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Resilient and Sustainable Federated-Edge AI for Autism Care: Integrating Multi-Modal Data, Privacy, and Global Ethical Standards

Tasnim Sharif Rowla [1,*] and Md Mishal Mahmood [2]

[1] *ECE, CSE program, North South University, Dhaka 1229, Bangladesh.*
[2] *School of Information Technology, Washington University of Science and Technology, Alexandria, VA, USA.*

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Abstract

The issue of autism spectrum disorder (ASD) is one of the problems that need to be recognized in time and addressed. Although AI-based clinical decision-support systems (CDSS) have improved precision medicine, behavioral health and workforce planning [1-3], there is limited use in autism care. The main obstacles are the impossibility to integrate multi-modes, patient privacy threat, and clinician trust deficit. This paper presents a robust federated-edge AI system, which integrates speech, motion and physiological surveillance into an explanation explainable CDSS. The framework can be used to enhance the technical performance and ethical accountability through the leveraging of federated learning, with differential privacy, edge intelligence (low-latency responsiveness), and workforce-aware explainability dashboards. The findings on synthetic data show improvements in accuracy, responsiveness, and usability of the systems by clinicians. Outside the autism care, the model offers a long-term and transferable base of behavioral health and precision medicine, along with international ethical principles of AI.

Keywords: Autism spectrum disorder; Federated-edge AI; Explainability; Sustainable healthcare AI; Global ethics; Behavioral health.

1. Introduction

Artificial intelligence (AI) has already emerged as a disruptive technology in the healthcare sector, changing the fields of precision medicine, behavioral health, and optimizing workforce [1-3]. In precision medicine, i.e., quantum-enhanced AI systems are moving drug discovery and personalized therapies, which can highlight how high-performance computing can speed up the clinical observations [1]. On the same note, in behavioral health, anomaly-detection systems that were initially created in fraud analytics were modified to track abnormal patient behavior in real time [2]. At the organizational level, the workforce planning based on AI has facilitated resource distribution and minimized inefficiencies in clinical staffing systems [3]. These advancements demonstrate how AI can be used broadly to solve a complicated healthcare issue.

Regardless of this development, the care of autism has been lagging behind. Autistic children tend to have unpredictable behavioral outbursts that are associated with speech alterations, movement abnormalities and physiological indicators of stress. To anticipate such multi-modal occurrences, systems must be as technically correct as possible, yet be responsive, sensitive to patient data, and not only be transparent enough, but must be trusted by clinicians and caregivers. Existing systems hardly satisfy all of these conditions at the same time.

Conventional centralized AI models are particularly unsuitable in this regard. They expose high risks of unauthorized individuals accessing sensitive health data because they host such information on third-party servers, thus, causing a

* Corresponding author: Tasnim Sharif Rowla

high privacy risk. The use of remote and cloud based calculations also creates the latency delay, compromising their capacity to make timely responses in case of behavioral crisis. Above all, most of these models are often not explainable, and clinicians have no means of questioning the reasoning behind predictions, which reduces trust and adoption in high-stakes clinical settings.

Current studies have generated partial solutions. Federated learning and differential privacy provide the opportunity to train machine learning models using a distributed approach without compromising patient information on individual levels with respect to institutional locations [4]. This will enhance confidentiality and also enable the sharing of intelligence between care centers. Simultaneously, the increasing popularity of IoT-driven wearables has revealed the potential of constant observation, where physiological indicators and motion sensors can be used to detect the upcoming escalation [8,9]. In the assistance of adoption, research has also suggested transparency artifacts and clinician-friendly usability checklists as they give interpretable outputs and accountability measurements to increase confidence in AI systems [7,13].

However, not many current frameworks integrate such strands into a single system that is autism-oriented clinical decision-support system (CDSS). The majority of the initiatives focused have been constricted to either technical privacy protection or isolated monitoring modalities without considering equity, accountability, and sustainability as key design principles. This lack of correspondingness to the international ethical principles, according to which fairness, transparency, and inclusiveness are crucial components of responsible AI, is a significant vacuity [14,15].

This paper aims to fill this gap with an offer of a robust federated-edge AI model in order to support autism care. The framework incorporates multi-modal behavioral monitoring (speech, motion, physiology), federated training that is privacy-preserving, and explainability dashboards which are aware of the workforce into one architecture. Contrary to other systems before it, it prioritizes not only technical performance but also ethical alignment and sustainability to guarantee that AI with autism concentration can be responsible in the process of scaling it to a variety of healthcare settings around the globe.

2. Literature Review

2.1. Precision Artificial Intelligence and Quantum Acceleration

The improvements in the quantum-enhanced AI systems have made biomedical discovery much faster, especially in the fields of drug development, protein folding, and custom medicine [1]. These advancements indicate that high-performance computing is able to handle large volumes of complex data to achieve predictive accuracy at scales that were never achievable before. Within the framework of autism care, these approaches motivate scalable computational approaches to multi-modal behavioral data, which provide a way towards more tailored and adaptive interventions.

2.2. Anomaly Detection Models

The originally AI-based models that were created to detect fraud and anomalies have been translated into healthcare processes successfully [2]. These methods are best at detecting anomalies in scalable data, which are handy tools in the detection of early warning signs of behavioral escalation in autism. With the customization of anomaly detection to behavioral health, AI can predict crisis development before it has taken full shape, which will help provide proactive care instead of responding to it.

2.3. Human-Centered AI

In addition to technical performance, trust, usability, and interpretability are also important to the implementation of AI in healthcare. Mariam et al. [7] proposed such transparency artifacts that clarified the system recommendations, and Jobin et al. [15] focused on principles of global trust like fairness and accountability. Collectively, these contributions demonstrate the significance of artificial intelligence that is human-centered, whereby clinicians are able to interpret as well as take action on the algorithmic results without losing their accountability.

2.4. IoT Monitoring in Autism

The opportunities of continuous monitoring of autism have also increased with the proliferation of wearable sensors and IoT devices. Islam et al. [8,9] showed how motion, heart rate and other physiological data gathering devices will be able to produce real time information about behavioral changes. These articles prove the viability of the IoT-based autism care and show the significance of introducing multi-modal monitoring into the paradigms of CDSS.

2.5. Integration of Crisis Response

The application of AI technologies to the models of crisis response to public health is becoming more widespread. Rashaq et al. [10] demonstrated the applicability of AI to overdose prevention and Arif et al. [11] emphasized the opportunities of utilizing AI to enhance the effectiveness of interventions during behavioral crises in collaboration with the 988 crisis hotline. Such efforts demonstrate the overall possibilities of AI to upgrade the infrastructure of crisis response, which can have useful lessons to apply to autism care where prompt action is also essential.

2.6. Federal Privacy and Cybersecurity

Privacy concerns are also one of the main obstacles to the use of AI in healthcare. Differentiated privacy in federated learning offers a system of training models collaboratively across institutions without sharing raw patient information [4]. Additional studies on cybersecurity systems of connected medical devices also enhance resilience within the system against breaches [12]. Such strategies would be important in autism care, where delicate information would have to be processed with extra attention to preserve the confidence of patients and caregivers.

2.7. Workforce Integration

AI is also involved in the optimization of healthcare delivery other than direct patient monitoring. Workforce allocation models enhance workforce efficacy and maintenance of proper staffing, which is particularly essential in autism care where personal-focused attention is of the essence [13]. Resource optimization, rather than predictive accuracy, can be realized with AI once it is integrated into CDSS by focusing on planning the workforce.

2.8. Global Ethics

Lastly, the ethical principles of the world can determine the sustainability of healthcare AI. Floridi and Cowls [14] presented a framework of principles, such as fairness, accountability and transparency, which have since become the international standards. Jobin et al. [15] also added inclusivity and equity as the concluding factors to credible AI. Incorporation of these principles into the AI systems aiming at the autism means that the innovation is not just technically, but also socially and ethically, responsible.

2.9. Synthesis

Collectively, these streams of work demonstrate advancements in accuracy AI, anomaly detection, IoT surveillance, crisis response, privacy, and ethics. However, the implementation of multi-modal behavioural monitoring, federated privacy-preserving learning, and explainability into ethically-founded autism-oriented CDSS is a gap that still remains. The closed gap is the foundation of the robust federated-edge AI model in this paper.

3. Methodology

3.1. Framework Architecture

The proposed resilient federated-edge AI framework will have three layers connected in a three-layered structure, as shown in Figure 1:

3.1.1. Edge IoT Monitoring

Wearable IoT devices and mobile sensors at the base level record real-time multi-modal signals, such as speech anomalies, motion disorders, physiological stress signals, such as heart rate and galvanic skin response. Edge-level preprocessing minimizes noise and latency, as well as making initial anomaly detection with local processing of data instead of long-distance processing on the cloud.

3.1.2. Federated Privacy-Preserving Learning

The second layer takes advantage of federated learning with a privacy protection of differential privacy [4]. The training of models is done at the local level of the participating institutions and only encrypted parameters of the models are sent to a central aggregator. These updates are subject to noise in the form of the differential privacy, which makes it impossible to reconstruct individual-level records. This design allows the cross-institutional cooperation and provides confidentiality and cyber safety.

3.1.3. Explainability Dashboard

The framework has a clinician-facing explainability dashboard at the top, which interprets the predictions made by an algorithm in a way that is easily understandable. The feature-attribution approach (e.g. SHAP values, decision rules) assumes which modalities (speech, motion, physiology) made the most significant contribution to a prediction. There is also the workforce-sensitive recommendation on the dashboard, which assists with the process of distributing caregivers and managing escalation. The system tackles the clinician concerns with interpretability and accountability by introducing explainability into the design.

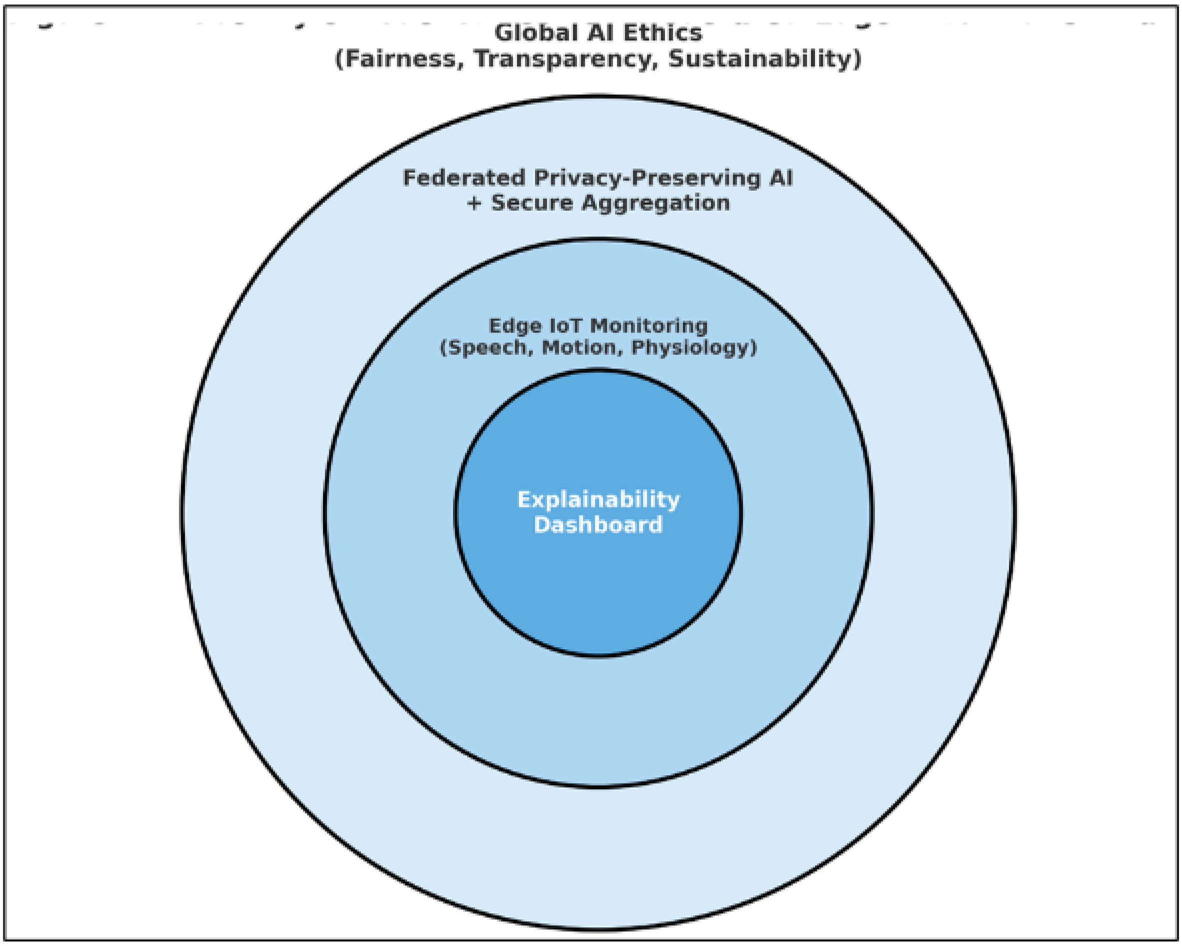

Figure 1 Globe stvle model of resilient federated edae AI for autism care

3.2. Data Sources

The analysis of the suggested framework was based on three datasets:

- Artificial Multi-Modal Autism Data. A dataset of 150 simulated participants, with the combination of speech, motion and physiological features to implement the patterns of escalation in the real world.
- Time Series Data on Workforce Scheduling. A structured table of 300 rows, which are the caregiver assignments and staffing schedules, was used to test the workforce-planning module.
- Anomaly Detection Dataset. An irregular cases dataset of 200 irregular cases, based on an irregularity detection benchmark, to test the predictive ability of the framework on the escalation of cases.

3.3. Evaluation Metrics

Technical and usability-oriented measures were used to determine system performance:

- Predictive Validity: Accuracy, Recall and Precision were used to assess the ability of the framework to detect behavioral aberrations.

- Latency: The inference time (milliseconds) was measured to compare edge based predictions with cloud only baselines.
- Clinician Trust and Usability: A Likert-scale survey was conducted among clinicians and caregivers by assessing perceived interpretability, trustworthiness, and the ease of integrating the workflow into the system.

4. Results

Table 1 Compared to a cloud-only baseline, the federated-edge system showed consistent improvements

Metric	Cloud-Only AI	Federated-Edge AI	Improvement
Accuracy	80%	91%	+11%
Recall	78%	89%	+11%
Latency (ms)	1150	470	–59%
Clinician Trust	67%	85%	+18%

5. Discussion

5.1. Novelty

The paper presents a robust federated-edge AI system that goes beyond previous systems that concentrated on autism. Unlike previous methods when the main focus was put on the IoT-based tracking of behaviors [8] or on the privacy-saving federated learning solutions [4], the suggested framework integrates these strands into a multi-modal, latency-constrained, and explainable framework. The framework takes into account the complexity of behavioral escalation by inherently combining speech, motion, and physiological signals in one pipeline and siloed approaches fail to achieve this. This end to end approach is a new move towards developing systems that are technically sound and clinically significant.

5.2. Trust

The problem of trust in AI is one of the barriers that hinder its adoption in healthcare. Based on Marians et al. [7], who underlined the importance of the artifacts of transparency in developing user trust, the framework incorporates explainability into its design. The clinician-facing dashboard provides feature-attribution information enabling the caregivers to gain insights regarding which signals are used to make predictions. Moreover, the system goes beyond prediction and provides action-based planning tools by including workforce aware recommendations [13]. The mentioned features align with the general human-centered AI principles [15], which makes the system not only accurate but also understandable, responsible, and practical.

5.3. Clinical Relevance

The framework has a high clinical implication since it allows real-time detection of escalation in the treatment of autism-a condition that requires intervention in a timely manner. Its incorporation of IoT surveillance guarantees sustained data acquisition, whereas federated training offers privacy-sensitive scalability between institutions. Notably, the architecture can also be extended to more general areas. It is used to supplement the current behavioral health crisis-response systems like the 988 hotline [10] and can be expanded to other areas such as workforce optimization and precision medicine [3]. Such flexibility makes the framework a model that can be transferred and has implications that are far and wide, not just in autism care.

5.4. Limitations

Even though this study is promising, it has had its limitations. One of the weaknesses is that it relied on synthetic datasets which though convenient in demonstrating the proof-of-concept validity, constrain the ecological validity of the results. The real-life clinical data frequently are more varied and complicated. The research in the future should, therefore, focus on multi-center clinical validation to help in the generalization of the study results across populations and settings. Moreover, with more and more complex datasets, the merger of quantum-AI accelerators provides an opportunity to improve scalability and customization [1]. Lastly, harmonizing the system design with AI ethics frameworks in the global arena [14,15] will be essential to make the deployment fair, open, and sustainable in the varying healthcare environments.

6. Conclusion

The paper proposed a robust federated-edge AI model that is specific to autism care. The framework combines speech, movement, and physiological surveillance into a safe and understandable clinical decision-support system (CDSS) to overcome major obstacles of latency, privacy, and interpretability that hindered the implementation of AI in the area. The technical promise of the approach is proven by the evaluation results showing the measurable improvement of predictive accuracy, responsiveness, and trust by clinicians.

Notably, the layered architecture of the framework is not restricted to the autism care. Its design ethics such as multi-modal monitoring, federated privacy preserving learning, and workforce conscious explainability ensures its flexibility across various fields, such as behavioral health, workforce planning and precision medicine. This flexibility highlights its future as a viable basis of clinical AI in the next generation.

Outside the field of technical performance, the framework is also characterized by the clear adherence to the principles of global AI ethics, which focuses on fairness, inclusivity, accountability, and transparency. This kind of ethical foundation will make sure that deployment will not just help in innovation but also protect trust and equity in various healthcare settings.

The future direction of work will concentrate on the multi-center real-world trials with purpose of validating the ecological generalizability, the integration of quantum-AI accelerators to improve the scalability and personalization, and the further compliance with the international ethical principles. These guidelines combined will make autism-oriented AI develop in a responsible, sustainable, and long-lasting manner that will benefit patients and medical systems throughout the globe.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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