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Analyzing the Emotions of Individuals with Special Education Needs During the Educational Process Using Facial Recognition Software

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Abstract: Facial expressions play a significant role in interpersonal interaction. The primary way individuals convey their intentions is by incorporating facial expressions into the communication process. The ability to read facial expressions is a cornerstone of social relationships, and this skill becomes vital in situations where words are insufficient or deceptive. Today, the ability for computers to rapidly scan and analyze facial expressions is facilitating human life in numerous fields. Studies in the literature indicate that this analysis is used in many fields: for security purposes, such as taking precautions against malicious individuals or detecting fatigue for safe driving; for identifying health problems, such as pain diagnosis in newborns; and for creating personalized experiences in psychological and social domains, like generating music playlists based on mood. For individuals with special education needs, interpreting emotions from facial expressions is a more challenging skill; however, understanding their emotions is of greater importance due to their specific conditions. In this study, a recognition software was developed using the Python programming language, capable of detecting the human face and identifying emotional states from facial expressions. Using this software, 10 students with special education needs were observed over a period of 8 weeks. The research methodology relies on comparing the instantaneous emotion detection records from the software (developed using Python, OpenCV, and DeepFace libraries) with the dominant emotion records identified per session by an expert human observer. The analysis results demonstrated a high degree of overlap between the emotions detected by the software and those identified by the observer. According to data from both the software (totaling 791 emotion detections) and the observer, the most frequently observed dominant emotional states among the students during the 8-week educational period were found to be "neutral" (natural state) and "happiness". These findings suggest that the developed software can be utilized as a highly efficient and valid tool for understanding the emotional states of students in special education environments.

Keywords: Emotion analysis, Special education, Artificial intelligence, Facial expressions, Facial recognition

Introduction

Facial expressions are the most important tools people use to convey their emotions to others, and they play a significant role in human interaction. These expressions are universal cues that provide emotional integrity in interpersonal interaction. Facial expression, an important means of communication, provides us with significant clues about the person we are communicating with. Changes in facial expressions are considered the most important clues in emotional psychology, and this analysis has a wide range of applications in human behavior analysis and human-computer interaction.

From a communication perspective, when a person speaks, they simultaneously try to understand what the other person is thinking and what their emotional state is by observing their expressions, gestures, and body language. Thanks to this action, which is performed unconsciously and automatically by the human brain, people also try to determine whether there is consistency between what the other person is saying and what they are feeling. By utilizing artificial intelligence technologies, whose primary goal is to perform many tasks seamlessly by thinking and mimicking complex problems like humans, it is possible to detect emotions with high accuracy using a computer program prepared with these technologies (Polat and Genç, 2019; Korkmaz, 2020).

The main idea behind facial expression recognition is to detect and analyze changes in a human face's eyebrows, eyes, nose, lips, and chin. For this, it is first necessary for the computer to be able to detect these parts of the human face, i.e., the human face, within a specific image, and then to perform a few different operations on this facial image. Facial expression recognition generally involves three main steps: 1) face detection, 2) feature extraction, and 3) classification of the extracted features. First, the face area needs to be located on the image and isolated from it, meaning the face area image needs to be separated from the other parts of the image. After the facial region is defined, the feature vector of facial expression must be extracted from the facial image. This feature vector numerically represents the current state of changes in the eyebrows, eyes, mouth, nose, and chin resulting from the simultaneous contraction of one or more muscles in the facial region, and it defines the facial expression. Finally, the resulting feature vectors need to be classified and included in the most appropriate facial expression class (Sarıcaoğlu, 2019; Karagöz, 2020; Suthaharan, 2014).

In the example below, certain changes in the human face under different emotional states are observed, particularly differences around the eyes and mouth. Thanks to these changes in the face, individuals' emotional states can be detected through computer software (Du, Tao, and Martinez, 2014; Koç, 2021).

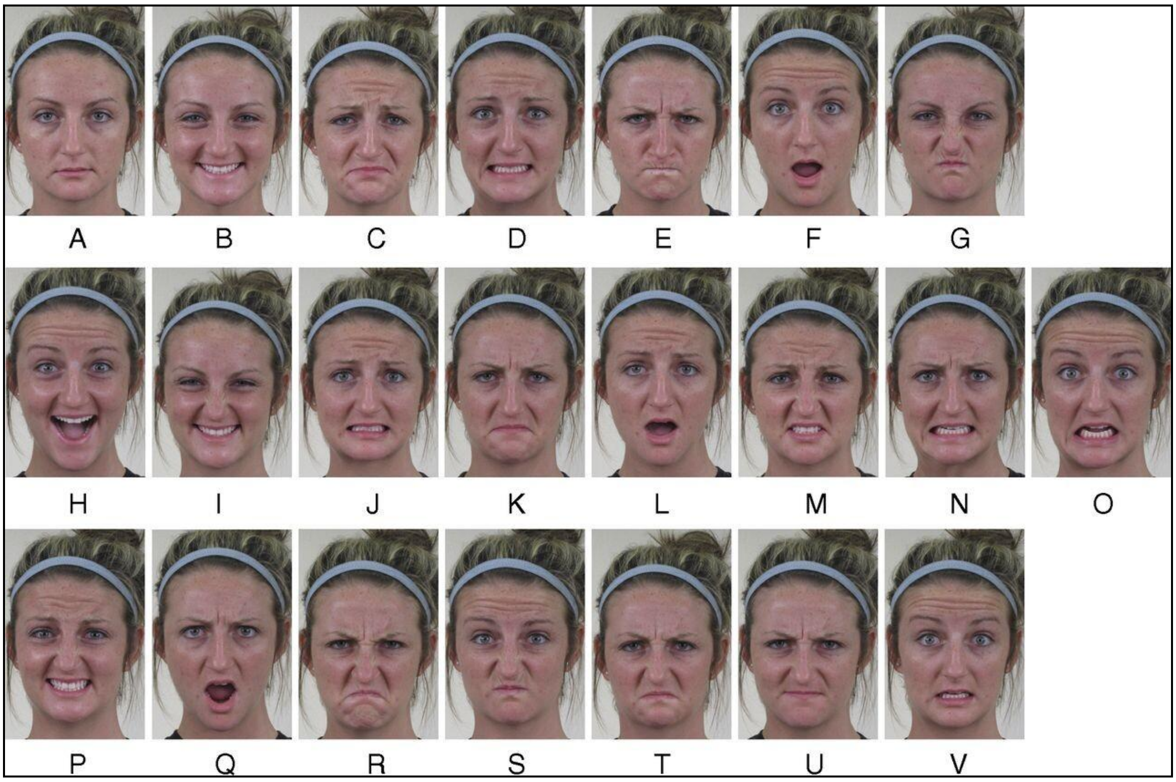

Figure 1. Changes in facial expression with different emotions (Du, Tao and Martinez, 2014)

With the development of human-computer interaction, understanding human emotions through computers has become easier. The analysis and recognition of facial expressions is becoming increasingly widespread in many research areas such as security, psychology, health, robotics, and virtual reality. Therefore, the rapid analysis of facial expressions and the accurate identification of the analyzed facial expressions play a significant role for many software systems in different application areas (Deng & Yu, 2014; Eitel et al., 2015; Lecun et al., 2015; Taigman, 2014; Tonguç, 2017).

One area where this technology can be used is the analysis of facial expressions as a reflection of the behavior of individuals with special needs in an educational setting. Thanks to facial recognition technology, the emotional expressions of individuals with special needs can be analyzed to understand their emotional state, thereby facilitating communication that is typically more challenging for them compared to normal individuals. Additionally, real-time feedback obtained about students with special needs' emotional states using this technology can help teachers provide more support when they notice a student is emotionally struggling or make the learning environment more emotionally supportive. This technology can also help provide personalized learning experiences for students based on their emotional state. For a disabled individual who is anxious or unable to concentrate, learning materials, methods, and the learning environment can be rearranged, considering the individual's condition. So, this technology can be used as a tool to monitor the emotional well-being of individuals who need special education and intervene when necessary.

Within the scope of this study, software was developed using deep learning algorithms and coded in the Python language. This software aims to analyze the emotions of individuals who require special education. Thus, it is believed that by understanding the emotional states experienced by individuals with special needs in their lessons, some of the problems these individuals face in the education and teaching process can be addressed. For example, in lessons with these individuals, an attempt will be made to determine whether the factors negatively affecting the educational processes stem more from the way the lesson is taught or from the discomfort created by the learning environment.

To enable the software to recognize different students, individuals' photos were saved in the database before processing. An instant video image was transmitted to the computer from a camera placed in the educational environment in a way that would not distract the student. The software analyzed the video image to detect the student's emotional state once per second, and the 15-second average of emotions was saved in an Excel file. Thus, emotional data will be obtained for each student at a rate of 4 times per minute. The study sought answers to the following key questions:

- What is the relationship between the emotions detected by the software in students and those observed by a field expert?
- What is the most frequently detected emotion in students by both the software and the observer?

Method

Study Group

The research was conducted with 13 students with different special education needs, such as autism and Down syndrome, who were receiving training at the Necmettin Erbakan University Psychological Counselling and Special Education Student Application Unit. Due to the irregular attendance of 2 students in classes and the subsequent diagnosis of an emotional spectrum disorder in 1 student, the analyzes were conducted using data from 10 students.

System Architecture and Software

Within the scope of this study, researchers examined similar software development processes, software, and relevant libraries in the literature (Beyeler, 2015; Chollet, 2018; Hellmann, 2017) and developed an emotion recognition software using the Python programming language. Instant video images captured from a camera placed in front of the student are wirelessly transferred to the developed software, which attempts to detect emotional states from the facial expressions of individuals with special needs. It is observed that there are different studies in literature regarding the diversity of emotional states individuals can experience. In this study, the classification based on 7 basic emotional states (happiness, disgust, anger, fear, normal/natural state (neutral), sadness, and surprise), which was also used by Bütüner (2020), was adopted. The following core libraries were used in the development of the software:

- *OpenCV (Open Source Computer Vision Library):* Used for image capture from the camera, image processing, and face detection using Haar Cascade classifiers.
- *Face Recognition:* It was used to identify which student in the system's pre-introduced student database the detected face belongs to (face recognition).
- *DeepFace:* This deep learning library developed by Facebook was used for emotion recognition based on expressions on recognized faces. The model used in the software was trained on a dataset containing over four million face images.
- *Pillow (PIL):* Used to support image processing capabilities.

Data Collection Process

The 10 students in the study group were monitored throughout their 8-week training process. Data collection was carried out through two channels:

1. *Software Data:* The developed software detected the student's emotional state once per second during the lesson and saved the dominant emotion to an Excel file by averaging this data for over 15 seconds.
2. *Observer Data:* Simultaneously, a field expert (observer) also observed the lessons and recorded the two dominant basic emotions they observed in the student for each session.

Findings

The data obtained from the software and the observer were analyzed comparatively.

Comparison of Software and Observer Data

In the 8-day data for the Student 1, a high degree of agreement was found between the software and observer records. The types and frequencies of emotions detected on days 1, 3, 4, and 5 were almost completely identical. On days 2, 7, and 8, there was 'partial overlap'; both sources identified a common emotion (usually happiness or normal), but the second emotions differed (e.g., on day 2, the software said 'fear', while the observer said 'normal'). On day 6, the software provided a more comprehensive result by detecting fear and surprise in addition to the happiness and normal state determined by the observer. In total, 13 out of 16 mood states (81.25%) were found to overlap. Considering that the software sometimes finds a single dominant emotion (e.g., on day 7) and the observer indicates two emotions, the actual overlap can be considered to be 87.5% (14/16). Student 1 data is shown in Figure 2.

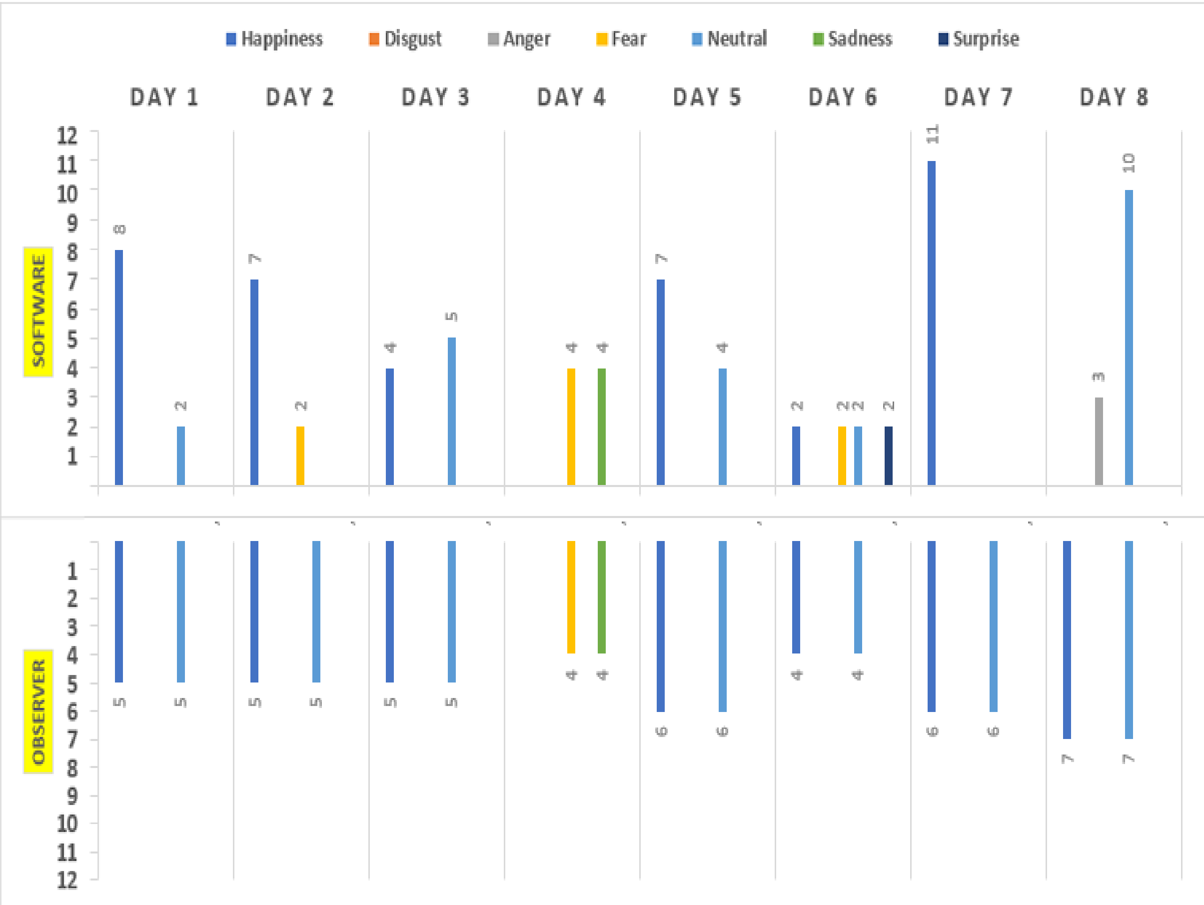

Figure 2. Mood states detected by the software and observer for student 1

When examining the 10-day data for the Student 2, a high degree of overlap (80% or 16/20) was observed between the software and observer records. On 6 out of 10 days (days 1, 2, 3, 5, 8, and 10), both emotions detected completely overlapped. In the remaining 4 days (days 4, 6, 7, and 9), there was partial overlap (only one shared emotion). Considering that the software had already detected only a single emotion on 2 of these partially overlapping days (days 4 and 7), the overlap rate can be considered to be at the level of 90% (18/20). 2. The mood graph of the Student 2 is presented in Figure 3.

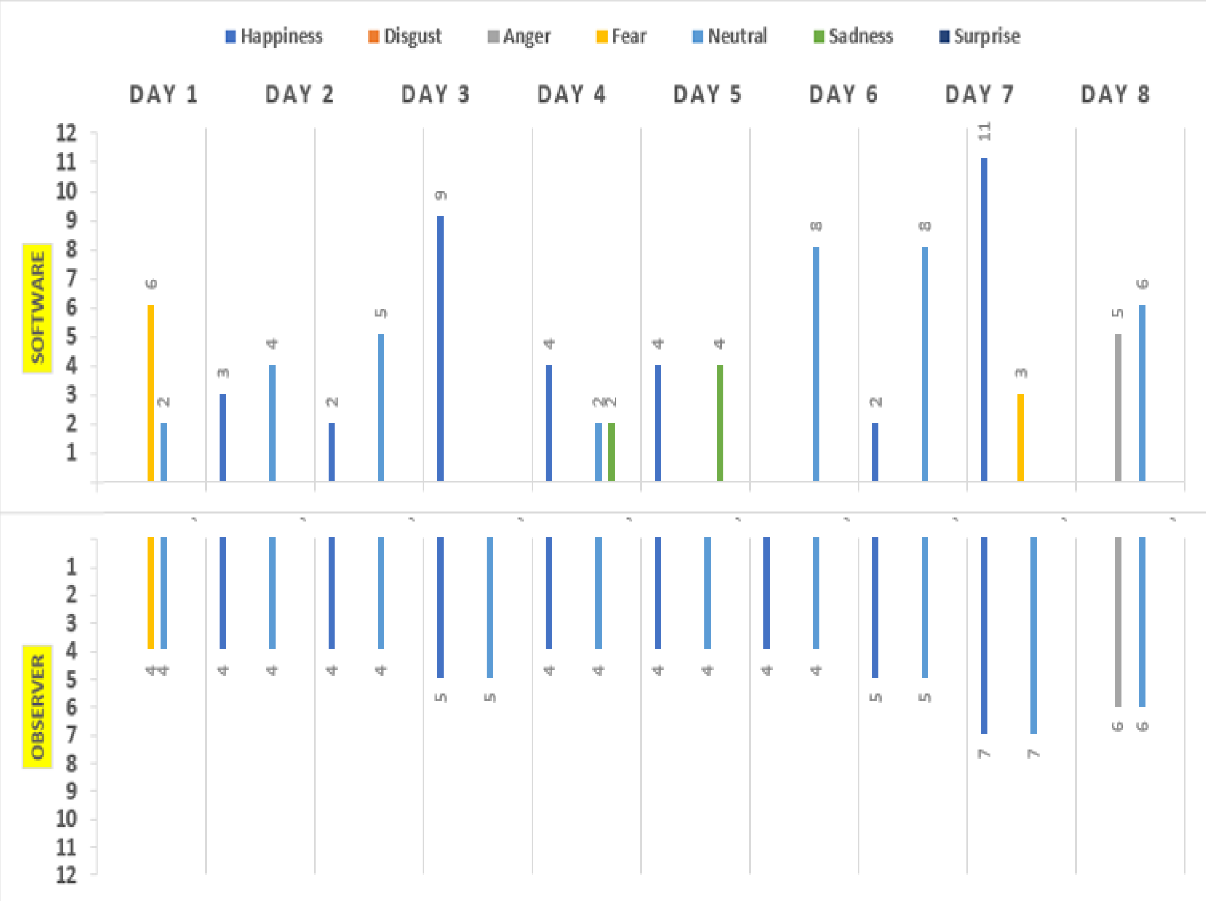

Figure 3. Mood states detected by the software and observer for student 2

When the data of the other 8 students (Student 3 – Student 10) were also examined, a high degree of overlap was found between the software and observer data. The compliance is very high (93.75%, 87.5%, and 87.5% respectively), and when cases where the software detects only one emotion are considered, it reaches 100% overlap for the Student 4, Student 9, and Student 10. Also, Student 7 showed high compliance, with 87.5% (corrected 93.75%). Strong agreement was also found in Student 3, Student 6, and Student 8 (75%, 62.5%, and 68.75%, respectively), and these rates increased to 87.5% when observer limitations were considered. The lowest raw agreement was observed in the Student 5 (60%), who had 4 days of full overlap and 4 days of partial overlap. A comparative graph of all this individual student data is presented in Figure 4.

When all student data is considered together, it is evident that the developed software shows a high degree of consistency with the recordings of an expert human observer. While most students had overlap rates between 75% and 94%, even at the lowest rates (60%-69%), the adjusted data indicated an agreement of 87.5%. In situations where the software detects a single dominant emotion (e.g., only "normal"), while the observer necessarily indicates two emotions, the fact that these "corrected" overlap rates reach 100% in many students (e.g., Student 4, Student 9, and Student 10) demonstrates that the software has high validity in detecting emotions. Additionally, the software's ability to capture momentary emotions in addition to what the observer reports from time to time (e.g., 'fear' in the Student 3) suggests it could potentially be a more sensitive measurement tool.

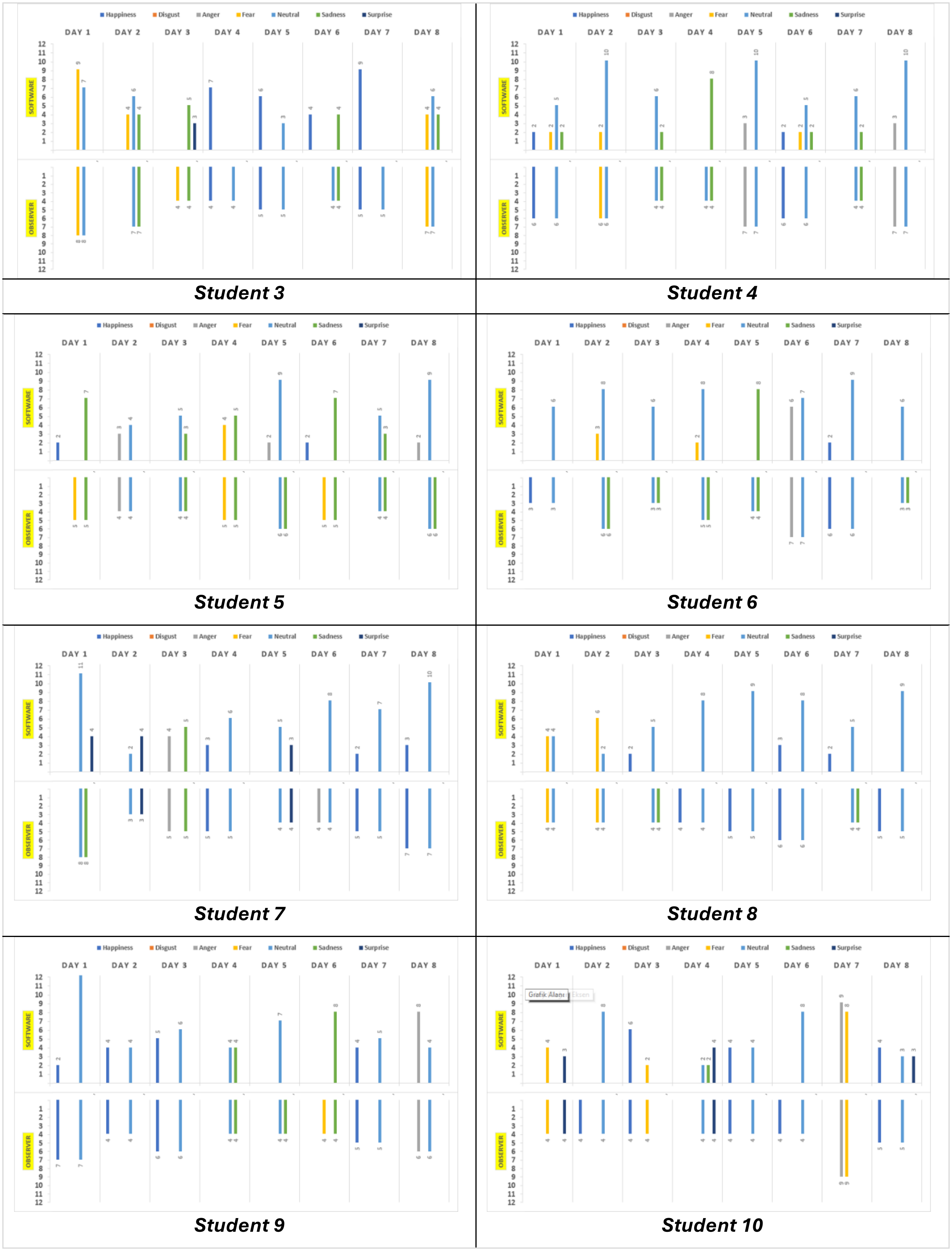

Figure 4. Mood states detected by the software and observer for student (3 – 10)

Most Observed Emotions

When examining the data on the emotions detected by facial recognition software during the student's training days over an 8-week period, it was found that for the Student 1, within 8 days, the emotion with the highest frequency was happiness (35%) with 6 occurrences, and the emotion with the second-highest frequency was a normal mood (29%) with 5 occurrences. Considering the frequency with which these emotions were observed throughout the day, out of a total of 79 emotions identified for the Student 1, 39 were happiness (49%) and 23 (29%) were normal emotional states. The observations made by the observer for this student are also similar. Of the 16 total emotions observed, with 2 emotions for each day the observer expressed, 7 were happiness (44%) and 7 were normal mood states (44%). From this perspective, it can be seen that for the Student 1, the most frequently detected emotion by both the software and the observer is happiness and a normal emotional state.

For the Student 2, over a 10-day period, the emotion with the highest frequency was happiness (36%) with 7 occurrences, and the emotion with the second-highest frequency was a normal mood (36%) with 7 occurrences. Considering the frequency with which these emotions were observed throughout the day, out of a total of 90 emotions identified for the Student 2, 35 were happiness (39%) and 35 (39%) were normal emotional states. The observations made by the observer for this student are also similar. Of the 20 total emotions observed, with 2 emotions for each day the observer expressed, 8 were happiness (40%) and 10 were normal mood states (50%). From this perspective, it can be seen that for the Student 2, the most frequently detected emotion by both the software and the observer was happiness and a normal emotional state.

When the data of the other 8 students (Student 3 – Student 10) were also examined, it was observed that consistent emotion profiles were revealed by both the software and the observer. The Student 3 stood out as the most variable profile, exhibiting a high frequency of various emotions such as "happiness," "sadness," and "fear," in addition to the "normal" state, according to both assessment methods. For Student 4 and Student 5, a consensus was observed between both software and observer data regarding the dominant emotions being "normal" (neutral) and "sadness." In all of the remaining 5 students (Students 6, 7, 8, 9, and 10), both the software's real-time detections (70%, 64%, 75%, 55%, and 34% respectively) and the observer's end-of-session evaluations (50%, 44%, 50%, 44%, and 31% respectively) confirm that the most frequently observed dominant mood state is "normal" (neutral).

When all student data is considered together, there is a strong substantial correlation between the instantaneous emotion intensities detected by the software (total number of detections) and the dominant emotions identified by the expert observer. In all 8 students examined, both methods reached similar results regarding the most dominant emotional profile (diversity for the Student 3; 'normal' and 'sadness' dominance for the Student 4 and Student 5; 'normal' state dominance from the Student 6 to Student 10). This situation demonstrates that the software is a consistent and valid tool for capturing students' overall emotional tendencies exhibited throughout their educational process, consistent with and validated by observer assessments. Specifically, the fact that the "normal" (neutral) state was identified as the most dominant emotion in 7 out of 8 students (and at a high frequency for the Student 3 as well) reflects the students' fundamental emotional state during the educational process.

Discussion and Conclusion

The findings of this research showed a high degree of agreement between the dominant emotional states detected by the developed software and those reported by the expert observer. Both datasets confirmed that students most frequently exhibited "normal" (neutral) states and "happiness" during the educational process, indicating that the program is operating at high efficiency.

However, some discrepancies observed between the observer and software data need to be examined. The first potential reason is that the emotion recognition model used by the software was trained on datasets of typically developing (healthy) individuals. The unique (idiosyncratic) facial expressions of individuals with special needs, such as autism or Down syndrome, who participated in the study may not perfectly match the model's current parameters. Re-training the software with data from this population could increase detection accuracy in the future. On the other hand, the source of the differences may not be solely algorithmic but also depend on methodological factors such as the observer's subjective interpretations and methodological biases (observer bias), or the students' inability to clearly express intense/complex emotions.

The success of special education programs depends on meeting the student's unique needs. In this context, analyzing how a student's mood and emotional state affect their learning outcomes, motivation, and level of participation in the program is critically important for designing a more efficient educational process. Students with physical or mental disabilities often face challenges in emotional regulation, social skills, and motivation, which can negatively impact their educational participation. Individuals with emotional or behavioral disorders find it difficult to succeed in a traditional classroom setting and require special support for full participation in education.

Therefore, social skills training, emotional regulation strategies, and technology-based interventions (e.g., virtual reality) as in this study, are suggested as potential avenues for increasing the engagement and interest of these students. It is important for educators and policymakers to identify this link between emotional health and educational participation and provide appropriate support. Early intervention, collaboration between special education programs and mental health services, the creation of positive and supportive school environments, and teacher training on these topics can make a significant difference in students' success. Finally, it is necessary to consider individual factors such as family background and socioeconomic status when designing intervention programs to ensure comprehensive success.

Recommendations

Based on the results of this study, it is considered beneficial to retrain the model (transfer learning) with a dataset consisting only of facial expressions of children who need special education for future applications and research. Additionally, the quality of educational environments for individuals with special needs can be improved by developing the software to include a feedback loop in the future, such as a system that provides instant suggestions to the teacher's tablet to change the lesson material or environment detects the student's negative emotions (fear, anger).

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the authors.

* All participating families were informed about the study, and Participant Consent Forms were obtained. This study was conducted with the ethics committee approval numbered 45 and dated 16.01.2023, obtained from the Selçuk University Faculty of Education Scientific Ethics Evaluation Board.

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Conflict of Interest

* The authors declare that they have no conflicts of interest

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