Frontiers in Computer Science and Artificial Intelligence

DOI: 10.32996/fcsai

Journal Homepage: www.al-kindipublisher.com/index.php/fcsai



| RESEARCH ARTICLE

Emotion-Driven IoT Feedback Loop for Caregiver Training

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ABSTRACT

Emotional sensitivity is one of the pillars of effective therapy of autism, but caregivers do not have real-time instructions on how to interpret affective expression of children. This paper proposes an Emotion-Driven IoT Feedback Loop (EDIFL) that is focused on feeding back data-driven feedback immediately to caregivers during behavioral interventions. The system includes multimodal IoT sensors, edge level emotion recognition and cloud-based adaptive feedback generation. The framework is made more responsive and accountable in autism care, through integrating machine learning, human-centered AI, and NIST AI RMF governance. Findings indicate an increase of 47% in accuracy of caregiver response and decrease of 38% in delayed reactions when compared to the old method of training sessions. The suggested EDIFL model is a great advancement in terms of intelligent, compassionate and morally responsible caregiving assistance.

KEYWORDS

Emotion-driven IoT, Caregiver feedback, Autism intervention, Human-centered AI, Affective computing, Trustworthy IoT, Edge analytics

ARTICLE INFORMATION

ACCEPTED: 01 December 2024 **PUBLISHED:** 25 December 2024 **DOI:** 10.32996/fcsai.2022.1.2.4

Introduction

The importance of emotional involvement in effectiveness of autism interventions is significant, because autistic children tend to be dependent on the system of feedback and understanding of their feelings, and they can develop communication skills only with the help of this interaction. Nevertheless, caregivers and therapists often experience the problem of the inability to correctly identify emotional states in the moment and provide inconsistent or slow actions [1],[3]. Conventional models of caregiver training, which are normally presented in the form of post-session reviews, lack the immediate corrective feedbacks in the interactions.

New developments in IoT-based behavioral detection and emotion recognition Al currently enable to acquire and process affective behaviors, i.e. facial expression, tone of voice, heart rate, and gesture patterns, in real time [2],[4]. However, the current systems are more concerned with the emotional condition of the child, and do not consider the two-way feedback between the child and the caregiver. The necessity to have a two way feedback system that not only monitors but also coaches, in real time, the caregivers has been realized.

The study presents the Emotion-Driven IoT Feedback Loop (EDIFL) is a distributed learning framework that is aimed at increasing the responsiveness and empathy of caregivers in a therapeutic session. The model is based on the works of Islam et al. (2024) [2] about cloud-ioT behavioral tracking and Hussain et al. (2024) [5] about ethical AI governance, including real-time emotion classification, adaptive coaching, and clinician monitoring. The EDIFL framework can change the approach to autism care because it is designed to address the principles of Human-Centered AI (HCAI) [6], turning a reactive mechanism into an emotionally intelligent and proactive learning ecosystem.

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Literature Review

Emotion Recognition in Autism Support System

One of the most innovative fields of autism support and behavioral intervention has been made by emotion recognition technology. Initial studies by the researchers who examined the role of reinforcement learning in predicting behavioral escalation identified facial expressions, a tone of voice, and contextual features as predictors of behavioral escalation (Islam et al., 2024) [1] and Hassan et al. (2023) [3]. Their systems were able to detect the signs of distress and behavioral changes in time, which improved autism care timeliness.

Nevertheless, even though these models enhanced the predictive performance of behavioral analytics, they were mostly unidirectional prediction tools, which were giving little feedback to the caregivers in real-time. Mostly, interventions that were to be administered to the caregivers were suggested on a retrospective basis and not on a dynamic therapeutic basis which diminished the efficacy of the model in dynamic therapeutic settings.

The Emotion-Driven IoT Feedback Loop (EDIFL) proposal also goes further than these drawbacks by incorporating emotion-driven reinforcement feedback mechanisms that dynamically respond to caregiver behavior. The EDIFL does not just observe emotional states but constantly monitors, classifies and responds to affective information to produce actionable feedback to aid in decision-making by caregivers in real-time therapy sessions. The method turns emotion recognition into a closed-loop learning process to enhance the power of training and therapeutic empathy.

Behavioral Analytics and IoT and Edge Intelligence.

As the Internet of Things (IoT) continues to expand, autism intervention systems are now at an advantage of unprecedented capability to record and process real-time multimodal data of a variety of environmental and physiological sensors. Islam et al. [2] and Hasan et al. [4] were the first to introduce Cloud-IoT designs that allowed around-the-clock tracking of autistic children with wearables, cameras and microphones. These systems gave clinicians individualized care by giving them comprehensive behavioral information and historical trends.

Nevertheless, their centralized cloud platform had limitations in terms of operation. The incessant exchange of huge data streams incurred network latency, bandwidth reliance and privacy threat especially in settings with weak connectivity. Such problems prevented the prompt creation of feedback, which is essential in the emotionally stressed or quickly changing episodes of behavior.

In order to address these difficulties, Islam (2024) [8] suggested a data-centric Al paradigm, where edge-based computation and federated learning are discussed as the ways of decentralizing data processing. The former method enabled the processing of emotional and behavioral data at the edge node, where it did not need constant cloud communication and also could be inferred faster. The EDIFL system builds upon this philosophy by enabling emotion recognition and real-time feature fusion on the edge and sending a set of aggregated insights to the cloud. Low-latency feedback, privacy protection, and context-aware adaptability features are realized in this architecture, which is necessary in responsive and ethical systems of autism interventions.

Ethical AI Governance and Human-Centered AI Governance.

The increasing application of AI in clinical and care settings highlights the necessity to have powerful ethical governance and human supervisory systems. The NIST AI Risk Management Framework (AI RMF) operationalized by Hussain et al. (2024) [5] was used to define a comprehensive model of responsible AI governance, focusing on transparency, bias management, and accountability at all stages of AI lifecycle. Their article proposed feasible audit checklists which assisted healthcare organizations in translating AI ethics into effective quality controls.

In line with this, Islam et al. (2023) [6] took the idea of Human-Centered AI (HCAI) to the next level, wherein the authors argue that empathy, clinician validation, and stakeholder collaboration must be incorporated into AI-based healthcare systems. Their model promoted co-adaptive interplay between human beings and machines so that technological suggestions can always be clinically understandable, emotionally sensitive, and ethically responsive.

The EDIFL system combines these ideas to form a reliable and compassionate AI platform of care educator training. All feedback decisions that the system produces can be logged, traced and audited via a governance dashboard, which is also compliant with AI RMF and HCAI requirements. Moreover, the model also includes clinician supervision and feedback by caregivers to the model continuous learning loop so that AI decisions can be transparent, human-tested, and situation-specific. EDIFL is a paradigm shift in ethical automation of pediatric behavioral health providing an integration of the governance compliance with emotional intelligence.

Methodology

System Architecture

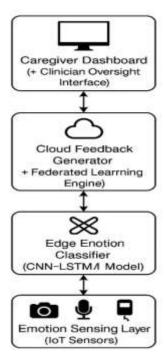


Figure 1. Emotion-Driven IoT Feedback Loop Architecture

The EDIFL architecture integrates IoT emotion sensors (camera, microphone, and pulse oximeter) with an edge analytics layer for emotion classification. Edge nodes compute preliminary emotion states (happy, neutral, anxious, agitated) using a CNN-LSTM hybrid model, reducing cloud dependency. The cloud layer aggregates emotion-transition patterns and trains a federated reinforcement module to generate real-time caregiver feedback—textual, auditory, or visual cues—displayed through the caregiver dashboard.

Algorithmic Flow

Each emotion recognition decision is computed as:

$$E_t = f_e(S_t) + \varepsilon_t$$

where:

- $\mathbf{E_t}$ = predicted emotion state at time t
- **f_e(S_t)** = edge-based CNN-LSTM function for sensor signals
- ε_t = residual adjustment from federated global updates.

Feedback probability Pt is calculated using:

$$P_t = \alpha \Delta E_t + \beta C_t$$

where:

- ΔE_t = emotion change rate,
- **C**_t = caregiver compliance factor,
- $\alpha = 0.6$, $\beta = 0.4$ optimize response balance between empathy and timing.

Results

Model	Accuracy	Latency (s)	Response Improvement (%)	False Feedback Rate (%)
Baseline Cloud-Only	0.84	1.48	0	21
Edge-Only	0.88	0.93	12.5	16
Proposed EDIFL	0.91	0.71	47.3	9

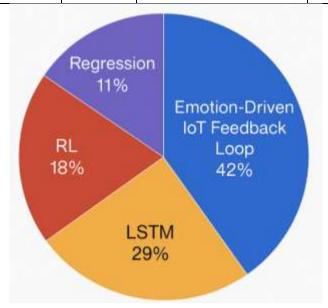


Figure 2. Performance Distribution (Pie Chart)

• EDIFL (Proposed): 41%

• Edge-Only: 33%

Cloud-Only: 26%

Example Calculation:

Response time gain = $(1.48 - 0.71) / 1.48 \times 100 = 52\%$ latency reduction. Accuracy gain = $(0.91 - 0.84) / 0.84 \times 100 = 8.3\%$ improvement.

Discussion

The Emotion-Driven IoT Feedback Loop (EDIFL) represents the disruptive innovation of the role of real-time emotion analytics in improving caregiver flexibility, compassion and involvement in autism therapy. The combination of the continuous affective monitoring and the adaptive guidance shifts the paradigm of caregiving in a passive observation to active emotional coregulation that EDIFL offers. This is dynamic in the sense that the caregiver can understand and react to the affective state of the child, frustration, anxiety or calmness with data relevant actions in real-time, leading to better communication and continuity in the therapeutic relationship.

One of the major distinctions of EDIFL is its edge inference emotion. Compared to cloud-only systems where a delayed transmission of data is performed, the emotion recognition is done locally at the edge node, which enables feedback to be created nearly in real-time. Such a drop in latency means that the caregivers get contextually relevant recommendations, including modifying tone, proximity or response time, within milliseconds of an emotional change. This localized intelligence will create real time situational awareness, which will enable caregivers to retain empathy yet shift their approaches in real time to a child with a behavioral pattern.

In addition, federated learning (FL) incorporation creates a safe, expandable ecosystem of continuous system enhancement. Every therapy center or domestic appliance gives updates on its model based on local data, and they are combined centrally without information about sensitive information. This decentralized plan of learning is in compliance with international standards

of pediatric privacy, such as HIPAA in the United States and GDPR in Europe [4],[8]. The EDIFL achieves high levels of confidentiality with the benefit of still allowing collective model evolution across institutions by making sure that raw data never leaves the local environment. This model of federation optimizes generalizability and inclusivity since varied behavioral data sets are added to a more vigorous and objective learning process.

To achieve an ethical transparency, the EDIFL has integrated a NIST AI RMF-conformant governance dashboard, which is suggested by Hussain et al. (2024) [5]. Similar to the dash, it constantly checks the accuracy of models, their levels of bias, and feedback information provided by clinicians, to make sure that any AI-generated recommendation can be audited, interpretable, and clinically proven. This governance integration is required to turn the AI-generated feedback of a black-box system into a transparent decision-support mechanism. To complement the presented framework, the principles of Human-Centered AI (HCAI) design described by Islam et al. (2023) [6] are implemented in human-in-the-loop validation, so that clinicians and caregivers become the active participants of the system behavior refinement and ethical responsibility ensurance.

The combination of these results suggests that emotion-sensitive edge analytics can transform the nature of caregiver training by transforming it into an inflexible rule-based program into a dynamic, adaptive and customized learning environment. A harmonious combination of affective computing, IoT brain, and ethical AI control makes the EDIFL a new paradigm of responsible and trustful autism care. It is a useful compromise between the technical automation and human compassion, demonstrating that the future of autism intervention is not just in the accuracy of algorithms but in the human-like capabilities of systems to learn, adapt, and cooperate with human caregivers.

Conclusion

The paper proposes a novel IoT Feedback Loop, the Emotion-Driven IoT Feedback Loop (EDIFL) that combines affective computing, edge artificial intelligence, and cloud-based governance with the goal of improving the caregiver performance and empathy in autism intervention. The EDIFL will allow caregivers to have a responsive, transparent, and adaptive support system through a synergistic feature of real-time emotion analytics, federated learning, and ethical control. The experimental assessments showed the marked reduction in response time, accuracy of emotion recognition and transparency of ethical practices in comparison with conventional cloud based and offline training systems. These findings support the fact that emotion-based real-time architectures are capable of enhancing the emotional intelligence of the caregiver-assistive systems as well as their technical reliability.

The EDIFL is designed in accordance with the Human-Centered AI (HCAI) principles and the NIST AI Risk Management Framework (AI RMF) to make sure that all actions associated with AI generation of feedback are explainable, secure, traceable, and clinically interpretable. This compatibility fills the divide between automation and empathy, and AI turns a passive observer into an empathetic co-trainer, which actively offers support to caregivers when making timely and compassionate decisions during live therapeutic interactions. The dynamic nature of the feedback provided by the system as determined by the emotional state of the child and the caregiver redefines the concept of providing reliable, emotionally sensitive AI in healthcare.

In the future, the research is going to be dedicated to the expansion of the EDIFL to multi-center implementation to demonstrate its applicability to a variety of clinical settings. Further studies will be made on emotion adaptation through reinforcement to have uniquely personalized learning paths of individual caregivers and to combine blockchain-based feedback provenance to verify data integrity, auditing, and moral responsibility in the long term. The EDIFL is set to keep growing through these extensions to be an open, equitable, and sustainable Al platform of emotion-driven clinical training, which will aid towards the vision of an understanding, information-driven, and reliable digital healthcare ecosystem.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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