

Method for Dysgraphia Disorder Detection using Convolutional Neural Network

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ABSTRACT

This paper describes a method for dysgraphia disorder detection based on the classification of handwritten text. In the experiment we have verified proposed approach based on the conventional signal theory. Input data consists of the handwritten text by dysgraphia diagnosed children. Techniques for early dysgraphia detection could be applied in the schools to detect children with a possible diagnosis of dysgraphia and early intervention could improve their lives.

The main goal of research is to develop a tool based on a machine learning for schools to diagnose dyslexia and dysgraphia. An experiment was performed on the dataset of 120 children in the school age (63 normally developing and 57 dysgraphia diagnosed). The main advantage is the simple algorithm for preprocessing of the raw data. Then was designed simple 3-layers convolutional neural network for classification of data. On the test data, our model reached accuracy 79.7%.

Keywords

Dysgraphia, Convolutional Neural Network, Machine Learning, Spectrum

1. INTRODUCTION

Dysgraphia is a learning disability characterized by problems with writing. It is estimated that 4 – 20 percent of the population has issues connected to writing. It is a neurological disorder that can affect children or adults. It can manifest at different ages with different symptoms. However, it usually occurs

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when children learn to write. In addition to writing hard-to-read words, people with dysgraphia tend to use the wrong word for what they are trying to communicate. Individuals who can potentially be diagnosed with dysgraphia will exhibit certain symptoms, such as irregular or slow writing; difficulty moving their hands across the writing surface; manipulation of the writing instrument is often incorrect; inadequate body positions when writing; or excessive leaning over the written text [DBC20, MFM16]. Moreover, typical symptoms may include omitting words, watching the hands when writing, inappropriate letter spacing and sizing, difficulties to take notes at work or school, avoiding tasks including drawing or writing etc.

The cause of dysgraphia is not always known. One of the most common causes is the presence of neurological disorders in the frontal lobe, which is associated with reading and writing. In adult individuals, it can sometimes manifest, for example, as a result of a traumatic event or in association with another cognitive disorder (e.g. Parkinson's disease) [KSG17, NiF11]. If dysgraphia is left untreated, it can cause poor performance at school or work, mental issues, low self-esteem and social contacts.

Dysgraphia is often associated with dyslexia - disorder characterized by reading below the expected level for their age, but these disorders are usually associated and does not always occur together. However, dyslexia often co-occurs with other problems, whether it is other specific learning disabilities such as dysgraphia (writing disorder), dysorthography (spelling disorder), dyscalculia (mathematical learning disorder) or attention deficit disorder (ADD/ADHD) [HV20]. In some case problems associated with dysgraphia are beginning affect older children. They are writing letters that are out of place, or that do not have the correct ratio of letter sizes. In the final form, the written text looks chaotic, they do not follow each other, do not stick line, have poor spacing within words or spacing between words. They do not follow the boundaries between words in the

writing, join words together or divide them illogically. Also, as in dyslexia, confuse similar letters for example 'm' and 'n', 'b' and 'd' or numerals 7 and 4 [CC16].

The research on methods for dysgraphia detection based on the machine learning started developing in the last decade, since quality graphic tablets (WACOM, XP-Pen) have become more available and widely used. They allowed to obtain more data and features for algorithms.

Application of machine learning algorithms shown promising results in the field of diagnostics tools. For example there are experiments with for diagnosis of: mild cognitive impairment (MCI) [GML21], autism spectrum disorder (ASD) [YHE18], schizophrenia [KBA21], bipolar disorder [SCC21] or obsessive-compulsive disorder [HMD13]. Methods are using various input data from functional magnetic resonance imaging (fMRI), electroencephalograph (EEG), eye-trackers and the others.

In the first part of the research paper we deal with the recent trends in methods for dysgraphia detection. Then is described our proposed approach used for data classification and the experiment, where data was classified into two groups – normally developing and diagnosed. Finally, we discuss achieved results and define future work.

2. RELATED WORK

This section mentions some important methods for dysgraphia detection based on handwritten data. In [DD20] authors verified classification methods on various features, like velocity, acceleration, rate of change of acceleration, total writing time and so on. Dataset is same as in our experiment. For classification of the data were used AdaBoost classifier, support vector machine (SVM) and random forest algorithm. AdaBoost algorithm outperformed the others and the reached accuracy 79.5% (STD \pm 3).

Paper [DDG21] describes experiment, where authors tested different classifiers to find the most suitable for this sort of data. A dataset consists of 580 children, where 122 are dysgraphia diagnosed. The conditions during handwritten text were the same for all children and graphic tablets by WACOM were used. Authors analyzed features and chosen 10 optimal according to Fisher criterion, for example record time, total writing time or number of stops. To classification were used different models, like - Long short-term memory (LSTM), Decision Tree, Random Forest or SVM with different kernels. The highest balanced accuracy achieved SVM with linear kernel and SVM with RBF (Radial Basis Function) – 77%.

Authors in [RS20] compared differences between dyslexic and dysgraphic children and in experiment analysis of pictures of a handwritten manuscript and

audio files, to create a classification model. Authors applied machine learning algorithms (Naïve Bayes, Logistic Regression and Random Forest) on each disorder – dyslexia and dysgraphia. Dataset of handwritten text is composed of 1481 pictures (198 of them are diagnosed with dysgraphia). With 10-fold cross validation, the best accuracy achieved Random Forest as 96.2% (STD \pm 2.7).

Experiment described in [KNH19] was aimed on the design of the tool for dyslexia, dysgraphia and dyscalculia (math learning disability characterized by issues with solving tasks and perform other basic math skills). Authors used tool that implements gamified environment to interact with children. There was used convolutional neural network and average precision for dysgraphia detection is 88%.

Dysgraphia is also associated with the other cognitive disorders. Authors in [MMG18] analyzed handwritten text and compared groups of 36 healthy and 33 Parkinson's disease diagnosed individuals. Data are based on the 9 handwritten tasks for each participant and during acquisition were used digitizing tablets (like WACOM Intous 4M). For classification authors used binary XGBoost (decision-tree-based) model. Authors analyzed different features and the best approach was conventional, where they selected horizontal velocity (median) of the sentence, with the highest classification accuracy 97.14% (STD \pm 5.71).

3. PROPOSED APPROACH

This section describes our method for classification of handwriting data of tested subjects. We previously proposed method used for dyslexia diagnosis based on the classification of eye-tracking data, described in [NPS21] and [NP21].

Most methods of classifying dyslexia are based on the assumption that subjects with confirmed dyslexia read significantly slower than subjects without dyslexia. However, in the case of dysgraphia, the assumption of slow writing is not so much used. The [NPS21] method eliminates the effect of time on the classification of subjects with dyslexia, so it could also be used as a basis for the classification of subjects with dysgraphia.

In the case of dyslexia, the eye movements of the subjects were recorded. Figures 1 and 2 shows a typical result of such eye movement in a subject with dyslexia compared to a subject without a disorder.

In the case of the examination of dysgraphia, the coordinates of the pen movement on the tablet were taken. Figures 3 and 4 shows a typical result of such pen movement in a subject with dysgraphia compared to a subject without a disorder.

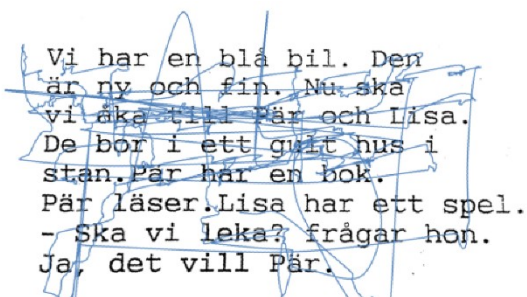


Figure 1. Eye movements of high risk (dyslectic) individual during reading.

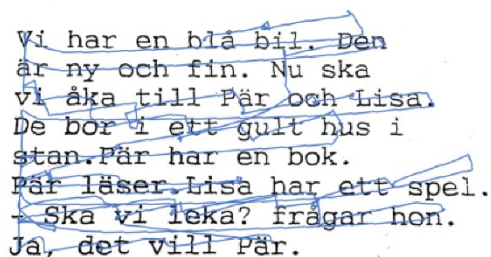


Figure 2. Eye movements of low risk (healthy) individual during reading.

The results shown in figure 1, 2 and 3, 4 have significant common features. They differ in that the writers do not have the same (or significantly similar) initial coordinates. They do not have to have a similar spatial resolution. This is due to the unequal font size. However, it does not affect the classification of dysgraphia. The use of DFT properties eliminates both of these problems, which is also solved by the [NPS21] method. It is important that all sequences of coordinates are the same length. The [NPS21] interpolation method solves this.

The method [NPS21] originally designed to classify dyslexia was applied to the unprocessed coordinates obtained by scanning the position of the pen during writing on the tablet of selected phrases by subjects [DD20].

The signals were first interpolated to the maximum length according to the slowest writing subject. This was used to remove irrelevant time information from the signals. The signal was interpolated using DCT3. The sequences thus obtained were used to calculate the magnitude spectrum DFT. The magnitude spectrum eliminates the spatial shift of the beginning of writing, to remove redundant information is used decorrelation, which very well and concentrates the most important shape properties of the written text into a smaller number of energetically important spectral components, similarly to text classification [PBV16].

Such preprocessing was done one-dimensionally in the x-direction and one-dimensionally in the y-direction. The preprocessed signals then enter the classifier. A convolutional neural network was used as a classifier in the experiment. Entry into it were pairs of preprocessed vectors x and y .

$$DCT3_{U_{k,n}} = \sqrt{\frac{2}{N}} c_n \cos\left(\frac{\pi((2k+1)n)}{2N}\right) \quad (1)$$

$$k, n = 0, 1, \dots, N-1;$$

$$DFT_{U_{k,n}} = \sqrt{\frac{1}{N}} \exp\left(-j \frac{2\pi kn}{N}\right) \quad (2)$$

$$k, n = 0, 1, \dots, N-1;$$

where k represents the order in the spectrum and the n order in time.

4. EXPERIMENT

This section describes dataset we have used for design of a method for dysgraphia detection based on handwritten data. The next part of the section presents classification algorithm.

Participants

Dataset consists of 120 children (40 female and 80 male) in the school age between 8 and 15 years. There is 63 normally developing (healthy) individuals and 57 dysgraphia diagnosed individuals. In the figures 3 and 4 the examples of the handwritten text are shown.

For data acquisition was used WACOM Intuos Pro Large tablet. During collection of the data were subjects requested to write: letter “l” at normal and fast speeds, syllable “le” at normal and fast speeds, simple word “leto” (summer), pseudoword “lamoken”, difficult word “hračkárstvo” (toy-shop), sentence “V lete bude teplo a sucho” (The weather in summer is hot and dry) [DD20].

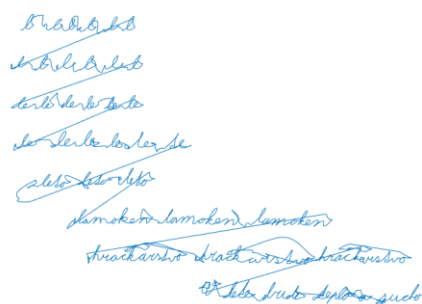


Figure 3. Handwritten text by subject 39 (normally developing).



Figure 4. Handwritten text by subject 114 (dysgraphia diagnosed).

Data are represented as x- and y- coordinates. Then were preprocessed as it is described in the previous section.

Classification

To classify the subjects into two groups we have used convolutional neural network (ConvNet). ConvNets belong to a class of artificial neural network in they have become dominant in computer vision tasks.

Convolutional neural networks are feedforward neural networks - data input to individual nodes of the network is in one direction only. The architecture is exemplified by the visual cortex in the brain (the part that processes visual information), which consists of alternating layers of simple and complex cells. There are currently several well-known network architectures, such as AlexNet, GoogleNet, LeNet, VGG-16, ResNet-50, Xception, Inception, Inception-v4, Inception-ResNet-V2, or ResNeXt-50. ConvNets generally consist of convolutional and pooling layers that are grouped into modules. The individual modules are then stacked in sequence and can thus form a deep neural network (DNN) [KRS18, RW17].

ConvNets uses relatively small preprocessing compared to other image classification algorithms. This means that the network learns the filters that were created manually in traditional algorithms. This independence from prior knowledge and human effort in designing functions is a major advantage [KRS18].

For purpose of our experiment we have used tools in MATLAB, to create a simple neural network for classification, which especially suited for image recognition. Our steps were as follows:

- loaded dataset of images;
- defined the network architecture;
- specification of training options;

- training of the network;
- prediction of the labels of new data and calculate the classification accuracy.

We have used 3-layers network. Model with this number of layers was also used in [NPS21], but we have tried to use various parameters of network, to find optimal network. The first layer of a model has filter size 3x3 with number of 8. The next convolutional layer has 16 filters, also with size of 3x3. The third convolutional neural layer uses 32 filters with size as previous layers. Stochastic Gradient Descent with Momentum (SGDM) is used to learn the convolutional neural network. The initial learning speed for SGDM is 0.01. After each iteration, the training data is rearranged. The maximum number of training epochs is 12. The used hardware is laptop with a configuration: CPU Intel Core i5-1135G7, GPU NVIDIA GeForce MX450 (2 GB) and 16 GB RAM and training time was approximately 6.5 minutes.

Net Name	Structures [kernel sizes;No. of kernels]
CNN3	[3x3, 3x3, 3x3; 8, 16, 32],

Table 1. Network Structures

10-fold cross-validation was used during training. Data was split into ratio 80-10-10, training, validation and testing, respectively. A problem is also small dataset. Optimal machine learning algorithm should be trained and tested on much more larger amount of data.

5. RESULTS

We have achieved average accuracy 79.7% (STD ±2.9), compared to method [DD20] where authors achieved best accuracy 79.5% (STD ±3).

True positive rate (TPR) and true negative rate (TNR) are calculated as follows:

$$TPR = \frac{TP}{TP + FN} \quad (3)$$

$$TNR = \frac{TN}{TN + FP} \quad (4)$$

Our model achieved TPR is 76% (STD ±4.9) and TNR is 80.6% (STD ±3). The results show that model is stable and standard deviation does not have high values. In the next section we will discuss the results and next step in research.

	3-layer CNN	Ada-Boost	SVM	RF
TPR [%]	76% ±4.9%	79.7% ±5%	74.5% ±4%	71.4% ±3%
TNR [%]	80.6% ±3%	76.7% ±2%	82.4% ±4%	83.3% ±2%
ACC [%]	79.7% ±2.9%	79.5%± 3%	78.8% ±2%	77.6% ±1%

Table 2. Result for the tested CNN structures and the reference methods

6. CONCLUSIONS AND THE FUTURE WORK

We have presented in this paper an approach for dysgraphia disorder detection. Method achieved comparable results to the other papers.

The next steps in our research will be improvement of the accuracy, for example by other approach to preprocessing of data or improvement of convolutional neural network model. The other experiment could verify our approach on the dataset of the written text in the different language.

Our goal is to create a dataset with collected data of handwritten text and recorded eye movements of the subjects to develop a method for detection of writing or reading disorders. This tool could be implemented in the schools and provide improvement in an early diagnosis of these disorders, with an impact on quality of children's live.

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