How many tests do you need to diagnose Learning Disabilities?

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Abstract

The diagnosis of Learning Disabilities (LD) is frequently subject to cognitive biases. In Italy, minimal diagnostic standards have been identified during a national Consensus Conference (2010). However, specialists use different protocols to assess reading and cognitive abilities. Thus, we propose to support LDs diagnosis with Artificial Neural Networks (ANN). Clinical results from 203 reports were input to investigate which ones can predict LD diagnosis. In addition, correlations among LDs were explored. Preliminary results show that ANNs can be useful to support a clinical diagnosis of LDs with an 81.93% average accuracy, and, under certain conditions, with a 99% certainty. Additionally, the 10 most meaningful tests for each LD have been identified and significant correlations between dyscalculia and dyslexia were found.

Keywords: Learning disabilities; artificial neural networks; dyslexia

1. Introduction

1.1 Learning Disabilities

Learning disabilities (LDs) represent an increasing problem affecting people studying at all school levels. Among them, dyslexia is the most widely studied, since it affects the fundamental capability of reading. In fact, dyslexia is currently defined as a neurodevelopmental disorder characterized by slow and inaccurate word recognition, causing difficulties in decoding words and, consequently, more general problems in learning (Ferrer, Shaywitz, Holahan, Marchione, & Shaywitz, 2010).

Broadly speaking, LD is a disorder in one or more areas of learning in the absence of neuromotor, sensitive and pre-existing psychopathological disorders. In addition to dyslexia, three main types of LDs are descripted: difficulties in writing (dysgraphia); impaired spelling in writing (dysorthography); difficulties in arithmetic (dyscalculia). In Italy LDs affects 3-4% of children during development age, with remarkable influences on school classes.

Even if many studies have been successfully conducted on LD over the last decade (for relevant meta-analyses see for example: Maisog, Einbinder, Flowers, Turkeltaub, & Eden, 2008; Swanson, 1999; Swanson & Jerman, 2006; Taylor, Rastle, & Davis, 2013), LD identification is still a difficult process, which is susceptible to lack of information. Reading, writing and doing mathematic are complex and slowly learned skills requiring the integration of multiple visual, linguistic, cognitive and attentional processes (Norton et al., 2014).

In Italy, the clinical diagnostic criteria are based on the ICD-10 standards (International Statistical Classification of Diseases and Related Health Problems 10th Revision), but clinicians should also consider the recommendations reported by the National Consensus Conference (2010) as well as the indications included in the Italian Law n. 170 (2010), that reports all the legal norms to be taken into consideration within educational contexts. Furthermore, the 5th edition of the DSM offers a different classification and, even though in Italy is not the legal standard; it is likely that clinicians may be influenced in their diagnostic practice also by this perspective.

When a child suspected of LD, the diagnostic pathway may take different directions. The different tests that are administered range from neurological tasks to psychological and speech assignments. Therefore, the diagnostic procedure frequently becomes complex and time-consuming. This procedure can last from some months to one year and can be expensive for families, which usually address to private structures because of long waiting times in public hospitals. The use of different batteries is probably due to the resources that clinicians need to make differential diagnosis, draw psychological profiles of children, and diagnose a specific LD (Vellutino, Fletcher, Snowling, & Scanlon, 2004). However, at present, it is still not possible to provide really tailored interventions based on a child's profile, so the use of so many tests might be underproductive.

For all these reasons, Artificial Intelligence (AI) could be useful for supporting clinical diagnosis, providing faster predictions and suggesting which tests could be useful for each given case. Once tested and adequately trained, the AI methods will provide additional advantages in eliminating possible human biases and supporting decisions in ambiguous cases.

1.2 Artificial Intelligence and Learning Disabilities

Progress in AI methods demonstrated a great potentiality in the application of neural modeling in both clinical and medical problems. In the present work, an Artificial Neural Network (ANN) was considered as powerful computational method to support decision-making (Lucchiari, Folgieri, & Pravettoni, 2014). This method may be especially useful in uncertain diagnosis, currently based on clinical experience and prone to possible errors.

The ANNs are structured as a network composed of units and nodes, organized in several layers (normally three), which connect inputs and outputs through one or more layers of hidden neurons. Each unit is connected to the other by different "weights", and the input units are initially combined in "on" and "off", generating an activation pattern that is spread across the network through connections. Inputs and outputs are reality representations, which are represented in a parallel process: the program computes data by evaluating all Parallel Distributed Processing inputs or outputs, overcoming the step-by-step algorithmic approach typical of classic AI. This way, the machine can address simultaneously the various aspects of a complex problem, thus significantly accelerating the processing time.

An essential aspect of ANNs is the ability to learn. Indeed, this approach typically begins with an initial training by means of a series of input-output data pairs, according to which the network adjusts initial weights by means of a trial-and-error method until the output reaches sufficient similarity to the desired one. Once the training is completed, the network is then able to apply this method to new cases making reliable predictions.

ANNs turned out to be efficient in making predictions over the past years and they have been largely used in supporting clinical diagnosis (Pravettoni, Folgieri, & Lucchiari, 2015); however, only a few studies applied them in recognizing learning disorders. From 1980 on, some papers have been published about AI applications to the topic: for instance, Geiman and Nolte (1990) proposed an expert system for LDs identification with rather positive results. Moreover, Baer (1991) designed a system to reduce bias in the diagnosis of students with suspected disabilities. However, the development of AI continued and was refined until today in conjunction with the advancement of its practical applications. An interesting example is the work of Wu, Huang and Meng (2006), whose research exploits ANNs and vector machines for the diagnoses of Learning Disorders in Taiwan. More recently, in Mumbai, Jain, Manghirmalani, Dongardive and Abraham (2009) devised an ANN with an input layer of 11 units, each representing a predisposition group for the disorders, and a single output unit. This ANN was able to predict LDs with 90% accuracy. Wu et al. (2006) used ANNs and Support Vector Machine to sustain LDs identification in Taiwan, while Kohli and Prasad (2010) realized an ANN to identify dyslexic students. Costet and Scalart (2011) realized a multivariate predictive model for dyslexia diagnosis in order to simplify the identification process. However, a possible limitation on these studies may be the inability to discriminate between the various LD types. to our knowledge, no previous studies with AI methods on Italian LD tests reliability have been published; thus, the present work could be a starting point for future research and clinical practice. Furthermore, the present study attempts to identify which tests may be considered meaningful.

In the following paragraph, an ANN designed to support LDs diagnosis will be described and the relations between the four main LDs will be explored by a correlational analysis. In addition, the procedure adopted to select significant tests will be examined. Results will be reported in terms of ANN accuracy and correlational indices. Finally, findings will be compared with other available work in the literature, with a particular focus on the possible clinical applications.

2. Materials and method

2.1 Dataset

Thanks to the collaboration of four public and private structures nearby Milan, 515 LDs diagnoses reports were collected thanks. After a first examination, 203 cases of Learning Disabilities were selected based on the inclusion criteria listed below:

- At least one diagnosis among F81.0 (dyslexia), F81.1 (dysorthography), F81.2 (dyscalculia), and F81.8 (dysgraphia) as assessed by ICD10 (World Health Organization, 2000);
- Possible co-occurrences with:
  - F80.1: Expressive language disorder;
  - F80.2: Receptive language disorder;
  - F80.9: Developmental disorder of speech and language, unspecified;
  - F81.9: Developmental disorder of scholastic skills, unspecified;

- F82.0: Specific developmental disorder of motor function.

- Age between 7 and 20 years-old at the diagnosis time;
- Data on the diagnosis pertaining to the last five years.

The number of collected tests amounts to 44, but some of them are further divided into more specific subtests for a total of 111 items (see Table 1).

In addition, together with the 111 tests and subtests, other variables such as "gender", "age", "familiarity for LDs", "handedness" and "previous language disorders" were considered, for 116 input values in total.

Most of the results are calculated in terms of standard deviations. Four different categories have been created to classify this kind of data, as shown below:

- From +1 on: optimum performance.
- From -1 to +1: adequate result;
- From -1 to -2: request of attention;
- From -2 on: request of immediate intervention;

However, some exceptions to this rule exist. The bell test, the calculus and numerical quotient, the VMI test, the London tower test, the Raven progressive matrices, the TROG-2, and the Peabody test scores range between 0 and 100. The WISC-III test uses a different categorization as well (Over 130: exceptionally high; 120-129: high; 110-119: average-high; 90-109: average; 80-89: average-low; 70-79: low; Less than 69: exceptionally low).

Outputs were represented by the various LDs, as assessed by ICD-10 codes:
F80.1: Expressive language disorder
F80.2: Receptive language disorder. Developmental disorder of speech and language, unspecified
F81.0: Specific reading disorder, or Dyslexia
F81.1: Specific spelling disorder, or Dysorthography
F81.2: Specific disorder of arithmetical skills, or Dyscalculia
F81.8: Other developmental disorders of scholastic skills, or Dysgraphia
F81.9: Developmental disorder of scholastic skills, unspecified
F82: Specific developmental disorder of motor function.

Finally, 75% of the dataset has been used as a training set, 15% employed as a testing set and the remaining 5% as verification set, namely the inputs for effective ANN predictions.

Table 1. Clinical assessment

Linguistic skills	**Arithmetic skills**	**Memory, visuo-spatial and executive functions**	**Graphic-motor skills**	**Intelligence**	**Batteries**
BVSCO, CAF, CMF, Dictation of words, Lexical fluency, Learning couples of words, MT dictation test, MT reading test, MT writing test, Peabody test, PVCM, Rustioni test, Similar words test, Syntactic comprehension test, TCGB, Token test, TOR, TVL, TROG-2, Repetition of sentences	BDE, MT math test	Bell test, Elithorn perceptual maze test, London tower test, VAUMeLF, Short verbal memory test, Ray figure, Span of syllables, TSMV	BHK, BVSCO 2, DGM-P, Ray figure	Raven progressive matrices, WISC III	BVN 5-11/12-18, DDE-2, Protocol of the institute for children neuropsychiatry "La Sapienza", Rome

2.2 ANN pattern recognition

The ANN was based on a dataset made by 203 rows (one for each subject) and 125 columns corresponding to input (116) and output variables (9). Each input corresponded to test scores (111) and 5 personal features (age, gender, handedness, previous learning disorders and years of education). A multilayer feed-forward neural network was designed with a back-propagation algorithm by using R-software (R Core Team, 2012). The supervised ANN can learn input and output mappings from training samples and, after a training period, it is able to apply the same relations to new input patterns. Back-propagation is a common algorithm for ANN training that iteratively adjusts the network parameters to minimize the sum of squared approximation errors using an optimization method such as gradient descent. This technique calculates the gradient of a loss function with respect to all the weights in the network and then updates the weights to minimize the loss.

The activation function is fundamental to produce numeric outputs. For our data, a logistic sigmoid activation function seemed to be the most efficient (Sibi, Jones, & Siddarth, 2013). Its equation is shown in Eq. (1):

$$f(x) = \frac{1}{1+e(-x)} \qquad (1)$$

Where x is the input to the network, equal to the sum of the products of the incoming activation levels with their associated weights. This incoming sum is computed (for a node j) as follows in Eq. (2):

$$S_j = \sum_{i=0}^{n} w_{ji} a_i \qquad (2)$$

Where:
- wji = incoming weight from unit i
- ai = activation value of unit i
- n = number of units that send connections to unit j

Sigmoid functions are very similar to the input-output relationship of biological neurons. Each neuron has an activation function, which specifies the output of a neuron to a given input. This function provides a 0<y<1 response, the neurons react with "1" when they are sufficiently activated and with "0" when they are not. Within our dataset, "0" corresponds to a non-disorder diagnosis and "1" to an LD. The pattern recognition ANN, designed to perform our experiment, is composed of a single input layer with 116 different entries, 20 hidden neurons, and 9 outputs.

3. Results

3.1 ANN pattern recognition

A network with 20 hidden neurons has been chosen for evaluation of the ANN accuracy. See in Table 2 the results of the training session and the estimated accuracy for each output column (Error Reached=0.001196421; Threshold=0.008560924; Steps=2141).

Table 2. Results of the training session and estimated accuracy for each output column

Disorder	**Accuracy**
F80.1: Expressive language disorder	92,75%
F80.2: Receptive language disorder	92,33%
F80.9: Developmental disorder of speech and language, unspecified	100%
F81.0: Dyslexia	77,68%
F81.1: Dysorthography	68,03%
F81.2: Dyscalculia	70,3%
F81.8: Dysgraphia	72,75%
F81.9: Developmental disorder of scholastic skills, unspecified	90%
F82.0: Specific developmental disorder of motor function	73,53%
Average accuracy:	**81,93%**

3.2 Test selection

The procedure allowed identifying the 10 tests and variables that most influenced dyslexia, dysorthography, dyscalculia and dysgraphia diagnosis ($.15<r<.50$), that are showed in Table 3.

Table 3. The 10 tests and variables that most influenced dyslexia, dysorthography, dyscalculia and dysgraphia diagnosis

Dyslexia	**Dysorthography**	**Dyscalculia**	**Dysgraphia**
- MT reading test	- BVSCO narrative text test	- ACMT, accuracy in writing operations	- Syllable span test
- MT comprehension test	- DDE-2 test 7, non-words dictation	- ACMT, rapidity in writing operations	- MT writing rapidity for "lelele"
- DDE-2 test 5, reading rapidity	- MT reading rapidity test	- ACMT accuracy in mental operations	- MT writing rapidity in number with capital letters
- DDE-2 test 5, reading accuracy	- BVSCO descriptive text test	- ACMT total time	- MT writing rapidity in cursive numbers
- DDE-2 test 6, reading rapidity	- Words dictation in articulatory suppression	- Numerical facts	- BHK writing rapidity
- DDE-2 test 6, reading accuracy	- DDE- 2 test 4 reading rapidity	- ACMT numeric knowledge	- DX-SX
- BVN reading test	- DDE-2 test 5 reading accuracy	- ACMT problem solving	- WISC III, verbal intelligence quotient
- DDE-2 dictation test	- DDE-2 test 5 reading rapidity	- ACMT numeric sets	- WISC III, total intelligence quotient
- London Tower Test	- Rustioni test	- Rapidity in backward enumeration	- Age
- WISC III, performance intelligence quotient	- DDE-2 test 3 reading accuracy	- BDE numeric quotient	- Raven test (P38)

4. Discussion

An 81.93% average accuracy is a valid result and allows predicting outputs with sufficient certainty. In particular, the average accuracy for language disorders (F80.1, F80.2, a developmental disorder of speech and language, unspecified, F81.9) resulted in 93.77%, while it was 72.19% for LDs (dyslexia, dysorthography, dyscalculia, dysgraphia). Thus, these preliminary results may be considered useful and satisfying, even if the model could be strengthened by further data.

Interesting results about LDs correlations also emerged from the consecutive test analysis. First, by simulating dyscalculia, possible dyslexia was obtained, while an opposite relation does not clearly appear since by simulating dyslexia from a starting ANN for dyscalculia gives only 31% of accuracy. Furthermore, tests for dyscalculia do not precisely delimit the disorder, as highlighted by the 80% accurate outputs, and the network is unable to make optimal predictions if compared to dyslexia results.

Previous data change among the studies, but it is proved that dyscalculia and dyslexia are somehow correlated. For instance, Lewis, Hitch and Walker (1994) estimated a 40% of co-occurrence, testing the population of 9- and 10-years-old in a single education authority district in England; similarly, Landerl, Fussenegger, Moll and Willburger (2009) showed that dyslexia and dyscalculia have two different cognitive profiles, so they proposed the term "co-occurrence" to define such relation. Alternatively, Wilson and colleagues (2015) found that, within a complex multifactorial model of comorbidity, dyscalculia and dyslexia showed independent domain specific deficits. However, the discussion is still open and further research is needed, in order to create a valid theoretical frame.

Several studies have been conducted to discover the cognitive bases of dyslexia and dyscalculia. For example, a study by Gillis and DeFries (1991) showed the presence of some genetic common factors for dyslexia and dyscalculia; Geary, Hamson and Hoard (2000) and Geary and Hoard (2001) found that dyslexia was associated with impaired activity in those regions also related to semantic and working memory in dyscalculia. Finally, Landerl, Bevan and Butterworth (2004) identified some fundamental factors for dyscalculia and for developmental dyslexia in memory, visuospatial, and attention deficits.

Turning to dysorthography and dysgraphia, our data cannot support the use of ANNs. In the first case, inputs were insufficient to design a specific ANN; in the second one, accuracy for dysgraphia after data manipulation remains over 60%. Both these LDs are rarely isolated since they are correlated with other disorders, as highlighted for example by Bindelli and colleagues (2009). The author recognized a 74% of co-occurrence between dyslexia and dysorthography and a 76% dyslexia-dysgraphia one, based on a study on 67 high school students. Consequently not enough data are available for the diffusion of dysgraphia and dysorthography in a pure form, rather than in a situation of co-occurrence.

4.1 On the most predictive tests

Our model strongly suggests that the most predictive tests for an LD are those that directly target the problem. Indeed, by the use of few direct measures, it is possible to predict if a person will o will not have a specifc diagnosis. In particular, the use of a reading test (able to measure both speeding and accuracy) is strongly suggestive of dyslexia. Furthermore, since dyslexia is correlated with executive functions, the reading test could be matched with another test like the

Hanoi Tower that could give to clinician a clearer picture of the subject's mind. Similar results were obtained for dysortographia and dyscalculia. Instead, the case of dysgraphia showed some differences. In fact, the diagnosis of dysgraphia is well predicted not only by targeted tests but also by more general tests, like WISC intelligence scale (total and verbal scores) and Raven Matrix. Also, age is a good predictor. These data suggest that dysgraphia is probably linked to a more general immaturity of the subject's mind that could be solved by a physiological (delayed) maturation and/or by targeted interventions.

To test if our ANN could also suggest interesting interactions between different diagnoses some further analyses were performed by manipulating the dataset. In fact, starting from previous data it is possible to force the ANN recognizing a dyscalculia by putting 1 on the most significant related test. In this way, we can ask the ANN to search for possible LD diagnosis starting by the certainty that the dyscalculia will be recognized. We found that our ANN suggests the presence of dyslexia when a dyscalculia is simulated, while the opposite is not true. Thus, the network has implicitly learned that a diagnosis of dyscalculia may suggest to investigate also reading problems, which maybe are less obvious. On the contrary, our ANN learned that dyslexia is not necessary associated with dyscalculia, thus without clear difficulties in learning arithmetic further tests are not needed.

5. Conclusions

In the present work, Artificial Neural Networks were tested as a possible support for the clinical diagnosis of learning disabilities. ANNs were also used to identify possible correlations among different kinds of LDs to verify possible relations.

Even if there is a consensus about the importance of speed and accuracy of reading in order to suggest dyslexia, more and more tests are used to investigate subjects' abilities. This attitude is probably due to the cognitive, emotional and behavioral differences that we can find in dyslexics. Unfortunately, even when we find differences in the cognitive systems of subjects, in many circumstances it is difficult to plan a real personalized treatment. This means that many tests do not give a concrete indication to face clinical problems; at the same time, increasing the number of tests that a subject undergoes may have negative effects on quality of life, self-esteem and compliance. Consequently, the present data are particularly interesting in suggesting a scaling attitude. Subjects should be tested first of all with the most important test within the problematic area reported by teachers, parents, or the kid him/herself. Second, only strongly correlated areas should be investigated. Third, subsequent evaluations should suggest not only if the treatment was effective or not, but also if further tests are necessary, for instance, to evaluate positive and/or negative trends due the physiological grow or other psycho-social factors.

The use of a limited number of tests and a rational deductive thinking to the data acquired can serve not only to empower the ability of the clinician to correctly diagnose a specific LD but also to improve subjective self-esteem, empowering self-efficacy and potentially the ability to compensate deficits.

The preliminary results of this study are promising and suggest that ANN could effectively be used to provide a second opinion in clinical LDs evaluation. ANN pattern recognition, so, turns out to be a considerable support for diagnosis. However, future studies should be devoted to improve the model in order to be applied in LD diagnosis.

A deeper study about the correlations between LDs using AI techniques could be a further development of the present research. Moreover, greater data collection could refine the model, thus allowing for a concrete proposal in support for the diagnosis.

Furthermore, the use of feature selection techniques could help to identify less significant variables as ANN input, thus simplifying traditional LD assessment.

Other experiments may concern EEG response from dyslexic people with visual, textual and auditory stimuli. In this context, previous work already analyzed EEG signals by BCI devices to explore the response of users to sounds and music (Folgieri & Zichella, 2012), visual stimuli (Banzi & Folgieri, 2012), video (Calore, Folgieri, Gadia, & Marini, 2012), and the engagement of cognitive and memory processes in learning (Folgieri, Lucchiari, & Cameli, 2015). The same experiments performed on dyslexic individuals could enlarge the set of input variables for an ANN together with biofeedback signals, thus enhancing the accuracy of LD diagnosis through ANNs.

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