*Article*

# Applying neural networks on biometric datasets for screening speech and language deficiencies in children communication

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**Abstract:** Screening and evaluation of developmental disorders include complex and tough procedures, exhibit uncertainties in the diagnostic fit, and require high clinical expertise. Traditionally, clinicians rely on diagnostic instrumentation, child observations, and parents' reports resulting occasionally to subjective evaluation outcomes. Current advances in artificial intelligence offer new opportunities for decision making, classification and clinical assessment. The current study explores the performance of different neural networks optimizers in biometric datasets for screening typically and non-typically developed children for speech and language communication deficiencies. The main motivation was to give clinicians a robust tool to help them identify speech disorders automatically by using artificial intelligence methodologies. For this reason, in this study a new dataset from an innovative, recently developed serious game that focuses on collecting a variety of data on children's speech and language abilities was used. Specifically, a variety of neural network approaches were used by utilizing state-of-the-art optimization algorithms such as the Broyden-Fletcher-Goldfarb-Shanno (BFGS), the Particle Swarm Optimization (PSO), and a Genetic algorithm, along with an Integer bounded Neural Network (INN). The results were promising, while INN proved to be the best competitor, opening new inquiring for future work towards automated classification supporting clinician's decisions on developmental disorders.

**Keywords:** SmartSpeech; Neural networks; optimization; genetic algorithms; biometrical data

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## 1. Introduction

Artificial Neural networks (ANNs) are parametric machine learning tools [1,2] that are utilizing a seires of parameters commonly called weights or processing units. These tools have found application in a variety of scientific areas, such as physics [3–5], solution of differential equations [6,7], agriculture [8,9], chemistry [10–12], economics [13–15], medicine [16,17] etc. Also, recently, neural networks have been used in solar radiation prediction [18], 3D printing [19], lung cancer research [20] etc. A neural network $N(\overrightarrow{x}, \overrightarrow{w})$ can be expressed as a summation of processing units as suggested in [21]:

$$N(\overrightarrow{x}, \overrightarrow{w}) = \sum_{i=1}^{H} w_{(d+2)i-(d+1)} \sigma \left( \sum_{j=1}^{d} x_j w_{(d+2)i-(d+1)+j} + w_{(d+2)i} \right) \quad (1)$$

where the constant $H$ defines the total number of processing units for the network and the value $d$ is considered as the dimension of vector $\overrightarrow{x}$. The function $\sigma(x)$ is called sigmoid function and it is defined as:

$$\sigma(x) = \frac{1}{1 + \exp(-x)} \quad (2)$$

The training error of the neural network is defined as:

$$E(N(\overrightarrow{x}, \overrightarrow{w})) = \sum_{i=1}^{M} (N(\overrightarrow{x}_i, \overrightarrow{w}) - y_i)^2 \quad (3)$$

where the set $(\overrightarrow{x_i}, y_i)$, $i = 1, ..., M$ is the training dataset for the neural network and $y_i$ stands for the actual output for the input pattern $\overrightarrow{x_i}$. Essentially, the training of the artificial neural network consists in determining the optimal vector of parameters $\overrightarrow{w}$ through the minimization of equation 3. During the recent years a variety of optimization methods have been proposed to minimize this equation such as the Back Propagation method [22,23], the RPROP method [24–26], Quasi Newton methods [28,29], Simulated Annealing [30,31], Genetic Algorithms [32,33], Particle Swarm Optimization [34,35] etc.

## 2. Data description

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## 3. Materials and Methods

## 4. Results

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**Table 1.** Experimental results for the EYE dataset using different methods for the neural network training.

| DATASET | BFGS | GENETIC | PSO | INN |
|---|---|---|---|---|
| DISORDER | 19.53% | 17.76% | 14.14% | 8.67% |
| DEPIK | 29.46% | 25.49% | 27.96% | 23.78% |
| EMD | 29.44% | 25.68% | 25.88% | 22.49% |
| NOITIKI | 40.30% | 31.50% | 37.33% | 26.63% |
| TADAF | 27.07% | 24.32% | 25.59% | 19.94% |
| TADEPY | 27.30% | 23.42% | 23.42% | 19.69% |
| **AVERAGE** | **28.85%** | **24.70%** | **25.72%** | **20.20%** |

**Table 2.** Experimental results for the HEART dataset using different methods for the neural network training.

| DATASET | BFGS | GENETIC | PSO | INN |
|---|---|---|---|---|
| DISORDER | 29.26% | 21.26% | 22.09% | 18.95% |
| DEPIK | 31.61% | 20.17% | 20.48% | 20.02% |
| EMD | 32.98% | 19.17% | 22.02% | 19.06% |
| NOITIKI | 31.13% | 20.89% | 24.98% | 19.61% |
| TADAF | 32.31% | 20.61% | 23.19% | 19.83% |
| TADEPY | 34.11% | 21.11% | 26.69% | 19.89% |
| **AVERAGE** | **31.90%** | **20.54%** | **23.25%** | **19.56%** |

**Table 3.** Experimental results for the GAME dataset using different methods for the neural network training.

| DATASET | BFGS | GENETIC | PSO | INN |
|---|---|---|---|---|
| DISORDER | 25.92% | 21.92% | 24.37% | 18.95% |
| DEPIK | 30.61% | 22.25% | 25.92% | 22.57% |
| EMD | 30.22% | 22.59% | 27.15% | 21.95% |
| NOITIKI | 29.62% | 22.64% | 26.67% | 21.25% |
| TADAF | 28.84% | 20.96% | 25.42% | 20.39% |
| TADEPY | 29.64% | 21.54% | 29.62% | 21.52% |
| **AVERAGE** | **29.14%** | **21.98%** | **26.53%** | **21.11%** |

## 5. Conclusions

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

**Author Contributions:** For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.", please turn to the CRediT taxonomyfor the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

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**Sample Availability:** Samples of the compounds ... are available from the authors.

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