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RESEARCH ARTICLE

Use of electroencephalogram and long short-term memory networks to recognize design preferences of users toward architectural design alternatives☆

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Abstract

In this study, we propose an electroencephalogram (EEG)-based long short-term memory networks model for recognizing user preferences toward architectural design images. An EEG is an approach that records the electrical activity in the brain, and EEG-based affection recognition is a technique used for quantitatively recognizing human emotion by analysing the recorded signals. Decision-makers' subjective reactions toward architectural design alternatives may play a key role in the architectural planning and design stage. In this regard, the proposed model enables the quantitative recognition of their preferences and supports architects in the planning and design stages. The suggested model classifies the recorded data using a deep-learning technique. To build the model, an EEG recording experiment was conducted with 18 subjects, who were asked to select their most/least preferred images among eight images of small-housing design. Post recording, a positive and negative affect schedule questionnaire was distributed to the subjects to rate their affection. Google TensorFlow and Keras were used to structure the model. After training, precision, recall, and f1 score metrics were used to evaluate and validate the model. This model can help designers to evaluate design alternatives in terms of decision-making. Moreover, as this model uses biosignal data, which is universal to humans, architectural design processes for children, the elderly, etc., may be supported. Furthermore, a data-driven design database may be proposed in a future research for cross-validating with previous methods such as interviews and observations.

Keywords: electroencephalogram (EEG); long short-term memory networks (LSTMs); deep learning; classification; architectural planning and design

1. Introduction

Recognition of emotional responses and preferences from potential users can play a key role in the architectural design process. Numerous researches have pointed out that communication among designers, clients, and other participants plays a critical part in the building design process (Shen, Zhang, Shen, & Fernando, 2013). However, despite its importance in the process, there is still a gap in designer–client interaction. This is due to clients' limited experience of dealing with architecture drawings as well as their inability to imagine the architectural design after construction (Lertlakkhanakul, Choi, & Kim, 2008). Moreover, from the designer's viewpoint, the absence of a model that could help them in monitoring design preferences of users and following requirements results in inefficiencies in the entire architecture design process that results in low quality of design (Kiviniemi, 2005). Building information modeling other related

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technologies have been used to facilitate building design, construction, and management. However, as these technologies are based on quantitative data of a building and its physical components, they do not take into account the subjective and personal responses of clients. Hence, an affection-based approach or a more user-centered approach is required. In addition, contrary to other studies of design such as product or industry, there are limitations of using numerous models and prototypes to convince and evaluate the design before construction, and iterating the previous process or replacing the suggested potential alternatives cannot be achieved in the design process. In these circumstances, an approach that offers designers, during the process, a way to evaluate alternatives in terms of users while simultaneously allowing users to represent their affection or preferences toward the given design is critical.

Brainwaves are electrical impulses in the brain, and electroencephalogram (EEG) is an approach for amplifying and recording these impulses by attaching sensors on subjects' scalps (Schomer & da Silva, 2010). Moreover, it is affection recognition method that attempts to recognize human emotional reaction in given situations using EEG and analysis techniques. Numerous studies on such methods (known as affection recognition) have been conducted in the neuroscience and physiology fields. For example, in 1970s, Schwartz, Davidson, and Maer suggested a possibility of recognizing human emotion using EEG (Schwartz, Davidson, & Maer, 1975). Since this research, numerous emotion models (e.g. dimensional and discrete models), analysing techniques (correlation analysis, support vector machine, deep learning, etc.), and questionnaires (Self-Assessment-Manikin, positive and negative affect schedule, etc.) have been developed.

Such approaches can be adopted in the field of architecture design to monitor and track preferences in the construction preface. However, this is challenging because of the complexity of EEG data and the lack of an analysis model oriented from architecture field. To address this issue, this study adopts a deep-learning based long short-term memory networks (LSTMs) that can classify the recorded EEG data. LSTM is one kind of recurrent neural networks model that has been proved to be effective in predicting and classifying time series data (Hochreiter & Schmidhuber, 1997).

In this regard, this paper aims to propose a LSTM model that recognizes preferences toward design alternatives via EEG. The remainder of this paper is organized as follows. Section 2 suggests the previous research in architecture that has dealt with EEG and its concept, the theoretical background of EEG-based affection recognition and the deep learning methodology. Section 3 presents the materials and the experimental procedure employed to record EEG data to construct a LSTM model. Section 4 suggests the trained model and its evaluation result. Finally, Section 5 presents the results and discussion of this paper.

2. Literature Review

2.1. EEG in the field of architecture

In architecture, EEG is used as a means for physically measuring occupants' comfort and productivity in given architectural environments. In the context of comfort, given the fact that observing the data pattern can reveal the quality of sleep, some studies have used EEG with the aim of determining the relationship between sleep comfort and surrounding architectural environments (Pan, Lian, & Lan, 2011; Lan, Pan, Lian, Huang, & Lin, 2014; Lan, Lian, & Lin 2016) In their research, EEG measurement was used for observing subjects' sleeping patterns and quality depending on the variation in thermal temperatures. On the other hand, Yao, Lian, Liu, and Shen (2008) and Yao, Lian, Liu, Jiang, Liu, and Lu (2009) measured subjects' EEG and other physiological signals to study occupants' thermal comfort. Other researchers have dealt with the effect of indoor plants (Qin, Sun, Zhou, Heng, & Lian 2013) and stress (Choi, Kim, & Chun, 2014). The studies that aimed to evaluate workers' productivity in a given architectural environment also investigated subjects' cognitive load by measuring the physiological signals and conducting a test that can evaluate workers' cognitive focus and performance (Lan & Lan, 2009; Zhang et al., 2017). In addition, some studies focused on using EEG to operate CAD systems. These studies aim to structure the brain-computer interface using physiological signals including EEG. Shankar and Rai (2014) and Nanjundaswamy et al. (2013) studied the use of EEG in the process of CAD modeling. Moreover, some studies were carried out to monitor and record EEG patterns of participants while they were involved in the specific design process to solve design problems (Alexioua, Zamenopoulos, Johnson, & Gilbert, 2009; Liang et al., 2017).

Previous studies using EEG in the field of architecture commonly have used the EEG technology to quantitatively measure an occupant's physiological reaction to changes in the environmental factors.

Although numerous studies in neuroscience and psychology have been conducted on recording the biosignal of subjects and predicting human preferences in situations where a specific image or video is presented, only a few studies have adopted this approach in the field. In the early stages of a project, the personal reactions of the client and user to the alternatives proposed by the architect are vital. In this context, this study proposes a model that can quantitatively measure the user's preferences toward architectural spatial images using affection recognition technology. This schematic is shown in Fig. 1. Unlike in the construction and maintenance stages, in the architectural planning and initial design stages, it is essential to consider the emotional evaluation of participants. In the past, architects have tracked and reviewed the affective reactions based on their experience alone. In this study, we aim to propose a method for quantifying such subjective reactions. In this regard, experiments were conducted to record brain signals, and the acquired data were analyzed using deep learning-based approaches.

2.2. EEG-based affection recognition

Brainwaves refer to the electric signals generated among neurons and their synaptic joints, and EEG is a method for recording, storing, and analysing the signals. EEG can be acquired by attaching a number of electrodes on subjects' scalps in accordance with the "International 10–20 System of Electrode Placement" guideline (Schomer & da Silva, 2010). In addition, affection recognition is a concept wherein adopting EEG techniques and analysing the data in a structured manner helps to indicate the human emotion. Since the research conducted by Schwartz, Davidson, and Maer revealed that the right hemisphere is lateralized to affection (Schwartz et al., 1975), numerous studies have been conducted. Most of the previous studies have been performed in the following order: (1) selection of emotion models, (2) conducting of experiments that measure the subjects' physiological signals and addressing questionnaires that correspond to the emotion model, and (3) analysis of the correlation between the measured EEG data and estimated human affection from the questionnaires. The emotion model can be de-

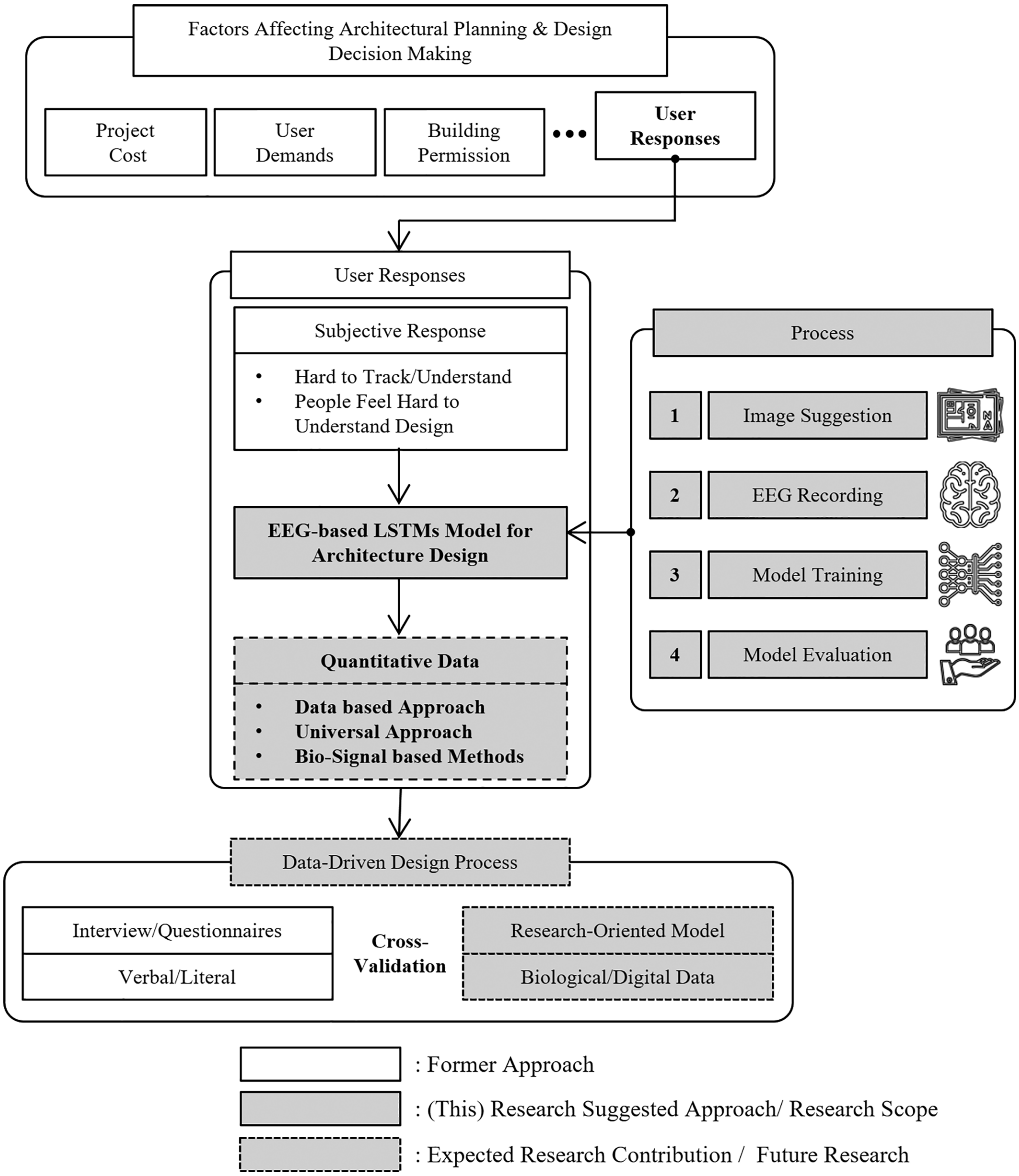


Figure 1: Suggested research framework overview.

fined as a theoretical/structured perspective of demonstrating human emotion (Ekman & Friesen, 1971; Russel, 1980; David, Anna, & Auke, 1988; David, & Anna, 1994). Two types of the models are mainly discussed in the field of affection recognition: a discrete model of Ekman's theory (Ekman, & Friesen, 1971) and a dimensional model of emotion, which considers emotion as a continuous state, rather than as a discrete state (Russel, 1980). While Ekman's theory divides human affection into six universal emotions (happiness, surprise, anger, disgust, sadness, and fear) (Ekman, & Friesen, 1971), dimensional models of affection describe emotion as continuous and combination of states (Russel, 1980). Among the numerous dimensional models of emotion, David, Anna, and Auke developed the positive and negative affect schedule (PANAS) mood scale, which comprises positive affect (PA) and negative affect (NA), and indicated that these two affections are broad, general, and dominant dimensions of emotion (David, Anna, & Auke, 1988; David, & Anna, 1994). In the process of affection recognition, after selecting the emotion model, the next phase is to conduct an experiment. In this phase, physiological signals such as EEG, electrocardiography, electrooculography, and skin temperature are simultaneously measured, and then, questionnaires are distributed. In the experiment, to stimulate subjects' emotions, some researchers have used methods such as showing movies or pictures with contents that can induce positive or negative feelings, some have used the mirror-neuron system (Rizzolatti & Craighero, 2004), and others have used a self-elicit sequence of emotions.

Regarding the analysis model, studies conducted around 1990s used an observatory approach, in which a point was marked on the scalp from where the signals were originated. Later in 2000s, the studies adopted a computerized approach of classifying the acquired data to recognize subjects' emotional

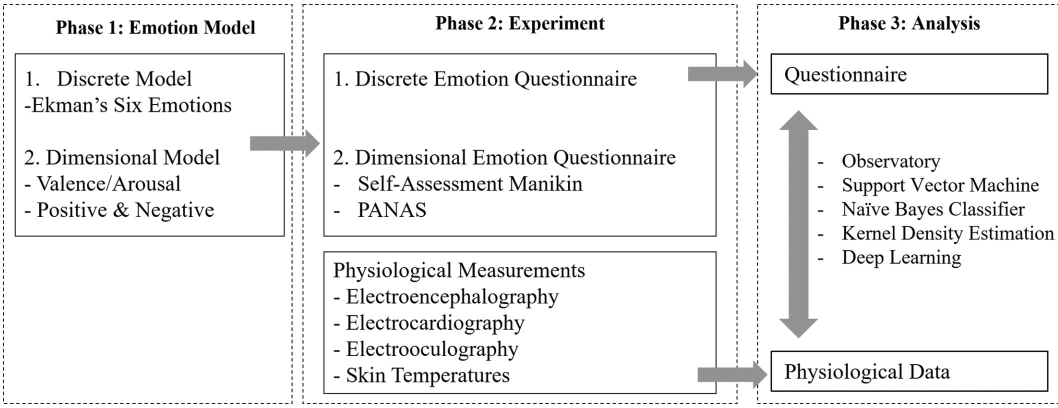


Figure 2: Process of EEG based affection recognition.

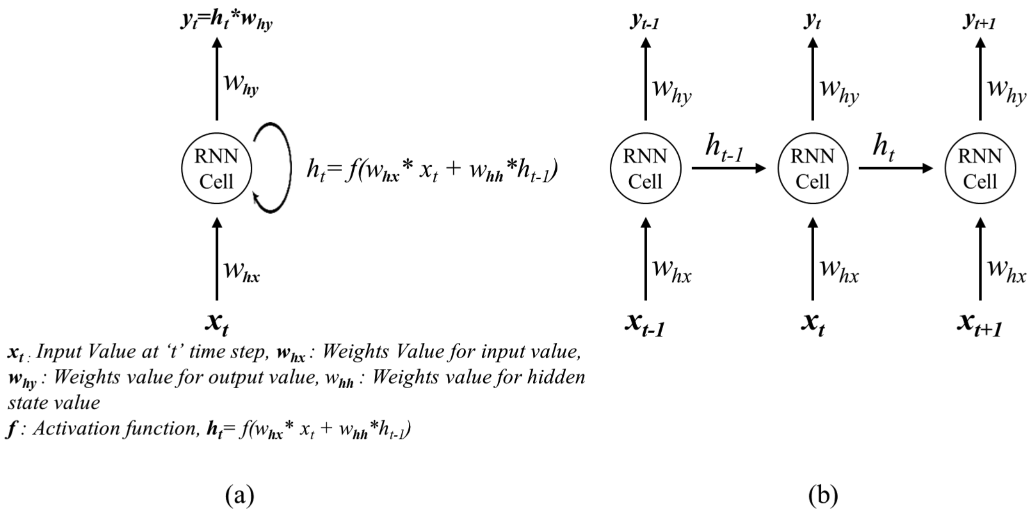


Figure 3: (a) A single RNN and (b) unfolded RNN.

states. For the analysis model, some researchers have adopted techniques such as support vector machines, fuzzy C-means clustering, etc. Since the development of deep neural networks and their related technologies have proved successful in the field, recent studies are attempting to use the technique to classify affection, which will be addressed in the latter part of the paper. The process involved in the study is shown in Fig. 2.

2.3. Recurrent neural networks and long short-term memory networks

Unlike other types of artificial neural networks, an RNNs has networks with loops, which allows information and context to persist, and those can be used to predict or classify time-series data based on the previous information. The difference between RNN and other neural networks is that RNNs comprises h $_t$, known as the hidden state, as well as the input value x_t and output value y_t at time t. The hidden state value at time t is calculated by reflecting both the hidden state value (h_{t-1}) of the previous time ($t-1$) and the input value at time t (x_t). This hidden state value is used once in the process of calculating the value of y_t at time t, and again in the process of calculating the value of y_t at ($t+1$), the next time point. As this structure is iterated, the information of the previous time is reflected in the result at the current time. The RNNs has three sets of weights comprising w_{hx}, w_{hh}, and w_{hy}, and these parameters are shared along with sequences. Fig. 3a shows the internal structure and data flow of one RNNs cell and Fig. 3b shows the unfolded structure of the single cell.

It is the point that RNNs may connect previous data (t_0, t_1, $t_2 \ldots t_{n-1}$) while analysing the present data (t_n), however, Bengio, Simard, and Frasconi (1994) have reported that RNNs may have difficulties in training if the gap between relevant data has long intervals that results in vanishing gradient.

In this context, Hochreiter and Schmidhuber have suggested LSTM networks. Unlike normal RNNs with hidden states value, LSTM has "carousel" that is so-called as "conveyer belt" of information and cell state values on it. Cell state values are selective information from the past that allows the networks not only to consider overall states of the cells but also selective and critical information to classify or predict the present task. The belt is controlled by multiple gate units that are able to open and close previous information access (Hochreiter & Schmidhuber, 1997). Fig. 4a shows the internal structure of one LSTM cell. The LSTM cell at time t receives both the hidden state (h_{t-1}) and cell state (c_{t-1}) from time $t-1$. In the forget gate layer, it is determined what information will be forgotten among the information transmitted from time $t-1$. In the input (update gate layer), the information input at the current point (x_t) and the hidden state value (h_{t-1}) at the previous point are concatenated to determine what information to add. Finally, in the output gate layer,

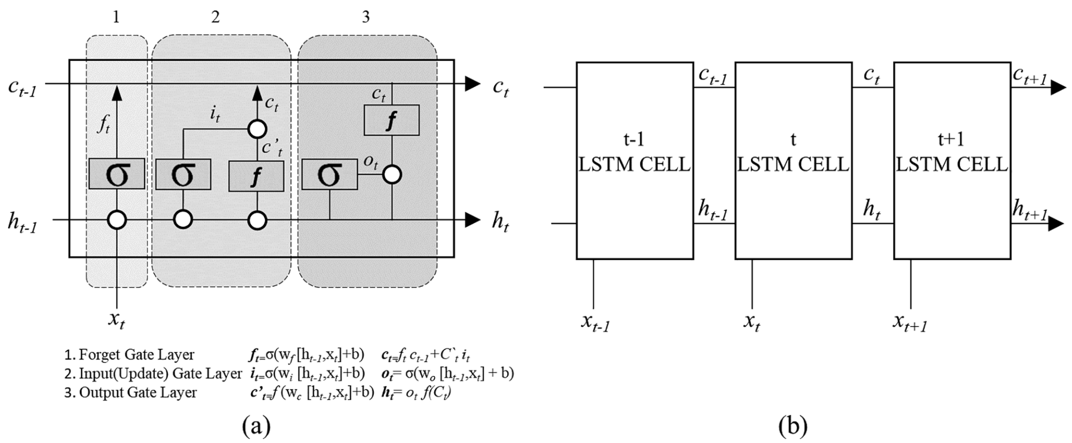


Figure 4: (a) A single LSTM cell and (b) sequential proposed LSTM cells.

the output value (y_t) is presented, and the hidden state value (h_t) is transmitted to the next point in time. Fig. 4b shows the unfolded form.

Previous approaches in machine learning have used features which are manually extracted from the signals. However, it is time consuming and causing in low performances. Recent studies in physiological signal processing and affection recognition have adopted the LSTM networks techniques and shown better results compare to the previous methods. This is because since preferences are not only time varying but also physiological signals including EEG are time dependent (Soleymani, Asghari-Esfeden, Pantic, & Fu, 2014). In this regard, this study suggests EEG-based LSTM networks model for recognizing potential users' design preferences toward architectural design alternatives.

3. Methodology

3.1. Research design and experiment procedures

The goal of this experiment was to analyze the EEG signals measured from subjects while they were watching the pictures of eight alternatives that they had selected as most/least liked in the preface. The materials were selected among the images introduced as examples of well-designed small housing interiors on the websites and some selective images of interiors that were actual residences of university students. They were selected under the supervision and evaluation of multiple experts. The temperature was set at 20°C and all other disturbances were under control. The EEG data were recorded using an Emotiv EPOC + 14 Channel Mobile EEG, which has 14 channels of EEG sensors (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) and 2 references for P3 and P4, with 128 samples per second (Emotiv Epoc Specifications, 2014); (EmotivPro, 2018).

In addition, PANAS questionnaire were distributed to recognize affection on the positive–negative scale (David, Anna, & Auke, 1988). In a study by Crawford and Henry (2010), the reliability and accuracy of the PANAS questionnaires was statistically proved (Crawford & Henry, 2010).

To avoid any disturbance during the experiment, we provided the subjects with private desks and 50-cm-high isolated partitions. In addition, during the procedure, lighting, temperature, and sound noises were controlled in order to verify the data. A total of 18 subjects, physically and mentally healthy 6 males and 12 females between 20 and 30 years of age participated in the experiment. Before the recording, they were provided with a full explanation of the experiment and consented agreement was taken.

The experiment procedure is described as follows: (1) image suggestion: eight images of small-housing are suggested, (2) image selection: subjects are asked to select most/least liked images. (3) calibration and relaxation: the recording gear calibration is accomplished using EmotivPro while the subjects are asked to remain calm and relaxed. Following the instruction of EmotivPro, the subjects close their eyes for 15 s and then gaze at the monitor with EmotivPro interface for 15 s. (4) EEG recording: The EEG data are recorded using Emotiv EPOC + 14 Channel Mobile EEG, 14 channels and 128 samples per second, while the subjects are watching the images they have selected as the most preferred one, (5) PANAS questionnaire: after recording the data, subjects are asked to fill out the questionnaire regarding the selected image by the subject. For the least preferred image, phases (3), (4), and (5) were iterated. The detailed process of the experiment is suggested in Fig. 5 and Table 1 shows the suggested four out of eight images which were selected among actual residences of university students.

3.2. Recording the EEG signals

The goal of this EEG recording was to collect the signals data that can be used to train the LSTM networks model. To train the model, this study used 14 channels of signals as feature columns (features) and the questionnaire results answered by subjects for the labels. We used eight images as the affection-stimuli. The images were presented on a 20-in. screen (1600px × 900px, width∗height). Since previous studies in affection recognition have suggested the possibilities of using image, videos and movie films to elicit human affection, we adopted the approach. In the experiment, the subjects were shown these images and asked to choose their most/least liked images. After two separate images were chosen, the data were recorded for 20 s using Emotiv EPOC + 14 Channel Mobile EEG and EmotivPro with 30 s of calibration with subjects' eyes closed and opened for 15s respectively and subject relaxation in the preface. To prevent the subjects' disturbance, which may interrupt sudden changes in the data, environmental factors such as lighting, room temperature and noise were controlled. The measurement was carried out twice for each subject, one for subjects watching the most liked image they selected, the other for the least liked image. Fig. 6a illustrates EEG measurements with subjects wearing the gear and Fig. 6b shows a captured image of EmotivPro software from the recording PC. Fig. 7 is a technical specifications image

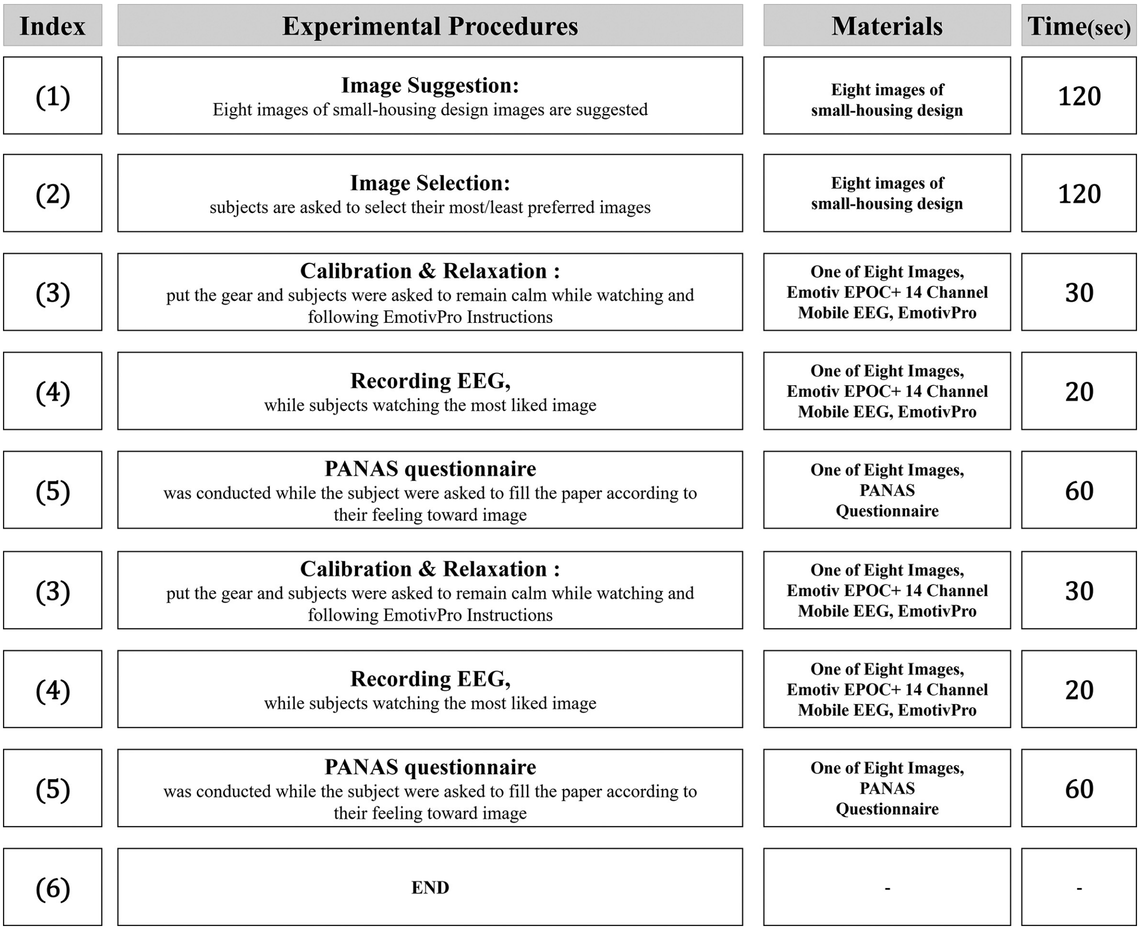
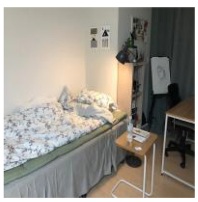
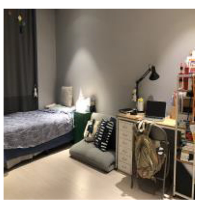
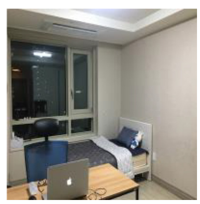


Figure 5: Process and materials of the experiment.

Table 1: Four of Eight images presented to subjects.

Image number	#1	#2
Image		
Image number	#3	#4
Image		

that shows sensor locations of the headset (Emotiv Epoc Specifications, 2014).

3.3. Positive and negative affect schedule questionnaire

The aim of this process was to quantitatively measure the subjects' emotion using PANAS. The previous research suggested a structure of affection that consists of two dominant dimensions: PA and NA. Based on the theory, the questionnaire was distributed to the subjects after recording their EEG. The subjects were asked to fill out the questionnaire based on their subjective feelings they experienced while watching the images they selected in preface. The questionnaire consisted of 20 questions:

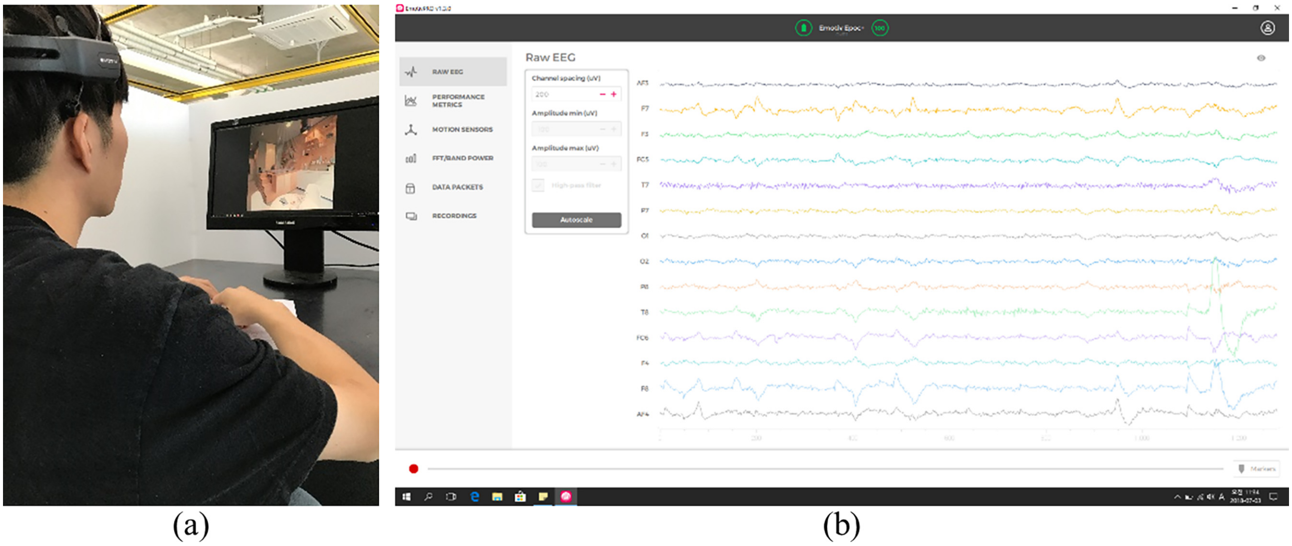


Figure 6: EEG recording: (a) a subject wearing "Emotiv EPOC + 14 Channel Mobile EEG" and (b) "EmotivPro."

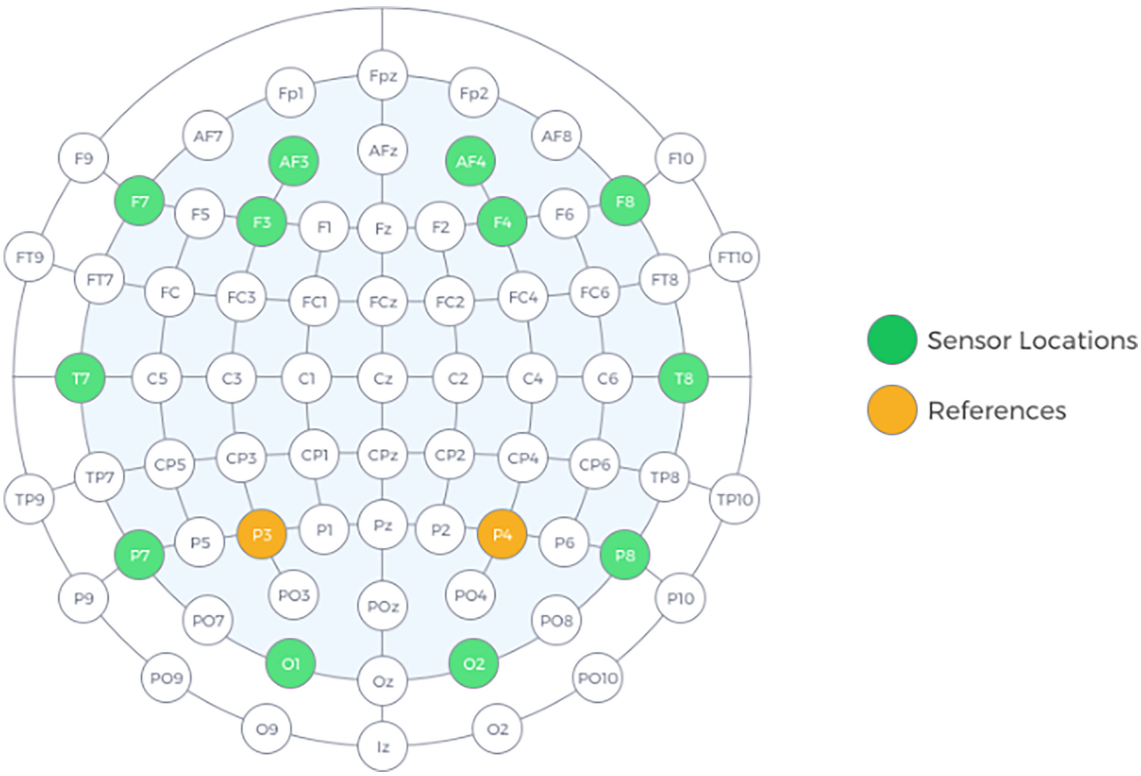


Figure 7: Emotiv EPOC + headset details, sensor locations for the EPOC + using the international 10–20 system (Emotiv Epoc Specifications, 2014).

10 for PA and the remaining 10 for NA. The subjects reported their subjective feelings by answering on five numeric scales, 1: not at all and 5: extremely. After the questionnaire was completed, two affections were scored based on the theory-given guideline. According to the guideline, for recognizing the two affections, items were added on 1, 3, 5, 9, 10, 12, 14, 16, 17, and 19 for PA and 2, 4, 6, 7, 8, 11, 13, 15, 18, and 20 for NA. As the previous research also presented the mean value and standard variation(SD) of the test and verified the normative and reliability of the data, we too adopt the mean and standard deviation for the two dimensions of affection. The suggested given mean and SD for PA are 29.7 and 7.9, respectively, and those for NA are 14.8 and 5.4, respectively.

4. LSTM networks model Implementation

4.1. PANAS questionnaire result analysis

This study used the "Scoring Instructions" from the previous research to rate the distributed questionnaire (David, Anna, &

Table 2: Mean and SD value comparison between David, Anna, and Auke (1988) and this experiment.

Type	A: David, Anna, and Auke (1988)	B: This experiment with 18 participants	A − B
Mean (PA score)	29.7	29.2	0.5
SD (PA score)	7.9	7.2	0.7
Mean (NA score)	14.8	27.4	− 12.6
SD (NA score)	5.4	7.4	− 2.0

Auke, 1988). PA score and NA score were rated. The calculated mean and SD value of the two affections in this experiment are 29.2 and 7.2 for positive affection and 27.4 and 7.4 for negative affection, respectively. The observed results show that participants rated their NA score higher, compared to the previous research. Table 2 shows the comparison between PANAS given values and experiment rated values.

More Specifically, among the 18 participants, 17 subjects rated their NA score higher than the mean value from the previous research. However, in the case of the PA score, eight subjects showed higher affection scores than the mean PA scores presented in previous studies. This result seems to suggest a hypothesis that while selecting the certain design alternatives, participants tended to avoid the worst alternatives rather than selecting the most liked design. Fig. 8 is a graph that demonstrates this suggestion. Fig. 8a shows two graphs from a PA score, with a continuous line for a normal distribution graph based on the previous research's given mean and SD value, while the other graph is for the calculated values from the experiment. This graph demonstrates that the experiment-calculated mean has a lower value than the research-given mean for PA. In contrast, Fig. 8b shows two graphs with the value from the NA score—one with a continuous and filled normal distribution graph that is based on the given mean and SD value, and another graph that consists of circles with subjects' names on them that is for the calculated result from this experiment. The graph shows that, compared with the normal distribution graph, the rated score from this experiment has a higher mean.

4.2. EEG dataset

The EEG dataset comprises EEG signals data acquired from the recording experiment and the subjects answered PANAS questionnaire scoring results. To prevent overfitting or underfitting of the model, only in the cases wherein each of the PA

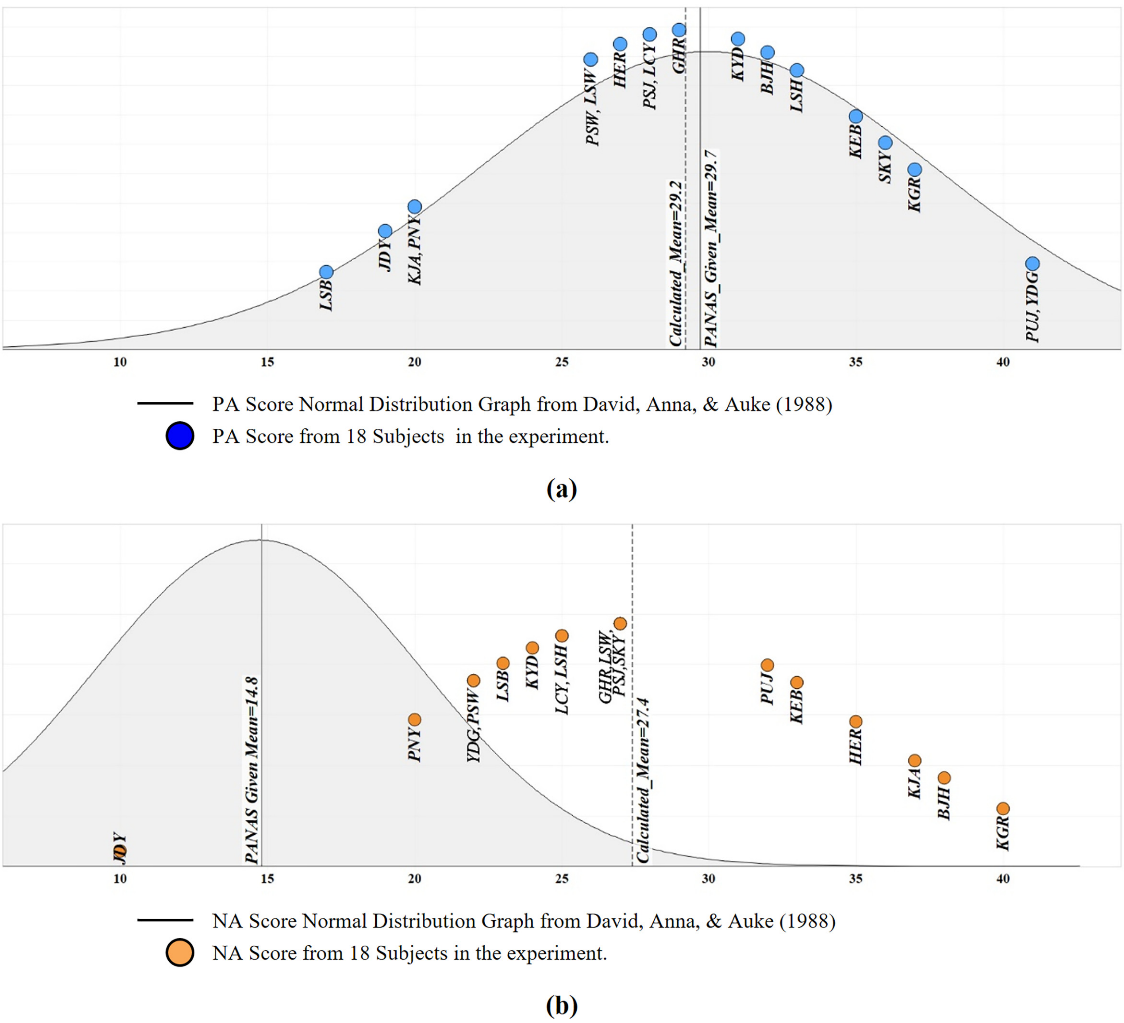


Figure 8: (a) PA score normal distribution (David, Anna, & Auke, 1988) compared with calculated PA score and (b) NA score normal distribution (David, Anna, & Auke, 1988) compared with calculated NA score.

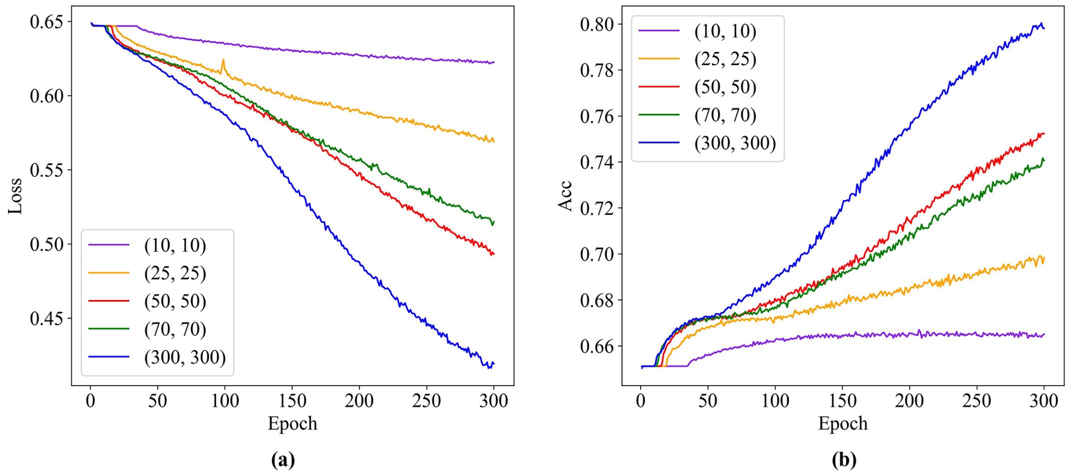


Figure 9: (a) Loss graph and (b) accuracy graph.

and NA scores, which are responses to the subjects' most/least preferred images, was larger than the mean affection score presented in previous studies, the corresponding brainwave data of the subject were used as the training dataset of the model. The dataset constructed in this study has two labels, "positive" and "negative," and comprises brainwave data recorded for 20 s for 8 subjects under "positive" and 17 subjects under "negative." The recorded brainwave data were normalized by each of the 14 channels so that a specific channel would not produce a bias in the result output.

4.3. LSTM networks model structure

The LSTM networks model was constructed to quantitatively analyze users' preferences toward architectural space images. In this process, Python version 3.6, Google's TensorFlow, and Keras libraries were used, and the development environment used was "Jetbrains PyCharm Community Edition 2019.1.2. (Keras, 2020; TensorFlow, 2020)." The model building, training, and evaluation hardware environments were set up using an "Intel i9-9900k" CPU, 16 GB RAM, and an "NVDIA GeForce RTX 2060."

In the process of the model training, the 14 channels of normalized EEG signals were input as the "X_features" values, and the subjects' questionnaire responses were input as the "y_labels" values into the model, and the model presented predictions every 2 Hz. In this study, some parameter values were limited due to the limited data size of the LSTM model and its characteristic vulnerability to overfitting or underfitting.

The "y_labels" values were one-hot encoded in the form of [0,1] for "positive" and [1,0] for "negative," using "LabelEncoder" provided by the machine learning API "sklearn."

The LSTM model can be categorized into the original LSTM, having the form of a single LSTM layer, and the stacked-LSTM model, in which two or more LSTM layers are stacked. The stacked-LSTM model requires a larger number of operations and higher computational cost than the original LSTM model; however, it exhibits a relatively higher accuracy than the original model in processing complex data. Therefore, in this study, we constructed a model with the 2-Stacked LSTM structure after running multiple pre-tests.

The proposed 2-Stacked LSTM model comprises the LSTM Layer #1, Dropout Layer #1, LSTM Layer #2, Dropout Layer #2, and Dense Layer (Output Layer). When constructing the LSTM model, "cuDNNLSTM" from Keras was used. In the case of "cuDNNLSTM," some parameter values are fixed in advance; however, it operates on a GPU environment and exhibits a faster computation speed than the general LSTM using CPU (NVDIA DEVELOPER, 2020). The Dense Layer is an output layer using "softmax" as the activation function. The "softmax" function presents the probability that the data input from the classification model belongs to a specific class, in addition to presenting a probability distribution, with the sum of the probability in each class being 1. For the loss function that measures the error between the predicted value of the model and the label value in the training process of the five-layer model, "categorical_crossentropy," which is often used in binary or multiclass classification problems, was used. In binary classification problems, "binary_crossentropy" can also be used; however, "categorical_crossentropy" was used in this study as a loss function because overfitting occurred more frequently in the model building process when implementing "binary_crossentropy" function. Moreover, adopting "categorical_crossentropy" function may suggest one possibility of classifying multi-class preferences classification problem in future research.

4.3.1. *Model evaluation 1—loss values and accuracy in 300 epochs training*

In this study, a test was performed to set the units of LSTM Layer #1 and LSTM Layer #2. Both the LSTM Layer #1 and LSTM Layer #2 Units were in the range of 10–1000, and 300 trainings were conducted with the same parameter values except for the unit for various combinations; loss and accuracy were measured for each epoch. As a result of the test, among the combinations of LSTM Layer #1 Unit and LSTM Layer #2 Unit, the five combinations of (10,10), (25,25), (50,50), (70,70), and (300,300) showed fewer occurrences of overfitting; moreover, as the training repeated, the loss decreased and accuracy increased. Fig. 9 shows the change in the loss and accuracy values for the five combinations of Layer #1 Unit and Layer #2 Unit, for 300 trainings. Fig. 9a shows the decrease in loss with the progress of 300 epochs and Fig. 9b shows the increase in accuracy. Among the five combinations, the combination (300,300), in which the values of LSTM Layer #1 Unit and LSTM Layer #2 Unit are both set as 300, represented in blue, exhibits the lowest level of loss and highest accuracy after the completion of 300 trainings. In terms of computational burden cost, the (300,300) model took 4096 sec, the

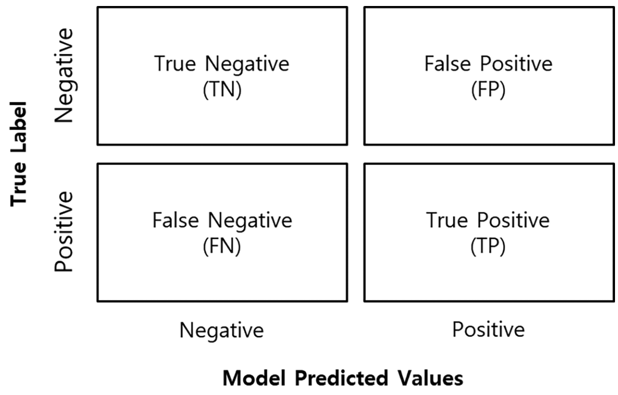


Figure 10: Confusion matrix.

longest time, and the (10,10) model took 3935 sec, the shortest time, for 300 training iterations.

4.3.2. *Model evaluation 2—precision, accuracy, and f1 score in confusion matrix*

To evaluate the proposed model, three metrics that are precision, recall, and f1 score were used. For this purpose, 1980 points of testing data that were pre-split from the entire training dataset were used for evaluation and a confusion matrix was created. Precision is the ratio of what the model classifies as True to what is actually True, recall is the ratio of what the model predicts as True to what is actually True, and f1 score is the harmonic mean of precision and recall. Fig. 10 shows the confusion matrix, comprising three matrices, which can be expressed as Precision = TP/(TP + FP), Recall = TP/(TP + FN), and f1 score = (2∗Precision∗Recall)/(Precision + Recall).

In this study, evaluation using the confusion matrix was performed for five models of different combinations of the two LSTM Layer units, and the results are presented in Fig. 11. As can be seen from Fig. 11, the model with 300 units for both LSTM Layer #1 and LSTM Layer #2 exhibited the highest values for precision, recall, and f1 score among the five models. In general, the metric values increased with the increase in the number of units; however, the models with the combination of Units 1 and 2, as (100,100), (200,200), and (400,400) exhibited overfitting, and those models only presented a specific classification value repeatedly (overfitting). Fig. 12 shows the actual confusion matrix that was used for the evaluation of the (300,300) model that shown the best performance among combinations.

5. Discussion

This study aimed to recognize subjects' emotional response toward small-housing design images via EEG, evaluating the subjects' affection with the PANAS questionnaire, and constructing a deep-learning-based LSTM networks classification model. During the process of selecting EEG-stimuli images, this study limited its scope to a particular spatial form. For this reason, the changes of users' emotions and brainwaves in response to various building types and variables could not be analyzed.

The following conclusions were drawn: First, The PANAS questionnaire detected a significant high score for negative affection relative to the positive one. The mean and standard deviation values of NA score in this experiment were 27.4 and 7.4, respectively, while the PANAS questionnaire suggested values of 14.8 and 5.4, respectively. In contrast, the values of PA score were 29.2 and 7.2, respectively, while the values in the previous research were 29.7 and 7.9, respectively. This may suggest that potential users try ti avoid the worst design that they have selected in the preface. Second, EEG and the LSTM networks based classification model appeared to reliably distinguish the subjects' affection in the given, restricted situation. Since EEG is time-series data, further research should in conducted in a way to recognize potential users' responses toward alternatives suggested not only images but also video, VR and AR, etc. Third, A concept of recording EEG data may suggest one quantitative approach in the field of design. Because the design field remains subjective and an area of personal interpretation, an adoption of EEG and the development of the following analysis model may offer a more qualified and objective perspective to the design. Fourth, Using EEG in the design can also provide designers with an opportunity to re-think their design alternatives in the design preface. Previously, conventional approaches for evaluating design were conducted solely depending on architects' personal intuition and experience, which was limited. Therefore, the use of computational approaches offers a means of overcoming this problem.

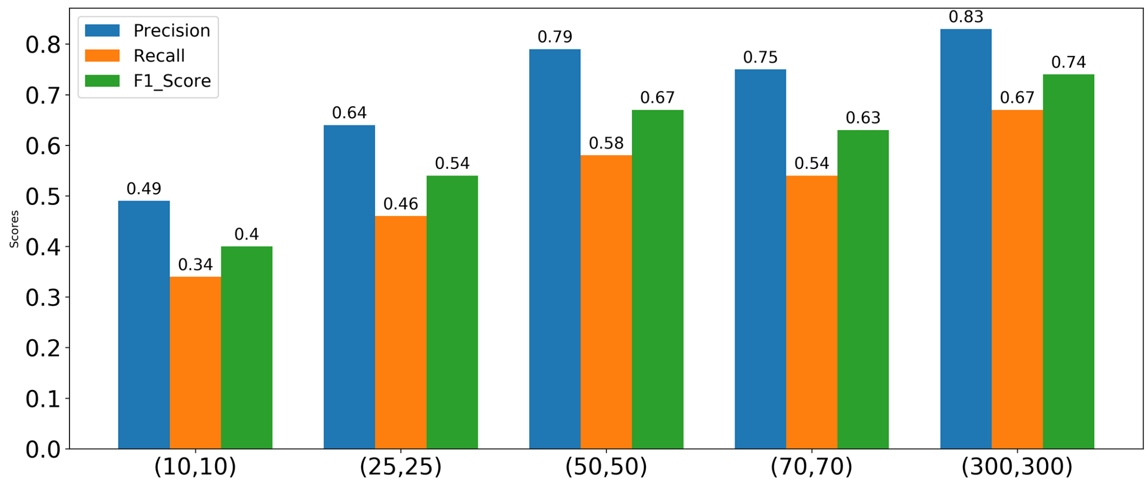


Figure 11: Comparison of precision, recall and F1_Score.

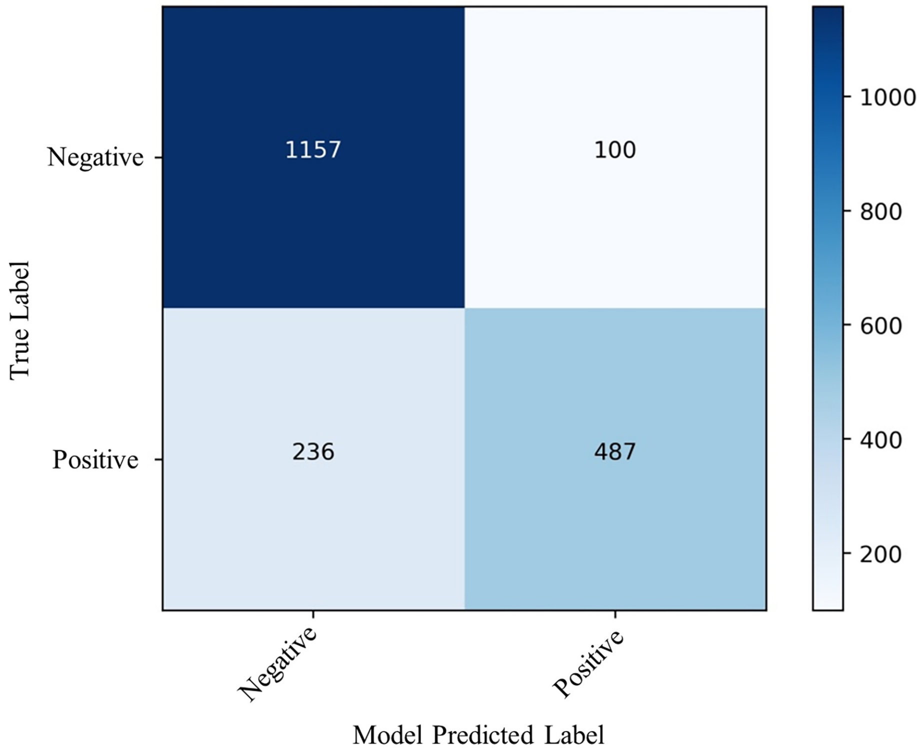


Figure 12: Model evaluation using confusion matrix.

At present, the EEG system is difficult to operate, the experimental procedure is delicate, and the signals are sensitive to external variables. Accordingly, this approach cannot be fully applied in a practical case. Further studies are required to quantitatively analyze a subject's response to architectural spatial form and indoor environmental variables by using the proposed model. After being analyzed, users' emotional responses can be mutually cross validated with previous design knowledge acquired by surveys and interviews and can be stored as a design database. In this way, such a design knowledge database can be used by architects for their design processes. This may be a subject of future work. In particular, the method proposed in this paper is expected to support an architectural design process for patients, the elderly, and children, to whom either the survey or the interview can scarcely be applied.

In addition, traceability and explainability may play critical role in the adoption of the proposed model. In other words, these concepts suggest that the decision-making process of the AI model is tracked and human participants understand and share the operation of the deep learning model. Moreover, causability issues in AI should be dealt in the further research. Such a process is necessary to use the model in practice. This also needs to be addressed in future studies.

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Conflict of interest statement

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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