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Hybrid deep-learning model to recognise emotional responses of users towards architectural design alternatives

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ABSTRACT

In architectural planning and initial designing process, it is critical for architects to recognise users' emotional responses toward design alternatives. Since Building Information Modelling and related technologies focuses on physical elements of the building, a model which suggests decision-makers' subjective affection is strongly required. In this regard, this paper proposes an electroencephalography (EEG)-based hybrid deep-learning model to recognise the emotional responses of users towards given architectural design. The hybrid model consists of generative adversarial networks (GANs) for EEG data augmentation and an EEG-based deep-learning classification model for EEG classification. In the field of architecture, a previous study has developed an EEG-based deep-learning classification model that can recognise the emotional responses of subjects towards design alternatives. This approach seems to suggest a possible method of evaluating design alternatives in a quantitative manner. However, because of the limitations of EEG data, it is difficult to train the model, which leads to the limited utilisation of the model. In this regard, this study constructs GANs, which consists of a generator and discriminator, for EEG data augmentation. The proposed hybrid model may provide a method of developing supportive and evaluative environments in planning, design, and post-occupancy evaluation for decision-makers.

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Generative adversarial networks; deep-learning classification; affection recognition; electroencephalography; TensorFlow

1. Introduction

1.1 Research background and aim

Architectural planning and initial designing involve communication among various decision-making participants including clients, designers, engineers, potential users, and local community members. In the architectural planning step, information that can be a basis for future decision making is generated. In the initial designing step, various design alternatives are suggested by the designer based on the information generated in the planning step. These design alternatives are then reviewed and revised by decision-making participants. The designing step is of considerable importance because as it proceeds, design alternatives are specified and used as the fundamental basis for future procedures (Sebastian 2007).

However, in architectural planning and initial designing, communication problems have constantly arisen between the client and designer (Siva and London 2012). There are inevitable limitations in the client gaining an accurate understanding of the suggestions of the designer and in the process of communicating requirements and aspects to be revised (Shen et al. 2013). In addition, it is difficult for the designer to grasp the client's requirements accurately

and to quantitatively track and review the responses of users towards revised design alternatives (Kiviniemi 2005). Therefore, design processes are often inefficient and the design quality is not guaranteed.

Building information modelling (BIM) technology is used to structure physical architectural elements and their relationships in a form of a database throughout the lifecycle of a building based on a digitalised building information management platform and to maintain the accumulated building information. BIM technology has been utilised in various fields such as building design, construction, and maintenance. It plays an important role in supporting the architectural design step, providing various types of building information that can be utilised in the decision-making process. However, BIM technology does not reflect the emotional evaluation of decision-making participants because it focuses solely on information regarding the physical attributes of buildings. This is a major limitation of BIM technology because in the planning and designing steps, the emotional evaluation of decision-making participants with regard to the design alternatives suggested by the designer can be an important basis for decision making. Against this background, research has been conducted actively in the fields of brain science and neuroscience on the emotional responses of users towards certain

conditions by utilising electroencephalography (Ekman and Friesen 1971). In the fields of architecture and design as well, quantitative research has been conducted actively on the emotions of users by utilising EEG. Brain waves are electric signals generated during different brain activities, and EEG is a technology to generate numerical data by attaching electrodes to the scalps of subjects for brain wave augmentation (Schomer and Silva 2010).

Recently, in the field of architecture, some research studies have presented design alternatives to subjects in the form of images while recording their EEG and analysing the EEG data using deep-learning classification models (Chang, Dong, and Jun 2018). The models proposed in these studies show the basic possibility of estimating the emotional responses of decision-making participants towards certain spaces. However, there are limitations in training the model because the brain wave data collected from experiments are insufficient. In this regard, as an alternative, a generative adversarial networks (GANs) may be utilised to generate virtual data using only a small volume of input data.

Goodfellow et al. (2014) proposed a GANs consisting of a generator and discriminator and generated virtual data through the augmentation of a small volume of input data. A GANs can be utilised when the available volume of data is not sufficient for the training and evaluation of a deep-learning model. The GANs concept is drawing attention in many fields, particularly in fields where data acquisition is challenging, such as facial recognition (Yang, Zhang, and Yin 2018) and voice recognition (Han et al. 2018).

Accordingly, this paper proposes an EEG-based hybrid deep-learning model that can classify the emotional responses of potential users towards architectural design alternatives. This model is a combination of a GANs and EEG-based deep-learning classification model. The GANs augments brain wave data acquired in previous studies, and the augmented brain wave data are provided to the classification model to train it.

1.2 Study method

The rest of the paper is structured as follows. Section 2 presents a theoretical investigation on previous studies that utilise brain waves in the field of architecture and establishes the theoretical background for GANs models and deep-learning classification models. Section 3 describes the development of a GANs model for brain wave data augmentation and an EEG-based deep-learning classification model for the data classification based on the findings of the previous studies; hence, a hybrid deep-learning model based on EEG is developed by combining these two deep-learning models. Section 4 presents the implementation of the proposed GANs

model for the augmentation of the brain wave data acquired under experimental settings and describes the details of an EEG-based deep-learning model training and evaluation using both existing data and augmented data. In the process of establishing the GANs model and EEG-based deep-learning classification model, the TensorFlow platform developed by Google is utilised, which is a core open-source machine learning library (TensorFlow, 2018). The proposed hybrid model in this research is built especially for EEG data augmentation and classification using the TensorFlow libraries. The brain wave datasets are recorded using the "EMOTIV EPOC+ 14 Channel Mobile EEG" device from Emotiv and the EmotivPro software (Emotiv 2018).

2. Theoretical investigation

2.1 Utilisation of brain waves in field of architecture

Brain waves are electric signals generated during brain cell and neurons activities. The numerical data of these waves are recorded using EEG, for which electrodes are attached to the scalps of subjects (Schomer and Silva 2010). Brain waves have drawn attention because it is possible to usually detect them in any person and to utilise their quantitative numerical data, which indicate the responses of the brain towards external stimuli. In the field of architecture, the quantitative data are utilised for research on the concentration and productivity of space occupants, dependence of sleep patterns on environmental changes, biological reactions of occupants or subjects in satisfaction analysis, and so on. Lan and Lian (2009), Lee, Choi, and Chun (2012), and Zhang et al. (2017) utilised brain waves to observe and verify changes in the productivity of occupants depending on the indoor temperature. Pan, Lian, and Lan (2011), Lan et al. (2013), and Lan, Lian, and Lin (2016) utilised EEG for obtaining quantitative data, using which they analysed the dependence of the sleep patterns and satisfaction of subjects on the spatial environment. All such studies utilise brain waves for obtaining quantitative data, which are used to examine the physiological changes in occupants depending on the physical architectural conditions.

Many previous studies relevant to architectural design have used EEG to grasp the emotional responses of users towards changes in the architectural space. One such research included a preference survey and brain wave experiments among youths, who were given indoor images with emotional vocabularies of community facilities in an apartment complex (Hwang, Kim, and Kim 2013). Hwang et al. (2014) used brain wave data to examine facility preferences among youths. Ryu and Lee (2015) examined the

correlations between colour changes in an indoor residential space and brain waves. Such studies are important in that they utilise the quantitative data obtained from brain to grasp the emotional responses of subjects in architectural design perspectives and to observe relevant changes. However, these studies have limitations in terms of establishing specific models for EEG data analysis. In contrast, Chang, Dong, and Jun (2018) recorded the brain waves of subjects while showing them images of a small residential space and asking them to select the most-preferred and least-preferred images. This study also proposed an EEG-based deep-learning classification model through which the recorded brain wave data could be analysed. This model is important in that it analyses the subjective emotional responses of users towards architectural spaces in a limited experimental situation, but the quantity of brain wave data obtained from experiments is limited. Therefore, it is difficult to apply this model universally, and further learning and evaluation of the model is required. In addition, the process of obtaining brain wave data is complicated and requires EEG equipment, making it difficult to apply this model to various other research areas. Thus, the present study aims to establish a generative adversarial networks model through which a small quantity of brain wave data acquired through experiments from previous studies could be augmented and converted into virtual data and to train the EEG-based deep-learning classification model using the acquired data. Figure 1 shows a diagram that illustrates how the proposed hybrid deep-learning model could be applied to an architectural design process.

2.2 Generative adversarial networks

Goodfellow et al. (2014) proposed the concept of a GANs, which is a deep-learning algorithm based on unsupervised learning. Supervised deep-learning

method algorithm processes data based on the feature values of input data, calculates differences(loss) between model predictions and actual data labels based on the user-given results, and proceeds to reduce the loss from such differences (Hinton and Salakhutdinov 2006). When this process occurs while classification values of actual data (labels) are provided, it is called supervised learning. When any classification values of actual data are provided, it is called unsupervised learning. However, in the case of supervised learning, model training is limited if any label values of actual data are provided or if the quantity of data is small. In contrast, the GANs model is different in that this algorithm is based on unsupervised learning and thus can generate virtual data based on input data even if the quantity of the input data is small. This data augmentation supports the process of training the supervised deep-learning algorithm. The GANs model consists of a generator and discriminator. The generator generates virtual data using latent data and delivers the generated data to the discriminator. The discriminator processes the data from the generator and the original data simultaneously, distinguishing the original data from the virtual data. As the training is repeated, the generator and discriminator continue to adjust the weight and bias values that indicate the extent of connection among the nodes in each hidden layer. The discriminator continues learning with regard to distinguishing the original data from the virtual data, whereas the generator proceeds to generate virtual data that are similar to the original data. Because the generator and discriminator continue learning in a hostile and competing environment, the algorithm is adversarial, competitive and generative.

The GANs model is utilised to increase the size of data whose actual classification values are hardly secured as well as to generate certain data types such as image, video, and voice. Caramihale, Popescu, and Ichim (2018) and Luo and Lu (2018)

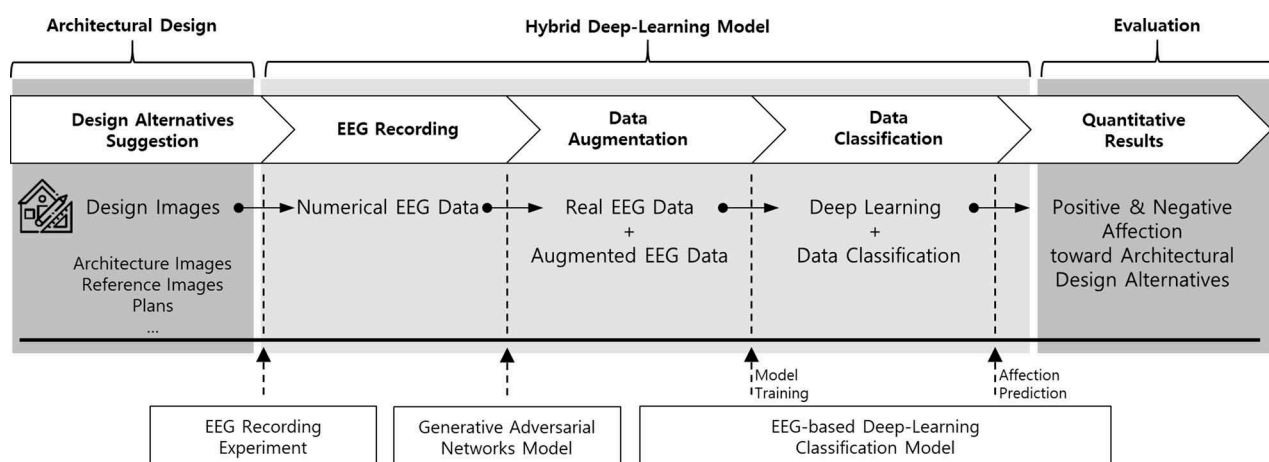


Figure 1. Application scenario.

augmented key facial expression data and brain wave data by utilising the GANs. Their finding indicates that as augmented data are utilised for training an emotional classification model, the model's accuracy is enhanced.

Figure 2 shows the structure of the GANs consisting of the discriminator and generator. The discriminator receives virtual data generated by the generator in addition to actual data, whereas the generator receives random data. Input datasets pass through the neural networks of both the generator and discriminator. The discriminator receives actual data and data generated by the generator simultaneously. It distinguishes the actual data from the fake data and calculates the loss. The generator and discriminator continue learning in a manner that reduces this loss.

2.3 Deep-learning classification

Hinton and Salakhutdinov (2006) proposed a concept of deep learning that combines multiple artificial neural networks. The deep-learning model is mainly divided into three types of layers: the input layer, hidden layers, and output layer. The hidden layers consist of multiple nodes and the weight and bias values that indicate the extent of connection between the nodes. These values pass through the activation function and then through the following layer. As data enter into the deep-learning model, computational operations are performed on them while they pass through each layer. The output layer presents the predicted values after the model classifies the data. In the case of the supervised learning classification model, both the labels and feature values of the data are put into the model. The difference between the classification values of the actual data and the values predicted by the model is calculated which is so called loss.

Figure 3 shows the structure of the deep neural networks. An input (x_n) is multiplied by a weight value

(w_n), and then, the result works as an input for the activation function. The activation function then calculates the input and transmits it to the following node as an output value.

If the classification values of the actual data are provided to the model in the process of entering data to the deep-learning model and training it, it is called supervised learning. If such values are not provided, it is called unsupervised learning. If the model is trained through supervised learning, the training may proceed in a manner that reduces the difference between the values predicted by the model and the classification values of the actual data. However, in this case, the learning may be limited if the quantity of data is small or if no classification values are provided. In contrast, the unsupervised learning method has limitations in that it may produce different values depending on the model's structure or parameters although it is possible to train the model even without the classification values of the data (Jain, Duin, and Mao 2000).

Accordingly, this study aims to develop an EEG-based hybrid deep-learning model that can recognise the emotional responses of users in the initial designing step. It consists of a GANs for brain wave data augmentation and an EEG-based deep-learning classification model for brain wave data classification. Brain wave datasets of subjects from previous studies are augmented through the GANs, and then, the augmented datasets are utilised to train and evaluate the classification model (Chang, Dong, and Jun 2018).

3. Proposed hybrid deep-learning model

In this work, two distinct deep-learning-based models are suggested. The first is a generative adversarial networks (GANs) model for EEG data augmentation, and the second is an EEG-based deep-learning model for data classification. The hybrid deep-learning model consists of a combination of these two models.

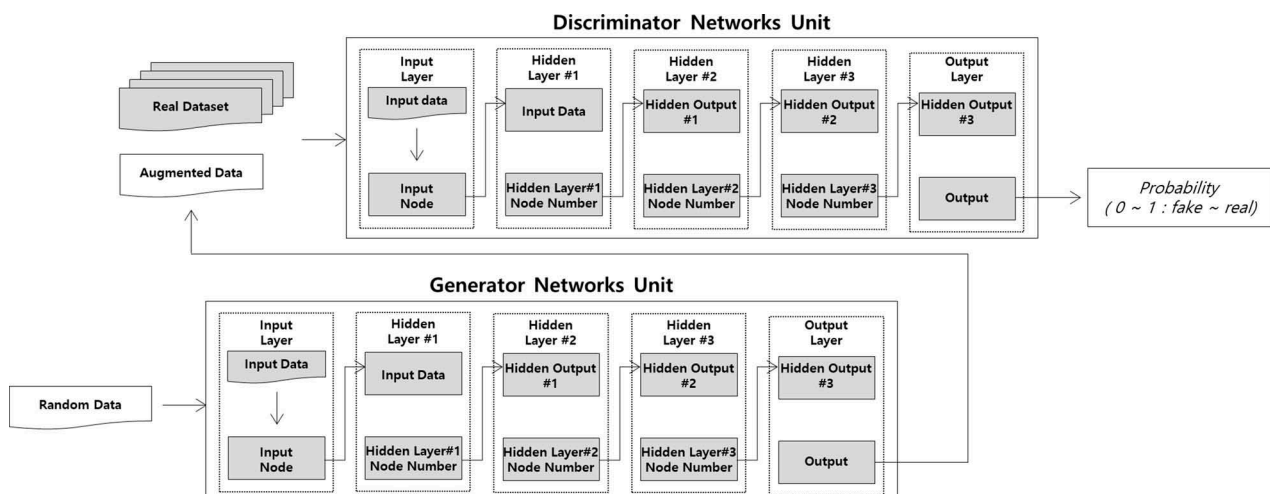


Figure 2. Generative adversarial networks (GANs).

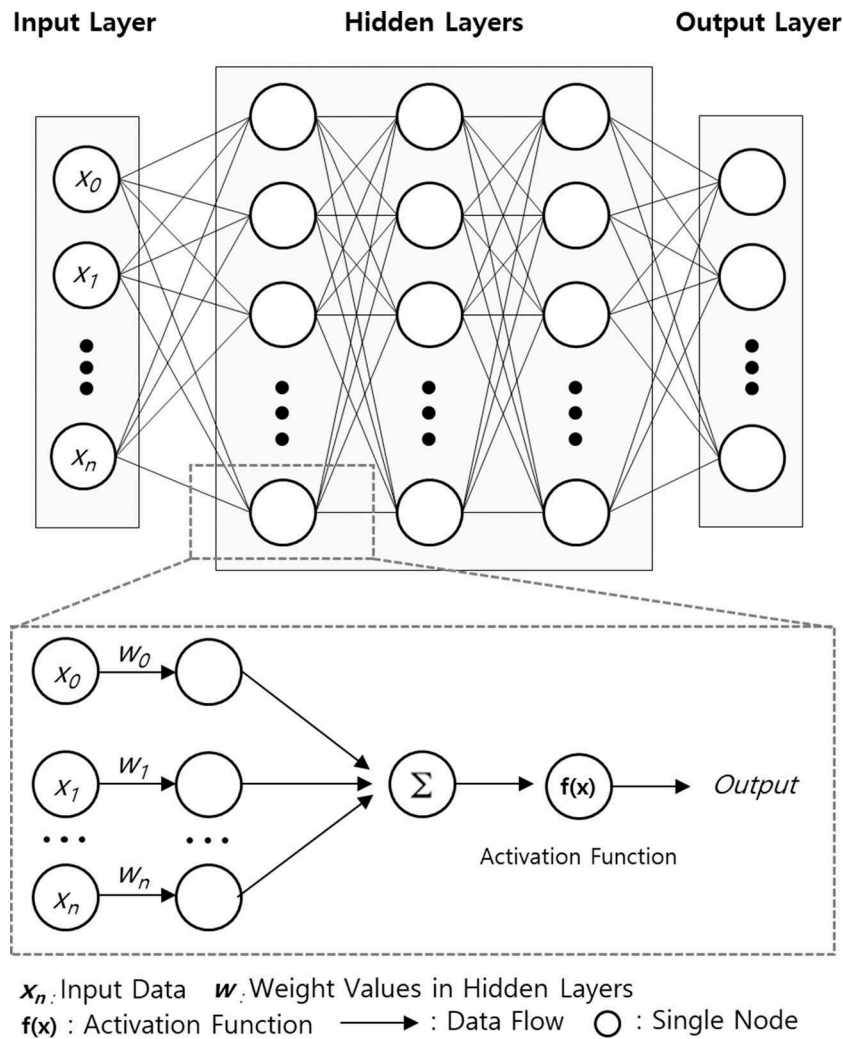


Figure 3. Deep neural networks (DNNs) structure.

Both these models were built in this study using Google TensorFlow, which is a core open-source library for machine learning and deep learning.

Brain wave data collected from experiments work as input values for GANs and then augmented in a competitive environment between the generator and discriminator. The augmented data work as input values for deep-learning classification model along with raw brain wave data collected through experiments, and then, the model proceeds with training and evaluation based on the data. Figure 4 shows how the GANs used for brain wave data augmentation is combined with the EEG-based deep-learning classification model used for EEG data classification.

3.1 Generative adversarial networks for brain wave data augmentation

This section aims to establish a GANs model to augment a small quantity of brain wave data collected in

previous studies. In the process of establishing this model, the open-source library Google TensorFlow was used.

The EEG data that are to be used by the established model have 14 channels, and datasets are normalised for each channel. This step is necessary to prevent data distortion in the event that the value of a certain channel is larger than that of another channel.

The generator and discriminator of the established GANs consist of three hidden layers, which consist of 50, 100, and 50 nodes, respectively. The number of nodes in each layer was determined after evaluations with multiple combinations of hyper parameters that showed the highest training speeds. The generator receives random values between 0 and 1 and generates virtual EEG data. The discriminator receives EEG collected through experiments and virtual data and distinguishes the original data from the virtual data. Once the training is completed, the EEG data generated by the generator are presented to users and saved as csv format. Figure 5

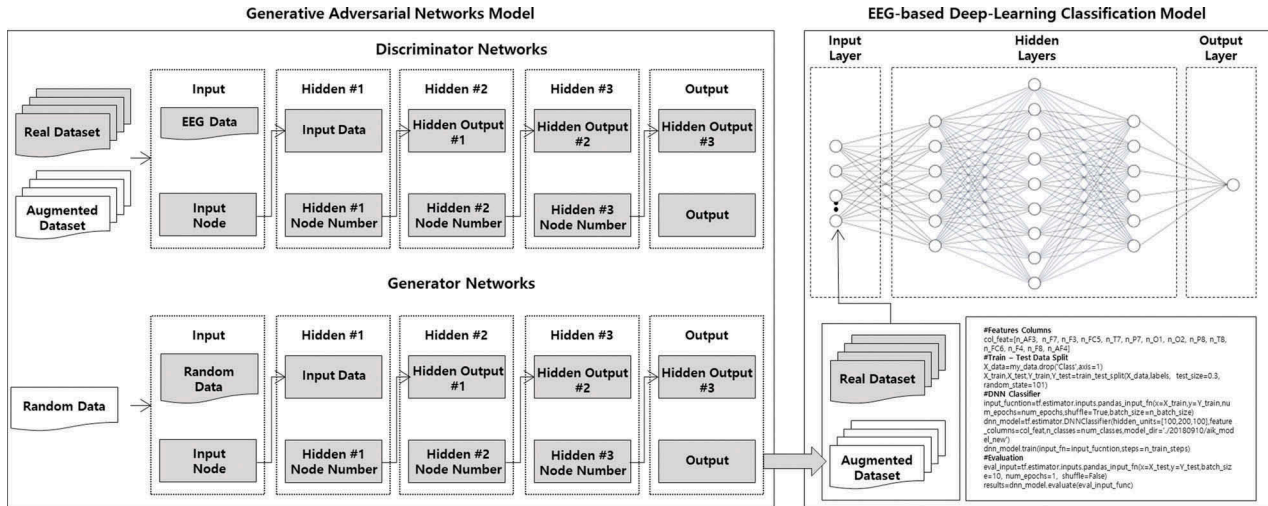


Figure 4. Hybrid deep-learning model - GANs + EEG-based Deep-Learning Classification Model.

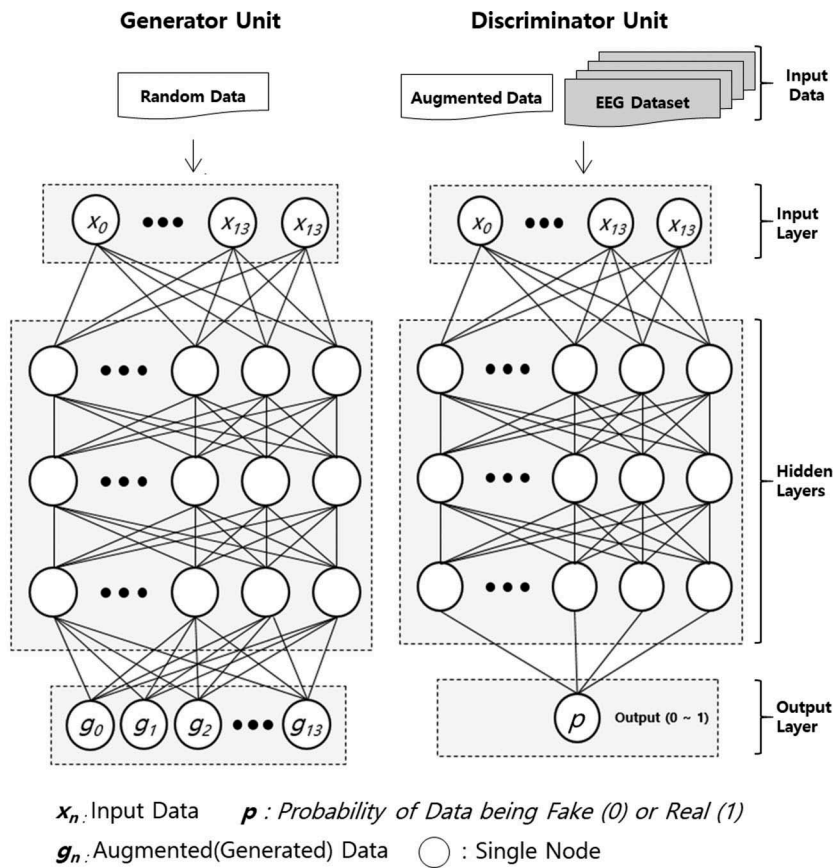


Figure 5. GANs generator and discriminator.

shows the structure of the generator and discriminator of the established GANs.

3.2 EEG-based deep-learning classification model for brain wave data classification

The purpose of the EEG-based deep-learning classification model is to classify the emotional states of

the brain wave data as “positive” or “negative” toward architectural design alternatives. The classification model utilises TensorFlow as well as application programming libraries related to supervised learning.

The model consists of three layers: the input layer, hidden layers, and output layer. And the hidden layers consist of three layers which consist of 100,200 and

5 points and “not at all” was given 1 point. In this manner, the scores of the “positive emotion” and “negative emotion” questions were calculated (Watson, Clark, and Tellegen 1988). Chang, Dong, and Jun (2018) excluded the emotion scores that were lower than the average scores of “positive emotion” and “negative emotion” presented in the research of Watson, Clark, and Tellegen (1988). Consequently, the brain wave data of 8 individuals for the “positive emotion” questions and the data of 17 individuals for the “negative emotion” questions were included in the dataset. From the brain wave data for 20 s, the data

for the first 5 s and last 5 s were excluded to remove noise, and the remaining brain wave data for 10 s were used. The number of rows in the “positive emotion” and “negative emotion” datasets was 10,240 (8 × 128 × 10) and 21,760 (17 × 128 × 10), respectively.

Figure 7(a) shows the result of the brain wave experiment performed on one subject, Figure 7(b) shows the brain wave recording software called EmotivPro(Emotiv 2018), and Figure 7(c) shows the electrode position of the “EMOTIV EPOC+ 14 Channel Mobile EEG” device, which is the EEG equipment used in this experiment (Emotiv 2018).

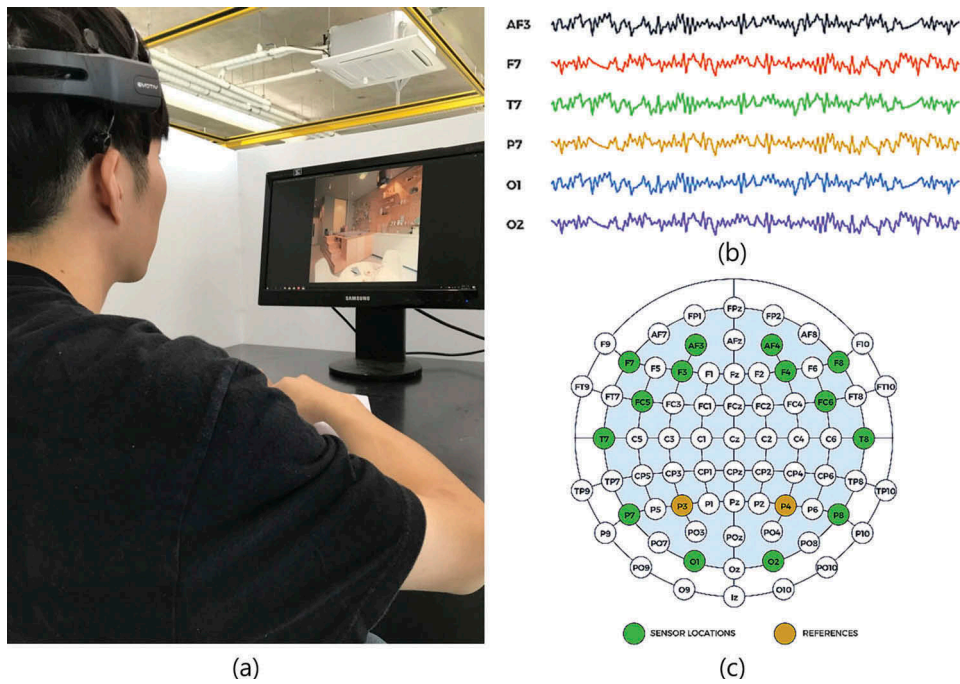


Figure 7. (a) Subject recording EEG, (b) EmotivPro software interface with recording EEG (Emotiv 2018), (c) “EMOTIV EPOC+ 14 channel mobile EEG” device technical specifications (Emotiv 2018).

AF3	F7	F3	FCS	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	Affection Labels	SubjectID	Chz
4171.281738	4175.897461	4154.871582	4165.641113	4179.487305	4167.179199	4157.94873	4071.794678	3949.230713	3972.820313	3938.974365	4196.410156	4017.435791	4187.692383	Positive	2 KGR	111
4199.487305	4184.615234	4191.281738	4190.769043	4194.358887	4206.666504	4197.436035	4211.281738	4193.333008	4211.281738	4213.846191	4198.461426	4209.230469	4201.538574	Positive	2 KJA	46
4230.769043	4276.922852	4217.436035	4232.820313	4235.384277	4245.641113	4227.179199	4198.974121	4199.487305	4231.281738	4226.153809	4241.025391	4483.589844	4238.461426	Positive	2 YDG	96
4168.717773	4192.307617	4211.281738	4197.436035	4241.538574	4203.07666	4202.05127	4214.358887	4198.461426	4198.487305	4212.307617	4166.666504	4223.589844	4197.436035	Negative	1 LSB	0
4206.666504	4152.820313	4184.102539	4187.692383	4216.410156	4198.461426	4202.563965	4213.333008	4200	4229.230469	4221.538574	4208.205078	4244.102539	4202.05127	Positive	2 KJA	96
4155.897461	4132.820313	4169.230469	4116.922852	4164.615234	4165.641113	4161.538574	4171.281738	4213.333008	4198.974121	4175.384277	4181.025391	4197.436035	4201.538574	Negative	1 KJA	38
4132.307617	4117.94873	4132.307617	4188.717773	4347.692383	4172.307617	4142.05127	4125.641113	4202.05127	4130.256348	4186.666504	4143.07666	4109.743652	4126.153809	Positive	2 PSW	87
4156.410156	4163.589844	4173.333008	4142.563965	4170.769043	4137.94873	4183.07666	4184.615234	4214.358887	4177.436035	4218.974121	4184.102539	4139.487305	4190.769043	Positive	2 LSW	56
4199.487305	4186.153809	4257.94873	4187.179199	4175.384277	4202.563965	4202.563965	4264.102539	4457.435547	4425.641113	4428.205078	4133.333008	4442.05127	4610.256348	Positive	2 GHR	41
4184.615234	4193.333008	4204.102539	4165.12793	4192.307617	4196.922852	4194.358887	4202.563965	4191.794922	4178.974121	4185.12793	4201.538574	4203.589844	4186.153809	Positive	2 PSJ	9
4138.461426	4192.307617	4178.461426	4201.538574	4207.179199	4201.025391	4218.461426	4202.563965	4179.487305	3058.461426	2989.743408	3230.769043	2942.05127	4190.256348	Negative	1 PNY	0
4235.897461	4238.974121	4257.436035	4240.512695	4254.871582	4257.436035	4272.307617	4259.487305	4272.307617	4270.769043	4286.153809	4223.07666	4263.589844	4287.179199	Negative	1 LSH	109
4198.461426	4167.179199	4218.974121	4193.333008	4231.281738	4198.461426	4192.307617	4177.94873	4139.487305	4172.307617	4123.589844	4158.461426	4046.666504	4227.179199	Positive	2 PUJ	16
4190.256348	4203.589844	4188.717773	4190.769043	4185.641113	4188.717773	4199.487305	4185.12793	4183.589844	4185.641113	4179.487305	4185.641113	4161.538574	4183.589844	Negative	1 LSW	121
4188.717773	4194.358887	4192.820313	4195.897461	4198.974121	4193.846191	4194.358887	4196.922852	4189.743652	3579.487061	3604.102539	3627.179443	3660.512695	4192.820313	Positive	2 PNY	0
4182.563965	4185.12793	4179.487305	4185.641113	4179.487305	4181.538574	4181.025391	4194.358887	4150.769043	4185.641113	4122.05127	4194.358887	4173.333008	4198.461426	Positive	2 KYD	110
4180.512695	4233.333008	4191.794922	4217.94873	4228.717773	4189.230469	4192.820313	4201.538574	4192.820313	4194.871582	4184.102539	4215.897461	4308.717773	4162.05127	Positive	2 YDG	10
4214.358887	4163.07666	4204.102539	4202.563965	4163.589844	4207.179199	4241.025391	4309.743652	4120	4122.05127	4138.974121	4287.179199	4205.641113	4147.692383	Positive	2 LSH	103
4153.846191	4125.641113	4152.307617	4161.025391	4197.436035	4186.153809	4153.846191	4182.05127	4190.769043	4196.922852	4229.230469	4182.05127	4220.512695	4172.307617	Positive	2 PSJ	106
4260.512695	4227.692383	4480	4323.07666	4173.333008	4174.871582	4029.743408	3053.846191	3212.307617	3396.923096	3103.5896	3232.307617	3344.102539	4072.820313	Negative	1 KGR	55
4185.641113	4150.769043	4157.94873	4215.384277	4172.820313	4172.820313	4161.538574	4122.563965	4055.384521	4066.153809	4073.845947	4168.205078	4087.179443	4198.974121	Negative	1 KGR	77
4181.538574	4218.461426	4166.666504	4202.05127	4222.05127	4186.153809	4190.256348	4204.615234	4106.153809	4112.820313	4126.666504	4175.897461	4133.846191	4137.436035	Positive	2 BJH	93
4202.05127	4195.384277	4213.333008	4193.333008	4198.461426	4201.025391	4198.461426	4201.025391	4213.333008	5174.871582	5156.922852	4535.384277	5135.384277	4196.922852	Negative	1 PNY	0
4202.563965	4193.846191	4199.487305	4233.333008	4075.384521	4190.769043	4193.846191	4192.820313	4546.153809	4183.07666	4078.461426	4073.333252	4126.666504	4194.358887	Positive	2 SKY	0
4197.94873	4184.615234	4188.717773	4189.743652	4191.281738	4189.743652	4187.179199	4192.307617	4200	4174.871582	4177.94873	4155.384277	4175.384277	4192.820313	Negative	1 JDY	5

Figure 8. EEG-based Deep-learning classification model training dataset: (a) Features: 14 channels of recorded EEG data, (b) Affection: Re-classified PANAS Questionnaire Results, (c) Labels: “Negative” = 1 and “Positive” = 2, (d) Subject Initials, (e) Frequency (Hz).

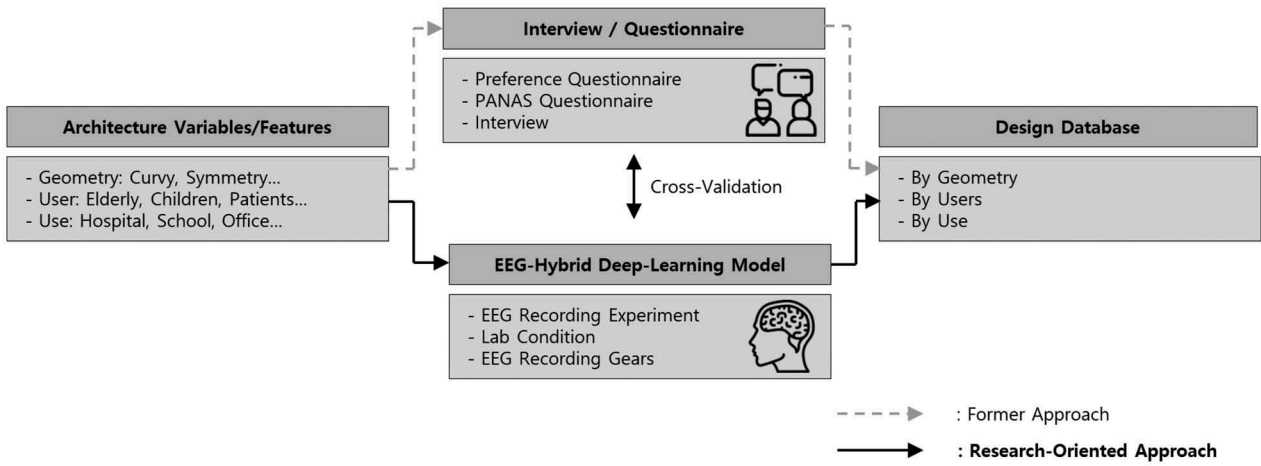


Figure 9. Suggested Model Use Research Scenario.

Figure 8 shows the structure of the EEG dataset. Figure 8(a) shows the raw brain wave data of 14 channels, which include feature values. Figure 8(b) shows the re-classified affection results of the PANAS survey. Figure 8(c) shows numerically casted values from the survey results. Actual classification values were entered into the model as follows: 1 for “negative” items and 2 for “positive” items. Figure 8(d) shows the initials of each subject, and Figure 8(e) shows the frequency.

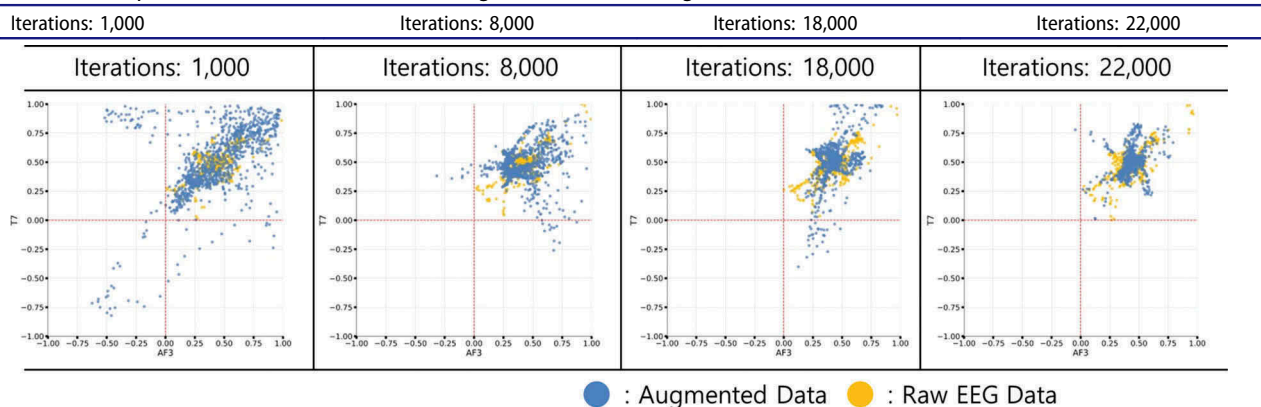
4.2 Brain wave dataset augmentation using generative adversarial networks

The learning process of the GANs includes the following four steps: (1) data input, (2) virtual data generation by the generator, (3) discriminator training, and (4) virtual data output. (1) In the data input step, the “positive emotion EEG dataset” and “negative emotion EEG dataset” recorded in the previous study were entered into the model. (2) In the step involving virtual data generation by the generator, random values between 0 and 1 were entered into the generator and the generator generated virtual brain wave data. (3) In the discriminator training step, the actual EEG data and virtual EEG data generated by the generator were entered into the discriminator

simultaneously. The discriminator distinguished the actual data from the fake data. In this phase, loss values of discriminator and generator are calculated. If generated data becomes similar to actual data during training process, generator loss decreases. (4) In the virtual data output step, virtual brain wave data generated by the generator were saved in csv format. In total, 30,000 rows were generated by the generator for the “positive emotion EEG dataset” and “negative emotion EEG dataset” items respectively.

Table 1 indicates that as the training was repeated, the virtual data in blue gradually became similar to the actual data in orange. Among the 14 channels of the “positive emotion” brain wave data, the two channels AF3 and T7 were visualised on the x axis and y axis, respectively. When the training was repeated 1,000 times, the generator generated data containing negative numbers with no actual data. When the training was repeated 8,000 times, the overlap of the virtual data with the actual data increased. As the training was repeated, the overlapped parts of the actual data and virtual data on the coordinate axes increased to the point that the discriminator could no longer distinguish the actual data from the virtual data. Accordingly, the generator’s loss decreased gradually.

Table 1. Comparison between real data and augmented data through iterations (Positive affection).



4.3 DEEG-based deep-learning classification model training using virtual brain wave data

The virtual EEG data generated using the GANs model were utilised in the process of training the EEG-based deep-learning classification model. The virtual brain wave dataset generated based on the “positive emotion EEG dataset” was added to this dataset, and then, the “negative emotion EEG dataset” was added in the same manner. Consequently, the “positive emotion brain wave dataset” and “negative emotion brain wave dataset” were combined with 40,240 and 51,760 rows, respectively.

The expanded “positive emotion EEG dataset” and “negative emotion EEG dataset” were then entered into the classification model for training. While the previous classification model utilised 32,000 datasets for training, in the present model, 92,000 datasets were utilised in training as virtual brain wave data were added. The final accuracy was 0.984, which was better than the existing accuracy (0.979). If more data are added in the future using the GANs model, the accuracy and universality may improve further.

4.4 Implications and model utilisation scenarios

The proposed EEG-based hybrid deep-learning model enables quantitative identification of user emotions towards architectural space images. At the design stage, the architects consider the emotional qualitative reviews of the decision makers, including owners and preliminary users, as well as the quantitative reviews, including legal and location-based reviews, on the design alternatives to be important. In this regard, the proposed model can be effectively used. However, at the current stage of research, because it is difficult to manipulate EEG recording machines and because the experimental procedures are complicated, applying the proposed model to actual design processes will require additional research in the fields of brain science and architecture in the future.

At present, we can present research scenarios that quantitatively measure specific subjects’ responses towards specific architectural spaces and build databases by obtaining measurement data and incorporating them into design knowledge using the proposed model. Previous studies on design knowledge databases mainly used surveys and in-depth interviews to measure the emotional responses of subjects to a specific type of architecture. However, if the model proposed in this study is adopted, architects can quantitatively measure the emotional responses of users under certain conditions and suitably incorporate them into the knowledge base to

reflect real business processes. This scenario is suggested in Figure 9.

5. Conclusion

The objective of this study was to establish an EEG-based hybrid deep-learning model through which the emotional responses of users towards a architectural space could be evaluated. To this end, brain wave data collected in previous studies were augmented using the GANs model, and an EEG-based deep-learning classification model was trained and evaluated by using both actual and virtual data. The findings of this study are as follows.

First, the GANs showed a major possibility of augmenting atypical EEG data. It is expected that this networks can be used in the field of architecture to augment and utilise datasets whose scale and availability are limited, such as simulation data, environmental sensor data, and observation data. Second, as the quantity of data increases, the accuracy of training and evaluating the deep-learning model will improve continually. The model has demonstrated that it can handle big data pertaining to architecture, traffic, and other environments that can be utilised in the field of architecture. Third, by using the brain wave data and EEG-based hybrid deep-learning model, the study has demonstrated the possibility of helping the designer in the architectural design step to grasp the emotional responses of future users or clients towards proposed design alternatives. In this study, it was possible to utilise brain wave data as indicators of the emotional responses or preferences of subjects only in limited environments.

In future studies, the following research activities should be considered. The proposed hybrid deep-learning model should be applied to actual design processes. The hybrid deep-learning model should be evaluated and verified. Experiments should be performed for recording additional brain wave data to facilitate the universal application of the model. The EEG-based hybrid deep-learning model should be combined with an eye tracking system for the evaluation of the emotional responses of users towards actual spatial environments.

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