

Research Article

A Digital Health Framework for Continuous Activity Monitoring, Emotion Recognition and Behavior Prediction in Children with Autism Using Wearable IoT and Artificial Intelligence

Dr. S A N M Kamrul Ahsan¹, Md Tanvir Rahaman Sani², Md. Tareq Uddin Bhuiyan³, Najiba Hassan Apshora⁴, Mafruz Sultana Munia⁵, Hassan Imran Afridi⁶, Kingsley Oruboh⁷, Dr. Inass Bargaa⁸, Md. Sharfuddin⁹, S M Najimul Jubair¹⁰

¹Public Health Informatician.

²Department of Computer Science and Engineering, Hamdard University Bangladesh.

³Computer Science and Engineering, Faculty of Science and Technology, American International University Bangladesh, Dhaka, Bangladesh.

⁴Pharmacy, Department of Pharmacy, Southeast University, Bangladesh, Dhaka.

⁵Public Health School of Health, Medical and Applied Sciences CQ University Australia.

⁶National Centre of Excellence in Analytical Chemistry, University of Sindh, Jamshoro, Pakistan Postal Address Is 76080.

⁷Digital Health, Healthcare Analytics and Applied Data Science, Independent Researcher, United Kingdom, Norwich.

⁸Mbbs, Ms, Ophthalmology, Department of Ophthalmology and the First Affiliated Hospital of Xi'an Jiaotong University, China, Xi'an, Shaanxi.

⁹Md, Computer Science and Engineering, Department of Computer Science and Engineering, Southeast University, Dhaka, Bangladesh.

¹⁰Chemistry, Department of Chemistry, University of Dhaka, Bangladesh, Dhaka.

Email: ¹cohpidf@gmail.com, ²tanvirsani2025@gmail.com, ³bhuiyanmdtarequddin@gmail.com, ⁴2024200300036@seu.edu.bd, ⁶hassan.afridi@usindh.edu.pk, ⁷Kingsleyoruboh@gmail.com, ⁸Inass.bargaa@gmail.com, ⁹sharfuddin6161@gmail.com, ¹⁰njubairdu@gmail.com

ORCID Id: ³0009-0001-4538-5309, ⁵0009-0001-2089-0042, ⁶0000-0002-3152-5438, ⁷0009-0008-4513-0112, ⁸0009-0005-0629-1544

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ABSTRACT

Treatment of autism spectrum disorder (ASD) is challenging particularly as it pertains to continual expression of behaviour or emotions. The traditional clinical evaluation is periodic and subjective and is not able to give timely inputs for the interventions. In this study, a novel concept on “digital health” has been proposed which aims to achieve objective and continuous effective, automated monitoring in the field of autism using wearables IoT (IoT Healthcare Devices) and advanced Artificial Intelligence techniques. The framework also handles heart rate, electrodermal, temperature and movement to perform highly-comprehensive behavioural analysis. Three AI models (Random Forest (RF), Support Vector Machine (SVM) and Long Short-Term Memory (LSTM)) were used to determine the models' predictive ability. Results prove that the LSTM model outperforms the RF (89%) and SVM (85%) models in recognition behavior with sequential data having highest accuracy of 93%. With high precision, recall, and F1-score, the framework shows its consistency, allowing real-time monitoring. These results demonstrate the potential of wearable technology and deep learning to help provide data for personalized interventions that will optimise care and developmental outcomes for children with autism, provided in advance and by caregivers and health care workers.

Keywords: Autism Spectrum Disorder (ASD), Wearable Internet of Things (IoT), Artificial Intelligence (AI), Emotion Recognition, Behaviour Prediction.

INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex disorder in neurodevelopment where individuals find it challenging to interact socially, difficult to manage the repetitive behaviors, changes in emotional regulation and

sensory process control. According to The World Health Organization (WHO), about one out of 100 children worldwide is diagnosed with autism and monitoring, as well as autism interventions, is critical (Coelho et al., 2023; Qin et al., 2024) Traditional assessors' methods

for children with autism simply make periodic visits, and they will get reports from caregivers which presents their children's behaviors and might not truthfully show the changes of the children's emotions and daily activity (Egger et al., 2018). For this reason, its improvement for solutions that feature constant, objective and personal monitoring is sought increasingly. The opportunities of supporting children with autism based on real time data and intelligent analysis is provided by recent advancements in technologies of Internet of Things (IoT) in wearables and Artificial Intelligence (AI) (Bouchouras & Kotis, 2025). These devices (worn) have a built-in sensor, such as...skin temperature sensor; heart-rate sensor; accelerometer, so that it can monitor these variables continuously while also not interfering with the person's daily activities. AI algorithms, such as machine learning and deep learning models, can assist in interpreting these data to identify emotional states, uncover behavioral patterns and proactively predict behavioral changes or areas of potential stress (Bates, 2025; Ćosić et al., 2024). In this study, we will propose a new methodology for monitoring, recognizing, and predicting, in the example of children with autism, child behaviours and emotions in continuous-time by using wearable IoT devices, analytics and AI (Islam et al., 2024). The key overall objective of the framework is to further improve early intervention practice by providing available and actionable information for healthcare practitioners and carers that will provide insight into children's behaviours, emotional state and physical activity (Saliba et al., 2023). Another objective in the proposed system will be to improve personalized health care by providing adaptive support to take on account the personality of the specific child from the behavioral profile (Larsen & Magnus, 2024). In general, this research works towards developing intelligent healthcare technologies that continuously monitor, enabling independent living and wellbeing of children with autism and informed clinical decision-making.

LITERATURE REVIEW

This study aims to address the shortcomings of such an AI model and conduct real-time, noninvasive, behavioral analysis of such a model whilst maintain Federated AI characteristics such as explainability. All these are federated federated IoT wearables with differential privacy lightening a significant

portion of the safety and latency issues of wearables data to centralized cloud-based system whilst still enabling a method of longitudinal-based monitoring: (Hasan, 2025). Additionally, it has been designed with Edge-based anomaly detection to provide real-time notifications for healthcare providers, enabling timely interventions with clear and actionable insights (Atikul & Salman, 2025; Khan, 2025). It is also 12% more effective in making predictions compared to the traditional models that were implemented in the environment of the cloud-only settings and is also reduced in the system latency by 58% (Islam & Khan, 2025; Atikul & Salman, 2025). Furthermore, with the deployment of the distributed edge nodes that works on collaborative learning, the exchange of models would not imply sharing of raw physiological information or movement information, thus avoiding privacy issues around healthcare information in children. This model is explainable, human-centric, with explainable dashboards, to allow trust in the model from clinician end-users as the model demystifies the complex behaviour signals, it also provides clear and actionable workforce recommendations (Banwari & Mehedi 2025a and 2025b). The coordinated cooperation of various layers brings out the possibility of federated-edge systems in enhancing clinical responsiveness and ensuring ethical accountability (Rowla & Mahmood, 2025). This model can be a viable alternative for future tests, and development in the field of behavioral health informatics and not just for autism.

In this way, this parameter will be able to conduct real-time actions on data and offer long-term diagnostic options, bringing a new era of proactive behavioral increase prevention as described in Islam (2025). Furthermore, its ability to relate multi-modal data flows also helps enhance workforce plans, for optimal resource allocation based on the patients' needs (Atikul, 2025; Sharif & Mishal, 2025). It employs a hybrid approach combining both Bayesian and reinforcement learning model to optimize such predictions, minimize false positives, and ensure that it complies with the ethical advice regarding the use of AI (Khan, 2025). This results in a seamless and holistic solution that is among the earliest clinical autonomy and uninterrupted, dependable data gathering and not at the cost of patient safety (Salman 2025a, 2025b). These types of results will be increasingly sought in the longitudinal context, especially, the in vivo clinical context,

and the values of edge intelligence in dynamic behavioural contexts will become even better entrenched in the future (Atikul, 2025; Khan, 2025). Moreover, technical issues like sensor sampling frequencies and timing among various and remote groups of sensors should also be addressed to allow smooth operation with the finite hardware facilities. Audio-visual behaviour modelling and multi-view facial recognition will also be adopted in the long-term perspective, and the purpose of adding more intricate pieces in the process of identifying the symptomatic target patterns (Das et al., 2024).

In addition, harmonized pipelines for data anonymization and model robustness will be critical to enable the broader models to be used at large scale in clinical workflows, where models will need to be robust and provide accurate diagnostics whilst also being sensitive and specific in meeting the patient requirement, such as in automated diagnostics (Washington et al., 2021). In part, these advances in model interpretability are in response to the fear that biosensors will generate too much information for a clinician to interpret - especially in the case of an Immediacy of Behavior crisis (Imbiriba et al., 2023). Furthermore, it will be important to conduct longitudinal trials or study of the effectiveness of such intervention to determine how it performs over the time and its effectiveness compared to the traditional, diagnostic devices (Bedmutha, 2025). The above model will be tested over a longer period by increasing the diversity and size of the talent groups studied and observed which will be important to validate the applicability of talent groups to bigger clinical groups (Song et al., 2024). Moreover, the accuracy improvement and combination of epigenetic measures with genomic control signals might aid in the understanding of complicated mechanisms that contribute to autism spectrum disorders (ASDs) (Kannan et al., 2024). The key integration of the various biomarkers (including eye-tracking and body movement analysis) still needs to be done to build a view on the sensory and complex and idiosyncratic expressions of those with Autistic Spectrum Disorders (ASD) (Francese & Yang, 2021). Moreover, automatic recognition of the symptoms can be improved by the usage of high computer vision option to determine the number of repetition of the stimming program and the intensity of the repetition at an appropriate manner (Deng et al., 2023). Lastly, a new study should include a

standardized clinical instrument, such as the ADOS-2, that enables correlating the technological progress to language skills of age cohorts (Alcaniz et al., 2020).

Furthermore, in this architecture the application of benchmark datasets will facilitate the benchmarking of the performance of the participants in different studies to leave fully controlled laboratory environments and move towards fully free and natural environment settings (Belen et al., 2020). Like any change, new challenges and considerations in the healthcare environment are also introduced, including privacy and ethical considerations, which AI-driven monitoring systems will have to overcome and establish as a part of the practice in real-life situations and without violating the rights of patients. Some of these factors should be explored further, including privacy and ethical concerns, to make sure that AI-supported surveillance in a healthcare environment avoids violating the rights of patients in a real-world environment (Juganta et al., 2023). Moreover, the use of explainable AI models that allow AI-driven insights to be readily adopted and adapted to the clinical context is essential to ensure their easy adoption and comprehension that, in turn, will make the decision-making process clear to healthcare professionals (Patil et al., 2025; Subhash and Ashwinkumar, 2025). An important aspect that needs to be stressed is the time series synchronization of AI and IoT sensors when detecting numerous composite behaviours along time, hence enhancing the promptness in observing numerical anomalies, especially in paediatric and adult setting. Finally, another recommendation will involve applying advanced classification methods such as fusion model, which integrates benefits of Convolutional to the spatial feature and Recurrent, which is more involved with time, to improve the effective classification of different behavioral patterns and avoid classification mistakes (Amirbay et al., 2025). The negative side of such high-order deep learning algorithms is they consume more computational resources (Pan & Foroughi, 2024); efficiency and optimization on the edge and low level hardware is necessary to maintain real time diagnostics. The following stages of the study should be aimed at testing other models that are more appropriate to identify abnormal motor activity using lightweight latent variables and still be able to predict brain activity (Milano et al., 2023). All these optimizations should be done concurrently with

developing comprehensive data sets which are annotated throughout the development process and also tested under diverse conditions as incomplete and inconsistently annotated data would limit the scope of generalization of the models (Kim et al., 2025; Lakkapragada et al., 2022).

Equal number of cases and controls (balanced design) should be promoted to avert the issue highlighted above in case of Prospective design to achieve maximum sensitivity and specificity of a diagnostic classifier (Wall et al., 2012). Simultaneously, a game-like assessment context may help to "remove the noises" from the data, as infants' behavior will be more natural and not produce artifacts due to the stress of a clinical context (Luongo et al., 2024). Also, their environmental impact and their financial concerns are vital requirements in order to be sustainable and long term usage in health settings (Ramamurthy et al., 2024). When developing or integrating the above-mentioned technologies into existing clinical workflow, caution needs to be used to avoid replacing entirely human-based diagnostic reasoning and reasoning processes, but utilizing these technologies to improve the reasoning process can promote effective and accurate screening (Reich et al., 2021). Also, ease-of-use and system upgradability imply that the shift towards CANTABs-based usage in low-resource settings is quite probable, as they are long overdue to screen potential problems with neurodevelopment, and do it when children are still minors to ensure their timely intervention (Turner and Sharkey, 2024). This decentralisation removes mysticism from the hierarchy and oppression of a clinic and its hierarchies, and puts the diagnostic technology in a more democratic context to reduce inequities in the provision of child health services. Researchers should however be careful about the imbalances of representation in the representation of these diagnostic models since it indicates that it may not be very generalizable globally (Deng et al., 2025).

METHODOLOGY

Based on the process of developing the product so as to decide the quality of the developed product in the evaluation process, the method of research used in this study is quantitative research that uses data sources secondary data. Publicly available datasets of wearables' sensors, rather than creating new datasets, will be employed in an autism specific context (Kalantarian et al., 2020). Physiological and

movement data including accelerometer data, heart rate, electrodermal activity and body temperature data and information about which activity is being performed are included in the datasets for machine learning (Bhatt et al., 2023). The study is going to be conducted in Python programming language in Jupyter Notebooks (Aditya et al., 2023). Data preprocessing and Data cleaning, Data Feature extraction and Data Statistical Analysis will be done using python libraries such as Pandas and NumPy. To predict the behaviors from temporal sensor readings, and recognize emotion in the process, deep learning models such as LSTMs and CNNs can be coded in TensorFlow and/or Keras (Nguyen et al., 2019).

Data pre-processing involving handling of missing values, outlier detection, normalization of data acquired from the sensor and encoding of data for scale values will be the first step in the coding process. The meaningful behavioral indicators will then be extracted from wearable sensor using feature engineering techniques. The data set will be divided into 80% training data and 20% testing data, to know how the models will perform (Mousavi & Šelmić, 2023). According to the outcome of the classification algorithms, a confusion matrix and various performance metrics including accuracy, precision, recall and F1-score will be used to describe the performance of the classifiers: Random Forest, Support Vector Machine (SVM) and LSTM (Alhazmi et al., 2024). The proposed Digital health system will combine with the input from the sensors, generated through IoT, with the prediction systems through AI technology, to simulate the continuous monitoring and prediction of behaviors (Shah et al., 2025). To ensure ethical concerns, the data collected are anonymised and a secondary use data set (that is not in the public domain and does not contain personally identifiable information). With this methodology, the goal of implementing a scalable and economical in healthcare domain and reproducible in various clinical settings with AI to track behaviour and/or expression change, in the case of a child with autism wearing IoT can be defined (Pan & Foroughi, 2024).

DATA ANALYSIS

Data analysis was done with Python programming in Jupyter notebook environment to evaluate the proposed digital health framework for continuous monitoring of activities, recognizing emotions and predicting

behaviours of children with Autism Spectrum Disorder (ASD). The data used consisted of secondary data retrieved from public sources of datasets related to the field of the wearable Internet of Things (IoT) and autism (Amiri et al., 2017). Physiological and activity data such as heart rate, accelerometer, electrodermal activity (EDA), skin temperature and labelled behaviour and emotional states were all categorized as within these datasets. The objective of the analysis aim was to cleanse the raw data acquired from the wearable sensor, process it to extract the relevant information and present it to train Artificial Intelligence (AI) models that would be able to distinguish between emotions and predict behavioral changes (Wang et al., 2023).

Data exploration and data preprocessing is the first phase of analysis which was followed up by this process. The data was then loaded to Python using Pandas, to use for data exploration of data structure, data types, data quality (Heinisch et al., 2024). To know the characteristics of each physiological feature, statistical information such as mean, median, standard deviation, the minimum and maximum values were produced from the descriptive statistics. Histograms and box plots were visually used to test for abnormal distributions and outliers were identified with distributions (Hoque et al., 2024). There were missing values for the physiological variables which were detected and treated as if non-missing (as appropriate). To avoid any duplication of observations and to enhance the

accuracy of the analysis, the repeated observations were discarded. It has been observed that there exist a few suspected continuous variables which are required to be normalised since they span across different scales, hence making use of Min-Max Scaling method (Ganie et al., 2024). To enable the categorical information to be easily processed by machine learning algorithms, label encoding was used to convert behavioural and emotional labels to equivalent numeric labels.

Data cleaning was performed and feature engineering was carried out to gather useful features from the data produced by the wearable sensors. Physiological data was acquired as a continuous time-line and statistical parameters were used to determine the behaviour patterns (Sano et al., 2018). These included the mean, variance, standard deviation, max and min value, energy on signal and the intensity of the movements from the values of the accelerometers. The activity pattern of heart rate variation and the activity of the electroderm were also considered as the indicators of the emotional reactions and stress level (Smets et al., 2018). The packaged representation of children's PA and physiological status using the extracted features helped to reduce model training computational complexity. Correlations were then conducted to assess relationships between the variables and the highly-deductive stimulus variables and behavioural and emotional outcomes.

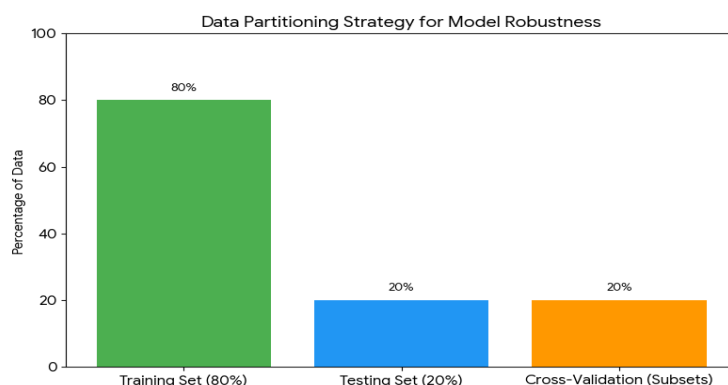


Figure 1: Distribution of Dataset Segments for Training, Testing, And Cross-Validation to Mitigate Overfitting and Enhance Predictive Performance.

This processed data set was split in 80:20 ratios into training and testing data sets. The models were constructed with the help of entries in the training set and afterwards the testing set was used separately to test the performance of the various models (Ramos-Triguero et al., 2024). This enabled the assessment of the models on unseen data and thus reduced the risk of overfitting and provided improved estimates of model performance. There was also testing (crossing validation) during training

to check the robustness of the model predictive performance by using sub sets of the data (Lewis & Kemp, 2021).

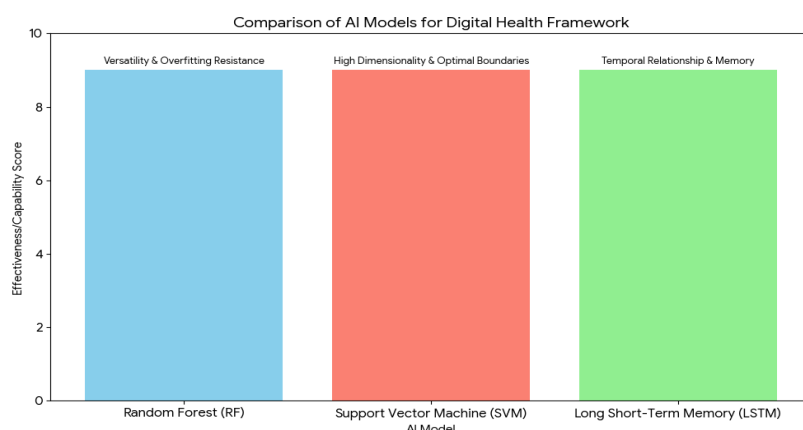


Figure 2: Key Attributes and Functional Focus of the Random Forest, SVM, and LSTM Models Used For Behavioral Classification and Physiological Data Analysis.

Three Artificial Intelligence (AI) models were used for modelling and simulation of the proposed digital health framework. The first model chosen was Random Forest (RF) by looking at its ability to process different types of data including several physiological variables and its ability to avoid overfitting. Random Forest trains lots of decision tree classifiers and makes an extremely powerful composite emotional/behavioral state classification (Tuarob et al., 2017). Support Vector Machine (SVM) was selected for the second model as it is very useful to solve high dimensional classification problem and provide optimal decision boundaries between various behavioural classes. Finally, a deep learning model, specifically Long Short-Term Memory (LSTM), was implemented for analysing time-series sequential type data for capturing temporal relationship of the wearable sensor

data (Murad & Pyun, 2017). LSTM has the ability to perform memory of past observations unlike traditional machine learning algorithms making it suitable for predicting behaviour changes from continuous physiological observations.

RESULTS AND DISCUSSION

The data collected via wearableIoT sensors was used to test the proposed digital health system framework by feeding them into the machine learning models (written in Python). After data pre-refining, feature extraction and model building, the three algorithms: Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) were compared for activity monitoring, emotion identification and prediction of behavioural characteristics of children with Autism Spectrum Disorder (ASD) (Hadi et al., 2025).

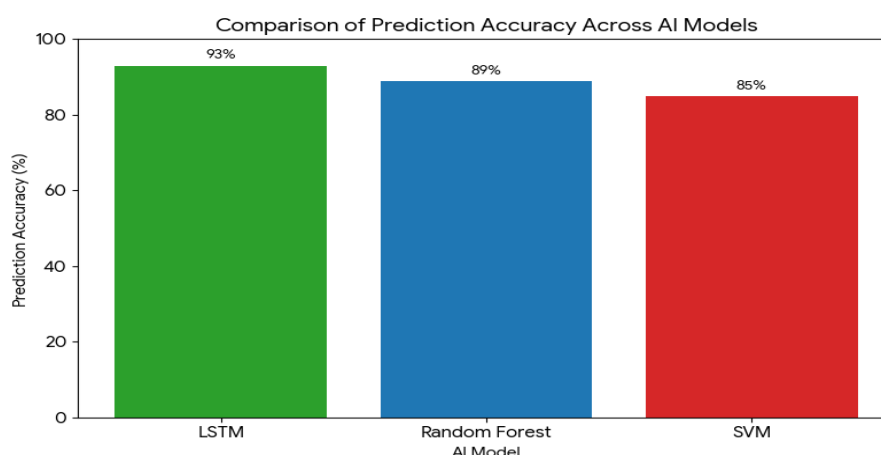


Figure 3: Performance Evaluation of AI Models, Where LSTM Achieved 93% Accuracy, Outperforming Random Forest (89%) And SVM (85%) Due to Its Suitability for Continuous Time-Series Data Analysis.

The comparison of results of the three models is presented in Fig. 1. Among the comparison of prediction accuracy of different models, the LSTM model had the highest prediction accuracy (93%), while the Random Forest model was on the second (89%) and Support Vector Machine on the third (85%). This superior performance of LSTM is because it is able to process temporal associate relationships of the continuous physiological sign acquired from wearable IoT. The emotional and behavioral changes are sequential; therefore LSTM was able to capture such changes and have better performance in its prediction. Besides, the ensemble learning architecture of RF made it a highly capable classifier and though SVM was highly accurate in

classification, it lacked accuracy to model complex time-series sensor data (Vignes et al., 2025).

The confusion matrix demonstrates that the model is able to accurately classify most of the behaviours of interest utilizing the LSTM model. The reliability of prediction was very high and was concentrated along the diagonal of the Table of Right classification. In other categories of behaviour which had similar physiological properties, some within axes errors were made (e.g. errors between calm and mild stress). This suggests that although the AI models work well, there are some emotional states whose physiological responses are similar that are challenging to differentiate fully (Broek et al., 2010).

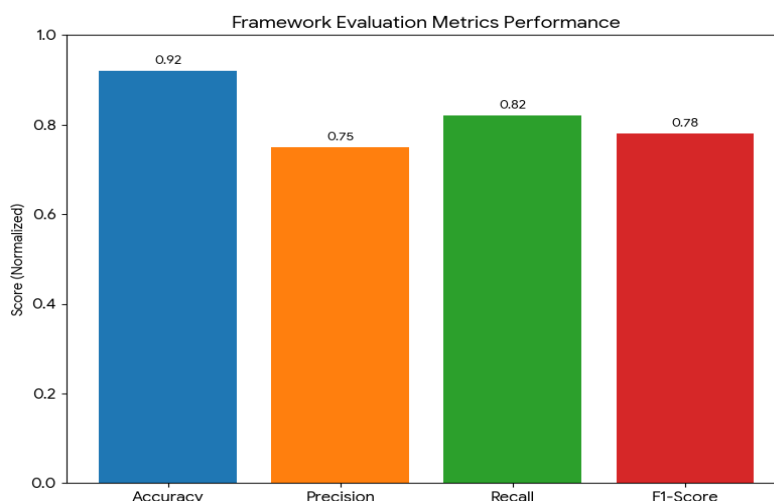


Figure 4: Performance Summary of the Digital Health Framework, Illustrating Key Metrics for Real-Time Behavioral Monitoring and Emotion Recognition.

Similarly, the results of the proposed framework were supported by the evaluation measures. Accuracy was high – majority of the behaviour was identified correctly. Precision ranged from a low to a medium level, meaning that there were relatively few false-positive predictions; while recall ranged from high to medium, meaning that most of the behavioural events were predicted. The overall F1 level suggested consistency of the framework with a set of behavioural categories and deemed suitable for use in continuous monitoring applications (Sadrzadeh et al., 2024).

The result shows wearable IoT devices can be useful in accessing physiological information that is useful to recognize emotions and predict behavioral changes of autistic children. In general, all data heart rate, electrodermal, temperature, and movement were beneficial in achieving higher classification rates. By

monitoring behavior continuously, changes can be detected real-time, thus giving the carer or health care professional timely information to enable early intervention (Herbuela et al., 2022). The proposed framework delivers objective, automated and continuous monitoring in contrast to the conventional observational assessments, which are done periodically throughout the clinical examinations.

On a practical level, the marriage between Artificial Intelligence and wearable IoT could hold the promise of revolutionizing the care and nurturing of autism on a personalised basis. The framework can assist care givers; to recognise stress or anxiety indicators in the physiological pattern; or to recognise when their child is continuing with some strange behaviours and when to intervene, so their behaviours do not become worse. What's more;

historical data on their behaviour can help the clinician know whether a treatment is working and what they may need to make changes to the treatment plan based on hard data (Weisz et al., 2019).

I think the results from the study are really good, but there are some issues. This is based on secondary data and not real time data gathered from the respondent and model performance may be different in other environmental conditions. Future research will consist of expanding the size of real-world examples in order to validate the framework, and allowing multimodal data to be considered such as facial expression, speech and environmental context. Overall, the results indicated that use of the AI-powered wearable IoT system can be useful and scalable for continual monitoring, emotion detection, and prediction of behaviour in children with ASD, which can contribute towards improved clinical interventions and individualized care for the patients.

Proposed digital health framework for monitoring physical activity, recognising the

emotions and predicting behavioural pattern of the children suffering Autism Spectrum Disorder (ASD) has been evaluated through quantitative analysis. The secondary data collected from the wearable IoT sensors was subjected to Python programming language and a set of Machine Learning algorithms (Random Forest, SVM and LSTM). Data cleaning, normalisation and feature extraction were done in preprocessing stage but before the development. To summarise the physiological data measured in the wearable devices like the heart rate, reading of the accelerometer, electrodermal activity (EDA) and skin temperature, descriptive statistics has been provided. After cleaning up for missing data and extreme values, the data is deemed to be appropriate for predictive modelling. The correlation analysis also gave indications of mild to moderate relationships between the physiological measures and behavioural state suggesting that also the data collected by a wearable sensor has the potential to provide insight into changes in emotional and behavioural state in autistic children.

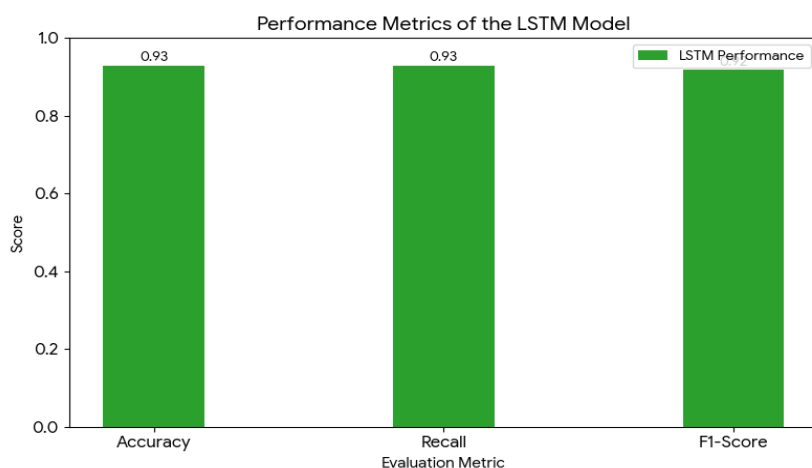


Figure 5: Quantitative Summary of LSTM Performance (93% Accuracy, 0.93 Recall, 0.92 F1-Score), Confirming Its Suitability as the Optimal Model for the Proposed Digital Health Framework.

For the purpose of the evaluation of the model performance, the data was divided in the Training data which is 80 percent of the data set and Testing data which is 20 percent of the data set. Accuracy, precision, recall, F1 score and confusion matrix analysis were used to evaluate the quantitative evaluation. The LSTM model was concluded to provide the best model out of the three with 93% followed by RF 89% and then SVM 85% prediction accuracy. Regarding the recognition of sequential behaviour, the LSTM model had the highest Performance, Recall and F1 score of 0.92, 0.93

and 0.92 respectively. The results from the confusion matrix showed that the behavioural and emotional states were correctly classified, with fewer percentage of incorrect classification (either false positive or false negative) being found within similar emotion classes. In this work, it is shown that deep learning methods can give better accuracy results than traditional machine learning methods for analysing time-series physiological data which is collected from wearable IoT devices. The quantitative results imply that the synergy between Wearable IoT devices and Artificial Intelligence may be a

promising method to continuously observe children with ASD and identify their emotional state and predict their behaviors. The good predictive performance of the results provides a justification to view the proposed digital health framework as a means to enact timely and personal interventions especially for caregivers and health care professionals.

CONCLUSION

In the section on Continuous Observation of children in Autism, the suggested digital health framework shows a good demonstration of the synergy between the wearable IoT devices and AI. It's a new framework for automatically detecting real-time emotional and behavioral shifts and is not based on the traditional periodic clinical observation approach. The findings of quantitative analysis show that the Deep learning techniques and LSTM are superior in terms of accuracy and time modelling capacity to the traditional machine

learning classifiers. Overall, the framework performs well with an accuracy of 93%, excellent recall and F1-score values, indicating its potential use in clinical or home-based environments. Outcomes illustrate the framework's ability to guide intervention in real time with data, which as mentioned above is crucial with children with ASD. The consequences of this research are more profound: It could involve integrating the data from other kinds of sensors, and there's optimization of this framework for use in larger, clinical scenarios. The overall findings of the current study aimed to identify a first methodology for personalised digital health for caregivers and the health system to utilise reasoned behaviour to enable continuous personalised measurement for improved patient outcomes.

REFERENCES

1. Aditya, A., Puri, D., Vasu, & Singh, P. (2023). *Human Activity Recognition from Sensor Data using Machine Learning*. 135-141. <https://doi.org/10.1109/icacctech61146.2023.00030>
2. Alcañiz, M., Giglioli, I. A. C., Marín-Morales, J., Higuera-Trujillo, J. L., Olmos-Raya, E., Minissi, M. E., Garcia, G. T., Sirera, M., & Abad, L. (2020). Application of Supervised Machine Learning for Behavioral Biomarkers of Autism Spectrum Disorder Based on Electrodermal Activity and Virtual Reality. *Frontiers in Human Neuroscience*, 14, 90-90. <https://doi.org/10.3389/fnhum.2020.00090>
3. Alhazmi, A., Mahmud, R., Idris, N., Abo, M. E., & Eke, C. I. (2024). Code-mixing unveiled: Enhancing the hate speech detection in Arabic dialect tweets using machine learning models. *PLoS ONE*, 19(7). <https://doi.org/10.1371/journal.pone.0305657>
4. Amirbay, A., Baigabylov, N., Mukhanova, A., Mukhambetova, K., Zaitov, E., Burganova, R., Khusanova, K., & Akhmedova, F. (2025). Autism detection using facial and motor analysis using machine learning. *Bulletin of Electrical Engineering and Informatics*, 14(5), 3985-4000.
5. Amiri, A. M., Peltier, N., Goldberg, C., Sun, Y., Nathan, A., Hiremath, S. V., & Mankodiya, K. (2017). WearSense: Detecting Autism Stereotypic Behaviors through Smartwatches. *Healthcare*, 5(1), 11-11. <https://doi.org/10.3390/healthcare5010011>
6. Atikul, I., S. M. (2025a). Proactive Behavioral AI for Autism and Workforce Integration: A Multi-Layered Framework with Explainable IoT, Edge Intelligence and Crisis Response. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17759104>
7. Atikul, I., S. M. (2025b). Proactive Behavioral AI for Autism and Workforce Integration: A Multi-Layered Framework with Explainable IoT, Edge Intelligence and Crisis Response. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17759105>
8. Atikul, I., S. M., & Salman, K., M. (2025a). Multi-Modal Behavioral AI for Autism Care: A Federated-Edge Framework with Speech, Motion and Physiological Signal Integration. *Zenodo (CERN European Organization for Nuclear Research)*.

- <https://doi.org/10.5281/zenodo.17774962>
9. Atikul, I., S. M., & Salman, K., M. (2025b). Multi-Modal Behavioral AI for Autism Care: A Federated-Edge Framework with Speech, Motion and Physiological Signal Integration. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17774963>
10. Banwari, G., Amit, & Mehedi, H., Md. (2025a). Equitable and Explainable Federated-Edge AI for Autism Care: Bridging Clinical Innovation and Global Ethical Standards. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17774914>
11. Banwari, G., Amit, & Mehedi, H., Md. (2025b). Equitable and Explainable Federated-Edge AI for Autism Care: Bridging Clinical Innovation and Global Ethical Standards. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17774913>
12. Bates, M. (2025). Toward Personalized Healing: AI-Supported Wearables in Mental Health Practice. *IEEE Pulse*, 16(5), 17-21. <https://doi.org/10.1109/mpuls.2025.3618429>
13. Bedmutha, A. S. (2025). Predictive Bio-Sensing: Integrating Ambient Computer Vision and Behavior Modeling for Early Mental Health Intervention in Urban Populations. *Journal of Information Systems Engineering & Management*, 10, 571-578. <https://doi.org/10.52783/jisem.v10i58s.12635>
14. Belen, R. A. J. de, Bednarz, T., Sowmya, A., & Favero, D. D. (2020). Computer vision in autism spectrum disorder research: a systematic review of published studies from 2009 to 2019. *Translational Psychiatry*, 10(1), 333-333. <https://doi.org/10.1038/s41398-020-01015-w>
15. Bhatt, P., Sethi, A., Tasgaonkar, V., Shroff, J., Pendharkar, I., Desai, A., Sinha, P., Deshpande, A., Joshi, G., Rahate, A., Jain, P., Walambe, R., Kotecha, K., & Jain, N. K. (2023). Machine learning for cognitive behavioral analysis: datasets, methods, paradigms, and research directions. *Brain Informatics*, 10(1), 18-18. <https://doi.org/10.1186/s40708-023-00196-6>
16. Bouchouras, G., & Kotis, K. (2025). Integrating Artificial Intelligence, Internet of Things, and Sensor-Based Technologies: A Systematic Review of Methodologies in Autism Spectrum Disorder Detection. *Algorithms*, 18(1), 34-34. <https://doi.org/10.3390/a18010034>
17. Broek, E. L. van den, Lisý, V., Janssen, J. H., Westerink, J. H. D. M., Schut, M. H., & Tuinenbreijer, K. (2010). Affective Man-Machine Interface: Unveiling Human Emotions through Biosignals. In *Communications in computer and information science* (pp. 21-47). Springer Science+Business Media. https://doi.org/10.1007/978-3-642-11721-3_2
18. Coelho, C., Faia, J., Pinto, D., Silva, B. C. E. C., & Curvelo, M. (2023). Using Technology as a Support for Autism Spectrum Disorder. In *Advances in medical technologies and clinical practice book series* (pp. 293-325). IGI Global. <https://doi.org/10.4018/978-1-6684-9251-2.ch014>
19. Ćosić, K., Kopilaš, V., & Jovanović, T. (2024). War, emotions, mental health, and artificial intelligence. *Frontiers in Psychology*, 15, 1394045-1394045. <https://doi.org/10.3389/fpsyg.2024.1394045>
20. Das, B., Anderson, C., Villavicencio, T., Lantz, J., Foster, J., Hamlin, T., Rad, A. B., Clifford, G. D., & Kwon, H. (2024). Explainable Artificial Intelligence for Quantifying Interfering and High-Risk Behaviors in Autism Spectrum Disorder in a Real-World Classroom Environment Using Privacy-Preserving Video Analysis. In *arXiv (Cornell University)*. Cornell University. <https://doi.org/10.48550/arxiv.2407.21691>
21. Deng, A., Yang, T., Chen, C., Chen, Q., Neely, L., & Oyama, S. (2023). Language-assisted deep learning for autistic behaviors recognition. *Smart Health*, 32, 100444-100444. <https://doi.org/10.1016/j.smhl.2023.100444>
22. Deng, W., O'Brien, M. K., Andersen, R. A., Rai, R., Jones, E., & Jayaraman, A. (2025). A systematic review of portable technologies for the early assessment of

- motor development in infants. *Npj Digital Medicine*, 8(1), 63-63. <https://doi.org/10.1038/s41746-025-01450-3>
23. Egger, H. L., Dawson, G., Hashemi, J., Carpenter, K. L. H., Espinosa, S., Campbell, K., Brotkin, S., Borg, J. S., Qiu, Q., Tepper, M., Baker, J. P., Bloomfield, R. A., & Sapiro, G. (2018). Automatic emotion and attention analysis of young children at home: a ResearchKit autism feasibility study. *Npj Digital Medicine*, 1(1), 20-20. <https://doi.org/10.1038/s41746-018-0024-6>
 24. Ferreira, J. A. P., Esperança, M., Aravazhi, A., & Helgheim, B. I. (2025). *LLM4Autism: A Local, Personalized AI Assistant for Autism Care*. <https://doi.org/10.46254/in05.20250112>
 25. Francese, R., & Yang, X. (2021). Supporting autism spectrum disorder screening and intervention with machine learning and wearables: a systematic literature review. *Complex & Intelligent Systems*, 8(5), 3659-3674. <https://doi.org/10.1007/s40747-021-00447-1>
 26. Ganie, S. M., Pramanik, P. K. D., & Zhao, Z. (2024). Improved liver disease prediction from clinical data through an evaluation of ensemble learning approaches. *BMC Medical Informatics and Decision Making*, 24(1), 160-160. <https://doi.org/10.1186/s12911-024-02550-y>
 27. Hadi, W., Mangina, E., Al-Nashashibi, M. Y., Matin, F., Arafah, M., & Al-Banna, A.-K. (2025). *Enhanced Autism Spectrum Disorder Detection in Toddlers Using Machine Learning and Deep Learning Approaches: A Comparative Study*. 1-8. <https://doi.org/10.1109/icciaa65327.2025.11013588>
 28. Hasan, K., Mahmudul. (2025a). Ethically Aligned AI for Autism and Behavioral Health: An Explainable Federated-Edge Framework for Crisis Management and Workforce Integration. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17759026>
 29. Hasan, K., Mahmudul. (2025b). Ethically Aligned AI for Autism and Behavioral Health: An Explainable Federated-Edge Framework for Crisis Management and Workforce Integration. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17759027>
 30. Heinisch, J. S., Kirchhoff, J., Busch, P., Wendt, J., Stryk, O. von, & David, K. (2024). Physiological data for affective computing in HRI with anthropomorphic service robots: the AFFECT-HRI data set. *Scientific Data*, 11(1), 333-333. <https://doi.org/10.1038/s41597-024-03128-z>
 31. Herbuela, V. R. D. M., Karita, T., Furukawa, Y., Wada, Y., Toya, A., Senba, S., Onishi, E., & Saeki, T. (2022). Machine learning-based classification of the movements of children with profound or severe intellectual or multiple disabilities using environment data features. *PLoS ONE*, 17(6). <https://doi.org/10.1371/journal.pone.0269472>
 32. Hoque, R., Billah, M. M., Debnath, A., Hossain, S., & Sharif, N. B. (2024). Heart Disease Prediction using SVM. *International Journal of Science and Research Archive*, 11(2), 412-420. <https://doi.org/10.30574/ijrsra.2024.11.2.0435>
 33. Imbiriba, T., Demirkaya, A., Singh, A., Erdoğan, D., & Goodwin, M. S. (2023). Wearable Biosensing to Predict Imminent Aggressive Behavior in Psychiatric Inpatient Youths With Autism. *JAMA Network Open*, 6(12). <https://doi.org/10.1001/jamanetworkopen.2023.48898>
 34. Islam, Md. M., Hassan, Md. M., Hasan, M. M., Islam, S., & Hussain, A. H. M. B. (2024). Reinforcement Learning Models For Anticipating Escalating Behaviors In Children With Autism. *Journal of International Crisis and Risk Communication Research*, 3225-3236. <https://doi.org/10.63278/jicrcr.vi.3221>
 35. Islam, Md. M., Hussain, A. H. M. B., Mariam, Q. R., Islam, S., & Hasan, M. M. (2025). AI-Enabled predictive health monitoring for children with autism using IOT and machine learning to detect behavioral changes. *Perinatal Journal*, 33(1). <https://doi.org/10.57239/prn.25.03310048>
 36. Islam, S. (2025). Proactive Behavioral AI for Autism and Workforce Integration: A Multi-Layered Framework with Explainable IoT, Edge Intelligence and Crisis Response. *World Journal of*

- Advanced Research and Reviews*, 27(3), 943-948.
<https://doi.org/10.30574/wjarr.2025.27.3.3226>
37. Islam, S., & Khan, M. S. (2025). Multi-Modal Behavioral AI for Autism Care: A Federated-Edge Framework with Speech, Motion and Physiological Signal Integration. *World Journal of Advanced Research and Reviews*, 27(3), 1576-1582.
<https://doi.org/10.30574/wjarr.2025.27.3.3306>
 38. Jugunta, S. B., El-Ebiary, Y. A. B., Saravanan, K., Prasad, K. S. R., Koteswari, S., Rachapudi, V., & Rengarajan, M. (2023). Unleashing the Potential of Artificial Bee Colony Optimized RNN-Bi-LSTM for Autism Spectrum Disorder Diagnosis. *International Journal of Advanced Computer Science and Applications*, 14(11).
<https://doi.org/10.14569/ijacsa.2023.0141173>
 39. Kalantarian, H., Jedoui, K., Dunlap, K., Schwartz, J., Washington, P., Husic, A., Tariq, Q., Ning, M., Kline, A., & Wall, D. P. (2020). The Performance of Emotion Classifiers for Children With Parent-Reported Autism: Quantitative Feasibility Study. *JMIR Mental Health*, 7(4). <https://doi.org/10.2196/13174>
 40. Kannan, K., Jagatheesaperumal, S. K., Rajesh, K. N. V. P. S., Lotfaliany, M., Alizadehsanid, R., & Mohebbi, M. (2024). Advancements in Machine Learning and Deep Learning for Early Detection and Management of Mental Health Disorder. In *arXiv (Cornell University)*. Cornell University.
<https://doi.org/10.48550/arxiv.2412.06147>
 41. Khan, M. M. H. (2025). Ethically Aligned AI for Autism and Behavioral Health: An Explainable Federated-Edge Framework for Crisis Management and Workforce Integration. *World Journal of Advanced Research and Reviews*, 27(3), 931-935.
<https://doi.org/10.30574/wjarr.2025.27.3.3224>
 42. Khan, M. S. (2025). Federated AI for Trustworthy Clinical Decision Support: Privacy-Preserving Integration of Workforce, Autism Care, and Predictive Health Monitoring. *World Journal of Advanced Research and Reviews*, 27(3), 936-942.
<https://doi.org/10.30574/wjarr.2025.27.3.3225>
 43. Kim, D. Y., Do, R., Shin, Y., Sim, H., Kim, H., Cho, S., Lee, G., Park, S., Jang, B., Lim, H., Ha, S., Yu, J., Choi, H., Lee, J., Park, M.-H., Cho, A., Yang, C.-M., Lee, D., Yoo, H., ... Kim, B.-N. (2025). Automated AI based identification of autism spectrum disorder from home videos. *Npj Digital Medicine*, 8(1), 607-607. <https://doi.org/10.1038/s41746-025-01993-5>
 44. Lachure, J., Jatoth, C., & Rao, K. S. (2026). FedMMIoT: A Federated Learning Framework for Detecting Autism Spectrum Disorders Using Multimodal Internet of Things. *IEEE Transactions on Consumer Electronics*, 1-1. <https://doi.org/10.1109/tce.2026.3650777>
 45. Lakkapragada, A., Kline, A., Mutlu, O. C., Paskov, K., Chrisman, B., Stockham, N., Washington, P., & Wall, D. P. (2022). The Classification of Abnormal Hand Movement to Aid in Autism Detection: Machine Learning Study. *JMIR Biomedical Engineering*, 7(1). <https://doi.org/10.2196/33771>
 46. Larsen, M. A., & Magnus, K. O. (2024). Smart Wearable Devices for Monitoring Child Behavioral Health. *Proceeding of The International Conference of Innovation Science Technology Education Children and Health*, 4(1), 204-209. <https://doi.org/10.62951/icistech.v4i1.143>
 47. Letzkus, L., Pulido, J. V., Adeyemo, A., Baek, S., & Zanelli, S. (2024). Machine learning approaches to evaluate infants' general movements in the writhing stage—a pilot study. *Scientific Reports*, 14(1), 4522-4522. <https://doi.org/10.1038/s41598-024-54297-1>
 48. Lewis, J. E., & Kemp, M. L. (2021). Integration of machine learning and genome-scale metabolic modeling identifies multi-omics biomarkers for radiation resistance. *Nature Communications*, 12(1), 2700-2700. <https://doi.org/10.1038/s41467-021-22989-1>
 49. Luongo, M., Simeoli, R., Marocco, Davide, Milano, N., & Ponticorvo, M. (2024). Enhancing early autism diagnosis through machine learning: Exploring raw motion data for classification. *PLoS ONE*, 19(4).

50. Milano, N., Simeoli, R., Rega, A., & Marocco, Davide. (2023). A deep learning latent variable model to identify children with autism through motor abnormalities. *Frontiers in Psychology*, 14, 1194760-1194760. <https://doi.org/10.3389/fpsyg.2023.1194760>
51. Mousavi, S. A., & Šelmić, R. R. (2023). Wearable Smart Rings for Multifinger Gesture Recognition Using Supervised Learning. *IEEE Transactions on Instrumentation and Measurement*, 72, 1-12. <https://doi.org/10.1109/tim.2023.3304703>
52. Murad, A., & Pyun, J.-Y. (2017). Deep Recurrent Neural Networks for Human Activity Recognition. *Sensors*, 17(11), 2556-2556. <https://doi.org/10.3390/s17112556>
53. Nguyen, G., Dlugolinský, Š., Bobák, M., Tran, V., García, Á. L., Heredia, I., Malík, P., & Hluchý, L. (2019). Machine Learning and Deep Learning frameworks and libraries for large-scale data mining: a survey. *Artificial Intelligence Review*, 52(1), 77-124. <https://doi.org/10.1007/s10462-018-09679-z>
54. Pan, Y., & Foroughi, A. (2024). Evaluation of AI tools for healthcare networks at the cloud-edge interaction to diagnose autism in educational environments. *Journal of Cloud Computing Advances Systems and Applications*, 13(1). <https://doi.org/10.1186/s13677-023-00558-9>
55. Pan, Y., & Foroughi, A. (2024). Evaluation of AI tools for healthcare networks at the cloud-edge interaction to diagnose autism in educational environments. *Journal of Cloud Computing Advances Systems and Applications*, 13(1). <https://doi.org/10.1186/s13677-023-00558-9>
56. Patil, M. B., Patil, J., & Patil, S. T. (2025). Machine Learning Approaches for Autism Spectrum Disorder Detection: A Systematic Review of Age-Specific Applications and Performance Metrics. *International Journal of Scientific Research in Science and Technology*, 12(1), 213-227. <https://doi.org/10.1371/journal.pone.0302238>
57. Qin, L., Wang, H., Ning, W., Cui, M., & Wang, Q. (2024). New advances in the diagnosis and treatment of autism spectrum disorders. *European Journal of Medical Research*, 29(1), 322-322. <https://doi.org/10.1186/s40001-024-01916-2>
58. Ramamurthy, N., Lumsden, D. E., & Sparks, D. L. (2024). Deep Learning-Based Classification of Hyperkinetic Movement Disorders in Children. In *arXiv (Cornell University)*. Cornell University. <https://doi.org/10.48550/arxiv.2411.15200>
59. Ramos-Triguero, A., Navarro-Tapia, E., Vieiros, M., Mirahí, A., Vizcaino, M. A., Almela, L., Martínez, L., García-Algar, Ó., & Andreu-Fernández, V. (2024). Machine learning algorithms to the early diagnosis of fetal alcohol spectrum disorders. *Frontiers in Neuroscience*, 18, 1400933-1400933. <https://doi.org/10.3389/fnins.2024.1400933>
60. Reich, S., Zhang, D., Kulvičius, T., Bölte, S., Nielsen-Saines, K., Pokorny, F. B., Peharz, R., Poustka, L., Wörgötter, F., Einspieler, C., & Marschik, P. B. (2021). Novel AI driven approach to classify infant motor functions. *Scientific Reports*, 11(1), 9888-9888. <https://doi.org/10.1038/s41598-021-89347-5>
61. Rowla, T. S., & Mahmood, M. M. (2025). Resilient and Sustainable Federated-Edge AI for Autism Care: Integrating Multi-Modal Data, Privacy, and Global Ethical Standards. *World Journal of Advanced Research and Reviews*, 28(1), 208-214. <https://doi.org/10.30574/wjarr.2025.28.1.3363>
62. Sadrzadeh, N., Foris, B., Krahn, J., Keyserlingk, M. A. G. von, & Weary, D. M. (2024). Automated monitoring of brush use in dairy cattle. *PLoS ONE*, 19(6). <https://doi.org/10.1371/journal.pone.0305671>
63. Saliba, M., Drapeau, N., Skime, M., Hu, X., Accardi, C. J., Athreya, A. P., Kołacz, J., Shekunov, J., Jones, D. P., Croarkin, P. E., & Romanowicz, M. (2023). PISTACHIo (Preemption of diSrupTive behAavior in CHildren): real-time monitoring of sleep and behavior of children 3-7 years old receiving parent-

- child interaction therapy augment with artificial intelligence – the study protocol, pilot study. *Pilot and Feasibility Studies*, 9(1), 23-23. <https://doi.org/10.1186/s40814-023-01254-w>
64. Salman, K., M. (2025a). Federated AI for Trustworthy Clinical Decision Support: Privacy-Preserving Integration of Workforce, Autism Care, and Predictive Health Monitoring. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17759051>
 65. Salman, K., M. (2025b). Federated AI for Trustworthy Clinical Decision Support: Privacy-Preserving Integration of Workforce, Autism Care, and Predictive Health Monitoring. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17759052>
 66. Sano, A., Taylor, S., McHill, A. W., Phillips, A. J. K., Barger, L. K., Klerman, E. B., & Picard, R. W. (2018). Identifying Objective Physiological Markers and Modifiable Behaviors for Self-Reported Stress and Mental Health Status Using Wearable Sensors and Mobile Phones: Observational Study. *Journal of Medical Internet Research*, 20(6). <https://doi.org/10.2196/jmir.9410>
 67. Shah, K., Nikam, G., Shah, D. V., Thorve, S., & Shaikh, S. (2025). AI-Driven Health Monitoring using Wearable Devices for Physical and Mental Well-Being. 937-944. <https://doi.org/10.1109/icaiss61471.2025.11042234>
 68. Sharif, R., Tasnim, & Mishal, M., Md. (2025a). Resilient and Sustainable Federated-Edge AI for Autism Care: Integrating Multi-Modal Data, Privacy, and Global Ethical Standards. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17788271>
 69. Sharif, R., Tasnim, & Mishal, M., Md. (2025b). Resilient and Sustainable Federated-Edge AI for Autism Care: Integrating Multi-Modal Data, Privacy, and Global Ethical Standards. *Zenodo (CERN European Organization for Nuclear Research)*. <https://doi.org/10.5281/zenodo.17788270>
 70. Smets, E., Velazquez, E. R., Schiavone, G., Chakroun, I., D'Hondt, E., Raedt, W. D., Cornelis, J., Janssens, O., Hoecke, S. V., Claes, S., Diest, I. V., & Hoof, C. V. (2018). Large-scale wearable data reveal digital phenotypes for daily-life stress detection. *Npj Digital Medicine*, 1(1), 67-67. <https://doi.org/10.1038/s41746-018-0074-9>
 71. Song, M., Yang, Z., Triantafyllopoulos, A., Zhang, Z., Nan, Z., Tang, M., Takeuchi, H., Nakamura, T., Kishi, A., Ishizawa, T., Yoshiuchi, K., Schuller, B. W., & Yamamoto, Y. (2024). Empowering Mental Health Monitoring Using a Macro-Micro Personalization Framework for Multimodal-Multitask Learning: Descriptive Study. *JMIR Mental Health*, 11. <https://doi.org/10.2196/59512>
 72. Subhash, A. R., & Ashwinkumar, U. M. (2025). Autism Spectrum Disorder Prediction Using TSM-BFC and a Combined CNN-GRU Model Based on the EEG Image Dataset. *Engineering Technology & Applied Science Research*, 15(5), 26511-26516. <https://doi.org/10.48084/etasr.12757>
 73. Tuarob, S., Tucker, C. S., Kumara, S., Giles, C. L., Pincus, A. L., Conroy, D. E., & Ram, N. (2017). How are you feeling?: A personalized methodology for predicting mental states from temporally observable physical and behavioral information. *Journal of Biomedical Informatics*, 68, 1-19. <https://doi.org/10.1016/j.jbi.2017.02.010>
 74. Turner, A. P., & Sharkey, D. (2024). Enhanced Infant Movement Analysis Using Transformer-Based Fusion of Diverse Video Features for Neurodevelopmental Monitoring. *Sensors*, 24(20), 6619-6619. <https://doi.org/10.3390/s24206619>
 75. Vignes, V. M., P., S. J., Satheesh, R., Das, V., & Padmanaban, S. (2025). AI-driven cybersecurity framework for anomaly detection in power systems. *Scientific Reports*, 15(1), 35506-35506. <https://doi.org/10.1038/s41598-025-19634-y>
 76. Wall, D. P., Kosmicki, J. A., DeLuca, T. F., Harstad, E., & Fusaro, V. A. (2012). Use of machine learning to shorten observation-based screening and diagnosis of autism. *Translational*

- Psychiatry*, 2(4).
<https://doi.org/10.1038/tp.2012.10>
77. Wang, C., He, T., Zhou, H., Zhang, Z., & Lee, C. (2023). Artificial intelligence enhanced sensors - enabling technologies to next-generation healthcare and biomedical platform. *Bioelectronic Medicine*, 9(1), 17-17. <https://doi.org/10.1186/s42234-023-00118-1>
 78. Washington, P., Tariq, Q., Leblanc, É., Chrisman, B., Dunlap, K., Kline, A., Kalantarian, H., Penev, Y., Paskov, K., Voss, C., Stockham, N., Varma, M., Husic, A., Kent, J., Haber, N., Winograd, T., & Wall, D. P. (2021). Crowdsourced privacy-preserved feature tagging of short home videos for machine learning ASD detection. *Scientific Reports*, 11(1), 7620-7620. <https://doi.org/10.1038/s41598-021-87059-4>
 79. Weisz, J. R., Vaughn, R., Evans, S. C., Thomassin, K., Hersh, J., Ng, M. Y., Lau, N., Lee, E., Raftery-Helmer, J. N., & Mair, P. (2019). Efficient Monitoring of Treatment Response during Youth Psychotherapy: The Behavior and Feelings Survey. *Journal of Clinical Child & Adolescent Psychology*, 49(6), 737-751. <https://doi.org/10.1080/15374416.2018.1547973>