



Unequal-Clustering and Routing (UCR) Approach for Efficient Data Collection from Autism Patients

Mr. Sagar Sudhakar Birade¹, Dr. Mallikarjun C. Sarsamba²

¹Department of Electronics and Communication Engineering, VSMSRKIT Nipani, India

²Department of Electronics and Communication Engineering,
Hirasugar Institute of Technology, Nidasoshi, India

Abstract—

This work presents a pioneering contribution to Autism-Spectrum-Disorder (ASD) identification, introducing an integrated approach that harnesses the capabilities of wireless network, feature optimization, and Machine-Learning (ML). The innovative framework establishes a systematic methodology for the comprehensive collection, optimization, and analysis of sensory and behavioral data. Through the Unequal Clustering and Routing (UCR) model, the approach ensures streamlined data flow from ASD patients using Internet-of-Things (IoT) nodes to a central gateway, facilitating real-time analysis and proactive ASD identification. Overcoming challenges in data collection, analysis, and scalability, this holistic solution proves effective in achieving accurate and efficient ASD identification for both children and adults. Experimental results demonstrate the UCR method's superiority over DECR, exhibiting a 5.74% higher delivery ratio and a 9.65% reduction in data transmission delays. These outcomes underscore UCR's efficiency in enhancing communication reliability and minimizing latency, showcasing its potential to optimize overall system efficiency.

Keywords- Autism, Wireless Network, Feature Optimization, Machine Learning, Clustering, Routing.

Introduction

Autism Spectrum Disorder (ASD) is a neuro developmental condition characterized by a range of challenges in social interaction, communication, and repetitive behaviors. Its impact is profound, affecting individuals across their lifespan, from childhood into adulthood [1]. In children, ASD often manifests in delayed speech development, difficulty in socializing, and repetitive behaviors [2]. Adults with ASD may face challenges in forming relationships, maintaining employment, and navigating social situations [3]. In recent years, there has been a notable increase in the prevalence of ASD. The studies have showed that children are at a higher risk of ASD than adults [4]. This upward trend may be attributed to improved awareness, early detection, and changes in diagnostic criteria. Identifying ASD early in life is crucial for implementing interventions that can significantly improve outcomes. Early intervention services, such as behavioral therapies and educational support, can enhance communication skills and social interactions. Moreover, understanding ASD in adults allows for tailored support in employment and social settings, fostering a more inclusive society. Efforts to raise awareness, enhance diagnostic tools, and promote research into the causes of ASD are essential in addressing its increasing prevalence. By fostering a better understanding of ASD, society can work towards creating a supportive



environment that accommodates the unique needs of individuals on the autism spectrum. Ultimately, proactive identification and appropriate interventions contribute to improved outcomes for both children and adults with ASD, enhancing their overall quality of life [5].

Existing works in the realm of ASD identification grapple with several pressing issues that pose challenges to the development and presentation of effective models. One prominent concern revolves around the collection of data from ASD patients [6]. The heterogeneity of symptoms and behaviors exhibited by individuals with ASD demands an important and comprehensive approach to data gathering. Often, the current methods lack uniformity and struggle to capture the diversity inherent in ASD, hindering the creation of robust and representative datasets. Furthermore, the analysis of ASD data extracted from patients confronts obstacles, particularly when dealing with the intricate nature of sensory and behavioral information [7]. The complexity of ASD manifests in various forms, making it challenging to discern meaningful patterns and indicators. Additionally, feature optimization techniques face hurdles in ensuring the relevance and accuracy of selected features, as the diversity within ASD datasets can lead to skewed representations [8]. A critical issue that compounds these challenges is the presence of imbalanced datasets [9]. The disproportionate distribution of ASD and non-ASD instances can bias the model, affecting its ability to accurately identify cases, especially in children and adults [10]. Addressing these issues is paramount for advancing ASD research, necessitating refined methodologies that can handle the intricacies of data collection, analysis, feature optimization, and identification in the presence of imbalanced datasets. Efforts in these areas will contribute significantly to the development of more reliable and inclusive models for ASD identification.

The core innovation of this work lies in the presentation of a novel framework specifically designed for the identification of ASD in both children and adult populations. This framework incorporates Machine-Learning (ML) techniques to analyse the optimized sensory and behavioral data, contributing to the accuracy and efficiency of the identification process. Moreover, a model is introduced for the systematic collection of data from ASD patients using Internet of Things (IoT) nodes, followed by clustering procedures to organize the information. The clustered data is then transmitted to a central gateway, enabling seamless and secure data flow for further analysis. This comprehensive model not only facilitates the identification of ASD but also introduces an efficient data collection and transmission system, harnessing the power of IoT. By employing cutting-edge technologies, this research aims to enhance the accuracy of ASD identification, paving the way for early interventions and tailored support for both children and adults with ASD, ultimately contributing to improved outcomes and quality of life. The contribution of this work is as follows

This work contributes by employing an integrated approach that combines IoT nodes, feature optimization techniques, and ML for the identification of ASD in both children and adults.

The introduction of a novel framework sets this work apart, providing a structured and efficient methodology for collecting, optimizing, and analyzing sensory and behavioral data. This framework enhances the accuracy and effectiveness of ASD identification.

The Unequal Clustering and Routing (UCR) approach presented in this research ensures a seamless flow of data from ASD patients using IoT nodes to a central gateway. This streamlined process allows for real-time data



analysis, clustering, and transmission, fostering a more responsive and proactive approach to ASD identification and intervention.

The manuscript is structured as follows: Section II delves into the literature survey, exploring research on collecting sensory and behavioral data from ASD patients using IoT nodes. It extends to feature optimization techniques and ML techniques. Section III introduces the novel ASD identification framework for children and the UCR approach. Section IV discusses results, evaluating the UCR approach and comparing it with existing work in terms of delivery ratio and delay. Lastly, Section V presents the conclusion of the work, summarizing key findings and contributions in the field of ASD identification.

Literature Survey

This study reviews existing research that focuses on collecting sensory and behavioral information from ASD patients using IoT nodes. The exploration extends to feature optimization techniques employed to refine and select optimal features from the collected sensory and behavioral data. Additionally, the study delves into the various ML identification methodologies proposed for effectively identifying ASD in both children and adults. By examining these components, the research aims to contribute insights into the current landscape of ASD identification methodologies, emphasizing the integration of IoT, feature optimization, and ML in the pursuit of accurate and efficient diagnostic models. In order to alleviate the overwhelming neurological responses experienced by people with ASD who are highly sensitive, a supportive approach was suggested in [11]. They proposed an Assistive-Companion for Hypersensitive-Individuals (ACHI) test, an ASD-afflicted technological supporter that can identify and retrieve information about sensations from technological sensors, use fuzzy-logic to make decisions according to that data, and finally send all of that data across the IoTs while simultaneously alerting caretakers. The results showed how the suggested ACHI treatment was assessed according to the standard rating of 93% provided by caretakers. To help youngsters with speech impairments understand complicated gestures, [12] suggested an IoT infrastructure that uses ML and has been placed on their bodies. To identify movements among kids with ASD, they collected sensor time-series information, extracted characteristics from both the frequency and time domain, and tested several algorithms. Next, they performed an accuracy comparison of four classification algorithms: Random-Forest (RF), Decision-Tree (DT), K-Nearest-Neighbor (KNN), and Artificial-Neural-Network (ANN). The findings demonstrated an accuracy rating of over 96 percent for ASD kid's movements. An IoT-based assistance solution for autistic children was introduced in study [13]. The detection devices within the suggested setup would scan the kid's immediate surroundings and flag any potentially dangerous situations. There was also a Global-System for Mobile-Communication (GSM) component that they utilized to talk with their caretakers. The device continuously monitored every information related to the immediate surroundings. It determines if a danger has taken place by comparing measurements from sensors with various threshold levels obtained from studies in various circumstances.

In order to extend the lifespan of WSNs, a Residual-Energy-Based Data-Availability-Approach (REDAA) was created with an emphasis on selecting reliable routes and Cluster-Heads (CHs) [14]. In order to formally represent the path while making data accessible anytime demanded, a cluster was established along with a pair of CHs were



developed using the Quadrature-Low-Energy-Adaptive-Clustering-Hierarchy (Q-LEACH) along with Multi-Hop LEACH (MH-LEACH) methods, respectively. Simulation findings show that suggested REDAA method outperformed the MH-LEACH method by 70 percent for energy-consumption and 37 percent for throughput, while the Q-LEACH method achieved an enhancement of 73 percent and 30 percent, respectively. A dependable and energy-efficient architecture was suggested in [15], which is an enhanced cluster-based secured routing system. Attacker-node surveillance, congestion management, encryption during transfer of data, packet mitigation and energy-consumption were some of the important features which this system takes into account to enhance the standard of managing data. They showed that the suggested method works by measuring its performance on many benchmarks, such as the speed of ransomware identification, the average remaining energy across stages, delay, efficiency optimization, and the fast identification of clone attacks.

In [16], the researchers set out to classify ASD information with the hopes of providing a quick, accessible, and easy way to back support the early detection of ASD. An example of this was to employ ML approaches like Support-Vector-Machine (SVM), Linear-Discriminant-Analysis (LDA), RF and KNN for classifying individuals as having or not having ASD. The ML repository's baseline information, that was divided into two categories—normal and autism—was used to evaluate and verify various ML methods. The dataset was divided into two parts: one to be trained and another for testing. When tested independently, the RF and SVM methods both reached a remarkable 100% accuracy level. The goal of the research conducted in [17] aimed to look at how youngsters with ASD's sensory features relate to their psychological and interactions with others. To compare youngsters who have ASD with their typically developing classmates, researchers used the Short-Sensory-Profile (SSP). Furthermore, they used RF and SVM techniques to have discussions about how the senses could forecast social behavior. Compared to the unaffected group, ASD children had reduced SSP scores, along with a statistically important negative connection ($P < 0.05$) was found among SSP ratings and diagnostic assessment ratings. The RF technique containing 7-characteristic variables provided the greatest precision, whereas the SVM and RF and SVM technique employing all the characteristics demonstrated superior sensitivities. Every one of the simulations had an Area-Under the Receiver-Operating-Characteristic (AUC-ROC) above 0.8.

Utilizing ML techniques for precise categorization, [18] created and tested a power-saving technique for signal processing. The empirical findings show that all the different ML techniques utilized achieved a sensitivity, F1-score and 100 percent, 95 percent and 96 percent, respectively. In comparison to broadcasting the unprocessed EEG signals, their technique used 97 percent less energy, according to the findings. Utilizing Flexibly-Analytic Wavelet-Transform (FAWT), a new method for automatic identification of ASD utilizing multidimensional EEG recordings was introduced in [19]. This method extracted EEG fragments with durations ranging from 5 to 20 s from the collected signals by filtering and segmenting them. Deep-Learning (DL) and ML techniques such as Convolutional-Neural-Network (CNN), RF, LR, KNN, and SVM approach with varying segmentation lengths, were applied to assess the feature vectors. The findings show that CNN achieved accuracy of 99.19 percent, sensitivity of 99.34 percent, specificity of 99.21 percent, AUC of 99.97 percent for 10-second EEG segment. By analyzing EEG neural activity characteristics, [20] were able to classify individuals with ASD and those without the disorder utilizing ML classification systems. To classify the participants with ASD and the members of the



control group, they used Feed-Forward Neural-Network, K-NN, DT, LR and SVM, as their classification methods. Utilizing Shannon-entropy, and multi-fractal wavelet estimations, and the k-NN method was able to obtain an accuracy of 90 percent in ASD classification. Utilizing the DFT characteristics, k-NN was able to reach an accuracy of 93 percent. The results of this research show that the characteristics of EEG remain adequate for separating ASD patients from control group.

By concurrently retraining two ML classification algorithms, SVM and LR, for the categorization of ASD variables and identifying ASD in adults and children, the Federated-Learning (FL) method was utilized in a novel way for detecting ASD in [21]. For the purpose of trying to find out whichever method is most successful in detecting ASD in people of all ages, the outputs generated by these classifications were sent to a centralized server through FL, wherein an extra classification was developed. For the purpose of obtaining features, four separate ASD patient datasets were retrieved from various repositories. Each collection had over 600 entries of affected individuals, ranging from kids to adults. With a success rate of 81 percent in adults and 98 percent in kids, the suggested approach correctly identified ASD. In [22], examined and predicted ASD in children and teenagers employing medical conditions ASD datasets utilizing ML techniques such as Naïve-Bayes (NB), RF, SVM and LR. At 93.69%, RF was the most accurate among the children dataset and 93.33%, for teenager's dataset. At 77.28%, SVM was the most accurate among the children dataset and 89.33% for teenager's dataset. In [23], they successfully analyzed datasets containing ASD children and correctly classified and identified ASD features using an ML framework which they created. After balancing the dataset using the SMOTE technique, they moved ahead to incorporating feature modification and selecting techniques. After that, they used a hyperparameter optimization strategy with multiple categorization methods. Amongst the classification methods, AdaBoost produced the most promising findings. The method achieved 99.85 percent of accuracy and AUC-ROC of 99.85 percent.

In [24], results are reported regarding a multiline, prospective investigation that assessed the efficacy of a smartphone-based autism testing application (app) given throughout a kid's well-child journey. The investigation included 475 kids aged 17-36 months, consisting of 206 girls and 269 boys. Among these kids, 49 were identified having autism along with 98 were identified with delayed development with no autism. A combination of various digital traits yielded impressive results in terms of accuracy for diagnosis. The method achieved an AUC-ROC of 90 percent. Furthermore, it demonstrated an adverse predictive value of 97.8% and a positive likelihood ratio of 40.6 percent. Using ML techniques and anomalies in anatomy discovered in Structurally Magnetic-Resonant-Image (sMRI) information pertaining to the ASD brain, [25] computerized the ASD diagnosing process. A diagnosis analysis was built and features were minimized using these structural relationships supplied into XGBoost (XGB). Among the best 18 characteristics, the average accuracy was 94.16 percent using XGB. In [26] suggested DECR, a method for dispersed energy-efficient two-hop routing and clustering, with the goal of serving WBANs that are supported by the IoT. Every node in DECR learns about its neighbors across a two-hop distance during the cluster's creation stage. For the purpose of optimizing routes and selecting CHs, they employed the altered Grey-Wolf optimizing method. While calculating the CH for every cluster, they took node connection and remaining energy into account simultaneously. They additionally came up with a mathematical

framework to find out how many clusters would be best for reducing the number and distance of transmissions, taking inter and intra-cluster distances for transmission into account. Last but not least, they suggested a routing strategy to guarantee the sink-to-CH energy-efficient packet transmission. In conclusion, the presented study comprehensively reviews diverse methodologies for ASD identification, highlighting notable interventions and technological advancements. These advancements collectively underscore the potential of technology-driven solutions for improving ASD identification and intervention.

Proposed Methodology

This proposed methodology introduces a novel framework for ASD identification. The approach includes a comprehensive clustering and routing strategy to enhance the efficiency and accuracy of ASD identification, addressing the complex challenges associated with sensory and behavioral data collection in individuals with ASD.

Framework

The novel framework for this work is presented in Figure 1. The proposed framework for ASD addresses the multi-faceted challenges involved in the comprehensive identification process. Beginning with the collection of data from ASD patients, IoT sensors play a pivotal role in capturing real-time sensory and behavioral information. The collected data undergoes a sophisticated process involving clustering, routing, and gateway implementation at the Edge-Cloud interface. This ensures efficient data transmission, analysis, and storage, optimizing the framework for scalability and real-time processing. The subsequent phase involves the analysis of ASD data, where the collected sensory and behavioral data undergoes rigorous evaluation. Feature optimization techniques are applied to refine and select the most relevant features, enhancing the quality and accuracy of the data. ML techniques are then employed for in-depth analysis, leveraging the power of algorithms to recognize patterns and indicators associated with ASD. Finally, the framework culminates in the identification of ASD in both children and adults. The proposed framework thus serves as a comprehensive solution, addressing the complexities of ASD identification through a systematic and technology-driven approach.

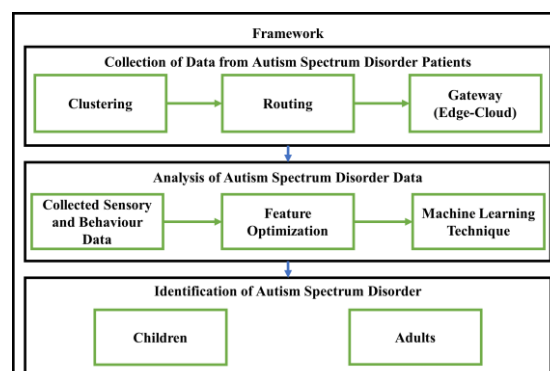


Figure 1. Framework.

In the next section the clustering and routing approach for collecting the data from the ASD patients is presented.

Unequal Clustering and Routing (UCR) Approach

The UCR framework, depicted in Figure 2, encompasses two crucial phases: setup clustering and multi-objective behavior data collection. In the setup clustering phase, nodes within the IoT network undergo an unequal cluster formation process. Subsequently, the CH selection occurs, employing Equation (1) for an optimal choice of CH. Transitioning to the multi-objective behavior data collection phase, two distinct approaches are implemented. In intra-cluster data collection, nodes relay information to their respective cluster heads. In contrast, inter-cluster data collection involves communication among cluster heads to transmit the aggregated data to the gateway, utilizing Equation (3). This dual-phase framework ensures efficient clustering, optimal CH selection, and a comprehensive approach for behavior data collection, fostering a robust system for managing and analyzing data in the IoT environment for applications related to behavior monitoring, healthcare, or similar domains.

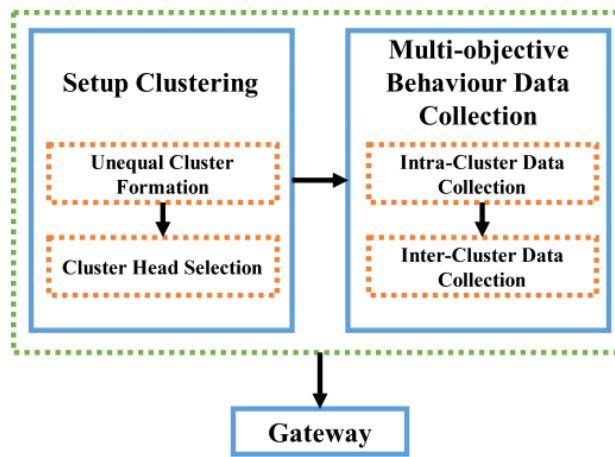


Figure 2. UCR Approach.

In UCR approach, for transmitting collected data from multiple nodes (patients) towards CH, a dynamic CH selection process is employed, followed by efficient routing towards the gateway. The selection of CH is based on a cost function, , to optimize the selection process. The parameter depends on various factors, including the mean distance between nodes, the initial energy of node, the number of nodes, and weights, assigned to objective parameters like mean distance, initial energy, and the number of nodes. The cost parameter is computed using [27] as follows

$$K_y = \frac{M_{\rightarrow} * D_m}{(X_v * D_x) * (E * D_e)} \quad (1)$$

The mean distance among node neighbors is calculated using [27] as follows

$$M_{\rightarrow} = \frac{K_b}{A} \quad (2)$$

Where is a constant, and represents the number of nodes in the network. Nodes with lower energy or fewer neighbouring nodes have smaller parameters, increasing their chances of becoming CHs. The CHs, with an optimal number of nodes, perform data collection to eliminate redundant data, preserving energy in the network. The approach utilizes Time Division Multiple Access (TDMA) for data transmission scheduling. In this work,



efficient routing paths are established to minimize energy consumption and delay [27] using the following equation.

$$L_M = E_v + G_l + G_l + L^p \quad (3)$$

Where E is the residual energy, v is the node, l is the expected hop number, l is the inverse of the expected hop number, and p is the minimum packet loss probability parameter. The routing process employs multipath communication to minimize latency, enhance flexibility, reliability, and fault tolerance, while also providing better load balancing.

The final selection of the best path is based on the highest value, catering to the transmission of sensory data that requires real-time performance. This approach not only conserves node energy but also minimizes delay for efficient real-time data delivery. The parameter is crucial for identifying multipath options, allowing separate paths for transmitting behavioural data. The results for the UCR approach are evaluated and discussed in the next section.

Results and Discussion

The experimental setup utilizes a Windows 11 operating system, a Pentium I-7 class Quad-core processor, and 16 GB RAM. The SENSORIA simulator [28] facilitates the study, enabling connectivity among IoT nodes, gateway server, and edge via IPV4 and IPV6 protocols. Implementation of UCR and DECR [26] is executed using C# programming language in Visual Studio Dot Net Framework 4.0 and above. Simulation parameters, detailed in Table 1, involve varying IoT nodes (250, 500, 750, 1000) for delivery ratio and delay analysis in UCR and DECR. The experimental outcomes are graphically represented, showcasing the impact on delivery ratio and delay under different IoT node scenarios.

Simulation parameter

Parameters	Value
Simulation area	100×100 meters
Number of IoT nodes	250~1000
Communication range	5 meters
Packet size	5000
Initial energy	0.1~0.2
Energy consumed during data collection	5 nJ/bit/signal
Sensor type/Sensing data	Behavior

Figure 3 illustrates the delivery ratio, evaluated concerning packet delivery by nodes (250, 500, 750, and 1000). The UCR method demonstrates a notable superiority, achieving an average 5.74% higher delivery ratio compared to the DECR method. This graphical representation emphasizes UCR's efficiency in enhancing packet delivery

performance across varying node scenarios, reinforcing its efficacy in optimizing communication reliability within the experimental framework.

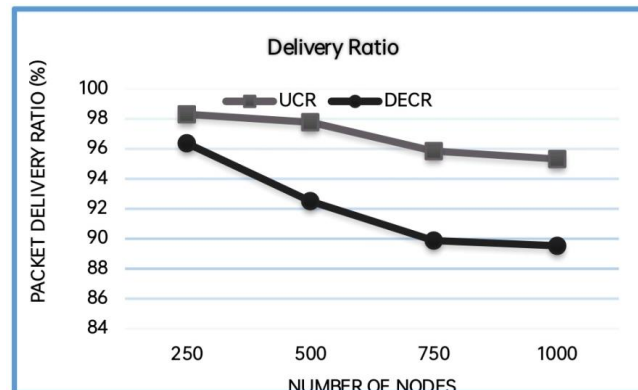


Figure 3. Delivery Ratio.

Figure 4 displays the delay, assessed in terms of transmitting collected data delays by nodes (250, 500, 750, and 1000). The UCR method showcases notable efficiency, achieving an average reduction of 9.65% in delays compared to the DECR method. This graphical representation emphasizes UCR's effectiveness in minimizing data transmission delays across varying node scenarios, highlighting its capability to enhance the overall efficiency and responsiveness of the system.

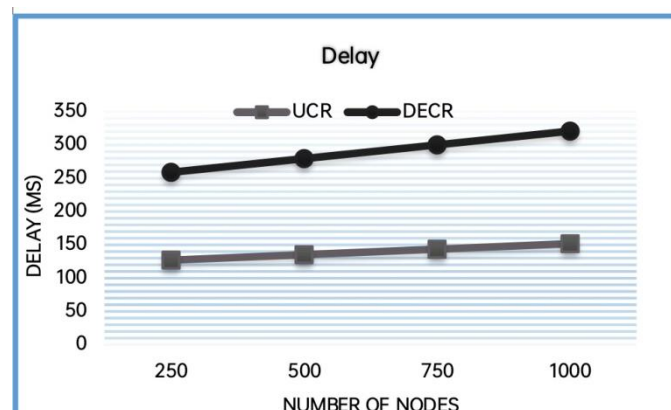


Figure 4. Delay.

In conclusion, the UCR method exhibits superior performance, surpassing DECR in both delivery ratio and data transmission delays across diverse node scenarios. With an average 5.74% higher delivery ratio and a 9.65% reduction in delays, UCR proves its efficacy in optimizing communication reliability and minimizing latency. These findings underscore UCR's potential to enhance overall system efficiency, making it a promising approach for IoT environments requiring robust and responsive data transmission. In the next section, the conclusion of the work is presented.



Conclusion

In conclusion, this work makes significant contributions to the field of ASD identification by introducing an integrated approach that leverages IoT nodes, feature optimization techniques, and ML. The novel framework offers a systematic methodology for collecting, optimizing, and analysing sensory and behavioural data. Through Unequal Clustering and Routing (UCR), the approach ensures efficient data flow from ASD patients through IoT nodes to a central gateway, enabling real-time analysis and proactive ASD identification. The comprehensive approach addresses challenges in data collection, analysis, and scalability, presenting a holistic solution for accurate and efficient ASD identification in both children and adults. The experimental results, highlight the superior performance of the UCR method over DECR, showcasing a 5.74% higher delivery ratio and a 9.65% reduction in data transmission delays. These findings underscore the UCR approach effectiveness in enhancing communication reliability and minimizing latency, emphasizing its potential to optimize overall system efficiency. In summary, the proposed integrated approach and UCR model present a promising advancement in the technological landscape of ASD identification, offering a structured and responsive solution for improved healthcare interventions and support. For the future work, more enhanced clustering method for data collection will be presented.

References

- [1] M. Jiang et al., "Autism spectrum disorder research: knowledge mapping of progress and focus between 2011 and 2022," *Frontiers in Psychiatry*, vol. 14, Apr. 2023, doi: <https://doi.org/10.3389/fpsyt.2023.1096769>.
- [2] W. H. Lin et al., "Restricted and repetitive behaviors and association with cognition and adaptive functioning in children with autism spectrum disorder in Singapore," *Frontiers in Psychiatry*, vol. 14, Nov. 2023, doi: <https://doi.org/10.3389/fpsyt.2023.1249071>.
- [3] G. Sala, J. M. Hooley, M. Hooley, and M. A. Stokes, "Comparing Physical Intimacy and Romantic Relationships of Autistic and Non-autistic Adults: A Qualitative Analysis," *Journal of Autism and Developmental Disorders*, Aug. 2023, doi: <https://doi.org/10.1007/s10803-023-06109-0>.
- [4] A. M. Metwally et al., "National screening for Egyptian children aged 1 year up to 12 years at high risk of Autism and its determinants: a step for determining what ASD surveillance needs," *BMC Psychiatry*, vol. 23, no. 1, Jun. 2023, doi: <https://doi.org/10.1186/s12888-023-04977-5>.
- [5] S. L. Odom et al., "Educational Interventions for Children and Youth with Autism: A 40-Year Perspective," *Journal of Autism and Developmental Disorders*, vol. 51, no. 12, Apr. 2021, doi: <https://doi.org/10.1007/s10803-021-04990-1>.
- [6] L. Balasco, G. Provenzano, and Y. Bozzi, "Sensory Abnormalities in Autism Spectrum Disorders: A Focus on the Tactile Domain, From Genetic Mouse Models to the Clinic," *Frontiers in Psychiatry*, vol. 10, Jan. 2020, doi: <https://doi.org/10.3389/fpsyt.2019.01016>.



- [7] M. M. Hassan and H. M. O. Mokhtar, "Investigating autism etiology and heterogeneity by decision tree algorithm," *Informatics in Medicine Unlocked*, vol. 16, p. 100215, 2019, doi: <https://doi.org/10.1016/j.imu.2019.100215>.
- [8] Y. Wang, J. Wang, F.-X. Wu, Rahmatjan Hayrat, and J. Liu, "AIMAFE: Autism spectrum disorder identification with multi-atlas deep feature representation and ensemble learning," *Journal of Neuroscience Methods*, vol. 343, pp. 108840–108840, Sep. 2020, doi: <https://doi.org/10.1016/j.jneumeth.2020.108840>.
- [9] N. Abdelhamid, A. Padmavathy, D. Peebles, F. Thabtah, and D. Goulder-Horobin, "Data Imbalance in Autism Pre-Diagnosis Classification Systems: An Experimental Study," *Journal of Information & Knowledge Management*, vol. 19, no. 01, p. 2040014, Mar. 2020, doi: <https://doi.org/10.1142/s0219649220400146>.
- [10] Y. Hus and O. Segal, "Challenges Surrounding the Diagnosis of Autism in Children," *Neuropsychiatric Disease and Treatment*, vol. 17, pp. 3509–3529, Dec. 2021, doi: <https://doi.org/10.2147/NDT.S282569>.
- [11] V. Khullar, H. P. Singh, and M. Bala, "IoT based assistive companion for hypersensitive individuals (ACHI) with autism spectrum disorder," *Asian Journal of Psychiatry*, vol. 46, pp. 92–102, Dec. 2019, doi: <https://doi.org/10.1016/j.ajp.2019.09.030>.
- [12] F. Ullah, N. A. AbuAli, A. Ullah, R. Ullah, U. A. Siddiqui, and A. A. Siddiqui, "Fusion-Based Body-Worn IoT Sensor Platform for Gesture Recognition of Autism Spectrum Disorder Children," *Sensors*, vol. 23, no. 3, p. 1672, Feb. 2023, doi: <https://doi.org/10.3390/s23031672>.
- [13] Shartaz Yeaser Feeham, T. Akter, S. Debnath, and Md. Solaiman Mia, "Risk Analysis and Support System for Autistic Children using IoT," Dec. 2022, doi: <https://doi.org/10.1109/sti56238.2022.10103277>.
- [14] Michaelraj Kingston Roberts and Jayapratha Thangavel, "An improved optimal energy aware data availability approach for secure clustering and routing in wireless sensor networks," *Transactions on Emerging Telecommunications Technologies*, vol. 34, no. 3, Dec. 2022, doi: <https://doi.org/10.1002/ett.4711>.
- [15] Michaelraj Kingston Roberts and P. Ramasamy, "An improved high performance clustering based routing protocol for wireless sensor networks in IoT," *Telecommunication Systems*, vol. 82, no. 1, pp. 45–59, Oct. 2022, doi: <https://doi.org/10.1007/s11235-022-00968-1>.
- [16] Hasan Alkahtani, Theyazn H. H. Aldhyani, and M. Alzahrani, "Early Screening of Autism Spectrum Disorder Diagnoses of Children Using Artificial Intelligence," vol. 2, no. 1, Jan. 2023, doi: <https://doi.org/10.57197/jdr-2023-0004>.
- [17] J. Zhai et al., "Correlation and predictive ability of sensory characteristics and social interaction in children with autism spectrum disorder," *Frontiers in Psychiatry*, vol. 14, Apr. 2023, doi: <https://doi.org/10.3389/fpsy.2023.1056051>.
- [18] S. Alhassan, A. Soudani, and M. Almusallam, "Energy-Efficient EEG-Based Scheme for Autism Spectrum Disorder Detection Using Wearable Sensors," *Sensors*, vol. 23, no. 4, p. 2228, Feb. 2023, doi: <https://doi.org/10.3390/s23042228>.



- [19] P. Chawla, S. B. Rana, H. Kaur, and K. Singh, "Computer-aided diagnosis of autism spectrum disorder from EEG signals using deep learning with FAWT and multiscale permutation entropy features," *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, vol. 237, no. 2, pp. 282–294, Dec. 2022, doi: <https://doi.org/10.1177/09544119221141751>.
- [20] Din and A. K. Jayanthi, "Detection of Autism Spectrum Disorder by Feature Extraction Of EEG Signals And Machine Learning Classifiers," *Biomedical Engineering: Applications, Basis and Communications*, vol. 35, no. 01, Dec. 2022, doi: <https://doi.org/10.4015/s1016237222500466>.
- [21] M. S. Farooq, R. Tehseen, M. Sabir, and Z. Atal, "Detection of autism spectrum disorder (ASD) in children and adults using machine learning," *Scientific Reports*, vol. 13, no. 1, p. 9605, Jun. 2023, doi: <https://doi.org/10.1038/s41598-023-35910-1>.
- [22] J. Talukdar, Deba Kanta Gogoi, and T. P. Singh, "A comparative assessment of most widely used machine learning classifiers for analyzing and classifying autism spectrum disorder in toddlers and adolescents," *Healthcare analytics*, pp. 100178–100178, Apr. 2023, doi: <https://doi.org/10.1016/j.health.2023.100178>.
- [23] M. J. Uddin et al., "An Integrated Statistical and Clinically Applicable Machine Learning Framework for the Detection of Autism Spectrum Disorder," *Computers*, vol. 12, no. 5, p. 92, May 2023, doi: <https://doi.org/10.3390/computers12050092>.
- [24] S. Perochon et al., "Early detection of autism using digital behavioral phenotyping," *Nature Medicine*, vol. 29, no. 10, pp. 2489–2497, Oct. 2023, doi: <https://doi.org/10.1038/s41591-023-02574-3>.
- [25] V. Gupta et al., "A Framework to Diagnose Autism Spectrum Disorder Using Morphological Connectivity of sMRI and XGBoost," *Studies in health technology and informatics*, Oct. 2023, doi: <https://doi.org/10.3233/shti230734>.
- [26] M. Y. Arafat, S. Pan and E. Bak, "Distributed Energy-Efficient Clustering and Routing for Wearable IoT Enabled Wireless Body Area Networks," in *IEEE Access*, vol. 11, pp. 5047-5061, 2023, doi: <https://doi.org/10.1109/ACCESS.2023.3236403>.
- [27] D. S. Nayagi, S. G G, V. Ravi, V. K R, and S. Sennan, "REERS: Reliable and energy-efficient route selection algorithm for heterogeneous Internet of things applications," *International Journal of Communication Systems*, vol. 34, no. 13, Jun. 2021, doi: <https://doi.org/10.1002/dac.4900>.
- [28] N. Ababneh and J. N. Al-Karaki, "On the Lifetime Analytics of IoT Networks," 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2020, pp. 1086-1090, doi: <https://doi.org/10.1109/ICCSP48568.2020.9182272>.