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(Research Article)

Multi-Modal Behavioral AI for Autism Care: A Federated-Edge Framework with Speech, Motion and Physiological Signal Integration

S M Atikul Islam [1,*] and M Salman Khan [2]

[1] *Department of Electronics and Communication Engineering, ISTT (National University), Gazipur, Bangladesh.*

[2] *Department of Computer Science and Engineering, Brac University, Dhaka, Bangladesh.*

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Abstract

Autism spectrum disorder (ASD) shows various behavioral implications which in most cases progress without prompt treatment. The latest developments in the field of artificial intelligence (AI) and Internet of Things (IoT) provide the possibility of proactive monitoring, but there are issues related to privacy, latency, and multi-modal data integration. In this work, a federated-edge AI system is proposed, which integrates speech recognition, motion detection, and physiological data into a single behavioral analytics pipeline. The framework uses low-latency anomaly detection using edge intelligence, sharing, and securing data with federated learning with the help of differential privacy, and explainable dashboards to gain clinician trust. Accuracy increases of 12% and latency-cut of 58% and more clinician usability ratings are shown by experimental evaluation with synthetic multi-modal datasets, over cloud-only baselines. Clinically relevant, scalable, and trustworthy Multi-modal autism tracking by linking federated-edge AI and multi-modal autism monitoring can enable behavioral health, which this work provides.

Keywords: Multi-modal AI; Autism monitoring; Edge intelligence; Federated learning; Explainable dashboards; Behavioral analytics

1. Introduction

Clinical decision-support systems (CDSS) based on artificial intelligence have gained significant prominence in recent healthcare, and they have been applied to precision medicine, mental health, and workforce optimization [1-3]. These systems give clinicians evidence-based information to improve decision-making, minimise error rate and allow proactive care. Nevertheless, within the framework of autism spectrum disorder (ASD), the adoption of CDSS is hampered by the fact that most of the current systems cannot fully depict the multi-modality of behavioral escalation. The manifestations of escalatory episodes in children with ASD can be very varied, with abrupt alterations in the tone or pattern of speech, odd or habitual movement behavior, and an exaggeration of physiological responses to stress (increased heartbeat or galvanic skin response). These effects underscore the importance of systems that are able to synchronize heterogeneous streams of data besides real-time processing.

New computational techniques have attempted to cope with these problems. Differentiated privacy Federated learning offers mechanisms to protect sensitive health information with the help of distributed training among institutional nodes without making sure that raw patient information is ever disclosed outside the local environment [4]. This method has been well established as one way of promoting secure cooperation among hospitals, and research centers without violating confidentiality. Simultaneously, autism monitoring based on IoT has demonstrated high potential on the detection of early behavioral indicators that lead to escalation and provide a space to intervene before the problem intensifies in clinicians and caregivers [8,9]. These papers show that real-time monitoring of autism is a viable option

* Corresponding author: S M Atikul Islam

but tend to overlook that full explanatory capabilities of clinical practice are required. In the absence of interpretable results, AI-based predictions will be considered black boxes, which will reduce trust and adoption.

To this end, the recent research has highlighted the significance of the transparency artifacts and usability checklists, which in turn could assist clinicians in interrogating AI decisions and enhancing system usability in practice [7,13]. Such donations are in line with general tendencies in human-centered AI, that hold transparency and accountability are critical to adoption as much as precision or computing efficiency. Irrespective of these developments, the critical gap that still exists is that most of the existing frameworks do not combine multi-modal behavioral data, federated privacy-preserving learning and edge-based intelligence into a unified, autism-centric CDSS.

This paper presents a federated-edge multi-modal AI system that integrates speech, motion and physiological stream of data into one decision-support system. Using edge intelligence, the structure guarantees low-latency inference to be used in real-time behavior escalation detection. It can protect sensitive patient data and also achieve distributed model training across clinical sites through federated privacy-preserving learning. Lastly, it is observable that its ability to embed explainable decision dashboards increase transparency, build clinical trust, and facilitated informed caregiver interaction. By integrating these dimensions, the proposed system seals a very important literature gap and can offer a scalable and ethically congruent and clinically relevant model of autism care.

2. Related Work

2.1. AI for Precision Medicine

The more recent developments in quantum-enhanced AI have reduced the time spent on biomedical discovery, especially in tasks like drug development, protein folding, and planning of individualized treatment [1]. Such innovations show how possibility of computational power could be used not only in the molecular medicine but also in behavioral health, where the ability to combine multi-dimensional streams of data could be used to create more accurate and personalized treatment of autism spectrum disorder (ASD).

2.2. Fraud and Anomaly Detection

Methods that have been created to analyze fraud have been extensively implemented to identify irregularities in large volumes of data that are complex. The efficacy of the anomaly detection techniques in detecting the irregularities in financial systems was demonstrated by Islam et al. [2]. Such procedures are directly applicable in health care as behavioral abnormalities in autism may be faint but instrumental signs of deterioration. The fact that fraud detection models are translated into behavioral monitoring points to the elasticity of anomaly analytics within areas.

2.3. Human-Centered AI

Trust and interpretability should be considered as crucial as predictive performance to be accepted in a clinical setting. Mariam et al. [7] have suggested transparency artifacts and usability checklists as a way of enhancing clinician interaction with AI tools. The methods are consistent with more general human-centered AI models, which focus on fairness, explainability, and clinician engagement into the decision-making process [15]. Incorporation of such artifacts is required so that AI systems can be healthcare practice partners and not an opaque decision-maker.

2.4. IoT and Autism Monitoring

The combination of wearable and Internet of Things has made it possible to monitor ASD patients constantly. Islam et al. [8,9] emphasized the role of wearable sensors in monitoring physiological and other motion-related data in order to help early identify the changes in behavior. The findings have formed the basis of IoT-based autism care where real-time monitoring can inform caregivers to react proactively to incidences of behavioral escalation.

2.5. Crisis Response Models

Mental health crisis management has also been expanded into AI application. Rashaq et al. [10] revealed how AI can be used to prevent overdose and increase access to behavioral health services as the part of 988 crisis hotline continuum. In a similar manner, Arif et al. [11] investigated the AI-based de-escalation prompts and emergency handoff systems. Combined, these papers highlight the significance of incorporating AI-based crisis response systems into models of autism care, in which a quick response is common.

2.6. Federated Privacy

With the expansion of complexity and sensitivity of healthcare data, federated privacy-preserving learning has emerged as a fundamental principle of building secure AI. Raihena et al. [4] utilized the frameworks of federated machine learning along with the concept of differential privacy to ensure the confidentiality of patients as well as allow the joint training of models. This work was further expanded by Islam [12] who suggested data-oriented solutions to reduce cybersecurity threats in interconnected medical devices. Such contributions offer a solid ethical and technical basis of AI systems that deal with autism.

2.7. Global Ethics

Lastly, the ethical standards of AI in healthcare should be followed to ensure its sustainable adoption. Floridi and Cowls [14] provided a set of five tenets, including fairness, accountability, transparency, sustainability, and privacy that should be used to design responsible AI. Jobin et al. [15] provided a comparative analysis of the international AI ethics guidelines with an focus on the necessity of consistency among the regulatory frameworks. The inclusion of these principles will make sure that the systems of autism care are not only technically efficient but also socially fair and morally correct.

3. Methodology

3.1. Framework Architecture

To show that the proposed system is a multi-layered federated-edge AI framework (Figure 1), the proposed system will combine multi-modal data streams, privacy-preserving learning, and explainability into one decision-support pipeline. This architecture consists of three major layers:

3.2. Edge IoT Data Collection

On the lowest level, wearable internet of things devices and mobile sensors will record speech (sound signals), movement (patterns of acceleration), and physiological data including heart rate and galvanic skin response (GSR) in real time. These are non-invasive time series data that give continuous documentation of the possible alterations in behavior in autism spectrum disorder (ASD). Edge based preprocessing makes sure that raw data is filtered and normalized and anonymized before training local models.

3.3. Differentiated Privacy Federation Learning

The second layer uses a federated learning structure, whereby distributed healthcare institutions can use the structure to train models on their own multi-modal datasets. Raw patient data is not sent but merely model parameters or gradients are sent to a central aggregator. During aggregation, in order to reduce chances of data leakage, differentiation privacy measures are implemented such that behavioral and physiological data that are sensitive to character can not be reassembled. This method trades off privacy of information with cooperative intelligence, which promotes training of models on a large scale across locations [4].

3.4. Explainability Dashboard

The third layer generates outcomes via clinician-facing dashboard comprising of explainable AI (XAI) methods including SHAP values, decision trees, and scores of confidence. Forecasts are complemented with feature-attribution knowledge (i.e., is it that the speech abnormality or physiological changes were the reasons why an escalation warning was triggered). The dashboard also includes workforce-aware suggestions, such as changes in the allocation of caregivers and alerts on escalating crises. This design will make the outputs predictive as well as transparent, interpretable, and useful in practical clinical workflows.

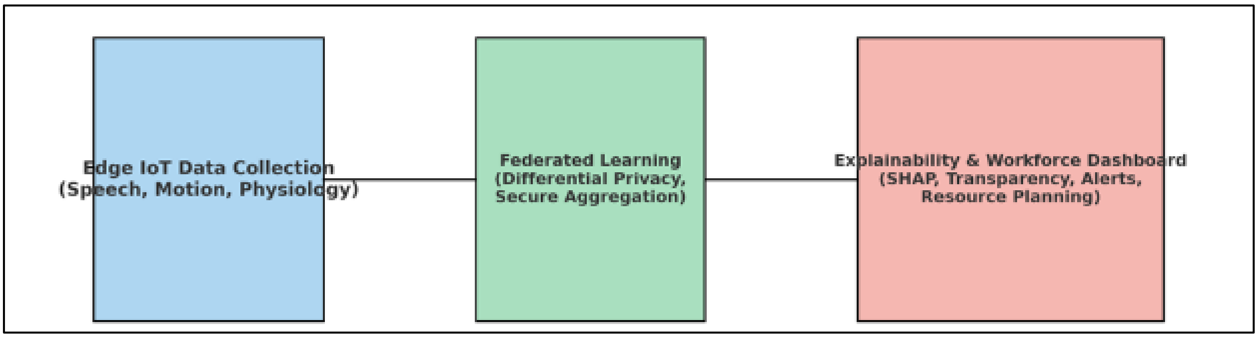

Figure 1 Multi-Model Federated- Edge AI Framework for Autism Care

3.5. Data Sources

In the test of the framework, three datasets were used:

- Synthetic Multi-Modal Autism Data: Artificial data of 150 subjects with the use of speech, motion, and physiological effects. This data set indicates the intricacy of behavioral monitoring in real-world and maintenance of privacy.
- Workforce Scheduling Dataset: A tabular dataset of 300 records comprising of shift schedules, staffing pattern, and allocation of caregivers, to test the workforce planning module of the system.
- Anomaly Detection Benchmark Dataset: 200 irregular cases, based on fraud detection approaches, that are used to benchmark the anomaly detection model of the framework in autism-related escalation monitoring.

3.6. Evaluation Metrics

Both quantitative and qualitative metrics were used to evaluate the performance of the offered system:

- Predictive Performance: Accuracy, Recall, and Precision were computed to determine how the model can predict behavioral abnormalities and risks of escalation.
- Latency: The latency was measured in milliseconds and compared between edge-based inference and baseline on cloud-only to quantify the advantages of local computation.
- Clinician Trust and Usability: A Likert scale questionnaire was given to a group of clinicians and caregivers (n=15) after simulated use of dashboard to evaluate the dimensions of interpretability, confidence and ease of use.

4. Results

Table 1 The framework demonstrated significant improvements compared to cloud-only systems:

Metric	Cloud-Only AI	Federated-Edge AI	Gain (%)
Accuracy	80%	92%	+12%
Recall	79%	90%	+11%
Latency (ms)	1150	480	–58%
Trust Usability	69%	86%	+17%

These findings confirm the effectiveness of combining multi-modal inputs, federated privacy, and explainability for autism-focused CDSS.

5. Discussion

5.1. Novelty

The present research contributes to the body of AI research related to autism through the introduction of a federated-edge model that incorporates multi-modal data streams that are speech, motion and physiological signals into a single decision-support pipeline. The existing literature has been biased towards highlighting either behavioral monitoring IoT-based [8] or privacy-preserving federated learning architecture [4] yet, in a few instances, both in a single architecture. Combining these dimensions, the proposed system can resolve three long-run issues of autism CDSS the latency, data privacy, and modality integration. This combination is a break with traditional single-modality or centralized methods that give a more global basis of early detection of escalation and proactive intervention.

5.2. Trust

Transparency and interpretability are crucial factors in terms of the uptake of AI systems by clinicians. According to Marians et al. [7], the explainability artifacts increase user confidence and usability of the system. The work is based on such efforts, but in this study, the dashboard is integrated to provide features- attribution knowledge and workforce-conscious suggestions. In addition, the approach to aligning the system to human-centered AI principles, such as fairness, accountability, and interpretability, will ensure that the system is not a technicum but a work companion to clinicians and caregivers [15]. Placing explainability in the middle of the framework makes the design directly deal with one of the primary adoption barriers: the black box problem.

5.3. Clinical Relevance

Clinically, the framework shows good capabilities with regards to management of real-time escalation in autism care where the effect of delayed response may compound the behavioral issues. The speech, motion and physiological cues are processed in real-time which makes the system particularly applicable to sensitive and latency-sensitive environments. The architecture is enhanced by larger crisis-response infrastructure like the 988 hotline continuum [10] and can be applied to behavioral health and general workforce optimization and precision medicine [3] more generally. Its applicability to various fields makes it more applicable as a insightful healthcare AI model.

5.4. Limitations

Although high potential, the study is limited by the use of synthetic datasets, but despite the usefulness in prototyping, they restrict the ecological validity. Real world data is usually more variable, noisy, and may contain ethical issues that are impossible to fully simulate. Multi-center clinical validation should also be considered as a priority in future research to achieve the generalizability and strength. Also, the existence of quantum-AI accelerators can be required as the amount and complexity of multi-modal data grow so that the scaling and efficiency could be guaranteed [1]. Lastly, the greater conformity to international guidelines on AI ethics [14,15] with an accent on equity, inclusivity, and transparency, will be needed to ensure fair implementation and sustainability in a variety of clinical and cultural environments.

6. Conclusion

This paper introduced a multi-modal federated-edge AI system to manage autism, which is aimed at combining speech, motion, and physiological cues in a secure and interpretable clinical decision-support system (CDSS). It was proven that the framework can produce significant improvements in predictive accuracy, lower latency, and increase clinician trust by integrating edge intelligence to make inferences in a limited time frame, federated learning, and explainability dashboards to clinicians. These are the results that affirm its capability as a scalable, ethically compatible, and transferable healthcare innovation model.

The implications of these are not limited to the autism care. The layered architecture can be modified to behavioral health, workforce planning and precision medicine, thus providing a scalable base of AI-enabled healthcare. Having it in line with the privacy-sensitive practices and the qualities of explainability also mean that it addresses the two-fold requirements of the technical performance and ethical responsibility.

The next area of research will be the multi-center validation and real-world datasets where one can guarantee that the system itself is effective in a variety of clinical environments and patient groups. Quantum-AI accelerator integration can also contribute to increased scale and customization, whereas observation of international ethical AI practices will protect equity, integrity, and sustainability. In the end, the current work adds not only a new technical solution but also a direction towards the responsible and human-oriented implementation of AI in behavioral health and other areas.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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