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Research Article

How Do Students Feel in Online Learning Platforms? How They Tell It: How Does Artificial Intelligence Make a Difference?

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Abstract: This study aims to investigate the effectiveness of an artificial intelligence (AI) model in determining students' emotional states during online courses and compares these AI-generated results with traditional self-report methods used in educational sciences. Conducted with 66 students from three different departments of a public university in Eastern Turkey during the 2021-2022 academic year, the study involved capturing facial images of students every 10 minutes during online lectures to analyze their emotional states using a deep learning-based CNN model. In addition, students provided their emotional states through a mood analysis form, which included personal information and subjective feelings such as happiness, sadness, anger, and surprise. The AI model achieved a high accuracy rate of 90.12% in classifying seven different emotional states, demonstrating its potential for real-time emotion recognition in educational settings. However, the study also found a 39% overlap between AI-determined emotional states and self-reported emotions. This finding emphasizes the need for a multifaceted approach to emotion measurement, integrating both advanced AI techniques and traditional self-report tools to more comprehensively understand students' emotional experiences. The results highlight the challenges and opportunities in combining technology with educational assessments and suggest directions for future research in improving emotion detection methodologies and their application in online learning environments.

Keywords: Emotions, Sentiment Analysis, Artificial Intelligence, Online Learning, Self-Report

1. Introduction

Distance learning has become significantly crucial on a global scale, particularly amidst the ongoing pandemic (Kim, 2020). The measures implemented during the crisis to sustain education using available resources are called emergency distance learning (Bozkurt, 2020). However, many teachers and students encountered distance learning for the first time. As a result of this experience process, the decrease in face-to-face interaction (Yolcu, 2020; Kumar et al., 2021; Sealy, 2021), the difficulty in keeping the motivation of the learners (Uçar, 2017; Gustiani, 2020), and the self-management and self-direction skills of the learners (Al-Taweel et al., 2020; Bozkurt, 2020) are listed as problems experienced in distance learning environments. Despite these limitations, developments in information and communication technologies offer important opportunities for formatting learning environments and increasing the motivation of learners (Pintrich, 2003; Bayrakçeken et al., 2021). In addition, these technologies are also used to determine the emotions of the students during e-learning. Research is being conducted on the effect of technology-enriched environments on student emotions (Imani & Montazer, 2019; Lacave et al., 2020). Additionally, certain features of these environments have specific effects on student emotions (Peng & Xu, 2020). There is also research on how emotions influence the use of self-regulation strategies (D'mello & Graesser, 2013; Taub et al., 2020). Finally, studies examine how students' emotions change during lessons (Sarrafzadeh et al., 2008; Bulut Ozek, 2018; Tonguç & Özkara, 2020; Hasnine et al., 2021).

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When the literature is examined, several key areas of research can be identified. One area explores the effects of technology-enriched environments (Imani & Montazer, 2019; Lacave et al., 2020). Another focuses on how certain features of these environments impact students' emotions (Peng & Xu, 2020). Additionally, there are studies on the effect of emotions on the use of self-regulation strategies (D'mello & Graesser, 2013; Taub et al., 2020). Finally, research has been conducted on how students' emotions change during the lesson (Sarrafzadeh et al., 2008; Tonguç & Özkara, 2020; Hasnine et al., 2021). However, recent studies in education have emphasized the critical role of emotions in decision-making, timing, and managing learning activities (Zembylas, Theodorou, & Pavlakis, 2008; Yadegaridehkordi vd., 2019; Chevalère et al., 2023; Sydänmaanlakka et al., 2024; Yuan et al., 2024), and increasing the motivation of students in learning (Bouhlal, et al., 2020). It has been stated that cognition, motivation, and emotion, which have very interconnected structures in the learning process, are handled one by one in research, and especially emotion is the least studied component (Öztüre et al., 2021). However, research showed that there are connections between these groups such as success-emotions (Putwain, Becker, Symes, & Pekrun, 2018), emotions-learning strategies (Imani, & Montazer, 2019; Obergriesser & Stoeger, 2020), motivation-emotions (Martínez, et al., 2016), and emotions-commitment (Gömleksiz & Kan, 2012). Aleven, McLaughlin, Glenn, and Koedinger (2016) argued that emotional attributes represent student characteristics that must be taken into account when designing adaptive online learning environments. Berikan (2020) stated that a lecture design that allows the use of emotions should be made to ensure social presence associated with teacher-learner interaction in online learning environments. Arzugül-Aksoy, Bingöl, and Bozkurt (2022) argue that emotions are one of the indicators of social existence that contribute to the formation of a meaningful learning experience.

As investigations into the impact of emotions within technology-enhanced learning environments on the learning process persist, it is argued that there is a need to understand how to design technologies to regulate emotions, especially in research during the pandemic (Graesser, 2020). In this context, the first requirement will be to determine the student's feelings. Scherer (2005) argues that when measuring emotions, one's self-report should be relied upon. However, Öztüre et al. (2021) stated that great advances have been made in neuroscience research on facial expression indicators, physiological indicators, and brain activity analysis, and these developments may contribute to studies on emotion. In addition, Eliot and Hirumi (2019) described the use of mostly self-report data collection tools as a limitation in determining emotions. The complexity of defining and measuring emotions in the educational context, given the intricate relationship between emotion and technology, has led to the use of various measurement approaches in research. Previous studies have utilized physiological measurements to assess emotions (Chandra & Calderon, 2005; Castro et al., 2009; Khezri et al., 2015; Mayer, 2020). Additionally, video and face analysis have been employed to determine emotions (Yoshitomi et al., 2000; Nicolaou et al., 2012; Taub et al., 2020; Wang et al., 2020; Schneider et al., 2022).

Artificial intelligence-based methods such as deep learning and machine learning have been used by various researchers for emotion identification from facial expressions. Artificial intelligence, which is called self-developing systems or machines that imitate human intelligence and can learn according to the information they collect, aims to create a more effective learning ecology in learning environments. Moreover, it facilitates the advancement of the learning process by enabling the collection, processing, reporting, and extraction of meaningful insights from big data within the digital environment. With the widespread utilization of artificial intelligence methods in education systems, it is easier to detect the motivating or distracting element based on physical or behavioral clues that motivate and distract students. Studies called sentiment analysis aim to determine the general emotions from facial expressions in Figure 1 using artificial intelligence techniques.

Figure 1

Examples of Seven Facial Expression Categories

In recent literature, there has been a noticeable increase in studies conducted after 2019, with a preference for deep learning methods over machine learning. This preference stems from the ability of deep learning algorithms to learn and make accurate predictions through their data processing, facilitated by the artificial neural network structure, enabling automatic feature extraction (Maithri et al., 2022). For instance, Sakalle et al. (2021) and Savci and Das (2023) utilized the long short-term memory (LSTM) network to classify three basic emotions: positive, negative, and neutral. They compared the performance of various models including K-nearest neighbors (KNN), Multilayer Perceptron (MLP), LIB-Support Vector Machine (LIB-SVM), Support Vector Machine (SVM), and LSTM-based deep learning models for classification, achieving an impressive accuracy performance of 92.66% with 10-fold cross-validation.

Similarly, Chen et al. (2019) applied the Difference Convolution Neural Network (DCNN) approach on CK+ and BU-4DFE datasets to classify six basic facial expressions, demonstrating promising performance. Furthermore, Muhammad & Hossain (2021) proposed an emotion recognition system utilizing a convolutional neural network (CNN) model from facial expressions. Additionally, studies by Devi & Ch. (2021), Chowdary et al. (2021), Do et al. (2021), Li & Lima (2021), and Said & Barr (2021) employed deep learning approaches to accurately determine emotions from facial expressions, achieving accuracy rates exceeding 95%.

In the existing literature, there are limited studies analyzing facial expressions to evaluate the efficacy of online learning systems and students' level of engagement in learning environments. This gap highlights the need for further research in this area to better understand how students interact with and benefit from online learning platforms. By analyzing facial expressions, researchers can gain valuable insights into students' emotional states and engagement levels, which are crucial for improving the effectiveness of online education. Sethi and Jaiswal (2022) conducted a study where they classified students' facial images during lectures as "Understanding" or "Not Understanding" using a Convolutional Neural Network (CNN), Support Vector Machine, and Naive Bayes. Their findings suggest that deep learning methods like CNN may offer better performance in classifying facial images compared to other machine learning techniques such as SVM and Naive Bayes. Furthermore, Kaddoura and Gumaei (2022) developed a deep learning model to predict student critical behavior continuously from facial expressions, aiming at real-time cheating detection during online exams. Maqableh et al. (2022) introduced a deep learning-based approach that utilizes facial expressions and heart rates to gauge students' engagement levels in learning environments. Lyu et al. (2022) proposed an automatic facial expression recognition method with transfer learning based on regional attention networks (RAN) to mitigate the impact of hand occlusion in students who inadvertently cover parts of their faces during online learning sessions. Their approach achieved an accuracy rate of 89% with the proposed architecture. Lastly, Bhardwaj et al. (2021) assessed student engagement in the online learning environment by analyzing facial expressions using CNN and calculating the average interaction score. Their study underscores the significance of emotion detection in determining student engagement during online learning sessions.

According to the findings derived from existing studies, it is evident that emotions play a crucial role in the learning process. This research endeavors to delve into the emotions experienced by students during lectures and, consequently, their engagement in online learning environments. Therefore, the main contributions of this paper include:

- To obtain quantitative data by designing an artificial intelligence model that can understand the emotions of students during the lesson
- Comparison of self-report methods commonly used in educational sciences and artificial intelligence methods such as deep learning to determine the emotional states of students' facial expressions. To our knowledge, this comparison represents the first attempt to determine emotional states in this manner.

In this research, the answers to the following questions will be answered based on the deep learning and face recognition measurement approach, which is one of the artificial intelligence approaches:

1. Which emotional states can be detected from the facial expressions of the students?

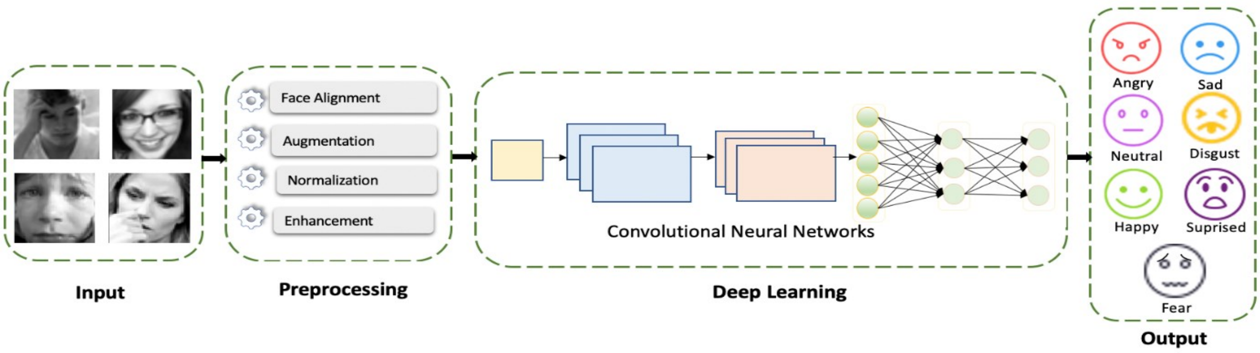
2. Do students' emotional states determined by face recognition match their self-reports?

2. Method

In this study, we investigated the emotional states of students to assess their engagement and motivation during an online lecture, where direct interaction between teachers and students is limited. To achieve this, we employed a two-pronged approach combining facial expression analysis with self-reported emotions. During the online lectures, students were encouraged to voluntarily turn on their cameras. Facial images were captured at 10-minute intervals to form a comprehensive dataset. This dataset included a range of facial expressions and hand movements, captured from various angles to enhance the robustness of our analysis. The facial images were then processed using a Convolutional Neural Network (CNN), a deep learning model known for its effectiveness in image classification tasks. Seven distinct emotional states—surprise, sadness, disgust, happiness, anger, fear, and neutral—were identified through the CNN model. To complement the facial expression analysis, students' emotional states were also evaluated using a self-report method. Students filled out a mood analysis form where they described their emotions during the lecture and provided reasons for their feelings. This self-report data provided an additional layer of insight into students' emotional experiences. The comparison of results from the CNN model and self-report forms allowed for a comprehensive analysis of students' emotional states. The CNN model's output was compared with the self-reported emotions to determine the level of agreement and discrepancies between the two methods. This approach highlights the potential of integrating advanced AI techniques with traditional self-report methods to gain a deeper understanding of emotional states in educational contexts. Figure 2 illustrates the block diagrams of the deep learning-based approach utilized in this study.

Figure 2

The Block Diagram of the Deep Learning-Based Model



2.1. Participants

The study involved 66 students (26 males and 39 females) from three distinct departments—Psychological Counseling and Guidance, Educational Technologies, and Science—at a state university in the eastern region of Turkey during the 2021-2022 academic year. This diverse participant pool was strategically chosen to enhance the study's generalizability and to provide a well-rounded perspective on student emotions and engagement in digital learning environments. Before the commencement of the study, participants were briefed on the research objectives and procedures, and all necessary ethical approvals were secured from the university's ethics committee. The participants were selected to represent a diverse cross-section of students to ensure a comprehensive understanding of emotional responses in online learning environments.

2.2. Data collection and analysis

Data collection and analysis were carried out using a two-pronged approach to comprehensively evaluate students' emotional states during online lectures. These are:

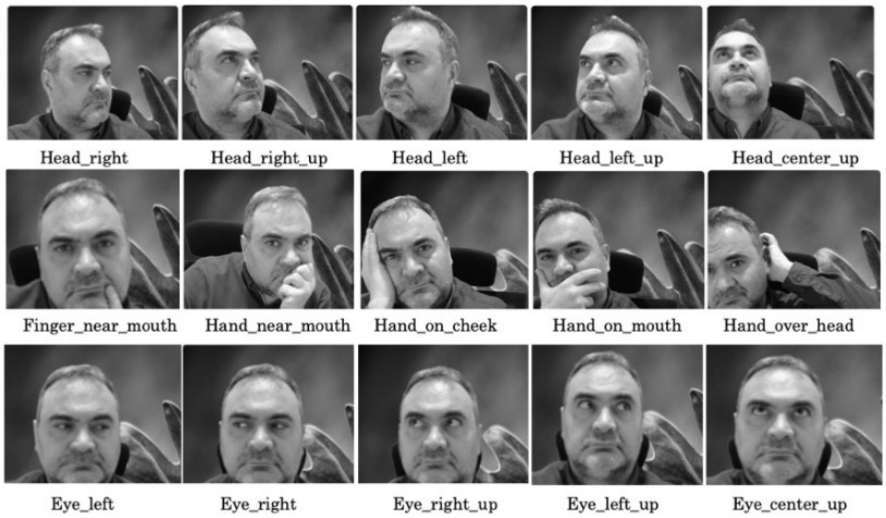
- *Facial Image Analysis:* The primary method involved the systematic collection of facial images from students during the online course. To capture a representative sample of students' emotional expressions, images were taken every 10 minutes throughout the lecture. This approach aimed to observe real-time changes in students' emotional states. Facial images were captured using screenshots from the online learning platform, with careful consideration given to various angles and positions to account for head movements and different viewing perspectives. The images were preprocessed to improve quality, including normalization and resizing to 48x48 pixels to reduce noise and distortion. The preprocessed images were then analyzed using a deep learning-based model, specifically a Convolutional Neural Network (CNN) with transfer learning. The CNN model, designed to detect seven distinct emotional states—surprise, sadness, disgust, happiness, anger, fear, and neutral—provided a quantitative assessment of students' emotions based on their facial expressions.
- Self-Report Analysis: Complementary to the facial image analysis, students were also asked to self-report their emotional states using a mood analysis form administered during the lecture. This form required students to indicate their current emotional state—such as happiness, sadness, anger, surprise, or any other relevant emotion—and provide a brief explanation for their feelings. This self-reporting method aimed to gather subjective data on students' emotions, allowing for a comparative analysis with the objective data obtained through facial expression analysis.

2.3. Deep learning-based model with transfer learning

Images of participants displaying various facial expressions were captured via screenshots. The objective was to analyze students' behavior and mood during e-learning sessions based on their facial expressions. The experiments lasted for a total duration of 75 minutes, with snapshots of the students taken every 10 minutes. As illustrated in Figure 3, students' heads are not consistently straight, and their eye movements vary.

Figure 3

Facial Expression with Hand Movements and Head Variations Captured Between 10 Minutes Intervals



It is observed that the students' heads move unevenly with their eyes, and sometimes they cover their mouths with their hands. These hand and eye movements may indicate that students are less interested in the lecture or are bored with e-learning. In order to provide more accurate training, these photos of students were also included in the training phase. It has also been preprocessed to improve the quality of the images and remove unwanted noise and distortion. In the preprocessing, the image was reduced to 48x48 size and normalized.

The Convolutional Neural Network (CNN), often regarded as the fundamental architecture of Deep Learning, comprises Convolution, Pooling, a Fully Connected layer, and a Classification layer. This model consists of multiple trainable components arranged sequentially and is followed by a training classifier. In the CNN architecture, the training process entails layer-by-layer operations after receiving input data. Subsequently, an output is generated and compared with the expected result. The disparity between the produced output value and the desired outcome yields the error, which is propagated to all weights through the backpropagation algorithm. To minimize this error, the weights are updated iteratively.

CNN has gained widespread adoption in computer vision applications in recent years. Transfer learning, a machine learning technique, involves reusing a model trained for one task in a related secondary task. With transfer learning, a base network trained on a large dataset is utilized, and in layers of this trained network are replicated as n layers of the target network. In pre-trained networks, the initial layer detects horizontal and vertical lines, while subsequent layers concentrate on features like edges and vertices. These networks specialize in specific image features in the final layers. Figure 4 illustrates the CNN architecture with transfer learning, while Table 1 provides a summary of the CNN model's layers and the parameters within these layers.

Figure 4

The Used CNN Architecture

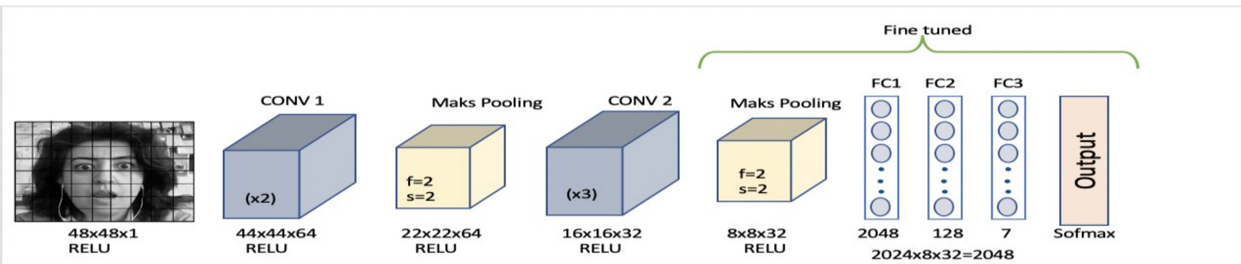


Table 1

The Parameters of the CNN Model

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 46, 46, 64)	640
batch_normalization (BatchNo)	(None, 46, 46, 64)	256
activation (Activation)	(None, 46, 46, 64)	0
conv2d_1 (Conv2D)	(None, 44, 44, 64)	36928
batch_normalization_1	(Batch (None, 44, 44, 64)	256
activation_1 (Activation)	(None, 44, 44, 64)	0
max_pooling2d (MaxPooling2D)	(None, 22, 22, 64)	0
dropout (Dropout)	(None, 22, 22, 64)	0
conv2d_2 (Conv2D)	(None, 20, 20, 32)	18464
batch_normalization_2	(Batch (None, 20, 20, 32)	128
activation_2 (Activation)	(None, 20, 20, 32)	0
conv2d_3 (Conv2D)	(None, 18, 18, 32)	9248
batch_normalization_3	(Batch (None, 18, 18, 32)	128
activation_3 (Activation)	(None, 18, 18, 32)	0
conv2d_4 (Conv2D)	(None, 16, 16, 32)	9248
batch_normalization_4	(Batch (None, 16, 16, 32)	128
activation_4 (Activation)	(None, 16, 16, 32)	0
max_pooling2d_1 (MaxPooling2)	(None, 8, 8, 32)	0
dropout_1 (Dropout)	(None, 8, 8, 32)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 128)	262272
batch_normalization_5	(Batch (None, 128)	512
activation_5 (Activation)	(None, 128)	0
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 7)	903
activation_6 (Activation)	(None, 7)	0

2.4. Mood analysis form

The mood analysis form was designed to collect students' self-reported emotional states during the lecture. Students then reported their emotional state from a list of categories including happiness, sadness, anger, surprise, fear, disgust, and neutrality in addition to the personal information of the students. Additionally, they provided a brief explanation or justification for their chosen emotion, offering context or reasons behind their feelings. This form aimed to complement the facial expression data collected through the deep learning model, providing subjective insights that facilitated a comparative analysis with the objective data.

3. Findings

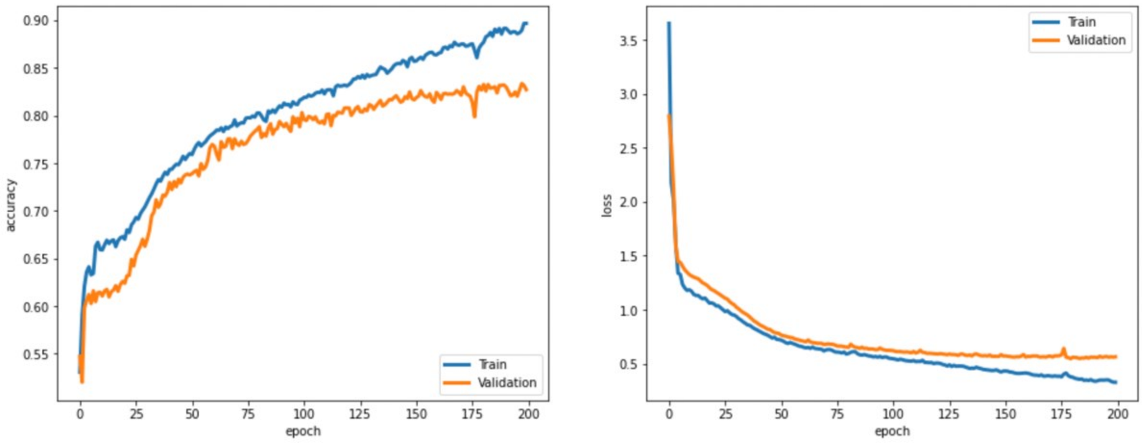
This section presents a comparative analysis of the study's findings, focusing on the effectiveness of various artificial intelligence techniques used for facial expression analysis and emotion recognition, as well as the accuracy of self-report emotion detection. The findings encompass the performance of the deep learning-based artificial intelligence model in detecting students' emotional states from facial expressions and compare these results with the students' self-reported emotions recorded through the mood analysis form. The analysis aims to highlight discrepancies and correlations between the AI-generated data and self-reports, offering insights into the strengths and limitations of each method in the context of online learning environments.

3.1. Detection of emotional states from facial expressions of students

In this study, students' emotional states were determined to determine their interest and motivation in online learning environments. The dataset is partitioned into 80% for training, 10% for validation, and 10% for testing purposes. Figure 5 depicts the loss and accuracy curves of the CNN model. In the study, seven different emotional states of the students were found with an accuracy value of 90.12%. There are many ways to measure the performance of the system in classification problems with deep learning. Accuracy and loss functions are among the most popular metrics. While accuracy quantifies the frequency of true predictions made by the classifier, the loss function assesses the error rate and performance of the model. This function computes the disparity between the model's prediction and the actual value, providing insight into the magnitude of deviation between them. Our study predicted seven different emotional states of the students with 90.12% accuracy.

Figure 5

The Loss and Accuracy Curves



During digital data collection, the fluctuation of students' emotions throughout the lecture was observed and recorded. Figure 6 shows the change in students' emotions during the 10-minute intervals of the lecture. Figure 7 shows the classification score of the emotional state for a sample student's facial expression.

Figure 6

The Change in Students' Emotions During the 10-Minute Intervals of the Lecture

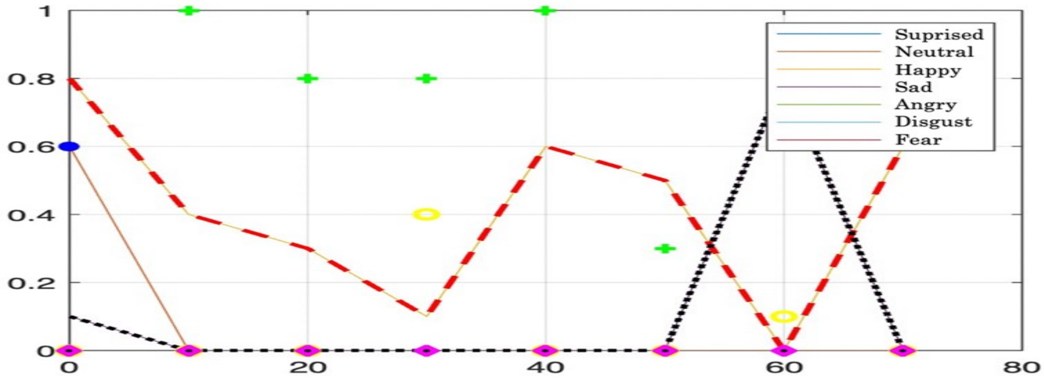
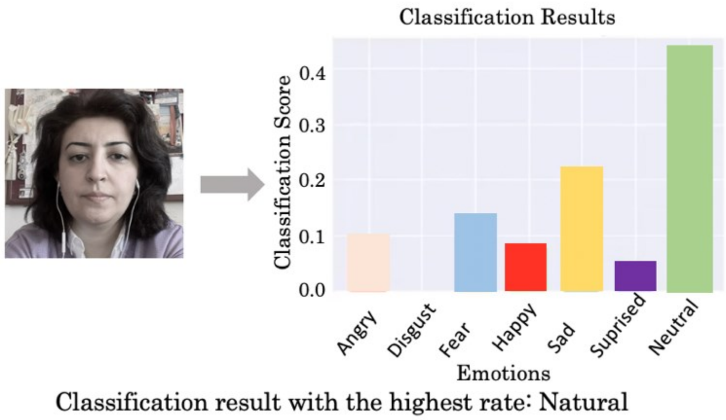


Figure 7

The Emotion Classification Score of a Sample Input



3.2. Comparison of students' emotional states determined by face recognition and self-reports

In this step of the research, the quantitative data (emotional states) obtained with the deep learning-based artificial intelligence model were compared with the self-reports of the students as seen in Figure 8. For example, the student indicated with S1 stated in his/her self-report that he/she was generally sad in the course, surprised during the use of Web 2.0 tools, and did not feel afraid, angry, bored, or happy. It was determined that the self-report of this student and the data obtained with the artificial intelligence model did not match as seen in Table 2. As a result of the comparison, some of which are given in Table 2, it was determined that the self-reports of 26 students out of 66 students matched, but the quantitative data of the remaining 40 students did not match. This corresponds to approximately 39% of the students.

Figure 8

Example of a Student's Emotional State as Determined by Facial Recognition and Self-Reports

Table 2

Comparison of Artificial Intelligence Model and Self-Report Emotional State

Students	Emotion Detection with AI	Emotion Detection with Self-report	Match or not
S1	0.8 Happy, 0.2 Neutral	Sad	No
S2	0.9 Happy, 01. Neutral	Neutral	No
S3	0.7 Neutral, 0.2 Sad, 0.1 Fear	Neutral	Yes
S4	0.6 Sad, 0.4 Neutral	Happy	No
S5	0.8 Neutral 0.2 Happy	Neutral	Yes
S6	0.6 Neutral, 0.3 Suprised, 0.1 Fear	Neutral	Yes
S7	0.7 Sad, 0.1 Neutral, 0.2 Fear	Happy	No
S8	0.9 Happy, 0.1 Neutral	Fear	No
S9	0.4 Sad, 0.6 Neutral, 0.1 Fear	Neutral	Yes
S10	0.8 Neutral, 0.2 Fear	Neutral	Yes
S11	…………….	……………….	………
…….	…………….	……………….	………

4. Conclusion and Discussion

This research aims to determine the emotional states of students with the deep learning-based artificial intelligence model designed during an online course and to compare the obtained quantitative data with the self-report measurement method, which is frequently used in educational sciences. In the artificial intelligence model developed to determine the emotions of the students during the course, a 7-class emotion detection experiment was carried out by using the Convolutional Neural Network, one of the deep learning models. When the studies in this field are examined, it is seen that data sets such as CK+, FER2013, and JAFFE are generally used in mood detection, and the performance of the system varies according to the dataset and deep learning models used. The reason for this is that the number of images in each emotion category varies between data sets. In addition, the performance of the system was affected by hyperparameters such as learning rate, hidden layers, iterations, and the selection of the activation function. Moreover, advancements in deep learning models and hyperparameter tuning play a crucial role in enhancing accuracy. In the Hua (2019) study, the emotion recognition study using the FER2013 dataset, 62.31% accuracy was achieved with the VGG19 model. Agrawal and Mittal (2020) achieved 65% accuracy using the CNN method on the same dataset. Liu et al. (2016) obtained 65.03% accuracy using the CNN-ensemble model.

In the CK+ dataset, Boughida et al. (2022) obtained an accuracy of 94.26% with the Gabor filter and Fallahzadeh et al. (2021) had 93.66% accuracy using AlexNet. Jaiswal and Nandi (2020) used the CNN method for the JAFFE dataset. They achieved a success performance of 64.32%. Hung et al. (2019) obtained an accuracy of 84.66% using VGG16 method. These variations underscore the importance of dataset selection and model customization in achieving high performance in emotion recognition tasks. In the study, instead of using ready-made data sets, a real data set was created by receiving facial images of the students at certain intervals of the course. This approach allowed for the collection of authentic and context-specific data, providing insights into real-world application challenges. With the CNN-based transfer learning model, the image classification performance was improved by using deep features, and a successful performance of 90.12% was achieved despite the small data set. The high accuracy demonstrates the potential of combining transfer learning with domain-specific data to enhance emotion recognition in educational settings.

The research findings revealed that there was a 39% overlap between the emotional states determined by artificial intelligence and those reported by the students themselves. This relatively low overlap suggests that while AI-based models can provide valuable insights, they may not fully capture the subjective nature of emotions as self-reports do. The determined rate is quite low. For this reason, although self-report measurement tools are accepted as reliable in the literature, it is thought that there is a need for diversity in data collection tools. However, upon reviewing the literature, it has been found that the majority of self-reported measurements in the field of education, particularly in the measurement of emotions, are conducted using instruments such as scales and questionnaires. Combining multiple data collection methods could offer a more comprehensive understanding of students' emotional states. Although Sherer (2005) emphasized the subjective aspect of emotion and stated that self-report should be trusted, he also stated that great progress has been made in neuroscience and artificial intelligence research and that these developments can contribute to studies on emotion. Öztüre, et al., (2021), argue that the relationships between emotion and technology in the educational context are multifaceted and this situation complicates the process of defining and measuring emotions.

This study contributes to the literature by integrating emotion and technology within the educational field, offering a new perspective on emotion recognition and its application in online learning environments. Mayer (2020) and Graesser (2020) specified that there is a need for research in the literature on how technologies should be designed to make sense of the cognitive and emotional processes during learning.

4.1. Limitations and future research

Recognizing emotions from facial expressions poses a significant challenge, as individuals may exhibit various emotions through the same facial expression. Open datasets available for emotion recognition are often insufficient and lack diversity. To improve the effectiveness of emotion recognition, a wider variety of data formats are required for training in deep learning models. Additionally, capturing facial expressions from multiple angles is essential for obtaining more accurate and reliable results. In the study, photographs of students at different moments and angles were taken during the course and their emotional states were determined from these photos. When the light conditions in the images change, the facial appearance can change, which greatly affects the results. In addition, occlusion, which is the situation where a certain part of the face is not visible or hidden, is one of the factors that cause the system to fail. It was observed that the students mostly covered their chin, mouth, or cheeks while listening to the course, which negatively affected the performance of the artificial intelligence trying to detect facial expressions. The limitations stemming from the quality of camera equipment and variations in the distance of students from the lens pose challenges in accurately capturing facial expressions in images. Additionally, the study's dataset is restricted to only 66 students, which limits the generalizability of the results. Future studies will aim to address this limitation by including larger and more diverse groups to enhance the robustness and generalizability of the findings. In addition, they could explore the integration of multimodal data, combining facial expressions with other indicators of emotional states, such as physiological measurements or behavioral data, to improve the accuracy and reliability of emotion detection in educational settings.

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