Detection of Dyslexia using handwriting images

A PROJECT REPORT

Submitted by

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in partial fulfilment for the course

DA 526: Image Processing with Machine Learning

Year – 2024

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Problem Statement :

Dyslexia poses significant challenges for individuals, impacting their ability to recognize words accurately and fluently, as well as their spelling and decoding skills. Detecting dyslexia early is essential for effective management and reducing its impact on academic and social growth. However, traditional screening methods often demand specialized assessments and expertise, consuming valuable time and resources.

To address this, our project aims to create an efficient system that identifies dyslexia by analyzing handwriting samples. Handwriting analysis offers a promising avenue for detection, as dyslexia can manifest in distinct patterns within writing. By leveraging technology to automate this process, we aim to streamline dyslexia identification, enabling quicker interventions and support for those affected.

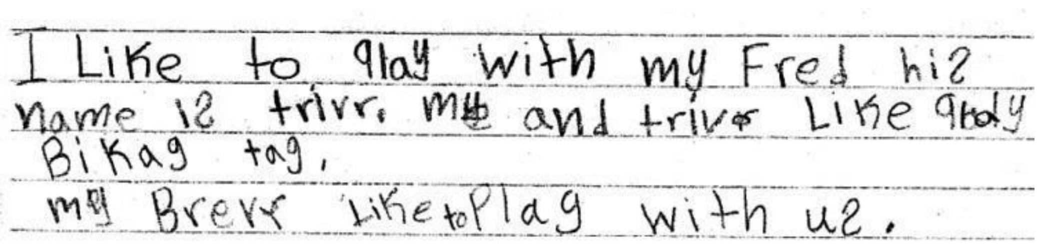
Ultimately, our goal is to develop a robust and accessible tool that enhances dyslexia detection in a cost-effective and time-efficient manner. By focusing on handwriting characteristics, we seek to provide educators and healthcare professionals with a valuable resource for early intervention, ultimately improving outcomes for individuals with dyslexia.

Dataset :

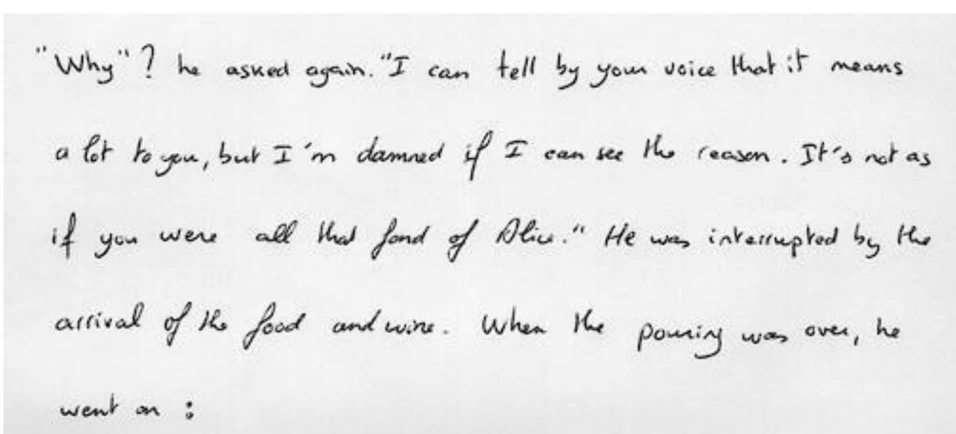
Our dataset will comprise handwriting samples from two distinct groups: individuals diagnosed with dyslexia and a control group without dyslexia. We'll ensure diversity across handwriting styles, ages, and linguistic backgrounds to bolster the model's applicability across various demographics. This inclusivity is pivotal for the model's generalizability, enabling it to effectively identify dyslexia across a broad spectrum of individuals.

With a total of 100 samples, evenly split between dyslexic and non-dyslexic individuals, we'll allocate 46 samples from each group for training purposes. This balanced approach ensures that the model learns from a representative set of data from both dyslexic and non-dyslexic individuals. Additionally, we'll reserve 4 samples from each group for testing, enabling us to evaluate the model's performance on unseen data and validate its effectiveness in distinguishing between dyslexic and non-dyslexic handwriting patterns.

By meticulously curating our dataset and adhering to a systematic approach for training and testing, we aim to develop a robust model capable of accurately identifying dyslexia through handwriting analysis. This dataset-driven methodology enhances the reliability and efficacy of our system, ultimately contributing to more timely interventions and support for individuals with dyslexia.



(a) Sample handwriting image of dyslexic person

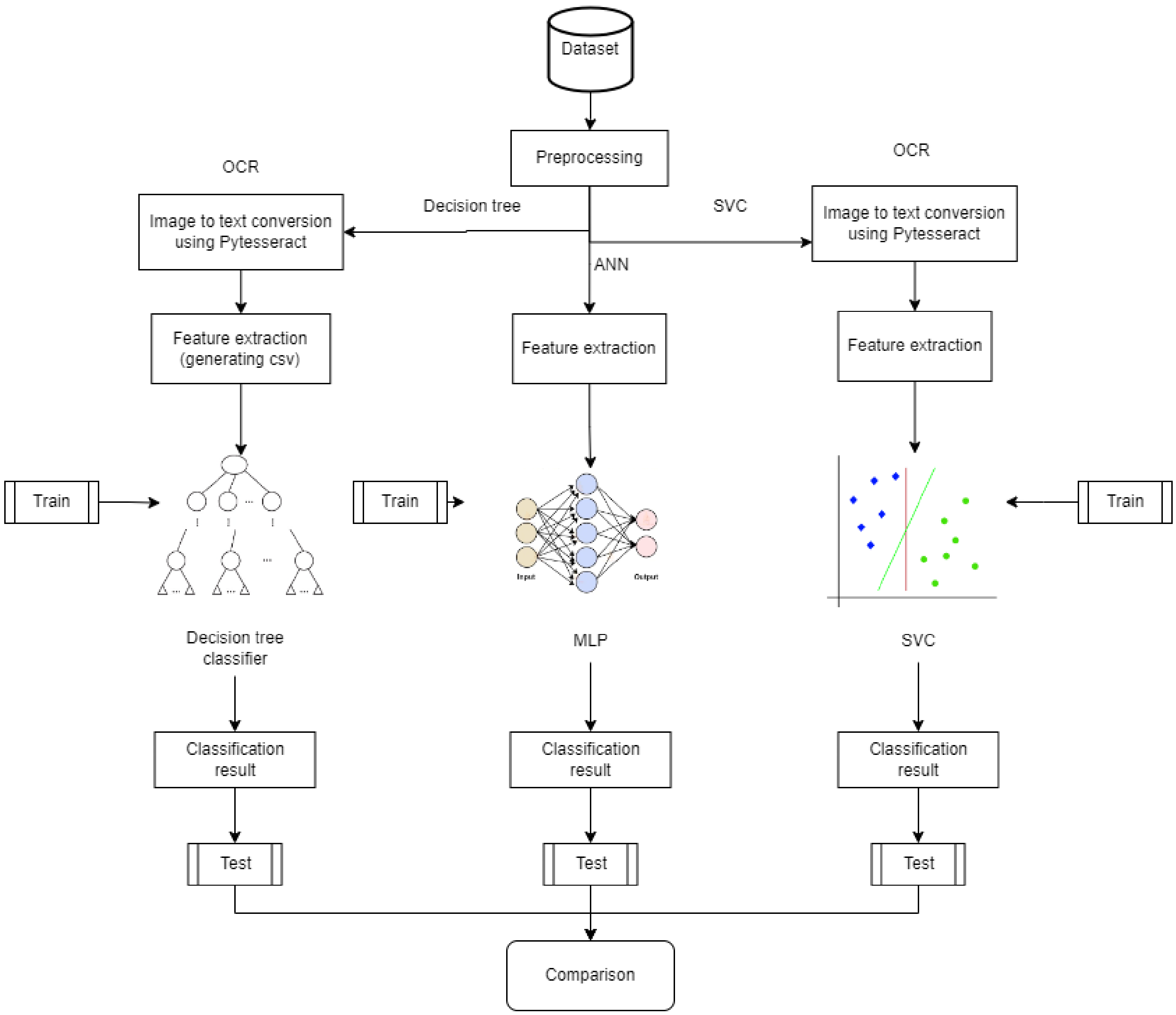


(b) Sample handwriting image of non-dyslexic person

Method :

1. Pre-processing :

   For pre-processing, we standardized the dataset by resizing all images to 300x800 pixels and converting RGB images to grayscale. This ensures uniformity in the dataset and prepares it for further analysis.



2. Feature Extraction :

   For feature extraction, we employed two main approaches:

   a) Image to Text Conversion: For training the Decision Tree and SVC classifier, we began by leveraging Optical Character Recognition (OCR) techniques to convert handwritten text from images into machine-readable text. This initial step is crucial as it allows us to extract textual data from the handwritten content.

Once we had the extracted text, we focused on refining its accuracy. We employed a combination of spelling and grammar correction techniques. First, we utilized TextBlob, a Python library, for basic spelling correction. Next, we employed the LanguageTool library for more advanced grammar correction. These correction processes helped ensure that the extracted text was as accurate as possible.

With the accurately corrected text, we proceeded to extract relevant features for dyslexia detection. Three primary features were extracted:

- Spelling Accuracy: This feature measured the percentage of correctly spelled words in the extracted text compared to the total number of words.
- Grammatical Accuracy: This feature assessed the grammatical correctness of the text, considering both spelling and grammar corrections.
- Percentage of Corrections: This feature quantified the percentage of corrections made to the original text during the spelling and grammar correction processes.

We evaluated our dyslexia detection model by applying it to a dataset of handwriting images. For each image in the dataset, we extracted features, classified the sample using our model, and generated a corresponding CSV file. This CSV file contained the extracted features along with a label indicating the presence or absence of dyslexia as shown below :

	spelling_accuracy	gramatical_accuracy	percentage_of_corrections	presence_of_dyslexia
35	86.715867	99.622642	40.350877	0
36	91.776316	99.665552	51.785714	0
37	85.173502	99.676375	52.941176	0
38	92.905405	99.655172	37.037037	0
39	87.692308	99.683544	52.307692	0
40	82.857143	99.270073	53.333333	1
41	92.682927	97.560976	44.444444	1

b) Extracting Features Directly from the Image: For training the ANN model, we extracted the following features directly from the image:

- Pressure Feature: Dyslexia can manifest in variations in pen pressure and stroke intensity. Analyzing the pressure exerted during handwriting provides valuable insights into motor control and coordination. By computing metrics such as average pressure and ink occupancy percentage, it becomes feasible to detect irregularities in pressure distribution, which may be indicative of dyslexic writing patterns.
- Zonal Features: Dyslexic handwriting often exhibits distinct characteristics across different zones of the written text. Partitioning handwritten samples into zones—such

as top, middle, and bottom—facilitates the analysis of stroke distribution and spatial coherence within each zone. Dyslexic individuals may demonstrate atypical stroke patterns or inconsistencies across zones, which can be captured through zonal feature extraction.

- GLCM Feature: Texture analysis using GLCM offers a powerful means of discerning dyslexic traits in handwriting. Dyslexia can manifest in irregularities in texture patterns and spatial coherence within written text. By quantifying texture properties such as dissimilarity, correlation, and contrast, GLCM analysis enables the detection of subtle textural variations indicative of dyslexic handwriting.
- Segmentation: Stroke segmentation can provide additional insights into dyslexic handwriting patterns by isolating individual strokes within the handwritten samples. Dyslexic individuals may exhibit irregular stroke shapes, sizes, and spacings, which can be analyzed through stroke segmentation. This optional step enhances the granularity of feature extraction and enables detailed analysis of dyslexic handwriting dynamics.

3. Training :

   In this phase, we train three different classifiers using the set of features extracted in the above step:

   a) Decision Tree

   b) SVC

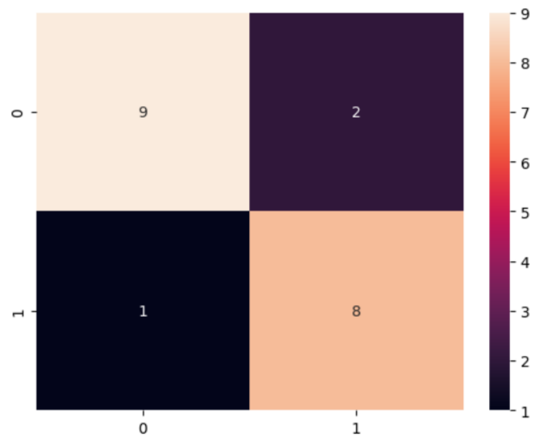
   c) ANN

4. Testing :

   The complete dataset comprises 50 handwriting images of both dyslexic and non-dyslexic individuals. From each set of 50 images, 46 were allocated for training, while 4 were reserved for testing. In the case of the ANN model, the test image was directly used as input. However, for the other classifiers, the test image was first converted into CSV format, and then the trained model was employed to make predictions.

Experiments and Results:

First, we tried Logistic Regression classifier on the features extracted from the text (obtained using OCR) and got accuracy score of about 0.55. The confusion matrix for the same is given below:



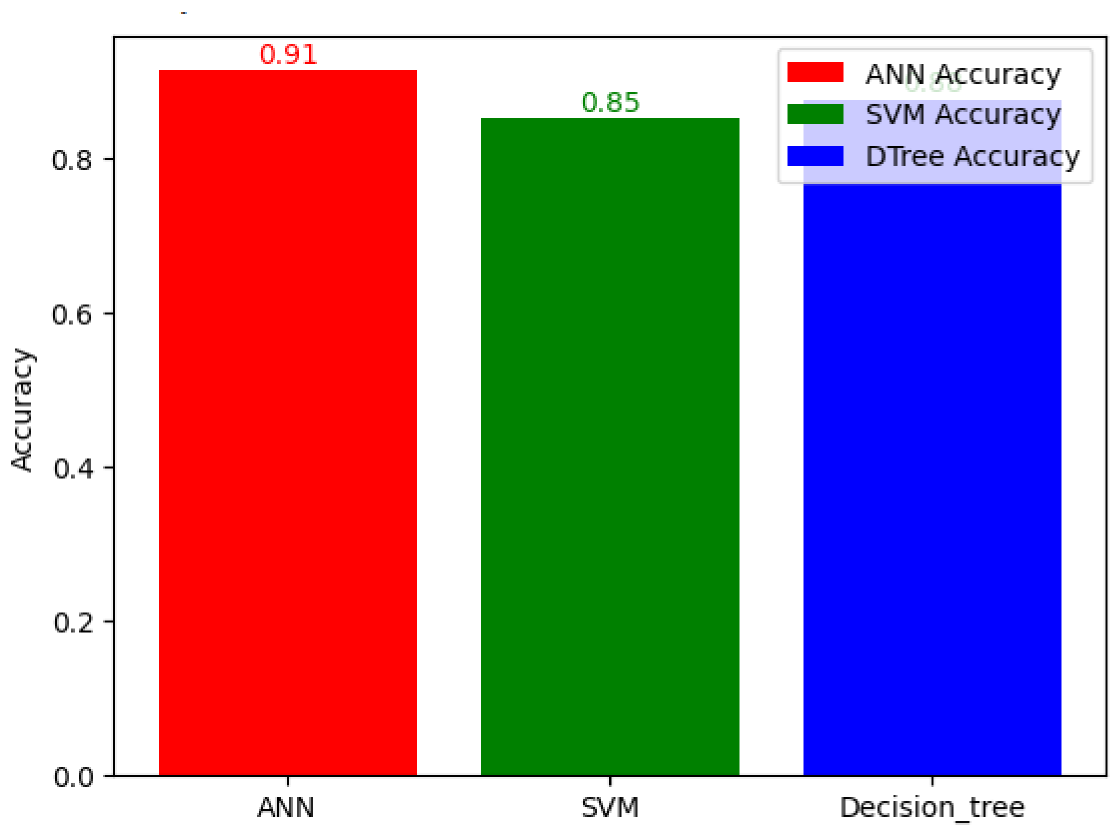
Then we tried three different classifiers given below:

1. **ANN Classifier:** The given classifier was trained using the features extracted directly from the image.
2. **Decision Tree Classifier:** The given classifier was trained using the features extracted directly from the image.
3. **SVC Classifier:** The given classifier was trained using the features extracted directly from the text (obtained using OCR).

Further details about the exact features used for training each classifier and their accuracies for the test data is given in the table below.

Classifier	Features used	Accuracy
ANN	Pressure features, zonal features, GLCM features	0.91
Decision tree	Pressure features, zonal features, GLCM features	0.875
SVC	Spelling accuracy, grammatical accuracy, percentage of corrections	0.85

Comparison:


0.91
0.85
ANN Accuracy
SVM Accuracy
DTree Accuracy
Accuracy
0.0
0.2
0.4
0.6
0.8
ANN
SVM
Decision_tree

Conclusion:

In our study on dyslexia detection, we evaluated three classifiers—Artificial Neural Network (ANN), Decision Tree, and Support Vector Classifier (SVC)—using feature sets derived from both images and text. The results highlight the superior performance of classifiers trained on image-based features, with the ANN achieving the highest accuracy at 0.91. This underscores the importance of features like pressure, zonal, and GLCM in detecting dyslexia. The Decision Tree also performed well with image-derived features, achieving an accuracy of 0.875. Although the SVC showed competency with text-based features, its accuracy was lower at 0.85. These findings indicate that combining image-based and text-based features could further enhance dyslexia detection algorithms.

Github:

Please find the code here.