Detection of Dyslexia using handwriting images

A PROJECT REPORT

Submitted by

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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.

Related Work :

This section deals with some of the existing works related to dyslexia detection is discussed, and they are as follows. The related works in dyslexia detection encompass various approaches and methodologies.

Rehman et al [1] developed an automated diagnostic model for classifying dyslexia existence or not in school kids. This work comprises three different modules: preprocessing, classifying the students as dyslexic and non-dyslexic using K-Nearest Neighbor. The final module is the development of analysis tool. We propose an automated diagnostic and classification system.

Vinitha et al [2] in their work of predicting chronic illness they used both structured and unstructured dataset. They used Map-reduce and Decision Tree based classification model and they proved that their developed model performed better with high accuracy and speedy convergence compared to standard network models.

Poole et al [3] introduced a screening model to detect phonological disorder using the aid of Lex. The presence of phonological dyslexic creates issues in inferring and understanding the part of the word. This work designed a web-based software tool which assists the parents to verify whether their child is at risk of dyslexic or not. The tests of rise time and oddity were the appropriate predictors of dyslexic child.

Mejia and Carolina [4] developed a web-based tool which focused on understanding the features of learning difficulties. It is designed in a visualized format for the student understanding, which increases the support reflection, awareness increases, and self-regulation is also enhanced.

Thomais et al [5] detected reading disorders using eye movements while reading text. They developed machine learning algorithms specifically SVM is used to design a DysLexML screening model for analyzing developmental dyslexia during silent reading by children by analyzing their eye movement.

McCrory et al [6] anticipated a map reduce base hive database in Hadoop environment. This work used PET images on three different environments to determine dyslexia presence. It is observed that there is no bigger difference among dyslexic and non-dyslexic while performing audio processing by it is noticed dyslexic has less stimulation in the right temporal lobe. Because of auditory repetition the deficit occurs, and this was not discovered in a previous study. The merits acquired from big data analytics greatly help in the field of health care.

Basco et al [7] used Hadoop framework which involves Electronic Medical Records (EMR) based complex pattern recognition of diabetes. This unstructured data is well handled using the assistance of big data to observe changes in cortical activity among dyslexics.

Laine et al [8] analyzed Magnetoencephalography (MEG) is used for finding the changes in pattern of reading words and sentences. The semantic analysis is a vibrant part of dyslexic detection, result reveals that the dyslexic patients intact with right hemispheres whereas non-dyslexics intact with left. And in addition, it is also observed that brain activity is an important consistent measure for detection of dyslexia presence.

Barkhordari, and Niamanesh [9] handled a very challenging task in healthcare is to discover the similarity among patients, they proposed a model which is scalable and distributable by developing map reduce framework. This model effectively finds the patients similarity issue on different data types and produces more accuracy and reduced execution time.

Carroll et al [10] involved in detection of dyslexia among kids under the age of 2 to 4 years old. They observed their visual and motor difficulties, which extends the difficulties in literacy. The multiple deficit view is considered in this work using standard case study and logistic regression.

Baltimore et al [11] developed a novel neurological method of dyslexia which studied the combined effect of motor syndrome and phonological deficit. Anomalies in cortical activities result in phonological deficit which induce pathways of sensory organs and it also extends to other parts inclusive of cerebellum which affects badly the capability to read. They proposed a MapReduce method along with mining approaches, to handle the data in an effective way by using an automated mobile health care system to predict diseases. It also supports self-health care and assists doctors to detect disease at earlier stages.

Li et al [12] in their work stated that sensory perception influences vital role in cognitive impairment. The prime factors for dyslexia are to study about the correlation among phonological processing and sensory perception. Study reveals the fact that rise time acts as a chief predictor for reading attainment. From the report it is observed that auditory sensory impairments would result in phonological impairment. The fruitful development in linguistic and phonological can be improved by using the conventional strategies of remediation like basis of rhythm and music.

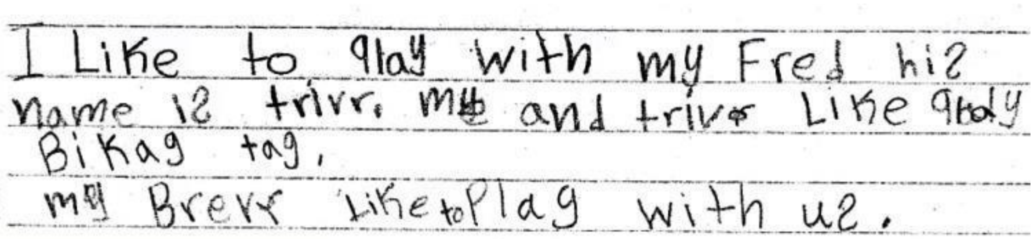
Goswami et al [13] introduced a smart home prediction model by using map reduce the framework and simple linear regression to predict the anomalies in health. By collecting information from wireless data, this model discovers the possible anomalies. It works in a parallel manner by applying map reduce on huge dataset generated by wireless sensors. This helps in predicting an earlier chronic disease among elders, by continuously monitoring their activities over a period of time.

Dataset :

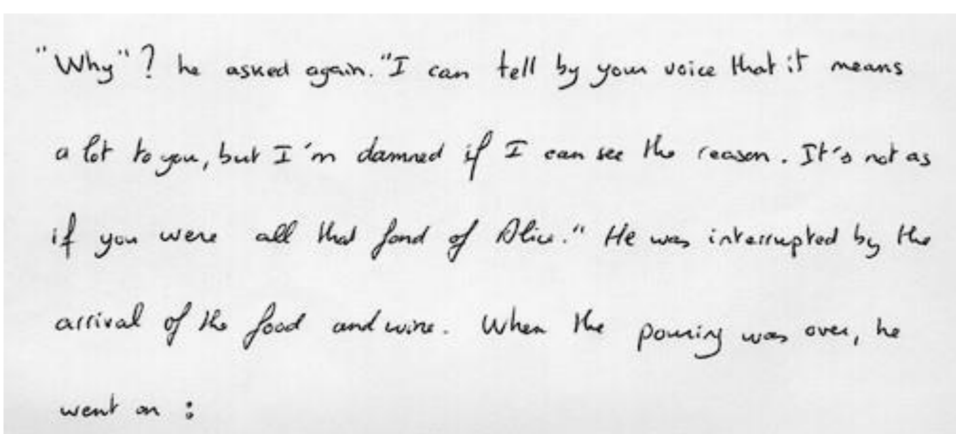
Our dataset will comprise handwriting samples from two distinct groups: individuals diagnosed with dyslexia and a control group without dyslexia. We'll ensure diversity across handwriting styles, ages, and linguistic backgrounds to bolster the model's applicability across various demographics. This inclusivity 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

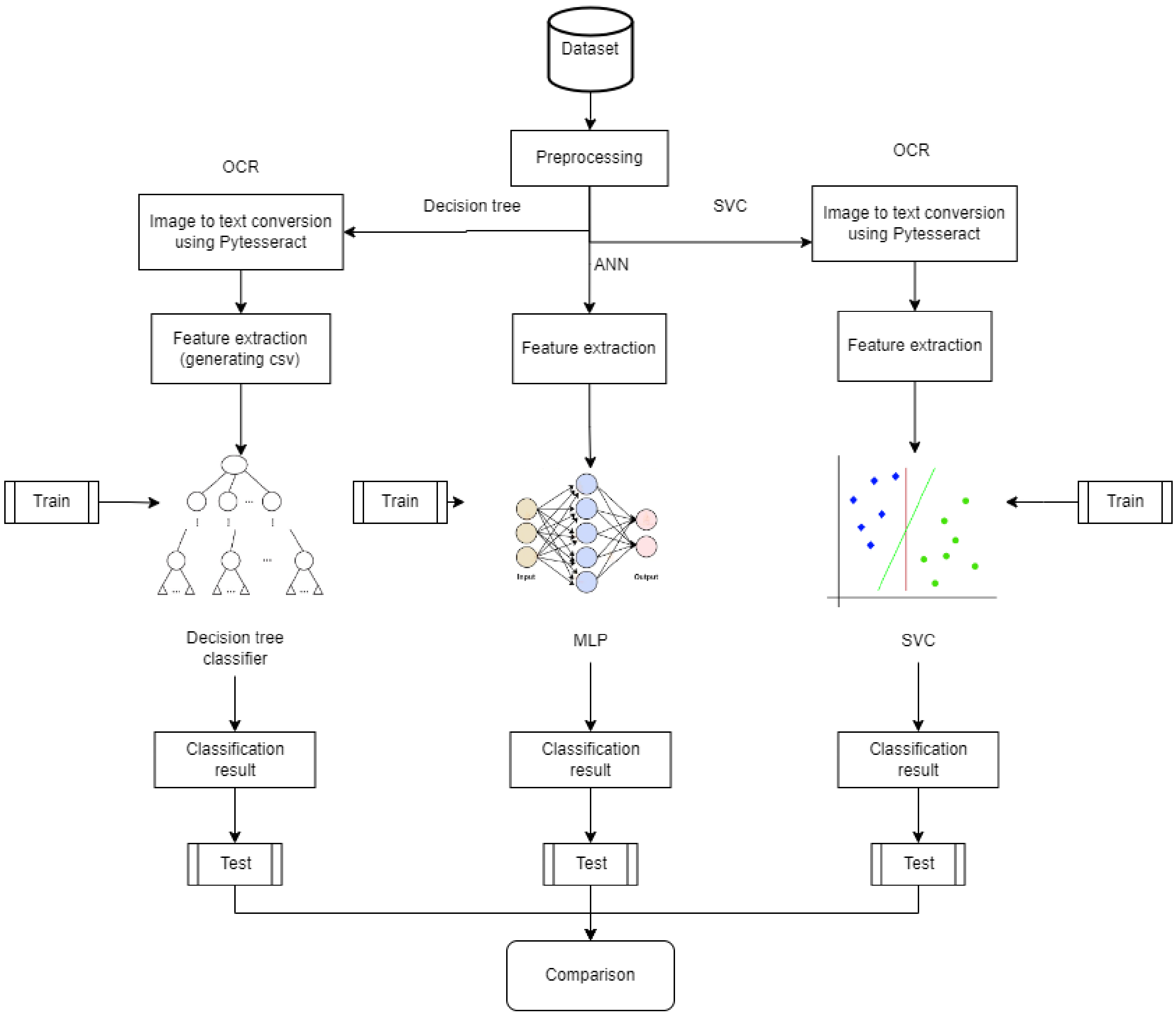


(b) Sample handwriting image of non-dyslexic person

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

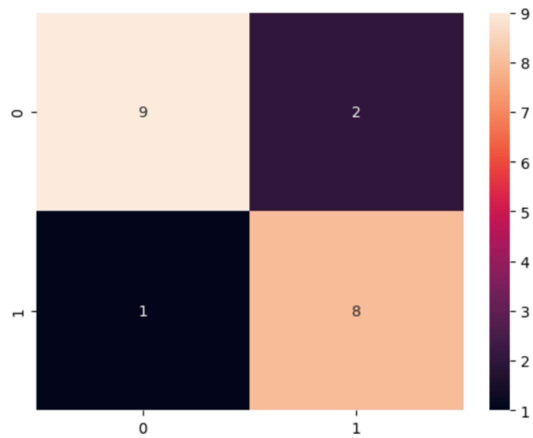
c) ANN

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:



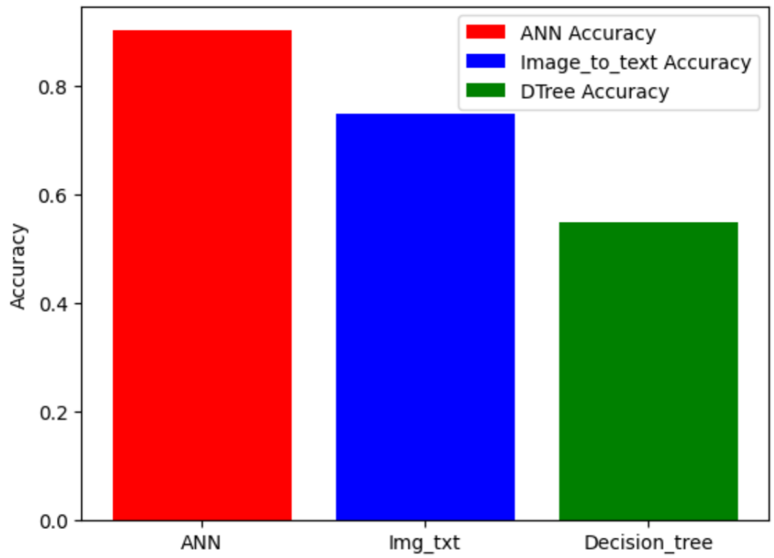
Then we tried three different classifiers given below:

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	0.92
Decision tree	Pressure features, zonal features, GLCM features	0.55
SVC	Spelling accuracy, grammatical accuracy, percentage of corrections	0.75

Comparison:


ANN Accuracy
Image_to_text Accuracy
DTree Accuracy
Accuracy
0.0
0.2
0.4
0.6
0.8
ANN
Img_txt
Decision_tree

Conclusion:

In our study on dyslexia detection, we evaluated three classifiers: Artificial Neural Network (ANN), Decision Tree, and Support Vector Classifier (SVC), utilizing different feature sets derived from either images or converted text. Notably, classifiers trained on image-based features outperformed those relying on text features. The ANN achieved the highest accuracy, scoring 0.92, emphasizing the significance of image-specific features like pressure, zonal, and GLCM features in dyslexia detection. While the SVC demonstrated competency with text-derived features, achieving an accuracy of 0.75, the Decision Tree struggled with image-derived features, yielding a lower accuracy of 0.55. These findings suggest the potential of integrating both image-based and text-based features for enhanced dyslexia detection algorithms.

Github:

Please find the code here.

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