EEG-Based Emotion Recognition Using Deep Learning Model for Workers Safety

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Recently, industrial robots and collaborative robots are widely used in industrial sites with the introduction of smart factory. In a human-robot collaboration environment, it is important to ensure the safety of workers above all. This study suggested an EEG-based deep learning model-based worker safety management system that guards employees by identifying their feelings when they perceive risk. We evaluated and examined the performance of the suggested CNN, DNN, LSTM, and CNN-LSTM models in order to determine which deep learning model would work best for EEG-based emotion identification. With 71.3% accuracy while utilizing the SEED dataset as input information, the CNN-LSTM model demonstrated good performance; with 74.4% accuracy, the CNN model demonstrated good performance when using the real gathered data set. The proposed deep learning model has a small number of parameters, a small size, and fast processing time, which is advantages for real-time application.

Keywords: Human-Robot Collaboration, Workers Safety, Brain-Computer Interface, Electroencephalogram, Deep Learning, Emotion Recognition.

1. Introduction

With the introduction of smart factory technology, more efficient manufacturing technology grafted with ICT technology is becoming more important in traditional manufacturing, and next-generation industrial robots and collaborative robots are expected to lead the future manufacturing market (Maya, 2021). Human-robot collaboration (HRC) combines the precision of robots with the skills of human workers to make manufacturing more flexible and improve product quality and productivity. One of the important issues of HRC is to ensure the safety of workers in collaboration (Pablo et al., 2022; Antonelli & Stadnicka, 2019). In general, HRC systems ensure the safety of workers by creating a collision-free trajectory based on distance between the human and the robot using a visual sensor (Halme et al., 2018). These robot collision avoidance algorithms are difficult to apply to new environments because defined parameters must be adjusted when the collaboration environment changes (Robla et al., 2017).

A Brain-computer interface (BCI) is a system through which a user can communicate with an external device such as a computer without involvement of peripheral nerves and muscles. The BCI collects brain signals that reflect the user’s intention, extracts features, and transfers these features to an external device to operate the external device in the way the user desires (Mudgal et al., 2020). Recently, non-invasive EEG devices are widely used for BCI applications. These devices are safe, easy to use, portable, and have high temporal resolution (Khosla et al., 2020). Thanks to these advantages, BCI systems based on EEG are applied to various fields such as wheelchair control, virtual reality, robot control, games, driver fatigue monitoring, and emotion recognition (Mamunur et al., 2020). In particular, in the field of emotion recognition, human emotions can be identified using facial expression, behaviors, words, and bio-signals. Since people can consciously or unconsciously hide their emotions, identification of emotions based on bio-signals is more reliable and objective (Torres et al., 2020). Compared to other peripheral nerve signals, brain signals change rapidly according to emotions, so the EEG-based BCI system is effective in recognizing emotions (Xiaowel et al., 2009).

Techniques for utilizing a variety of AI models to identify emotions from EEG data have been presented recently. While deep learning models, like convolutional neural networks (CNNs) and long short-term memory (LSTM), automatically learn features and classify emotions, machine learning models require a preliminary process of extracting features from training data (Alhagry et al., 2017; Wang et al., 2020; Sharma et al., 2020). Furthermore, by employing spectral components from EEG data, such as spectral density (PSD) and differential entropy (DE), this research increased the accuracy of deep learning models in recognising emotions (Du et al., 2020; Yin et al., 2021; An et al., 2021). Excellent performance for emotion identification was demonstrated by the deep learning algorithm based on EEG characteristics; nevertheless, its high computational complexity is a drawback. Across various domains, the prevailing approach involves employing deep convolutional networks. These networks are used for segmenting features, extracting essential information, and categorizing diseases in plants, animals, and fish (Cho et al., 2024; AlZubi, 2023; Wasik and Pattinson, 2024). Furthermore, they are extensively utilized in the manufacturing industry (Porwal, 2024).

This study aims to develop a collision avoidance technique that guarantees the safety of workers by recognizing negative emotions from the EEG that occur when workers feel danger. In order to do this, we put out a deep learning model that can identify unpleasant feelings. Additionally, comparisons and analyses were done on the suggested deep learning model's performance. The EEG-based workers safety management system that this study suggests is depicted in Figure 1. The structure of this document is as follows. Section 2 examines earlier research on deep learning technology-based emotion identification, while Section 3 presents the study's data, data gathering techniques, and suggested deep learning models. Section 4 compares and analyzes the performance of the proposed deep learning model, and section 5 summaries and discusses the future work.

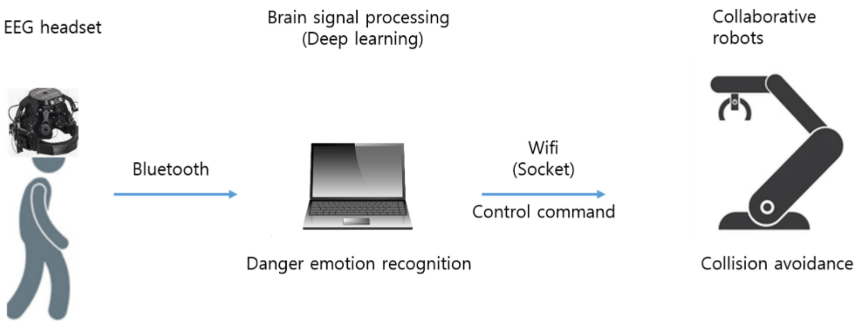

Fig. 1: The Structure of Proposed Worker Safety Management System

2. LITERATURE REVIEW

2.1 Emotion Model

Psychologists have mainly used two techniques to classify emotions: the basic emotion model and the dimensional model. Emotion models widely used in emotion recognition research are the Ekman model (Ekman & Oster, 1979) and the Russell circumplex model (Russell, 1980). Ekman proposed six basic emotion categories: sadness, surprise, happiness, disgust, fear, and anger. Russell defined emotion as a two-dimensional valence-arousal dimension model, as shown in Figure 2. First area is high arousal-positive valence (HAPV), area 2 is high arousal-negative valence (HANV), area 3 is low arousal-negative valence (LANV) and area 4 is low arousal-positive valence (LAPV).

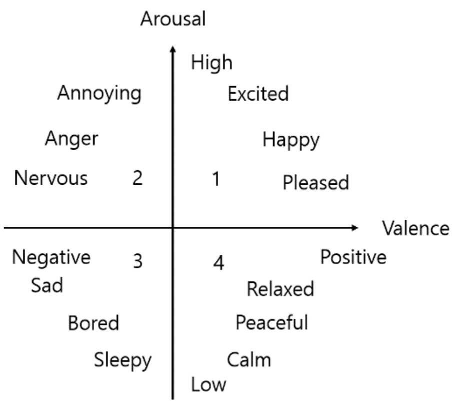

Fig. 2: The 2D Emotion Model

2.2 Feature Extraction

Typically, the most important step in a machine learning system is feature extraction from a training dataset. Feature extraction removes unnecessary information, extracts key information, and reduces the dimension of data to reduce the amount of computation and memory. This improves the efficiency and performance of the analysis system. In the case of EEG-based emotion recognition, it is not easy to extract effective features because each person has a significant difference in the cognitive process. There are various techniques for extracting features of EEG data, such as differential entropy (DE) (Cui et al., 2022), power spectral density (PSD) (Maeng et al., 2020), fast fourier transform (FFT) (Hasan et al., 2021), Hjorth (Falvão et al., 2021), band power (Anubhav et al., 2020), wavelet-based features (Cheng et al., 2021) were mainly used. Among these techniques, FFT is the most widely used method for feature extraction and is known to be very effective in classifying various emotions.

2.3 Deep Learning Methods for EEG Emotion Recognition

Recent research on emotion identification has made extensive use of deep learning models, which have a high classification accuracy. Du et al. used an LSTM model to classify emotions after calculating DE from the EEG. In order to categorize emotions, Yin et al. computed DE from the EEG and created a graph for a graph convolutional neural network (GCNN) and LSTM. Additionally, a 3D CNN model was used by an et al. to classify emotions after calculating DE by separating EEG by frequency sub-band and reconstructing it into 3D spatio-temporal data. Hasen and colleagues used a DEAP dataset to conduct FFT. Using a CNN model to extract characteristics, emotions were categorized. These experiments demonstrate that by extracting significant characteristics, deep learning models may achieve higher recognition accuracy. According to recent research, the deep learning model's classification accuracy varies from 61.25% to 97.56%, demonstrating that it outperforms the current machine learning approach in terms of emotion categorization (Houssein et al., 2022).

3. RESEARCH METHODOLOGY

3.1 Dataset

In this study, the SEED dataset (Lu, 2013), which is open data, was used for EEG-based emotion recognition. Also, raw EEG data was collected using IAPS images (Lang et al., 2008). The SEED dataset consists of happy, sad, and neural film clips to induce positive, negative, and neutral emotions. The SEED dataset consists of data from a total of 15 participants (7 males and 8 females). The EEG was collected using a 62-channel ESO NeuroScan System while the participants watched film clips of different emotions. The SEED dataset has 675 (45 * 15) EEG data, and consists of 15 happiness, 15 sadness, and 15 neutral emotion data for each participant. EEG was collected at a basic sampling rate of 1000Hz, and noise was removed using a 0-75Hz bandpass filter. Additionally, EEG recordings were down-sampled to 200Hz to speed up the calculations. The most widely used tool for emotion induction is the IAPS. The IAPS consists of 1200 images in total of 20 groups, each group containing 60 images. Each image is assigned an arousal and a valence. In this study, images were used to induce positive and negative emotions. Based on valence, images exceeding 6 were selected as positive, and images below 4 were selected as inducing negative emotions.

3.2 Data Collection

The EEG data in this study was collected using Wearable Sensing's DSI-24 device. DSI-24 is a wireless EEG device using a dry sensor with 21 channels, with a bandwidth of 0.003-

150Hz and a sampling rate of 300Hz. The channels used for data collection are six channels including Fp1, Fp2, F3, F4, F7, and F8 based on the international 10-20 system. It is known that the selected locations are closely related to emotions (Nakajima et al., 2022). Figure 3 shows the international standard 10-20 electrode system.

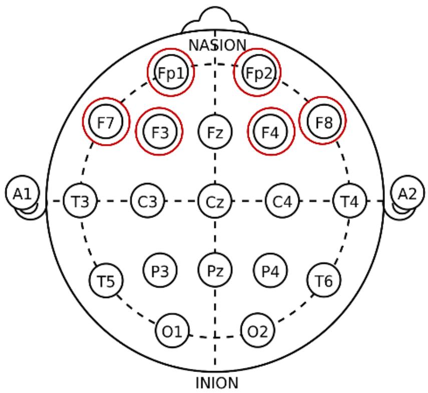

Fig. 3: International 10-20 Electrode System

The participants in the experiment were 5 adult males in their 20s, with an average age of 25.5 years. Before the experiment, the participants listened to the explanation of the experiment method and precautions, signed the consent form, and then participated in the experiment. IAPS images were used for emotion induction, and Figure 4 shows the experimental procedure for EEG data collection.

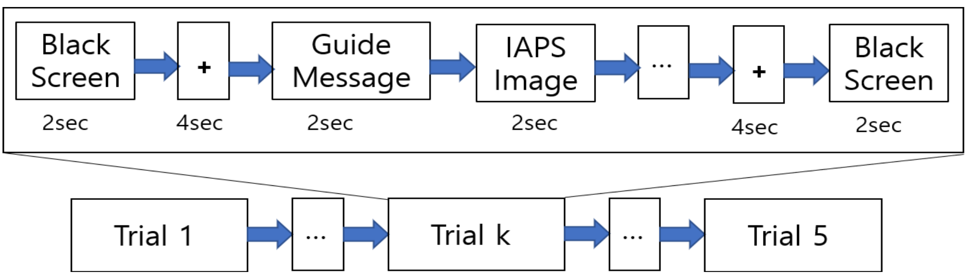

Fig. 4: Experiment Procedure for Collection of EEG Data

A total of 5 experiments were conducted for one participant, and each experiment consisted of a black screen for 2 seconds, a cross mark for 4 seconds, a guide message for 2 seconds, and an emotional image for 2 seconds. In one experiment, 20 IAPS images related to positive or negative emotions appeared randomly. EEG data was used as neutral emotion data when a cross mark appeared.

3.3 Deep Learning Model Overview

Data Preparation

EEG data obtained from and EEG device is difficult to use as input data for a deep learning model, and must be expressed in an appropriate form for deep learning model training. In this paper, the SEED dataset and the EEG dataset collected through Figure 4 were used as input data for the proposed deep learning models. Two types of data, raw EEG and FFT-converted EEG, were used as input data for the deep learning model. The SEED data file has the size of 6 rows and 2000 columns by considering 10 second EEG as one data. The collected EEG data file has a size of 6 rows and 600 columns, considering 2 second EEG as one data. For the feature extraction, FFT was applied to each EEG file, and the input data after applying FFT is the same as the data size of the raw EEG data. Table 1 shows the array sizes of input data for the SEED and collected dataset.

Table 1: Array size for train-test split of 80/20 ratio for EEG experiment

Data Set	Array	Shape	Contents
SEED	Train Data	15 x 45 x 16 x 6 x 2000	#Subjects x #Videos x #Num of video splits x #Channel x #EEG quantized signal
	Train Label	15 x 45 x 16 x 6 x 3	#Subjects x #Videos x #Num of video splits x #Channel x #Label (positive, negative, neutral)
	Test Data	15 x 45 x 4 x 6 x 2000	#Subjects x #Videos x #Num of video splits x #Channel x #EEG quantized signal
	Test Label	15 x 45 x 4 x 3	#Subjects x #Videos x #Num of video splits x #Channel x #Label (positive, negative, neutral)
Ours	Train Data	5 x 328 x 6 x 600	#Subjects x #Pictures x #Channels x #EEG quantized signal
	Train Label	5 x 328 x 3	#Subjects x #Pictures x #Channels x #Label (positive, negative, neutral)
	Test Data	5 x 82 x 6 x 600	#Subjects x #Pictures x #Channels x #EEG quantized signal
	Test Label	5 x 82 x 3	#Subjects x #Pictures x #Channels x #Label (positive, negative, neutral)

Structure of Deep Learning Model

In this paper, we proposed 4 types of deep learning models to find the most effective deep learning model for EEG data related to emotion recognition. In order to recognize the negative emotions of workers collaborating with robots and deliver them to the robot, not only the accuracy of emotion classification but also the processing time are important factors. Therefore, we proposed deep learning models with a possible small model size while maintaining appropriate classification accuracy. Figure 5, 6, 7, and 8 show the structures of the CNN, DNN, LSTM, and CNN-LSTM models proposed. Also, Table 2 shows the number of parameters and hyperparameters of each model.

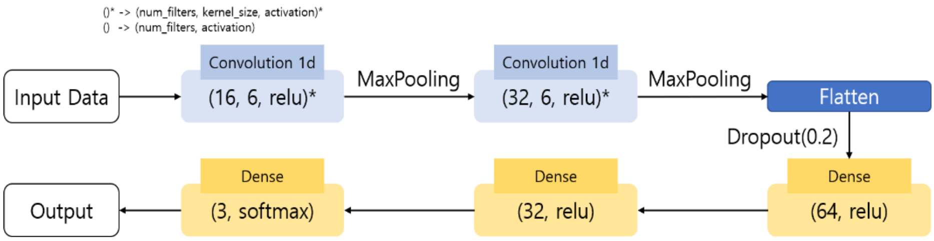

Fig. 5: CNN model

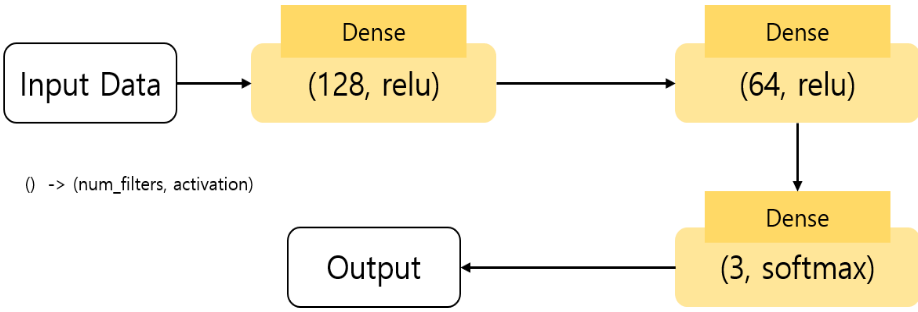

Fig. 6: DNN model

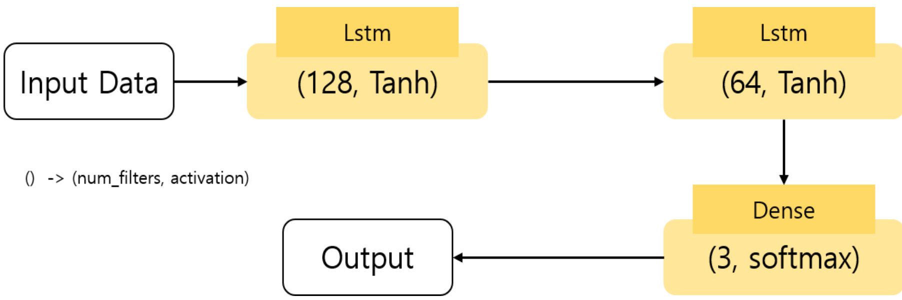

Fig. 7: LSTM model

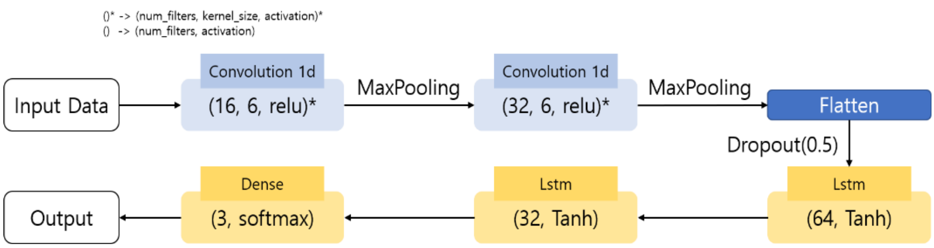

Fig. 8: CNN-LSTM model

Table 2: Parameters of proposed deep learning models

Model	Layers (filter, activation)	Num. of Parameter	Dropout Rate	Learning Rate
CNN	2 Conv (16, 32, relu) + 3 Dense (64, 32, relu) (3, softmax)	38,707	0.2	0.01

Model	Layers (filter, activation)	Num. of Parameter	Dropout Rate	Learning Rate
DNN	3 Dense (128, 64, relu) (3, softmax)	469,379	0	0.01
LSTM	2 LSTM (128, 64, Tanh) + 1 Dense (3, softmax)	1,958,851	0	0.01
CNN-LSTM	2 Conv (16, 32, relu) + 2 LSTM (64, 32, Tanh) + 1 Dense (3, softmax)	41,043	0.5	0.01

4. RESULT AND DISCUSSION

4.1 Classification Performance

Model performance was evaluated to find the most effective model for emotion recognition among the proposed deep learning models. Table 3 shows the performance of each proposed model when the SEED dataset and the collected dataset are used as input data. It also shows the difference in performance between the models when using raw EEG data as input data and when using data after FFT transformation. When using the SEED dataset, the CNN-LSTM model was found to be the most effective, and the model accuracy was 68.4% for raw EEG data and 71.3% for FFT converted data. In addition, when using the collected dataset, the CNN model showed the highest performance, and the model accuracy was 74.4% for raw EEG data and 65.3% for FFT converted data. This result shows that the CNN model is more effective than other models despite the small number of parameters. The CNN-LSTM model using the SEED dataset was consistent with the results of previous studies that feature extraction through FFT conversion improves the accuracy of deep learning models. However, the CNN model using the collected dataset was not consistent with previous studies.

Table 3: Classification performance of the proposed deep learning models

Data Set	Model	Raw EEG		FFT	
		Accuracy	Loss	Accuracy	Loss
SEED	CNN	0.621	0.860	0.675	0.816
	CNN-LSTM	0.684	0.750	0.713	0.680
	DNN	0.418	1.372	0.615	1.056
	LSTM	0.413	1.079	0.560	1.015
Ours	CNN	0.744	0.642	0.653	0.857
	CNN-LSTM	0.600	0.896	0.628	0.919

Data Set	Model	Raw EEG		FFT	
		Accuracy	Loss	Accuracy	Loss
	DNN	0.644	1.106	0.616	4.485
	LSTM	0.642	0.799	0.716	0.704

In this study, various evaluation metrics such as recall, precision, F1-score, and accuracy were used to evaluate the performance of the proposed models. Each evaluation metric is defined as Equation (1)-(4).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{F1} - \text{score} = \frac{2 \times Precision \times Recall}{Recision+Recall} \quad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative

Table 4 and 5 show the 4 evaluation metrics values in using the SEED dataset and the collected dataset as input data. Similar to the result in Table 3, when the SEED dataset was used, the CNN-LSTM model was 0.652(recall), 0.684(precision), 0.668(F1-score), and 0.683(accuracy). Also, when using the collected dataset, the CNN model showed the best performance with 0.676 (recall), 0.692 (precision), 0.684 (F1-score), and 0.714 (accuracy).

Table 4: Classification performance of the deep learning models using SEED dataset

Input Data	Model	SEED			
		Recall	Precision	F1-score	Accuracy
Raw EEG	CNN	0.520	0.534	0.527	0.584
	CNN-LSTM	0.556	0.572	0.563	0.654
	DNN	0.375	0.375	0.375	0.396
	LSTM	0.352	0.355	0.353	0.355
FFT	CNN	0.610	0.664	0.636	0.642
	CNN-LSTM	0.652	0.684	0.668	0.683
	DNN	0.555	0.561	0.558	0.592
	LSTM	0.482	0.489	0.485	0.502

Table 5: Classification performance of the deep learning models using our dataset

Input Data	Model	Ours			
		Recall	Precision	F1-score	Accuracy
Raw EEG	CNN	0.676	0.692	0.684	0.714
	CNN-LSTM	0.553	0.554	0.553	0.592
	DNN	0.589	0.596	0.592	0.611
	LSTM	0.590	0.592	0.591	0.602
FFT	CNN	0.652	0.655	0.653	0.700
	CNN-LSTM	0.489	0.532	0.515	0.532
	DNN	0.477	0.499	0.488	0.522
	LSTM	0.594	0.602	0.598	0.610

4.2 Processing Time Performance

The EEG-based worker safety management system is important to quickly recognize workers' negative emotions to protect workers. Therefore, we used the TensorFlow library as a function for measuring time. The training time is the elapsed time from compile () function is called to the end of fit () function. Testing time is the elapsed time from when predict () function is called until predict () function ends. In addition, transformation time refers to the time required for EEG data to be converted appropriately for deep learning model input. It refers to the elapsed time from the time data is loaded until the reshape () function of the numpy library ends. All times are expressed in seconds. Table 6 shows the training time, testing time, and transformation time when the training-testing dataset ratio is 80:20. Each experiment was performed for 30 epochs using the proposed models. The system environment used is as follows.

CPU = Ryzen 5900, GPU = Geforce 3060, GPU Memory = 12 GB, RAM = 36 GB

Table 6: Comparison of the training, testing, and transformation time among the proposed models

Data Set	Model	Raw EEG			FFT		
		Training	Testing	Transformation	Training	Testing	Transformation
SEED	CNN	95.823	0.283	2.229	97.188	0.310	5.253
	CNN-LSTM	260.316	0.799	2.229	282.802	0.824	5.253
	DNN	46.451	0.176	2.383	45.547	0.152	4.713

Data Set	Model	Raw EEG			FFT		
		Training	Testing	Transformation	Training	Testing	Transformation
	LSTM	231.771	0.859	2.320	228.379	0.832	5.045
Ours	CNN	3.423	0.039	0.072	3.393	0.077	0.092
	CNN-LSTM	7.212	0.361	0.072	7.989	0.362	0.092
	DNN	2.301	0.056	0.071	2.333	0.054	0.091
	LSTM	7.339	0.428	0.072	6.753	0.345	0.090

Regardless of the input dataset, the training, testing, and transformation time were found to be faster for DNN and CNN models, which are relatively simple deep learning model. This result was similar to the raw EEG and FFT data as input data. Overall, the transformation time of the collected dataset was significantly faster than that of the SEED dataset. This is because EEG data for 6 seconds was used as one data in SEED dataset, and EEG data for 2 seconds was used as one data in collected dataset. In the case of the CNN-LSTM model using the SEED dataset, it took 282.802 seconds to training, 0.824 seconds to testing, and 5.253 seconds to transform. The CNN model, which showed relatively good performance, it took 97.188 seconds to training, 0.310 seconds to testing, and 5.253 seconds to transform. This result shows that the training and testing times are significantly reduced while maintaining similar performance to the CNN-LSTM model. In the case of the CNN model using the collected dataset, it took 3.423 seconds to training, 0.039 seconds to testing, and 0.030 seconds to transform. These results indicate that the CNN model is effective as an EEG-based emotion recognition model, and the proposed CNN model takes less than 0.1 second by adding the transformation time and testing time assuming that 2 seconds of raw EEG data is input. This means that emotion classification is performed almost simultaneously with EEG data collection.

5. CONCLUSION AND FUTURE WORK

Ensuring worker safety during HRC at industrial sites is of great importance. The worker safety management system that we presented in this study uses electroencephalography (EEG) to detect the negative emotions of workers and communicates them to cooperating robots. To this aim, a deep learning framework was put up to recognize the emotions of workers. Using the gathered data and the SEED dataset, we examined and contrasted the CNN, CNN-LSTM, DNN, and LSTM models' performances. Moreover, FFT was employed as a method for extracting features, and raw EEG data and FFT data were utilized as input data to assess if it had an impact on the deep learning model's performance. With an accuracy of 71.3% when utilizing the SEED dataset, the CNN-LSTM model had the greatest performance among the suggested models; with an accuracy of 74.4% when using the gathered dataset, the CNN model demonstrated the highest performance. Furthermore, a comparison was conducted between the training, testing, and transformation times of the suggested models for real-time implementation. Specifically, the CNN model accomplishes emotion categorization in less than 0.1 seconds after receiving two seconds of raw EEG data as input. This outcome demonstrates that a variety of applications requiring real-time application may make use of the suggested CNN model. We intend to obtain more datasets in the future in order to investigate a broadly applicable model and raise the model's classification accuracy.

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