IJESRT: 10(1), January, 2021 ISSN: 2277-9655

International Journal of Engineering Sciences & Research Technology

(A Peer Reviewed Online Journal)

Impact Factor: 5.164

IJESRT

Website: www.ijesrt.com Mail: editor@ijesrt.com

RESEARCHERID
THOMSON REUTERS

[Dhamija *et al.*, 10(1): January, 2021]
IC™ Value: 3.00

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

SCREENING FOR DYSLEXIA USING EYE TRACKING

Hemant Dhamija*[1] & Ajay K. Dhamija[2]
*[1]Birla Institute of Technology and Sciences, Pilani- Goa Campus, Pilani, India
[2]Defence Research & Development Organisation (DRDO), Delhi, India

DOI: Will get Assigned by IJESRT Team

ABSTRACT

Dyslexia is a neuro developmental reading disorder that degrades the speed and accuracy of word recogni- tion, and as a consequence, impedes reading fluency and text comprehension. Between 5 and 10 percent of the population are normally affected by it. It has long been known that the eye movements of dyslexic readers differ from those of typical readers. The dataset for this study has been taken from the dataset used by a similar study (Benfatto et al., 2016). The experiments reported by the authors are based on eye tracking data from 185 subjects participating in the Kronoberg reading development project, a longitudinal research project on reading development and reading disability in Swedish school children running between 1989 and 2010. For our present study, we use eye movement recordings made while the subjects were reading a short natural passage of text adapted to their age. Recordings were available for 185 subjects, 97 High Risk (HR) subjects (76 males and 21 females) and 88 Low Risk(LR) subjects (69 males and 19 females

Machine learning based predictive model developed in this study employ feature set based on eye fixations and saccades parameters and can be used to give individual level diagnosis with high sensitivity and specificity. Using statistical cross-validation techniques on a sample of 97 dyslexic and 88 control subjects, we achieve a classification accuracy of over 96% with balanced levels of sensitivity and specificity. Diagnostic follow-up of a screening result is always necessary so that intervention strategies can be personalized. Nevertheless, early identification of individuals in need of support is the first important step in this process and using eye tracking along with this system during reading may prove very useful. The system's accuracy can be further enhanced by collecting a larger sample and then training these and other classification models.

KEYWORDS: Dyslexia; Eye tracker; Naive Bayes' Classifier; Decision Tree; Random Forest; Gradient Boost; XGBoost; Saccade; Fixation.

1 INTRODUCTION

Dyslexia is a neuro developmental reading disorder that degrades the speed and accuracy of word recognition, and as a consequence, impedes reading fluency and text comprehension. Between 5 and 10 percent of the population are normally affected by it. (Habib, 2000; Sandak et al., 2004; Shaywitz and Shaywitz, 2005). Such estimates, however, depend on the definition and criteria used for diagnosis. Dyslexia is best considered a difficulty along this continuum with no defined limits. Dyslexia is known to occur in varying degrees of severity, and therefore, a subjective cutoff needs to be set on a continuous variable for proper diagnosis. The only way of cure for kids with reading difficulties is early identification and knowledgeable skilled support. It's very difficult to handle once we recognize youngsters formally diagnosed with a learning disability (Casalis, 2004; Siegel, 2006). Although the disorder varies from person to person, trouble with accurate and fluent reading, spelling, and phonological processing are some common charac- teristics among people with dyslexia (Vaughn et al., 2010). Instead of the paper-pen based tests which can take lot of effort and time, our data mining system provides a better and more accurate approach for screening the child using computers and eye tracker device. If it is diagnosed early, it is very difficult to catch up to grade level in reading because the problems associated with dyslexia usually interfere with overall school performance and cause psycholog- ical and emotional distress, amplified by low self-esteem, lack of motivation and depression (Alexander-Passe, 2006, 2010). Therefore, it is imperative to have an early diagnosis, especially in the context of rural India.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

It has long been known that the eye movements of dyslexic readers differ from those of typical readers (Rubino and Minden, 1973; Elterman et al., 1980; Olson et al., 1983; Rayner, 1985). The system designed in this study will prove to be an effective tool for early and more objective diagnosis. Machine learning based predictive model developed in this study can be used to give individual level diagnosis with high sensitivity and specificity. Using statistical cross-validation techniques on a sample of 97 dyslexic and 88 control subjects, we achieve a classification accuracy of over 96% with balanced levels of sensitivity and specificity.

2 OBJECTIVE

The aim of the study is to use the eye tracking measures which can be mapped to estimate the reading difficulties that helps in diagnosing dyslexia. The system showcases the significant differences in the eye movements of Dyslexic and control group. The system further categorizes the subjects based on their reading skill.

3 DATASET

The dataset for this study has been taken from the dataset used by a similar study (Benfatto et al., 2016). The experiments reported by the authors are based on eye tracking data from 185 subjects participating in the Kronoberg reading development project, a longitudinal research project on reading development and reading disability in Swedish school children running between 1989 and 2010. For our present study, we use similar dataset which icludes eye movement recordings made while the subjects were reading a short natural passage of text adapted to their age. Recordings were available for 185 subjects, 97 High Risk (HR) subjects (76 males and 21 females) and 88 Low Risk(LR) subjects (69 males and 19 females).

The Kronoberg reading development project adhered to the principles of the Declaration of Helsinki. Written informed consent was obtained from the next of kin, caretakers, or guardians on behalf of the children enrolled in the study.

The data of each subject is stored in separate file containing five columns namely, timestamp (in milliseconds), left eye X-coordinate, left eye Y-coordinate, right eye X-coordinate and right eye Y-coordinate. Recording has been done for 30-40 seconds for each subject. The last digit of the datafile gives details about the subject. Subjects with filename ending in 1 or 2 were reading disabled, Subjects with filename ending in 3 or 4 were controls, Subjects with filename ending in 1 or 3 were male and Subjects with filename ending in 2 or 4 werefemale.

4 APPARATUS AND STIMULI USED IN THE ORIGINAL STUDY

(As adapted from Benfatto et al. (2016))
A goggle-based infrared corneal reflection system, Ober-2TM (Formerly Permobil Meditech, Inc., Woburn, MA), was used to track eye position over time. It sampled the horizontal and vertical position of both eyes at the frequency of 100 Hz. Under well-controlled experimental conditions, the system afforded a spatial resolution of 5 minutes of arc along the horizontal axes, as per the manufacturer's specification. During recording, subjects wore a pair of lightweight (80g), individually adjustable goggles mounted on head in which four arrays of infrared transmitters and detectors were mounted and arranged in a square around each eye. To minimize head movements and to stabilize the viewing distance at 45 cm, a chin and forehead rest was added. Calibration was performed manually prior to each recording by setting the signal gain of each axis separately for each eye. Thus, first set was the gain for horizontal movements of the left eye and then the second set was the gain for horizontal movements of the right eye and so on for vertical movements (Information on whether or not monocular occlusion was used during the calibrations is not available. We have reasons to assume it was but cannot confirmthis.)

Every subject read one and the same text which was presented on a single page of white paper with high contrast. The text was distributed over 8 lines and consisted of 10 sentences with an average length of 4.6 words. The subjects were instructed to read the text silently and then to answer three questions about its content afterwards. The questions mainly encouraged the subjects to read for comprehension. The actual outcomes were not used in any step of our analysis.

5 Data Structures Design

a. **Fixation Detection:** Fixation is defined as consecutive samples with an inter-sample distance of less than a set amount of pixels (disregarding missing data.

arguments

- x - numpy array of x positions
- y - numpy array of y positions
- time - numpy array of EyeTribe timestamps

keyword arguments

- missing - value to be used for missing data (default = 0.0)
- maxdist - maximal inter sample distance in pixels (default = 25)
- mindur - minimal duration of a fixation in milliseconds; detected fixation cadidates will be disregarded if they are below this duration (default = 100)

returns

- Sfix - list of lists, each containing [starttime]
- Efix - list of lists, each containing [starttime, endtime, duration, endx, endy]

b. **Saccades Detection:** Saccade is defined as consecutive samples with an inter-sample velocity or acceleration of over a velocity threshold or an acceleration threshold.

arguments

- x - numpy array of x positions
- y - numpy array of y positions
- time - numpy array of tracker timestamps in milliseconds

keyword arguments

- missing - value to be used for missing data (default = 0.0)
- minlen - minimal length of saccades in milliseconds; all detected saccades with len(sac) < minlen will be ignored (default = 5)
- maxvel - velocity threshold in pixels/second (default = 40)
- maxacc - acceleration threshold in pixels / second**2 (default = 340)

returns

- Ssac - list of lists, each containing [starttime]
- Esac - list of lists, each containing [starttime, endtime, duration, startx, starty, endx, endy]

Regression Detection: Backward saccade is called as regression. The detection is similar to saccade detection except that ending X or Y coordinates are less that starting X or Y coordinates.

6 RESEARCH DESIGN

Classification Methods: Five classification methods are used and compared in this study

- Naive Bayes' Classifier: These are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong naive independence assumptions between the features.
- Decision Tree: A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules.
- Random Forest: It consists of a large number of individual decision trees that operate as an ensemble. Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction
- Gradient Boost: An ensemble is just a collection of predictors which come together (e.g. mean of all predictions) to give a final prediction. The reason we use ensembles is that many different predictors trying to predict same target variable will perform a better job than any single predictor alone. Ensembling techniques are further classified into Bagging and Boosting. Bagging is a simple ensembling technique in which we build many independent predictors/models/learners and combine them using some model averaging techniques. Example of bagging ensemble is Random Forest models. Boosting is an ensemble technique in which the predictors are not made independently, but sequentially. This technique employs the logic in which the subsequent predictors learn from the mistakes of the previous predictors. The predictors can be chosen from a range of models like decision trees, regressors, classifiers etc. We need to choose the stopping criteria carefully or it could lead to overfitting on training data. Gradient Boosting is an example of boosting algorithm. Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak

prediction models, typically decision trees.

- XGBoost: XGBoost is an implementation of gradient boosted decision trees designed for speed and per- formance induced by parallelization, hardware optimization and tree pruning. In prediction problems involving unstructured data (images, text, etc.) artificial neural networks tend to outperform all other algorithms or frameworks. However, when it comes to small-to-medium structured/tabular data, decision tree based algorithms are considered best-in-class right now.

The sample of 185 subjects is randomly divided to training set (70% of the subjects) and test set (30% of the subjects). The model is trained on the training set in order to isolate the pertinent features. Finally, the prediction accuracy is found on the test set. The sensitivity and specificity of the model have also been worked out for better picture.

7 RESULTS

Following are the interesting metrics, which are generally explored in the study.

a. **Fixation Count:** Number of fixation points in the dedicated region of the text in the grid.
b. **Fixation Duration:** The duration of each fixation points in the dedicated region of text in the grid.
c. **Regression:** Eye movement between two fixations is termed as saccade. Backward saccade is called as regression.
d. **Scan Path:** It is the path of eyes when scanning the visual field and viewing and analyzing any kind of visual information.
e. **AOI:** It is a tool to select sub regions of the displayed stimulus and to extract metrics specifically for these regions

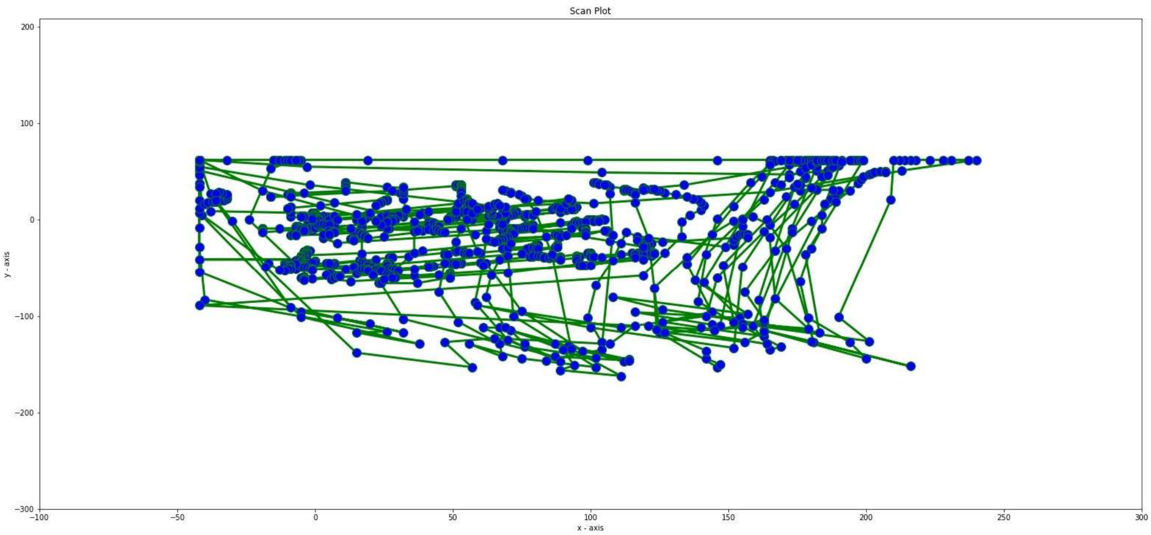

Figure 1: Normal Subject, LeftEye

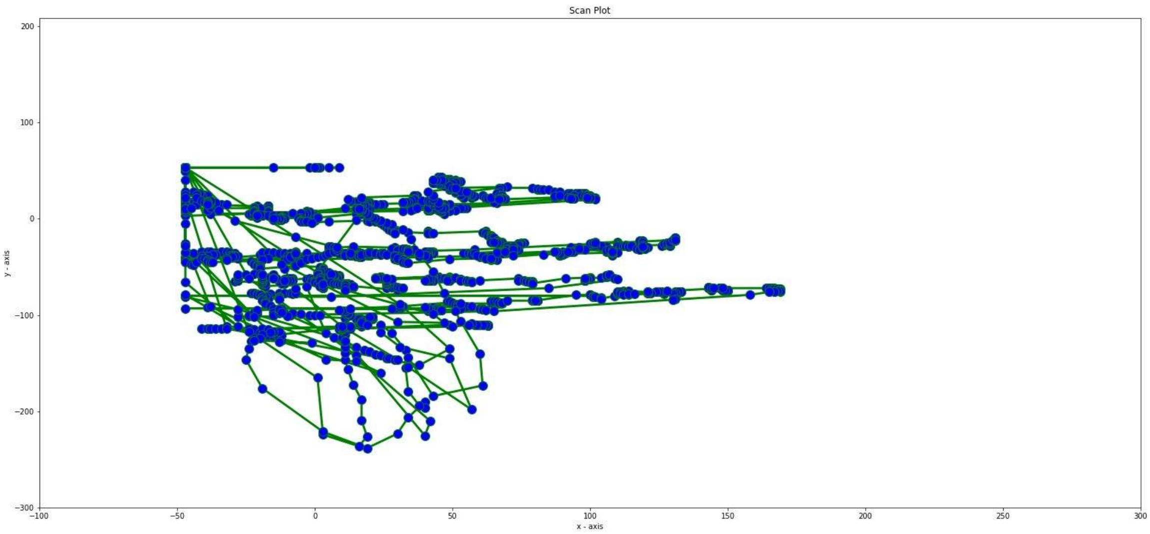

Figure 2: Dyslexic Subject, LeftEye

Figures 1 and 2 show the left eye patterns of a normal and a dyslexic subject. Figures 3 and 4 show the right eye patterns of a Normal and a dyslexic subject. The differences between the normal and dyslexic subject isclearly visible in the sense that dyslexics tend to have more regressions, fixations of longer duration and more number of fixations. Their eye movement is very random where as normal readers have their eye movements along the text.

The results of the experiment are displayed in Table 1. Naive Bayes' method gave an accuracy of 92.86% with sensitivity and specificity of 0.97 and 0.89 respectively. Sensitivity (also called the true positive rate, the recall, or probability of detection in some fields) measures the proportion of actual positives that are correctly identified as such (here, the percentage of dyslexic subjects who are correctly identified as having the condition). Specificity (also called the true negative rate) measures the proportion of actual negatives that are correctly identified as such (here, the percentage of healthy people who are correctly identified as not having the condition). Decision Tree method.

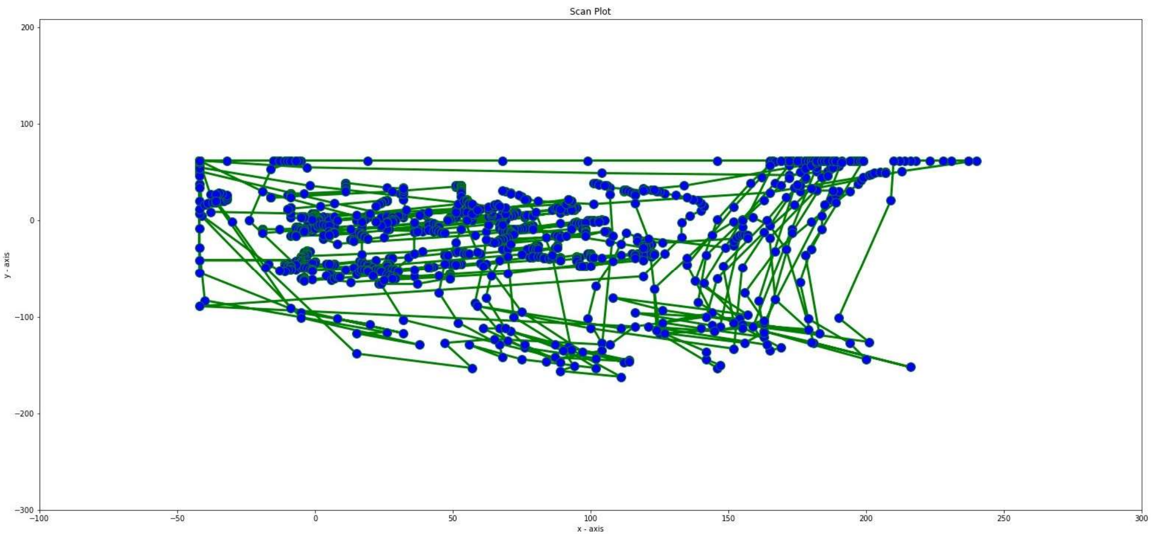

Figure 3: Normal Subject, Right Eye

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

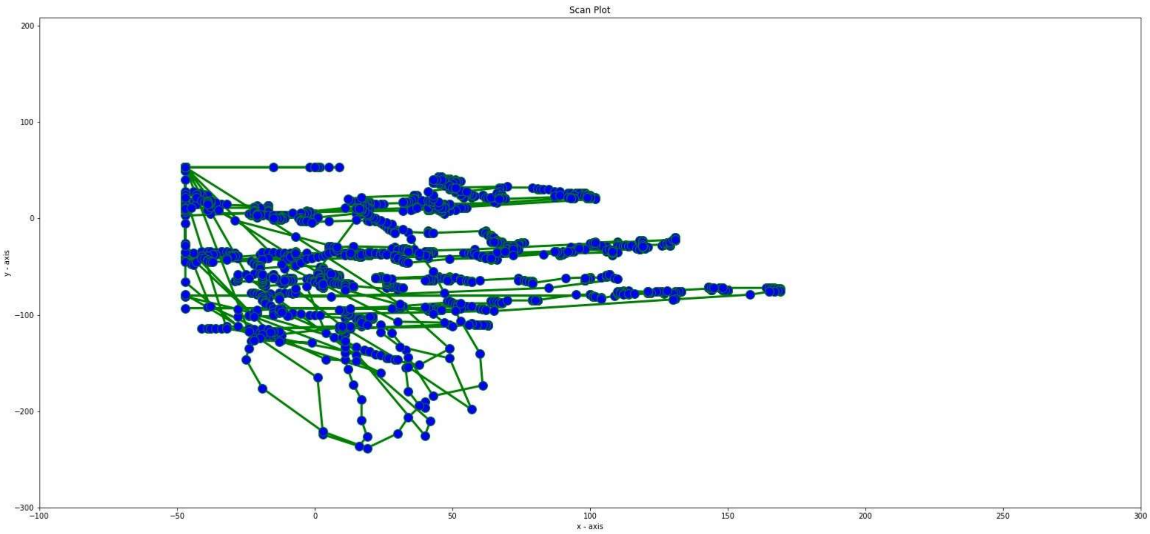

Figure 4: Dyslexic Subject, Right Eye

gave an accuracy of 92.86% with sensitivity and specificity of 0.90 and 0.96 respectively. Decision Tree method gave an accuracy of 92.86% with sensitivity and specificity of 1.00 and 0.89 respectively. Gradient Boost method gave an accuracy of 96.43% with sensitivity and specificity of 1.00 and 0.93 respectively. XGBoost method gave an accuracy of 94.64% with sensitivity and specificity of 1.00 and 0.88 respectively. Therefore, the best in class method is Gradient Boost method which correctly classifies over 96% of the subjects. We can see that all the Dyslexic subjects are correctly classified and 93% of the normal subjects are correctly classified. Therefore, the both the sensitivity and specificity of the system are high.

8 CONCLUSION

With the available data set the classifier system has classified the subjects with over 96% accuracy. The accuracy of classifying dyslexic subjects is 100%. This can prove to be a useful screening tool for identifying dyslexia at the early stages.

9 DISCUSSION

Despite of the fact that the system is found to classify dyslexic subjects is 100% accuracy, follow-up clinical screening is necessary for diagnosis. It is important to emphasize that not all children who experience persistent difficulties in learning how to read fit in the same neuropsychological profile. There is considerable symptom overlap between dyslexia, ADHD and language impairment. It is also necessary to differentiate between different subtypes of dyslexia. Therefore, diagnostic follow-up of a screening result is always mandatory so that intervention strategies can be personalized. Nevertheless, early identification of individuals in need of support is the first important step in this process and using eye tracking along with this system during reading may prove very useful.

The only way to overcome dyslexia is through continuous reading practices or reading sessions. Through the eye-tracker and developed model, we can identify the words which are felt difficult by the students. Those words can be included in their practice reading materials and it helps to improve their reading skills and thereby helping students overcome dyslexia at an earlier stage. This can be used in schools. This system can further be used in counselling centers, clinics, hospitals for diagnosis purposes. The system's accuracy can be enhanced by collecting larger sample and then training these and other classification models.

REFERENCES

[1] Alexander-Passe, N. (2006, 11). How dyslexic teenagers cope: An investigation of self-esteem, coping and depression.
[2] Dyslexia (Chichester, England) 12, 256–75.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

[3] Alexander-Passe, N. (2010, 01). Dyslexia and depression: The hidden sorrow: An investigation of cause and effect.
[4] Dyslexia and Depression: The Hidden Sorrow: An Investigation of Cause and Effect, 1–349.
[5] Benfatto, M., G. Öqvist Seimyr, J. Ygge, T. Pansell, A. Rydberg, and C. Jacobson (2016, 12). Screening for dyslexia using eye tracking during reading. PLOS ONE 11, e0165508.
[6] Casalis, S. (2004, 01). The Concept of Dyslexia, pp. 257–273.
[7] Elterman, R., L. Abel, R. Daroff, L. Dell'Osso, and J. Bornstein (1980, 02). Eye movement patterns in dyslexic children. Journal of learning disabilities 13, 16–21.
[8] Habib, M. (2000, 12). The neurological basis of developmental dyslexia: An overview and working hypothesis.
[9] Brain 123 (12), 2373–2399.
[10] Olson, R., R. Kliegl, and B. Davidson (1983, 01). Eye movements in reading disability. Eye movements in reading
[11] : perceptual and language processes / ed. by Keith Rayner. - New York [u.a.] : Acad. Press, 1983. - (Perspectives in neurolinguistics, neuropsychology, and psycholinguistics), S. 467-479 .
[12] Rayner, K. (1985, 01). Do faulty eye movements cause dyslexia? Developmental Neuropsychology - DEVELOP NEUROPSYCHOL 1, 3–15.
[13] Rubino, C. and H. Minden (1973, 07). An analysis of eye-movements in children with a reading disability. Cortex; a journal devoted to the study of the nervous system and behavior 9, 217–20.
[14] Sandak, R., W. E. Mencl, S. J. Frost, and K. R. Pugh (2004). The neurobiological basis of skilled and impaired reading: Recent findings and new directions.
[15] Shaywitz, S. and B. Shaywitz (2005, 07). Dyslexia (specific reading disability). Biological psychiatry 57, 1301–9.