Evaluation of DysLexML; A Screening Tool for Dyslexia Using Machine Learning

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***Abstract*—Eye movements during text reading can provide insights about reading disorders. Via eye-trackers, we can measure when, where and how eyes move with relation to the words they read. Machine Learning (ML) algorithms can decode this information and provide differential analysis. In our earlier work[1], we 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. We had evaluated its performance using measurements collected in the first systematic field study with 69 native Greek speakers, children, 32 of which were diagnosed as dyslexic by the official governmental agency for diagnosing learning and reading difficulties in Greece. In that field study, the measurements were collected using a custom-made eye-tracker developed by Medotics AG[2]. Here, we evaluate our system using a larger dataset from the second field study which consists of 135 children, 62 of which were diagnosed as dyslexic. In both works, we 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.**

I. DysLexML

The main modules of the DysLexML algorithm include the feature extraction, the feature selection for identifying the dominant features, and its classifiers that employ these dominant features. DysLexML extracts general (non-wordspecific) features and word-specific ones that take into account the word the subject is looking at. Examples of non-word specific features are the number of fixations on the screen, mean and median duration of fixations and related to saccades, the mean and median length of saccades, i.e., the Euclidean distance between consecutive fixations, and characterization of the types of eye movements. DysLexML creates a feature vector of 35 features in total. DysLexML consists of two phases: It first employs the LASSO Regression five-fold cross-validation to identify the dominant features. Based on the dominant features, it applies various classification algorithms.

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[1]T. Asvestopoulou, V. Manousaki, A. Psistakis, I. Smyrnakis, V. Andreadakis, I. Aslanides, M. Papadopouli, "DysLexML: Screening Tool for Dyslexia Using Machine Learning" submitted at Eusipco, 2019

[2]I. Smyrnakis, V. Andreadakis, V. Selimis, M. Kalaitzakis, T. Bachourou, G. Kaloutsakis, G. D. Kymionis, S. Smirnakis, I. M. Aslanides, RADAR: A novel fast-screening method for reading difficulties with special focus on dyslexia., PLoS ONE, 2017.

II. PERFORMANCE ANALYSIS

Field Study: A commercial tracker was employed for the acquisition of data. The model of the eye tracker was the Tobii 4C eye tracker, and was designed and manufactured by Tobii AB. This tracker has 90Hz frequency, whether the tracker in our previous study was 60Hz. In addition, the use of chin rest is not necessary anymore, hence the participants can freely move their head making the procedure completely non-invasive. Moreover, this study is much larger than the previous one, almost double in participants number. We have acquired data from 135 participants in total, 73 of them classified as typical readers and 62 of them classified as dyslexics. All the participants were native Greek speakers and the age span was from 7 years old to 17 years old.

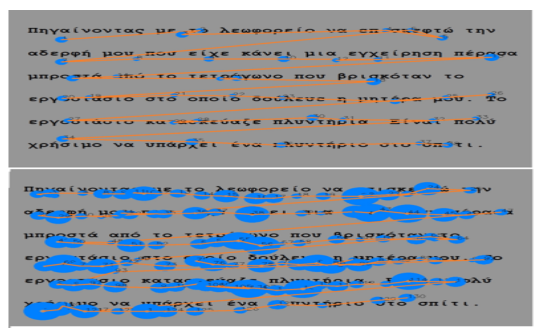

Fig. 1. Reading "path" from a typical reader (top) and from a reader with dyslexia (bottom). The blue circles are the fixations and the orange lines the saccadic movements. The larger the circle, the longer the fixation.

III. CONCLUSION

Our system achieves its best performance using linear SVM model, with an accuracy of 97% for the small dataset and 74% using the K-means algorithm for the larger dataset. This performance is achieved over a small feature set, namely saccade length, number of short forward movements, and number of multiply fixated words. Furthermore, we 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.