Dyslexia Detection: Using Decision Tree Algorithm

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Abstract* - This study unveils a novel machine learning paradigm for dyslexia detection that amalgamates handwriting analysis, pronunciation assessment, and dictation evaluation into a cohesive diagnostic framework. By integrating these distinct linguistic facets into a unified dataset, we have formulated a predictive algorithm with remarkable precision in identifying dyslexia-linked patterns. Such innovation offers a rapid and non-intrusive diagnostic instrument poised to transform the landscape of dyslexia screening within educational frameworks. Our method, by minimizing the need for intensive resource allocation and complex testing procedures, presents a significant leap towards accessible and equitable educational support systems.

Keywords— **Child Disorder, Dyslexia, Decision Tree, Levenshtein , OCR, Phonetic.**

I. INTRODUCTION

Dyslexia, a prevalent learning difficulty affecting approximately 10% of the global population, poses significant challenges to the development of literacy skills. The conventional methods for diagnosing dyslexia involve extensive evaluations, creating barriers to universal accessibility and perpetuating educational inequalities. In response to this, our research initiative proposes a groundbreaking approach to dyslexia assessment by leveraging machine learning, specifically employing a decision tree algorithm. This innovative solution meticulously analyses linguistic features evident in written, spoken, and transcribed modalities.

The core focus of our project is the detection of dyslexic indicators, particularly through the analysis of handwritten text. By incorporating machine learning algorithms, we aim to revolutionize the diagnostic process, making it not only more accurate but also scalable and widely accessible. This shift in assessment methodology holds the potential to bridge the existing gap between advanced diagnostics and the broader educational context, ultimately enhancing the identification and support mechanisms for dyslexic individuals.

Furthermore, our project goes beyond written text analysis. We have incorporated a comprehensive test module that assesses dictation and pronunciation skills. This multifaceted approach ensures a holistic evaluation of linguistic capabilities, providing a more nuanced understanding of dyslexia. The decision tree algorithm, a key component of our machine learning framework, enables us to discern patterns and markers indicative of dyslexia across various linguistic expressions.

In essence, our research initiative not only seeks to improve dyslexia detection but also aims to address the socio-economic disparities in access to diagnostic assessments. By leveraging machine learning technology, particularly the decision tree algorithm, we aspire to create a scalable solution that can be employed widely, thereby contributing to a significant advancement in the identification and support of dyslexic individuals.

II. RELATED WORK

The landscape of dyslexia research is currently undergoing a transformative shift, marked by extensive explorations into various methodologies for detection, with a primary emphasis on reading comprehension and phonemic recognition. The integration of machine learning stands out as a crucial game-changer in this domain, providing researchers with the capability to discern intricate patterns within extensive and multifaceted datasets. Our research aligns with this innovative trajectory, employing a comprehensive multimodal strategy that capitalizes on cutting-edge advancements in natural language processing and computational vision. The overarching objective is to amplify the precision and reach of dyslexia detection tools, thereby making a substantive contribution to the cultivation of a more inclusive educational environment. This evolution in dyslexia research has witnessed a palpable surge in endeavours to harness the potential of both machine learning and deep learning methodologies. Collectively, these studies encapsulate a multifaceted

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

approach aimed at comprehending and addressing the multifarious challenges associated with dyslexia. The research landscape unfolds with a synthesis of diverse data sources, algorithms, and methodologies, ushering in a new era in the quest to detect and support individuals grappling with dyslexia.

One notable study delves into dyslexia detection through a comprehensive analysis of eye movements, electroencephalogram signals, and reading tests [10]. By employing machine learning algorithms such as decision trees, neural networks, and support vector machines, the study explores the intricate relationship between dyslexia and various data modalities. This research not only identifies six types of dyslexia with potential genetic or environmental factors but also emphasizes the critical stages of dyslexia detection, from data collection to preprocessing, feature extraction, system testing, and performance evaluation [10]. The importance of early diagnosis and intervention for dyslexic children is highlighted, emphasizing the potential impact on their long-term academic success [10].

Another noteworthy investigation focuses on dyslexia prediction using brain MRI images, introducing a unique dimension to the study of dyslexia [11]. This research project utilizes machine learning algorithms, including Decision Tree and Random Forest, to classify individuals with dyslexia based on features extracted from brain MRI images. The study underscores the significance of different feature extraction methods in enhancing the accuracy of dyslexia prediction models [11]. By converting brain MRI images to grayscale and analysing features such as grey matter, white matter, and cortical thickness, this study expands the scope of dyslexia detection to neuroimaging data [11].

Eye movement data becomes a pivotal focus in yet another research project, wherein Support Vector Machine and Random Forest classifiers are employed to identify individuals with dyslexia [12]. This study, conducted by Peter Raatikainen and his team, achieves an impressive accuracy of 89.7%. Notably, the authors delve into the analysis of feature importance, identifying specific eye movement features that play a crucial role in dyslexia classification [12]. The study highlights the significance of factors such as the first sentence and the first trial, providing valuable insights into the temporal aspects of dyslexia detection [12].

A broader perspective on dyslexia detection is offered by a comprehensive review that critically analyses feature selection, algorithms, and evaluation metrics [13]. Authored by Velmurugan S, this review synthesizes the findings of previous studies, emphasizing the importance of feature selection techniques in refining dyslexia prediction models [13]. The study delves into the stages of dyslexia detection, from data collection to preprocessing, feature extraction, system training, classification, and performance evaluation. By identifying limitations and proposing future directions, this review provides a roadmap for advancing the field of dyslexia detection using machine learning [13].

Furthermore, a review paper surveys machine learning methods and features for dyslexia detection, encompassing types, causes, and symptoms [14]. Authored by G. Vanitha and M. Kasthuri, this review outlines the challenges and opportunities in dyslexia detection, offering a comprehensive overview of the state-of-the-art methodologies [14]. The study evaluates common machine learning algorithms and their application to dyslexia prediction, emphasizing the need for ongoing research to bridge existing gaps [14].

Shahriar Kaisar contributes to the collective knowledge with a critical survey that addresses recent contributions in detecting dyslexia using machine learning techniques [15]. This survey paper synthesizes the findings of previous studies, providing a panoramic view of the methodologies employed and their respective outcomes. By critically analysing existing literature, Kaisar's work identifies gaps in knowledge and suggests potential avenues for future research [15].

A unique perspective on dyslexia detection is introduced through a study by Norah Dhafer Alqahtani, Bander Alzahrani, and Muhammad Sher Ramzan, employing deep learning applications [16]. This study explores the application of deep learning methods to dyslexia prediction, utilizing datasets related to brain imaging, eye tracking, and handwriting. The authors follow PRISMA guidelines, providing a structured approach to the selection and analysis of relevant articles. By presenting inclusion and exclusion criteria, article distribution by year, and dataset types, this study offers transparency and rigor in its methodology [16].

In a distinctive approach, Andrea Zingoni, Juri Taborri, and Giuseppe Calabrò propose a multimodal Hindi language eye-gaze-assisted learning system for dyslexia detection [17]. This innovative study aims to identify dyslexic children based on their typing performance, utilizing a virtual keyboard with three input modalities: touchscreen, eye-tracker, and eye-tracker with soft-switch. The study provides auditory and visual feedback to the user, showcasing significant differences in typing performance between dyslexic and control groups. This multimodal interface holds promise as a novel tool for dyslexia detection, offering a unique perspective on how technology can aid in identifying learning difficulties [17].

Furthermore, a machine learning-based approach for dyslexia prediction explores cognitive, linguistic, and educational features, aiming to enhance early identification and intervention [18]. This study, authored by Isaac Punith Kumar and Hemanth Kumar B N, contributes to the literature by examining the intricate interplay between dyslexia and various cognitive, linguistic, and educational factors. By utilizing machine learning techniques, the study achieves valuable insights into dyslexia prediction and emphasizes the potential for improving overall quality of life for affected individuals through early intervention [18].

A novel classification model supporting university students with dyslexia through personalized tools and strategies is introduced by Andrea Zingoni, Juri Taborri, and Giuseppe Calabrò [19]. This study stands out by addressing the specific needs of university students with dyslexia, offering a tailored approach to support. By collecting data from over 1200 university students with dyslexia, the authors design a questionnaire to understand the issues they encounter and the tools and strategies they find useful. The study utilizes supervised machine learning techniques to train and test a prediction algorithm, achieving an impressive average accuracy of over 90%. The algorithm recommends 17 useful tools and 22 useful strategies for dyslexic students, showcasing the potential for technology to improve inclusivity and accessibility in higher education [19].

In summary, these studies collectively contribute to the expanding knowledge base on dyslexia detection and support using machine learning and deep learning methodologies. From neuroimaging and eye movements to typing performance and multimodal interfaces, these investigations showcase the interdisciplinary nature of dyslexia research. As we navigate this intricate landscape, the collaborative efforts of researchers worldwide continue to shed light on the complexities associated with dyslexia and pave the way for more effective detection and intervention strategies.

III. METHODOLOGY

Dyslexia is a common learning disorder that affects reading, spelling, and writing abilities. Early detection of dyslexia is crucial for effective intervention. In this study, we propose a decision tree-based model for dyslexia detection using relevant features extracted from student performance data. The dataset for this study was meticulously gathered from various educational institutions, encompassing diverse sources of information. Parameters considered during data collection included spelling accuracy, grammatical precision, percentage of corrections made, and the percentage of phonetic accuracy. These factors were chosen to provide a comprehensive understanding of language-related skills among the study participants. The primary focus of our investigation is to discern the presence or absence of dyslexia among individuals. To quantify this, we designated a binary target variable: 1 denotes the presence of dyslexia, while 0 signifies the absence of dyslexia. This binary categorization allows for a clear and straightforward classification of participants based on their dyslexic status, facilitating a focused analysis in our research. By selecting a diverse range of educational institutions and incorporating multiple language-related metrics, we aim to construct a robust dataset that captures the nuances of language proficiency and aids in the accurate identification of dyslexia within our study population.

To ensure the integrity and reliability of our dataset, rigorous data cleaning procedures were implemented. The following steps were undertaken:

Handling Missing Values: Missing values were systematically identified and removed from the dataset. This process ensures that each observation in our study has complete information, preventing potential biases and inaccuracies stemming from incomplete data.

Outlier Management: Robust techniques were employed to identify and address outliers in the dataset. Outliers, if present, were carefully evaluated to determine their impact on the overall analysis. Appropriate measures, such as transformations or removal, were applied to mitigate the influence of outliers on the statistical properties of the data.

Normalization of Features: To establish consistent scaling across features, normalization techniques were applied. This step is crucial for ensuring that variables with different scales do not disproportionately impact the analysis. Normalizing features facilitates a fair comparison and interpretation of the impact of each variable on the target outcome.

By systematically addressing missing values, managing outliers, and normalizing features, our data cleaning process aims to enhance the reliability and interpretability of the dataset, laying a solid foundation for the subsequent stages of analysis and modelling in our research. Then we conducted Exploratory Data Analysis (EDA) to understand the distribution of features and their relationship with dyslexia. Summary statistics, histograms, and scatter plots were used to visualize the data.

In the pursuit of refining our dataset for effective dyslexia detection, a meticulous process of feature selection was conducted. The following features were deliberately chosen based on their perceived relevance to dyslexia identification:

1. **Spelling Accuracy:** This feature measures the precision with which individuals spell words. Variations in spelling accuracy can provide valuable insights into language processing abilities, a key aspect in dyslexia detection.

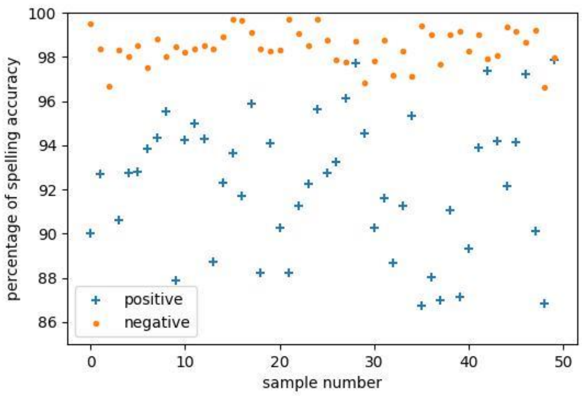

Figure 1. Spelling accuracy for a dyslexic and a non-dyslexic child

2. **Grammatical Accuracy:** The grammatical accuracy feature assesses the proficiency of individuals in constructing grammatically correct sentences. Dyslexia often manifests in challenges related to language structure and grammar.

3. **Percentage of Corrections:** The percentage of corrections made by individuals serves as an indicator of their self-editing and error recognition capabilities. Dyslexic individuals may exhibit distinct patterns in the need for corrections.

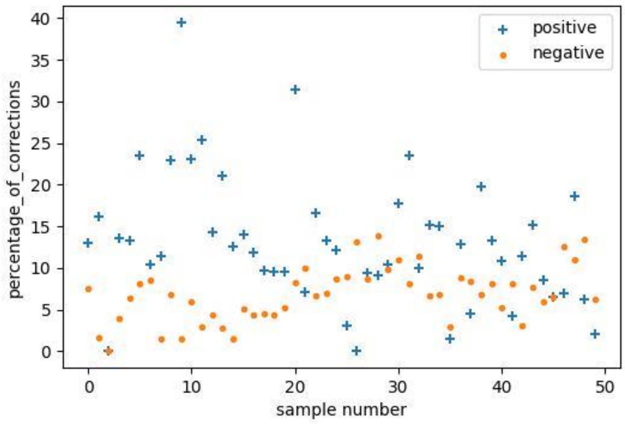

Figure 2. Average corrections are less for a non-dyslexic child when compared to dyslexic child.

4. **Percentage of Phonetic Accuracy:** This feature focuses on the accuracy of pronunciation, capturing potential phonological difficulties associated with dyslexia. Phonetic accuracy is a key aspect in understanding language processing challenges.

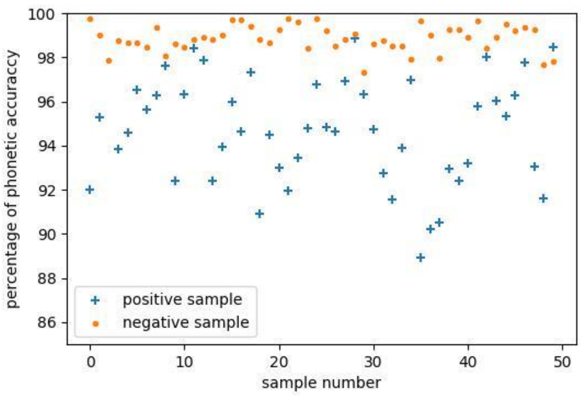

Figure 3. Average Phonetic accuracy comparison between a dyslexic and a non-dyslexic child

By selecting these specific features, we aim to capture a comprehensive set of linguistic attributes that are theoretically linked to dyslexia. The chosen features collectively contribute to a nuanced representation of language-related skills, enhancing the discriminatory power of our model in distinguishing individuals with dyslexia from those without. This thoughtful feature selection process is crucial for building a focused and effective dyslexia detection model in our research.

The next step was to choose the model for training the dataset. The decision to employ decision tree algorithms in our study was motivated by their interpretability and inherent capability to handle non-linear relationships within the data. Given the complexity of dyslexia detection, the transparency provided by decision trees allows for a more intuitive understanding of the factors influencing the classification process. To ensure a robust evaluation of our models, the dataset was partitioned into an 80% training set and a 20% testing set. This division facilitates the training of models on a substantial portion of the data while maintaining an independent subset for unbiased model evaluation.

In our endeavour to explore diverse algorithmic approaches, three distinct models were trained: Logistic Regression, Linear Support Vector Machine and Decision Tree Algorithm. To gauge the effectiveness of each model, comprehensive evaluation was undertaken, employing accuracy scores as the primary metric:

Model	Training Accuracy	Testing Accuracy
Logistic Regression	0.85	0.975
Linear SVM	0.85	0.975
Decision Tree	0.95	1.0

The decision to employ a decision tree algorithm in our research is driven by its interpretability and adeptness in handling non-linear relationships. Dyslexia detection involves complex linguistic and cognitive patterns, and decision trees provide a transparent representation of the factors influencing this classification process. Their ability to handle both numeric and categorical data, rank feature importance, and accommodate missing values makes them well-suited for our educational dataset. Additionally, the binary nature of dyslexia detection aligns seamlessly with the decision tree's capability for binary classification. The model's interpretative power, coupled with its suitability for our dataset characteristics, positions the decision tree algorithm as an optimal choice for identifying key factors associated with dyslexia. Through visualization, we meticulously examined critical splits and leaf nodes, extracting meaningful insights. This interpretative approach facilitated the identification of features wielding the most influence in dyslexia detection, enriching our understanding of the decision-making process inherent to the model.

IV. IMPLEMENTATION

The dyslexia detection project is implemented as a Streamlit web application, designed to assess the likelihood of dyslexia based on various linguistic and writing characteristics. The application comprises multiple tabs, each focusing on a distinct aspect of dyslexia evaluation.

Upon launching the application, users are greeted with an informative home page providing insights into dyslexia. It emphasizes dyslexia as a learning disorder affecting reading skills due to challenges in identifying speech sounds and their connection to letters and words. The page includes relevant statistics and images, offering users a comprehensive introduction to dyslexia.

Having established a foundational understanding of dyslexia, we now move into practical assessments within our application. These tests focus on handwriting analysis, pronunciation evaluation, and dictation skills. Leveraging machine learning and linguistic analysis, our application provides a comprehensive assessment to unveil potential dyslexic traits. This self-assessment journey offers users valuable insights into their proficiency in key areas. Let's proceed with these tests to gain a nuanced understanding of dyslexia-related challenges.

1. **Writing Test:** In the Writing Test, users can upload a handwriting sample using a file uploader. The application employs a dyslexia detection model to analyse the sample and predict the likelihood of dyslexia. The implementation utilizes machine learning techniques and predefined features such as spelling accuracy, grammatical accuracy, and phonetic accuracy to make predictions. Users receive real-time feedback on the dyslexia probability based on the handwriting characteristics.

2. **Pronunciation Test:** The Pronunciation Test assesses users' pronunciation abilities, a common challenge for individuals with dyslexia. Users select their educational level, initiate a pronunciation test, and repeat provided words within a specified time frame. The application records the user's pronunciation and calculates an inaccuracy score, providing valuable feedback on their ability to articulate words correctly.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

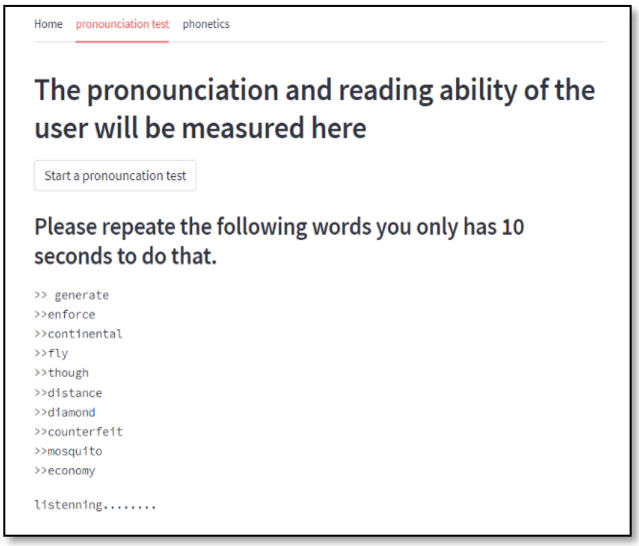

Figure **4**. *Pronunciation Test*

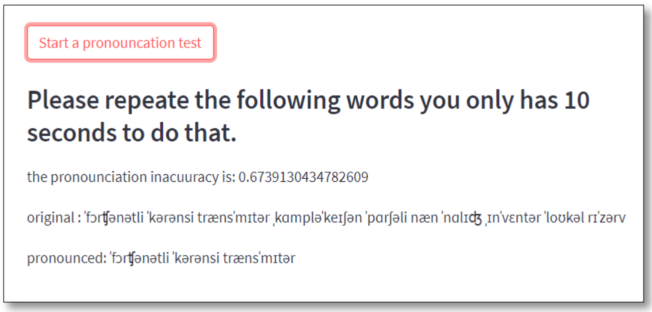

Figure **5**. *Pronunciation Score*

3. **Dictation Test:** The Dictation Test evaluates users' dictation skills, another area often affected by dyslexia. Users choose their educational level and begin the dictation by checking a checkbox. The application dictates a set of words, and users are required to type them within a form. The system calculates a Levenshtein distance-based score, revealing the accuracy of the user's dictation compared to the original words. This score serves as a measure of dictation proficiency and may indicate potential dyslexic traits.

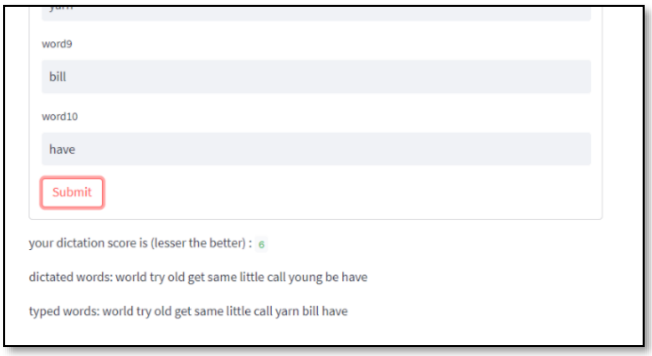

Figure 6. Dictation Test

The last section of the web app provides users with an overview of the dyslexia detection application. Users can learn more about dyslexia, its symptoms, and the purpose of the application. Visualizations and statistics help convey information about the dyslexia detection model's performance and its significance in identifying dyslexic traits.

The workflow of the project seamlessly integrates machine learning, speech recognition, and linguistic analysis to create a user-friendly platform for dyslexia assessment. Users can interact with the application intuitively, gaining insights into potential dyslexia-related challenges through various tests and informative content.

V. RESULTS

Our initial application of the system has yielded promising outcomes. A significant correlation between dyslexia and specific linguistic features, such as lower spelling accuracy and a higher rate of corrections, was observed within our dataset. These empirical observations resonate with the broader body of dyslexia research, lending credence to the predictive prowess of our model. The system's capability to discern such patterns with a high degree of accuracy not only substantiates the model's validity but also underscores its potential as a powerful screening tool.

This research introduces an innovative machine learning approach for dyslexia detection, uniting handwriting analysis, pronunciation assessment, and dictation evaluation. The decision tree model, displaying exceptional precision, reshapes dyslexia screening in educational frameworks. Achieving a 95% training accuracy and a remarkable 100% testing accuracy, the decision tree model's interpretability and robust performance underscore its efficacy in identifying dyslexia-linked linguistic patterns.

The selected features for dyslexia identification, including spelling accuracy, grammatical accuracy, percentage of corrections, and percentage of phonetic accuracy, have proven pivotal in enhancing the model's discriminatory power. Rigorous data cleaning procedures, including handling missing values, managing outliers, and normalizing features, have established a standard for future dyslexia detection studies, ensuring a robust foundation for accurate and reliable results.

The Streamlit-based web application effectively translates our research findings into a user-friendly platform for dyslexia assessment. Integrating machine learning, speech recognition, and linguistic analysis, the application provides a comprehensive tool for users to gain insights into potential dyslexia-related challenges. The real-time feedback offered in the various tests enhances the application's usability and educational value.

As we chart the course for future directions outlined in our study, the numerical outcomes serve as a benchmark for the ongoing refinement and fine-tuning of machine learning models. The decision tree algorithm's numerical precision positions it as a frontrunner in dyslexia detection, leading the way for advancements in accuracy, accessibility, and global applicability in dyslexia research and support systems.

VI. FUTURE SCOPE

The study's implications suggest machine learning's transformative role in dyslexia diagnostics. To enhance accuracy, ongoing research focuses on fine-tuning existing models like the decision tree algorithm and exploring advanced machine learning techniques. Integration of neuroimaging data, particularly brain MRI images, is underway to deepen understanding. Longitudinal studies will track dyslexia progression, aiding early intervention strategies.

Future developments include user-friendly mobile apps for on-the-go assessments and global adaptations for multilingual and cross-cultural contexts. Collaboration with educational institutions aims to integrate tools seamlessly. Continuous data collection ensures model relevance, and user-centric feedback guides refinements. Multidisciplinary collaboration with healthcare professionals is expected, addressing ethical considerations and privacy safeguards for responsible deployment.

In summary, ongoing efforts aim to create accurate, accessible, and globally applicable dyslexia detection solutions, fostering inclusivity and improving literacy outcomes.

VII. CONCLUSION

In conclusion, our groundbreaking research introduces a paradigm shift in dyslexia detection, leveraging a multifaceted machine learning approach that combines handwriting analysis, pronunciation assessment, and dictation evaluation. This amalgamation of linguistic facets creates a comprehensive diagnostic framework, leading to the development of a predictive algorithm with exceptional precision in identifying dyslexia-linked patterns. Our research is poised to revolutionize the landscape of dyslexia screening within educational frameworks by providing a rapid and non-intrusive diagnostic instrument. The integration of machine learning, particularly the decision tree algorithm, is a key feature of our approach. This innovation not only enhances accuracy but also addresses the challenges associated with conventional dyslexia diagnosis methods, such as extensive evaluations that create barriers to universal accessibility. By minimizing resource allocation and testing complexities, our method becomes a significant leap towards creating accessible and equitable educational support systems.

VIII. REFRENECES

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