, the speed of the algorithm is slowed down, and the learning cannot be completed before the point at which the cost function is minimized. On the other hand, if the learning rate is too high, overshooting can occur without the minimum value being reached [28].

Settings 1, 2 and 3 in Table 3 show the process of setting the hyperparameter value of the valence classification model, and the numbers of layers and nodes. Settings 3 and 4 are part of the process of setting the hyperparameter with a fixed number of layers. As the result of Setting 3, if the neural network becomes larger, the number of parameters increases. Thus, the performance of the algorithm may be lowered. Therefore, Setting 3 is not predictable when the degree of valence is high (1).

2. Experimental Results

We classified the values of arousal and valence through the proposed LSTM model as low (0) and high (1). Thereafter,

Table 2. Performance comparison of the arousal classification model by hyperparameter setting

	Setting 1	Setting 2	Setting 3	Setting 4
Number of layer	1	1	2	2
Number of node	6	4	[6, 4]	4
Batch size	64	128	64	128
Epochs	30	30	30	30
Learning rate	0.1	0.5	0.1	1
Momentum	0.1	0.7	0.1	1
Forge gate bias	1	1	0.6	1
Accuracy (%)	62.5	68.12	33	74.65

Table 3. Performance comparison of the valence classification model by hyperparameter setting

	Setting 1	Setting 2	Setting 3	Setting 4
Number of layer	1	1	2	2
Number of node	4	2	[8, 6]	2
Batch size	50	128	50	128
Epochs	30	30	30	30
Learning rate	1	0.0001	1	0.0001
Momentum	0.1	0.1	0.1	0.1
Forge gate bias	0.5	0.8	0.5	1
Accuracy (%)	36.2	68	high(1) unpredictable	78

we arranged the results of the physiological data as the values of arousal and valence between 1 and 9. Figure 3 shows the distribution of the classification results using a two-dimensional coordinate plane with the arousal and valence axes. In Figure 3, darker color of the circles represents greater density of arousal or valence data in coordinates. Larger size of the circles indicates that accumulation of frequency of arousal or valence data.

Figure 4 shows the accuracy of the arousal classification model and the valence classification model; the LSTM-based valence classification model using physiological signals showed 78% accuracy. In the experiment, the proposed arousal classification model had 2 layers, 4 nodes, 128 batch sizes, and a learning rate, momentum, and forget gate bias of 1, 1, and 1, respectively. The number of iterations was set to 8. As a result, the LSTM-based arousal classification model using physiological signals showed 74.65% accuracy. In addition, the proposed valence classification model had 2 layers, 2 nodes, 128 batch sizes, and a learning rate, momen-

tum, and forget gate bias of 0.0001, 0.1, and 1, respectively. The number of iterations was set to 7. As a result, the LSTM-based valence classification model using physiological signals showed 78% accuracy. Figure 5 compares the accuracy of the model developed in this study to that of Wang and Shang [11]. As shown in Figure 5, although emotion classification is very personal and variable, in comparison with the results of other studies, each of the results is more than 20% better than those of previous studies.
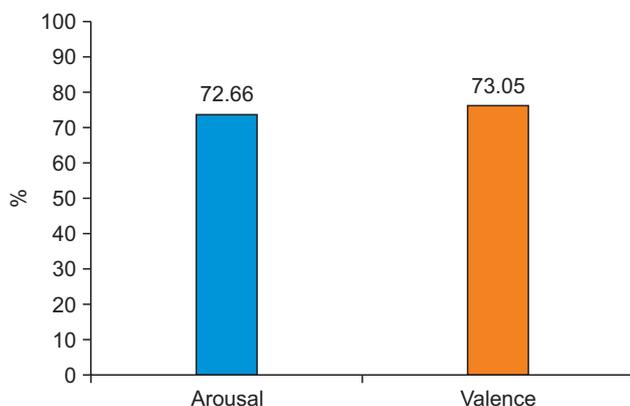
IV. Discussion

In this paper, we proposed an arousal and valence classification model based on LSTM using physiological signals obtained from the DEAP dataset for mental healthcare management. The performance of the emotion classification model depends on the number of layers, nodes, and hyperparameters. If the neural network becomes too large, it is important to find the appropriate number of layers and nodes due to the increase in the number of parameters.

Although, there were some limitations of the study, such as the lack of comparison with other classification methods, such as non-deep learning technique classification models, including naïve Bayesian, decision tress, and support vector machine and so on. To improve the accuracy of the arousal and valence status classification results, more systematic profile generation including hyperparameter settings will be performed in a future study.

1. Comparison with Other Previous Research
When the optimized parameters are set by these criteria, the proposed arousal and valence classification models based on LSTM achieve 74.65% and 78% accuracy, respectively. In addition, the performance of the proposed emotion classification model proposed is compared with the performance
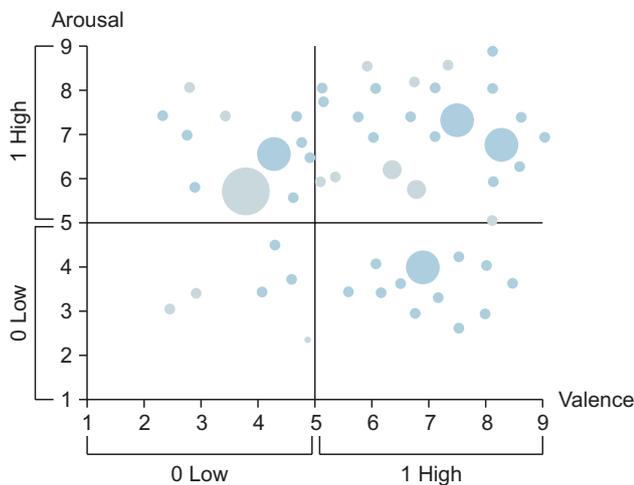

Figure 3. Experimental results using a coordinate plane.

Figure 4. The accuracy results of the arousal classification and valence classification model.
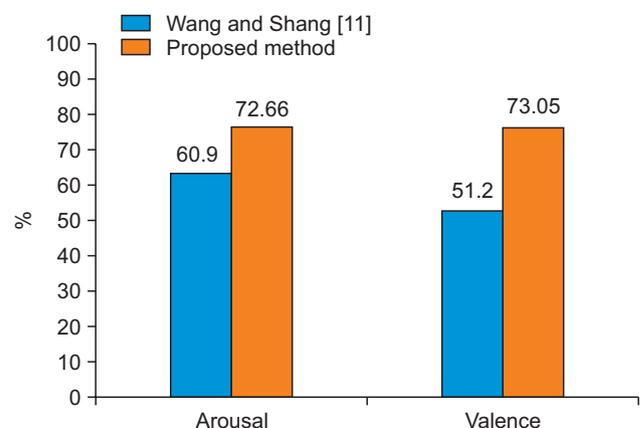

Figure 5. Accuracy comparison of emotion classification models.

of the emotion classification model proposed by Wang and Shang [11], who classified the degree of arousal, valence, and liking based on DBN by using autonomic nervous system signals (hEOG, vEOG, zEMG, tEMG) of four channels as input data from the DEAP dataset. In that work, the classification accuracies for arousal, valence, and liking were 60.9%, 51.2%, and 68.4%, respectively. In this paper, only the degrees of arousal and valence were classified; therefore, only the classification accuracy of arousal and valence were compared. Practically, the results of the LSTM model proposed in this paper achieved higher accuracy for arousal (1.99%) and valence (4.95%) than those of a previous study by Song [29], in which the arousal accuracy was 72.66%, and the valence accuracy was 73.05%.

Thus, we confirmed that the LSTM-based emotion classification model using the central nervous system and autonomic nervous system signals is more suitable for classifying emotions than the DBN-based emotion classification model using autonomic nervous system signals. Those results indicate that the designed classification model has tremendous potential to facilitate and enhance personal mental healthcare if it is adopted in mental health management systems, such as mobile or web-based applications. It can support individuals managing their own mental health, and it can be used in clinical care systems to enhance existing treatment processes, such as medical examination through interviews.

2. Conclusion

In this paper, we proposed an emotion classification model based on LSTM using central and autonomic nervous system signals obtained from the DEAP dataset.

It has been confirmed that, according to the situation or purpose, emotion classification is possible based on the LSTM, which extracts features from the time series data by itself using the central and autonomic nervous system signals. The model can quantitatively measure and analyze emotion without reflecting subjective judgment. Therefore, it is expected that emotion analysis using physiological signals based on LSTM will be possible without processing. In a future study, the classification model will be adopted in mental healthcare management systems.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

Acknowledgments

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