Using Spelling and Language Ability as a Metric to Identify Dyslexia in Children

Students: Tasmiya Malik (tm06183), Hana Ali Rashid (hr05940),
Supervisors: Abdul Samad, Faisal Alvi

May 12, 2023

Abstract

Dyslexia is a learning difficulty that impacts approximately 15% of the global population and has a long-term impact on education acquisition and quality of life. As such, it is imperative that it is diagnosed at an early age and that children have been assisted accordingly. Being a "reading disability", dyslexia impacts language acquisition, and language assessment based on spelling and vocabulary may help detect dyslexia at an early age. This study aims to assess the potential of an online screener for dyslexia which uses spelling ability as an indicator of language level compared to neurotypical children of the same age. This will be done by using natural language processing to detect spelling errors characteristically made by children with Dyslexia and use them to predict risk of Dyslexia. This will be done on handwriting samples of children between the ages 5 - 15, with and without Dyslexia.

1 Introduction

According to the Learning Disabilities Association of America, learning difficulties refer to "a number of disorders which may affect the acquisition, organization, retention, understanding or use of verbal or nonverbal information" [oAL]. Dyslexia is a Learning Difficulty (LD) characterized by the struggle in reading and (by extension) writing. Its diagnosis and intervention are critical as if left unattended, it can cause hindrance in academic activity, self-esteem, and long-term quality of life. Owing to the complex traditional processes for diagnosis, a contextual gap in methods, and general lack of availability of remedial therapists and clinical psychologists in Pakistan, this study explores the potential of computationally screening for Dyslexia by analyzing children's handwriting to make screening more accessible, based on assessing their language development. This will be done by assessing their spelling abilities compared to neuro-typical children of the same age. The insights gained from the type of spelling errors will give more information about the sub-type of dyslexia that the child may be struggling with, such as dysphonetic (unable to integrate symbols with their sounds), dyseidetic (unable to perceive letters and whole words as configurations or gestalts) [Bod73].

2 Literature Review

Dyslexia is often referred to as a "reading difficulty", as it causes a hindrance in relating the visual shape of letters (and by extension of words) to their sounds. Therefore, this causes difficulties in their writing as well, as they have trouble remembering what letters to use to spell what they wish to write. Learning difficulties like dyslexia occur on a spectrum, i.e. the type and intensity of difficulties vary from child to child. Therefore, the kinds of errors made by children with dyslexia relate to the kinds of difficulties they may have. As such, written errors have been used by researchers to study dyslexia and diagnose it [RBYL14]. Compared to neurotypical people, dyslexic people are likelier to make more errors due to phonological processing deficits, spelling knowledge, and lexical mistakes [SFR+98]. The spelling error rate is also being used as a diagnosing factor in various diagnosing tests [RBYL14].

While there is has been much work done to understand spelling acquisition in children, there is not much work to understand spelling errors made by dyslexic children. According to [BJUT22], only six studies have attempted to compile corpora of texts to analyze the writing and errors specific to dyslexics, to design specific tools. These are further limited due to them being in different languages (French, Spanish, and English), as dyslexia manifests differently depending on the language which limits the transfer-ability of insights about spelling errors.

There has been some work done to develop automatic spell-checkers for people with dyslexia. PoliSpell [QLST13] is a spellchecker and spelling prediction software with an easy-to-use interface that adapts itself to individual users, developed particularly for people with dyslexia, and is based on spell checking involving non-word error detection, isolated non-word error correction, and context-dependent, real-word error correction [QLST13]. Another study used a similar premise for their study that spell checkers for neurotypical people differ from the needs of spell checkers for dyslexics and develop an adaptive spellchecker based on real-word errors to overcome this gap [Kor08]. Similarly, [SE97] uses permutations of errors typically made by dyslexics to develop a user model Babel for spellchecking. It also refines itself based on user feedback when they select predictions from a list, thus providing a more accurate and individualized experience [SE97]. Another study worked on a more specific need for spell checking, i.e. assisting dyslexics with writing on social media [WRLG19]. They developed Additional Writing Help (AWH) which uses the neural machine translation (NMT) model and translates dyslexia style to non-dyslexia style writing and received positive user feedback. While this is not specific to spelling, it might aid our process and give insights we may transfer to our project. Lastly, [RBB15] developed a spellchecker called Real Check for people with dyslexia which used a probabilistic language model, a statistical dependency parser, and Google n-grams to detect real-word errors. This was made keeping in mind spelling errors particular to dyslexia, which were documented as a list DysList in an earlier study by the same researchers [RBYL14].

Our project aims to refer to the work done by these projects and develop a scoring system that identifies the patterns in writing styles of Dyslexic children, such as spelling errors, inverted alphabets, confusion between similar alphabets, etc. The classes that our model will identify will then be systemized into a scoring scheme and integrated with an online screener. Dyslexia, being a complex condition, does not have known sub-types but a spectrum. This means that it is diagnosed as a probability, not categories. The sub-categories are only theoretical, and are not used in diagnosis. As such, through our tool we aim to be able to diagnose likelihood of Dyslexia based on patterns in spelling-errors, and provide an accurate screening via handwriting samples.

3 Problem Statement

Dyslexia is a learning disability that affects reading ability, however, it also manifests in handwriting. While the former is widely used for diagnosis by remedial therapists, the latter has huge potential too. Our goal is to explore if we can develop computerized tools to classify the handwriting samples of dyslexic and neuro-typical children. The dimension that we are following heavily uses OCR to assess patterns in spelling errors in written words and assess their potential as a discriminating feature between the two classes.

4 Methodology

4.1 Data Collection

The project uses primary handwriting data collected by 21 children. Half of the participants were diagnosed with Dyslexia, and the other half were neurotypical (typically developing children). The data was collected by sharing a booklet with handwriting tasks among the participants, which they filled out and returned to us. Figure 2 shows the tasks designed to collect this data, chosen based on the nature of errors usually made by children. The first task is to write the names of days and months from memory. As per our research, children are made to memorize these spellings in school, but given the non-intuitive nature of these spellings, children with Dyslexia will often try to spell them out by sound rather than memory. For instance, one participant wrote “sataeday” instead of “saturday”. Thus, finding spelling errors in this task can potentially allow us to flag spelling difficulties in children which is a significant indicator of Dyslexia. The second task is to use the given image as a prompt and write a few lines. The key is for the child to write anything that comes to mind, without us dictating what they write. This will allow us to assess how complex their chosen vocabulary is, and what kinds of spelling errors they make. Another frequent type of error made by Dyslexic children is mis-spelling the same word in different ways, and that is another type of error we aim to target in this task. The third task is to copy the given short paragraph onto a given piece of lined paper. This is to assess spelling mistakes that occur despite having the spellings in front, which can indicate that the child is having trouble recognising the characters and is simply copying shapes. This is another significant indicator of Dyslexia.

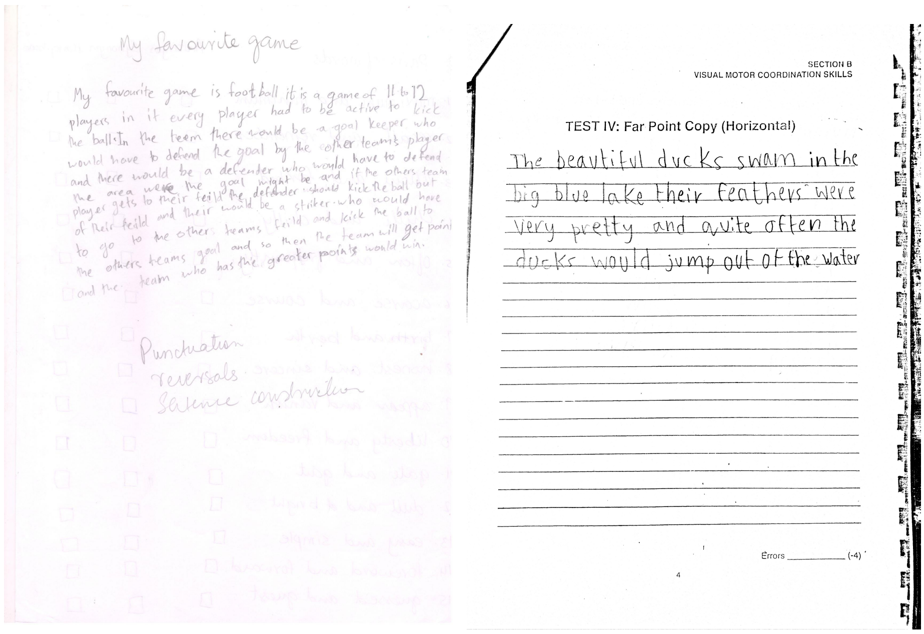

Figure 1: Samples from the handwriting dataset collected by us for children with and without Dyslexia.

4.2 Preprocessing

Since we are using offline handwriting (paper-based) as our data, we first scanned these pages to obtain images of the writing samples. Then, we performed image processing to remove noise in the images and thresholded them to make them black-and-white, as well as remove lines, so as to make character recognition more accurate.

4.3 Offline Handwriting Recognition

The next step was to detect the text written by the children. For this, we explored several OCR options (including the popular PyTesseract library), but these were not performing well. Pytesseract, for instance, was unable to detect individual characters or even words, and was only able to detect the entire block of text which it could not transcribe. We then shifted strategies to use pre-trained models that could recognize handwriting. Among these was the Google Cloud Vision API. This performed really well for the handwriting scans but required a credit card to use, which we were unable to sign up for. We did come across a free pre-trained model for this, called SimpleHTR, which was trained on the IAM Handwriting Dataset. This performed better than the other OCR libraries we had used, in that it was able to detect the characters. However, it was inaccurate in the detected characters. As Figure 4 shows, the model detected the sentence "The beautiful ducks swam in the big blue lake" as "T berufifyc ducks som in the . bie."

We are still in the process of exploring more accurate handwriting recognition options, but for the scope of this project, we have also decided to manually transcribe the handwriting samples, so as to continue with the spelling analysis. This is to continue exploring the potential of NLP in detecting Dyslexia-specific spelling errors, as is the primary aim of this project.

4.4 Spelling Analysis Results

For identifying spelling errors, we referred to the paper [Kor08] that lists spelling errors made frequently and characteristically by children with Dyslexia.

Of the 12 types of errors, we chose the following 4 to implement in the initial stages:

- Phonetic Errors
- Unstressed Vowel
- Adding Extra E
- Doubling Consonant

Figure 2: Writing tasks done by participants. The first task is to write the days of the week, and months in a year from memory. The second is creative writing based on a pictorial prompt. The third is to copy the given paragraph onto a lined piece of paper.

```
Init with stored values from nlp-spelling-dysign/model/snapshot-13
Recognized: "T berufifyc ducks som in the . bie."
Probability: 2.8638671434322305e-09
```

Figure 3: Result of SimpleHTR for handwriting recognition on a handwriting sample.

Error Type	*Example*	*Sources & Frequency*
Add Final 'e'	'toll' spelled 'tolle'	Short vowel: **0.04** Long vowel: **0.20** (Bourassa, et al., 2003) (incl. non-final 'e') **32/1377** (Yannakoudakis, et al., 1983)
Delete Final 'e'	'gone' spelled 'gon'	(incl. non-final 'e')**72/1377** (Yannakoudakis, et al., 1983)
Doubling of Consonant	'pine' spelled 'pinne'	**0.45** (Bourassa, et al., 2003) **96/1377** (Yannakoudakis, et al., 1983)
Singling of Consonant	'allow' spelled 'alow'	**227/1377** (Yannakoudakis, et al., 1983)
One-to-Many Phoneme Mapping	'photo' spelled 'foto'	Vowel (incl. phonetic errors): **850/1377** Consonant (incl. doubling): **280/1377**
Phonetic error	'bank' spelled 'pank'	**0.31**(Finucci, et al., 1983)
Silent Consonant elided	'bomb' spelled 'bom'	**35/1377** (Yannakoudakis, et al., 1983)
Syllable	'library' spelled 'libry'	Elision: **8/1377** (Yannakoudakis, et al., 1983)
Typing Errors	Very variable	**1%** clearly **identifiable**(Yannakoudakis, et al., 1983)
Unstressed Vowel	'record' spelled 'recurd'	Omission of ə: **0.17** (Bourassa, et al., 2003)
Vowel Cluster	'dream' spelled 'drim'	**413/1377** (Yannakoudakis, et al., 1983)
Consonant Cluster	'create' spelled 'reate'	**0.26** (Bruck, et al., 1990)

Figure 4: Description of Error types and frequencies [Kor08].

We started the analysis by using data from Task 3 (copying), as it has a ground truth value we can compare with. To do so, we first made a dictionary for the vocabulary of the given paragraph. Another dictionary sim_con was made that mapped consonants with others that have similar shapes that children often substitute while writing. A third dictionary sim_vow was made that mapped vowels with other vowels with similar phonetic sounds that were frequently substituted and caused spelling errors (Figure 5). These dictionaries were used to detect spelling errors in the following ways.

4.4.1 Source and Target are Same Lengths

In this case, the string can be compared to the ground truth. If it is the same, there are no errors. If it is different, there are possible errors:

- A consonant has been substituted by a similar-shaped consonant i.e. a phonetic error (Error 1).
- vowel has been substituted by a similar-sounding vowel i.e. an unstressed vowel error (Error

```
sim_con = {
    'b': ['d','h','q','p'],
    'd': ['b', 'h', 'q','p'],
    'h': ['b', 'd', 'q', 'p'],
    'q': ['b', 'd', 'h', 'p'],
    'p': ['b', 'd', 'h', 'q'],
    'f': ['t'],
    't': ['f'],
}
```

```
sim_vow = {
    'o': ['u', 'e'],
    'i': ['e'],
    'a': ['e'],
    'e': ['i', 'a', 'u']
}
```

Figure 5: Dictionaries sim_con and sim_vow used in spelling analysis.

2).

4.4.2 Source and Target are Different Lengths

In this case, there are extra characters in the written string. This can mean the following scenarios are possible:

- There is an extra "e" added at the end of the string (Error 3).
- A consonant has been doubled (Error 4).
- A phonetic error (Error 1).

There are also cases where letters have been omitted, but those errors are not included in these 4 and will be included as the project progresses.

For each handwriting instance in the input dataset, the following errors were assessed and saved in a CSV file as generated features along with the participants' diagnosis (dyslexia or not). Once more features (types of errors) have been calculated, these will be used to train binary classifiers to classify input samples based on the risk of Dyslexia.

4.5 Vocabulary and Word Complexity

For additional insights into signs of Dyslexia from writing, other than spelling, we also incorporated the vocabulary length of each writing sample as a feature. This meant counting the number of unique words the child was using in their writing. How many words a child uses in their writing gives insights on how proficient they are in the language. Moreover, we also calculated complexity of their vocabulary, by counting the number of unique words that appear more than once. This tells us if the child is repeatedly using the same words over and over which tells us that the child is not confident in writing, or if they are using newer words in their writing, which implies a better control over language.

5 Results and Discussion

We trained 5 Machine Learning models on both streams of data (Spelling errors with and without complexity), and the results are as follows: By comparing we can see that adding Word complexity

	SVM		Logistic Regress.		Naive Bayes		Random Forest		Decision Tree	
	A	F1	A	F1	A	F1	A	F1	A	F1
Spelling Errors	0.5	0.0	0.5	0.0	0.5	0.66	0.66	0.5	0.66	0.5
Word Complexity	0.66	0.5	0.66	0.5	0.5	0.66	0.66	0.74	0.66	0.5

Table 1: Accuracy and F1 score of the algorithms

worked better than just spelling errors, but it might also be the case because of the small dataset. Out of all five algorithms, random forest performed the best for word complexity with 66% accuracy and an F1 score of 0.74.

6 Conclusion and Future Work

From our experimentation, we can conclude that the results are promising, and NLP can help in assessing the risk of dyslexia. From the comparison of our data streams, word complexity performed better than spelling errors; so a more complex procedure of collecting creative writing samples of children and training a model based on the complexity level can give good results. Spelling errors can aid as a supplementary feature to give better accuracy by detecting the repetitive pattern of errors if there are any in the creative writing of children. Future work would include collecting more data, as a larger dataset would give more conclusive results on the effectiveness of this method.

References

[BJUT22] Johana Bodard, Celine Jost, Gerard Uzan, and Isis Truck. Spelling errors made by people with dyslexia. *Language Resources and Evaluation*, October 2022.

[Bod73] Elena Boder. Developmental Dyslexia: a Diagnostic Approach Based on Three Atypical Reading-spelling Patterns. *Developmental Medicine & Child Neurology*, 15(5):663–687, 1973. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8749.1973.tb05180.x.

[Kor08] Tuomas Korhonen. Adaptive Spell Checker for Dyslexic Writers. In Klaus Miesenberger, Joachim Klaus, Wolfgang Zagler, and Arthur Karshmer, editors, *Computers Helping People with Special Needs*, Lecture Notes in Computer Science, pages 733–741, Berlin, Heidelberg, 2008. Springer.

[oAL] Learning Disabilities Association of America (LDA). New to LD.

[QLST13] Alberto Quattrini Li, Licia Sbattella, and Roberto Tedesco. PoliSpell: An Adaptive Spellchecker and Predictor for People with Dyslexia. In Sandra Carberry, Stephan Weibelzahl, Alessandro Micarelli, and Giovanni Semeraro, editors, *User Modeling, Adaptation, and Personalization*, Lecture Notes in Computer Science, pages 302–309, Berlin, Heidelberg, 2013. Springer.

[RBB15] Luz Rello, Miguel Ballesteros, and Jeffrey P. Bigham. A Spellchecker for Dyslexia. In *Proceedings of the 17th International ACM SIGACCESS Conference on Computers & Accessibility*, ASSETS '15, pages 39–47, New York, NY, USA, October 2015. Association for Computing Machinery.

[RBYL14] Luz Rello, Ricardo Baeza-Yates, and Joaquim Llisterri. DysList: An Annotated Resource of Dyslexic Errors. May 2014.

[SE97] Roger I. W. Spooner and Alistair D. N. Edwards. User Modelling for Error Recovery: A Spelling Checker for Dyslexic Users. In A. Jameson, C. Paris, and C. Tasso, editors, *User Modeling*, International Centre for Mechanical Sciences, pages 147–157, Vienna, 1997. Springer.

[SFR+98] Christopher Sterling, Marion Farmer, Barbara Riddick, Steven Morgan, and Catherine Matthews. Adult dyslexic writing. *Dyslexia*, 4(1):1–15, 1998.

[WRLG19] Shaomei Wu, Lindsay Reynolds, Xian Li, and Francisco Guzmán. Design and Evaluation of a Social Media Writing Support Tool for People with Dyslexia. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, pages 1–14, New York, NY, USA, May 2019. Association for Computing Machinery.