Dystech Team

Dyslexia and AI: what's up?

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This booklet is dedicated to all the individuals struggling in their day-to-day lives, just because they are different !

Preface

This booklet aims to provide an overview of what has been done so far to diagnose dyslexia with the help of Artificial Intelligence (AI). Accurately diagnosing dyslexia is a long-standing topic of research for the neuroscience community. Till now, the diagnostic is mainly delivered by accredited professionals, based on the scoring of a diverse battery of tests. From another viewpoint, in recent years, AI has made tremendous progress: it is now used in our day to day life, from face recognition to natural language understanding, through to driverless vehicles. The medical field is not an exception: a lot of AI-based applications provide accurate support to clinicians, and it is expected that much more will come in the future. It should not come as a surprise that some scientists try to investigate how AI could improve dyslexia diagnosis, and why not, in a near-future, replace human experts. In this booklet, we start with a brief history of dyslexia: despite dyslexic people most likely pre-existing the concept, this history is less than 200 years. Diverse theories are competing to explain the causes. At this stage, there is no clear winner in this competition. As this booklet is not dedicated to an in-depth investigation of the existing theories, which are somewhat sophisticated, we visit their main lines, which allows considering what kind of input an AI algorithm could need to provide accurate diagnostics. We also provide extensive references for interested readers. The main object of this booklet is a review of the recent works involving AI technologies for dyslexia diagnostics. These works are described, and their results explained. We also clearly indicate to what extent these works lead to a publicly available tool or if they still are at a research-level. In the case of a publicly available tool, we indicate the necessary links to access it.

We hope this booklet could be considered a good overview of current research and development pipeline for helping dyslexic people with AI. As such, this booklet might be useful for parents, teachers, scientists, and anyone interested in what AI can bring for dyslexic people.

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Thank you again, Carmel!

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Chapter 1
Origin: Word Blindness

Abstract In this chapter, we provide a quick view of the context of our work: a brief historical perspective and what is the current situation in terms of understanding and diagnosing dyslexia. We provide extensive references for readers interested in more details.

1.1 Brief historical perspective

As far as we know, nothing related to dyslexia as we understand it today, has been scientifically reported before the year 1800. Due to our understanding of dyslexia today, it seems obvious that 'dyslexia' as such existed prior to the year 1800, but we cannot refer to any scientific investigation before 1800.

After the year 1800, some very important scientific observations occurred, allowing the distinguishing of 'dyslexia' from intellectual or physical inabilities.

The concept of "word-blindness" (in German: "wortblindheit"), as an isolated condition, was first developed in 1877 by a German physician: Adolph Kussmaul (1822-1902). Kussmaul was a highly skilled clinician, better known for his numerous works in medicine. He is considered as being the first to rigorously describe the difficulties related to what is known today as dyslexia.

The term 'dyslexia' itself however, was first coined 10 years later by Rudolph Berlin (1833-1897), a German ophthalmologist, in a paper (in German) still available online at https://gdz.sub.uni-goettingen.de/id/PPN513409602 (Eine besondere Art der Wortblindheit (Dyslexie) - 1887). The word is drawn from the Greek prefix *dys* meaning "hard, difficult" and *lexis* meaning "speech, word". Berlin used the term dyslexia to describe partial reading loss in an adult patient. Today, this acquired reading loss would be called *alexia* for 'acquired dyslexia', as opposed to congenital dyslexia also called *developmental dyslexia*[1].

[1] From now on, in this document, we use the term *dyslexia* to refer to *developmental dyslexia*.

There are schools of thought who believe that Oswald Berkhan (1834-1917), a German physician, is the one who properly identified dyslexia in 1881 (still named 'Wortblindheit' i.e. 'word blindness' at that time). Nevertheless, there is no consensus about the input of Berkhan in this matter.

A Scottish ophthalmologist, James Hinshelwood (1859-1919), having been faced with children unable to learn to read despite no other impairment, published in 1917 a book *Congenital word blindness*, reusing the initial German wording. The book was following diverse scientific publications on the subject. He considered that dyslexia was due to some congenital brain damage but could be managed via personal instruction.

William Pringle Morgan (1861-1934), a British general practitioner is credited with providing in 1896 the first concise description of (developmental) dyslexia. He also suggested a neurological cause. Morgan's publication is sometimes considered as a serious catalyst for research on the subject in France, Scandinavia, and the United States. It could be argued that a lot of other names should be added to this brief historical review, scientists who brought a lot to our understanding of dyslexia. We refer to [24] for a recent investigation.

After more or less 150 years, both the fields of medicine, psychology, neurosciences in the large and education have made notable contributions to the comprehension of dyslexia. As a consequence, today there is a huge amount of literature available on this topic.

The History of Dyslexia is a project which started in 2016 at St John's College, University of Oxford. A lot of up-to-date information can be found on the project web site: https://dyslexiahistory.web.ox.ac.uk/. This project is mainly devoted to the historical evolution of the concept of dyslexia. As such, it is not intended as a project surveying all neuroscientific research to find the cause of dyslexia. A very recent article [24] (referenced above), issued from this project, provides a deep investigation of dyslexia from a unique historical perspective.

1.2 Current situation

Developmental dyslexia [45] is an extensively researched learning disorder. It is considered as one of the most common causes of reading difficulties. Despite the fact there is no clear figure about the number of dyslexic people on earth, it is widely accepted by the community that dyslexia affects about 5%-10% of school-age children and, if we include adults, then it can go up to 15% (see [49] for instance). The Diagnostic and Statistical Manual of Mental Disorders also known as DSM–5 [2], from the American Psychiatric Association, is often considered as a reference document on this matter.

1.2.1 A definition

Dyslexia is:

- defined as a basic deficit in learning to read (i.e. decode print) (see [52]),
- characterized by a significant impairment in the development of reading skills,
- observable by reading performances well below the normal range for given age groups and IQ levels (see [26]),
- not explained by sensory deficits such as visual, hearing impairment, insufficient scholarship or overall mental development only (see [26]).

At least, the scientific community agrees on this even if some technical details are debatable [54]. When it comes to understanding the causes of dyslexia, the situation is a little bit more chaotic.

1.2.2 Causes: no scientific consensus

Today, the causes of dyslexia remain opaque and there is no scientific consensus about the exact causes. Several theories coexist, some of them have already been discredited by empirical observation, others still remain as serious candidates waiting for confirmation. Testing these hypotheses is a challenging task: dyslexic people do not form a homogeneous population and exhibit diverse patterns of errors. That is also why dyslexia is often divided into sub-types (phonological, visual, etc.), possibly originating from deficits at various stages of the comprehension system. Roughly speaking:

i) Written words (i.e. sequence of symbols) are encoded representations of spoken words.

ii) Spoken words (i.e. sequence of sounds) are encoded representations of environmental experiences and entities.

iii) Learning to read is learning to establish the correspondence between written and spoken words.

As a whole cognitive process, learning to read involves different sub-processes and diverse brain abilities such as permanent memory, short term memory, visual coding, linguistic coding, etc. [52] provides a complete description of the process with concise schemata. For instance, a child will have to acquire *phonological awareness* i.e. a conceptual understanding and explicit awareness that spoken words consist of individual speech sounds (phonemes) and combinations of speech sounds (syllables).

As dynamic processes, all of these sub-processes/cognitive abilities need, in a way, to be synchronized, even if there is no clear understanding of this temporal organization. If one of the sub-processes is in deficit, the whole chain will be broken. We briefly mention in the following some of the theories which have been put forward as candidate explanations for a broken process.

- Global visual perceptual and visual memory deficits: these theories suggest deficiencies in the visual system. Unfortunately, it has been observed that these deficits are no more prevalent in poor readers than they are in standard readers.
- Low-level visual deficits: reading disability is then attributed to visual tracking problems associated with oculomotor deficiencies (see [15, 9] for instance).
- It is also tempting to attribute the cause of dyslexia to a specific brain structure [25]. Rare postmortem studies of brains did not bring definitive light on the issue. Modern technologies such as MRI (Magnetic Resonance Imaging) or fMRI (functional MRI) which are complex imaging methodologies, have just confirmed the well-known fact that the left hemisphere ([10, 41]) is an important factor in reading ability, without giving a clear answer to the initial question. With the same type of imagery, some authors investigate the link with dyslexia: for instance the role of the right hemisphere [55], the role of grey matter [53].
- Genetic origins: Some studies have shown evidence for a role of environmental factors markers on chromosome 1 and 2, without wide scale confirmation ([17]).
- From another viewpoint, according to [5], a gap in speed of processing between the different brain entities activated in the word decoding process may prevent the precise synchronization of information necessary for an accurate decoding process. This is known as Asynchrony Theory : confirmation of this theory is still required. See also [30].
- Very recently, two scientists [27] observed that asymmetry between two specific eye areas appear to be an essential condition for brain connectivity for normal development. By contrast, they suggest that the lack of asymmetry might be the underlying cause of reading and spelling disabilities in people with dyslexia, perturbing the connectivity of different regions in the brain and inducing commonly observed visual and phonological difficulties. Still, there is no consensus on this hypothesis in the scientific community despite the fact a company Lexilife (https://lexilife.com) sells a lamp LexiLight supposed to be a reading aid designed for dyslexics and is based on this asymmetry principle.
- A complete list of options can be found in [52] with exhaustive references of the theories up to 2004.

It is also admitted that gender has a role to play in the story (see for instance for large-scale investigation of at-risk readers[35]). The role of family has also been deeply investigated in [43], highlighting the fact that dyslexia could also be an heritable disorder. Finally, auditory problems have also been observed for many dyslexic children [23], without establishing a direct link. All these theories (some of them outdated) could be considered as partial explanations of dyslexia. Still a lot of work has to be done to get a clear understanding of what causes dyslexia.

In any case, at this stage of scientific knowledge, dyslexia is considered a lifelong disorder. Nevertheless, via an appropriate education strategy, we can help dyslexic children to cope with the difficulty, allowing them to implement compensatory strategies when confronted with reading difficulties. Obviously, this will give an external observer the misleading impression that dyslexia disappears with time. This is actually not the case! It is then paramount to diagnose dyslexia as early as possible.

1.2.3 Diagnostics: diverse approaches

Today, detecting dyslexia is a complex process: a professional is looking for many different indicators, intended to detect whether reading, writing and also calculus skills are being acquired at a proper rate. Still, at this stage, there is no unique way to do it [47]. Generally, reliable diagnoses can currently only be determined behaviourally and after some years of education, when the discrepancy between normal cognitive and reading abilities becomes apparent. The diagnostic is done via a battery of (mainly paper-based) tests. The process starts with a general questionnaire to acquire information regarding medical history, social environment, school performances, etc. This is mainly a self-report which can be supervised by the tutor. Then some abilities are tested and marked by the professional in charge of the diagnostic. This is where specific tests come into play. We provide below a brief non-exhaustive list of such tests:

- Language Skills test: for instance, measuring the child's ability to distinguish between real and nonsense words [51]. These words can be read aloud or displayed on a computer screen. Also, paying attention to the reaction time (RT) before starting to read a word, with the time required to say it, response duration (RD) [8].
- Verbal comprehension: obviously this type of test is age-related. For instance, trying to estimate the level of understanding by asking simple questions after the reading (aloud or not) of a short text. Also paying attention to responsiveness-to-instruction which could be a marker of dyslexia [12].
- Short-Term Memory Test: for instance, trying to estimate the number of digits (i.e. numbers and letters) a person can retain and recall. The participant has to retype these digits after the last one of a series has been presented.
- Some practitioners add IQ tests (often based on Raven's Progressive Matrices [6, 37]).
- Etc.

As we understand it, not only do the list of tests undertaken by the individual vary, but the protocol in implementing a test is itself subject to a lot of variations.

Nevertheless, the main conclusion is that it is possible to identify dyslexia with a relatively high reliability, although the exact causes of dyslexia are still unknown.

1.2.4 AI-based approaches

This is the main topic of this booklet: the new potential brought about by AI to diagnose[2] (or screen) dyslexia. Among the AI-based approaches to diagnose dyslexia, we can distinguish:

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[2] At this stage, it would be more appropriate to use the word screening instead of diagnostic. In the remaining of this booklet, we use the 2 words indifferently.

1. Approaches using the results of human-expert scoring to provide a diagnostic. In that case, the diagnostic process does not change a lot: still the user has to undertake a battery of tests and these tests are human-marked. From time to time, the marking can be computer-assisted to avoid/limit human reporting errors via the use of excel spreadsheets. When it comes to diagnosing children, it may be difficult to maintain their attention throughout the tests. An option is then to include all the tests in a serious game, allowing to better grab the attention of the participant. The final diagnostic is done via an AI algorithm.
2. Approaches taking as an initial assumption one of the theories explaining dyslexia. In that case, the AI algorithm is fed with data related to the underlying theory. In the case of neurological explanations for dyslexia, the authors use brain scans or EEGs to distinguish between dyslexic and non dyslexic people. In cases of oculo-motor deficits, the authors use eye-tracking techniques.
3. The approach like the one used by Dystech: monitoring observable symptoms and analysing the corresponding data.

These approaches will be presented in the following chapters, how they work and what is their current status.

1.3 What we do and what we do not do

It is very important to get a clear understanding of the scope of this booklet: what we do but also, what we do not do.

1.3.1 What we do

- Provide a complete overview of what has been done recently i.e. less than 10 years in terms of AI to diagnose dyslexia, both in terms of research and development,
- Refer to all works and tools which have received validation in the scientific literature with at least one peer-reviewed paper,
- Describe the current status of the works: still under research investigation or publicly accessible tools,
- Give the relevant links to access public tools when they are available.
- Dedicate a chapter to works, still not peer-reviewed, but which nevertheless provide interesting perspectives.

1.3.2 What we do not do

- Add our voices or opinions about the causes of dyslexia,
- Provide a complete overview of the literature about dyslexia,

- Consider works before 2010 as AI was not sufficiently developed at that time,
- Provide a list of available training and remediation methods.

1.4 Conclusion

Despite the fact that there is no clear explanation for dyslexia, professionals in the field are able to provide a diagnostic. Generally, this diagnostic is based on the (human) scoring of diverse tests. The complexity of administering paper-based diagnostic tools, and the time they require, have led the turn towards computer-assisted screening methods. At least, human reporting errors are drastically reduced with this assistance.

Still there is the issue of accuracy and human expertise variability. This is where AI might bring a final touch, providing high accuracy, and insuring the same diagnostic will be given when provided with the same data. Ultimately, with AI, there is the potential of designing a very accurate screening process with no human in the loop.

Chapter 2
Multi-tests approaches

Abstract Currently, for diagnosing dyslexia in early childhood, children have to undertake diverse tests. These tests are usually scored by human experts who ultimately decide whether the children require further consideration on the basis of their marks. As a consequence, one of the most straightforward ideas is to feed an AI algorithm with the results of these human-managed tests. Obviously, these tests can also be computer-assisted or game-based, avoiding the error-prone process of human reporting. The advantages are straightforward: this does not perturb the classical way to proceed and the algorithm is just responsible for the final diagnostic. When the tests are marked by an expert, the drawback is that there still is a human-in-the-loop, leaving some tracks of subjectivity which might distort the final result.

2.1 Main philosophy

The approaches considered in this chapter take as input the results of tests undertaken by the user. These tests can be:

- predefined tests as explained in the introduction. The tests at hand vary and are generally administered by an accredited professional. In this case, the tests can also be marked by the practitioner. Optionally a computer-assisted marking process is implemented.
- specifically designed computer-based tests capturing information relevant to dyslexia. In this case, there is no need for a professional except to supervise in the case of a child user.

Then the output of these tests are fed into an AI algorithm which ultimately provides a diagnostic as a likelihood of dyslexia (i.e. a number between 0 and 1).

2.2 Diagnosis of dyslexia with low quality data with genetic fuzzy systems (2010)

The work of [33] was supported by the Spanish Ministry of Education and Science and by Principado de Asturias.

The main idea is to use AI to automatically provide the final decision, based on the human expert's scoring. The main challenge is to reconcile uncertain or even conflicting information. Conflicts arise when experts assign different scores to the same set of answers, which is not uncommon. Finally, when there is doubt between different scores, it is comfortable to assign an interval of values instead of a single value (i.e. we consider the score on this test to be between 10 and 15 instead of giving an exact value of 14 for instance). In their work, the authors propose a specific algorithm able to cope with such uncertainty and impreciseness. This algorithm is part of a web-based, automated pre-screening application that can be used by parents for detecting these symptoms.

Methods and Results

The authors have collected data from 65 schoolchildren from Asturias province (Spain). All tests are in Spanish. Then they have applied their algorithm, able to cope with vague information. The use of genetic tools, with crossover and mutation, amounts to approximately 10,000 evaluations. All the datasets are publicly available on the website of the KEEL project (http://www.keel.es). KEEL stands for Knowledge Extraction based on Evolutionary Learning) and is an open source Java software tool that can be used for a large number of different knowledge data discovery tasks.

The work has been done with Spanish speaking children, but we feel that the method is still relevant whatever the language. The algorithm does not deal with the raw data but the scores given by human experts. So, provided that the same tests are undergone by the children, the method should still be accurate.

The main objective was, starting from low quality data, to obtain a system that could be used by unqualified personnel to detect whether a child has suspicious symptoms and then suggest consulting with a professional if needed. This objective is mostly achieved, but the percentage of errors remains high.

Available tools and conclusion

Despite the data being publicly available, as far as we know, there is no public tool available at the moment using this approach.

2.3 Computational Approach for Screening Dyslexia (2013)

The work of [7] has been supported by Associacao Nacional de Dislexia, Associacao Brasileira de Dislexia, Carlos Chagas Filho Foundation for Research Support of Rio de Janeiro State (FAPERJ) and CAPES.

The idea of the authors is to use only characteristics like personal history, language, education, disease, trauma, disorders, family history, etc. leading to 144 parameters to estimate. These parameters are acquired via face-to-face interviews with the participants. With this approach, there is no need for any test: as a consequence, the result of the algorithm is an estimation of the risk of dyslexia based on the social-cultural background of the user. As such, this is not really intended to be a diagnostic tool.

Methods and Results

The authors implement a neural network to distinguish between dyslexic and non dyslexic participants. Such networks are powerful tools for such binary classification tasks. Their experiences were implemented using a batch of 52 participants between 9 and 18 years old. They obtain an accuracy rate of 80%.

Available tools and conclusion

The authors have built a tool, namely DysDTool, developed via a client-server technology. But as far as we know, this tool has not been publicly deployed.

2.4 Diagnosis of Dyslexia using Computing Analysis (2017)

This work of [1] was supported by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah.

The input of the authors algorithm is constituted by the records of individual's results in what is known as the 'Gibson test'. Initially, the test was designed in 1999 by Dr. Ken Gibson. The test is supposed to identify cognitive performances. As such, the test (see https://www.thegibsontest.com/ for instance) provides a measure of some factors related to dyslexia as : effect of working memory, auditory (hearing and speech), visual memory and cognition, visual and auditory perceptions, writing and motor skills, math and time management, behavior, health, development and personality, etc.[1]

[1] Please note that the Gibson test is seriously contested as a valid cognitive skills estimator and has never been supported by peer reviewed research papers.

Methods and Results

Therefore the authors have implemented diverse classifiers to analyze their dataset that includes 80 children's records (between 7 to 13 years old).

Available tools and conclusion

There is no tool publicly deployed: the tool is still at a research stage.

2.5 Classification Techniques for Early Detection of Dyslexia Using Computer-Based Screening Test (2017)

This work of [42] was partially supported by Universiti Sultan Zainal Abidin, Terengganu Darul Iman, in Malaysia. The works of [42] starts from the same hypothesis as the previous work: it is possible to automatically distinguish between dyslexic and non dyslexic children by using the results of standard tests. The team has developed a tool called I-Dyslex: this system allows the collection of data with a computer, eliminating the need of a human expert at this stage. I-Dyslex consists of five modules: Reading, Spelling, Puzzle, IQ Test and Listening. A child has to undertake the 5 modules in order for the results to be fed to a classification algorithm.

Methods and Results

The participant cohort consisted of 49 students recruited either from the Dyslexia School located at Ampang or Showme Kids School located at Kuala Terengganu. An I-Dyslex module contains ten questions: the user needs to answer each question in sequence before going to the next module. This is supposed to avoid incomplete data. Such a session leads to 58 parameters. The whole process was assisted by a teacher. They got an accuracy in the range of 97% which is very good. Nevertheless, the very small size of the dataset does not allow to guess what would be the performance in the real world.

Available tools and conclusion

The results of [42] show that I-Dyslex tool allows the capture of data which is very discriminant on their dataset. This shows that the data collected using computer-based screening tests can be a very good alternative discriminating dyslexic children at an early stage. I-Dyslex is still an academic tool to acquire data in a controlled environment. At this stage, there is no publicly available diagnostic tool which could be added to I-Dyslex.

2.6 Screening Dyslexia for English Using HCI Measures and Machine Learning (2018)

The work of [39] has been supported by the US Department of Education and the National Science Foundation. The main idea is to observe how people interact with a linguistic computer-based game Dytective[2]. The game takes into account (i) the empirical linguistic analysis of the errors that people with dyslexia make, and (ii) specific cognitive skills related to dyslexia: Language Skills, Working Memory, Executive Functions, and Perceptual Processes.

Methods and Results

The participant cohort consists of 267 children and adults (from 7 to 60 years old). The first part of the study consisted of a questionnaire collecting demographic data. Then, all participants are exposed to the same linguistic items integrated into the online game Dytective and are given 20 minutes to complete the test. The model reaches around 85% accuracy when using the most informative features. Due to the small size of the cohort, it is not easy to guess the accuracy in the real world.

Available tools and conclusion

As far as we know, Dytective is available in English and Spanish on the app stores (free for a trial period):

- Apple (https://apps.apple.com/us/app/dytective)
- Google (https://play.google.com/store/apps/details?id=org.changedyslexia.newdytective)

Using the app, a session duration is between 10 to 20 minutes. A lot of information is given on their website https://www.changedyslexia.org/ (both in English and Spanish).

2.7 Can We (and Should We) Use AI to Detect Dyslexia in Children's Handwriting? (2019)

The works of [44] are original in the sense that they start from a quite different assumption. In fact, they build upon previous work which examined the potential of modern machine learning methods to identify possible indicators of dyslexia in handwriting. If we compare with the previous approaches using standardized tests, interviews or online sessions, handwriting samples are relatively easy to collect. On top of that, numerous researches in school psychology show that *reading is intimately*

[2] Dytective is a cross-platform web-based game available at https://www.changedyslexia.org.

connected to writing, and children who struggle to learn to read often struggle to write. So a handwritten document still has a substantial amount of information regarding dyslexia.

Methods and Results

They start from a dataset of 56 photos of handwriting samples of grades K-6, collected from parents. Using an off-the-shelf neural network, patches of handwriting are used as input and the network classifies the patch as either indicative of dyslexia or not. The experiments yielded 77.6% accuracy in determining whether a patch of handwriting was written by a second-grade student with dyslexia or not.

Available tools and conclusion

Right now, this work is still at the research stage. There is no publicly available tool.

2.8 Short conclusion

As we have seen in this chapter, there is still only a limited number of tools based on multi-tests to detect dyslexia. In the future, we can imagine that much more options will come, as the variety of available tests is endless.

Chapter 3
Serious games approaches

Abstract Developmental Dyslexia cannot be diagnosed before starting primary school simply because Dyslexia is observed at the reading stage of a child's learning. Therefore, it is still a challenge to obtain an early identification during preschool years. This is the aim of these works to create digital systems composed of various (serious) games whose output are used to provide a dyslexia risk. It is assumed that using a computer with mouse and keyboard, or a tablet with touch screen might be more attractive for young children.

3.1 Main philosophy

When it comes to (developmental) dyslexia assessment, one question immediately arises: can we avoid the boring tests, interviews, etc. usually needed by professionals? Especially, if we want to target a population of very young children (let's say under 7), it becomes crucial to design a data capture process which is sufficiently attractive so that children will display a higher motivation and a longer attention span. As a result, a more accurate measurement can be taken. Serious games are therefore natural candidates for this task. The serious game paradigm is well known: they maintain user attention just because it is a game! An early attempt has been done by [28], but it was before the effective emergence of AI. The works of [50] within the the DYSL-X project and the works of [13] are targeted to this aim: they designed serious games, dedicated to young kids, available on computers or tablets and allowing the measurement of some parameters characteristic of dyslexia.

3.2 DIESEL-X: A game-based tool for early risk detection of dyslexia in preschoolers(2015)

DIESEL-X is a computer game that was developed in [16] to detect a high risk for developing dyslexia in preschoolers. The game includes three mini-games that test the player on three skills that are considered to yield measurable outcomes that predict the onset of dyslexia: the detection threshold of frequency modulated tones, a test on phonological awareness in which the player has to identify words that have the same phonetic ending, and a test on letter knowledge. The duration of the test is more or less 1 hour. In order to keep the motivation of the player high enough during testing, these tests are embedded in a computer game. Nevertheless, these tools require a minimum of linguistic knowledge.

Methods and Results

Available tools and conclusion

The software was written in Unity for a very specific tablet (Samsung Galaxy), and is not suitable for other platforms. At this stage, there is no publicly available tool.

3.3 Towards the Prediction of Dyslexia by a Web-based Game with Musical Elements (2017)

The works of [36] have been supported by the National Science Foundation (NSF) and the National Institute on Disability, Independent Living, and Rehabilitation Research.

Several theories on the underlying cause of dyslexia are converging on the idea that one fundamental problem derives from abnormal neurological timing, or "temporal processing" [23]. As a consequence, music training, requiring very accurate timing skills, may help for the development and improvement of temporal processing skills (particularly in the auditory and motor domains) [32]. Reversing the reasoning, it becomes natural to think that observing children listening to music and getting some data from these observations could help to distinguish between dyslexic and non dyslexic children. As such, this way to proceed avoids a direct reference to letter knowledge or phonological awareness.

Starting from this assumption, [36] proposes DysMusic, a prototype which aims to predict the risk of having dyslexia before acquiring reading skills. The prototype was designed to observe children playing games, listening to music using the think aloud protocol, varying different acoustic parameters such as frequency, duration, or intensity, which relate with perceptual parameters such as pitch, loudness, or timbre. The game aims to detect differences in the perception of auditory elements for children with and without dyslexia.

Methods and Results

The participant cohort is 10, all German native speakers. At this stage, we understand that any figure in terms of accuracy would be meaningless.

Available tools and conclusion

One of the advantages of DysMusic could be language independence. If this is the case, it could be used by pre-readers. Today, there is no public tool available. Nevertheless, due to the very small number of participants in the experiments, it would be very ambitious to predict any figure in terms of accuracy for a real life application !

3.4 Serious Games for Early Identification of Developmental Dyslexia (2017)

The work of [14] has been supported by the MIUR/PRIN ALTER-NET 2009RC-PLRZ, the UNIPD/PRAT Web Squared projects, the CARIPARO Foundation and the University of Padua. Their games are similar to DIESEL-X (discussed above) but lowering the requirements for players and their equipment. For instance, there is no need to know the letters even if they appear on the screen. Each game is supposed to engage the child's diverse neuro-cognitive skills. Their set of 6 serious games, using 2D graphic design, are implemented to be accessible from any device, a computer with mouse and keyboard, but also a tablet with a touch interface for younger children.

Methods and Results

A cohort of 24 five-year-old (Italian) children attending the last year of kindergarten are included in the study. The cohort is divided into 2 groups: a No Risk (NR) group and a Risk (R) group. Children's performance are analysed with respect to each serious game. Then the authors compare the outcome from the 2 groups. It appears that some of the games can discriminate between the performances of the two groups, but not all of them, probably due to the small size of the participant cohort.

Even though the games were played by a limited set of children, they resulted in embodying a valid predictor of dyslexia since the NR and R groups have shown different performances.

Available tools and conclusion

[14] work is a step in a larger project: the authors would like to refine the set of games by adding new ones, involving other reading related skills such as visual-spatial attention for instance. They are also trying to validate the efficacy of the approach over a larger population of pre-readers. As far as we know, there is no publicly available tool at the moment.

3.5 Short conclusion

It seems that there is huge potential using serious games to diagnose dyslexia, and even more, to help dyslexic children after diagnosis. Their power lies in the fact that, when properly designed, they become addictive and are not anymore considered as a boring activity. So, they offer, more or less for free, a lot of input for any AI algorithm. Nevertheless, we are still in the infancy of this technology for dyslexia screening.

Chapter 4
Neuro-based approaches

Abstract Neuro-based works start from the widely admitted assumption that dyslexia is linked to a specific brain configuration, either in terms of anatomical shape or in terms of functional organisation. Then, it is a natural option to get brain information from both dyslexic and non dyslexic persons, during reading activity. This can be done via modern techniques of neuro-imaging, and then the input to an AI algorithm of 3D brain scans. Or by monitoring brain activity via an Electro-EncephaloGram (EEG): in that case the input of an AI algorithm are electric signals.

4.1 Main philosophy

4.2 Machine learning and dyslexia: Classification of individual structural neuro-imaging scans of students with and without dyslexia (2016)

This work of [46] is part of the Research Priority Program 'Brain and Cognition' at the University of Amsterdam and was supported by the Dutch national public-private research program COMMIT.

This is in line with previous works of [20] where brain measures are also used to detect dyslexia via statistical methods. In fact, [46] has also the ambition to shed some light on the correlation between brain anatomy and dyslexia, for instance by investigating the volume of grey matter. They found that some parts of the brain are more reliable for classification but there is no clear correlation with the volume of grey matter: studies show contradictory results on this topic.

Methods and Results

The first experience starts with a total cohort of 49 students (22 students with dyslexia and 27 students without dyslexia, all native Dutch speakers from 18 to 21 years old). Three dimensional whole-brain scans are acquired from each subject, each acquisition sequence lasting approximately 6 minutes. Using a standard classifier they achieved an overall accuracy of 80%.

Then, from a second and independent sample of 876 young adults of a general population, the trained classifier of the first sample was tested, resulting in a classification accuracy of 59% , showing a large decline in performance. In fact, their algorithm provides a large percentage of false alarms, i.e. many people without dyslexia are labelled with dyslexia.

Available tools and conclusion

The team is still working on a follow-up study. But due to the Covid 19 pandemic, they had to postpone some new experiments. As for now, there are no publicly available tools. Nevertheless, due to the highly technical nature of brain scanning, this method could only lead to tools usable in a medical environment.

4.3 Features and Machine Learning for Correlating and Classifying between Brain Areas and Dyslexia (2018)

The work of [11] has been supported by the Caesarea Rothschild Institute and by NVIDIA Corporation to the Neurocomputation Laboratory in Haifa, Israel.

The main idea is to monitor the brain activity of the participant during a session. Monitoring is triggered by brain activity and observed via Event Related Potentials (ERP) signals.

No human intervention is needed in the analysis process. This work also validates the assumption that the most of the differences between dyslexic and non dyslexic readers is located in the left hemisphere of the brain.

Methods and Results

The cohort of participants is constituted with 32 native Hebrew-speaking children of grades 6-7 recruited from two schools. Of these, 17 were selected on the basis of a previous diagnosis for dyslexia and 15 were verified as skilled readers. All participants performed a Lexical Decision Task, during which event-related potentials (ERPs) were elicited by the presentation of words and pseudo-words. Each subject was presented with a total of 96 moderate to high frequency words in the Hebrew language and 96 pseudo-words created by substituting 1-2 letters in the real words.

In this way, they increased the chances that the participant understood the word (or silently read it) before a decision. Participants had to judge whether the words seen (displayed on a computer screen) were meaningful or meaningless: so they do not need to read the words aloud on the screen. Pseudo-words were generated just by changing one letter in the "root" of the word. Brain activity is observed via Electroencephalographic (EEG) signals recorded using 64 scalp electrodes. Eye movements are also monitored by a separate electrode placed below the left eye. After proper pre-processing of their data (which are basically electric signals), the authors fed diverse machine learning based classifiers. The best one provides an accuracy close to 80%. Their methodology also allowed to confirm theories regarding the role of the left hemisphere in the reading process in developmental Dyslexia.

Available tools and conclusion

At this stage, there is no public tool available. Like the previous approach using brain imagery, using EEG to detect dyslexia can only be done in a medically controlled environment (at least in the current state of the technology).

4.4 Short conclusion

Detecting dyslexia by using information coming from the brain is just starting to appear. Due to the heavily controlled environment needed at the moment to capture the data, it is unlikely these will lead to a publicly available tool anytime soon. Nevertheless, they could shed a very serious light on the neurological underpinning of dyslexia.

Chapter 5
Eye tracking-based approaches

Abstract A small but significant part of the neuro-psychology community considers that dyslexia may have, among its causes, a dysfunction within the oculo-motor process. In this case, both eye fixations and saccadic[1] movements during reading activity are valid sources of information to distinguish between dyslexic and non dyslexic readers. Starting from this, some scientists within the AI community have developed screening tools based on the idea that dyslexic people's eye movements (during reading activity at least) depart from the ones of non dyslexic ones.

5.1 Main philosophy

The idea that tracking human eye movements could contribute some relevant information is not new. One of the most obvious applications within the automotive industry is when adequate cameras can detect if a driver is focused or not on his driving. Within the digital world, it helps to improve advertisements, announcements and product placements in various digital media [31]. Eye-tracking can even provide serious insight into perceptual/cognitive processes [34]. Despite the fact that the work of [22] tends to dismiss the oculo-motor dysfunction hypothesis of dyslexia, it is a fact that most studies today agree that there is a link between visual-attention and oculo-motor control during reading: see for instance [4, 21] for recent publications on this topic. From an AI perspective, it is then natural to monitor the eye movement of a user during reading activity. Gathering relevant information is done via eye-tracking devices. Providing this information as input to an AI algorithm will classify the reader as dyslexic or non dyslexic.

[1] A saccade is a quick, simultaneous movement of both eyes between two or more phases of fixation in the same direction.

5.2 Detecting Readers with Dyslexia Using Machine Learning with Eye Tracking Measures (2015)

The work of [38] has been supported by the US Department of Education, National Institute on Disability and Rehabilitation Research.

Taking into account the contradictory results coming from neuro-psychology literature, [38], considering that the vast majority of people with dyslexia have a language processing deficit, their eye movements simply reflect their difficulty processing language. As such, they might be a good indicator of dyslexia. People with dyslexia have longer reading times, make longer fixations, and make more fixations than readers without dyslexia. [38] gathers and uses these characteristics to train a machine learning model.

Methods and Results

The whole dataset is derived from the eye tracking monitoring of 97 subjects, all native Spanish speakers, with normal or corrected-to-normal vision, with ages ranging from from 11 to 54. During a session, each participant has to read 12 different texts with 12 different typefaces. The readings of each text are monitored using eye tracking devices. From each record, 12 features are extracted including:

- The number of visits: Total number of visits to the area of interest.
- The mean of visit: Duration of each individual visit within the area of interest (the text).
- And other related features.

Having pre-processed the dataset, a standard model is applied reaching 80.18% accuracy when using the most informative features.

Available tools and conclusion

Despite one of the authors being the founder of changedyslexia.org, selling a mobile app called Dytective, a dyslexia screening tool, no eye-tracking has been integrated so far in the Dytective app.

5.3 Screening for Dyslexia Using Eye Tracking during Reading (2016)

The work of [29] was supported by The Ulla and Ingemar Dahlberg Foundation, Sweden's Innovation Agency (VINNOVA), and The Promobilia Foundation.

The method involved in [29], similar in some sense to the previous one, originates from Kronobergsprojektet, a research project on reading development and reading disability in Swedish school children. The project has run between 1989 and 2010. Eye-tracking during reading was conducted on children in 3rd grade, and reading difficulties were assessed until adulthood. What makes the Kronobergsprojektet study unique is: 1) children were monitored over a long period of time and 2) the integrity of the recorded eye movement data.

Methods and Results

The experiments are based on eye tracking data from a cohort of 185 subjects participating in the project. Each participant (all Swedish speakers) has to read one and the same text presented on a single page of white paper with high contrast. For each session, using eye-trackers, the authors record a lot of numerical parameters among which, for a saccade for instance, the duration of the event, the distance spanning the event, the average eye position during the event, the maximum range between any two positions, etc. Having gathered all these data and properly pre-processed their data set, the authors have implemented a standard classifier showing a high degree of accuracy (around 96%). It is important to note that the model also takes into account the results from a battery of other common tests, such as rapid automatized naming, reading of non-words, etc. One interesting feature of the process is that the prediction can occur after as little as 30 seconds of reading for the user.

Available tools and conclusion

Starting from this approach, Lexplore (https://www.lexplore.com/) has been founded in 2016 in Sweden (originally known as Optolexia). They expanded to the United States in 2017. Lexplore is a web app that has to be downloaded on a computer. Simply plug in an eye tracker and external monitor to your computer and run Lexplore. A session is completed in about 3 minutes. Lexplore is currently being used by schools, tutors and therapists around the world. As far as we know, there is no mobile app currently available. The necessity to connect an eye-tracking device could be an obstacle for mobile development. But probably not for long !

5.4 DysLexML: Screening Tool for Dyslexia Using Machine Learning(2019)

The work of [3] is based on the same assumption as the previous works: eye movements during text reading can provide insights about reading disorders. The team has developed DysLexML, a screening tool for developmental dyslexia that applies various ML algorithms to analyze fixation points recorded via eye-tracking during silent reading of children.

Methods and Results

The participants cohort is constituted of 69 children, native Greek speakers. They examined a large set of features based on statistical properties of fixations and saccadic movements and identified the ones with prominent predictive power, performing dimensionality reduction. Specifically, it achieves its best performance using a linear SVM model, with an accuracy of 97%, over a small feature set, namely saccade length, number of short forward movements, and number of multiply fixated words. Furthermore, they analyzed the impact of noise on the fixation positions and showed that DysLexML is accurate and robust in the presence of noise. These encouraging results set the basis for developing screening tools in less controlled, larger-scale environments, with inexpensive eye-trackers, potentially reaching a larger population for early intervention.

They compare the performance of diverse standard classifiers. The best one achieves an accuracy as high as 97% on their data. It is also robust in the presence of noise.

Available tools and conclusion

As far as we know, there is no publicly available tools at the moment. The work is still under investigation.

5.5 Short conclusion

There is still only a very limited number of eye-tracking-based screening systems publicly available. This could be due to the relatively high cost of eye-trackers up to recently or to the relative complexity of a screening process involving an eye-tracking system.

Chapter 6
Dystech approach

Abstract One of the main symptoms of dyslexia is difficulty in reading. That is why Dystech has chosen to concentrate on the recording of reading in children (and adults) and to apply cutting-edge machine learning techniques to implement a predictor. As far as we know, this is the first time an approach using audio recordings has been implemented to predict dyslexia.

6.1 Main philosophy

The idea is to consider what can be easily observed from an individual, showing reading difficulties but without forcing a highly controlled environment or introducing external devices. One of these elements is to record people reading words. After gathering sufficient recordings, we run an algorithm to distinguish dyslexic readers from non dyslexic readers, just by analysing the audio records.

6.2 Detecting Dyslexia from audio records: an AI approach (2020)

Because one of the most obvious symptoms of dyslexia is difficulty in reading, it has been decided in [48] to only gather the reading of audio recordings, from both dyslexic and non dyslexic readers, then to apply machine learning algorithms. Instead of analysing images, brain signals, eyes movements, Dystech directly analyses audio signals i.e. small wav files. We agree that poor reading performance is not an ultimate marker of dyslexia, but Dystech results demonstrate that a dedicated machine learning algorithm associated with proper audio signal processing can extract patterns that are not accessible to a human expert.

Methods and Results

Every individual has to read 32 words (no sentences, only words). It is well-known that dyslexic children struggle when it comes to reading words they have never seen or heard. They have also difficulties with some letters, or combination of letters (*p* and *q* for instance) and certain syllables. Our initial corpus is coming from a set of 82 children's books extracted from the Gutenberg Project [18]. We clean the texts and remove proper nouns. We obtain a list of around 100 000 words. Then we produce two lists : one with words from 4 to 6 letters, one with words from 7 to 9 letters. In each list, we consider only words with high a frequency of occurrence to guarantee the words are known from children. After filtering, each of the two lists contains around 2000 words. In a second step, we create two lists of nonsense words. We also need to guarantee that the nonsense is pronounceable. In order to achieve that, we build a Long-Short Term Memory neural networks (LSTM) [19] that learn to build such nonsense words. We are then able to generate an infinite list of nonsense words[1]. As for the real words, we build two lists of nonsense words with different size (1000 nonsense words with 4 to 6 letters, 2500 nonsense words with 7 to 9 letters) and we keep only nonsense words that fit with the following constraints :

- Every subset of 4 consecutive letters exists in an English word (to guarantee the word is pronounceable)
- It contains difficult letters or difficult combinations of letters for dyslexic people.

The final list of 32 words to be read by the participant is obtained by choosing 16 words in the list of real words and 16 words in the list of nonsense words. These lists of words are randomly generated and are age-related: short words with simple syllables for children from 7 to 8, more difficult for children from 9 to 13, then most difficult for children over 14. It is then very unlikely that 2 sessions lead to the same list of 32 words[2]. Note that 50% of the words are displayed with the Times New Roman font and 50% are displayed with the Open Dyslexic font. At the moment, for every audio record, we consider 2 parameters:

- The Reading Reaction Time (RRT) is the interval between the initial display of the word and the start of the reading.
- The Reading Time (RT) is the time it takes for the participant to read the corresponding word.

RRT and RT evaluation is done via a computer (no human in the loop). Consequently, from a session of 32 audio records, we extract 6 numbers which will be used in our ML experiments:

- average RRT for 32 words, average RRT for 16 real words, average RRT for 16 nonsense words
- average RT for 32 words, average RT for 16 real words, average RT for 16 nonsense words

[1] We also use the expression 'generated words' because they are the output of an AI process.

[2] In fact, recently, we have decided to put at the end of the lists, 2 easy real words: it is better to finish a session on a positive tone!

With the help of speech pathologist partners, we set up a cohort of 93 users, among whom 43 are dyslexic and 50 are non dyslexic readers. All in all, we get 93 x 32 = 2976 audio records. We have compared the performances of state of the art classifiers: Logistic Regression (LR), KNN, SVM with polynomial kernel (SVC), SVM with linear kernel (LSVC), Naive Bayes NB, Random Forest (RFC) and Decision Tree (DTR). The best results are obtained by the neural network that Dystech has designed. The network, providing an accuracy of more than 80% could probably be tuned to get better performances. But due to the relatively small available cohort, this could lead to overfitting without giving a clear picture of the accuracy in a real environment. This could be partially overcome by considering more data. This method satisfies the requirements needed to build a mass market screening tool:

- We focus on the human observable symptoms of dyslexia,
- We do not use any other data than the audio records,
- We do not use any external device to gather data,
- A screening session is between 10 to 15 minutes long.

Available tools and conclusion

At the moment, Dystech has 2 versions of its predictor:

- One version, Dyscreen is available on the app stores (Google and Apple) for free. This app delivers a free screening for Dysgraphia [40], by analysing a sample picture of a handwritten text as well as a 20USD screening of dyslexia starting from 32 audio records. The result is provided instantly at the end of a session. The user receives a PDF report giving the full details of what has been done.
- One version is a web application available only on a computer equipped with a microphone. The web application is accessible via the link dyscreen.dystech.com.au. This web version does not produce a screening for dysgraphia and focuses only on dyslexia. The algorithms used with the web application are the same as the ones used for the app store app. An instant prediction is given and a full PDF report is provided to the user.

6.3 Short conclusion

This is a matter of fact that machine learning techniques are much more advanced when it comes to dealing with pictures. Analysis of audio signal is still a relatively recent topic for the ML community and we can expect a lot of improvements in the coming years. This could explain why Dystech seems to be the only company dealing with audio records to predict dyslexia. In any case, getting more data and the introduction of other parameters like reading errors for instance should lead to a better accuracy.

Chapter 7
Non peer-reviewed approaches

Abstract In this chapter, we focus on real systems, which are not (yet) backed by a peer reviewed paper related to dyslexia but which are at least clinically validated to a certain extent. We leave apart the systems using a computer-based battery of tests or questionnaires without introducing a new algorithm on top. They are just the digital transcription of human expert tests, and predictions are usually based on statistics. We target recent systems (less than 10 years old) which bring new algorithms on top of the data they capture from a user.

7.1 Main philosophy

There is a lot of Dyslexia Screening Assessments available on the net. One can see for instance https://www.bdadyslexia.org.uk or even http://dyslexiahelp.umich.edu which provides a comprehensive and well organised list of tests commonly used to diagnose dyslexia and language disorders from preschool through adulthood. Few of them are AI-based. And few of the AI-based ones are formally peer-reviewed. Obviously, when there is no peer-reviewed paper or not even a white paper on the web site of a company, it is quite difficult to get a clear understanding of the algorithm they use. Nevertheless, when there is an academic environment available, or when the company is supported by a well-known university, we may consider that the product is innovative and with solid foundations. These are the works we investigate below.

7.2 Oppimi group

The Oppimi group, founded in 2015 and based in Montreal, Canada, provides a fair amount of information on their web site: https://oppimi.org/. Their tools are supposed to tackle diverse learning disorders such as dyslexia, dysgraphia, ADHD, etc. They have established collaboration with Chinese and Italian universities and have been able to test their approach on large populations.

In terms of dyslexia, they propose a complete solution to help diagnose and support efficient dyslexia treatment. Via a series of games including handwriting, cognitive and fine motor skills exercises, they capture data which help to provide accurate feedback about childrens' abilities.

They also claim that their ML based algorithms 'are able to understand the needs of every kid and customise the tasks based on them, in order to personalise the treating phase and make it more efficient'.

Available tools and conclusion

Everything can be found on their web site https://oppimi.org/. They provide different platforms for doctors, parents, kids, and data collection. There is a web app also usable on tablets.

7.3 EarlyBird Education

EarlyBird shares an aim with Oppimi Group: early detection of literacy challenges. Founded in 2018 by a research team at Boston Children's Hospital (USA), the EarlyBird tool is mainly based on Nadine Gaab research (https://www.gaablab.com/) on the best early predictors of reading difficulties. They have developed an app that uses a gamified, interactive storyline to assess a child on six early indicators of later reading performance. A session duration is relatively short: 15 to 20 minutes. The screening is designed to be self-administered: there is an auto-scoring program saving the time of the supervising teacher. Final diagnostic starting from the data gathered during a session is given by an algorithm designed by one of the co-founders Dr. Yaacov Petscher (Associate Professor of Social Work at Florida State University). At the moment, the prediction is not delivered immediately as they are testing automatic speech recognition algorithms.

Their first validation study examined 350+ kindergarteners in the Greater Boston area. They also collected data from other states (Missouri, Montana, New York, Louisiana, etc.) to examine the predictive accuracy of the app.

Available tools and conclusion

Everything can be found on their web site https://earlybirdeducation.com/.

7.4 Short conclusion

Despite not having been formally validated by a scientific reviewing, the works we have mentioned in this chapter are worthy of consideration. They bring innovative ideas to practice. If they succeed, we can guess they will get their peer-reviewed articles.

Chapter 8
And tomorrow?

Abstract AI as a candidate tool to establish an accurate screening of dyslexia is still in its early infancy. There is no doubt that very soon; such AI-based technologies will support the works of professionals in charge of diagnosis. Nevertheless, beyond the obvious benefits of AI-based approaches, the potential for misuse also exists.

8.1 Potential uses

By a large majority, the technologies described in the previous chapters were initially conceived to help dyslexic children, whatever the underlying technology. But we can think about other options such as:

- University students, i.e. individuals more advanced in their education, might also be undiscovered dyslexics. It appears that some students struggle more than their teammates just because they have dyslexia but have never been diagnosed. Many universities have a special department in charge of helping students with handicaps, and usually, dyslexia is considered such. A simple, easy to administer screening process will help in this matter, to provide appropriate supports.
- Helping adults still struggling with their dyslexic background in the workplace: team members, full of creativeness but sloppy and slow when it comes to paperwork, could have dyslexia. Having this information, a company could adapt its communication style and make workplace adjustments to provide precise and comfortable communication flow with dyslexic colleagues. Understanding why people struggle ultimately leads to acceptance.
- Justice departments equipped with an easy, fast, accurate and cheap screening tool, could get a clear idea of the proportion of dyslexic inmates. A better understanding of the potential correlation with dyslexia might help establish better politics for dyslexia management in the education process.

AI technology has the potential to bring such tools to life very quickly.

8.2 Potential misuses and weaknesses of AI

As it is often the case with new software, their weaknesses and potential misuses cannot be overlooked. These software were initially conceived to help people and are in no way intended to cause harm. Nevertheless, we can imagine adverse outcomes, coming from the inherent weaknesses of AI or bad human intentions such as:

- AI errors: While a false positive would refer a student for testing who may not need it, a false negative has more dire consequences. If that student has dyslexia but has been told he/she does not, that could prevent him/her from ever understanding their struggles with reading. This could then lead to wrong conclusions in terms of supports. Fortunately, those problems should be overcome as soon as enough data is available to ensure very high accuracy rates.
- Incomplete data: Whatever the experiences mentioned in this survey, all data used are neither completely clean nor representative of the real population. Remember that considering 10% of the world population is dyslexic, this leads to more or less 780 million people struggling to read (the world population is 7.8 billion as of August 2020 according to the most recent United Nations estimates - https://population.un.org). Not completely clean because we get misclassified samples (i.e. a sample coming from a dyslexic person who has been not detected as such). Not completely representative because the experiments use only small sample data coming from specific schools involving, for instance, mainly white children with college-educated parents. In such a case, we have no clean information about the effectiveness of the classifier outside a narrow slice of the population. Still such issue can be overcome by the collection of more data.
- Use outside of the intended use: For instance, such tools, due to their expected large availability, could be used by HR departments or employment agencies to get information about their staff and discriminate on the basis of screening results. This is similar to face recognition technology: it is difficult to know what usage will follow !

8.3 Final conclusion

Dyslexia became a scientifically established concept less than 200 years ago. On another side, usage of AI for dyslexia screening has been explored for less than 10 years. With the rate of AI development, there is no doubt that AI-based tools will belong to the day to day life of speech pathologists, teachers, neuroscientists, etc. very soon. Would it be for diagnostics, as this is the preliminary task, then, as a next step, to support adequate learning strategies.

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