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Utilizing Constructed Neural Networks for Autism Screening

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Abstract: Autism Spectrum Disorder is known to cause difficulties in social interaction and communication, as well as repetitive patterns of behavior, interests, or hobbies. These challenges can significantly affect the individual's daily life. Therefore, it is crucial to identify and assess children with Autism Spectrum Disorder early to significantly benefit the long-term health of children. Unfortunately, many children are not diagnosed or are misdiagnosed, which means they miss out on the necessary interventions. Clinicians and other experts face various challenges during the diagnostic process. Digital tools can facilitate early diagnosis effectively. This study aimed to explore the use of machine learning techniques on a dataset collected from a serious game designed for children with autism to investigate how these techniques can assist in classification and make the clinical process more efficient. The responses were gathered from children who participated in interactive games deployed on mobile devices, and the data were analyzed using various types of neural networks, such as multilayer perceptrons and constructed neural networks. The performance metrics of these models, including error rate, precision, and recall, were reported, and the comparative experiments revealed that the constructed neural network using the integer rule-based neural networks approach was superior. Based on the evaluation metrics, this method showed the lowest error rate of 11.77%, a high accuracy of 0.75, and a good recall of 0.66. Thus, it can be an effective way to classify both typically developed children and children with Autism Spectrum Disorder. Additionally, it can be used for automatic screening procedures in an intelligent system. The results indicate that clinicians could use these techniques to enhance conventional screening methods and contribute to providing better care for individuals with autism.

Keywords: Autism Spectrum Disorder (ASD); screening; classification; machine learning; constructed neural networks

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1. Introduction

Child development is a complex process involving various aspects, such as physical, speech, language, hearing, and motor abilities, as well as cognitive processes and emotional well-being. Cognitive development includes problem-solving, critical thinking, logical reasoning, and understanding the surrounding environment. Socio-emotional development involves emotional growth, social development, self-concept, self-esteem, and emotional intelligence. Child development is interconnected, and progress in one domain can positively impact others. Neurodevelopmental disorders (NDs) can harm a child's development and brain growth, resulting in communication, learning, behavior, cognitive, and emotional shortages [1–3].

Autism Spectrum Disorder (ASD) is an ND that can be diagnosed at any age but usually appears within the first two years of life [4]. The prevalence of ASD is estimated to be around one in one hundred children worldwide, though some studies report higher

rates [5,6]. As a neurodevelopmental condition, it has been characterized by specific criteria defined in DSM-5 [1–3,7]. Individuals with ASD experience persistent shortages in social communication and interaction skills across numerous settings, and they exhibit repetitive and restrictive behaviors that can impair their functioning. ASD impacts personal, social, academic, and professional life. The term "spectrum" in ASD is used to describe a range of symptoms that vary in severity from person to person. Some individuals may have mild symptoms, while others may have moderate or more severe symptoms. It is common for individuals with ASD to also have other NDs, which can require intensive care. This can significantly impact the individual with profound impairments, their family, and the community [2,3,8,9]. On the other end of the spectrum, individuals with ASDs can also be intellectually talented, verbally fluent, and independent adults [10]. This represents the opposite end of the functional spectrum.

The recommendation of the American Academy of Pediatrics is to monitor and screen for developmental delays in children to detect disabilities such as ASD early and allow for prompt treatments supporting the child's overall growth and development [11–13]. Developmental surveillance for children using clinical judgment during health supervision visits involves a comprehensive approach, which includes the documentation of developmental history, reference to parents' concerns, a thorough observation of the child's behavior to identify potential risks, maintaining records, and sharing the findings with professionals outside the child's primary medical care provider [12,13]. Developmental screening uses proven techniques at predetermined ages or whenever monitoring indicates a particular cause for concern. Diagnostic examinations are used to further examine and identify developmental disorders in children who are at risk through surveillance and screening procedures and are typically conducted by developmental experts [11,12].

The intricate and diverse nature of symptoms and manifestations in ASDs present significant challenges in their identification, often making the tasks of monitoring, screening, and diagnosis complicated due to imprecise characterizations and the presence of comorbid conditions [12,14–19]. This complexity is apparent in the fact that more than one in three children with ASD display symptoms that also meet criteria for other disorders, resulting in a variety of possible diagnostic combinations [20]. Furthermore, traditional evaluation methods often rely on subjective assessments and prolonged evaluation processes, leading to delays and inaccuracies in diagnosis [21]. Innovative diagnostic processes help customize ASD treatments, improving brain flexibility and mitigating symptoms. This leads to a better quality of life for children and their families [22]. Clinicians must build policies and practices by considering the type of condition and the child's abilities and skills for individualized interventions [23–25].

The field of machine learning (ML) has recently gained much attention for its ability to distinguish children with typical development (TD) from those with ASD [22]. Automated measuring tools are increasingly used in ASD research for decision-making, categorization, and clinical assessment, offering new prospects for aiding clinical decision-making [14,22,25,26]. The identification and diagnosis of ASD involves various methods like brain imaging (PET, SPECT, fNIRS, EEG, fMRI, etc.) [27–30], diffusion tensor imaging [31], and biometrics to analyze neurological and behavioral aspects [32]. Also, gesture analysis using motion capture, sensory input assessment, and eye tracking are employed [25,33–35]. These techniques, though comprehensive, face challenges like data accessibility and sensory sensitivities in ASD children. ML is increasingly used to process these data for a more effective diagnosis and treatment of ASD [36]. For instance, ML algorithms, in combination with eye-tracking technology, are increasingly showing significance in the early identification and diagnosis of ASD utilizing various stimuli, tasks, datasets, and algorithms [25,32,33,37–39]. Evidence of ML methods combining physiological data (EEG) with behavioral data (eye fixation and facial expression) has been developed to identify children with ASD [40]. This hybrid fusion strategy reported EEG to be the most effective in distinguishing between children with ASD and TD children. It achieved an accuracy rate of 87.50%, reducing costs while increasing efficiency.

Furthermore, child's play is a natural process that helps children learn essential life skills. Serious Games (SGs) use play to enhance purpose in education, healthcare, marketing, science, and more [41]. SGs have been employed for mental health issues, physical activity rehabilitation, and other areas. These games are not only for entertainment but can also serve as learning tools and cultivate skills. SGs can be designed with explicit instructional objectives, which immerse children in activities that simulate real-life situations and difficulties—all within a supervised and secure setting [41]. Moreover, it is documented that children with NDs can enjoy better, anxiety-free activities with SGs [42,43]. By integrating ML into SGs, they may become powerful tools for the automated screening and assessment of ASD [32,44]. Studies show that ML in SGs can aid the classification of ASD and help children with early identification, diagnostic assessment, objective metrics, engagement, motivation, and tailored therapy [35,45]. Virtual Reality (VR) adventure SGs can enhance social skills in ASD adolescents with multisensory interactions [46]. Augmented Reality SGs for social-emotional communication, designed for adolescents with ASD, indicated the potential to assist in identifying comorbidity with ADHD symptoms [47]. A recent study conducted with the help of a mobile game-based health app captured video footage of 95 children involved in gameplay in their own homes [48]. The study compared the gaze patterns of TD children and those with ASD. The findings showed distinct differences in the way the two groups fixated their eyes, with children with ASD having their own specific visual scanning patterns. A deep learning model trained on gaze fixation had low ASD detection power. Evidence of digital healthcare addressing healthcare access disparities has been reported with an SG that uses naturalistic gaming data and a random forest classifier to classify ASD and TD children (AU-ROC = 0.745, recall = 0.769) [49]. On the same gameplay dataset, another study achieved 79% accuracy utilizing a convolutional neural network to classify children's audio as either ASD or TD [50]. In addition, by imitating a model's dancing moves using Kinect Xbox motion tracking, researchers using a support vector machine approach reported a valid biomarker: children with ASD showed worse imitation compared to TD children, which is also linked to more excellent core autistic symptoms and discrimination (accuracy = 87.2%) between the two groups [51].

Although machine learning (ML) is widely used in Serious Games (SGs), there is a need for more research that combines ML and SGs in the healthcare industry [52]. Most studies focus on rehabilitation to provide individualized and entertaining healthcare and less on prevention and diagnosis to address personalized screening, performance assessment, monitoring, risk modeling, and treatment response prediction [52–54]. Further, standardized diagnoses and objective evaluations are repeatable [42]. However, ML algorithms in SGs addressing communication, cognition, emotion, and behavior in children with ASD require further research to create personalized, effective, and successful clinical experiences [55].

This study aims to explore how neural networks can be developed to classify children into two categories: TD and children with ASD. The results can be utilized in an intelligent system with automated results to enhance assistance for healthcare professionals and upscale decisions and evaluations regarding screening procedures discriminating between TD children and those with ASD. The study used a new biometric dataset and created various neural networks with optimizers to categorize children automatically.

The study continues with Section 2, which provides background knowledge on constructing neural networks and implementing optimizers. Next, Section 3 describes the research methods and the dataset. Section 4 presents the results of this study, including statistical analysis and experimental results. Finally, Section 5 presents the research's final findings, including limitations and ideas for future research.

2. Background Information

This part presents the necessary background information for this research and its related methods. More specifically, it focuses on artificial neural networks (ANNs) and the optimizers related to them used in this study.

2.1. MLP Description

Artificial neural networks [56] are a type of machine learning tool that has been successfully applied to various in different scientific fields, including chemistry [57–59], economics [60,61], and medicine [62,63]. A neural network is commonly defined as a function $N\left(\vec{x}, \vec{w}\right)$ where $\vec{x}$ is the input vector of patterns and $\vec{w}$ is the so-called weight vector of the parameters that needs to be estimated. The estimation of this vector can be achieved by minimizing the error function defined as:

$$E\left(N\left(\vec{x}, \vec{w}\right)\right) = \sum_{i=1}^{M}\left(N\left(\vec{x_i}, \vec{w}\right) - t_i\right)^2 \quad (1)$$

The training data for the neural network are defined by the set of pairs $\left(\vec{x_i}, t_i\right)$. To minimize the error function, various methods such as the back propagation method [64] or the RPROP method [65] have been used, along with global optimization methods like quasi-Newton methods [66], genetic algorithms [67,68], particle swarm optimization [69], and more. For the experiments in this study, a radial basis function (RBF) neural network [70] and two optimization methods were used: the limited-memory Broyden–Fletcher–Goldfarb–Shanno (BFGS) [71] method and a BFGS variant of Powell [72].

RBF neural networks are a specialized type of neural network with three layers: an input layer that receives data, a hidden layer using radial basis functions (typically Gaussian) for transforming inputs based on their distance to a central point, and an output layer that synthesizes the hidden layer's outputs to make predictions. RBF networks excel in localized input processing, quick learning, and complex function modeling, and they can approximate any continuous function with sufficient neurons. The RBF neural network excels in machine learning tasks like classification, regression, and clustering [70]. Particularly effective in high-dimensional spaces, RBF networks are known for their capability to tackle complex patterns efficiently. Their key advantages over other neural architectures include their rapid training and testing phases and the precise approximation of continuous functions [73].

BFGS is an iterative optimization technique primarily used in various domains [74], including machine learning [75], mainly aimed at estimating the inverse of the Hessian matrix (matrix of second-order partial derivatives). With the help of an estimate, we can determine the search direction to minimize the objective function. Furthermore, this method enhances its estimation with each iteration by using gradient information for correction. BFGS is a widely used approach in machine learning to optimize neural network weights because of its excellent convergence capabilities. It is beneficial for solving high-dimensional problems. However, if the initial estimate is not chosen carefully, the BFGS algorithm may end up with a suboptimal solution for objective functions that are not convex. On the other hand, convex optimization problems provide both quick and reliable solutions.

The neural minimizer method [76], previously based on RBF neural networks [77], has now been updated with an artificial neural network that is trained using a local minimization technique called limited-memory BFGS (L-BFGS). This technique is relatively inexpensive regarding calculations and storage space [71]. This modified neural minimizer method has been widely used in optimization problems like image reconstruction [78] and seismic waveform tomography [79]. Proposed modifications have been suggested that would utilize contemporary parallel computing systems [80]. Sometimes, the large number of parameters in an artificial neural network makes it impossible to use an RBF neural network in a global optimization method for minimizing the error. When dealing with large and complex problems, approximating an artificial neural network using an RBF neural network is not feasible. While a small artificial neural network can be efficiently approximated using an RBF neural network, an underpowered RBF neural network is used

in more complex cases, which is not an efficient approximation of the original artificial neural network.

2.2. Neural Network Construction Description

This method uses grammatical evolution [81] to guide the neural network construction (NNC) topology and estimate the weight vector. The technique was initially suggested by Tsoulos et al. [73] and has been used in many cases, such as in solving differential equations [82], chemistry problems [83], medical problems [84], etc. The algorithm employs a combination of genetic operations and local search to evolve a population of neural networks toward better fitness, which could be performance on a specific task like classification, regression, or solving differential equations. The iterative process is designed to continuously improve solutions until a maximum number of iterations is achieved or until an optimal or satisfactory solution is found [85]. Figure 1 illustrates the utilized NNC algorithm.

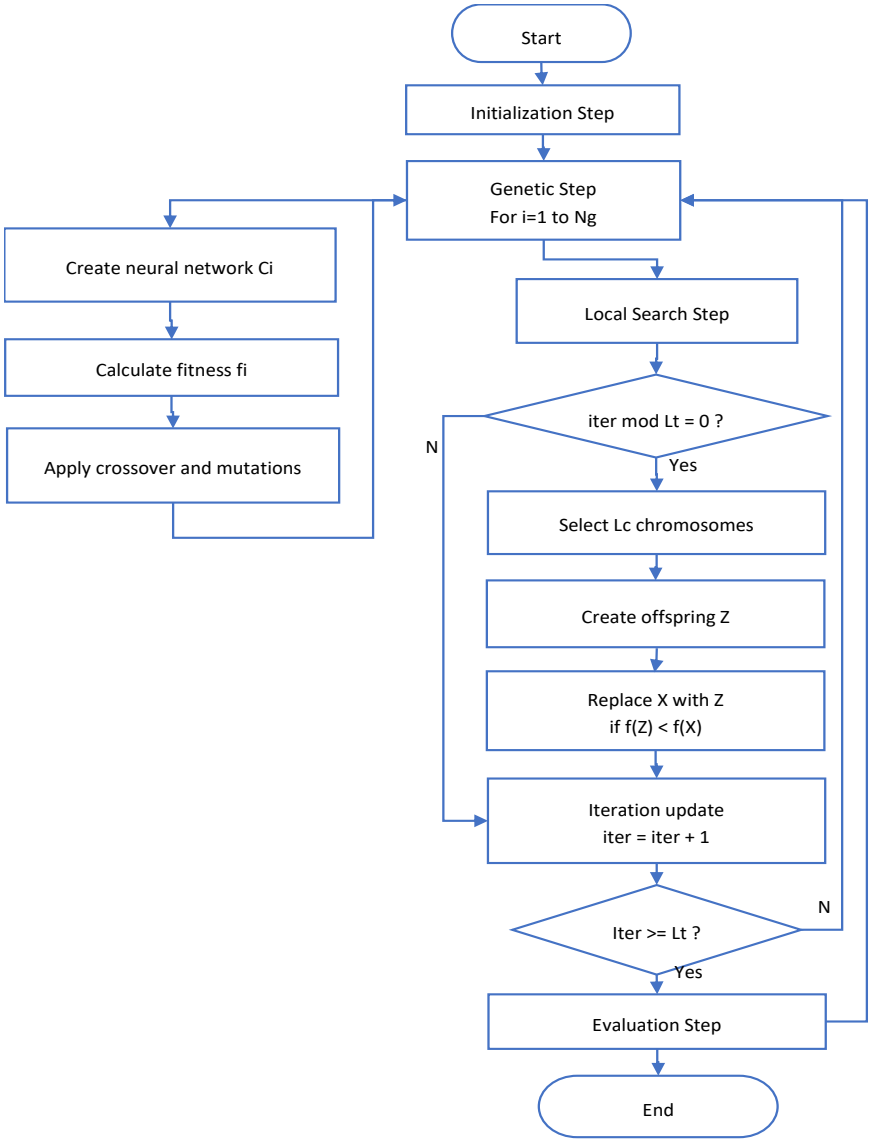

Figure 1. Flowchart of the Neural Network Construction (NNC) algorithm.

The source code NNC.tar.gz is available from https://github.com/itsoulos/NNC (accessed on 10 February 2024). The software is written in ANSI C++ and needs QT, a free programming library from http://qt.io (accessed on 1 February 2024). First, run the software

with any library version, then install by following https://github.com/itsoulos/NNC/wiki. After compiling, access NNC, a command line program, and use -p to load a data file or differential equation in shared library form or -c to obtain the genetic population's chromosome count. The BNF language in https://github.com/itsoulos/NNC/wiki (accessed on 10 February 2024) allows grammatical evolution to generate neural networks. Future versions may include an upgraded BNF language for more complex neural networks.

2.3. Integer Rule-Based Neural Networks (INN) Description

This method was initially suggested in [86]. It aims to efficiently find the value intervals for the parameters of the artificial neural network using partition rules. These rules are expressed in a series of integers, and their efficient estimation is carried out using a genetic algorithm.

The INN is a cutting-edge approach to training artificial neural networks that involves finding the most suitable initialization and training interval using genetic algorithms [86]. The aim is to identify the optimal interval, and a global optimization technique, such as the genetic algorithm, is utilized to initialize and train the artificial neural network within this interval. Figure 2 illustrates a visualization summarizing the INN approach algorithms in steps [86]: initialization phase; first GA—locating best rules; second GA—network training; and parallel processing techniques.

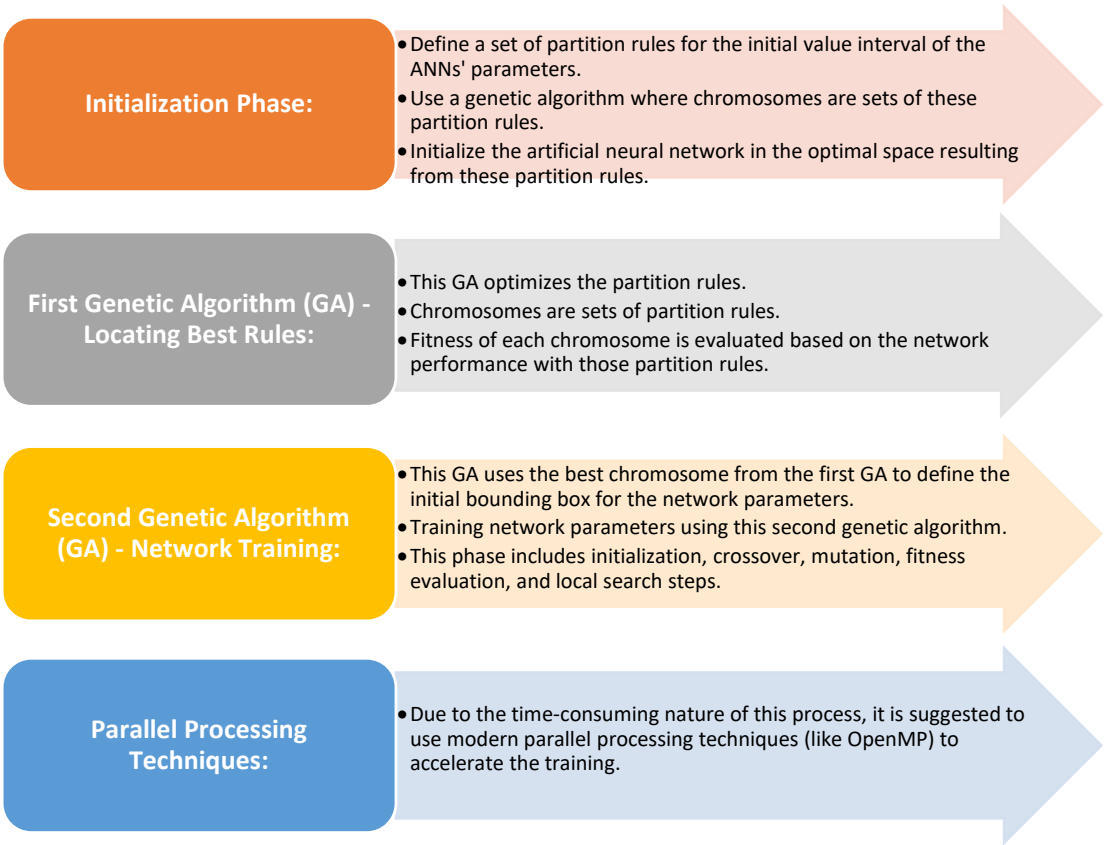

Figure 2. Summary of the INN Training Approach Algorithms.

Data were employed to evaluate the approach's effectiveness and classification; function learning was employed; and the outcomes were encouraging. The experiments were performed using the freely available in-house software from https://github.com/itsoulos/IntervalGenetic (accessed on 1 February 2024).

3. Methods

This study builds upon the research project "Smart Computing Models, Sensors, and Early Diagnostic Speech and Language Deficiencies Indicators in Child Communication", or in short, SmartSpeech, which was funded by the Region of Epirus and backed by the European Regional Development Fund (ERDF).

A recruitment sample was conducted in response to requests from the health and education sectors to assist TD children and children with ASD. Parents were given a thorough briefing about the project's details and scope, the protocols involved, and the permission granted (Reg. Num.: 18435/15.5.2020) by the Research Ethics Committee of the University of Ioannina, Greece, in compliance with General Data Protection Regulation GDPR. Afterward, parents filled out the consent form. Participants were asked to register in the database and answer questions about their child's developmental characteristics. With the guidance of a clinician, each child interacted with the game designed for this task. Ultimately, the variables examined in the research were obtained from the gameplay.

The study gathered responses from children who participated in playing the Serious Game on a mobile device. The game involved different activities related to screening and assessing individuals for ASD [87]. During the gameplay, the children complete several activities related to their developmental skills. Therefore, the automated procedure of this phase gathers many measurements to form a child's developmental profile and provides a rich database specifically designed for screening TD children from children with ASD. The responses of the child-player are represented as variables and generally can be hand motions on the touch screen like clicks, drag, and drops, as well as speech from the child's verbal responses to questions and directions. For the latter, the system incorporates an automatic procedure that records speech via a microphone and translates it into text. For this purpose, the software Whisper v20230314 performs multilingual speech recognition [88]. The software is free from https://github.com/openai/whisper (accessed on 2 April 2023). Then, a software service was created to compare the transcripts of the audio files with the predefined answers, generating a score representing the matching percentage between the spoken and correct words. The overall game activities correspond to the assessment categories reported in Figure 3 below. There are, in total, 18 variables that comprise our dataset. Some of them contain word recognition, such as in Articulation and Phonology. All variables are scaled and take values in the range [0, 100].

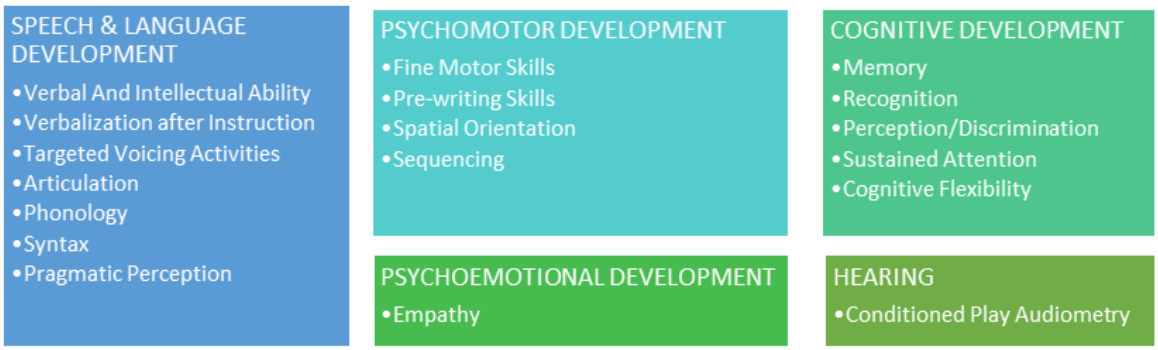

Figure 3. Areas of assessment and corresponding variables.

The participants in this study are mainly children aged 3 to 12 years old. The children were enrolled with the help and support of their parents, along with their written consent. In total, 320 children were recruited, of which 276 were typically developed, and the rest 44 of them had ASD.

This dataset fed the machine learning models selected, namely MLP, INN, and NNC. Each model was trained and tested using the 10-fold validation method. The objective was to find the most suitable method for classification; that is, to distinguish the ASD population from the typically developed population. The goal was to establish a screening tool to help clinicians safely and accurately in their diagnostic procedures.

Our dataset underwent statistical analysis. In the next section, we present the means and standard deviations of the game scores for TD and ASD children and compare the statistical differences between the two groups. Since the dataset variables do not have a normal distribution, we used the non-parametric Mann–Whitney U Test.

For the classification experiments, we evaluated the performance employing commonly used metrics in machine learning [89–91]. More specifically, most predictive models categorize data points into one of four groups for accuracy assessment [89]: (1) True Positive (TP), occurring when the model correctly predicts that a child has ASD; (2) True Negative (TN), happening when the model accurately predicts that a child does not have ASD; (3) False Positive (FP)—in this case, the model incorrectly predicts that a child without ASD has it; and (4) False Negative (FN), occurring when the model wrongly predicts that a child with ASD does not have it.

The test set's average classification error was used to classify the datasets. The classification error is the percentage of patterns in the test set allocated to a class that was not predicted. The error rate was calculated using the formula given in Equation (2) as follows:

$$\text{Error rate} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2}$$

The precision metric was used to measure the accuracy of our optimistic predictions. It represents the proportion of projected positive points that occurred. The definition of precision is shown in Equation (3):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

The percentage of positive cases that our algorithm correctly identified was measured by recall. Out of all the examples categorized as positive, it shows how accurate our model is in classifying positive instances. Recall and sensitivity were used interchangeably in some contexts. Equation (4) specifies recall as follows:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

Finally, Figure 4 visualizes the methods of this study.

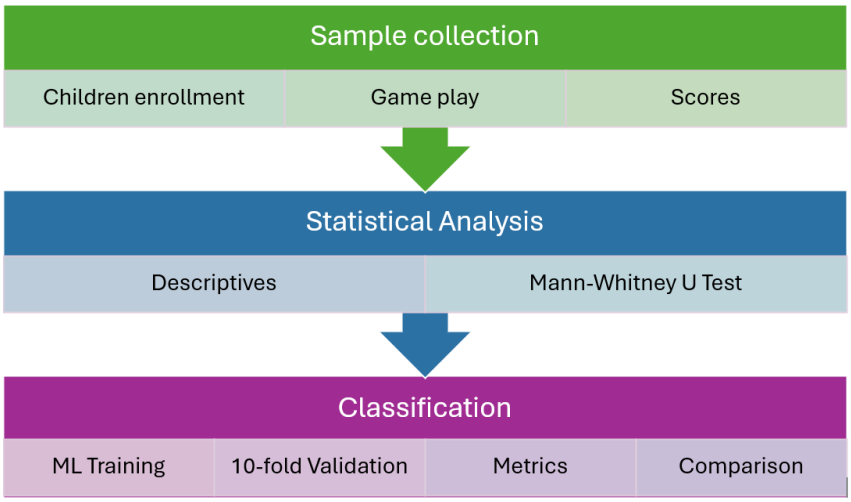

Figure 4. Methods of the study.

4. Results

The results of this study are presented in two parts: statistical analysis of the new dataset and classifiers' application and experimental results.

4.1. Statistical Analysis

We first provide an overview of the statistics of our dataset before explaining the classification process. We used IBM SPSS v20.0 statistical software to perform descriptive statistics and hypothesis tests.

Table 1 displays the mean values and standard deviations of TD children's scores and those of children with ASD. The game-score values range from 0 to 100.

Table 1. Mean values and standard deviations of the game scores for the two groups of participants: children with TD and children with ASD.

Variable	TD		ASD	
	Mean	STD	Mean	STD
Verbal And Intellectual Ability	35.50	7.54	29.81	8.80
Verbalization after Instruction	26.28	26.99	19.07	23.53
Targeted Voicing Activities	37.63	27.08	41.52	26.24
Articulation	22.64	8.47	16.77	6.09
Phonology	83.61	24.20	69.06	25.89
Syntax	45.04	37.33	31.93	38.55
Pragmatic Perception	85.53	18.79	75.52	22.14
Fine Motor Skills	72.38	29.15	71.30	31.68
Pre-writing Skills	31.47	18.08	29.68	17.68
Spatial Orientation	37.68	12.10	39.52	14.35
Sequencing	61.20	13.82	53.24	18.51
Memory	31.31	21.37	19.32	20.51
Recognition	58.06	12.10	54.20	13.42
Perception/Discrimination	38.48	14.25	40.45	15.09
Sustained Attention	29.55	7.84	27.61	8.88
Cognitive Flexibility	65.00	19.88	64.94	19.87
Empathy	41.37	11.00	34.15	14.78
Conditioned Play Audiometry	35.81	26.72	29.27	24.20

We examined the data's normality using the Shapiro–Wilk and Kolmogorov–Smirnov tests at a significance threshold of 0.05. It was discovered that there is no normal distribution for any of our variables. Therefore, we used the Mann–Whitney U test, a non-parametric test for two independent samples, to compare each variable of interest of the two groups of children (TD, ASD) for statistical differences. The results are summarized in Table 2, showing if a variable can distinguish the two populations. As such, nine variables—verbal and intellectual ability, articulation, phonology, syntax, pragmatic perception, sequencing, memory, recognition, and empathy—exhibit statistically significant differences between the two groups (TD and ASD), while the remaining variables do not.

Table 2. Statistically significant differences between the two independent groups of children (TD—ASD) using the Mann–Whitney U Test.

Variable	Mann-Whitney U	Wilcoxon W	Z	*p*-Value
Verbal And Intellectual Ability	3529	4519	−4.462	0.00
Verbalization after Instruction	5241.50	6231.50	−1.48	0.14
Targeted Voicing Activities	5467.00	43,693.00	−1.07	0.28
Articulation	3379.00	4369.00	−4.73	0.00
Phonology	3513.50	4503.50	−4.78	0.00
Syntax	4801	5791	−2.284	0.02
Pragmatic Perception	4309.5	5299.5	−3.286	0.00
Fine Motor Skills	5868	44,094	−0.405	0.69
Pre-writing Skills	5811	6801	−0.458	0.65
Spatial Orientation	5399	43,625	−1.183	0.24
Sequencing	4603	5593	−2.582	0.01
Memory	3954.5	4944.5	−3.716	0.00

Table 2. *Cont.*

Variable	Mann-Whitney U	Wilcoxon W	Z	*p*-Value
Recognition	5019	6009	−1.969	0.05
Perception/Discrimination	5329	43,555	−1.329	0.18
Sustained Attention	5213.5	6203.5	−1.892	0.06
Cognitive Flexibility	5980.5	44,206.5	−0.162	0.87
Empathy	4539.5	5529.5	−2.689	0.01
Conditioned Play Audiometry	5266	6256	−1.419	0.16

4.2. Application Details and Experimental Results

The classifiers' application details and parameterization are explained in this part, followed by experimental results.

Table 3 provides critical parameters of the INN and NNC methods using the gameplay dataset. This table outlines the specific settings used in these methods, which are crucial for understanding the experimental setup and the nature of the ML algorithms employed. Five hundred chromosomes were utilized in the models, suggesting a broad search space for finding the optimal network configuration. The number of 200 iterations allows for an extensive exploration of the solution space. The 10% selection rate implies that only the top 10% of chromosomes will be used to create the next generation based on their fitness or performance. This rate is crucial for balancing the exploration and exploitation in the algorithm. The 5% mutation rate used signifies a moderate level of randomness in the evolution of the solutions.

Table 3. INN and NNC values.

Parameter	Value
Number of Chromosomes	500
Number of Generations	200
Selection Rate	10%
Mutation Rate	5%

Next, Table 4 reports on the experimental results. It displays the performance comparison of the classification methods. The RBF neural network method shows an error rate of 18.70%, which is relatively high compared to others. Its precision is 0.54, and recall is 0.58, indicating moderate effectiveness in classifying the dataset accurately. The MLP BFGS method shows a similar classifying attitude to the RBF, presenting an error rate of 19.28%, the highest compared to others. Its precision is 0.58, and recall is 0.60, indicating moderate effectiveness in accurately classifying the dataset. Next, the MLP LBFGS method has an error rate of 17.31%, slightly better than RBF and MLP BFGS. The precision of 0.56 is somewhat lower but has a higher recall of 0.68, suggesting it is better at identifying relevant instances. The NNC model has a further reduced error rate of 16.05%, with precision equal to MLP BFGS (0.58) but better recall (0.66). This indicates that it is more effective than MLP BFGS and MLP LBFGS in accurately classifying the dataset. Finally, the INN method demonstrates the best performance with the lowest error rate of 11.77%, a high precision of 0.75, and a recall of 0.66. The results suggest that INN is better at avoiding false classifications (high precision) and maintains a reasonable rate of correctly identifying relevant instances (recall).

Table 4. Comparing Classification Methods with Error Rate (%), Precision, and Recall Metrics.

Method	Error Rate (%)	Precision	Recall
RBF	18.70%	0.54	0.58
MLP BFGS	19.28%	0.58	0.60
MLP LBFGS	17.31%	0.56	0.68
NNC	16.05%	0.58	0.66
INN	11.77%	0.75	0.66

5. Conclusions

This study's goal was to investigate the use of constructed neural network models for the early detection of ASD in a gameplay dataset, which is a practical and child-friendly tool. The study aimed to use gameplay data as an engaging and non-intrusive medium for assessment; differentiate between children diagnosed with ASD and TD children; and provide a supportive tool for clinicians in diagnosing ASD, enhancing the screening process with the help of ML.

The study recorded significant statistical differences between TD and ASD children using the Mann–Whitney U test for verbal and intellectual ability, articulation, phonology, syntax, pragmatic perception, sequencing, memory, recognition, and empathy. The best-performing ML model was INN, demonstrating the lowest error rate, highest precision, and good recall. It proved to be the most effective model in distinguishing children with ASD from typically developed ones in the gameplay dataset. Combining gameplay data and ML, we propose a novel, child-friendly approach to ASD screening, providing a non-intrusive and engaging way to assess children. This method has the potential to support clinicians in early diagnosis, which is crucial for timely intervention in ASD.

However, the study involved a smaller proportion of children with ASD (44 out of 320), indicating that sample size and diversity could be considered limitations of this study. A more extensive and diverse sample could provide more robust and generalizable results. While the INN model showed promising results, its effectiveness in different contexts or with other data types remains to be tested.

Future research may address broader and more diverse data collection involving a more extensive and diverse participant pool, including variations in age, cultural backgrounds, and ASD severity levels. Additionally, expansion to different data types could provide a more holistic understanding of ASD. Moreover, supplementary development and the refinement of algorithms and comparisons with other emerging ML methods could enhance their effectiveness and accuracy.

In summary, this study presents innovative methods for ASD detection utilizing machine learning and gameplay data. Future research should focus on addressing limitations and exploring potential applications.

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