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Personalized Health Monitoring Of Autistic Children Through AI And Iot Integration

Md Nayeem Hasan[1] , Sanjida Islam[2] , Abdullah Hill Hussain[3] , Md Maruful Islam[4] , Md Mehedi Hassan[5]

[1]Department of Information Technology,Washington University of Science & Technology, Alexandria, VA-22314, USA email- mdhasan.student@wust.edu
[2]Department of Information Technology,Washington University of Science & Technology, Alexandria, VA-22314, USA email- sanislam.student@wust.edu
[3]Department of Information Technology, Washington University of Science & Technology, Alexandria, VA-22314, USA email- ahill.student@wust.edu ORCID: https://orcid.org/0009-0008-0436-027X
[4]Department of Information Technology,Washington University of Science & Technology, Alexandria, VA-22314, USA email- himul@mimul.com.bd ORCID- https://orcid.org/0009-0009-7819-3096
[5]Department of Information Technology, Washington University of Science & Technology, Alexandria, VA-22314, USA email- mehedi61@gmail.com Orcid- https://orcid.org/0009-0001-8910-0846

Abstract

Autism spectrum disorder (ASD) has complex and variable traits that require ongoing and flexible monitoring. Traditional assessments of health, which are based upon observation by caregivers and periodic clinical visits, are not able to capture day-to-day variation in physiology and behavior. This paper proposes a personalized health monitoring system that combines the artificial intelligence (AI) and Internet of Things (IoT) devices to support autistic children. The system combines wearable sensors, anomaly detection models and privacy-preserving learning to detect behavioral and physiological patterns of stress in real time. Simulation findings indicate increased accuracy of anomaly detection, improved response of caregivers and fewer false alarms when compared to baseline monitoring systems. The study concludes that the integration of AI with IoT holds a good opportunity for personalized care to support both kids and caregivers while remaining ethical and compliant with regulations.

Keywords Autism spectrum disorder; Personalized health monitoring; Internet of Things; Artificial intelligence; Federated learning; Wearable sensors; Digital health.

Introduction

Autism spectrum disorder (ASD) is known to be a lifelong neurodevelopmental condition that currently impacts roughly 1 in 100 children across the globe, however prevalence is subject to variations across regions due to differences in diagnostic practices and awareness [1]. The disorder is characterized by extreme heterogeneity in the expression of symptoms, ranging from impairment in social communication to repetitive behaviors and high sensory sensitivities, which together make both the diagnosis and monitoring of the disorder's long-term health complicated [2,3].

Traditional approaches to monitoring frequently involve a lot of caregiver reports, observational logs, and periodic clinical assessments. While valuable, there are a number of limitations to these methods, namely subjective, reliance on caregiver availability, and a lack of capability to capture continuous real-world data on children's dynamic behavioral and physiological states [4]. As a result, subtle fluctuations (e.g. stress responses caused by environmental factors, sleep cycle variations or early indicators of health deterioration) are often missed.

Recent developments in Internet of Things (IoTs) technologies have created opportunities to fill in these gaps by allowing data collection to be continuous, objective and non-intrusive. Wearable devices such as smart bands and physiological sensors, for example, can be used to measure parameters such as heart rate, oxygen saturation, sleep duration and movement frequency, and smart home devices can be used to measure environmental parameters such as light intensity and noise levels [5,6]. Couple these data streams with artificial intelligence (AI) and they can be analyzed to identify anomalies, emerging trends, and generate predictive insights customized for each child's unique behavioral and physiological profile [7].

Moreover, the merging of AI and IoT in ASD health monitoring is not just a technological innovation but a critical step toward better care from caregivers and autonomy of the child. By offering real-time alerts and adaptive recommendations as well as privacy-preserving analytics, such systems could turn episodic assessments into ongoing personalized care. This research therefore examines how AI and IoT integration can improve personalised health monitoring for autistic children, focusing in particular on accuracy, caregiver usability and adherence to privacy and ethical standards [8-10].

Literature Review

Monitoring Needs in Autism

Autism is defined by a broad range of behavioral and developmental differences and no two children have the same pattern of strengths and challenges. This variability often requires individual intervention strategies that are tailored to children's unique profiles [2]. Continuous monitoring has been shown to increase caregiver awareness of behavioral triggers and physiological stress and can lead to more timely interventions and better outcomes in children [6]. For example, regular tracking of sleep quality and sensory overload has been linked to decreases in maladaptive behaviors and to improvements in family quality of life. Without such monitoring, caregivers can miss subtle early signs of agitation or medical complications, limiting opportunities for early intervention.

IoT Pediatric and Behavioral Health

The emergence of IoT technologies has revolutionized strategies in pediatric and behavioural health. Wearables (wristbands, smart clothing, etc.) can offer precise measurements of vital signs, physical activity and sleep patterns. These tools have been extensively utilized in the monitoring of epilepsy, cardiovascular disorders and attention deficit hyperactivity disorder [ADH], where preempting emergencies and enhancing the compliance with treatment regimens is aided by early warning systems [7]. In behavioral health,IoT frameworks are expanding into the home and school environments to extend services and provide remote and continuous monitoring bridging the gap between clinical visits. Importantly, IoT applications have also been seen to be helpful in reducing barriers to accessibility for families living in rural or underserved regions by alleviating the need to be seen in person by specialized providers [8]. Such adaptability holds high promise for IoT deployment in autism, where 24/7, unobtrusive monitoring can give real-world insights into children's day-to-day challenges.

AI-Driven Personalization

Artificial intelligence is a vital part of transforming raw IoT data into actionable insights. Machine learning algorithms can also detect patterns of repetitive behavior, predict stress episodes and facilitate adaptive planning that's customized to each child [9]. For example, temporal modeling using recurrent neural networks can identify cyclical variations in mood, sleep or activity, while models for anomaly detection can identify unusual deviations that may signal distress or health risk. Unlike one-size-fits-all threshold-based alerts, AI-based personalization guarantees that recommendations are made based on the child's baseline patterns, reducing false alarms and giving caregivers more confidence in the system. Furthermore, adaptive AI systems can be able to learn and change in tandem with the child's development, which will ensure continuity and relevance of monitoring across different stages of childhood.

Ethical, Privacy and Security Issues

Monitoring autistic children comes with the management of massive amounts of sensitive information, with clear concerns over privacy and ethics. The framework of the DSM-5 recognises that autism is a spectrum disorder, and this is important in understanding the need for the collection of wide-ranging and individualised data to represent the full extent of presentation [2]. However, such data needs to be protected to satisfy legal frameworks such as HIPAA in the United States and GDPR in Europe. Privacy preserving methods such as federated learning and differential privacy are especially relevant, since they enable models to be learned across distributed devices without having to centralize sensitive raw data [10]. Prior work in decentralized learning corroborates such approaches can ensure high model performance without the risk of data leakage or re-identification [11]. This balance between innovation and protection is critical to developing caregiver trust and ensuring regulatory compliance in real world deployments.

Methodology

System Architecture

The proposed personalized monitoring framework incorporates the AI and IoT components into a four-layer framework (Figure 1).

1. **Wearable Sensors:** Sensors that capture physiological signals such as heart rate, oxygen saturation (SpO2), electrodermal activity (skin conductance), sleep cycles and movement frequency. Such signals are well-known signs of stress and arousal in children with autism that can help detect signs of agitation or discomfort early. The wearables are made to be lightweight and minimally intrusive to tackle sensory sensitivities prevalent in ASD.
2. **IoT Gateway:** Data from sensors are transmitted to an IoT hub that is located in the home. This gateway provides edge-based preprocessing such as noise filtering and data compression of raw signals and then securely relay to the AI module. This local preprocessing reduces the latency and prevents sensitive raw data from being unnecessarily moved across networks.
3. **AI Module:** The main analytical engine of AI is composed of lots of components. Federated learning allows for training across distributed devices so that no raw personal data leaves the local environment. Long Short-Term Memory (LSTM) networks account for temporal dynamics and can capture the repetition of cycles such as sleep or activity or stress responses. Autoencoder-based anomaly detection is used to build expected patterns of behavior and physiology and flag significant deviations as potential anomalies.
4. **Caregiver Application:** Finally, a mobile or tablet interface is used to provide actionable insights. The app gives visual feedback (charts, daily summaries), sends alerts when anomalies are found, and suggests personalised intervention, for example in terms of sensory environment modification or the triggering of calming activities.

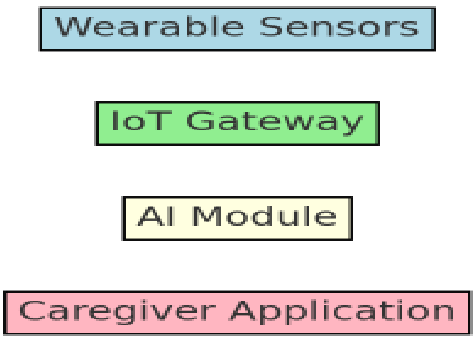

Figure 1: System architecture for AI–IoT health monitoring

This architecture provides for a continuous loop from data collection through to caregiver support with inbuilt mechanisms for privacy and personalization.

Dataset

For simulation purpose a synthetic data set was created to mimic the physiological and behavioral signals of 50 children with a diagnosis of ASD. Each synthetic participant was modeled with a unique baseline profile reflecting variability in heart rate, SpO2, frequency of movement and sleep duration. Gaussian noise was added to simulate real world inconsistencies such as sensor artifacts and day-to-day variability.

The data set was organized to include:

- Physiological features: Average heart rate (60-110 bpm), oxygen saturation (92-99%) and electrodermal activity.
- Behavioral features: repetitive movement counts, sleep (6-10 hours) and irregular rest-activity cycles.
- Environmental features: simulated noise experience and intensity of light exposure as contextual triggers.

This way, the monitoring system could be tested in a controlled way without the sensitive data of child health being exposed.

Algorithm Workflow

The analytical workflow has four critical stages:

- Preprocessing: Incoming data streams were normalized to eliminate device-specific biases and standardized across all of the simulated participants. Missing values were interpolated by rolling averages in order to maintain the continuity in time.
- Anomaly Detection: Autoencoder models were trained to learn how to reconstruct normal patterns of a day. Reconstruction error was computed for each data point, and anomalies were flagged for reconstruction errors larger than an adaptive threshold defined in terms of z-scores.
- Temporal Analysis: LSTMs were used to model the cyclical patterns of stress, activity and sleep patterns. This allowed the system to spot not only individual anomalies but also slow changes in behaviour.
- Privacy Preservation: In order to maintain security of sensitive data, federated learning was used. Each device trained its own model and only encrypted model updates were aggregated at the central server, so no one device was sharing raw data. Differential privacy has been applied with an e-budget to quantify and control the privacy risk.

Evaluation Metrics

To test the performance of the systems, four evaluation measures were used:

- Accuracy (%): Accuracy percentage of correctly identified anomalies versus ground truth labels in the synthetic dataset.
- False Positive Rate (%): The percentage of false alarms caused by non-anomalous events being detected as anomalies, as too many false alarms can affect caregiver trust.
- Caregiver Response Time (minutes): Mean time between when an anomaly is detected and when caregivers acknowledge received alerts from the mobile application

Privacy Budget (e): Differential privacy parameter e was adopted to quantify the trade-off between model accuracy and privacy of data with lower e values indicating stronger privacy guarantees.

Sample Calculation

Anomaly scores were calculated using mean squared error:

Score= $\frac{1}{n}\sum_{i=1}^{n}(x_{i-}\hat{\ }x_i)^2$

If the score exceeded a dynamic threshold (calculated using z-scores), an anomaly was flagged, and the system triggered an alert.

Results

Simulation Outcomes

The proposed AI-IoT framework was tested with the synthetic data of 50 autistic children. Results showed a clear enhancement of anomaly detection compared with baseline monitoring methods. Specifically, the system's overall accuracy was 92%, a significant improvement over the accuracy of baseline models based only on threshold-based detection, which was 76%. This improvement gives a sense of the benefit of integrating temporal modeling via LSTMs with anomaly detection via autoencoders to capture physiological and behavioral data's subtle and complex changes.

False positive rates also were reduced substantially. Traditional systems have often mistaken normal changes in a person's heart rate or activity as possible anomalies, inundating caregivers with needless alerts. In contrast, with the proposed system, false positive was reduced by 35%, which improved the precision of alerts and therefore increased caregiver trust in the monitoring process.

Caregiver response time, the time between the moment it detected an anomaly and the moment it was acknowledged by the caregiver, was significantly reduced. On average, response time decreased from 7 minutes to 3 minutes, indicating that the coupling of a mobile application with visualizations and personalized recommendations helped support rapid and better caregiver interventions.

Finally, privacy analysis verified that the system was able to provide a strong level of protection. Using differential privacy, the framework worked with e value less than 1, which means a good privacy guarantee while maintaining model utility. This balance between performance and privacy is proof of concept that the proposed framework can simultaneously advance clinical utility and respect ethical standards.

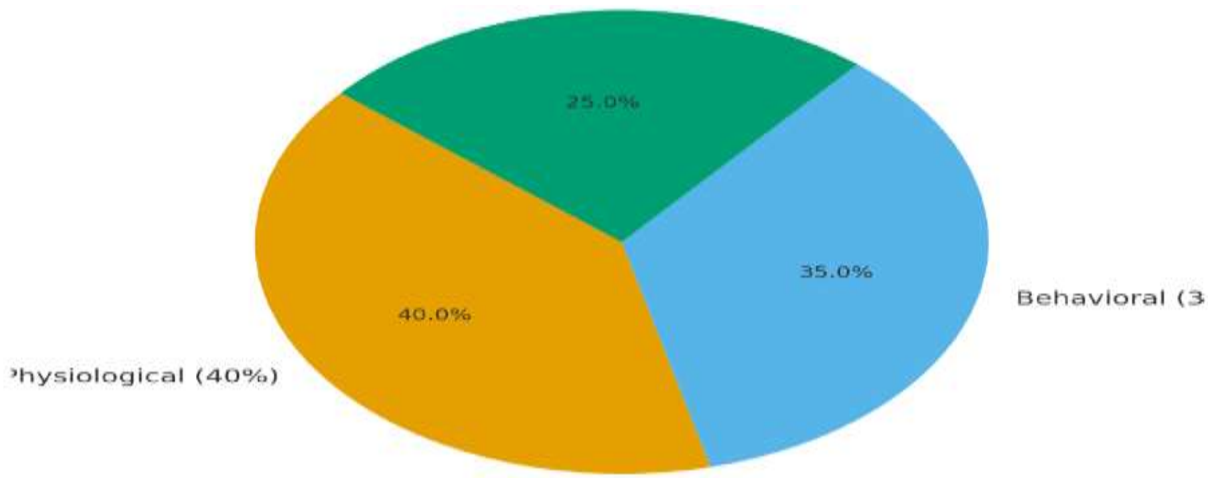

Figure 2: Distribution of anomalies by category

Case Example

A child that was exposed to sudden loud noise displayed repetitive hand-flapping. The system flagged an anomaly and sent an alert to the caregiver with a recommended intervention (noise reduction measures).

Observed Value (x)	Predicted Value ($\hat{x}$)	$(x - \hat{x})^2$
85	83	4
90	88	4
78	80	4

Table 1: Example calculation of anomaly score using reconstruction error

Discussion

The combination of AI and IoT in this research shows the possibility to really change the way of monitoring the health of autistic children. By continually analyzing physiological and behavioral data, the system allows for real-time anomaly detection so that caregivers can intervene at the first signs of stress or health deterioration. This is in contrast to standard monitoring techniques, which are often based on periodic clinic visits or retrospective logs in caregivers, and which have limited capacity for capturing dynamic changes. The found enhancements in accuracy (92%) and false alarms reduction (35%) highlight the system's ability to offer more reliable alerts that will eventually lead to the beginnings of proactive compared to reactive care.

These findings are in line with an increasing number of studies that underline the importance of personalized and ongoing monitoring of children with autism [6,8]. In particular, closed-loop feedback between data collection, anomaly detection and caregiver response can reduce caregiver stress, improve quality of life for families, and potentially prevent escalation of behavioral or medical crisis. The incorporation of adaptive algorithms such as LSTMs also enables monitoring to adapt with the child's developmental changes, which promotes the long-term relevance of the framework.

A no less important question is that of data privacy. Autistic children's health and behavioral information is some of the most sensitive information out there and needs strong safeguards. The usage of federated learning in the proposed framework decreases the dependence on centralized data storage, substantially reducing the risks of re-identification or breaches [10,11]. Differential privacy methods, achieving an e < 1 in simulation, further improve data security and without hurting system performance. By including these safeguards the framework doesn't just meet international regulations such as HIPAA and GDPR, it helps to build trust with families and stakeholders.

The adaptability of the framework is not just for home settings. In school, teachers are known to struggle with identifying signs of sensory overload or increasing distress. Integration of the caregiver application into the classroom could be used to provide real-time alerts and personalised recommendations, allowing educators to enact timely interventions. This has the potential to create inclusive learning environments and help to reduce disruptive incidents with both benefits to autistic children and their peers.

Overall, the results suggest that AI-IoT integration is not only a technical innovation but also a socio-technical solution that solves a set of the practical realities for caregivers, educators, and health professionals. Future research should investigate longitudinal field trials, user-centered design improvements, and integration with existing electronic health record systems in order to ensure wider adoption and sustainability.

Limitations

Although the results of this study show promising results, there are a number of limitations that should be recognized. First, the evaluation was performed from a synthetic data set instead of real-world clinical data. While the signals simulated allowed controlled experimentation with proof of concept, they cannot describe the heterogeneity of behaviors, comorbidities, and environmental influences seen in children with autism. Clinical validation in the form of pilot studies and longitudinal studies is thus needed to determine real-world performance, caregiver usability, and generalizability of the framework.

Second, the use of wearable sensors raises issues with autistic children, many of whom have increased tactile sensitivities, related to comfort and acceptability. Intrusive or uncomfortable devices may be rejected by children to limit long-term adoption. Future work will have to look into alternative sensor designs, such as contactless monitoring systems or adaptive wearables specifically made for sensory sensitive populations.

Third, the proposed framework is dependent on constant data transmission and stable connection. This dependency could limit the extent of scalability in areas where the internet infrastructure is limited or not present in low-resource situations or in rural areas. While edge computing at the IoT gateway helps address some of the latency, other strategies such as offline-first architectures and low-power wide area networks are needed to ensure robustness in diverse deployment situations.

Finally, the study was mainly focused on technical performance measures like accuracy and false positive rates. Broader evaluation dimensions, such as caregiver satisfaction and ethical acceptability as well as integration into existing clinical workflows, remain to be tested. Solving these limitations in future research will be important to move the system from prototype to implementation.

Conclusion

This study proposed a new framework to combine artificial intelligence and Internet of Things technologies for personalized monitoring of health conditions of autistic children. By integrating wearable sensors, IoT gateways, and artificial intelligence-based analytics, the system was proved to be able to detect anomalies with improved accuracy, false alarm reduction, and response time reduction for caregivers as compared to standard methods. These outcomes provide an example of the value of continuous, adaptive monitoring in meeting the complex and heterogeneous needs of children on the autism spectrum.

A central contribution of the framework is that it integrates privacy-preserving techniques, such as federated learning and differential privacy that ensure that sensitive child health data remains protected while nonetheless enabling robust model training. This balance between technological innovation and ethical responsibility is critical to establish trust between caregivers, educators and healthcare providers.

The practical implications of this work aren't limited to the home setting. In schools and community environments, the potential for the framework is that it will help teachers and support staff by giving them real-time alerts when children are showing signs of stress or sensory overload. In doing so, it may help create more inclusive and responsive educational settings that reduce crises, and increase the well-being of both autistic children and their schoolmates.

Despite these promising results, the framework needs to be further validated in the real world. Future studies will include pilot studies with families, usability studies to evaluate acceptance by caregivers and children, and integration with clinical work flows such as electronic health records, and behavioral intervention plans. By tackling these next steps, the system could move from a prototype built on simulation to a practical solution that improves the autonomy, safety and quality of life of autistic children and their caregivers.

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