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Developmental Dyslexia Detection using Machine Learning Techniques : A Survey

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Abstract

Developmental dyslexia is a learning disability that occurs mostly in children during their early childhood. Dyslexic children face difficulties while reading, spelling and writing words despite having average or above-average intelligence. As a consequence, dyslexic children often suffer from negative feelings, such as low self-esteem, frustration, and anger. Therefore, early detection of dyslexia is very important to support dyslexic children right from the start. Researchers have proposed a wide range of techniques to detect developmental dyslexia, which includes game-based techniques, reading and writing tests, facial image capture and analysis, eye tracking, Magnetic reasoning imaging (MRI) and Electroencephalography (EEG) scans. This survey paper critically analyzes recent contributions in detecting dyslexia using machine learning techniques and identify potential opportunities for future research.

Keywords: Dyslexia, machine learning, survey, EEG

1. Introduction

The word 'Dyslexia' is originated from the Greek language and it means difficulty with words. Dyslexia is a type of specific learning difficulty (SLD) in which a person has difficulty in fluently reading, spelling, and writing despite having average or above-average intelligence [1]. The Australian Dyslexia Association (ADA) [2] suggests that 10% of the Australian population are estimated to be affected by Dyslexia while the number raises up to 20% for other English speaking countries, such as Canada and the UK. Dyslexic children often suffer from anger, frustration, and low self-esteem [3]. Therefore, it is important to identify and take appropriate action to help dyslexic children at an early stage to overcome their learning difficulties.

Dyslexia can be classified as developmental or acquired [4]. The developmental dyslexia is often detected in early childhood, while the acquired one occurs due to brain injury or stroke. Researchers have proposed several techniques for detecting developmental dyslexia using data obtained from various sources, such as reading/writing tests, web-based word games, eye tracking while reading/writing, MRI and EEG scans, video and image capture while reading/writing. Recently, machine learning approaches have become popular in detecting dyslexia as they provide higher detection accuracy and better prediction outcomes. Although a few survey papers have addressed dyslexia detection techniques [3, 5, 6], their main focus is not machine learning approaches and they do not cover recent advancement in dyslexia detection using machine learning. This survey paper critically reflects on recent advancement in dyslexia detection using machine learning approaches and highlights the scope for future research.

2. Dyslexia Detection using Machine Learning

The detection of developmental dyslexia using machine learning techniques uses four steps: i) data collection, (ii) preprocessing, feature extraction and feature selection, (iii) system training and classification, and (iv) performance evaluation. Figure 1 shows a schematic representation of the steps which are discussed below.

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Article	Year	No of User	User's age	Language	Data type	Test Type	Machine learning Technique	Performance metric
Graphical models Lakretz *et al.* [7]	2015	313	7-62	Hebrew	Text	Reading	LDA and Naive Bayes	Accuracy, Perplexity
Detect readers Rello and Ballesteros [8]	2015	97	11-54	Spanish	Eye tracking	Reading	SVM	Accuracy
Eye-tracking Benfatto *et al.* [9]	2016	185	9-10	Swedish	Eye tracking	Reading	SVM	Accuracy
WM connectivity Cui *et al.* [10]	2016	61	10-14.7	Mandarin	MRI scans	Reading	SVM, logistic regression	Accuracy, sensitivity, specificity, PPV and NPV
Multi-Parameter Plonski *et al.* [11]	2017	236	8.5-13.7	French, German and Polish	MRI scans	Reading	SVM, logistic regression and random forest	Accuracy, and area under curve
DCS Khan *et al.* [12]	2018	857	7 (avg.)	Malay	Text	Reading	K-NN	Accuracy
Dytective Rello *et al.* [13]	2018	267	7-60	English	Text	Online game	SVM	Accuracy, precision, recall
ERP Frid and Manevitz [14]	2018	32	grades 6-7	Hebrew	EEG scans	Reading	SVM, Neural network	Confusion matrix
EEG pattern Perera *et al.* [15]	2018	32	≥ 18	English	EEG scans	Typing and writing	SVM	Accuracy, sensitivity, and specificity
Adaptive learning Hamid *et al.* [16]	2018	30	7-12	Malay	Video and image	Reading	SVM, Naive Bayes and K-NN	Accuracy
DysLexML Asvestopoulou *et al.* [17]	2019	69	8.5-12.5	Greek	Eye tracking	Reading	SVM, Naive Bayes and K-means	Accuracy, MSE
EEG local network Rezvani *et al.* [18]	2019	44	grade 3	Dutch	EEG scans	Reading	SVM and K-NN	Accuracy, sensitivity, specificity and precision
Handwriting Spoon *et al.* [19]	2019	150	grades k-6	English	image	hand-writing	Convolutional Neural Network	Accuracy

Table 1: Dyslexia detection using machine learning techniques

2.1. Data collection

The first step of dyslexia detection is to conduct a user study to collect user-data. For conventional dyslexia detection techniques, psychologists examine behavioral aspects of participants during standardized tests, such as reading and writing, phonological awareness and working memory. Dyslexic individuals are identified based on their

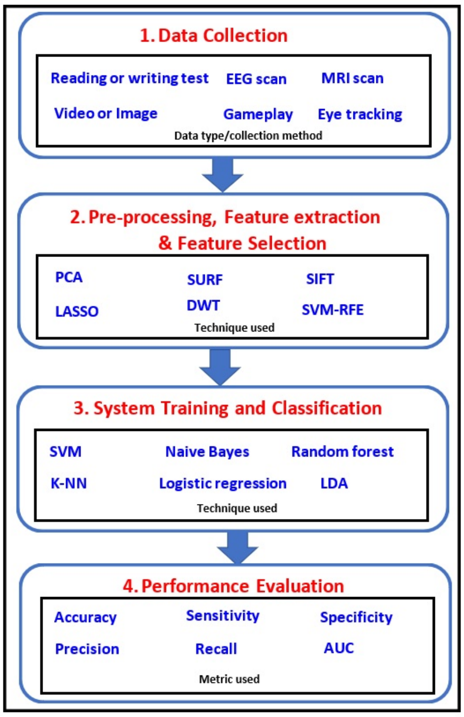

Figure 1. Steps of Dyslexia detection using machine learning techniques

poor marks in those tests. However, these techniques are often time-consuming and ineffective for a large group of participants as the symptoms vary across individuals. Therefore, machine learning approaches are used by researchers, which are less time consuming and often inexpensive . In this case, a wide range of tests, such as reading [7, 12, 17, 9, 8, 10, 11, 14, 18, 16], writing and typing [15], handwriting [19], and web-based game [13] are conducted to collect various types of data, such as text [7, 12, 15, 13], Eye-movement [9, 8, 17], MRI scans [10, 11], EEG scans [14, 15, 18], and image [16, 19]. The age of the participants varied within 7 to 62 while the native language of the participants across different studies were Spanish, Hebrew, Swedish, Mandarin, French, German, Polish, Malay, English, Greek, and Dutch. However, most of these studies were conducted in a specific language and hence a game-based language independent test [20] would be a better choice in this regard. Although a language-independent data collection is used in [20], it did not use any machine learning algorithm. A few approaches also require the use of customized tools, such as EEG headset [15], customized camera [17], infrared corneal reflection system [9], MRI scanner [10] and eye tracker [8] in a lab environment to collect EEG or MRI scan data. Although these approaches achieve higher accuracy, they are expensive, can only cover a small set of users and may result in participants behaving in an unusual way under observation or test environment. In this regard, computer based reading or writing tests along with game-based approaches can be more beneficial. Nowadays smart mobile devices are becoming popular and hence an app-based data collection technique will also help to reach a broader user base.

2.2. *Pre-processing, feature extraction, and feature selection*

The collected data needs to be pre-processed and filtered before being used in machine learning techniques. The first part of this requires converting the data into a quantitative (numbers) or qualitative (textual categories) format. To achieve this, EEG scan data requires to be converted to high pass and low pass filters. Different wavelet transform techniques are used in this case, e.g., Frid *et al.* [14] used discrete wavelet transform . Some of the studies also used manual pre-processing and feature extraction [16, 12] while other used tools, such as FreeSurfer [11], PANDA [10]. The purpose of pre-processing is to identify relevant attributes and remove null values. After pre-processing the feature extraction is completed where relevant features are identified and assigned a range of values. The values can be numerical or categorical. The number of features varied across different studies from 12 to 226 [8, 13]. The next step is to identify the set of dominant features that are more important for determining the class of the object. To achieve this, a few studies used manual selection [14] while others used techniques, such as least absolute shrinkage and selection operator (LASSO) [17] and SVM-RFE [9]. LASSO can be simultaneously used for improving accuracy and interpretability as it can simultaneously perform regularization and variable selection. They are suitable for regression models. On the other hand, SVM-RFE selects features considering their importance for SVM classifiers to separate classes. This technique starts with a full feature set and starts eliminating a number of features in consecutive iterations. Appropriate feature selection is an important task when the number of features is high due to the computational complexity. However, comparative performance analysis of different feature selection techniques is not presented in existing works.

2.3. System training and classification

After feature selection, system training and classification is conducted using machine learning algorithms. The dataset is divided into training and testing parts. Existing literature mostly used 10-fold cross-validation where the dataset is divided into 10 equal parts, and 9 of them are used for training the algorithm while the other set is used for testing its performance [8, 11, 13] while others used a different split (e.g., five-fold [17], leave-one-out-cross-validation (LOOCV) [18, 10, 11], and 70-30 [12]). Since the training dataset already contains the class information, i.e., dyslexic or non-dyslexic, the supervised classification algorithms are used for testing purposes. Existing studies mostly used support vector machine (SVM), Naive Bayes, Logistic regression, Neural network, K-Nearest Neighbour (K-NN) and Linear discriminant analysis (LDA) as the machine learning algorithm to classify participants. SVM was the most common algorithm used across multiple studies. Since the problem is essentially a binary classification problem, i.e., identify dyslexic and non-dyslexic users, SVM is expected to provide good performance when the number of dimensions is higher than the number of samples, and the feature space is sparse. However, the interpretation of SVM is a complex task and it does not perform well when the dataset has more noise. On the other hand, a method such as logistic regression is easier to implement and understand and expected to provide a very good solution for binary classification problems. Overall, the selection of appropriate classification techniques would essentially depend on the data itself and hence studies should produce a comparative performance to show the outcome of different machine learning models rather than reporting the performance of a selected one. In this regard, application of ensemble methods can also be beneficial to achieve better performances.

2.4. Performance evaluation

Existing literature used MATLAB, WEKA, and python based tools for performance evaluation. In this case, different metrics were used for evaluating the performance of dyslexia detection techniques using machine learning approaches. This includes accuracy, sensitivity, specificity, precision, recall, mean square error (MSE), positive predictive value (PPV), negative predictive value (NPV) and area under the receiver operating characteristic (ROC) curve. Accuracy measures the number of correctly classified objects to the total number of objects while sensitivity and specificity measures the ratio of correctly identified dyslexic and non-dyslexic users, respectively. Precision or positive predictive value refers to the fraction correctly identified dyslexic users with respect to the total number of identified dyslexic users while recall is the fraction of the total amount of dyslexic users that were correctly identified. EEG-based methods achieved 60-80% accuracy in different works [15] while MRI scan-based method achieved an accuracy of 83.61% [10] and the game-based technique achieved an accuracy of 80.24% [8]. Overall, it would be interesting to see how the performance of these techniques changes if data from multiple sources are combined together . Table 1 highlights different aspects of the techniques proposed for dyslexia detection using machine learning approaches.

3. Future direction and conclusion

Dyslexia is a learning disability and affecting about 10% of the world population. It is highly important to identify dyslexic children at an early stage to provide them with appropriate learning facilities. Researchers have proposed several techniques to identify dyslexic children. This paper summarized existing dyslexia detection techniques that use machine learning approaches. Although these approaches attain acceptable accuracy and success rates, their performance can be further improved. In this regard, the collection of data from multiple sources (e.g., image, text, game and scans) can be combined to make the prediction models work better. The development of a language-independent data collection method would also be helpful in this case. It would be interesting to see the impact of ensemble methods where prediction from multiple models are combined together to improve accuracy of machine learning techniques. Overall, a combination of the above-mentioned techniques is expected to provide better results in detecting dyslexia.

Conflict of interest

The authors declare that there is no conflict of interest in this paper.

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