

Comparison of Brainwave Sensors and Mental State Classifiers

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ABSTRACT

Brain-computer interfaces (BCIs) have been attracting attention as a research topic. BCI has various applications, such as at home and in the medical sector. BCI is an interconnection between the human brain and a computer, which is a communication pathway between external peripheral devices. Brainwave sensors play a significant role when applying BCIs in practice. In this study, data from such sensors are analyzed to classify the mental states of users. This study used two different brainwave sensors: Neurosky MindWave Mobile and Emotiv EPOC+. Several types of machine-learning techniques (support vector machine, random forest, and long short-term memory) have been applied to classify brainwave data. This study aimed to compare the accuracy of the two sensors, analyze data, and identify the most accurate machine-learning method. Finally, a BCI toy with MaBeee, which is a battery-type internet-of-things device, was designed as a BCI application that reflected the analysis results.

KEYWORDS

BCI, BCI Toy, EEG, IoT, LSTM, Machine Learning, Random Forest, SVM

1. INTRODUCTION

Brain-computer interfaces (BCIs), which can be applied in various areas, such as home use, robotics, and medical settings, have been widely investigated. BCIs represent an interconnection between the human brain and the computer and serves as a communication pathway between external peripheral devices. Previously, BCI was a complex term for non-researchers; furthermore, previously, specific equipment and environments required to measure the different states of the brain were not easily accessible. Over the past decade, portable and simplified electroencephalogram (EEG) sensors have been developed. An EEG is used to evaluate the electrical activity of the brain and is one of the most popular non-invasive techniques for recording brain activity. Currently, many EEG sensors are available, thus allowing BCIs to be investigated extensively. Examples include the operation of computers (Márquez et al., 2018) and web browsing applications (Halder et al., 2015), control of wheeled robots (Alsammarraie & Inan, 2022; Hiraishi, 2015) and robot arms (Ranky & Adamovich, 2010), cognitive state analysis in sports (Hiraishi, 2021) and driving (Hiraishi, 2020), patient monitoring (Kumar et al., 2015), and some medical applications (Saravanarajan et al., 2021; Ting et al., 2021). Thus, many topics related to BCI in diverse areas have been reported.

Brainwave sensors play a significant role in BCI application, and the data from such sensors are analyzed to classify the mental states of users. Therefore, the authors used two different brainwave

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sensors: Neurosky MindWave Mobile and Emotiv EPOC+. These sensors have been widely used in many studies, such as the ones mentioned above. Several types of machine-learning techniques have been applied to classify brainwave data. This study aimed to compare the accuracy of the two sensors, analyze the data, and identify the most accurate machine-learning technique. The following machine-learning methods were the focus of this study: the support vector machine (SVM), random forest, and long short-term memory (LSTM). SVM and random forest are among the most popular and effective methods to be proposed before the advent of deep learning. LSTM is a deep learning method—a type of recurrent neural network—and is advantageous in that it allows the analysis of time-series data such as brainwaves. These methods are typically used for brain data analysis (Costantini et al., 2009; Edla et al., 2018; Liao et al., 2018; Roy et al., 2019; Ting et al., 2021). That is the reason why they were selected in this study.

This study focused on three classes of mental states: “attention,” “meditation,” and “other.” The brainwave data for each class were obtained using each sensor from three subjects and then analyzed using each method. Subsequently, the characteristics of the brainwave sensors and mental state classifiers were clarified by comparing the accuracy of each combination. Finally, a BCI toy with a battery-type Internet-of-Things (IoT) device was designed as a BCI application to demonstrate the analysis results.

2. BRAINWAVE SENSORS

Figure 1 shows the two brainwave sensors adopted in this study, namely MindWave Mobile from NeuroSky Inc. (on the left) and EPOC+ from Emotiv Inc. (on the right), both of which are EEG sensors.

Figure 1. MindWave Mobile (left) and EPOC+ (right)



EEG scans are performed by placing small metal disks—known as EEG electrodes—on the scalp. These electrodes identify and record electrical activity in the brain. The obtained EEG signals are amplified, digitized, and then sent to a computer or mobile device for storage and data processing.

MindWave Mobile is an extremely simple and user-friendly sensor with a single channel, which comprises only two electrodes at the forehead and ear. The headset’s sensor measures the brain’s electrical activity between the forehead and ear; it transfers the data via Bluetooth to a computer,

smartphone, tablet, or laptop. This sensor has been adopted in several studies (Anwar, 2017; Donmez & Ozkurt, 2019; Hiraishi, 2020; Hiraishi, 2021).

EPOC+ is an advanced brainwave sensor comprising 16 electrodes and 14 channels. Similarly to MindWave Mobile, this sensor transfers data via Bluetooth to a computer and has been used in many studies (Das et al., 2014; Hooda et al., 2020; Ranky & Adamovich, 2010). This sensor is expected to achieve higher accuracy compared with other sensors. However, the pads of the electrodes must be dipped into a physiological salt solution and exchanged frequently.

Table 1. Brainwaves obtained by each sensor (The numbers in parentheses indicate the frequency for spectral analysis)

	MindWave Mobile	EPOC+
Brainwaves	Delta (0.5–2.75 Hz)	
	Theta (3.5–6.75 Hz)	Theta (4–8 Hz)
	lowAlpha (7.5–9.25 Hz)	Alpha (8–12 Hz)
	highAlpha (10–11.75 Hz)	
	lowBeta (13–16.75 Hz)	lowBeta (12–16 Hz)
	highBeta (18–29.75 Hz)	highBeta (16–25 Hz)
	lowGamma (31–39.75 Hz)	Gamma (25–45 Hz)
	highGamma (41–49.75 Hz)	

EEG results characterize the neural activity in the human brain. The brain emits electrical signals that can be measured by placing an electrode in contact with the scalp. The resulting EEG readings initially comprise voltage measurements; subsequently, a spectral analysis of the measured data is performed to obtain the signal frequency. Table 1 lists the brainwaves extracted by each sensor. MindWave Mobile and EPOC+ can obtain eight and five types of brainwaves, respectively. Meanwhile, the sensor used in EPOC+ comprises 14 channels, and 5 brainwaves are measured at every channel; thus, 70 brainwave samples can be obtained. In this study, the software for sending brainwave data to a computer was programmed using the software library of each sensor. These data were sent every second and then stored in a CSV file.

3. MENTAL STATE CLASSIFICATION

This section provides the analysis results of the mental state classification performed on the brainwave data, obtained using two brainwave sensors from three subjects. The data were analyzed using three machine-learning methods, namely SVM, random forest, and LSTM.

Most studies considered only two classes of mental states, such as attention and meditation, particularly when a sensor that adopts the brainwave-measurement module from NeuroSky, Inc., such as MindWave Mobile, was used. In addition to the brainwaves listed in Table 1, the sensor measures specific values of “attention” and “meditation” levels using an algorithm known as eSense (Neurosky, 2022). They are defined such that “attention” and “meditation” are associated with the generation of beta and alpha waves, respectively. However, the algorithm for calculating each value is not publicly available. Therefore, these parameters were not used in this study. The mental states of attention and meditation were classified based on brainwaves, as presented in Table 1. The three classes of mental states were defined as attention, meditation, and other. As reported by (Hiraishi, 2015), a specific mental state is difficult to create intentionally. Therefore, the following tasks were conducted to create specific mental states:

- **Attention:** Solving calculation problems using a smartphone application.
- **Meditation:** Listening to ambient music.
- **Other:** Being idle; sitting on a chair.

The profiles of the three subjects are as follows:

- **Subject A:** Male student, Nepalese, 27 years old.
- **Subject B:** Male student, Nepalese, 26 years old.
- **Subject C:** Male student, Chinese, 25 years old.

Each subject executed three tasks using two sensors. Six experiments were performed for each subject, and each experiment lasted 4 minutes. Therefore, 240 datasets were obtained, and each dataset included the brainwave data of three mental states. In total, 180 datasets were used to generate the classification model, and 60 datasets of test data were used to evaluate the accuracy of the model. For data analysis, Waikato Environment for Knowledge Analysis (Weka)—a Java-based application developed at Waikato University (Srivastava, 2014)—was adopted in this study. Weka supports various methods of data analysis and machine learning, including SVM, random forest, and LSTM, and the same input file can be employed for performing analyses using these methods.

4. EXPERIMENTAL RESULTS WITH MINDWAVE MOBILE

Figures 2–4 show the experimental results obtained via MindWave Mobile using SVM, random forest, and LSTM, respectively. Each graph indicates the change in the accuracy as the number of datasets increases. For the SVM, a linear kernel was used as it exhibited the best accuracy. The network of LSTM comprised two layers: an LSTM layer and an output layer. The number of nodes to connect these two layers was set to 10. The default settings of Weka were used for other settings.

Figure 2. Accuracy of MindWave Mobile and SVM

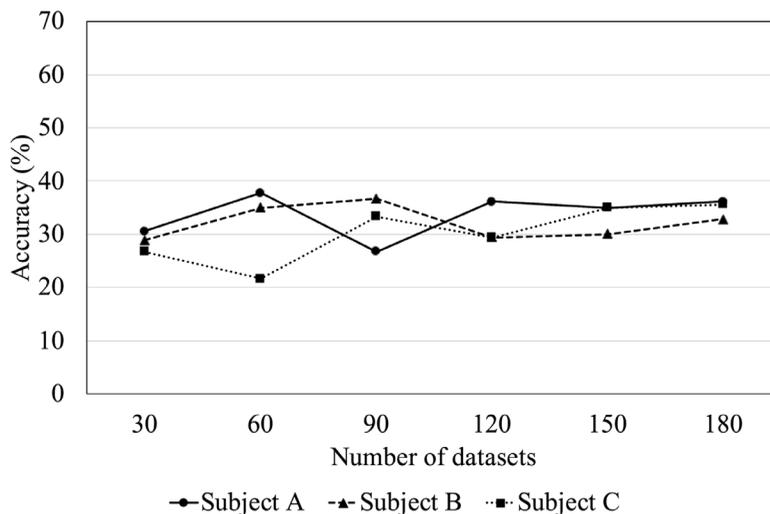


Figure 3. Accuracy of MindWave Mobile and random forest

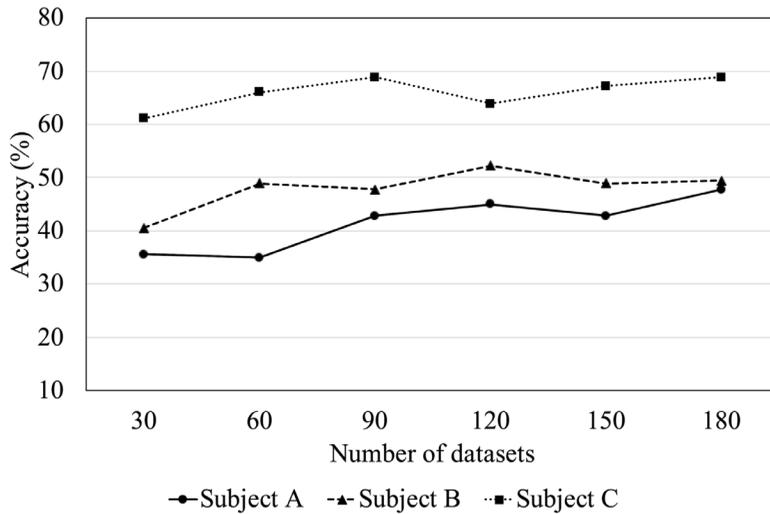
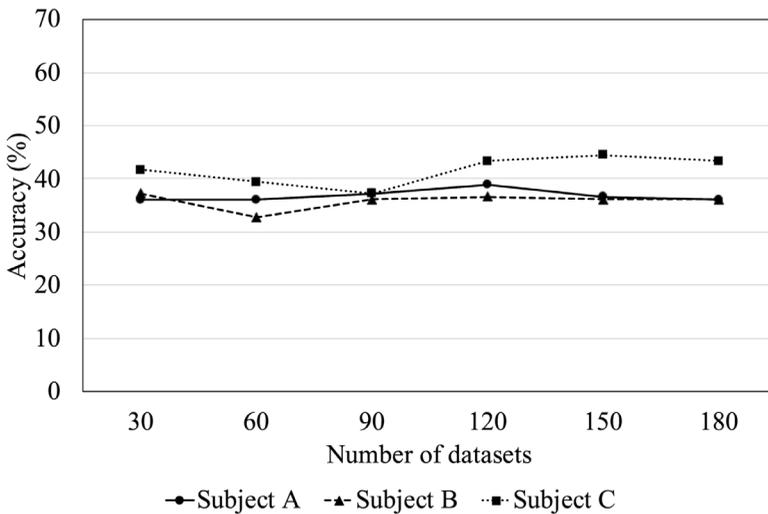


Figure 4. Accuracy of MindWave Mobile and LSTM



Figures 2–4 show that the accuracy increased or stabilized gradually as the number of datasets increased. The accuracy varied as follows: it increased for datasets similar to the test data and decreased for dissimilar datasets. However, when a sufficient number of datasets was obtained, the model could manage various types of data, and the accuracy of the model stabilized. The results of SVM (Figure 2) show that the accuracy decreased when the number of datasets was insufficient, and vice versa. Meanwhile, the accuracy of random forest (Figure 3) improved steadily as the dataset increased. LSTM (Figure 4) demonstrated a relatively higher accuracy even in the early stage. For all methods, the accuracy stabilized when approximately 120 datasets were used.

Table 2. Average and standard deviation of accuracy for MindWave Mobile (%)

	Two Classes		Three Classes	
	Average	Standard Deviation	Average	Standard Deviation
SVM	49.72	1.92	34.81	1.79
Random Forest	68.61	11.10	55.37	11.73
LSTM	55.00	3.82	38.52	4.17

However, the overall accuracy was unsatisfactory. Although the highest accuracy of approximately 70% was achieved by Subject C using random forest, the overall accuracy was less than 50%, whereas the SVM could not achieve 40%. Subsequently, two classes (attention and mediation) were identified by removing other data from the datasets obtained. Table 2 shows the average and standard deviation of the accuracy of the three subjects for 180 datasets in two classes and compares the data of three classes. Random forest showed the highest average value, whereas the SVM showed the lowest in both classes. By contrast, in terms of standard deviation, SVM exhibited the lowest value, whereas random forest exhibited the highest value for both classes. These results imply that the accuracy of SVM is low for all subjects, whereas that of random forest varies by the subject. However, random forest achieved an accuracy of approximately 70% in the two classes. This result is consistent with the findings of (Hiraishi, 2015), who performed a two-class analysis of the mental states for a robot controller. Although we analyzed three classes in our study, it can be assumed that MindWave Mobile can only manage two classes.

5. EXPERIMENTAL RESULTS BASED ON EPOC+

Figures 5–7 show the experimental results for EPOC+ using the SVM, random forest, and LSTM, respectively, and each graph indicates the change in the accuracy as the number of datasets increases. The settings of each method were the same as before.

Figure 5. Accuracy of EPOC+ and SVM

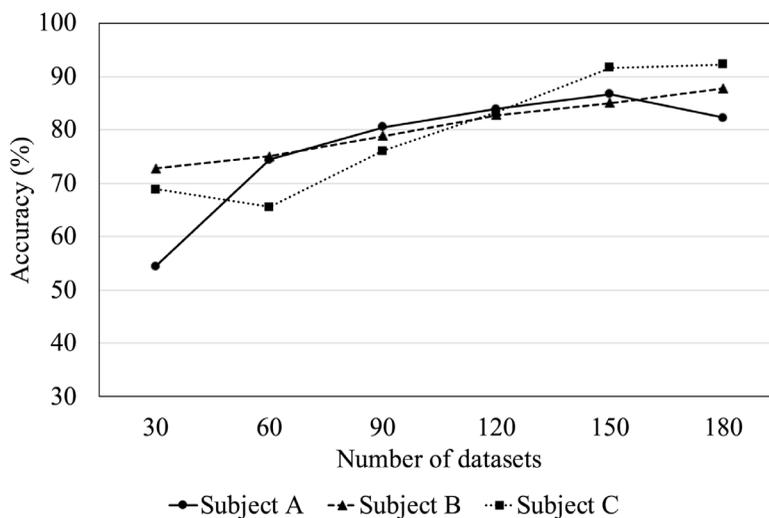


Figure 6. Accuracy of EPOC+ and random forest

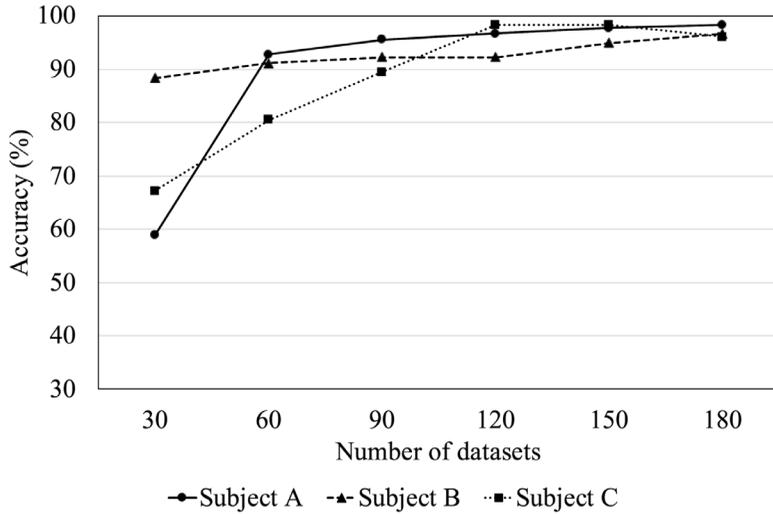
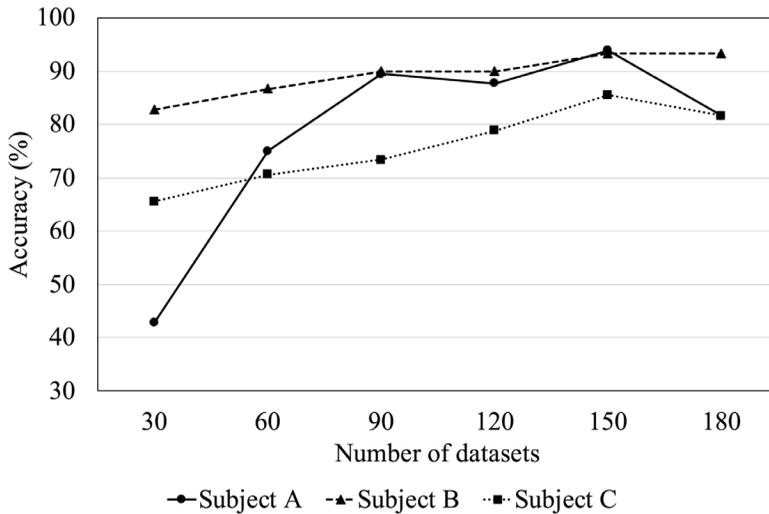


Figure 7. Accuracy of EPOC+ and LSTM



Each graph shows that the accuracy improved as the number of datasets increased, where the trend presented is similar to that of MindWave Mobile. The accuracy of the SVM varied at the early stage (Figure 5). Random forest improved steadily (Figure 6), whereas LSTM stabilized in the early stage (Figure 7). In all cases, the accuracy exceeded 80% when approximately 120 datasets were used.

In the case of EPOC+, much higher accuracies than MindWave Mobile were achieved, as expected, for all three classes. Table 3 shows the average and standard deviation of accuracies for 180 datasets. All the average accuracies exceeded 85%. Random forest achieved an accuracy exceeding 97%, and the standard deviation was the lowest. This implies that random forest achieved higher accuracy for all subjects stably and was the best-performing method for EPOC+.

Table 3. Average and standard deviation of accuracy for EPOC+ (%)

	Average Accuracy	Standard Deviation
SVM	87.41	5.01
Random Forest	97.04	1.16
LSTM	85.55	6.73

6. DESIGN OF BCI TOY

This section summarizes the results of the previous sections and presents the design of a BCI toy as an application that reflects the results. The analysis results of this study indicate that a complete operation could not be achieved using the brainwaves. The application of the BCI to critical operations is difficult. Therefore, a game or a toy that permits “operation miss” may be a suitable application of the BCI. In this study, an IoT device was used to realize a BCI toy. The design and operation of the BCI toy were compared between two sensors.

The BCI toy uses MaBee (Figure 8), which is produced by Novars Inc. MaBee is a battery-type IoT device that can control the output voltage from an electronic device (such as a smartphone) via Bluetooth communication. The voltage was controlled from 0 to 100, where 0 implies 0 V and 100 is the maximum voltage of the battery. A BCI toy can be created easily using MaBee. In fact, it can operate any toy that operates with a battery using brainwaves, such as a car toy, a train toy, or an illumination toy, as shown in Figure 8.

Figure 8. MaBee and toys that operate using battery



The results detailed in the previous sections are summarized as follows:

- Random forest is the best-performing machine-learning method in every aspect.
- Regarding MindWave Mobile, two-state analysis is a limitation for mental state classification.
- Regarding EPOC+, higher accuracies can be obtained for all three classes.
- The accuracy stabilizes when approximately 120 datasets are used.

For the design of the BCI toy, random forest was adopted as a data analysis method. For MindWave Mobile, mental states were classified into two classes: “attention” and “meditation”; for EPOC+, they were classified into three classes, the two classes mentioned earlier and “other.” The BCI toy generates a model on the spot (instead of using previously generated models) because it can achieve sufficient accuracy even when using a small dataset.

Figure 9. Application of BCI toy

The image shows a mobile application interface titled "BCI toy application". It features several sections for user configuration:

- Sensors:** Two radio button options: "NeuroSky MindWave Mobile" (selected) and "Emotiv EPOC+".
- Mental States:** Three radio button options: "Attention" (selected), "Meditation", and "Other".
- Action Buttons:** Three large grey buttons: "COLLECT DATA", "CLEAR DATA", and "CONNECT MABEEE".
- Mabeee Level:** A horizontal slider with a red dot at the beginning.
- Execution Mode:** Two radio button options: "Attention Mode" (selected) and "Meditation Mode".
- Final Button:** A large grey button labeled "EXECUTION".

Figure 9 shows an Android smartphone application for the BCI toy. The first step in this application is data acquisition. A user selects the sensor that is being used, verifies “Attention,” “Meditation,” or “Other” (the last state can be verified only for EPOC+), and presses the “COLLECT DATA” button. Subsequently, the application begins to obtain data and subsequently generates a model automatically. The application obtained data for 30 s at a time and saves the data on a smartphone. After obtaining data repeatedly, the dataset can be expanded to generate a model for mental state classification. The saved data and generated model are removed by the “CLEAR DATA” button.

After generating the model, the BCI toy is operated. The “CONNECT MABEEE” button connects the application with MaBeee, and “MaBeee Level” indicates the output level of MaBeee. The following two execution modes can be selected.

- **Attention Mode:** The output of MaBeee is increased if the state is judged as “attention,” and decreased if the state is judged as “meditation.” The output does not change in the case of “other.”
- **Meditation Mode:** The output of MaBeee is increased if the state is judged as “meditation,” and decreased if the state is judged as “attention.” The output is not changed in the case of “other.”

For example, using the “Attention Mode,” a higher concentration increases the speed of the toy car during a game. For the train toy, the concentration shifts to the train during the game, and relaxation halts the train at a specific point, such as at a station. Meanwhile, an illumination toy can be operated using the “Meditation Mode,” and lighting is increased with more relaxation. Finally, a BCI toy is operated by pushing the “EXECUTION” button.

When operating a train toy in the “attention” mode in real-life experiments, operation is extremely difficult when using MindWave Mobile. Because this sensor only supports two classes, the state is always judged as attention or meditation. Therefore, the train always undergoes repeated acceleration or deceleration. Consequently, it is difficult to stably control the train. By contrast, in the case of EPOC+, a relatively stable operation is possible because of its higher accuracy and the “other” mental state.

As regards the BCI toy designed in this study, the operation becomes more stable if the data are obtained under stable mental states. In this case, the accuracy of the model will increase, which allows the users to achieve a specific mental state easily. Therefore, the operation of the BCI toy through brainwaves not only affords an entertaining aspect but also an appealing data acquisition method to generate a higher performance classification model.

7. CONCLUSIONS

In this study, two brainwave sensors—Neurosky MindWave Mobile and Emotiv EPOC+—were compared in the classification of three mental states. Data analysis was performed using three machine-learning methods: SVM, random forest, and LSTM. Notably, the accuracy for the three classes was unsatisfactory when using MindWave Mobile; furthermore, it could support a maximum of only two classes. By contrast, EPOC+ demonstrated a significantly higher accuracy for three classes.

Results of the data analysis showed that the accuracy of the SVM varied when the number of datasets used was insufficient. The accuracy of the random forest improved steadily as more datasets were used. In addition, the LSTM demonstrated a relatively higher accuracy even at in the early stage. In all the cases, the accuracy stabilized when approximately 120 datasets were used. Random forest showed the best performance for every aspect.

Finally, a BCI toy was designed for application to reflect the analysis results. MindMobile is easy to use; however, its accuracy is unsatisfactory because it comprises only one channel, and only two-state classification is available. Therefore, MindWave Mobile is limited to simple operations, such as ON and OFF controls. Meanwhile, EPOC+ is time-consuming. In particular, the pads of the electrodes must be dipped into a physiological salt solution and then exchanged frequently. However,

for tasks that require detailed and varied operations, higher-channel brainwave sensors such as EPOC+ should be adopted.

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