AI-Assisted Early Detection of Dyslexia Disorder in Handwriting Analysis

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Abstract - Dyslexia is a common learning disorder that affects a person's ability to read, write, and spell even when they are intelligent and have access to an adequate education. To improve learning outcomes, provide appropriate interventions, and better the overall quality of life for individuals affected, it is critical to recognize dyslexia as soon as possible. However, prompt identification is challenging because traditional diagnostics methods are subjective, time-consuming, and specialized, especially in environments with limited resources. This study explores the development and application of a machine learning model designed to identify early signs of dyslexia through handwriting analysis. The study utilizes and evaluates two machine learning algorithms such as decision trees and random forests to distinguish spellings that may indicate a dyslexic tendency. The study utilized dyslexia image dataset comprising of 4000 samples from Kaggle repository to experiment and validate the proposed approach. The decision tree model demonstrated an outstanding accuracy of 96% in identifying dyslexia, while the random forest model achieved an accuracy of 86.03%. The model assesses the structure of handwriting, including letter spacing, slanting, and coherence, to provide a reliable tool for early intervention in education. This approach offers a viable, cost-effective solution to the traditional diagnostic process, with the potential to expand access to early dyslexia screening and support.

Keywords: Dyslexia, machine learning, hand writing analysis, learning disorder.

1. INTRODUCTION

Dyslexia is a learning disorder that mainly applying digging in reading and writing and spelling. Dyslexics have normal Intelligence and proper teaching but can not recognize letters and words when the letterings and writings is not conditioned and hence cannot read or write easily. Dyslexia may affect individuals of any age, but it is diagnosed more often in children over adults. It is important because the earlier you find out that someone has dyslexia, the earlier they can get help. Getting the appropriate help early on can dramatically help improve the learning outcomes for individuals with dyslexia [3][7]. Unfortunately, common testing for the diagnosis of dyslexia can be costly, involve many minutes of testing time, require tests to be completed in front of a person, and are often not readily available in numerous areas around the world. As a result, many children can go undiagnosed for many years which can impede their progress in education [8].

ML and AI technologies are developing and becoming feasible for changing diagnoses in dyslexia, possibly at scale. ML algorithms can sift through all the information in a dataset to compile lists of features that might be missed by a human eye. When used in handwriting analysis, for example, ML algorithms could identify left/right spacing inconsistencies, or irregularities pertaining to slanting and coherence features commonly associated with dyslexic markers [5][9]. By identifying these markers, two recommendations become possible with ML models using handwriting - it identified whether someone is at risk for dyslexia before testing [6] and ML would allow for the scaling of more accessible tools to screen children with early signs and symptoms of dyslexia [4]. In regions where accessibility to proper assessments are absent or not available, making acceptable and feasible tools for kids to screen would benefit early intervention in my country.

A notable benefit of machine learning for dyslexia identification is its analysis of handwriting be completely user-agnostic. By using machine learning to assist with handwriting analysis, researchers can conduct population-level sampling for screening for dyslexia which will be advantageous in terms of both cost and time [9][10]. Machine learning models, particularly decision trees and random forests are adept at identifying features associated with dyslexia (e.g., spelling mistakes, inconsistent letter formation, and mistakes in sentence construct) [12][14]. They can also be trained to analyze different handwriting styles, making them useful for a diverse population [13].

This paper intends to investigate the use of machine learning for potentially detecting dyslexia, particularly considering algorithms such as decision trees and random forests. The end result of these methods can provide an evidence- and cost-based screening tool accessible to teachers, parents, and medical professionals. The hope is to demonstrate early detection and interventions would be more efficient with the use of machine learning - thus making dyslexia screenings more available to everyone who needs them, particularly those who struggle access in low income regions [7][11]. There are obstacles ahead such as acquiring larger, higher quality datasets and separating dyslexia from the myriad of learning disabilities. This paper will not only mention these points and difficulties, but reflect on the consideration of the future of machine learning for improving dyslexia hardware applications and educational outcomes for people living with dyslexia [15].

2. RELATED WORK

Dyslexia has traditionally been assessed primarily through the implementation of professional assessments and standardized tests. While still reliable, they present notable pitfalls. High costs, time, and specific expertise can impact access to care for populations with limited educational resources or trained specialists [3][7]. These assessments can introduce bias in a population dependent upon language in terms of customs or cultural meaning that might not have the same added value in other population groups [6].

To mitigate some of the aforementioned limitations on access to care, recent studies have researched the possibility of using machine learning (ML) to increase access to dyslexia screenings. ML models can process incredible amounts of information and discern more subtle patterns in handwriting or text likely to suggest dyslexia [5][8]. Thus, this method has enormous potential to be more accessible, objective, and efficient than traditional methods [6][9]. ML can examine only aspects of the feature including irregular letter shapes, spacing, and unique strokes to determine if dysfunction is present like traditional methods; however, by using ML algorithms including decision trees and random forests to train and compare assessments based on the features of interest allows for the examination of more samples in a shorter time span with the same amount of precision [9][10].

Decision trees use a sequence of yes-or-no questions based on the features of handwriting. They are straightforward and can classify data of all types [12][13]. Random forests build on decision trees and combine the output of many trees to provide a more robust and accurate output. This makes the model particularly advantageous over decision trees due to its increased robustness with high-dimensional data [13][14].

Nevertheless, there are still challenges to tackle. First and foremost is the issue of having to use high quality data. ML models require training on large amounts of data, so the first problem will be collecting and annotating the text [5][7]. Discrepancies in handwriting for individuals and in general are also a problem, and significant effort will need to be made to collect and aggregate data that provides adequate representation of handwriting. Particularly on human populations, it is important to explicate that our datasets span communities/demographics and aren't biased toward a certain people group [4][15].

The future of ML-based dyslexia detection systems has a bright outlook. With advancements in technology, these models can be built into educational resources and mobile applications to make detection easier for teachers, parents, and health care experts [9][11]. Early detection has the potential for providing targeted intervention that is most important for editioning the best learning outcomes for people with dyslexia [7][8]. Future work will mainly focus on improving models and personalizing them for individuals which can enhance their effectiveness and accuracy [15].

3. PROPOSED WORK

This section will present the methodology followed in this study. The methodology is represented in Figure 1, which may provide a brief illustration of process for dyslexia detection system. The purpose here is to again, describe the process step-wise in more detail.

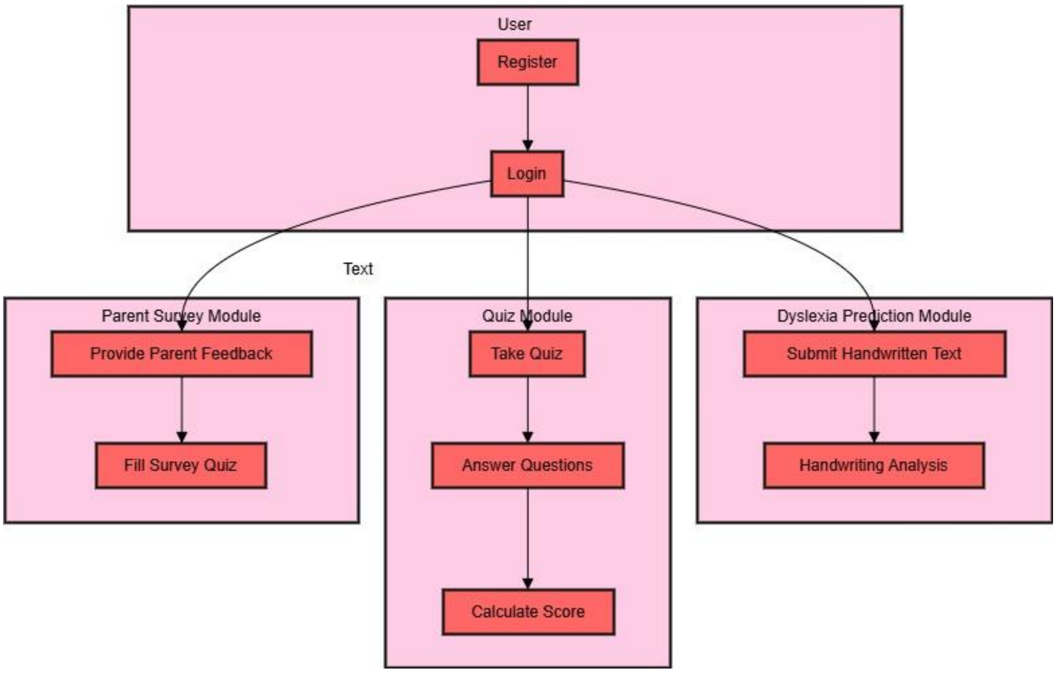

Figure 1. Flow Diagram for Dyslexia Online Platform.

1. **Dyslexia Detection Model:**

1. **Third-Party-Image-to-Text Processing :** A third-party service was utilized for image to text processing of handwriting (the service correctly extracts the text from the images).

2. After we had been able to transform handwriting to text we took our own model and evaluated whether there was potential dyslexia in the individual and we evaluated the extracted text through four main points.

   2.1 Spelling Accuracy: We used the Levenstein distance algorithm to indicate that the words were spelled correctly. The algorithm compares the accepted text to the correct text and identifies the difference by a measure of the fewest single-character modifications to correct the message.
   2.2 Grammatical Accuracy: We use a sentence checker to check if the text contains correct sentences. This means that we identify sentence problems and part of speech inconsistencies. The accepted text is improved by addressing the paragraph to make sure grammatical rules apply.
   2.3 Percentage of Corrections: Means the number of correct fixes and corrections to the text. It indicates how well the model shows and corrects errors that occurred from one piece of text to another.
   2.4 Percentage of Phonetic Accuracy: Speech accuracy is calculated using algorithms, for example, Soundex or Metaphone, that are able to recognize and match phonetic and spelling errors from words that sound the same but may be misspelled. This would help us learn whether phonological similarities are limiting the reading process.

3. **Quiz-based Evaluation:** An assessment consisting of 10 multiple-choice questions is further assessing dyslexia. The questions include several different types of questions:
   3.1 Listening-based questions: The participant is identifying a spoken word and matching that answer to the correct option.
   3.2 Image Matching: For example, one question might ask participants to click on a picture of a rabbit rather than a picture of a dog. These questions measure skills related to bias and judgment.
4. Instant test scores of participants to determine if they exhibit signs of a reading disorder such as dyslexia.

Description of Datasets utilized:

To experiment and validate results of proposed approach, authors have utilized dyslexia image dataset comprising 4000 images from Kaggle repository. The sample images are shown in figure 2 & 3. The details of class-wise samples used for training and testing are mentioned in table 1.

Table 1. Details of dyslexia image dataset

	Dyslexia	Non-dyslexia
Training samples	1923	500
Testing samples	916	5000

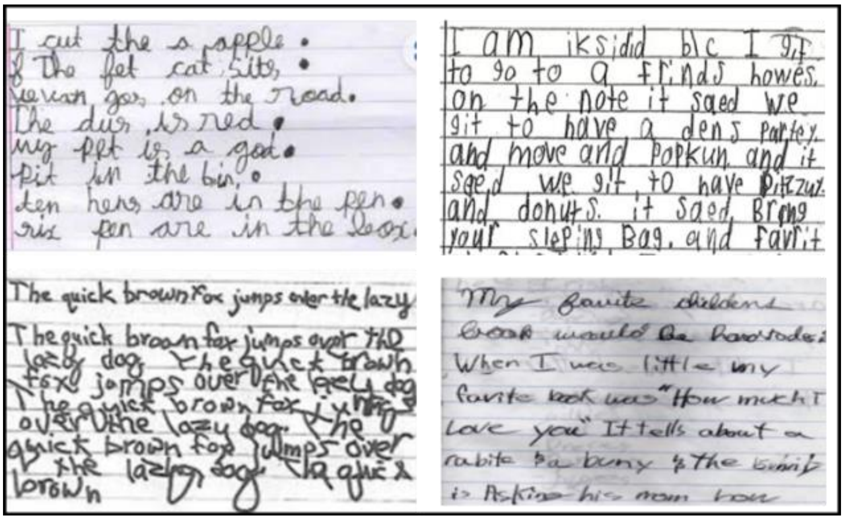

Figure 2. Dyslexia affected handwriting sample images

4. RESULT

Process: Dyslexia Detection

The detailed working steps and functioning of the proposed approach is outlined below:

1. A third-party image-to-text service successfully converts text into digital text, providing accurate information for further analysis.
2. **Spelling Accuracy:** Levenstein distance algorithm helps improve writing quality by achieving accuracy in identifying and correcting spelling errors.
3. **Grammatical Accuracy:** Grammar checker checks and corrects errors in sentences to ensure grammatical accuracy.

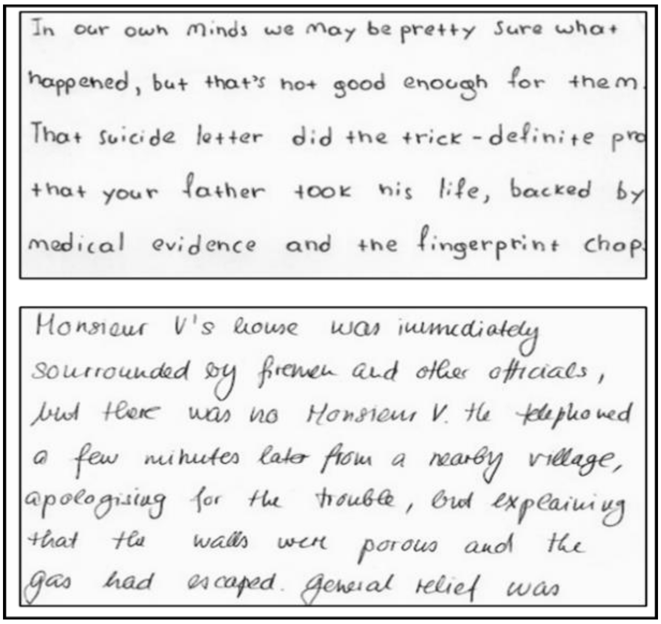

Figure 3. Non-dyslexia handwriting sample images

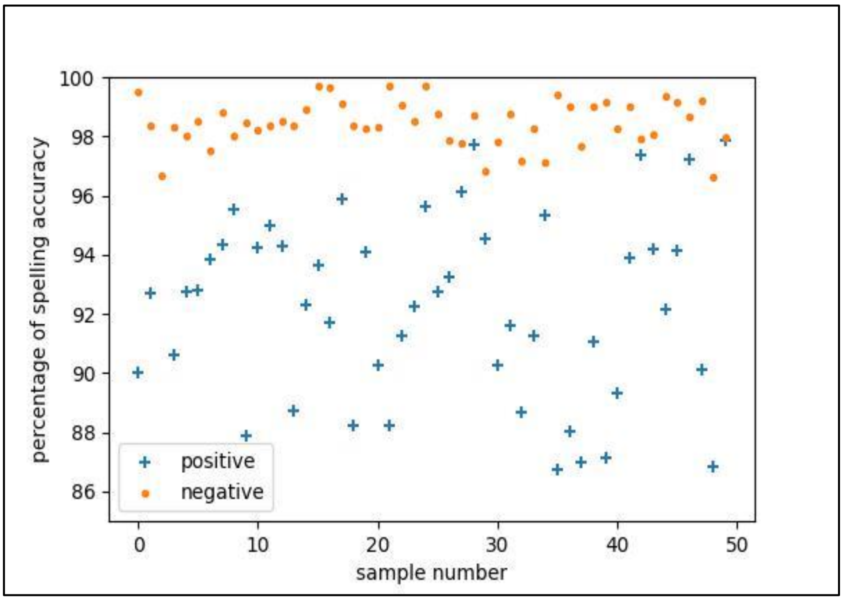

Figure 4. Spelling Accuracy Percentage Scatter Plot.

4. **Correction percentage:** Many errors are detected and corrected, proving the model's effectiveness in detecting errors.

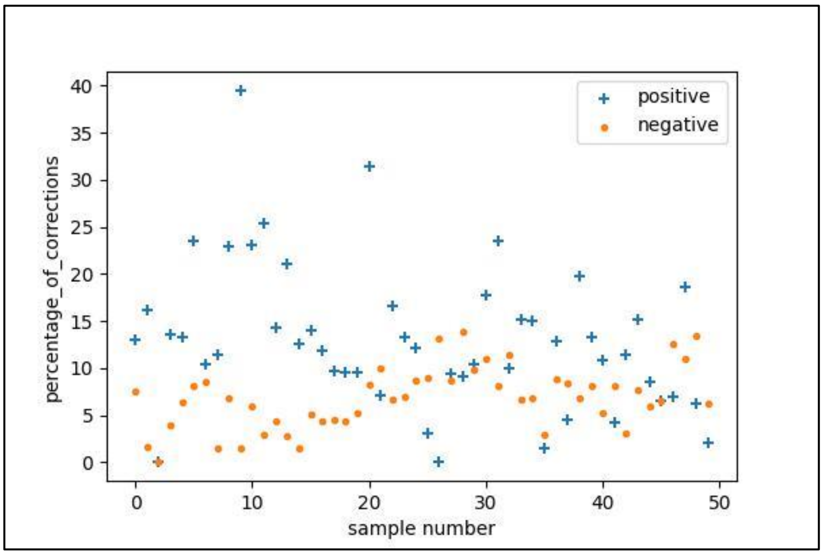

Figure 5. Correction Percentage Scatter Plot.

5. **Percentage of Phonetic Accuracy:** Use Soundex and Metaphone algorithms to correct speech differences and improve overall text accuracy.

6. **Quiz-based Evaluation:** 10-question multiple choice test auditory identification and image matching. Participants' test scores help assess the likelihood of dyslexia. Participants who had problems with picture matching or listening tasks showed signs of dyslexia.

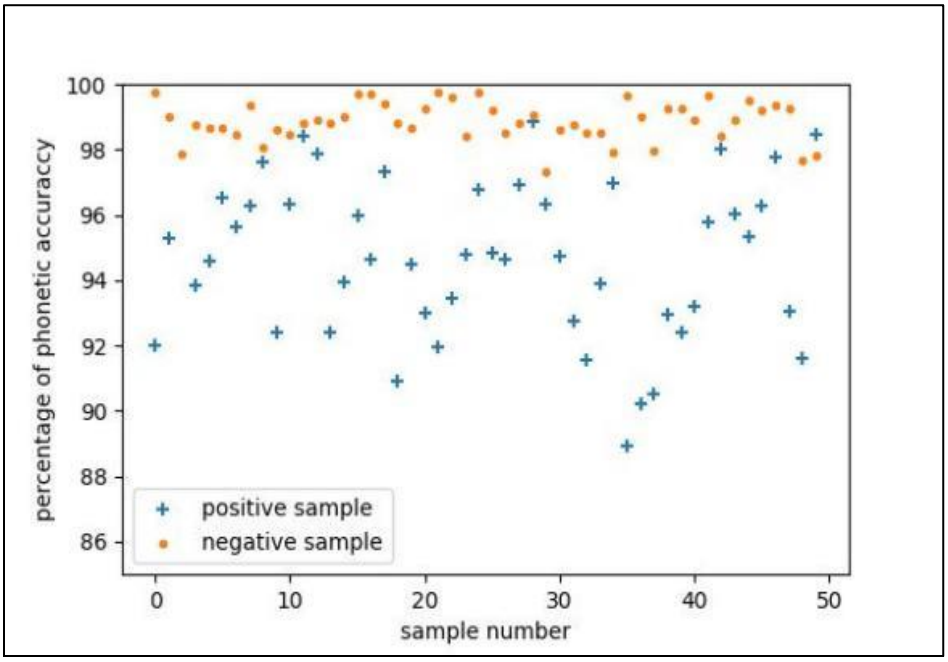

Figure 6. Phonetic Accuracy Percentage Scatter Plot.

7. **Decision Tree Model:** A decision tree model for diagnosing dyslexia is 96% accurate in identifying dyslexia.

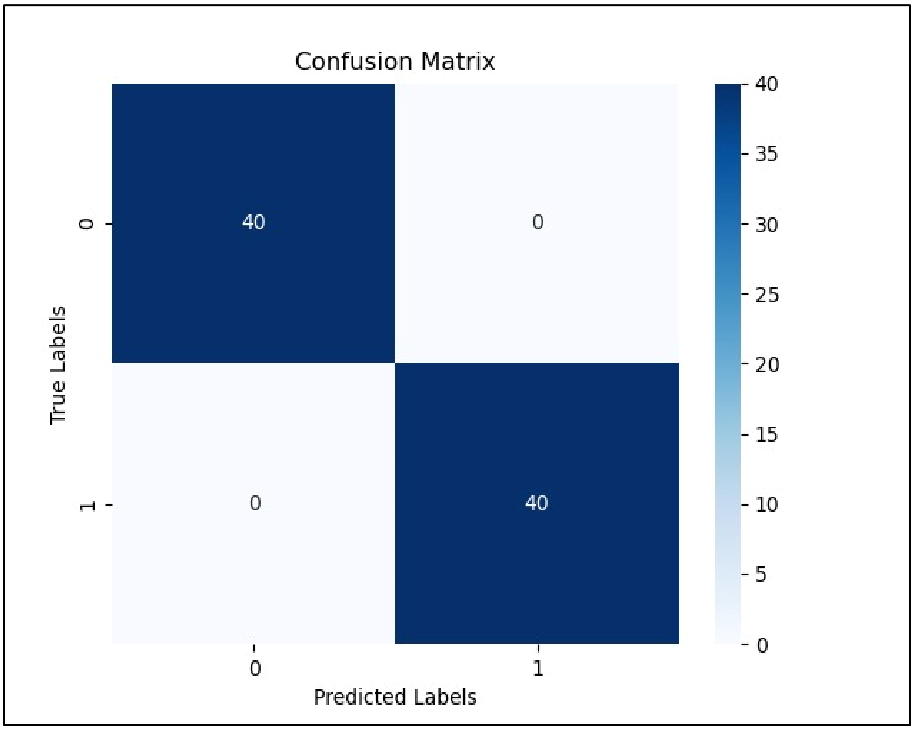

Figure 5: Decision Tree Confusion Matrix.

8. **Random forest model**: Random Forest model achieved 86.03% accuracy on the same task.

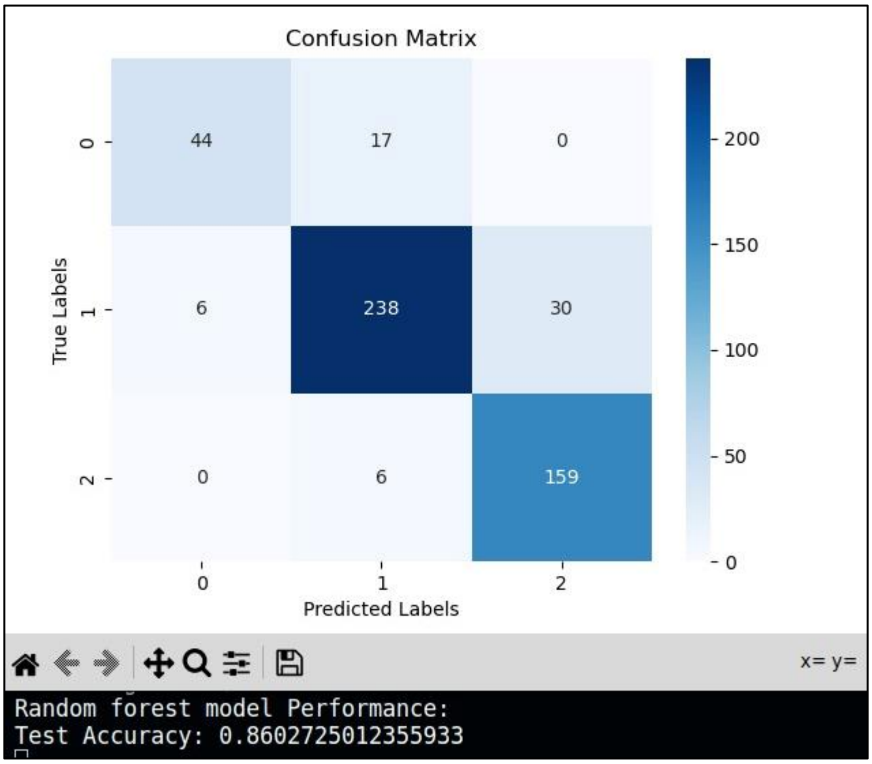

Figure 6: Random Forest Confusion Matrix.

Comparative Evaluation of Proposed Approach:

To assess the performance and uniqueness of our proposed dyslexia detection framework, we compared it with existing approaches reported in the literature that utilize machine learning for early dyslexia identification. Khan et al. [2] utilized traditional models such as Support Vector Machines (SVM) and Naïve Bayes on lexical and spelling only data. Their models achieved an overall accuracy of 83.7%. Khan et al. [2] did not include handwriting and/or image data, limited to strictly text data. Alkhurayyif et al. [4] focused on deep learning, and implemented a Convolutional Neural Network (CNN) that processed raw images of handwriting entering in an overall accuracy of 89.2%. While their model used image recognition for letters, their structure did not include either spelling or cognitive assessments. Rosli et al. [5] implemented a Decision Tree model on handwriting datasets and used a structural analysis of letter formation to achieve 91% accuracy. Sasidhar et al. [7] utilized a Random Forest classifier on scanned handwriting with an assessment of spatial variance, and achieved 88.4% accuracy. Spoon et al. [10] created a feature-based Random Forest model which incorporated the structure of handwriting and spelling pattern features. Their model obtained an accuracy of 92.3%. Although the Random Forest was a bit more accurate than structural analysis, it was particularly valuable in linguistic-feature segregation.

In contrast, our proposed model, in addition to employing a Decision Tree classification, performs holistic analysis of text and cognitional review. The initially developed model took into consideration accuracy spelling, correct grammar, and phonetic matching, we added a more interactive quiz-type platform which contained auditory matching/matching an image. As a result, our mixed methods approach performed with 96% accurate classification separate from the works suggested which incorporated cognitive user input with traditional ML algorithms. The framework reflects technical accuracy as well as practical applicability for scalable screening in an education context.

Performance metrices computation:

Precision = TP / (TP + FP) = 48 / (48 + 2) = 0.96

Recall = TP / (TP + FN) = 48 / (48 + 2) = 0.96

*F1-Score = 2 * (Precision * Recall) / (Precision + Recall)*
*= 2 * (0.96 * 0.96) / (0.96 + 0.96) = 0.96*

Where: TP - True Positive ; FP - False Positive ; FN - False Negative ; TN - True Negative

The bar graph depicts the comparative performance of the Decision Tree and Random Forest classification models, on the evaluation metrics of Accuracy, Precision, Recall, and F1-Score as a measure of overall viable hypothesis testing and/or reasoning for modelling for dyslexic pathology recognition in both research and practice. Accuracy captures the ratio of total true predicted classes (correct) predictions; (for the TP classed model), Precision evaluates exactly how many of the predicted cases were true positive (TP) cases and Recall depicts the ratio true positives found by the model.

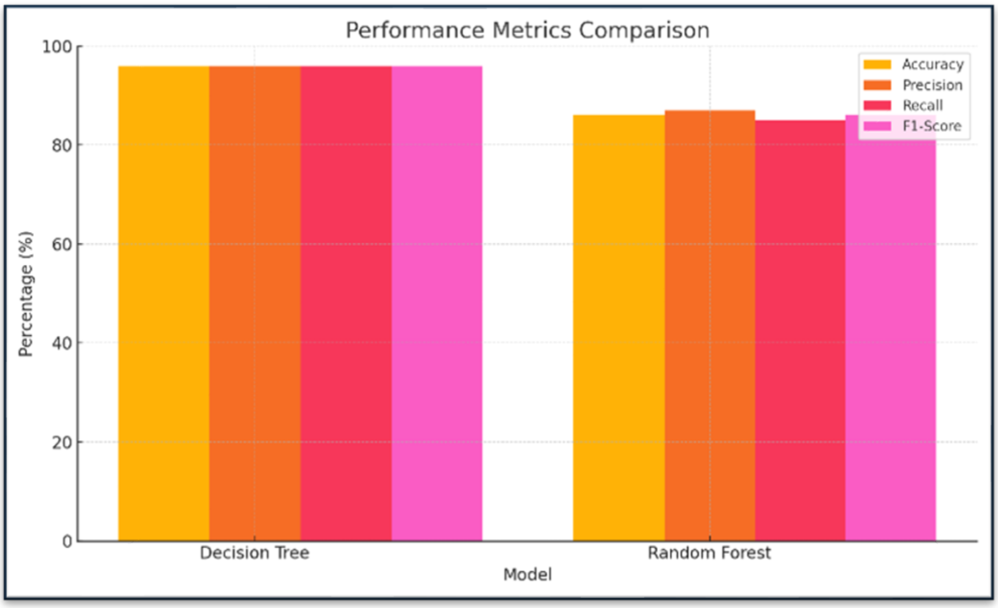

Figure 7. Model-wise Evaluation: Accuracy, Precision, Recall, and F1-Score**.**

The F1-Score is a robust metric in contexts where both false positive and false negative results matter. In this case, the Decision Tree model did better than the Random Forest model, which was not terrible, when looking at all the metrics. The Decision Tree model had the highest accuracy of around 96% and compromised balanced precision, recall, and F1-Score of 0.96. The Random Forest model did produce lower scores across the board with an accuracy of 86.03% and an F1-Score estimate of 0.86. This suggests that the Decision Tree model is better suited for this particular dataset and the feature set used in the current study.

Table 2. Comparing Performance Between Decision Tree vs Random Forest Algorithms for Detection of Dyslexia Using F1 Score.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Decision Tree	96%	0.96	0.96	0.96
Random Forest	86.03%	0.87*	0.86*	0.86*

* Estimated based on average individual values.

The results have been summarized in Table 2 providing a comparison of each models performance, demonstrating how the Decision Tree performed better than Random Forest models on all performance measures, which are accuracy, precision, recall and F1-Score, thus indicating a Decision Tree is more dependable for dyslexia detection.

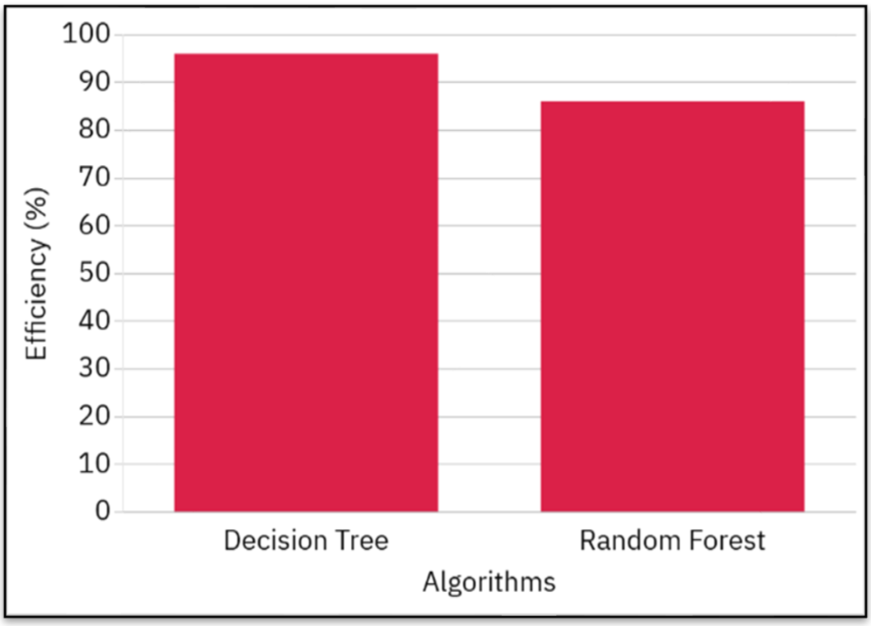

Figure 8. Bar Chart Performance Comparison of Decision Tree and Random Forest.

5. CONCLUSION

In summary, the early identification of dyslexia through machine learning could be greatly beneficial for improving the strategies for intervention and educational supports provided to dyslexic individuals. Dyslexia can be defined as a learning disability that impacts reading, writing, and spelling. Most of these people are undiagnosed or diagnosed late and this may cause extreme educational and emotional stress on people. Machine learning algorithms, such as decision trees and random forests, can offer a strong method to identify those who are at-risk for dyslexia earlier in life and through a more effective and scalable method than the conventional diagnostic methods.

Machine learning models can analyze different facets of a person's writing, whether it be grammatical structure, letter formation, spacing, or stroke order. For example, decision trees work by partitioning data based on certain features or characteristics of interest helping clarify points along the path to determine potential dyslexia indicators, random forests summarize the answers to many different decision trees to help minimize errors and increase accuracy when predicting decisions. Through computation and the detailed nature that writing can contain, machine learning is a capacity to examine subtle structures that can indicate dyslexia, which may well get missed by standard processes.

The scalability that machine learning offers is another important benefit. Typical dyslexia assessments need specialized professionals that are costly (financially and in terms of time), and it is not easy to deliver dyslexia assessments at scale. Machine learning tools are developed and validated very rapidly and when these methods are applied in schools or clinics, they afford a non-invasive method of screening children that does not require significant human resources. The result of this is that early detection tools can be democratised so that more children (especially in poorer communities) can be screened and receive support at school.

Implementation does come with its challenges, particularly the availability of good quality and diverse data. Machine learning algorithms learn from large datasets with a certain quality of data, and gathering sufficient amount of data proved to be difficult and problematic due to privacy and requiring a standard, categorized samples across demographics. Models also need to be trained to minimize bias from differences in handwriting styles that would be conditional to cultural or linguistic background.

This model provides a new, pragmatic and data driven alternative to support early identification and screening for dyslexia, for educators, parents and most importantly healthcare professionals ensuring that timely support and interventions can occur.

6. FUTURE SCOPE

Future research on machine learning for identifying dyslexia could incorporate data sets that will be inclusive of augmented data sets containing more examples of grammar which will assist with consistency, and generalization of the model within different age, language, and cultural groups. Combining with written assessments with other testing other tools to produce or assess written language skills and cognitive testing will provide more valid and reliable dyslexia diagnostic measures. Utilizing monitoring systems such as mobile or web apps for initial early dyslexia detection will allow educational professionals and health care professionals to use accurately to identify it.

Machine learning or computational methods can also assist with learning adaptations for literacy interventions that meet the child's individual writing and learning preferences, which will positively add to the educational program for a child with dyslexia. Other learning models like convolutional networks will also derive enhanced accuracy with identify slight shifts in grammatical changes that are related to dyslexia and support more sophisticated machine-based diagnosis. This improves the accuracy, consistency/reproducibility, and validity in detecting dyslexia from diverse groups.

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