Chapter 15
Print ISBN: 978-93-91595-34-0, eBook ISBN: 978-93-91595-42-5

An Efficient Machine Learning Model for Prediction of Dyslexia from Eye Fixation Events

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DOI: 10.9734/bpi/naer/v10/11914D

ABSTRACT

Dyslexia is a type of learning disability in which a person has trouble spelling and reading words fluently. Dyslexia is not curable, but with the correct remedial help, dyslexics can achieve great success in school and in life. Eye movement patterns during the reading process can provide a deeper knowledge of dyslexia-related reading difficulties. Eye movements can be recorded with an eye-tracker, and the relationship between how eyes move in proportion to the words they read can be deduced. Based on statistical measurements, a collection of binocular fixation and saccade properties were derived from raw eye tracking data in this study. Based on statistical measurements, a collection of binocular fixation and saccade properties were derived from raw eye tracking data in this study. Machine learning algorithms such as the Random Forest Classifier (RF), the Support Vector Machine (SVM) for classification, and the K-Nearest Neighbor (KNN) for prediction of dyslexia were investigated to provide classification models for dyslexia prediction. In comparison to SVM and RF, KNN provided 95 percent accuracy over a small feature set associated to fixations and saccades. These characteristics of the eyes can be exploited to design screening tools for dyslexia prediction. Early detection of dyslexia can assist children in receiving treatment, allowing them to achieve academic success.

Keywords: Dyslexia; eye movements; KNN; RF; SVM.

1. INTRODUCTION

Emile Java was the first to report eye movements while reading in 1879. He was the first to notice that eye movements are not continuous, but rather follow diverse patterns, such as quick movements known as saccades and longer stops known as fixations.Since 1970, researchers have been focusing on the association between human eye movements and cognitive ability [1]. The introduction of low-cost personal computers prompted substantial research on a variety of user groups, particularly persons with reading difficulties.It is also commonly utilised by businesses to better their operations by gaining insight into their consumers' interests through their reading habits [2-4]. Eye movements are used for prediction of dyslexia, cognitive and Alzheimer. Machine learning techniques can be used to analyse eye movement patterns in order to better predict dyslexia [4,5].

Dyslexia is a unique learning problem in which a person with a high IQ finds it difficult to read fluently. Dyslexics have trouble matching the letters on a page to their sound, making it difficult for them to read and type words correctly. Dyslexia cannot be cured but when diagnosed earlier and given right remedial support can help them become successful [6,7,8]. Various computational models to prediction of dyslexia exist in literature but none of them are remarkable. The research done in this paper is to come up with a machine learning model for detection of dyslexia from eye movement reading patterns. This paper proposes to use statistical measures to derive the eye movements and

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features from the raw eye tracking data and develop a machine learning model for classification of dyslexia using these features and movements.

In the second section of this paper, relevant literature work carried out on eye tracking studies in dyslexia, medicine and other applications are discussed. The third and fourth sections of the paper discuss the data collection and methodology respectively. Fourth and fifth section shows the results of the experimentation and comparative analysis with other existing models. Sixth section discuss the conclusion of this research work

2. RELATED WORK

Eye movements of Chinese children both dyslexic and controls were observed while performing Stroop Color and Word test (SCWT). Eye Link II eye tracker was used to record the eye movements. It has been observed that Chinese dyslexic children show low accuracy and slow response time. Dyslexic children have abnormal eye movements such as a greater number of fixations and saccades, lower frequency fixations and short mean saccade distance. It has also been observed that dyslexic children have Visual Attention span disorder which contributes to abnormal eye movements [9-11].

A screening tool for Dyslexia has been built by recording the eye movements of children during reading silently. There are many features that correlate the eye movement with the words they read. A larger feature set was derived from statistical properties of fixations and saccades. Lasso regression is used for dimensionality reduction to get a lesser feature set that include median and mean of saccade length, count of short forward movements and total count of fixation words. Classification was performed using machine learningalgorithm SVM [12].

Eye movements were observed while performing letter naming speed test conducted on children with and without dyslexia. Naming speed is the ability to identify or name a set of letters quickly and accurately. Analysis of eye movements was done, and it has been observed that increased similarity in visual representation of letters decreased the speed of naming letters. Children with dyslexia were observed to have more pause times while reading, more fixations and more regression errors when compared to the control group. Pause times and fixation duration were observed to be primary predictors for reading [13].

In this work, prediction of reading mistake has been done from real world teaching using eye gaze features. Ensemble of different classifiers was used for classification. The data was collected in a noisy environment and have few missing data. The model has shown good performance even with noise. Fifteen features related to fixation where considered as major ones for prediction. This model can be used for personalizedtext simplification [14].

A study has been conducted to explore the association between eye movements and learning difficulties. It has been observed that the eye movement of dyslexic individuals shall contribute for difficulties in visual reading. It has been reported that the difference in eye movement pattern for dyslexics is because of visual magnocellular impairment. Magnocellular system plays a vital role in visual guidance of eye movements. However, this was tested on a small sample and if the child has other phonological and auditory disorders,it is hard to detect magnocellular impairment [15].

This work has studied saccadic movements vertically in dyslexic kids. Infrared video-oculography system is used to capture the left and right eye movement patterns It has been reported that dyslexic children have longer latency compared to control group. From the findings it has been suggested that impairment in cortical areas could be a cause of this abnormal vertical saccades' performance in dyslexics [16].

Screening of dyslexia from their eye movements and machine learning analysis has been done for prediction of dyslexia. Horizontal and vertical eye movements are recorded and analyzed using Support vector machine (SVM) algorithm. Feature reduction is done by using SVM- Recursive Feature Elimination (RFE) algorithm. Accuracy of94% has been achieved using linear SVM [17].

Poor binocular synchronization of saccades has been observed in dyslexic kids while performing single word reading test. Also, stereo type pattern is not observed in dyslexics as in control group. No proper divergence occurs during saccade movement and no proper convergence occurs at the end of the saccade. It has been reported that the reason for this abnormality could be due to deficits in ocular motor learning system [18, 19].

German dyslexics were compared to English dyslexics. Eye movements of 13-year-old boys were recorded while reading text passages and list of pseudo words. It has been observed for both the cases, dyslexics were observed to have more fixations and less regression. More the length of the word and more the complexity of word caused increased number of fixations in dyslexics than normal readers. Findings show that German dyslexics have fewer regressions compared to English and Italian dyslexics and this could be due to syllabic complexity of the German language [20, 21, 22].

This work explores the fixation visually in dyslexics and non-dyslexics. Binocular eye movements both horizontally and vertically were recorded. Fixations and saccadic movements have been reported that dyslexics have more unwanted saccadic movements when compared to the other two groups. This poor visual fixation ability in children may be because of poor attention skills and due to immature cortical areas, which is responsible for fixation control [23,24,25].

This works explores the difficulties faced by dyslexics in interpreting graph data. Dyslexics find hard to interpret graphs when compared to normal text because of their orthogonal deficits. They find difficult to process and interpret orthographic components of graph such as axes labels and legends. Dyslexics were able to interpret graph free of orthographic components [26,27-29].

2. DATA COLLECTION

Ober-2, eye gaze tracker is used for capturing eye movements. The eye position is tracked for almost a minute in milliseconds (t). The children were to read a passage that is appropriate for their age. The data used in this work was collected from the work of Benfatto, et al. [30]. The dataset contains raw recording data of 185 subjects studying grade 2. 97 were dyslexics and 88 were non-dyslexics.

3. METHODOLOGY

This research work comes up with a set of features that can be used for building an accurate prediction model for dyslexia. The proposed system architecture is shown in Fig. 1. A set of fixation and saccade related features were derived from binocular eye movement data using statistical measures.

A. Data Preprocessing

The data recorded by the eye tracker has five readings Lx, Ly, Rx, Ry, t. x and y denote the eye coordinates on the monitor of computer. Lx is left eye's x position, Ly is left eye's y position, Rx is right eye's x position, Ry is right eye's y position and t is time taken for reading in seconds. When the subjects blink, the data value will be set to blank.

B. Feature Selection

Feature selection is a process by which we can select data or attributes that contribute more for prediction or the output variable. Irrelevant and redundant features can reduce the accuracy of the predictive model. The main benefits of performing feature selection is to reduce overfitting and increases accuracy [31-35].

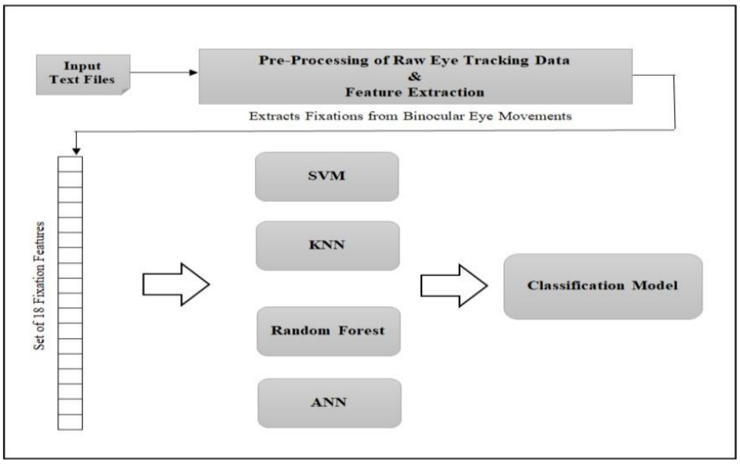

Fig. 1. Proposed System Architecture

In this work, Recursive Feature Elimination (RFE) and cross validated selection of best features is experimented. This method removes the irrelevant or redundant features recursively. A set of features related to fixation events were derived from the raw data using statistical measures. A fixation state is when the user gazes continuously at a point for a minimum of 80 milliseconds. The fixation related parameters must be measured both horizontally and vertically for both the eyes.

A. Support Vector Machines for Classification

SVM is a classification algorithm for both linear and non-linear data. Each piece of information is depicted as a vector of n-dimensions. For linear information, to separate all rows of a class, it draws an obviously maximum separating hyper plane. There may be several dividing lines, the one with the least classification error is the best hyperplane. By looking for maximum marginal hyper plane, SVM selectt he highest hyper plane. The margin provides the classes the biggest separation. It handles non-linear data by transforming in a greater order dimension the initial training data. For this new dimension, the linear hyper plane is being searched. For this mapping, the kernel function in SVM is helpful. Polynomial, linear, quadratic, radial basis task and Sigmoid are different kinds of kernels commonly used [36-39, 35,40-45].

Algorithm 1 Recursive Feature Elimination (RFE)

1: for each fold do
2: Partition the dataset into training and testing records
3: Train the model to learn the training set with all features
4: Predict the testing samples
5: Determine the importance of each feature
6: for each subset size Ki, i = 1. . . N do
7: Hold the Ki most relevant features
8: Train the model using these Ki features
9: Predict the testing samples
10: end for
11: end for
12: Calculate the accuracy of testing data
13: Select the number of features to be retained
14: Predict final list of features for the model
15: Fit the model based on the optimal Ki using the trainingset

Fig. 2. Recursive Feature Elimination Algorithm

SVM has been shown to operate better with standardized information. Our information ranges from – 1 to 1 and is therefore already standardized. In literature, SVM worked well with a small set of features for small datasets. SVM showed better predictive performance in disease prediction. Taking these inputs into account, SVM with different kernels such as linear, radial basis function (RBF) and sigmoid are chosen for experimentation this research work. The predictive accuracy achieved was 93.5%, 93% and 92% for linear, RBFand sigmoid kernels respectively.

Hybrid SVM-Kernel proposed in [30,40-45] which is a combination of linear and quadratic kernels was tested and gave an accuracy of 95 %.

B. KNN for Classification

KNN algorithm is widely used for both classification and regression problems. KNN algorithms classify new data points based on similarity measures such as distance function using the available data. Classification is done by majority voting technique to its neighbors. The data is assigned or labeled to the category or class which has the nearest neighbors. The main advantages of KNN are it is highly insensitive to outliers and does not make any assumptions about data. It works best with numeric and nominal values. In literature, KNN has been widely used in health care industry for prediction of diseases.

In this work, 5 fixation related features were given as input to KNN algorithm. The numbers of neighbors were chosen by trial and error method and the algorithm gave highest accuracy when the numbers of neighbors are 3. The predictive accuracy achieved was 95%. KNN out rated SVM and RF interms of accuracy.

E. Random Forest for Classification

Random forest learning model is an ensemble of decision trees that is widely used for classification problems. Random forest (RF) is a combination of bagging approach and random feature selection methods. It can identify critical variables from a big set of input variables. It is a random subspace method for constructing groups of decision trees called as decision forests. It uses bagging technique to construct every decision tree of the ensemble using sample with replacement method. The sample size is usually 64% of total instances with at least one instance in every sample. Instances in and out of a sample are called in-bag instances and out-of-bag instances respectively. Every tree serves as a base classifier for finding the class label of unknown instances. Class label is identified using majority voting technique where each classifier gives their vote for a class label. The unknown instance will be assigned to the class label with highest vote. This procedure is termed as random forest.

Random forests show improved accuracy in classification and regression problems. Main advantages of Random forest are its robustness in noisy data, and it does not cause over fitting. Over fitting refers to the model that is trained too well. It works well on training data but fails in testing data. An over fitted model show has less predictive performance due to lack of generalization. Generalization refers to the performance of the model in new data which is not part of training data. Over fitting degrades the performance of the model and adds unwanted complexity. Classification model that are over fit will tend to have less error rate in in-bag (training) instances and high error rate for the out-of-bag (testing) instances. Random forest overcomes the over fitting problem easily by averaging all the predictions to avoid biased results. Random Forest has been experimented in this work mainly to avoid over fitting as the dataset is small and Random forest have performed well in prediction of diseases.

4. RESULTS AND DISCUSSION

The experimental results of the current research work are discussed in this section. In this experimental set up, dyslexics belong to positive class and non-dyslexic to negative class. Performance is evaluated by using metrics such as False Positive Rate (FPR), sensitivity, specificity, recall and False Negative Rate (FNR). The classification model was trained using Support Vector

Machine, Random Forest Classifier, K-Nearest Neighbor and Artificial Neural Network. The results show that K-Nearest Neighbor Model and Hybrid SVM model used in this work achieved higher level of accuracy compared to Support Vector Machine and Random Forest. The comparative results of the experimented classification models are shown in Table 1.

Table 1. Classification results of different ML algorithms

	Machine learning algorithms					
			SVM		**KNN**	**RF**
	Linear	**RBF**	**Sigmoid**	**Hybrid**		
Accuracy	0.93	0.93	0.92	0.93	0.94	0.91
Precision	0.92	0.90	0.91	0.90	0.93	0.94
Recall	0.94	0.97	0.94	0.96	0.96	0.88
Specificity	0.92	0.87	0.89	0.88	0.92	0.94
F1 score	0.93	0.93	0.92	0.93	0.95	0.90

5. CONCLUSION

This research work identifies a set of fixation related eye features which can be used to develop a prediction model for dyslexia. Accurate prediction depends on the features which are used to build the prediction model. Hence this work focuses on identifying features that contribute for better prediction and, then build an appropriate prediction model. Fixations play a key role in prediction of dyslexia. In this work, features related to fixations were derived from raw eye tracking data. Different machine learning classifiers were experimented to develop a better predictive model for dyslexia. From the experiments on different ML algorithms such as SVM, KNN and RF, it is observed that KNN achieved highest accuracy of 95% compared to other models

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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This chapter is an extended version of the article published by the same author(s) in the following journal.
International Journal of Engineering and Advanced Technology (IJEAT), 9(1S3): 235-240, 2019.