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Constructing Features for Screening Neurodevelopmental Disorders Using Grammatical Evolution

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Featured Application: This study is part of an ongoing research project titled "Smart Computing Models, Sensors, and Early diagnostic speech and language deficiencies indicators in Child Communication", with the acronym "SmartSpeech". The SmartSpeech project aims to assist clinicians in decision making regarding early diagnosis for children with neurodevelopmental disorders. SmartSpeech employs a serious game designed explicitly by the interdisciplinary team for this project, with activities aiming to evaluate the child's developmental profile. The game is implemented in a tablet application and utilizes voice, and biomarkers of heart rate and gaze, for additional physiological measurements. A back-end system supports user registration, data collection, data analysis, and decision making. The potential application of this work is to allow the SmartSpeech machine learning model to better capture underlying patterns in the data, determine the most effective feature construction techniques for the given problem, and employ the results of this study to enhance the screening automated prediction results of the machine learning model in neurodevelopmental disorders.

Abstract: Developmental domains refer to different areas of a child's growth and maturation, including physical, language, cognitive, and social–emotional skills. Understanding these domains helps parents, caregivers, and professionals track a child's progress and identify potential areas of concern. Nevertheless, due to the high level of heterogeneity and overlap, neurodevelopmental disorders may go undiagnosed in children for a crucial period. Detecting neurodevelopmental disorders at an early stage is fundamental. Digital tools like artificial intelligence can help clinicians with the early detection process. To achieve this, a new method has been proposed that creates artificial features from the original ones derived from the SmartSpeech project, using a feature construction procedure guided by the Grammatical Evolution technique. The new features from a machine learning model are used to predict neurodevelopmental disorders. Comparative experiments demonstrated that using the feature creation method outperformed other machine learning methods for predicting neurodevelopmental disorders. In many cases, the reduction in the test error reaches up to 65% to the next better one.

Keywords: neurodevelopmental disorders; screening; feature construction; grammatical evolution; evolutionary techniques

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1. Introduction

Neurodevelopmental disorder (ND) refers to a variety of disorders disturbing neurological development that impact on several domains, including communication, learning, social interaction, behavior, cognitive processes, and emotional functioning. Neurodevelopmental disorders (NDs) typically manifest during childhood [1,2]. Autism Spectrum

Disorders (ASD), Attention Deficit Hyperactivity Disorder (ADHD), Intellectual Disability (ID), Specific Learning Disorder (SLD), and Communication Disorders (CD) are among the conditions that fall under the umbrella of neurodevelopmental disorders (NDs) [1].

Specific characteristics associated with each disorder are outlined in the Diagnostic and Statistical Manual of Mental illnesses, Fifth Edition (DSM-5), which offers descriptions for mental illnesses [1,3]. ASD is an ND with clinically severe functional deficits in distinctive, recurring patterns of behavior, interests, or hobbies, along with persistent challenges in social interaction and communication [1,2,4]. ASD can impact individuals' educational experiences, employment opportunities, and social relationships [5]. ADHD is another ND with hallmarks on inattention, impulsivity, and hyperactivity, with a disruptive impact on daily functioning [1,2,4]. It can affect academic performance, work productivity, and interpersonal relationships [6,7]. ID is an ND characterized by deficiencies in general mental skills that affect adaptive functioning, such as verbal skills, learning aptitude, logical reasoning ability, and practical intelligence (problem-solving) [1,8]. ID can limit individuals' independence and ability to live a fully inclusive life [9,10]. SLD is characterized by a major impairment in one or more of the following domains: oral expression, listening comprehension, basic reading and/or writing skills, and mathematical calculation and/or problem-solving abilities [1,2,11]. SLD can lead to challenges in academic settings and impact individuals' self-esteem and confidence [12,13]. CD encompasses a collection of disorders, including speech sound disorder, language disorder, childhood-onset fluency disorder, social (pragmatic) communication disorder, and unspecified communication disorder [1]. These disorders are characterized by ongoing challenges in the acquisition, comprehension, and/or utilization of spoken or written language, resulting in an inability to express themselves, engage in meaningful conversations, and participate fully in social and professional interactions and effective communication [14].

Although NDs are frequently detectable in their early phases, the main obstacle is the lengthy and subjective character of conventional diagnostic techniques [2,15]. Consequently, there exists a minimum waiting period over a year between the initial suspicion and the subsequent confirmation of diagnosis. The process of diagnosis requires a significant amount of time, around 10 h [15]. Moreover, there is a persistent and increasing demand for appointments that surpasses the maximum capacity of pediatric clinics in many countries [16]. Apart from being time-consuming and expensive, conventional diagnostic techniques carry a considerable risk of receiving an incorrect diagnosis. This can lead to unnecessary prolonged pharmaceutical therapy, decreased functionality, and increased vulnerability to further health and social complications [17]. This backlog in diagnostic procedures has led to significant delays in providing timely treatment and intervention for children with suspected developmental disorders. Consequently, many children may go undiagnosed and may be left without the necessary support and resources they require during this critical period of their development. Early detection and intervention of NDs are of the utmost significance, as they contribute significantly to the reduction or mitigation of symptoms, eventually enhancing the individual's overall quality of life. Nevertheless, due to the temporal intervals between the onset of worry and the establishment of a diagnosis, a significant amount of precious time is squandered while this condition persists undiscovered. Clinicians need to use digital tools, such as artificial intelligence, to aid in efficient early detection. Machine learning techniques possess the potential to not only expedite and enhance the accuracy of assessing the risk for NDs, but also play a crucial role in optimizing the entire diagnostic procedure and facilitating expedited access to vital therapeutic interventions for individuals and affected families [18].

It is well documented that to ensure accuracy and cost-effectiveness, it is necessary to employ swift and sophisticated standards [17,19–21]. The study of Alam et al. highlights the use of machine learning (ML) tools and deep learning (DL) techniques, such as convolutional neural network (CNN) and Deep Learning APIs (Application Programming Interface), to detect and treat signs of ADHD and ASD at an early stage [17]. The diagnostic procedures that utilize machine learning (ML) decrease the time required for intervention, enhance accuracy, and also facilitate comprehension of the techniques and algorithms employed for various types of data. Multiple studies have been conducted on ASD [22–28], ADHD [29–31], ID [9,10,32], SLD [33,34], CD [35], and NDs [4,19,20,31,36–38], providing evidence that ML algorithms can enhance diagnostic strategies for NDs. Further, more research efforts that seek to investigate ML approaches for early detection and diagnosis of NDs in real-life situations are crucial for ensuring timely intervention and optimizing lifelong outcomes [17,19,20,39–41]. This way, early intervention can help children with NDs develop their skills and abilities to the fullest extent possible. Even further, evidence in the literature suggests that SGs offer a flexible and innovative approach to assessing neurodevelopmental issues [3,40,42–44]. This is due to their ability to actively engage, adapt, and conduct tests that help to ensure more accurate, reliable, and user-friendly evaluations, eventually enhancing our understanding of NDs and enabling appropriate interventions.

SmartSpeech is an ongoing project intended to support and enhance screening and early detection procedures of NDs, utilizing smart computing models, sensors, and early diagnostic speech and language deficiency indicators [45]. The ultimate goal of this smart project is to improve children's communication abilities in the context of digital healthcare, thus leading to a positive economic outcome in line with current digital trends. The project includes an online environment for gathering data from parents and physicians as well as a serious game (SG) for the child to interact with. The SG fosters active participation and motivation in individuals with NDs by providing an attractive and stimulating environment with 3D animations that bring life to characters guiding the child in the SG's adventurous story. The SG also simulates real-world scenarios incorporating various modalities, including visual, auditory, and tactile elements, leading to more accurate observations of behavior and abilities in contexts that closely resemble everyday situations and enabling a more comprehensive assessment of diverse skills, like sensory processing, motor coordination, and social interactions. The SG design is adapted to suit the specific needs and abilities of each individual, ensuring that assessments are tailored to the unique characteristics of those with NDs, providing a more accurate representation of their skills and challenges [40]. Data collection is handled through a mobile application that collects child responses to game activities and biometric data using sensors and timestamps. The game data are processed on a dedicated server back-end service to examine early clinical screening/diagnostic patterns on specified domains or skills towards automated indications. The SmartSpeech ML approach enables automated decision-making based on the child's communication profile and biometrics.

The primary objective of this study is to contribute to creating new digital tools and procedures aiding clinicians in their decision-making processes. Precisely, this study investigates a new proposed method that creates artificial features from the original ones derived from the SmartSpeech project, using a procedure guided by the Grammatical Evolution technique. The new features from an ML model are used to predict NDs. Comparative experiments are used to identify speech, language, hearing, psychomotor, cognitive, and psychoemotional impairments in both typically developed (TD) children and children with NDs. In a range of neural networks, different optimizers were employed and evaluated using our novel datasets. The objective was to automatically classify individuals in a screening procedure based on neurodevelopmental abilities.

Next, Section 2 "Background information" provides a detailed explanation of the chosen approach's architecture for feature construction and classification tasks, outlining the algorithms employed to compare the suggested method. In Section 3, the materials and methods are described. Section 4 presents a comparison between the proposed approach and three machine learning methods. Section 5 "Discussion—Conclusions" critically analyzes and evaluates the proposed method and summarizes the findings of this study.

2. Background Information

This section offers a concise overview of the necessary background material and algorithms pertaining to the study.

Learning data are typically categorized into two distinct parts: training data and test data. Learning models adapt their parameters by utilizing the training data as input and, subsequently, undergo evaluation using the test data. The quantity of learning model parameters is directly influenced by the dimensionality of the input problem, namely, the number of features. Large problems require significant memory resources to store and manage learning models with an impact of input problem dimensionality on the efficacy of neural networks. Feature construction refers to the process of creating new features by applying mathematical operations, transformations, or combinations to existing ones. The ultimate goal of this method is to enhance the model by adding more details or connections that may not be immediately apparent in the original features [46].

Feature construction includes various techniques such as polynomial feature creation, interaction term generation, and the application of mathematical transformations, such as logarithmic transformations. To put it simply, feature construction specifically focuses on generating new features by applying mathematical operations or transformations, and it is often used when discussing the enhancement of machine learning model performance. Techniques like PCA, MRMR, and auto-encoder are used to reduce input data dimensionality [46,47].

2.1. The Proposed Method

The proposed method is based on Grammatical Evolution [48] to generate new artificial features from existing ones. Grammatical Evolution is an evolutionary algorithm, used to produce valid programs in any language defined by a BNF grammar, and it has been used in a variety of cases, such as solving trigonometric identities [49], automatic composition of music [50], combinatorial optimization problems [51], etc. The feature construction method was initially proposed by Gavrilis et al. [52] and was applied in many real world problems, such as classification of EEG signals [53], prediction of COVID-19 cases [54], Hemiplegia type detection [55], etc. The feature construction method creates artificial features from the original ones through Grammatical Evolution, and every set of potential features is evaluated on the training set using a machine learning method. For the purpose of this article, the freely available software QFc, version 1.0 [56] was selected and the evaluation machine learning model was a Radial Basis Function (RBF) network [57,58] with H processing nodes. The main steps of the used method are as follows (Algorithm 1):

Algorithm 1. The main steps of the used method

Initialization Step

1. **Denote** as N_C the number of chromosomes in the population, with N_G being the maximum number of allowed iterations and N_F the number of constructed features.
2. **Set** the selection rate p_S and the mutation rate p_M.
3. **Initialize** the chromosomes as random integer numbers.
4. **Set** iter = 1

Genetic Step

1. **Calculate** fitness.
    1. **For** Every chromosome g_i, i = 1,. . ., N_C **do**
    2. Create N_F artificial features for the g_i chromosome, using the Grammatical Evolution procedure.
        1. Apply the new features to the training set.
        2. Set the fitness value fi as the training error of an RBF network on the modified training set.
    3. **End For**
2. **Apply** crossover. Firstly, they are sorted according to their fitness values. The first $(1\text{-}p_S)N_C$ chromosomes are copied intact to the next generation. The rest will be replaced by offsprings created in the crossover procedure. Every new offspring is created with one-point crossover from two distinct parents selected by tournament selection.
3. **Apply** the mutation procedure to the chromosomes with p_M rate.

Algorithm 1. *Cont.*	
Termination Check	
1.	**Set** iter = iter + 1
2.	**If** iter >= N_G then terminate else **goto** Genetic Step.

2.2. Comparative Methods

The following methods were used for comparison.

The RBF neural network is a specific type of neural network that incorporates radial basis functions as activation functions. The Radial Basis Function (RBF) is a mathematical function employed in diverse machine learning techniques, specifically in kernelized approaches like Support Vector Machines (SVMs). The RBF kernel, also called the Gaussian kernel, is utilized to quantify the similarity or distance between data points in a modified feature space [59,60]. RBF neural networks are widely used for various tasks such as classification, regression, and clustering. It has proven to be effective in dealing with problems that involve high-dimensional input spaces and intricate patterns [58,61,62]. Compared with other neural network architectures, the RBF network has numerous advantages, such as its ability to process high-dimensional data, quick training and testing times, and the ability to approximate any continuous function with unrestricted accuracy [58,63]. The RBF network has three layers: input, hidden, and output. The multilayer perceptron train with the BFGS optimization method (MLP BFGS) is also employed. The hidden layer uses radial basis functions as activation functions to convert the input data into a new representation. Subsequently, this representation is used for subsequent analysis in the output layer. The network's output is calculated by taking the modified inputs and combining them linearly. Therefore, the result is a binary determination expressed as either TRUE or FALSE, representing the two outcomes (NDs is predicted, NDs is not predicted) [40]. The radial basis networks were used in the construction phase of the artificial features since they are distinguished not only for their fast training method but also for their ability to approximate any function if a sufficient number of computing units are available [64].

MLP BFGS is a specific type of artificial neural network trained with the BFGS optimization method. The application of the Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm to train a Multilayer Perceptron (MLP) represents a departure from conventional methods. In this approach, the BFGS algorithm, designed for unconstrained optimization, is employed to minimize the MLP's loss function. The MLP architecture comprises layers of neurons with weighted connections, and the BFGS algorithm iteratively updates the weights by considering the inverse Hessian matrix. This methodology entails a distinct departure from the standard stochastic gradient descent approaches commonly used in neural network training. The study of Hery, Ibrahim, and June [65] illustrated the efficacy and robustness of this unconventional MLP training strategy for small-dimensional test problems. The BFGS algorithm's capacity for non-convex optimization is leveraged to achieve convergence towards optimal parameter values, showcasing its potential as an alternative in neural network optimization paradigms. It has been utilized in various experimental studies using machine learning, for instance, in automatic EEG epilepsy detection [66], feature extraction for hemiplegia type detection [55], Neural Networks on Biometric Datasets for Screening Speech and Language Deficiencies in Child Communication [41], machine learning for the performance and early drop prediction for higher education students [67], and many more.

MLP PCA is an application of MLP that involves a two-step training process. Initially, Principal Component Analysis (PCA) is employed to reduce the dimensionality of the input data, extracting principal components that capture the essential variance [68]. The resulting transformed features, representing a subset of principal components, serve as inputs for training the MLP. The MLP, with its layered architecture, learns intricate patterns and relationships within the reduced-dimensional data [52]. This approach offers advantages such as mitigating the curse of dimensionality and potentially improving the MLP's generalization to new, unseen instances [69]. Careful hyperparameter tuning, including selecting the optimal number of principal components and configuring the MLP architecture, is crucial for effective implementation. Overall, the MLP PCA algorithm integrates dimensionality reduction with the capacity of MLPs, presenting a solution for handling complex data with high dimensionality [52].

3. Materials and Methods

This work was part of the project SmartSpeech, with the full title "Smart Computing Models, Sensors, and Early diagnostic speech and language deficiencies indicators in Child Communication" funded by the Region of Epirus and supported by the European Regional Development Fund (ERDF). The participants were recruited through private and public health and education institutions; they were mainly children, and their parents were informed thoroughly regarding the project's scope and procedures, and asked to provide written consent and details about their child's developmental and communication profile. Also, the parents were notified about the approval of this study from the University of Ioannina Research Ethics Committee with compliance to the General Data Protection Regulation (GDPR). The child's active role in this study involved playing the serious game (SG), part of the SmartSpeech system.

The SG consists of children-specific activities with the objective of gathering data regarding the developmental skills of the child and biometric data such as heart rate and gaze responses. These biometric data were collected in order to investigate their role as bio-markers and their potential use for classification purposes.

The interaction of the child with the game involved several activities, each with the goal to actively participate and help to overcome missions/tasks and advance to the next level. All the activities had visual context directed in a way that they were entertaining and attractive, as seen in Figure 1. Nevertheless, behind the scenes activities also served as clinical tools trained toward measuring several speech, language, and developmental skills. The child followed a narrated story and had to solve puzzles through its chapters, select or drag objects on the touchscreen, identify images and shapes, recall names and events, recognize emotions, and even answer questions verbally.

Figure 1. Screenshots from the in-house SG.

Regarding the child verbal responses, for word recognition, we used the speech-to-text program CMUSphinx, version 5.0.0 [70], which is an open-source project that is free of charge, has cross-platform support for desktop and mobile systems, and can be used offline. Also, there exists a model for Greek language that was created and trained for this software [71].

For the biometric samples, we used a smartwatch with bio-sensors and a software-based eye-tracking module that monitors the gaze of the child while looking at the screen.

The smartwatch the individual wore during the SG activities captured and sent their cardiac rhythm to the SmartSpeech database for analysis. Heart rate variables were computed for each activity, including HRV, which was estimated using heart rate standard deviation and range statistics due to challenges in directly calculating HRV from the wearable device's heart rate data. Thus, for each activity, we obtained three variables that were the mean, the standard deviation, and the range of the heart rate.

SeeSo software, Unity mobile SDK version 2.4.4, was used for eye tracking [72] to determine where the user's eyes focused while performing certain activities on the mobile device. It recorded gaze points with X and Y coordinates of the screen at specific time intervals during SG activities. The variables obtained by the software are relevant, with the fixation being the fundamental metric for eye-tracking. A fixation is defined as a cluster of gaze points close to each other in space and time, which means the individual is looking at a specific region. Fixations are the most common measures of visual attention. During the game, certain areas on the screen are predetermined as areas of interest (AOI). An AOI may be, for example, a face, an animal, or a moving object, and it is defined as a rectangular region with specific coordinates and a specific time duration. The software extracted three fundamental variables from the eye movement experiments:

- Fixation count (FC), i.e., the total number of fixations in an AOI;
- Time to first fixation (TTFF), i.e., the time needed after an AOI is visible until the first fixation is counted on it;
- The total duration of fixations (TS), i.e., the total time that an individual spends looking at a specific AOI.

The data collection of the eye-tracking software depends on how the subject reacts to stimuli. The subjects, especially children, move around a lot; thus, the camera fails to take some measurements. Therefore, due to missing values in our datasets, in the final variables selected after clearing the data, there were no variables with TTFF metrics. Eliminating missing values was necessary, and we needed to ensure that all cases were filled with valid data.

After finishing the game, all data were exported and automatically stored as variables in a remote server. The abovementioned variables belong to 3 categories: the game variables (25), which were the scores from the game activities; the eye-tracking variables (16); and the heart rate variables (15) [3]. The data variables for the game score, eye-tracking, and heart rate datasets are illustrated in Figures 2–4, respectively, also presenting the dimensionality of each dataset. Table 1 illustrates in more detail the description of the variables for the game dataset.

For the experiments, in total, 435 children aged 8.8 $\pm$ 7.4 years participated, of which 224 were boys and 211 were girls. The parents provided written consent along with the child's neurodevelopmental or medical history. After completion of all the games, data were gathered for each child that belong to the three aforementioned sources—game scores, eye-tracking, and heart rate—forming the three datasets in the study. The eye-tracking dataset had 309 cases, the heart rate dataset had 181 cases, and the game scores had 435 cases. The sample was further divided into two groups according to the existence of a specific neurodevelopmental disorder or not, inserting a new variable in the datasets with the name Disorder. This variable denotes whether an individual has one of the Diagnostic and Statistical Manual of Mental Disorders [1], which defines one or more of the following five disorders: Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), Intellectual Disability (ID), Specific Learning Disorder (SLD), and Communication Disorder (CD). The Disorder variable is binary with values true/false, denoting two classes for the classification procedures that follow.

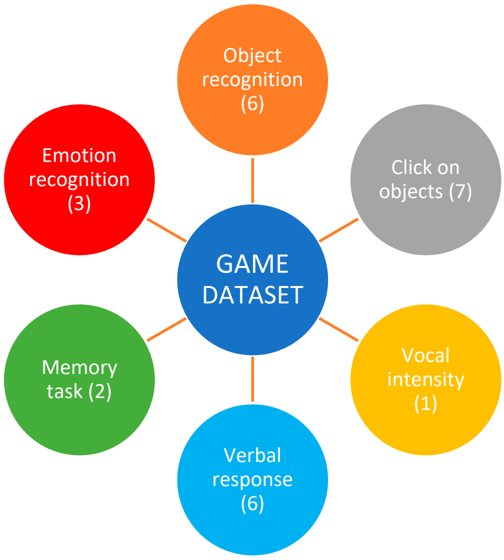

Figure 2. Variables comprising the game scores dataset.

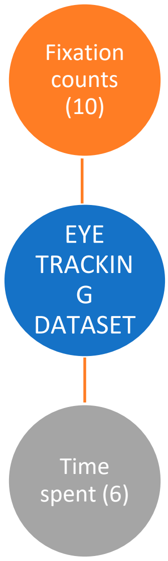

Figure 3. Variables comprising the eye-tracking dataset.

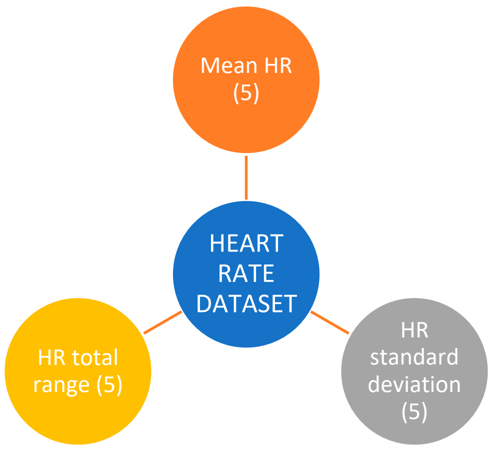

Figure 4. Variables comprising the heart rate dataset.

Table 1. Description of variables.

Variable Type	Description—Examples
Objects recognition	Identification of shadow (shape) Identification of object by acoustic stimuli Categorization (i.e., distinguishing fruits from vegetables) Time sequences (i.e., setting pictures to correct order)
Click on objects	Burst balloons Color sequences (i.e., fill bridge gap with colored boards) Pre-writing skills (i.e., move a teleferic with hand) Cognitive flexibility (i.e., lead character out of a maze) Sustained attention (i.e., catch thrown fruits in basket) Fine motor skills (i.e., solve classic puzzle with pieces) Sequences for size (arrange boards according to size)
Vocal intensity	Avoid clouds using voice intensity in a flying game
Verbal responses	Repeat a vocalization (word) Naming objects Answer questions Naming feelings
Memory tasks	Recall names of characters Remember object's position in a grid
Emotion recognition	Color sequences (i.e., fill bridge gap with colored boards)

4. Experiments

4.1. Experimental Datasets, Methods, and Parameter Details

This section reports on the assessment of the proposed FC2RBF technique's efficacy in creating artificial features for feature learning and class prediction using the three datasets from the SmartSpeech project (see Section 3). These issues have been extensively examined by numerous scholars in the pertinent academic discourse, encompassing a diverse array of research domains spanning from economics to health [3,40,54,55,73,74].

The parameters used in the employed algorithms are shown in Table 2. The following methods were used:

1. RBF—an RBF neural network with H processing nodes.
2. MLP BFGS—an artificial neural network with H hidden nodes, trained with the BFGS optimization method.
3. MLP PCA—an artificial neural network with H hidden nodes and trained with the BFGS method. The neural network is applied on two constructed features produced by the PCA method.
4. FC2RBF—an RBF network with 10 processing nodes applied on two artificial features constructed by the proposed method.

Table 2. Experimental settings parameters.

Parameter Name	Value	Parameter
N_C	500	Chromosomes
N_F	2	Number of constructed features
N_G	200	Maximum number of generations
H	10	Processing nodes
p_S	0.10	Selection rate
p_M	0.05	Mutation rate

To establish a higher level of trust in the outcomes of the experiments that were carried out, the technique of ten-fold cross validation was implemented for each and every experimental dataset. Each experiment was performed a total of thirty times, with a unique seed being input into the random number generator each time. Also, the experiments were executed 30 times using different seeds for the random generator each time. Finally, the same pre-processing and initial manual feature extraction stage was applied in all experiment runs to avoid any bias between the compared methods.

The code utilized was written in ANSI C++ and optimized with the help of the OPTIMUMS programming library. This library, which can be downloaded for free at https://github.com/itsoulos/OPTIMUMS/, was used to implement the code (accessed on 12 September 2023). The software was developed with the ANSI C++ programming language and relies on the freely accessible QT programming library. The software exhibits compatibility with a wide range of operating systems, including mobile platforms such as Android and iOS. The software can be freely downloaded from the official GitHub repository located at https://github.com/itsoulos/QFc (accessed on 1 September 2023).

A visual representation of the overall flowchart and study structure is included in Figure 5 outlining the structure of this study. This visualization includes the steps involved in the feature construction process, the application of machine learning methods, and the comparative analysis framework.

Most prediction models place the data points that they use in one of these four categories:

1. True positive (TP)—the individual in question does in fact have NDs and our prediction was accurate that the individual does have NDs.
2. True negative (TN)—the individual in question does not in fact have NDs and our prediction was accurate that the individual does not have NDs.
3. False positive (FP)—although the individual in question does not in fact have NDs, our prediction was inaccurate that the individual does have NDs. The term for this kind of error is a Type 1 error.
4. False negative (FN)—although the individual in question does in fact have NDs, our prediction was inaccurate that the individual does not have NDs. The term for this kind of error is a Type 2 error.

For the classification of the datasets, the reported error is the average classification error, as measured in the test set. The classification error refers to the percentage of patterns in the test set that were assigned to a class that was not the anticipated one. Error rate is calculated by Equation (1):

$$\text{Error rate} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

The precision metric quantifies the degree of accuracy of our positive predictions, meaning that it indicates the proportion of projected positive points that really occurred. Equation (2) defines precision:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

The recall metric quantifies the proportion of positive instances that our model successfully recognized. In other words, it assesses the accuracy of our model in correctly classifying positive instances out of the total number of instances classified as positive. Recall and sensitivity are synonymous. Next, Equation (3) specifies recall:

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

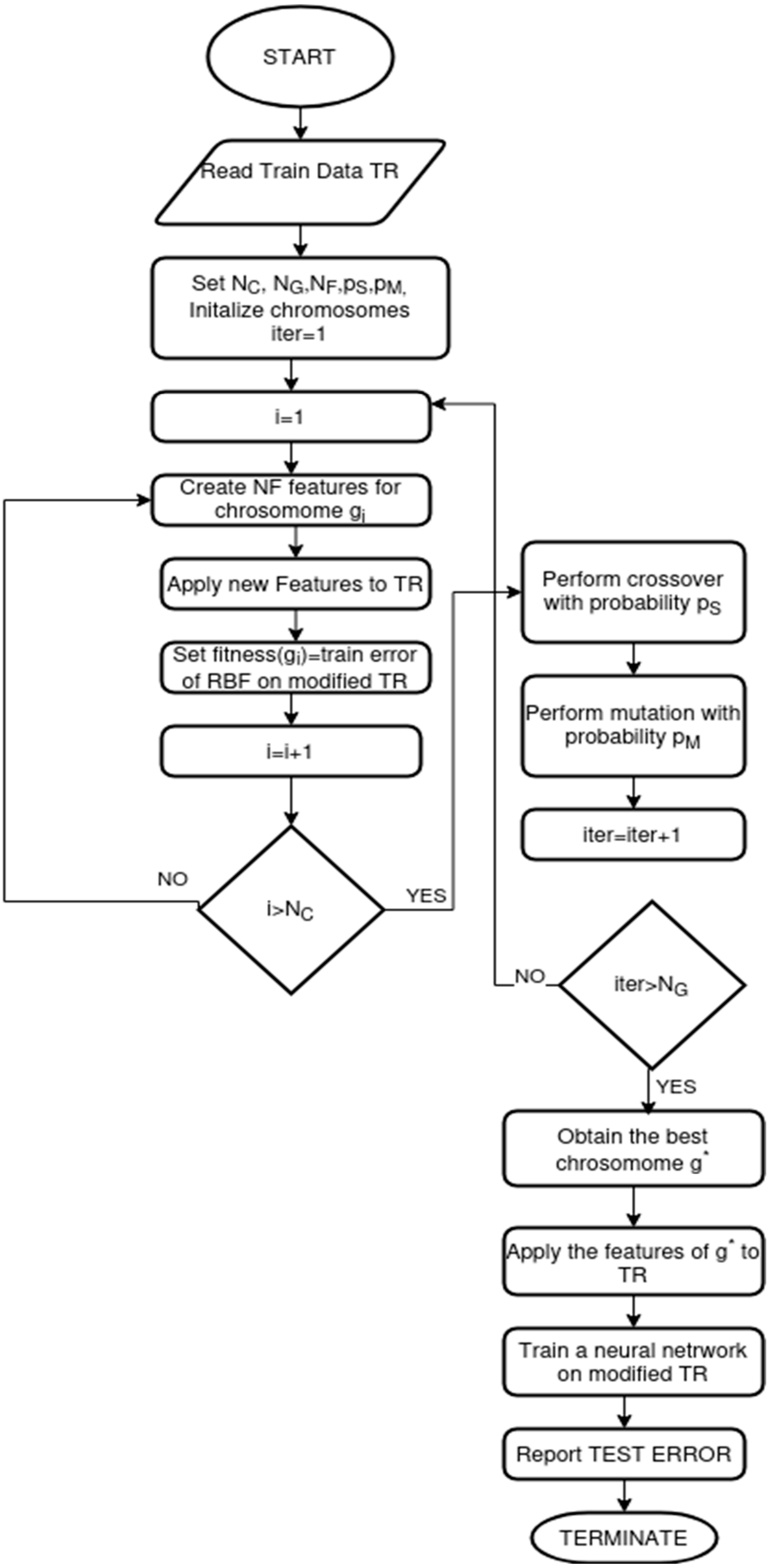

Figure 5. Overall flowchart and study structure (g* stands for the best chromosome of the population).

4.2. Experimental Results

Table 3 shows the results of the classification experiments for each of the methods in use in terms of error rate percentage. The experiments took place separately for each of the three datasets. Figure 6 presents a visualization of the error rates results.

Table 3. Error rates (%) of the methods applied for the classification procedures.

Method				
FC2RBF	**RBF**	**MLP BFGS**	**MLP PCA**	**DATASET**
5.41%	15.48%	14.45%	27.16%	Eye-tracking
21.85%	23.28%	35.19%	28.58%	Heart rate
20.33%	21.81%	27.20%	25.04%	Game scores

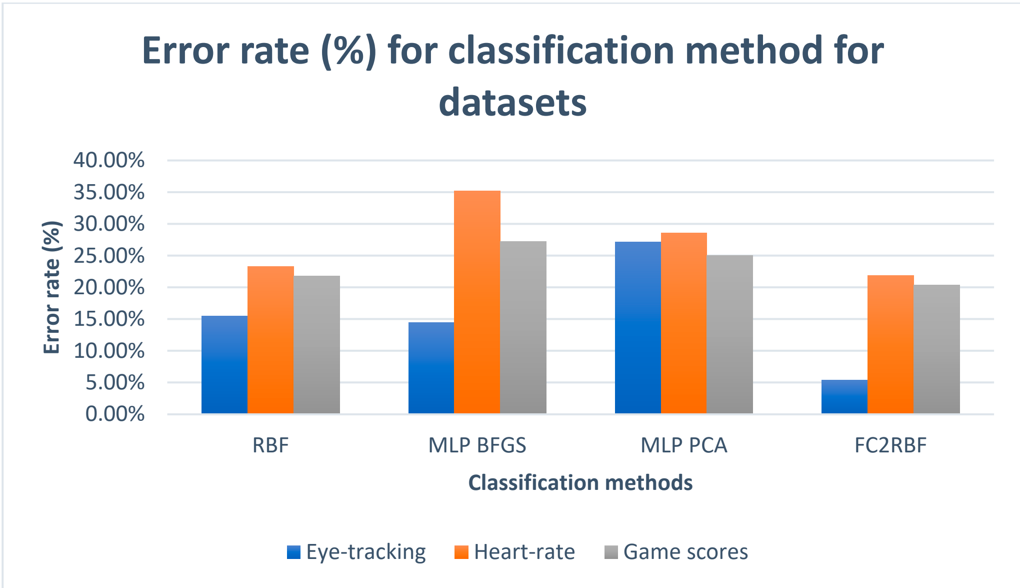

Figure 6. Error rate results visualization.

The precision results of the classification studies for each of the employed methods are presented in Table 4. The experiments were conducted individually for each of the three datasets. The results indicate that the FC2RBF method bested the other three approaches in terms of precision, with great performance on the eye-tracking dataset. A visualization of the precision results is depicted in Figure 7.

Table 4. Precision of the methods applied for the classification procedures.

Method				
FC2RBF	**RBF**	**MLP BFGS**	**MLP PCA**	**DATASET**
0.9125	0.6887	0.7644	0.5558	Eye-tracking
0.5748	0.5264	0.5067	0.5006	Heart rate
0.5604	0.5344	0.5574	0.5344	Game scores

The recall findings for each of the methods utilized in the classification experiments are presented in Table 5, designated as sensitivity. The experiments were conducted separately for each of the three datasets. Figure 8 shows a visualization of the recall findings.

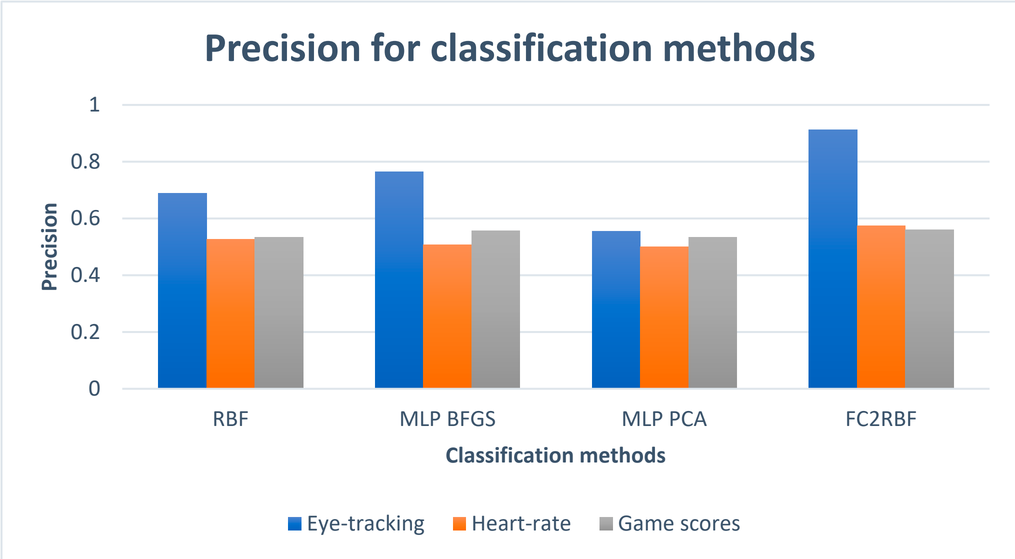

Figure 7. Precision results visualization.

Table 5. Recall of the methods applied for the classification procedures.

Method				
FC2RBF	**RBF**	**MLP BFGS**	**MLP PCA**	**DATASET**
0.9371	0.8906	0.8231	0.6004	Eye-tracking
0.7639	**0.8076**	0.5405	0.5545	Heart rate
0.7065	0.6905	0.5872	0.5598	Game scores

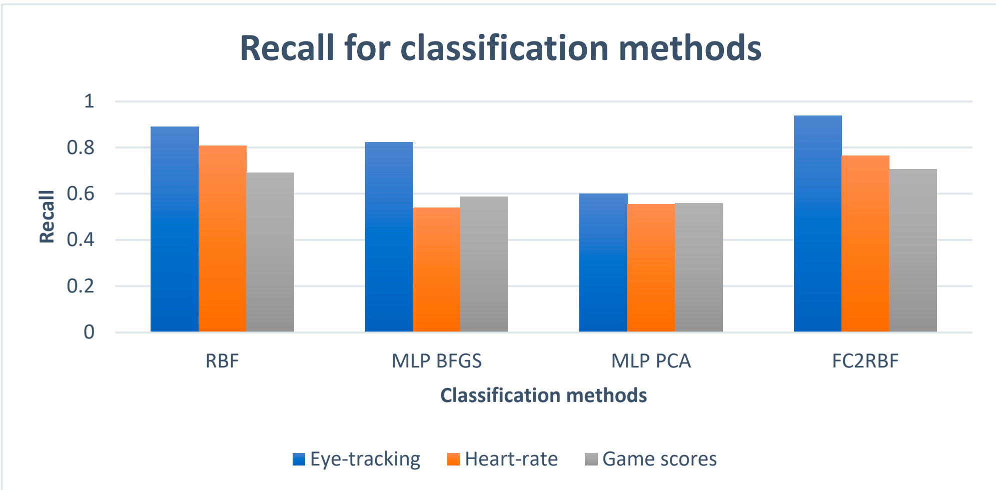

Figure 8. Recall results visualization.

5. Discussion—Conclusions

This study contributes to identifying the most accurate and efficient algorithms for a practical application such as SmartSpeech by proposing and comparing ML methodologies on these particular, consistent datasets. It offers valuable analysis of the advantages and disadvantages of various algorithms, enabling informed decision-making in the development and implementation of the SmartSpeech ML solution that may serve as a valuable screening tool for clinicians and other specialists to identify NDs from non-NDs children and, thus, plays a crucial role in their rehabilitation strategy.

In this study, a novel method called FC2RBF has been proposed for feature construction, which aims to improve the machine learning model by incorporating additional details or connections that may not be directly discernible in the original features. Feature construction involves generating new features by applying mathematical operations, transformations, or combinations to existing ones. The primary objective of this method is to enhance the model by introducing more details or connections that may take time to become apparent in the original features. The experimental results presented in Section 4.2 confirm that the optimized features generated by the FC2RBF algorithm in the comparative experiments demonstrated that using this feature creation method outperformed other machine learning methods for predicting neurodevelopmental disorders. The use of the FC2RBF algorithm on the SmartSpeech datasets showed significant results. In the eye-tracking dataset, the test error was reduced by up to 65% compared with the MLP BFGS algorithm, which was the next best-performing algorithm. In the heart rate dataset, the test error was reduced by 6.14% compared with the RBF neural network, the next best-performing algorithm. Similarly, in the game scores dataset, the test error was reduced by 6.78% compared with the RBF neural network, which was again the next best-performing algorithm. Moreover, the proposed technique achieves high success rates using only two artificial features, which are generated as non-linear combinations of the original features in each dataset. Also, the proposed method was applied without any modification in the different SmartSpeech datasets.

The number of learning model parameters is directly related to the dimensionality of the input problem, which is determined by the number of features. Therefore, complex problems, such as the evaluation and screening of neurodevelopmental disorders, require substantial memory resources to accommodate and handle the learning models. Moreover, as the number of parameters within computational models increases, it takes more time to modify those parameters. With a higher dimensionality of the data, a larger number of samples (patterns) is needed to achieve high learning rates. In this study, we managed to reduce the error rate and the dimensionality of the screening NDs features; for instance, in the game scores dataset, from 24 original features to two new artificial features produced from the original ones from non-linear transformations. Hence, only two features are required to obtain a low error rate in each dataset. Based on the results, the proposed technique performs better than the compared ones. Thus, it is faster, more accurate, and has higher sensitivity and specificity, especially for the eye-tracking dataset.

The study's findings demonstrate the method's effectiveness with outstanding results in analyzing the SmartSpeech eye-tracking dataset, exhibiting lower error rates and, thus, higher accuracy, together with higher precision and sensitivity. This method can be integrated into the SmartSpeech machine learning model to support automated prediction in neurodevelopmental disorders (NDs), and to further assist clinicians in distinguishing children with NDs from those without during screening procedures.

Future research may focus on addressing challenges and exploring innovations to enhance the efficiency, interpretability, and generalization capabilities of models addressing real-world challenges in NDs.

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