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The Application of Emotion Detection System (EmoD) in Online Learning

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ABSTRACT

Measuring the student's emotions can help the teacher increase student engagement during Teaching and Learning (TnL) and simultaneously help the teachers measure the effectiveness of the TnL activity. However, most online TnL activities do not consider the learner's emotions and affection. Not all facial recognition methods can detect emotion, especially in real-time. To overcome this problem, we developed an Emotion Detection System (EmoD) to recognize and identify the emotion based on its class using ResNet 50. Using the System Usability Scale (SUS), the EmoD was reported as acceptable (mean = 78.5). Other than that, the EmoD system can be utilized for online consultation and classes. In the future, the EmoD will be enhanced so that it can be used to detect more than one user to make it more useful for online learning.

Keywords:
Emotion recognition; ResNet 50; Online learning

1. Introduction

Online learning can be divided into synchronous and asynchronous learning [1]. Asynchronous learning is when the educator uploads all the learning materials, such as videos, assignments, quizzes, and all activities (not in a real-time), so students can have ample time to download and review all the activities. Meanwhile, synchronous learning involves real-time interaction between educators and students. [2] have discussed all the features covered in these two methods. Note that the learning process should be a two-way interaction between student-educator and make the subject more interesting. This situation will increase student satisfaction and develop positive emotions toward the learning process [3-6]. Based on the lay theory [5], an agent is a reasoner who can produce emotions when there are emotional stimuli and interaction of mental states. Hence, speech, body language, facial expressions, or further actions can signal this.

E-learning can be categorized into two parts: blended learning and Massive Open Online Courses (MOOC). Recently, a study on emotion recognition has been discovered and discusses the software

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employed to evaluate users' emotions using a website camera (webcam) in real-time [7]. The study used facial expressions captured by webcams to increase the efficiency level of TnL [9]. The use of this method can provide a quick response during e-learning.

It is hard to observe student reactions during online learning, especially when you have many students. The same problem occurs for self-paced e-learning. The crucial challenges were uncaptured emotions for the student, which affected the achievement of learning activities. Not all facial recognition methods can be used to detect emotion detection, and there are still a few adequate strategies to discourse the existence of emotion during learning. Note that emotion recognition involves facial detection, extraction, and classification. In [10], wavelet transform, and K-Nearest Neighbors (KNN) algorithm were utilized to detect faces and classify emotions. On the other hand, Support Vector Machine (SVM) presented better results in identifying facial expressions using the Gabor wavelet and shape feature [11]. Out of many techniques used in emotion detection, the deep neural network approach has become more popular. For example, the convolution neural network (CNN) in [12] increases the efficiency of feature extraction, accuracy, and classification.

During the TnL process, educators who use Google Meet, Zoom, and Webex cannot determine each student's degree of interest [13]. There are many factors to be considered when we want to detect student emotions through online learning. [14] discuss the limitation of these, including the notion that most students tend to turn off their microphone and cameras during online learning. They also utilize different devices, such as laptops, smartphones, and tablets, which might affect image quality. Because of this, educators have difficulties recognizing student emotions when they can only see half of the student image. Furthermore, the environment is different compared to a real classroom. The effectiveness of the TnL can be assessed using active learning during class activities [15]. To do so, the educator should be able to identify their student emotion.

Numerous research has been conducted to identify user emotions, including surveys and discussion boxes. This method is easy to implement but is often criticized because it is unsuitable during the TnL activity [16]. Other than that, several studies have been done to classify emotions into certain classes in the past five years. It aims to make it easier for teachers to identify the emotional level of their students during online learning in real-time or through video recording [17-20]. Most studies apply the Ekman and Friesen model, which divides emotions into seven parts: anger, disgust, fear, happiness, sadness, surprise, contempt, and neutral [21]. In some studies, they do not only focus on this emotion but also cater to the student's attention level [19]. Meanwhile, [22] classified the emotion into eight groups and combined the user's eyes condition (eyes open, eyes closed, eyes semi-open) with their situation (pleasant, fatigued & distracted).

Emotions can be classified based on various features obtained from the multimodal. Multimodal is where you use more than one feature to classify the emotion [23]. Studies that use multimodal can be seen in [17,18]. Some of them do not only use facial expressions but also hand gestures and body posture to classify emotions more accurately. In addition, [18] stated that audio and text features are used to classify the emotion. Apart from that, some studies use single features such as facial expressions to classify emotions [16,19,20,22,24,25].

Emotion recognition not only supports educators in analysing student emotions but can also assist students in learning. In addition, students can self-assess their emotions utilizing emotion recognition [22,24,25]. To ensure it is useful to help students and educators make effective emotional feedback and self-assessment, [16] evaluated FaceReader2.0 regarding the system's effectiveness during computer-based assessment (CBA). The evaluation result presents that FaceReader2.0 is efficient in measuring emotion, and there is no significant difference between genders except for sad emotions.

Most of the studies implemented CNN as a method for emotion recognition. These studies recorded good results for classifying each emotion into its class [17,18,20,22,25]. Apart from that, there is also a study by [14], who employed a hybrid method between deep learning and CNN. Furthermore, the emotional back propagation neural network (EmBPNN) was also utilized by [21] to increase emotion recognition results. Finally, in a study by [26], they tested and compared the result for VGG 19, ResNet 50, Mobile Net, and Inception V3.

The success of emotion recognition is not only based on the model alone but also on the dataset used during training. Several datasets are often used in other studies, such as FER2013 and CK+48 [20]. The difference between each dataset is in terms of the image stored in the data. For example, some images only contain different face angles, and some do not. Other datasets that have been applied for emotion are EmotiW [15], DAISEE [25], iSAFE [25], ISED [25] and Jaffe [20]. Table 1 presents the summary of the paper for the related work.

Table 1
Summary of Related Work

Author	Year	Emotion	Online Learning Focus	Features	Dataset	Method/Technique
Terzis V., Moridis C.N., Economides A.A.	2013	Disgusted Surprised Neutral Angry Scared Sad	Assessment	Facial	Not mentioned in the article	Statistical method - z test
Tseng C.-H., Chen Y.-H.	2018	High-attention level Low-attention level	Teaching	Facial	Not mentioned in the article	Microsoft Cognitive Service
Sudha Kishore R., Sudarsan Reddy A., Chittibabu R.	2019	Happy Sleepy Confused Concentrated Nervous Bored	Learning	Facial	Not mentioned in the article	Emotional Back Propagation neural networks (EmBPNN)
T. S A., Guddeti R.M.R.	2020	Engaged Bored Neutral	Teaching	Facial expression, hand gestures, and body posture	Not mentioned in the article	Deep learning-based hybrid CNN
Author	Year	Emotion	Online Learning Focus	Features	Dataset	Method/Technique
Wang W., Xu K., Niu H., Miao X.	2020	Anger Disgust Fear Happiness Sadness Surprise Contempt Neutral	Teaching	Facial	Jaffe, CK+,and FER2013	CNN

Thiruthuvanathan M.M., Krishnan B., Rangaswamy M.	2021	Anger Disgust Fear Happy Neutral Sad Surprise Confusion Engaged Frustrated Boredom	Learning	Facial	DAISEE, iSAFE, and ISED	CNN models
Wang S.	2021	Eyes open and pleasant Eyes open and calm Eyes open and fatigued Eyes semi-closed and pleasant Eyes semi-closed and fatigued Eyes closed and calm Eyes closed and fatigued distracted from learning	Learning	Facial	Not mentioned in the article	CNN
Chowdry, M. K., Nguyen T. N. & Hemanth, D. J.	2021	Anger Fear Sadness Happiness Surprise Disgust	None	Facial	CK+48	CNN: VGG 19, ResNet 50, Mobile Net, Inception V3
Savchenko A.V., Makarov I.A.	2022	Angry Disgust Fear Happiness Sadness Surprise	Teaching	Audio, text, and facial	EmotiW 2018–2020 challenges	CNN

2. Methodology

2.1 FER2013 Dataset

The FER2013 dataset is divided into two sets: training and testing. Note that FER2013 can be downloaded through the Kaggle website [27]. Both datasets include seven different emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. The images stored in this dataset are from the front angle and different angles of a person's face, which is also in a grayscale form.

Figure 1 illustrates the number of datasets in training.

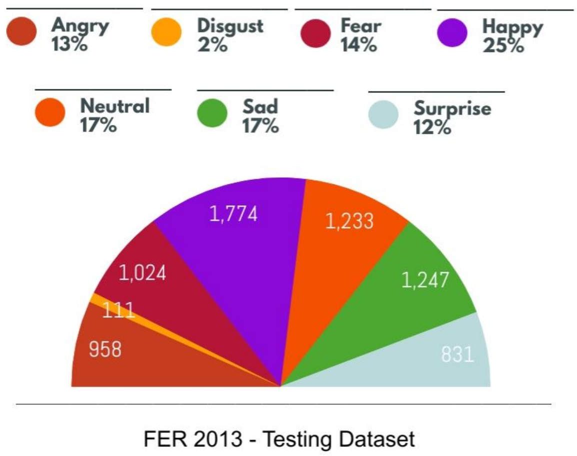

Fig. 1. FER2013 testing dataset

Figure 2 portrays the number in the training sections.

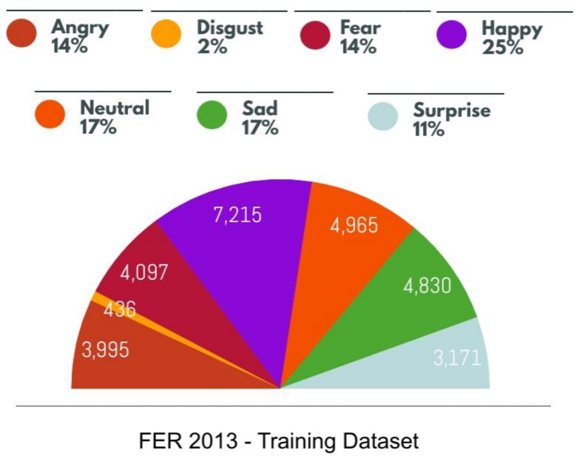

Fig. 2. FER2013 training dataset

Meanwhile, Figure 3 shows an example of the dataset.

Fig. 3. Example of anger dataset from FER2013 dataset

2.2 CK+48 Dataset

Kanade initially developed this dataset [27], later improved by other researchers, and is known as CK+48. Similarly, this dataset can be downloaded from Kaggle [29]. In total, CK+48 contains 750 datasets for five different emotions. The dataset has multiclassification, and there is no specific dataset for training and testing as in FER2013. The emotions involved are anger, fear, happiness, sadness, and surprise. Note that all data are front-view pictures in grayscale format. The emotions described in Figures 4 and 5 display an example of the dataset for the anger emotion.

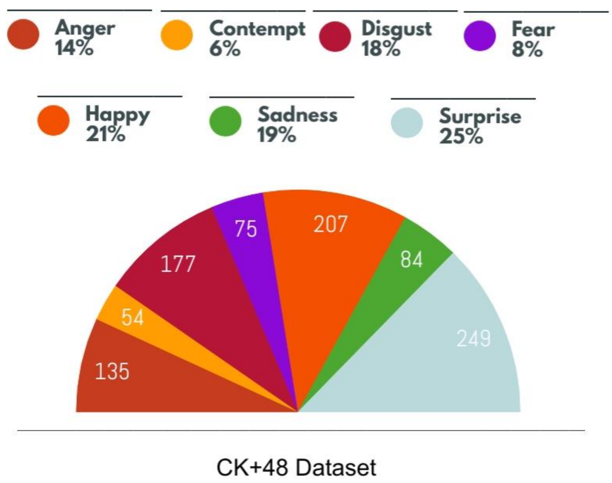

Fig. 4. Emotion in CK+48

Fig. 5. Example of anger dataset from CK+48

2.3 Emotion Recognition

Two datasets from FER2013 and CK+48 was applied to choose the best training dataset for EmoD development. Hence, the parameter in Table 2 is utilized to run both of the datasets with ResNet 50. Based on the accuracy and value loss result, the FER2013 was chosen to develop EmoD.

Table 2
Parameter

Parameter	Value
batch_size	32
num_epochs	50
image_size	(48,48)
input_shape	(48, 48, 1)
validation_split	.2
verbose	1
num_classes	7

2.4 EmoD System

The EmoD System was built using the ResNet 50 model and FER2013 dataset. To use the EmoD, users need to start the EmoD and open the webcam. Note that EmoD can be used to detect single user faces only. Subsequently, the captured image is cleaned up using pre-processing and trained using ResNet 50. Finally, users can display the predicted emotion and download the file in excel format. The EmoD system was developed using Python 3, including Keras and TensorFlow.

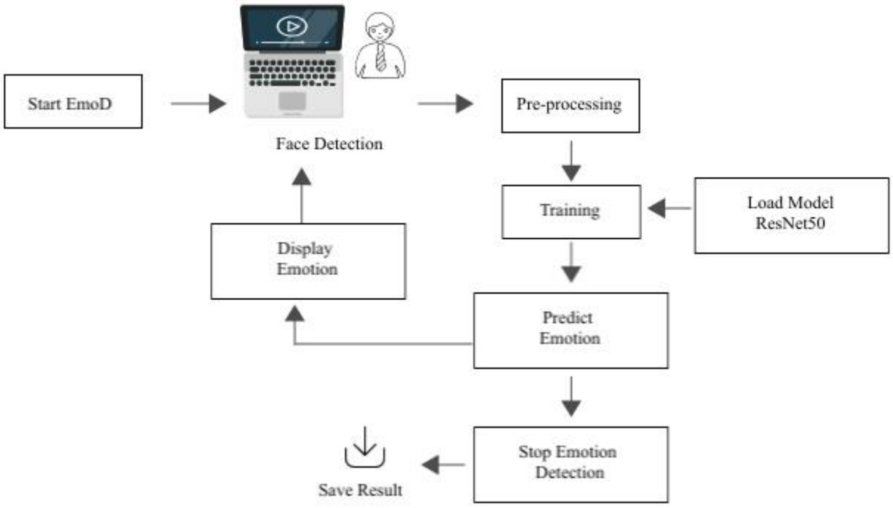

Fig. 6. EmoD architecture

2.5 System Usability Scale

Various criteria are employed to analyse the usability elements. One of them is usability testing, which involves observing how users use the system. To evaluate the EmoD system, we decided to use the SUS. The SUS was applied by [30] Garcia *et al.,* to measure the usability of emotion recognition technologies to teach children with an autism spectrum disorder. For this study, we utilized the SUS item that consists of 10 questions. All participants were asked to complete the question using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Here, we modified the SUS Item, as shown in Table 3. Overall, there are 30 respondents involved in the evaluation.

Table 3
SUS Item

SUS Item	Modified SUS Item
1. I think I would like to use this system frequently.	1. I think I would like to use the EmoD system frequently.
2. I found the system unnecessarily complex.	2. I found the EmoD system unnecessarily complex.
3. I thought the system was easy to use.	3. I thought the EmoD system was easy to use.
4. I think that I would need the support of a technical person to be able to use this system.	4. I think I would need the support of a technical person to use the EmoD system.
5. I found the various functions in this system were well integrated.	5. I found the various functions in the EmoD system were well integrated.
6. I thought there was too much inconsistency in this system.	6. I thought there was too much inconsistency in the EmoD system.
7. I imagine that most people would learn to use this system very quickly.	7. I imagine that most people would learn to use the EmoD system very quickly.
8. I found the system very cumbersome to use.	8. I found the EmoD system very cumbersome to use.
9. I felt very confident using the system.	9. I felt very confident using the EmoD system.
10. I needed to learn many things before getting into this system.	10. I needed to learn many things before getting into the EmoD system.

3. Results and Discussion

3.1 Experiment

Detail experiment was performed to see how different datasets would affect the result for the ResNet 50. At first, the ResNet 50 was trained using FER2013 and Adam optimizer. Consequently, details of the finding are recorded in Table 4. The loss for the validation dataset is slightly higher than the loss in the training dataset. However, there is not much difference between the training and validation accuracy.

Table 4
Result for FER2013 using ResNet 50

Dataset	Training		Validation	
	Loss	Accuracy	Loss	Accuracy
FER2013	0.86	0.68	1.05	0.61

The loss and accuracy curves for FER2013 were plotted in Figure 7 to see the details of the performance. Note that the loss curves graph for validation is higher before epoch 10, but after epoch 30, it starts optimal. For the accuracy curves, validation is dropped from epoch 30 onward, but the difference is less than 0.05.

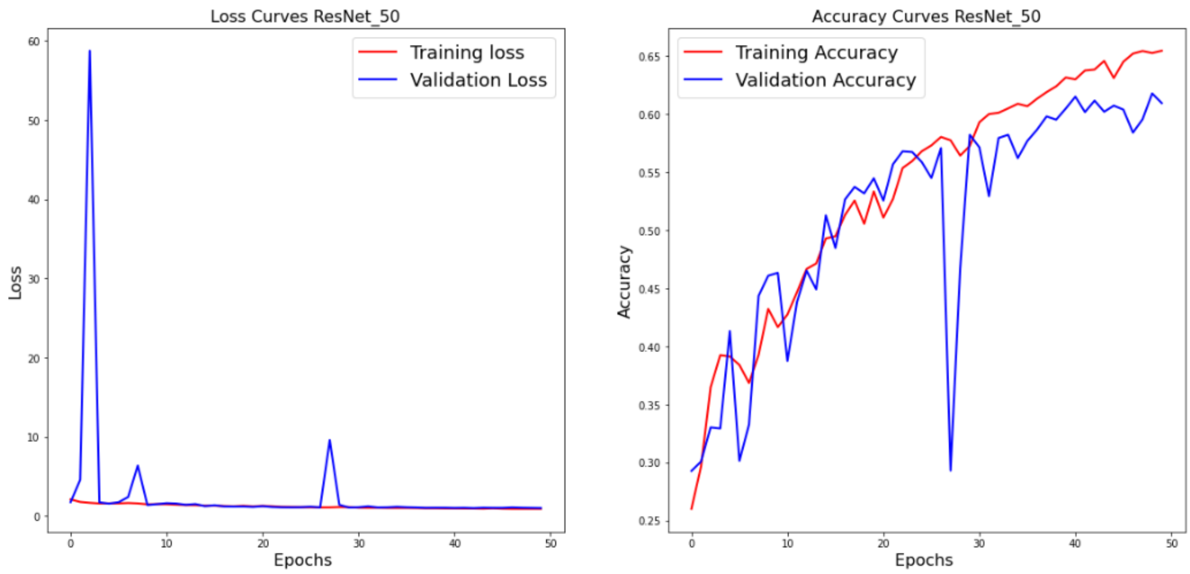

Fig. 7. Loss and accuracy curves using FER2013 (Optimizer: Adam)

Figure 8 is a confusion matrix for ResNet 50 using the FER2013 dataset. From 61% of accuracy, the highest predicted emotion is happiness (19.72%), and the lowest emotion is disgust (0.84%). Other than that, the model does not class if class fear and class happiness with class anger data. A total of 354 data for class sadness were misclassified by the model, which is the highest misclassification rate among all the classes. This resulted in the model being challenging in differentiating between sadness and anger.

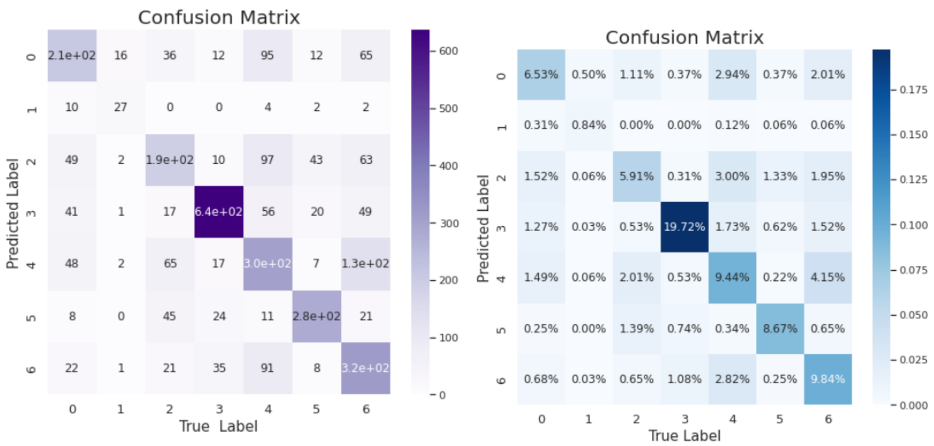

Fig. 8. FER2013 confusion matrix (0=anger, 1=disgust, 2=fear, 3=happiness, 4=sadness, 5=surprise, 6=neutral)

Alternatively, we also tested the ResNet 50 with the CK+48 dataset to compare the result. The ResNet 50 was trained using CK+48 and Adam optimizer. Details of the finding are recorded in Table 5.

Table 5
Result for FER2013 using ResNet 50

Dataset	Training		Validation	
	Loss	Accuracy	Loss	Accuracy
CK+48	0.13	0.95	0.26	0.9

The loss validation is a bit higher than the training dataset loss. However, there is not much difference between the training and validation accuracy. Note that the loss and accuracy curves for CK+48 were plotted in Figure 9 to see the details of the performance. The loss curves are optimal after epoch 2. There is a slight difference between training and validation accuracy before epoch 30.

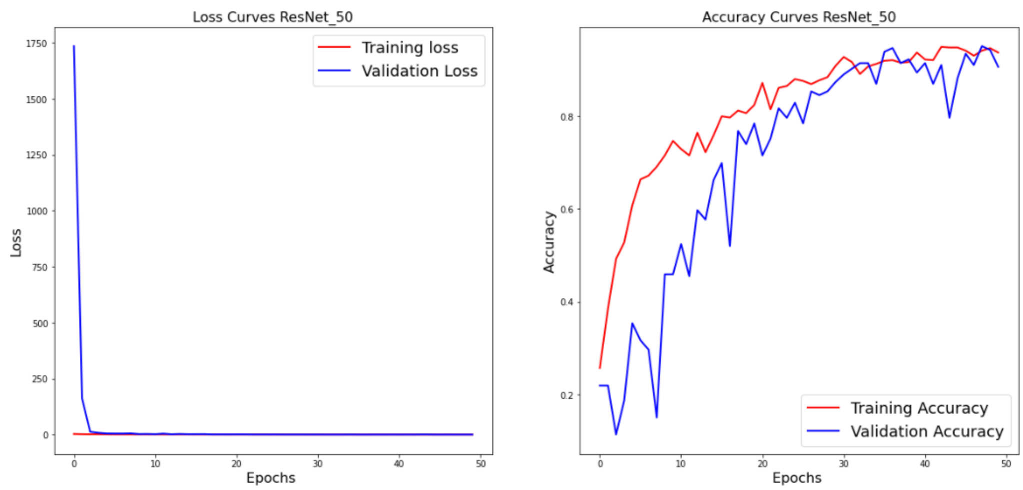

Fig. 9. Loss and accuracy curves using CK+48 (Optimizer: Adam)

Figure 10 is a confusion matrix for ResNet 50 using the CK+48 dataset. There is a difference between the accuracy using FER2013 and CK+48 datasets due to the different image amounts in both datasets. Note that the CK+48 can produce higher accuracy compared to FER2013. Based on the confusion matrix, class anger, fear, and sadness were reported as higher predicted data than others.

The lowest emotion is class happiness, with 3.66%. Here, the model misclassified 6 data for class fear and class sad as it struggled to differentiate between class fear and class surprise from all classes.

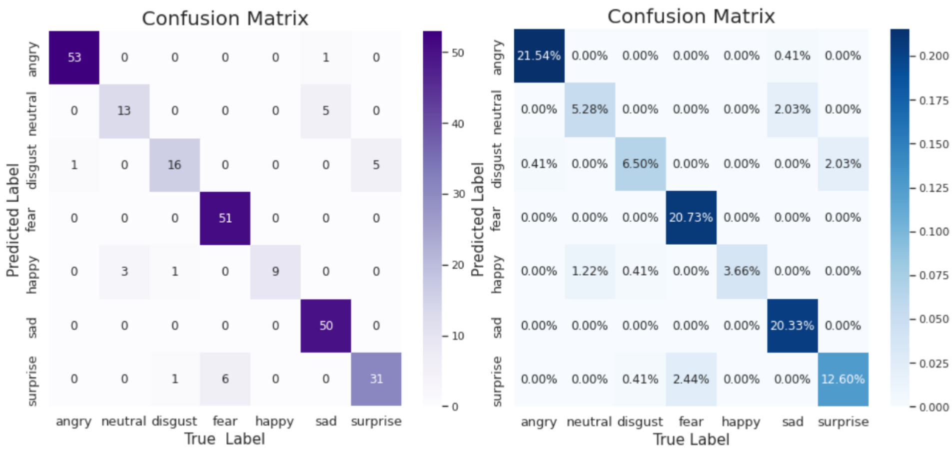

Fig. 10. CK+48 confusion matrix

3.2 EmoD System Result

After a detailed investigation, this study utilized the FER2013 database and the ResNet 50 model to develop the EmoD system for online learning. Even though the accuracy produced by FER2013 is not higher compared to CK+48, we opted to use it as the FER2013 contains more images with different angles of faces. Figure 11 illustrates the use case diagram for the system. Users need to start the EmoD system by clicking the start button and activating their cameras. For this study, we only cater to desktop webcams. Subsequently, EmoD will capture the user's face as a feature and pre-process the image. Using the ResNet 50, the EmoD classifies the emotion based on seven classes (angry, fearful, neutral, disgusted, happy, surprised, and sad).

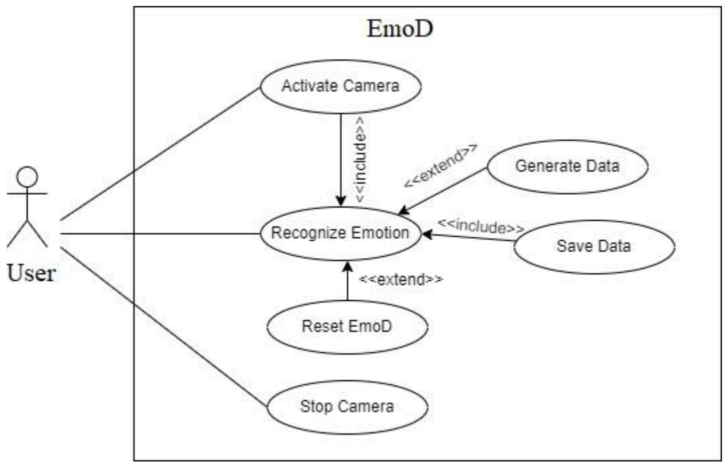

Fig. 11. EmoD use case diagram

Figure 12 demonstrate the interface for the EmoD system and how it can capture the user's emotions during live consultation. During emotion detection, users can minimize the EmoD window without interrupting the emotion detection process.

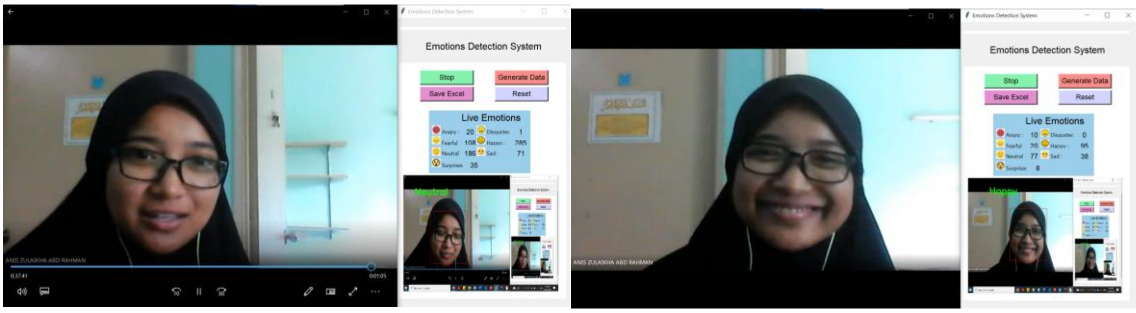

Fig. 12. EmoD detecting emotion changes during an online consultation

3.3 EmoD SUS Result

From Item 1, 67% (mean 3.80) of respondents agree that they will use the EmoD system frequently. This result indicates that the respondent has a very high tendency to use this app during online learning. Regarding ease of use (item 3), 7 respondents agree, and 22 strongly agree. This implies that 97% (mean 4.7) strongly agreed that the EmoD system is straightforward. For items 5 and 7, only 3.3% of respondents disagree with items. From the mean for items 5 (mean = 4.2) and 7 (mean = 4.4), we can infer that the average respondent agrees that EmoD is well integrated and people would learn to use it very quickly. Other than that, they learn to utilize EmoD very fast. In response to item 2, 50% of the participants disagreed with the statement that the EmoD system is unnecessarily complex.

Additionally, 80% disagree that using the EmoD requires technological assistance. It obliquely supports item 3, where most respondents concur that the system is easy to use. With a mean value of 2.2, 63% of respondents of item 6 disagreed with the claim that there was much inconsistency in the EmoD system. The means for items 8 and 9 are 1.8 and 1.7, respectively. Most of the respondents disagree with the statements that the EmoD system is difficult to use and that there is a lot to understand before using it. Table 6 presents the overall SUS result.

Table 6
Overall, SUS Item Result

SUS Item	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean	SD
1. I think I would like to use the EmoD system frequently.	0	1	9	14	6	3.8	0.7915
2. I found the EmoD system unnecessarily complex.	6	9	6	6	3	2.7	1.2905
3. I thought the EmoD system was easy to use.	1	0	0	7	22	4.6	0.8087
4. I think I would need the support of a technical person to use the EmoD system.	13	11	4	1	1	1.9	1.0080
5. I found the various functions in the EmoD system were well integrated.	0	1	6	9	14	4.2	0.8867
6. I thought there was too much inconsistency in the EmoD system.	9	11	8	0	2	2.2	1.0854
7. I imagine that most people would learn to use the EmoD system very quickly.	0	1	3	9	17	4.4	0.8137
8. I found the EmoD system very cumbersome to use.	15	10	4	1	0	1.7	0.8367

9.	I felt very confident using the EmoD system.	0	0	6	7	17	4.4	0.8087
10.	I needed to learn many things before getting into the EmoD system.	16	12	1	0	1	1.6	0.8550

The average SUS score for all participants is shown in Figure 13 in graph form, with a minimum score of 57.5 and a maximum score of 97.5.

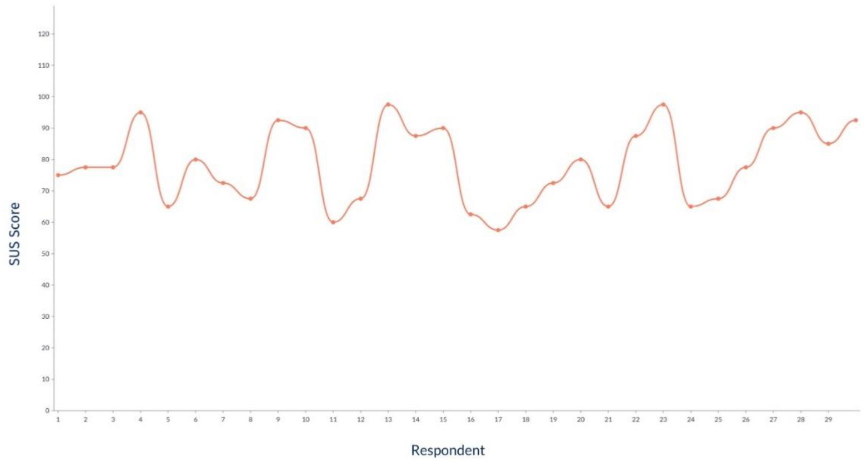

Fig. 13. SUS score for all respondent

Meanwhile, the mean result for the overall modified SUS item is shown in Table 7.

Table 7
SUS score rating summary

Modified SUS Items	Overall, SUS Score	Rating
10	78.5	Acceptable

Figure 14 demonstrates the posterior mean and 95% credible interval from the t distribution for the EmoD system. The min and max indicate the overall results of the minimum and maximum scores for the single-participant SUS score. The frequencies for single-user SUS are shown using the circle, where a larger circle represents many scores [31]. As we can observe, the mean for the SUS score is 78.50, which falls under acceptable.

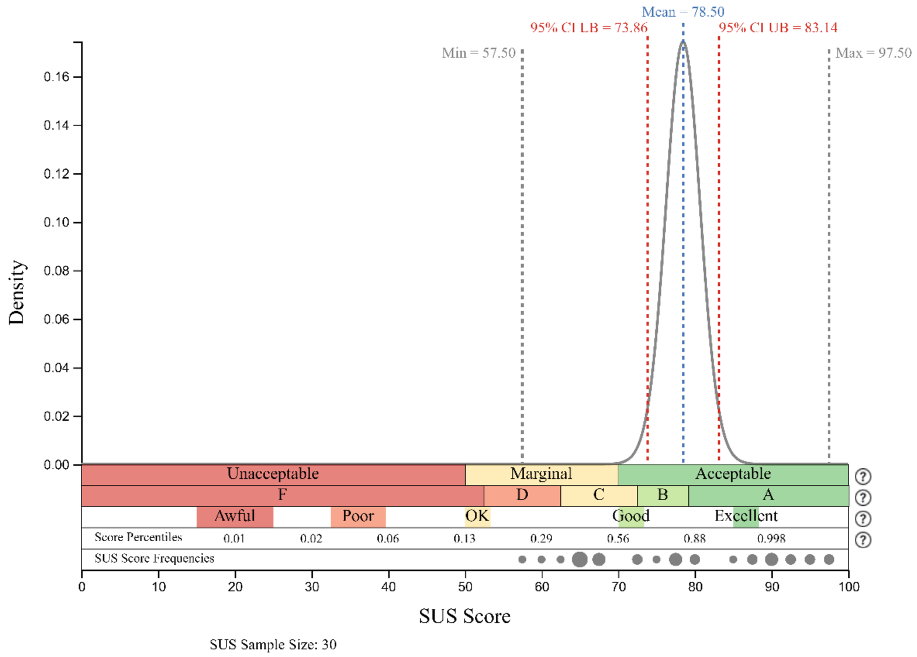

Fig. 14. Posterior mean for EmoD system

4. Conclusions

This study aimed to develop an emotion recognition system to detect emotion. The EmoD system can assist educators and learners in analysing emotions during TnL activities. We investigated two datasets for emotion recognition which are FER2013 and CK+48. Even though CK+48 produces higher results, the dataset in FER2013 is more detailed than CK+48. To develop the complete system for EmoD, we employed ResNet 50. Regarding usability, 30 respondents who were involved in online learning were asked to use the system and completed the SUS item. Overall, the EmoD system was reported as acceptable, with a mean value of 78.5%. This system will be expanded to accept text and face to classify emotions during online learning.

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