Assessment of postoperative pain in children with computer assisted facial expression analysis☆

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ABSTRACT

Purpose: The present study was conducted to evaluate the use of computer-aided facial expression analysis to assess postoperative pain in children.

Design and methods: This was a methodological observational study. The study population consisted of patients in the age group of 7–18 years who underwent surgery in the pediatric surgery clinic of a university hospital. The study sample consisted of 83 children who agreed to participate and met the sample selection criteria. Data were collected by the researcher using the Wong Baker Faces pain rating scale and Visual Analog Scale. Data were collected from the child, mother, nurse, and one external observer. Facial action units associated with pain were used for machine estimation. OpenFace was used to analyze the child's facial action units and Python was used for machine learning algorithms. The intraclass correlation coefficient was used for statistical analysis of the data.

Results: The pain score predicted by the machine and the pain score assessments of the child, mother, nurse, and observer were compared. The pain assessment closest to the self-reported pain score by the child was in the order of machine prediction, mother, and nurse.

Conclusions: The machine learning method used in pain assessment in children performed well in estimating pain severity.It can code facial expressions of children's pain and reliably measure pain-related facial action units from video recordings.

Application to practice: The machine learning method for facial expression analysis assessed in this study can potentially be used as a scalable, standard, and valid pain assessment method for nurses in clinical practice.

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Introduction

Pain is a subjective experience that can occur in any period of life (Zieliński et al., 2020). Children experience moderate to severe pain after surgery (Smeland et al., 2018). Pain leads to negative effects on children's health (Ferland et al., 2018; Witt et al., 2016). When not controlled, pain increases the risk of complications in children. It negatively affects the child's sleep and eating patterns (Brand & Al-Rais, 2019; Law et al., 2022). These changes can prolong hospital stay, increase resistance to medical procedures, and cause children to develop pain sensitivity and trauma. (Brand & Al-Rais, 2019; King et al., 2011; Olmstead et al., 2010). For these reasons, it is very important to control pain.

The first step in pain management is the assessment of pain. Pain assessment can be done through self-reporting, behavioral observation, or biological observations (Brand & Al-Rais, 2019; Dwamena et al., 2020; Hauer & Houtrow, 2017). The standard method in pain assessment is self-reporting (Bahreini et al., 2015). However, interpretation of self-reported pain can be difficult. In some cases, it may not be possible to evaluate pain in disadvantaged groups such as children who cannot express their pain, who have communication problems or who have a serious illness (Ashraf et al., 2009; Zieliński et al., 2020). There are many valid and reliable scales that can be used in pain assessment (Gai et al., 2020). However, various difficulties arise when using these scales (Brand & Al-Rais, 2019; Zieliński et al., 2020). In a systematic study conducted to determine the severity of pain in children, among the many scales evaluated the authors failed to recommend a single scale that can be used in accordance with the pain types and age groups of

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children (Stinson et al., 2006). Therefore, the search for pain assessment tools that can be used in children continues.

Proxy pain assessment is also commonly used in children. A nurse or parent can assess the child's pain. In the study conducted by Smeland et al. (2018), it was determined that nurses had difficulties in assessing children's pain. Similarly, limited use of pain assessment tools by nurses is consistent with the findings of other studies (Hadden et al., 2015; Zhou et al., 2008). When using observational scales, health professionals may be biased and underestimate the severity of patients' pain (Hla et al., 2014; Jaaniste et al., 2019). Some studies reported that nurses often disagreed with the parent's proxy report of pain and relied on their own assessment (Vasey et al., 2019; Zontag et al., 2022). Taken together, these limitations show that there is a need to develop more automated, standardized, unbiased, and scalable pain assessment tools (Sikka et al., 2015).

Behavioral scientists have identified reliable and valid indicators of facial pain (Ashraf et al., 2009). In addition to the body position and verbal expression of pain, facial expression can also be used to evaluate the pain status of an individual experiencing pain (Sikka et al., 2015; Xu et al., 2019). Studies investigating pain symptoms in children found that the most frequently expressed pain symptoms by nurses were children's crying and facial expressions (Göl & Onarıcı, 2015; Nimbalkar et al., 2014). There are ongoing studies around the world in which facial expression analysis is used in pain assessment. Studies using the Facial Action Coding System (FACS) have used several facial movements displayed continuously while experiencing pain, including lowering the brows, lid tightening, raising the upper lip, opening of the mouth, and various combinations of these for facial expression research (Kunz et al., 2019; Sikka et al., 2015). Sikka et al. (2015) used facial expression analysis in post-operative pain and worked on a new automated pain identification system in their study. Similar to this study, Xu et al. (2019) performed one-dimensional analyses with machine learning models to evaluate facial expression in postoperative pain in children. In these two studies, machine learning algorithms were found to be effective in the accurate assessment of pain.

An important component of healthcare is the ability to provide effective pain control in pediatric patients (Kulshrestha & Bajwa, 2014). Pain assessment is among the duties and responsibilities of nurses (Dwamena et al., 2020). Evaluation of pain is very important in order to ensure success in pain control and to determine effective pain relief methods (Brand & Al-Rais, 2019). Continuous, automated and real-time quantitative detection of pain will enable healthcare professionals to respond in a timely manner to clinical situations and improve patients' hospital experience (Liu et al., 2018). Therefore, the aim of the present study was to evaluate postoperative pain in children with computer aided facial expression analysis.

Methods

Research design and hypothesis

The aim of the present study was to evaluate postoperative pain in children with computer aided facial expression analysis. The study was designed as an observational methodological research.

Sample

Study sample consisted of 83 patients aged 7–18 years, who underwent surgery in the pediatric surgery clinic of a university hospital in Bursa between November 2019 and June 2021. Of the participants, 68 patients had two follow-ups while 15 patients had only one follow-up. The pain assessment of 15 patients could not be done because they were discharged before the 2nd follow-up. A total of 151 pain assessment data were included in the study. A pilot study was conducted with 46 pain assessment data, and minimum sample size (pain assessment data) was determined as 151 for 80% power and 5% type I error.

When the children were included in this study, the following inclusion criteria were as follows: the patient was awake and oriented after the surgery, between the ages of 7–18, the mother stayed with the patient as a companion, having surgery under general anesthesia, and parental voluntary signed consent and child consent. Exclusion criteria were as follows: the presence of any facial anomalies that may alter facial expression analysis, neurological and mental disorders of the patient, regular opioid use for the last six months, and surgical procedures requiring the patient to be in the prone position.

Recruitment

The researcher informed children and their families about the study. Those who expressed an interest were briefed on the particulars of the study. Informed written consent was obtained from each mother and child. Verbal assent was obtained from the child again before the video recording started.

Data collection tools

Wong Baker Faces Pain Scale (WBS): The scale consists of 6 different facial expressions that start with a smiling face and end with a crying face (Brand & Al-Rais, 2019).

Visual Analog Scale (VAS): This scale is a horizontal or vertical straight line 10 cm long. On the scale, 0 indicates "no pain" and 10 indicates "unbearable pain" (Brand & Al-Rais, 2019; Drendel et al., 2011).

Facial Action Coding System (FACS): This system is a detailed, objective, anatomically-based coding system that categorizes facial expressions using a comprehensive operational description of specific actions. There are 46 different facial action units (AUs) in the system (Ekman & Friesen, 1978). Facial Action Coding System AUs are the actions of individual or a group of facial muscles. For example, AU 6 (cheek raiser), is caused by contraction of the orbicularis oculi muscle and AU 12 (lip corner puller) is caused by contraction of the zygomatic major muscle (Cohn & Sayette, 2010).

The defined functional neuroanatomical movements are necessary and sufficient to encode any facial expression. The system has been used in clinical studies in children and adults (Sheu et al., 2011; Sikka et al., 2015).

OpenFace: It is a facial image analysis tool that can perform facial landmark detection, head pose estimation, facial action unit (AU) recognition, and eye-gaze estimation by utilizing computer image algorithms. There are many facial AUs in the software. AU1 (inner brow raiser), AU2 (outer brow raiser), AU4 (brow lowerer), AU5 (upper lid raiser), and AU6 (cheek raiser) etc. can be given as an example of the facial AUs in this program (Baltrusaitis et al., 2018; Baltrušaitis et al., 2016).

Python: Python is a dynamic programming language frequently used for scientific computing. It is used for algorithmic development and exploratory data analysis (Dubois, 2007). It is designed to be easy to understand and use. It has a large standard library that provides tools suitable for many tasks such as creating graphical configuration, connecting relational databases, making predictions. Python is widely used in artificial intelligence and web platforms, thanks to its flexibility and versatility (Liu et al., 2023).

Data collection

Data were collected by the researcher from the child, mother, nurse, an independent observer, and machine estimation based on facial expression analysis. Wong Baker Faces Pain Scale and VAS were used for pain assessment. Video recordings containing facial expressions of children were used for machine learning. Pain assessment was performed with two follow-ups after surgery (within the first 12 h and between the 24th and 36th hours). Video recording of the child's face and pain assessments were obtained at both visits. A video camera (1920 × 1080 pixel resolution) was placed in the postoperative recovery room in front of the

patient's bed at a distance that could clearly view the face of the patient. The camera recorded the patient's face. The recording took one minute. Simultaneously, the child, the child's mother, and the caregiver nurse were asked to evaluate the patient's pain using pain assessment scales (WBS and VAS). An independent observer (a master's graduate of the pediatric nursing department) evaluated the child's pain by watching the recorded videos. These data were collected blindly.

Data measurements

Camera recordings of the child's facial expressions were analyzed by OpenFace to measure facial AUs. To ensure image standardization in the OpenFace program, facial expressions of 90% reliability and above were evaluated in the analyzed facial expressions (Baltrusaitis et al., 2018; Baltrušaitis et al., 2016).

Facial AUs that could affect pain expression were determined by the researchers. These facial AUs were AU4: brow lowerer, AU6: cheek raiser, *AU7: lid tightener, AU9: nose wrinkler, AU10: upper lip raiser,* AU12: lip corner puller, AU17: chin raiser, AU20: lip stretched, AU25: lips part, AU26: jaw drop, AU45: blink (Fig. 1).

Facial AUs were separated into two variations within the scope of the study design. AU17 was the variable unit between the variations. The first variation included AU17 (machine V1), while the second variation did not (machine V2). For each patient follow-up data, the arithmetic averages of the facial AU codes consisting of 1200 face frames obtained during the one minute video recording were calculated and used. These averages provided the input for the subsequent machine learning steps. After these analyses, pain intensity was processed with machine learning algorithms in Python and used for pain assessment. The estimated pain score ranged from 0 to 10. Numpy, pandas and matplotlib libraries were used for machine learning. As suggested in

the literature, machine learning algorithms were created with test size = 0.33 and random state = 0 to ensure reliability (Auffarth, 2020). Simple linear regression was used to evaluate the severity of pain in children. The pain score obtained from computer assisted facial expression analysis, or machine estimation, was statistically compared with the pain scores of the child, mother, nurse and observer.

Data analysis

Descriptive statistics were expressed as mean, standard deviation, or median (minimum-maximum) for quantitative data. The intraclass correlation coefficient (ICC) model and 95% confidence intervals were used to evaluate the reliability of the intraclass correlation coefficients of the quantitative data. Statistical analysis of data was performed with IBM SPSS 23.0 (IBM Corp. Released 2015. IBM SPSS Statistics for Windows, Version 23.0. Armonk, NY: IBM Corp.) statistics package program.

Ethical and legal aspects of research

The study was examined and approved by the Bursa Uludağ University Faculty of Medicine Clinical Research Ethics Committee with the decision dated 18.09.2019 and numbered 2019_15/9 (IRB no: 00004769; decision no: 2019_15/9). Institutional permission was obtained from Bursa Uludağ University Faculty of Medicine, Health Practice and Research Center Hospital Pediatric Surgery Department. The clinical trial registration number was NCT05345275.

Written informed consent was obtained from the children and mothers participating in the study. The anonymity and confidentiality of the data were emphasized to the children and their families before recording the video. The children's video recordings were recorded so that only their faces were exposed and visible. It was shared with the child and family that the researcher will archive the video recording to be used in the pain assessment of children as research data.

Results

Sample characteristics

Eighty-three children were included in the study. The mean age of the children participating in the study was 12.57 ± 0.41. Approximately 70% of the children were male, While 50.6% of the children had previous surgery, 39.8% had gastrointestinal system surgery. (Table 1).

The pain severity scores reported by the children according to the WBS pain scale were compared with the pain scores estimated by the mother, nurse, observer, and machine. It was found that the pain score closest to the pain intensity reported by the child was the machine learning version V2 (Table 2; $p < 0.05$). The mother, nurse, and machine learning version V1 were the other evaluators closest to the child's pain.

Fig. 1. The Action Unit list associated with pain.

AU	Full Name	Illustration
AU4	Brow Lowerer	
AU6	Cheek Raiser	
AU7	Lid Tightener	
AU9	Nose Wrinkler	
AU10	Upper Lip Raiser	
AU12	Lip Corner Puller	
AU17	Chin Raiser	
AU20	Lip Stretched	
AU25	Lips Part	
AU26	Jaw Drop	
AU45	Blink	

Table 1
Descriptive characteristics of children ($n = 83$).*

	n (%)
Gender	
Female	25 (30.1)
Male	58 (69.9)
Surgery History	
Yes	42 (50.6)
No	41 (49.4)
Type of Surgery	
Gastrointestinal System Surgery	33 (39.8)
Urinary System Surgery	23 (27.7)
Thoracic Surgery	14 (16.9)
Oncological Surgery	7 (8.4)
Otorhinolaryngology Surgery	6 (7.2)
Age, years (mean ± sd)	12.57 ± 0.41

* Data are expressed as mean ± standard deviation and n (%).

Table 2

Comparison of pain scores evaluated by wong baker faces pain scale.

	Machine V1	Machine V2	Mother	Nurse	Observer
Child					
ICC*(95%CI)	0.273	0.355	0.315	0.276	0.199
Lower bound	−0.007	0.084	0.051	0.012	−0.087
Upper bound	0.513	0.577	0.542	0.509	0.454
p value	0.028**	0.006**	0.010**	0.021**	0.085

*ICC: intraclass correlation coefficient, CI: Confidence Interval, ** $p < 0.05$.

There was no significant correlation between the pain score reported by the child and the pain score estimated by the observer.

The pain severity scores reported by the children according to the VAS pain scale were compared with the pain scores estimated by the mother, nurse, observer, and machine. The pain score closest to the pain severity evaluated by VAS was found to be the machine learning version V2. The machine learning versions (V1 and V2) showed better results when using the VAS for pain assessment (ICC = 0.358 and ICC = 0.414). When all data were compared, it was determined that the highest fit was between the pain score estimated by the machine learning algorithm V2 and the VAS scale (Table 3; p < 0.05).

Discussion

Postoperative pain assessments of the children participating in the study were made with the WBS, VAS scales, and machine estimation. There was a significant agreement between the pain severity scores reported by the children according to the WBS and VAS and the pain intensity estimation made by machine learning algorithms. The results of the study showed that machine estimation (machine V2) yielded the closest score to the pain severity assessed by the child. Similar to the findings of the present study, Sikka et al. (2015) analyzed painful facial expressions in children after appendectomy. They found a significant correlation between machine estimation and self-reported pain severity in children. Xu et al. (2019) developed a machine learning model for the assessment of pain in children aged 10–15 and found that this model was highly correlated with self-reported pain in children. There are no studies in the literature reporting contradictory results. However, studies using facial expression analysis and machine learning models in pain assessment in children are very limited. In a study conducted in adults to evaluate postoperative pain intensity, artificial intelligence algorithms were found to be successful against nurses in recognizing painful facial expressions (Fontaine et al., 2022). Othman et al. (2021) also reported that the performance of neural networks trained to assess pain intensity based on facial expression analysis is better than human performance. The machine learning algorithms used in the present study to assess pain in children performed well in estimating pain severity. These results show that there are advances in machine learning algorithms used in pain assessment.

According to the results of the present study, the pain severity scores reported by the children according to the WBS and VAS pain scales showed a significant agreement with the pain scores evaluated by the

Table 3

Comparison of Pain Scores Evaluated by Visual Analog Scale.

	Machine V1	Machine V2	Mother	Nurse	Observer
Child					
ICC*(95%CI)	0.358	0.414	0.390	0.284	0.136
Lower bound	0.096	0.159	0.132	0.017	−0.147
Upper bound	0.357	0.619	0.600	0.516	0.399
p value	0.005**	0.001**	0.001**	0.019**	0.173

*ICC: intraclass correlation coefficient, CI: Confidence Interval, ** p < 0.05.

mother and the nurse. The pain assessment closest to the pain score self-reported by children was found to be machine V2, mother, machine V1, and nurse, respectively. Similar to the results of the present study, a recent study reported that pain assessments recorded by parents and nurses were in agreement with children's pain scores (Zontag et al., 2022). In the same study, it was determined that parental assessment was significantly closer to children's pain assessment compared to the assessment of nurses (Zontag et al., 2022). Rajasagaram et al. (2009) compared the self-reported pain scores of children with the assessments of the parents and nurses. The pain scores evaluated by the nurses were found to be significantly lower than the scores evaluated by the parent and reported by the child, while no significant difference was found between the pain scores evaluated by the parent and reported by the child (Rajasagaram et al., 2009). While the result of this study supports the agreement between the pain score evaluated by the parent and reported by the child also determined in the present study, it is contradictory to the agreement between the pain score evaluated by the nurse and reported by the child. This may be due to the different clinics where the studies were conducted and the cultural characteristics of the respective regions. In order to improve pain management in pediatric postoperative care, nurses should also involve parents. It has been determined that the opinions of the parents are important in the evaluation of postoperative pain in children (Wu et al., 2022). In another study, pain assessment by parents and physicians were compared in children treated in the pediatric emergency department (Brudvik et al., 2017). Contrary to the findings of the present study, the correlation between child-physician and parent-physician in pain assessments was found to be low (Brudvik et al., 2017). The difference may be due to the fact that nurse as a healthcare personnel was included in the pain assessment in the present study. Since nurses are primarily responsible for the health care and pain assessment of patients, they are likely to be more experienced in this regard.

In a study conducted by Hla et al. (2014) with pediatric patients after surgery, pain scores evaluated by the child, parent, nurse, and an independent observer were compared. It was found that children and parents tended to record higher pain scores than nurses and independent observers, but the difference was not statistically significant. These results are consistent with the findings of the present study. The clinical implication that can be drawn from these findings is that parents' assessments of their children's pain are better than nurses' assessments in pediatric departments. This may be due to the fact that parents are primary caregivers for their children. In addition, the fact that the independent observer, another healthcare professional, reported significantly lower pain levels in the present study indicates that the observer did not have enough experience in pain assessment. This may also be due to the fact that the observer was not in a face-to-face environment while assessing the child's pain, and facial expressions of the child were evaluated through video recording.

Limitations

The machine learning algorithms used in the present study to assess pain in children performed well in estimating pain severity. We recognized several study limitations. One limitation of our study was the small size of the dataset. Another limitation of this study was that it did not include children of all age groups and various ethnic groups. Within the study design, facial AUs were evaluated with two different machine learning variations. Increasing the number of variations with combinations of different facial AUs could have enriched the content of the study. In future research, different facial AUs variations can be used in pain assessment. Only facial analysis was evaluated in the study. Another vital component of a pain assessment system, especially for children with communication disabilities, is estimating the specific location of the pain source. Future research needs to include pain stimulations applied to several body locations.

Implications of the clinical practice

This method used in the present study can be used by nurses as an alternative method for pain assessment in clinics for the benefit of humanity.

Conclusion

The original aspects of the present study included the OpenFace program, in which we evaluated facial AUs, together with the facial AUs that were associated with pain. The results of the study show that machine learning can be used by nurses as a real-time, standard, scalable, continuous, reliable and valid method in the assessment of postoperative pain in children. This study can also be performed in disadvantaged groups who cannot express their pain.

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Ethical approval

The study was examined and approved by the Bursa Uludağ University Faculty of Medicine Clinical Research Ethics Committee with the decision dated 18.09.2019 and numbered 2019-15/9 (IRB no: 00004769; decision no: 2019-15/9).

CREDIT Statement

Ayla İrem Aydın: Conceptualization, Methodology, Software, Investigation, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Nurcan Özyazıcıoğlu:** Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

There is no conflict of interest between the authors of the article.

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