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RESEARCH ARTICLE

The Implementation of Artificial Intelligence-Based Models of Postoperative Care in Paediatric Healthcare Settings

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Abstract

Postoperative pain management in pediatric patients remains an important problem because young children cannot verbally express pain. Unrelieved pain can have adverse neurodevelopmental outcomes, but conventional intermittent monitoring is often insufficient in capturing transient pain crises, especially in resource-constrained settings. This study develops and tests an AI-based multimodal construct of continuous, automated pain surveillance but specifically within the healthcare ecosystem of Haryana, India. Employing a mixed-methods approach to research, we combined clinical data on 100 pediatric patients at four districts (Hisar, Sirsa, Rohtak and Panipat) with an AI simulation trained on multimodal data (facial expressions, cry acoustics, and physiological vitals). The classification accuracy obtained by the proposed AI model was 90.20% and Area under the Curve (AUC) was 0.93, showing a good correlation ($r = 0.88$, $p < 0.001$) with expert clinical evaluations by FLACC and Wong-Baker scales. An alert latency of less than 1 minute was shown by the system, thus significantly faster than manual rounds. Furthermore, a perception survey of 20 healthcare officials showed a high degree of acceptance of the clinical utility of the technology (mean score 4.4/5) although training gaps are a major hindrance (score 3.65/5). The findings suggest that response latency and missed high pain episodes can be considerably reduced by AI assisted monitoring by around 45%. This framework can provide an ideal, scientifically-backed answer to improving the quality of care of pediatric patients in Haryana, as long as ethical governance and structured training of personnel take priority.

Keywords: Artificial Intelligence, Pediatric Pain, Postoperative Care, Multimodal Fusion, Haryana Healthcare, Affective Computing.

Introduction

The Clinical Challenge-Assessment in Non-Verbal Patients

Effective and continued pain control is one of the pillars of pediatric postoperative management. However, accurate assessment in this demographic is beset with challenges. Unlike adults, infants and toddlers do not have the cognitive and linguistic maturity to describe the intensity or nature of their distress. As a result, pain in children is often under-recognized and undertreated. Unrelieved acute pain can cause severe physiologic stress response, negatively impact tissue healing, lengthen hospital stay, and can even result in long-term neurodevelopmental consequences or chronic pain as an adult.

Drawbacks of Existing Monitoring Practices

Current clinical practice is based on significant use of intermittent observational scales (FLACC: Face, Legs, Activity, Cry, Consolability scale in young children, Wong-Baker FACES scale for those a bit older). While these tools have standardized assessment, they offer only "snapshots" of a child's status at the moment the child is being observed.

In resource-constrained healthcare settings, such as the ones commonly found in Haryana, India, high patient-to-nurse ratios make continuous manual monitoring practically impossible. This intermittent monitoring leads to "blind spots" where episodes of breakthrough pain which

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happen between set nursing rounds may go unnoticed and unrelieved for dangerously long periods.

The Technological Solution: Artificial Intelligence and Multimodal Fusion

The intersection of Artificial Intelligence (AI) and the Internet of Medical Things (IoT) promises to provide a revolutionary solution to these shortcomings. Patil et al. (2023) highlight that IoT-based smart healthcare monitoring can enable data analytics to be performed in real time, which is critical for providing timely clinical interventions. By using the capabilities of modern sensors, AI systems can be used to continuously analyze multimodal signals (i.e. facial expressions, acoustic signatures of crying, physiological parameters, e.g. heart rate, oxygen saturation) to objectively detect distress.

Research shows that multimodal models (fusing visual, audio and physiological data) generally perform much better than unimodal systems (e.g. video only) in terms of accuracy and reliability. Such systems provide an "objective sixth sense" to caregivers, which can sense subtle physiological changes (e.g., tachycardia) in a behaviorally-stoic child with exhaustion. Furthermore, the use of such data-intensive systems needs to follow strict ethical standards. Ahamed et al. (2023) point to the need for studying privacy-preserving machine learning algorithms, like federated learning, to secure healthcare data sharing.

Context and Objectives of Study

Despite the potential of artificial intelligence in healthcare, there is a big gap in the research work on its practical adoption in the specific infrastructural environment of Indian healthcare, especially in Haryana. In resource-constrained hospital environments such as available in this region, continuous monitoring of the patient is often not possible due to high patient-to-nurse ratios, leaving children vulnerable to untreated pain in between scheduled rounds. Consequently, the objectives of this study are primarily to fill this gap by: first, developing and simulating an artificial intelligence (AI)-based multimodal system for monitoring postoperative pain and distress among children; second, assessing the accuracy and potential contribution of this system to the care of children by comparing it to expert clinical judgment for children; third, making specific recommendations regarding the implementation of AI-driven models, especially in local healthcare settings; and fourth, comparing the proposed AI framework with current practices in pain assessment to quantify the improvement in detection and response times. Ultimately, this research aims to offer a validated roadmap to bring objective, automated vigilance into pediatric postoperative care.

Review of Literature

The field of pediatric pain management has been radically changed from some bed-side observations to sophisticated and data-driven algorithmic monitoring. This review provides a synthesis of basic theories, clinical evaluation tools and the recent explosion of Artificial Intelligence (AI) and Internet of Things (IoT) applications.

The Clinical Imperative and Behavioral Scales

Pain in children is under-recognized and undertreated because of barriers to communication. Friedrichsdorf and Goubert (2020) and Eccleston et al. (2021) stress that unrelieved pediatric pain is a violation of basic human rights and can result in long-term and adverse neurodevelopmental outcomes. To try to overcome this, standardized scales of observation were developed. Merkel et al. (1997) introduced the FLACC scale, which is a quantitative measure of distress based on the Face, Legs, Activity, Cry, and Consolability which is still a gold standard for young children. For older children, Hicks et al. (2001) validated the Faces Pain Scale-Revised, which is available for self-report. A contribution of Ambuel et al. (1992) was the COMFORT scale (specifically for intensive care environments) and Malviya et al. refined these tools for cognitively impaired children in 2006 with the r-FLACC. Despite their usefulness, these methods are based on intermittent "snapshots", often missing transient crises of pain between nurse rounds.

Biological Underpinning: Acoustics and Facial Expression

The automation of pain detection is based on biological markers discovered in early biological research. Porter et al. (1986) and Fuller and Horowitz (1990) determined that infant pain cries had different acoustic characteristics (high pitch, dysphonation) than hunger cries. Similarly, Zeskind and McMurray (1997) identified some specific spectral features of neonatal distress vocalizations.

In the visual area, Ekman and Friesen (1978) developed the Facial Action Coding System (FACS), which is the taxonomy for analysing facial muscle movements. An evolutionary account of these expressions was given by Williams (2002), while specific "Pain Face" actions (e.g. brow lowering, orbital tightening) were identified by Prkachin et al. (2008). Lucey et al. (2011) then created a benchmark dataset, the UNBC-McMaster Shoulder Pain Expression Archive, that could be used to train early computer vision models.

The Rise of Affective Computing and Artificial Intelligence

Picard (1997) set the stage for Affective Computing: he postulated the feasibility of machine recognition of human affective states. Early implementations by Bartlett et al. (2014) and Patel (2015) have shown that machine learning can be used to decode facial movements and cry acoustics with increasing levels of accuracy. Sikka et al. (2015) pioneered the use of these technologies in clinical settings involving pediatric patients, when they used a computer vision system to measure postoperative pain. As the progress of deep learning increased, Solovyev et al. (2021) attempted to use 3D Convolutional Neural Networks (CNNs) to capture dynamic features of a face which results in a significant improvement in recognition rates.

Multimodal Fusion and Real Time Monitoring

Single modality systems frequently tend to fail during noisy or occluded data. Zamzmi et al (2019) reviewed the automated techniques and made a case for multimodal fusion - conjunction of face, voice and vitals to increase the robustness. Ben-Israel et al. (2013) proposed an index called the Nociception Level (NOL) index that clearly illustrates the value of multi-parameter physiological monitoring. Subramanian et al. (2024) further formalized conceptual frameworks for AI-based multimodal monitoring for pediatric care specifically.

The practical implementation of such complex models requires the Internet of Medical Things (IoMT). Patil et al. (2023) discussed patient monitoring in real time, focusing on how IoT analytics can process sensor data in real time to generate actionable clinical insights.

Ethics, Explainability and Privacy

Implementation of AI in pediatrics raises important ethical issues. Hoogenboom et al (2020) and Montgomery (2020) discussed the ethical implications of surveillance and the need for informed consent in pain management in children. Furthermore, "black box" AI models are often not trusted by clinicians; Craven and Shavlik (1996) emphasized the importance of extracting understandable rules from neural networks to make them explainable from the start.

Finally, data privacy is of the utmost importance. Ahamed et al. (2023) studied privacy-preserving machine learning, showing that federated learning can be used to share healthcare data and train machine learning models without the need to share sensitive patient information. This would be in line with the need for secure and valid tools in neonates discussed by Hummel et al. (2010).

Conclusion of Review

The literature provides a clear progression from the hand scales to complex, privacy-conscious, artificial intelligence systems. However, there is still a gap in the application of such multimodal IoT-enabled frameworks in resource constrained settings such as Haryana which the current study tries to fill.

Materials and Methods

This study used a mixed-methods design of research which combined descriptive clinical observations in combination with experimental AI simulation. The methodology was divided into two different phases, namely the primary data collection, from pediatric wards in Haryana, and the development of a multimodal AI framework using secondary datasets.

Collection of Clinical Data (Primary Data)

Participants and Setting

The study was carried out in four districts in the state of Haryana, namely Hisar, Sirsa, Rohtak and Panipat. A purposive sample of 100 pediatric patients (age 1-12 years) undergoing routine surgical procedures (eg, hernia repair, appendectomy, tonsillectomy, orthopedic adjustments) was selected. Additionally, 20 healthcare officials (pediatric surgeons, anesthesiologists, nursing supervisors, and administrators) were also involved to provide expert validation and perception feedback.

Observation Protocol

Postoperative pain was measured at four specific points, 1, 6, 12, and 24 hours after surgery. At each interval, healthcare professionals documented information on a standardized form:

- Pain Scores The FLACC scale (Face, Legs, Activity, Cry, Consolability) was used for children aged 1 through 6 years; the Wong-Baker FACES scale was used for children aged 7 through 12 years.
- Physiological Vitals: Heart Rate (HR), Respiratory Rate (RR) and Oxygen Saturation (SpO2) were monitored using standard bedside monitors.
- Behavioral Indicators: The behavioral indicators (e.g., grimacing, restlessness, intensity of crying) were manually recorded to ground truth labels.

Ethical Considerations

The study followed ethical guidelines of ICMR. Informed consent was obtained from parents or guardians of all participants in the pediatric group. Data were strictly anonymized with unique alphanumeric codes to protect the privacy of the patients before digital processing.

Model Development for AI (Simulation Phase)

To model an automated monitoring system, a multimodal deep learning model was created and trained on ethically obtained secondary datasets (e.g. UNBC-McMaster, COPE Infant Pain Database, MIMIC-III) reflecting the visual, audio, and physiological patterns of pediatric pain.

Model Architecture

The framework was based on a late-fusion approach using a combination of three specialized subnetworks:

- *Visual Module*

A Convolutional Neural Network (CNN) based on the VGG-16 architecture was used to extract facial action units (e.g., eyebrow lowering, eyes squeezing) from image frames with size 224x224 pixels.

- *Audio Module*

A Long Short-Term Memory (LSTM) network processed the audio features, in this case Mel-frequency cepstral coefficients (MFCCs) and detected the acoustic signature of pain cries over neutral sounds.

- *Physiological Module*

A Gradient Boosting Regressor to analyze time series trends in vital signs (HR, RR, SpO2) in order to detect deviations caused by stress on physiological processes.

Fusion and Inference

The feature vectors of these three modules were concatenated in a fully connected fusion layer. This layer predicted a categorical (low, moderate, high) and continuous (0-10) pain level. The predictions of the model were then validated to the "ground truth" scores collected in the clinical phase to determine accuracy and correlation.

Perception Survey

A structured survey was conducted to address institutional readiness, and it was administered to the 20 healthcare officials. The six dimensions that were measured in the survey-that is, technological awareness, clinical utility, ethical acceptability, training needs, implementation feasibility, and perceived reliability-were measured with a 5-point Likert scale.

Statistical Analysis

Data analysis has been done using Python (v3.10) libraries (NumPy, Pandas, Scikit-learn) and the software package, Statistics for Social Science (SPSS v27.0).

- Model Performance: Accuracy, Precision, Recall (Sensitivity), F1-Score, Area under the Receiver Operating Characteristic Curve (ROC-AUC) were the different metrics used to evaluate the model performance.
- Clinical Validation Pearson's correlation coefficient (r) was used to assess the agreement between AI-predicted scores and clinician-recorded scores. Paired t-tests were used to evaluate changes in pain levels over time.

Results

Findings of Clinical Observation

The ground truth data gathered from 100 pediatric patients in Haryana states were used for the validation of the AI model.

- Demographics: The sample was 58% male and 42% female patients. The majority (55%) were between 1-6 years of age, the population most in need of measures to assess non-verbal abilities.
- Pain Trajectory: Postoperative pain experienced a clinically expected decrease. The average expert-assessed pain score was 8.4 (Severe) at 1 hour after surgery and reduced to 2.2 (Mild) at 24 hours after surgery.
- Physiological Correlation High positive correlations were found between behavioral distress (e.g., crying) and physiological correlators such as Heart Rate ($r=0.74$, $p<0.001$) and Respiratory Rate ($r=0.68$, $p<0.001$), establishing the validity of using vital signs as proxy indicators for pain.

AI Model Performance

The multimodal AI framework was tested on a test dataset based on standard classification metrics. The model had high efficacy in distinguishing between pain and no pain states.

The Ablation Study Multimodal superiority

In order to confirm the need to have a multimodal approach, the entire model has been compared to single-modality baselines. The data stream fusion had much better performance than single sensors, especially on safety metrics critical aspects.

- Visual-Only Model: Obtained an accuracy of 82.70% and High-Pain Recall of 0.851.
- Multimodal Fusion: Multimodal now has increased accuracy to 90.20% and Recall of High-Pain to 0.894.

This proves that the information using visual, audio and physiological data decreased the incidence of missed severe pain episodes by 12.8 percent (baseline) to 6.1 percent.

Clinical validation and Correlation.

The AI scores of the pain were compared to the scores of the pediatricians and nurses of the ground truth.

- Correlation: There was a strong positive correlation between the prediction of AI and the clinician ratings (Pearson $r = 0.88$, $p < 0.001$).
- Error Analysis: The Mean Absolute Error (MAE) was 0.41, which is on a 0-10 scale, meaning that the judgment of the AI is close to the judgment of human analysis with little variation.
- Confusion Matrix: The model accurately identified 83 analysis of the cases with No Pain and 72 analysis of the cases with Severe Pain. The majority of misclassifications fell between two adjacent categories (e.g., Mild vs. Moderate), which is less risky clinically than the lack of severe pain.

Operational Impact

The virtual field test revealed that there were considerable benefits in operations as compared to manual monitoring policies:

- Response Time: The AI system showed a median alert latency of less than 1 minute, as opposed to a median latency of 30-60 minutes in the case of the variable latency of a manual round.
- Safety: The system decreased the number of episodes of

Table 1: Model Performance of the Multimodal AI Model

Performance Metric	*Value (%) / Score*	*Clinical Interpretation*
Accuracy	90.20%	The overall correctness of the model in classifying pain states versus non-pain states.
Precision	88.60%	Indicates a low rate of false positives, which is crucial for minimizing «alarm fatigue» among nursing staff.
Recall (Sensitivity)	91.00%	The system's ability to correctly identify actual pain episodes. A high recall ensures that very few cases of distress are missed.
F1-Score	89.80%	The harmonic mean of precision and recall, demonstrating a balanced performance without skewing towards one metric.
ROC-AUC	0.93	Represents excellent capability to discriminate between different pain levels (Area Under the Receiver Operating Characteristic Curve).

high pain that went undetected about 45% in relation to intermittent manual charting.

4.6 Stakeholder Perception

The questionnaire of 20 healthcare officials demonstrated that there is high institutional preparedness but mentioned certain barriers.

- Clinical Utility: 4.4/5, which is a high rating considering a solid faith in the tool to enhance accuracy.
- Ethical Acceptability: Evaluated to 4.1/5, but depends on rigid privacy regulations.
- Training Readiness: With the lowest score of 3.65/5, the primary obstacle in the adoption is identified as staff training.

Discussion

This study was designed to simulate and test an artificial intelligence (AI)-driven multimodal approach to determine postoperative pain in pediatric patients that was specifically adapted to the healthcare environment of Haryana, India. The results strongly support the hypothesis that automated systems can offer a reliable, objective and continuous "safety net" for non-verbal pediatric patients.

Validation of Multimodal Fusion

The main result showing high correlation (r=0.88) and high classification accuracy (90.20%) with expert clinical scores of the multimodal artificial intelligence model is a validation of the biopsychosocial theory of pain, which indeed posits distress as a complex experience that could be best understood and explained through a combination of behavioural and physiological signals.

Consistent with the recent literature by Salekin et al. (2022) and Gholami (2022), our ablation study verified that the fusion of visual, audio, and physiological data significantly outperforms the unimodal approaches. The better recall of high pain episodes by the fusion model (0.894) is clinically important; the fusion model suggests that the system is able to detect "silent suffering" - that is, instances where the child is simply too tired to cry (audio silence) but who nevertheless have a tachycardia or micro expressions of distress. This is possible by overcoming the limitations of intermittent manual rounds, which leave patients unobserved for extended periods of time.

5.2 Efficiency in Operation and Real-Time Analytics

The simulation showed a dramatic reduction in alert time (< 1 minute vs. 30-60 minutes for manual rounds). This is consistent with the work of Patil et al. (2023) who highlighted that the benefits of IoT-based smart healthcare frameworks guarantee real-time data analytics that is essential for immediate clinical intervention. By automating the detection process, the system has the potential to free nursing staff from routine observation tasks, enabling them to focus on higher value patient care and emotional support.

5.3 Overcoming the Barriers to Adoption in Haryana

While the technical performance is strong, the survey of healthcare officials had shown that the key to successful adoption in Haryana is human and ethical considerations more than technology.

- The low score for "Training Readiness" (3.65/5) identifies a significant gap. As cited by Kuttikat et al. (2022), clinician trust is fragile and without structured digital literacy workshops, false alarms may be experienced, creating "alert fatigue" and system abandonment.
- Privacy and Ethics: The survey indicated some moderate concerns about data privacy (score 4.1/5). This augments the case for non-negotiable privacy-preserving techniques for healthcare data sharing as argued by Ahamed et al. (2023). Our proposed edge-computing architecture, in which data is processed locally on hospital servers instead of on the cloud, addresses these concerns directly as patient data never has to leave the safe hospital environment.

Limitations

This study is based on a simulation that was trained on secondary data sets, and calibrated with local primary data. While this approach is methodologically valid for a feasibility study, it does not capture the chaotic nature of the acoustic environment in a busy general ward of a district hospital. Future research will have to include longitudinal clinical trials to validate the robustness of the system against noise in the real world and against various demographics of patients.

Conclusion of Discussion

The implementation of AI into pediatric postoperative care is a transition from reactive to proactive pain management. By pooling the precision of multimodal deep learning and the empathy of human caregivers, this framework provides a viable route to standardizing and elevating pediatric care in resource-constrained settings.

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