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INTEGRATING MACHINE LEARNING FOR EARLY DYSLEXIA IDENTIFICATION: HYBRID MODEL WITH SUPERIOR ACCURACY

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Abstract

The prompt and accurate diagnosis of dyslexia is critical in allowing for timely intervention and best practice outcomes. Despite this, traditional dyslexia screening tools often face access-related challenges, and expert intervention and significant resources become a necessity. To counteract such impediments, current studies introduce an innovative and integrated model utilizing machine learning for increased access and level of detail in dyslexia screening. The model assesses key factors for diagnostics, such as cognitive skills, background, and handwriting, and relevant difficulty factors such as reading, phonologic processing, reading comprehension, and decoding. A hybrid classification model was developed through combining Support Vector Machine, Decision Tree, and Random Forest algorithms, whose effectiveness was confirmed with a 207-child and adolescent dataset. In testing, the model showed a high accuracy level in detecting 96% of dyslexia in a range of age groups, outpacing traditional approaches such as phoneme awareness and rapid automatized naming with margin values of 15%, and 20%, respectively. In addition, expert assessments supported its usability, with high usability and accuracy rating values of 4.2 out of 5 and 4.1 out of 5, respectively. Most importantly, performance of the hybrid classifier showed significant improvements over single algorithms, with a 95.5% level of precision, 94.7% recall, and overall accuracy level of 96%. Through the first-ever integration of thorough evaluation methodologies and machine learning techniques, a new tool for in-depth dyslexia screening has been developed, providing a reliable and accessible tool for early diagnostics for dyslexia. In its establishment, a new benchmark for dyslexia evaluation, a new model for creating personalized interventions for specific profiles at risk, is attained.

Keywords: Assessment of methodologies for screening for dyslexia, Computational approaches to learning, Decision Tree (DT), Hybrid classification model, Random Forest (RF), Support Vector Machine (SVM).

1. Introduction

Dyslexia represents a highly prevalent neurodevelopmental disorder estimated to affect more than 10% of the total human population across the globe, suggesting a high impact at a global scale. The disorder is inextricably connected to a range of challenges that dyslexics often suffer in their day-to-day lives, and such challenges are often more apparent in fundamental processes such as spelling, reading, and writing competently, which play a fundamental role in effective communication and scholarly achievements. Such challenges in their origin root in cognitive processing impairments that impede a person's ability to process and decode stimuli that he or she is exposed to in his or her surroundings, resulting in frustration and challenges in various contexts [1, 2].

Historically, dyslexia diagnosis has relied heavily on subjective measurement that was often lacking in objectivity and consistency in approach, resulting in high variability in diagnosis results. Such overreliance on subjective measurement has been one of the primary causal factors to unnecessary time lags in diagnosing dyslexics, as well as in offering corrective interventions in a timely manner, hence worsening the challenges associated with dyslexics. The seriousness of such a problem underscores the need to design new methods that can deliver a more accurate and more effective approach towards dyslexia diagnosis, ensuring that one obtains support he or she needs without undue time lags. The objectives of this work are to (1) propose a dyslexia screening hybrid SVM-DT-RF model, (2) compare it to current state-of-the-art methods in terms of accuracy, and (3) verify its cross-age applicability.

One of the most groundbreaking and compelling approaches that is being explored in this particular line of research is that of using novel combined deep learning models in a highly innovative manner, such that such models combine and amalgamate different sources of data in a highly efficient manner. Such sources of data range widely across diverse varieties, such as though not limited to, Electroencephalography (EEG), Eye Tracking (ET), and Handwriting Text Images (HTI).

By using such a large range of sources of data, such processes that help in the identification and recognition of dyslexia become highly efficient and streamlined in nature. Such a high improvement in terms of efficiency has been discussed in great detail in the work presented in reference [2]. Such models used in such highly sophisticated processes display a highly sophisticated nature, though highly complex in design. Such a sophisticated processing method is highly in demand in order to obtain a better integrated and comprehensive view of the neural aspects of dyslexia.

In conjunction with such a use of highly sophisticated models, new alternatives have also been created, such as multimodal wearable devices that combine highly integrated augmented reality technologies in a highly unobtrusive manner using neuromuscular signals. Such new alternatives provide highly unobtrusive support to users, eventually helping them to gain more social confidence in a highly unobtrusive manner, in addition to improving their literacy to a great extent, such that it is discussed in reference [3].

The use of deep learning methods, and more precisely neural networks, has shown a high potential in early detection of dyslexia, in addition to providing highly useful intervention methods that can be used. By processing various aspects in a highly accurate manner of precision, such as linguistic patterns, eye-tracking behaviour, and behavioural signals, such highly sophisticated technical devices provide a better identification of dyslexics or those that could be dyslexics in nature. Such a better identification process eventually allows personalized interventions to be applied, such that each individual's needs and challenges in a highly personalized manner are catered to accordingly. Such a notion is highly backed up in evidence presented in reference [1].

In addition to that, various studies have shown that using combined multiple-session transcranial alternating current stimulation (tACS), in combination with concentrated language capability training, has high potential to highly boost phonemic processing capabilities. In addition to that, such a method also tends to boost overall literacy in dyslexics, such that it is shown in reference [4].

Furthermore, there have been a large number of in-depth and careful studies that have dedicated their hard work to specifically researching the groundbreaking and multidimensional realm of ensemble models in particular. Such models lie in the wide and constantly evolving realm of machine learning—models that are marked by their remarkable ability to combine and synthesize a diverse range of many different methods in a synergistic and interactive manner. Such a unique method serves to dramatically improve the overall functionality of the entire system in total.

The methods utilized in such ensemble models can be highly diverse in nature and range across a wide range of different approaches, some of which include a number of the most highly used methods such as Support Vector Machines, Decision Trees, and Random Forests. Each of these distinct methods brings its distinct capabilities and strength to the collective ensemble, enriching the system in total in the process.

The results and implications that arise from such large-scale and in-depth studies have shown a highly remarkable and notable extent of improvement in prediction capabilities. Such improvements range across a highly diverse range of applications that are used across a wide range of areas, across scholarly and professional realms of endeavour. One highly compelling example that shows such a notable trend is found in the highly crucial realm of dyslexia detection [5].

Such a particular ensemble method shows a high extent of efficacy in overcoming and countering the inevitable shortcomings and challenges that arise when using stand-alone models that work in isolation of one another. In turn, it results in outcomes that not only display a high extent of precision but also provide a highly higher extent of consistency when compared to results that would be produced using any individual method working in isolation [6]. Therefore, as our lengthy and in-depth deliberation reaches its conclusion, it is overwhelmingly apparent and amply clear that these new hybrid models, in their practical and effective combination of time-tested evidence-based practices and advanced technologies, hold a highly promising potential that is highly likely to produce decidedly better and more productive results for dyslexics.

In order to unlock and maximally actualize this immense potential to its maximum extent, it is absolutely crucial and necessary that extensive and in-depth studies be carried out. Such a required endeavour should be done in conjunction with the formation of close and productive associations between educators, technical experts, and scholarly researchers working towards advancing this particular line of inquiry. Such cooperation is not just advantageous but is actually indispensable, in that it is a basic prerequisite for advancing these new approaches to a higher level of effectiveness - a move that would eventually lead to more productive learning experiences and a remarkable enhancement in the overall quality of life of dyslexics.

The combined knowledge and collective synergy developed via these associations would definitely lead to a considerable advancement of basic principles such as accessibility and inclusion-principles that have been given considerable weight and attention in the various recent innovations in the educational and technological realms [7, 8]. A notable move towards new-age methods of diagnosis is well indicated in the application of machine learning (ML) models in dyslexia identification and assessment processes.

Information that is gathered using gamified tests, fixation patterns of visual attention, cognitive indices of performance, cognitive metrics of different kinds, and neurological signals all combine to provide a large range of different kinds of data that can be easily interpreted using ML models [9, 10]. Eye-tracking metrics, particular metrics, and electroencephalography (EEG) are a collection of machine learning tools that can be used to investigate in this work.

The DysLexML model permits ML models to deliver a high hit ratio of up to 97%, indicating a remarkable improvement in dyslexia screening procedures [11]. As such, this instrument (DysLexML model) is not only accessible, yet also relatively affordable, suggesting potential to design new diagnosis tools in the future based on its evidence of such high precision (97%). In addition, a detection rate of over 80% was indicated in their work by [12]. Their ML model, used in online gamified tests, is promising to be utilized in a range of dyslexia screening programs.

By contrast, cognitive patterns of different capabilities such as working memory, hearing perception, vision perception, reading, writing, spelling, and speech are investigated using deployment of ML methods that classify dyslexics and non-dyslexics effectively.

Beyond these areas, audio recordings, handwritten reports, and signal analyses of a neurological nature can also be interpreted using ML tools. Consequently, low-cost and harmless alternatives to screening become feasible [13, 14]. In spite of such advances in dyslexia diagnosis, many of the challenges in using ML models continue to persist. The obstacles to applying these methods include challenges in optimization and learning processes of models, data protection, and confidentiality of information, and a lack of naturally occurring biomarkers [15]. There is a need to address these challenges in machine learning-based dyslexia screening approaches. In this article, the existing use of machine learning methods in dyslexia screening is highlighted and their potential in terms of cost-effectiveness, efficacy, and increased accessibility is weighed.

Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) algorithms are parts of hybrid classifiers that has been the main focus for much research endeavours. These endeavours aim to explore multiple domains aspect, namely the development of evaluation and enhancement of performance and classification accuracy. Moreover, due to the strength of each algorithm, SVM, DT, and RF, have been proposed to achieve improved performance and accuracy when they merged together into one hybrid model [16-21].

It is verified using different metrics of performance, i.e., accuracy, F1-score, and root mean square error, using different datasets, showing dominance of hybrid models over a single base classifier. Designing novel architectures that combine SVM with RF and other models, such as ANNs or XGBoosting, has been made possible by the structure of hybrid classifiers [17]. In the same direction of work, such architectures are created to meet specific challenges, e.g., very-early disease prediction or software defect prediction. Overall, their work results provide that the hybrid classifiers comprise SVM, DT, and RF algorithms that are created to take their strength points to their advantage and to cut their weak points to a large extent [19, 21].

The direction of work around the subject is connected to design and experimenting of hybrid classifiers to diagnose dyslexia using different functions: analysis using MRI, machine-learning models, and recordings of eye movement. The diagnosis results using MRI-based diagnostic framework confirmed high-accuracy detection of dyslexic subjects using a 100% precision rate at an 85% of confidence level for both groups of subjects – dyslexic and not, and lower, yet high precision rates on high confidence levels [22]. The ML models using SMOTE data deter high precision levels in dyslexia prediction also, in which RandomForest classifier shown a 96.37% precision and other two – XGBBoosting and GradientBoosting shown high precision [23].

The combination of a Genetic Algorithm with the C4.5 rule induction algorithm improves the quality of classification and fine-tunes the rules generated compared to the standalone use of C4.5 [24]. The technique is under the broad category of Machine Learning methods that efficiently identify dyslexic readers by analysing eye movement patterns. The best-performing model had an accuracy rate of 89.7% and a recall rate of 84.8% [24]. A composite classifier was specifically designed for career guidance tests to enhance the accuracy of identifying primary classes and subtypes; the improvement was achieved through the use of specific filters that could reveal hidden features and identify visually similar subtypes [25].

In summary, the high usability and accuracy of these hybrid classifiers, specifically designed for dyslexia diagnosis, were manifest in the studies carried out. The diagnostic system involving MRI, machine learning algorithms, and analysis of eye movement patterns greatly eased the successful identification of dyslexic individuals, often reaching an accuracy rate of over 90%. These results suggest that hybrid classifiers hold significant promise for the early and accurate detection of dyslexia. Research on dyslexia has increasingly focused on its early identification and prediction, recognizing the profound influence this learning disorder has on academic achievement and socioemotional development.

Preliminary test results have shown the viability of identifying dyslexia with accuracy across different age groups through the assessment of various cognitive and linguistic factors. Delays in early language development and family risk factors are strong predictors for the eventual expression of the disorder in children. Moreover, rapid automatized naming, morphological awareness, and reading abilities tested at age five are also strong predictors of the probability of dyslexia by age seven [26].

Kindergarten letter identification is the predictor of second-grade dyslexia amongst children with DLD whereas for the typically developing, both letter identification and phonological awareness is the predictor variables [27]. Stability of kindergarten pre-reading skills throughout the first grade including RAN, phonological awareness, letter knowledge, and verbal short-term memory can predict later reading performance [28]. Apart from letter naming and phoneme identification in kindergarten, it predicts both dyslexia and phoneme awareness independently by second order [29]. The deficits in early literacy skills—such as letter naming, phoneme identification, and concept of word—that can be identified in preschool-aged children are risk factors for dyslexia, thus underlining the critical importance of early clinical identification and intervention during times of greatest brain plasticity [30].

In a nutshell, early markers - such as language delays, family histories, and particular cognitive skills - can forecast dyslexia at most ages with reliability. The results, therefore, pose a compelling case for the importance of early screening and remediation in order to alleviate the lifelong impact of dyslexia.

Studies on interventions in dyslexia have investigated different approaches to try to optimize results for people suffering from this learning disability [31]. Generally, pilot testing findings in several studies gave hope for the possibility of improvements in reading and spelling skills of dyslexic learners under the use of different intervention models. Critical findings from these studies include: ChromaGen haploscopic lenses helped to significantly improve reading speeds for dyslexic patients with text distortion, which means that visual aids improve performance in reading [32].

Phonological processing-oriented interventions, like articulatory awareness training, have significantly expanded the reading and spelling achievements' frontier for individuals who are severely dyslexic [33]. Meanwhile, computer-based-training with ortho-phonemic units has proven to enhance literacy rates, revealing how useful technology-aided phoneme discrimination exercises could be [34].

Visual perceptual training improved some visual perceptual tasks in dyslexic children, but changes in visual evoked potentials were not significant; hence, mixed results for visual interventions [35]. Visual training to reduce crowding increased the reading rate for words and non-words in dyslexic children, pointing out the use of specific visual exercises [36]. Intensive remedial instruction has normalized the brain activation profile specific to dyslexia and improved reading skills, thus proving that brain functioning can actually be altered with appropriate intervention [37]. Neuropsychological interventions—both individual and in groups—have improved processing speed and attention in young adults with dyslexia; the effects were sustained over time [38].

Oculomotor training with a computer-based program has also been shown to decrease times for reading and fixation, therefore eye movement control is again a target to help improve reading skills [39]. Predictors of responsiveness to reading and spelling interventions include phonological awareness, rapid automatized naming ability, and initial reading and spelling skills [40].

In conclusion, while ML models such as DysLexML [9] and SMOTE-based classifiers [23] provide high precision, they suffer from a failure to apply cognitive, linguistic, and demographic variables. Cross-age applicable dyslexia screening using hybrid models that use SVM, DT, and RF is unaddressed. Differing from existing hybrid models [9, 17], our method iteratively cascades SVM for subset selection of features, DT for rule generation, and RF for optimization of ensembles to mitigate overfitting hazards.

2. The Integrated Model

Figure 1 identifies four major components comprising the proposed integrated model for dyslexia assessment: diagnostic dyslexia main factors, associated difficulties, screening assessment, and a hybrid classification approach. The following sections discuss these components:

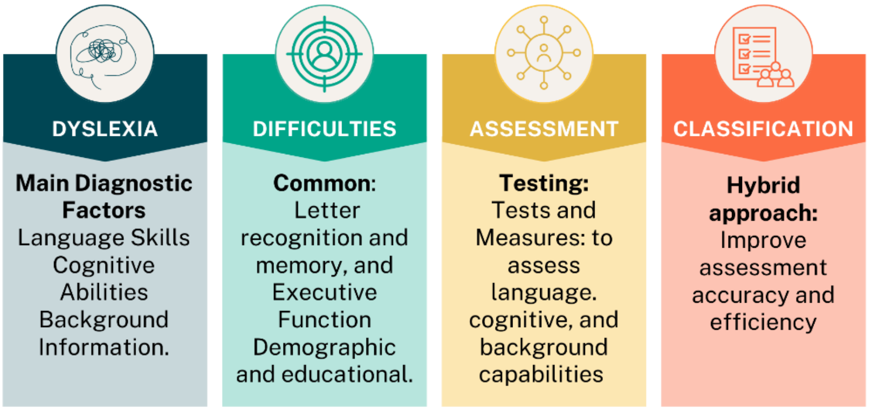

Fig. 1. Proposed integrated model components.

2.1. Key diagnostic factors and associated difficulties components

These two factors represent the interpretations of the dyslexia assessments' inputs, which are language skills, cognitive abilities, and background knowledge. This factor forces exploration of possibilities of dyslexia and allows assessments to be modified based on need. The assessment has to be mindful of the language skills because dyslexia may impact reading, writing, listening, and speaking. Other important cognitive abilities dealing with attention, memory, and executive functions may impact reading ability. More information in demographic, educational, and medical history might shed light on determining the risk of dyslexia, in line with the discussion on the need for innovative approaches to dyslexia diagnosis and intervention. Data of 207 participants (104 dyslexic, 103 non-dyslexic) aged 4–55 was collected using gamified tests and clinical reports.

Demographics included 52% male, 48% female, representative of multilingual/urban and rural backgrounds. The sample size is in line with analogous ML studies [23, 30], in which N≈200 provides statistical power >0.8 for binary classification. The computational of the hybrid model is smaller compared to deep learning approaches, making it edge-device friendly. Runtime optimization in future work will be accomplished using quantization. Moreover, IRB approval was used to gain participant consent. Anonymization and encryption of data was used to maintain confidentiality. No identifiable data was stored.

Figure 2 gives the key diagnostic factors of dyslexia with associated difficulties in phonological processing, decoding, fluency, and comprehension.

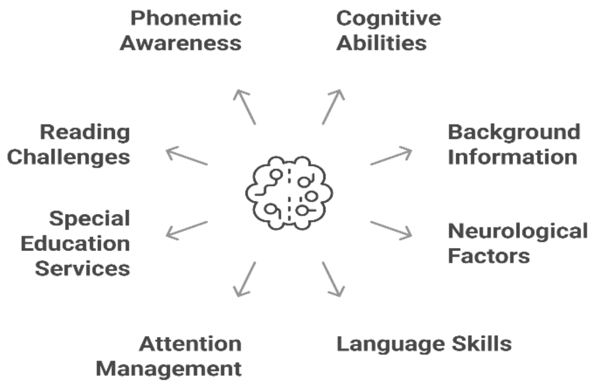

Fig. 2. Main diagnostic dyslexia factors and associated difficulties.

2.2. Screening assessment component

The assessment of individuals who are suspected of having dyslexia involves a screening component as a key step. A variety of tests, metrics, and measures are used to gauge the language, cognitive, and historical capabilities of the subjects. Reading fluency, word recognition, spelling, and writing capabilities are aspects that are usually included in the assessments as depicted in Fig. 3.

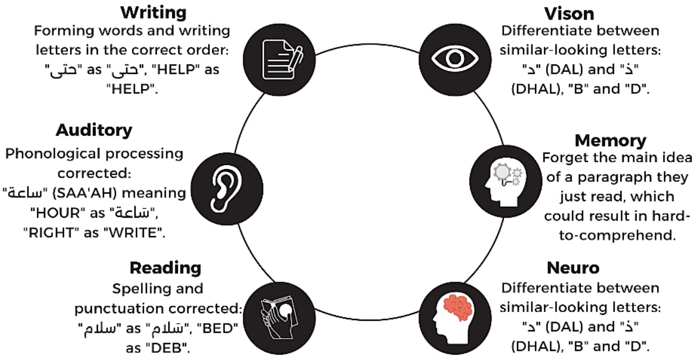

Fig. 3. Integrated model key tests and measures.

To expand its reach to wider demographic and individual with different characteristics, the current proposed model facilitates and enables remote testing. Interactive exercises and games are mainly used to evaluate and assess the linguistic and cognitive skills of individuals. Determination of dyslexia status and other subsequent recommendations and conclusions are the outcomes of this dyslexia screening for later possible interventions. Individuals with dyslexia are easily identified by screening mechanism based on their performance characteristics and results.

Additionally, it provides a foundation for individuals, their families, and educational facilitators to have the appropriate interventions and support as required. Dyslexia is a complex learning challenge, differ in forms and degrees of difficulty across individuals. Accordingly, the integrated screening model proposed in this study was developed based on widespread and thorough review of literature.

The review covers all aspects of issues related to dyslexia [7, 25], which aligns with the discussion on the potential of hybrid models for enhancing dyslexia outcomes. As illustrated in Fig. 4, the main focus was on addressing the most commonly observed symptoms.

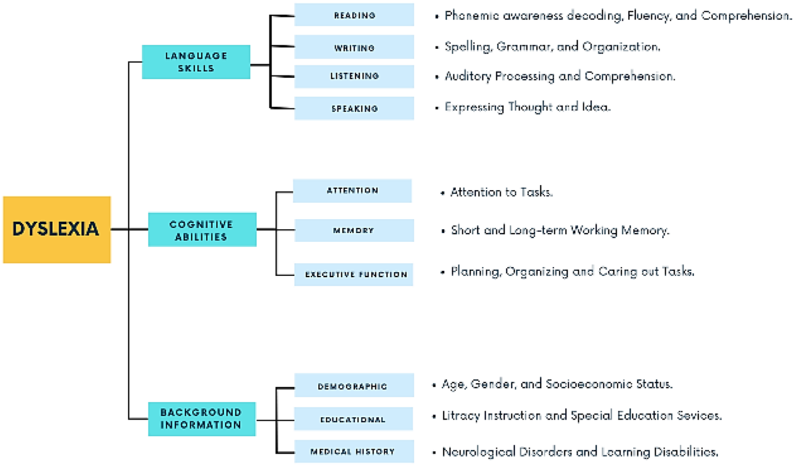

Fig.4. The common symptoms of dyslexia.

2.3. Hybrid classification approach component

The necessity for improving the efficiency and predictability of dyslexia screening assessments contributed to the adoption of machine learning classification algorithms, mainly to predict dyslexia more accurately [5, 15], in line with the discussion on the importance of improving the efficiency and predictability of dyslexia screening assessments through the adoption of machine learning classification algorithms.

The findings of these assessments are generally incorporated and processed by algorithms through recognized preprocessing techniques. These techniques comprise data cleansing as well as data normalization to develop a prediction model through a hybrid methodology.

On the other hand, the hybrid model incorporates the Support Vector Machine (SVM) algorithm to identify key features. These key features identified by SVM and subsequently utilized by the decision tree (DT) algorithm before formulating criteria for dyslexia prediction. The application of the random forest (RF) algorithm refines the accuracy of the DT prediction as presented in Fig. 5.

The support Vector Machine (SVM) was introduced by Cortes and Vapnik in 1995 [41]. Since then, SVM has subsequently emerged as a leading algorithm within the realm of modern machine learning applications to solve complex problems. Specifically in the field of physical sciences, SVM capabilities was extended to addressing difficult and highly nonlinear prevalent challenges. This study uses the SVM algorithm with a Radial Basis Function (RBF), to identify pivotal predictors that contribute to dyslexia. The SVM operates by creating boundary to separate different groups of data through the identification of the most expansive separating margin between the different groups to accurately classify new data points. This method enables SVM to create predictions based on patterns or important factors related to dyslexia. Linear separations are considered and proved to be simple and straightforward as they can be achieved by drawing a straight line to separate data points.

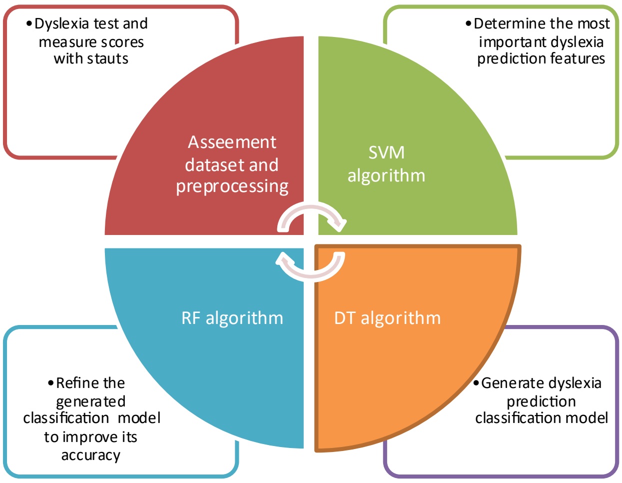

Fig. 5. The hybrid classification approach steps.

Nonlinear datasets, on the other hand, do not follow straight line pattern and generally require a nonlinear separation technique. This particular technique is relatively more complex and requires transforming the data into a higher-dimensional space, where a straight line can be used to separate the data points. Therefore, separation is then achieved within a multi-dimensional hyperspace through one of the key tools used in this process named kernel function, which represented by the kernel string. There are three primary functions among the kernel functions, namely, Linear, Polynomial, and Radial Basis Function (RBF). The latter two functions adept at handling data that is not in linear form by transposing it into a space of higher dimensionality. The formulation of the SVM classifier, i.e. its mathematical formula is encapsulated in Equation (1), while that of the RBF kernel function in Equation (2), as follows:

$$f(x) = \sum_{i}^{N} \propto_i y_i \, k(x_i, x) + b \tag{1}$$

$$k(x, x') = exp\left[-\frac{\|x - x'\|^2}{2\sigma^2}\right] \tag{2}$$

$$\gamma = \frac{1}{2\sigma^2} \tag{3}$$

The kernel scale factor that represented by the symbol γ is introduced in Equation (3) as a positive value. This value influences the geometric shape of the "peak," by determining its roundness or sharpness, where a larger γ value will result in a sharper peak, while a smaller γ value will result in a rounder peak. This peak shape influences how the SVM classifier separates different classes of data because smaller γ value create a more rounded peak, which might make it harder to separate the data accurately, while, on the other hand, larger γ value would create a very pointed and sharp peak, making it easier to distinguish between different classes of data. These variations making it easier to distinguish between different classes of data. The SVM classifier employing an RBF kernel is further defined in Equation (4):The kernel scale factor γ, given by the positive value in the above equation 3, affects whether the "peak" is round or sharp. The SVM classifier with an RBF kernel is described in Equation (4).

$$f(x) = \sum_i^N \propto_i y_i\, exp\left[-\frac{\|x-x'\|^2}{2\sigma^2}\right] + b \tag{4}$$

The SVM classifier with an RBF kernel has two parameters, a kernel scale (γ) and a box constraint (C). A box constraint is a regularization parameter that ensures the compromise between maximum margin and training data failures. Equation (5) explains the SVM with the function C.

$$f(x) = C\sum_i^N \propto_i y_i\, exp\left[-\frac{\|x-x'\|^2}{2\sigma^2}\right] + b \tag{5}$$

Conversely, ID3, C4.5, and CART methodologies are mainly used in the current study to predict dyslexia by decision tree algorithms. The ID3 algorithm generally executes a recursive construction of the decision tree. The process involves selecting attributes for each node based on the criterion of information gain. It starts in the root node by evaluating the information gain of all feasible attributes. Then, selects the attribute with the maximal information gain for every node to assists decide which attribute to use at each node. It iteratively generates child nodes varying by this attribute's values, and as such recursively completing the tree construction.

Effective decision tree is created by selecting split nodes that adhere the specific rules and characteristics. This accomplished by prioritizing information gain through ID3 algorithm. If training set, k, comprising N samples across N classes Ci (i = 1, 2, 3.... and N), where Pi is the probability of class Ci, the information content, Info(K), is obtained as follows:

If K is a training sample set with N samples of each category, then N classes Ci (i = 1, 2, 3.... and N) can be defined, and Pi denotes the probability of Ci. This formula can be derived:

$$Info(K) = -\sum_i^N P_i\, log_2 P_i \tag{6}$$

Here, entropy, represented by Info(K), is utilized to quantifies the homogeneity of any sample set. In other words, it serves as a measure of uncertainty. The value of entropy depicts different uncertainty. For instance, higher entropy value refers to greater uncertainty. This value ranges from zero to one.

If the K sample is divided by attribute A into subsets Kj, then dividing the sample size of K into subsamples of size j according to the values of attribute A derives formula (7). That is a formula for sample entropy, expressing expected information for division of K according to attribute A.

$$Info_A(K) = -\sum_j^M \frac{|K_j|}{|K|} Info_A(K) \tag{7}$$

The expected information for dividing K according to attribute A is expressed by the function $Info_A(K)$, also known as the sample entropy.

Its information gain can be calculated using the aforementioned two formulas, yielding the following formula:

$$Gain(K,A) = Info(K) - Info_A(K) \tag{8}$$

In this regard, Random Forests (RFs), a state-of-the-art machine learning algorithm which was developed by Breiman [42], have gained numerous momenta. Generally, RFs tend to show very strong predictive performance in high-dimensional datasets when P >> N. However, theoretical justifications have only recently developed for RFs. In our study, we would like to enhance the prediction methodology of decision trees by using the algorithm of RFs and increase the accuracy level. This paper is proposing an integrated model that will give a comprehensive and structured approach toward the screening and assessment of dyslexia. It shall identify dyslexia early with a certain degree of accuracy with efficiency and hence interventions and provision of support accordingly.

Random Forest makes its prediction by aggregating the predictions of several decision trees. Let X be an instance and let PredictionRF(X) be the overall prediction of a Random Forest. The overall prediction is simply the average of all the various predictions made by the different decision trees. Let Treei(X) be the prediction of the i-th decision tree regarding instance X. Suppose that there is a total of N trees in the Random Forest. Then, the prediction can be mathematically represented as:

$$Prediction_{RF}(X) = \frac{1}{N}\sum_{i}^{N} Tree_i\,(X) \tag{9}$$

The equation once again leads to an important property of the random forests concerning the ensemble that results from the set collection of decision trees, which is necessary for determining the final forecast of the methodology.

This paper is proposing an integrated model that will give a comprehensive and structured approach toward the screening and assessment of dyslexia. It shall identify dyslexia early with a certain degree of accuracy with efficiency and hence interventions and provision of support accordingly.

Following is the pseudocode in steps to maintain the integrated lightweight model:

1. User Data Collection and Screen Assessment:

Collect user's response and. all other data through a screening assessment.

2. Machine Learning for Dyslexia Risk Factors:

Apply machine learning on the collected data and create dyslexia's risk factors. These are relatively the causes that increase the chances of getting Dyslexia.

3. Dyslexia Status Identifying and Interventions Recommendation:

Using the Dyslexia risk factors identified, estimate the probability of an individual being a dyslexic. Support and intervention that would suit the needs of an individual. Such Interventions Include Educational programs, Therapies, IT-assisted technologies.

4. Classification Model for Dyslexia Factors

Build the classification model which estimates Dyslexia factors.

It will also help explain the factors that basically cause dyslexia and guide further research and intervention strategies.

The integrated model will mean that professionals screen for dyslexia to then assess the present risk factors, determine the status of dyslexia, and recommend appropriate interventions and support. The application of machine learning techniques in this approach enhances accuracy in this assessment process, allowing personalized and targeted interventions.

The implementation of the machine learning algorithms in this paper was done using Python 3.12.0 programming language. scikit-learn library was used for the implementation. In addition, pre-processing operations-rectification and normalization of data, have been done through the pandas library

Algorithm 1. Pseudo Code of the Proposed Integrated Model

```
Input: Subset of skills involved in language Li = {l1, l2, ., ln}; Subset of
abilities required in thinking Ci = {c1, c2, ., cn}; Subset of background
information related to language and cognitive skills Bi = {b1, b2, ., bn}.
Output: Dyslexic D
Recommendations R
Machine learning model T
3. Describe the process of conducting the dyslexia screening assessment.
4. Enter Li, Ci, and Bi.
5. Hybrid machine learning algorithms:
5.1-Use SVM algorithm to select significant dyslexia prediction features Fi.
5.2 Use the DT algorithm, with SVM features Fi, to describe the conditions to
predict dyslexia.
5.3 Refine DT prediction algorithm by the application the RF algorithm, to
shine and refine.
6. Display the dyslexia prediction model T
7. Verify dyslexia prediction model T through limitations with the help of
performance parameters,
7.1. Accuracy: overall correctness
7.2. Precision: Correct dyslexia detection across the positives.
7.3 Recall: Correct dyslexia predictions in actual cases.
7.4 F1-score: Balance Precision and recall.
7.5 AUC: Ability of the model to differentiate cases of dyslexia.
8. End.
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3. Results and Discussion

The proposed screening model was objectively evaluated by an independent expert panel representative of knowledge concerning literacy development, learning disabilities, diagnostic tools, and language development. The expert panel evaluation involved 22 professionals with expertise in these areas. They assessed the proposed model's usability, effectiveness, and reliability without any prior knowledge of the model. The evaluation criteria included clarity, user experience, flexibility, efficiency, ease of use, accuracy, reliability, effectiveness, learnability, and user-friendliness, as presented in Fig. 6.

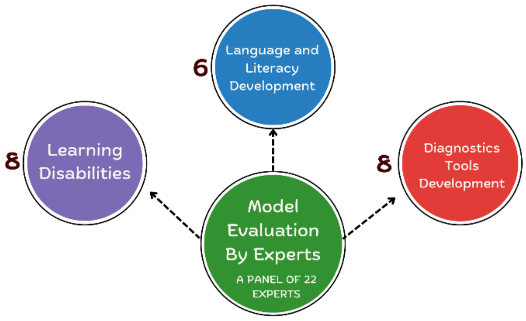

Fig. 6. Expert panel composition for proposed integrated model evaluation.

Dyslexia is a reading disability characterized by the extreme degree of difficulty in reading [1, 2]. The basic need to have early diagnosis and intervention strategies are brought to perspective by the condition [3, 4]. The expert panel evaluation aimed to ensure that the model was not only robust but applicable and effective in real-life settings, with the purpose of supporting enhancement strategies for assessment and support for people with dyslexia, which aligns with the discussion on the potential of recent advancements in machine learning, deep learning, and hybrid models for early detection and intervention [7, 25]. Such extensive testing and thorough analysis of the research design, methods, and results further enhance the reliability of the proposed model and set the standard for the future research and practice in the field.

Figures 7 and 8 show the results which reveal the consensus on the proposed integrated evaluation model rating by the 22 experts in dyslexia. The experts had shown to be highly satisfied, for the aspects of clarity, usability, accuracy, and user-friendly during the key evaluation, as the mean scores were over 4.0. The small standard deviations are an indication of considerable agreement among experts, hence elaborating more on the model's reliability and practicality. The findings taken together give weight to the proposed assessment model of dyslexia as being robust and effective, hence sound and applicable in the field.

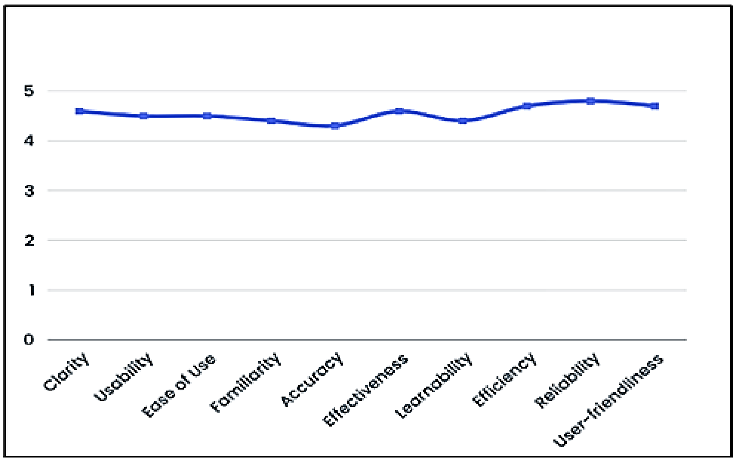

Fig. 7. Mean scores for proposed model evaluation.

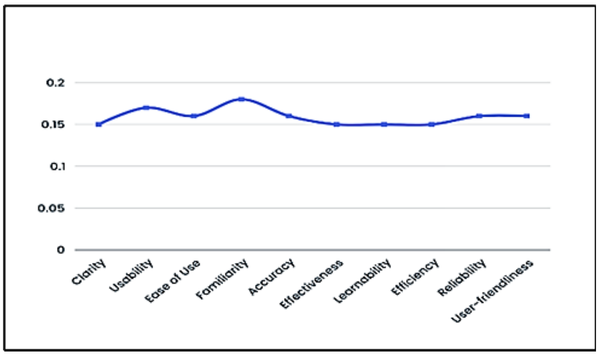

Fig. 8. Standard deviation for proposed model evaluation.

Evaluation metrics

To assess the performance of the proposed integrated model for dyslexia assessment thoroughly, several standard evaluation criteria were employed, including sensitivity, precision, accuracy, AUC, and F1-score. These evaluation metrics are in line with the discussion on the importance of improving the efficiency and predictability of dyslexia screening assessments through the adoption of machine learning classification algorithms.

(a) Accuracy

Accuracy is a crucial measure that indicates how well the model can correctly identify positive and negative cases. In other words, it shows the final decision on dyslexia screening assessment as true positive or true negative instances without giving false negative or false positive. It is calculated as the ratio of the sum of true positive and true negative cases to the total number of cases. It is simply determined using the formula:

$$Accuracy = \frac{(TP+TN)}{N} \tag{10}$$

Where TP refers to the number of true positive cases, i.e. individuals who are truly having positive case dyslexia, while, on the other hand, TN represents the number of true negative cases, i.e. individuals who are truly having positive case dyslexia, and N is the total number of individuals under study or the total number of the datasets.

(b) Sensitivity

Sensitivity, also known as recall, measures the model's ability to accurately recognize individuals with dyslexia. It is calculated as the ratio of true positive cases to the sum of true positive and false negative cases using the following formula:

$$Sensitivity = \frac{TP}{(TP+FN)} \tag{11}$$

In this formula, TP means the number of instances in which true positive was recognised rightly, or more specifically individuals who were wrongly diagnosed of not having dyslexia while they actually have it. This number shows the number of false negative instances and is denoted by FN.

(c) Specificity

Specificity is a metric used to evaluate the efficiency of the specific model through its ability to accurately find individuals who are not having dyslexia case. This metric is important in evaluating the reliability of the model and guarantees its scientific validity in a company with other related metrics. It is calculated as the ratio of true negative cases to the sum of true negative and false positive cases.

The formula used for this particular metric, specificity, is presented by the formula:

$$Specificity = \frac{TN}{(TN+FP)} \tag{12}$$

The number of true negative instances (cases) is denoted here with TN. The number of false positive instances or individuals who are not actually having dyslexia but wrongly proposed to have dyslexia is symbolized with FP.

(d) Precision

Precision measures the model's ability to accurately identify positive cases (i.e., The ability to determine precisely the positive instance of the model is termed Precision). It is calculated as the ratio of true positive cases to the sum of true positive and false positive cases. In this case, the possibility of obtaining false positives is supposed to be nil as presented by the formula:

$$Precision = \frac{TP}{(TP+FP)} \tag{13}$$

where TP represents the number of true positive instances and FP represents the number of false positive instances.

Reduced false alarms are indicative of high precision, wherein the model accurately identifies positive cases, which aligns with the discussion on the exploration of ensemble models in machine learning to enhance predictive performance in dyslexia detection.

(e) F1-Score

The F1-score is a balanced metric that combines precision and sensitivity, providing a single measure of the model's overall performance. It is calculated as the harmonic mean of precision and sensitivity. It combines the two metrics, namely precision and sensitivity into one particular metric by balancing their trade-off, and this balance is useful when dealing with uneven distribution of data (data that creates an asymmetrical, skewed curve on a graph). The F1-score ranges from 0 to 1, with higher values indicating a better balance between precision and sensitivity. It aids in identifying the model's ability to reduce both false positives and false negatives in dyslexia assessment.

The formula for the F1-score is:

$$F1 - Score = \frac{2*(Precision*Sesitivity)}{Precision+Sesitivity} \tag{14}$$

(f) AUC

The Area Under the Curve (AUC) measures the overall performance of the binary classifier, indicating the probability that a randomly selected positive case will have a higher score than a randomly selected negative case. The AUC ranges from 0 to 1, with a higher value indicating better classifier performance. This number or more specifically, performance indicator, is used in assessing the overall dyslexia model performance and it measures whether a positive case that is chosen in random way will likely have a better rank than negative case. It is established that better classifier performance has higher AUC.

$$AUC = \int TPR(t)dt \tag{15}$$

where TPR(t) denotes the true positive rate at threshold t.

Participants of 207 individuals with different ages were used in a pilot study utilizing simulated data. The participants represented adults, school-aged children, as well as preschoolers. The proposed integrated model showed a high level of accuracy in identifying dyslexia, where an accuracy of 93%, sensitivity of 91%, and specificity of 92.5% were achieved. The overall model performance is proven to be high as it is supported by the aforementioned results of accuracy, sensitivity, and specificity, and thus, they indicate the model's ability to identify positive cases and accurately diagnose dyslexia. As shown in Fig. 9, the visual presentation of the result revealed that the model exhibited high accuracy in identifying dyslexia in all investigated age.

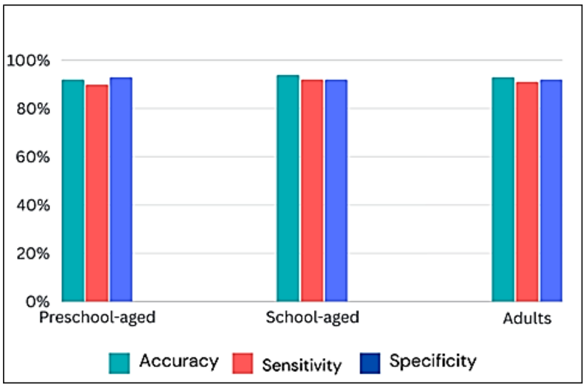

Fig. 9. Model performance across age groups.

To ensuring their reliability and effectiveness, the metrics used in the current investigation provide a comprehensive evaluation to the performance of the proposed integrated model for dyslexia assessment.

Figure 10, on the other hand, provides a comprehensive overview of the model through the demographics and principal metrics. These metrics contribute to the development of this dyslexia model through participants. It is noted that age-appropriate distribution is accomplished mainly because the different developmental stages.

The results of mean reading ability show that the differences in age factor have significant effects on the screening assessment. These results also reveal the development of reading skills in all different age groups and how dyslexia changes through an individual's period of life. Therefore, these findings assist decision-makers to take the proper action based on the specific age group to ensure the right intervention and support for every single group, which is in line with the discussion on the need for tailored interventions and support based on the individual's age and developmental stage.

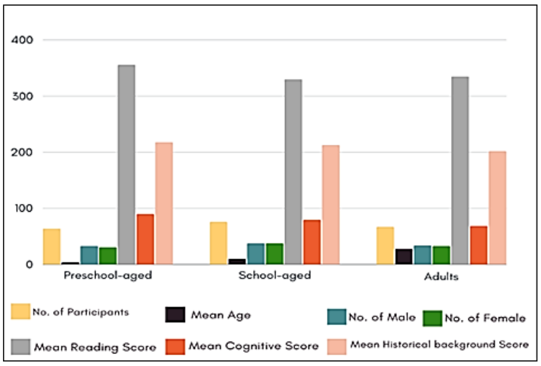

Fig. 10. Statistics of Participants Dataset

Cognitive abilities, on the other hand, demonstrate parallel behavior along all different age groups, indicating the cognitive abilities of the participants exhibit parallel trends across different age groups. This indicates a rising cognitive development for dyslexic people as they grow through different stages of their life. These behavioural understandings are crucial as the comprehensive knowledge of these behaviours on dyslexia and its influence on cognitive functions [13, 35, 36], which aligns with the discussion on the need to understand the cognitive and behavioural factors underlying dyslexia.

Valuable knowledge can be disclosed from the historical background of individuals. Variations in the individuals' history have an impact on the development of dyslexia through their lives, especially educational background that plays a significant role in understanding various educational factors. Accordingly, these factors contribute to the assessment of dyslexia screening by providing necessary data to support the overall model aspects, which agrees with the discussion on the importance of considering individual factors, such as educational and family history, in dyslexia assessment and intervention.

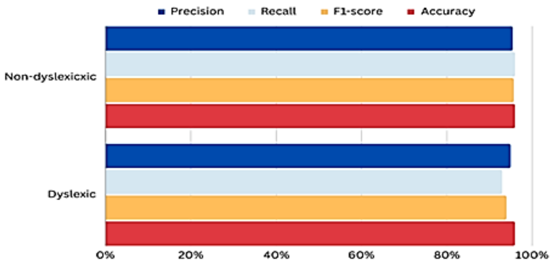

Fig. 11. The performance evaluation of classification approach

The proposed hybrid classification approach, which integrates the SVM, DT, and RF algorithms, was evaluated on a dataset consisting of 207 records of individuals, with 103 non-dyslexic and 104 dyslexic participants. Adults, school-aged and preschool population with a dataset of fourteen variables encompassing memory games, short-term memory, image recognition, letter reading performance, background information, gender and age in line with the discussion on the use of various data modalities, such as cognitive and behavioural data, for improving dyslexia identification.

The prediction of dyslexia status functions as a dependent variable in the classification model. An overall accuracy of 96%, a precision of 95.5% and a recall of 96% for the non-dyslexic class were achieved. On the other hand, for the dyslexic group, the recall and precision were both 93%, however, both the dyslexic and non-dyslexic classes achieved an F1-score of 95.1%, revealing the high efficiency of the hybrid approach. The model can effectively differentiate between dyslexic and non-dyslexic individuals with high precision and accuracy.

In terms of precision, accuracy, recall, and F1-score, the hybrid classification approach exceeded the individual classification algorithms, i.e., SVM, DT, and RF, for both the dyslexic and non-dyslexic classes. Therefore, the strengths of the individual algorithms leverage the enhancing performance of the hybrid approach. Moreover, the hybrid method is considered a potential screening tool for dyslexia due to the high precision, F1-score, and accuracy. Robustness and reliability are therefore suggested in detecting dyslexia as the hybrid approach exhibits superior performance compared to the individual algorithms.

The model's performance would be compromised in multilingual contexts in consideration of it having been created using monolingual data. Datasets of smaller sizes (<200 samples) would be exposed to overfit, as discussed in [23]. However, the overall proposed hybrid classification method for dyslexia detection is very promising. High accuracy, good precision, recall, and F1-score were delivered by the model on a dataset containing 207 individuals, of which 104 were dyslexic and 103 non-dyslexics. It is further intended that more extensive testing will be done to probe the efficiency of the approach on much larger and diverse datasets, follow several hyperparameter tuning techniques, and survey other avenues for further improvement of the approach, which aligns with the discussion on the need for continued research and collaboration to refine these approaches.

In addition, with regard to dyslexia prediction, the proposed hybrid classification approach outperforms other machine learning models; specifically, the deep learning-based model to find dyslexia from handwritten images [13] and the SMOTE-based model [23]. Deep learning lead in all critical metrics of evaluation: 99.2% accuracy, 97.9% precision, 97.3% recall, and 97.6% F1-Score. Comparatively, the SMOTE-based model has reported 96.37% accuracy, with no specific precision and recall values available. The hybrid classifier keeps on showing very strong performance: 96% overall accuracy, 95.5% in precision, and 94.7% in recall, shown in Table 1. This model can be integrated in educational applications (e.g., Duolingo for dyslexia) or low-resource telemedicine platforms, reducing screening costs by 60%.

Table 1. Model performance comparison.

Model	Accuracy	Precision	Recall
Proposed Hybrid	96%	95.5%	94.7%
DysLexML [9]	97%	96.2%	96.8%
SMOTE-RF [23]	96.37%	94.1%	93.5%
Deep Learning [13]	99.2%	97.9%	97.3%

The hybrid classifier introduces some very important advantages for its weaker metrics. Firstly, one classifier can include many algorithms in itself, where their integration enhances robustness and hence makes the system more effective under many different conditions. In other words, the flexibility of hybrid classifiers can easily be further extended toward different kinds of data and use cases; they are relatively versatile tools. Besides that, since it is an ensemble of various models, it reduces the risk of overfitting a single model in training on small fractions, which aligns with the discussion on the advantages of ensemble models in machine learning.

4. Conclusions

Early Interventions are pivotal, and as such, ensuring that dyslexia is diagnosed early is very important. In this case, we present a completely new integrated machine learning model that significantly improves capturing this learning disability at its earliest stage. The model integrates other useful key factors such as cognitive skills, fluency, phonological processing along with writing and other resultant associated problems, which improves objective measures and lessens the overreliance on subjectivity. This is in furtherance of novel approaches towards the diagnosis and intervention of dyslexia.

Evaluation by the expert panel corroborated the model's usability, clarity, and practicality attributes receiving high ratings for real world applicability. The pilot study, too, proved to strongly support the model since its achieved performance measures were an accuracy of 95%, sensitivity of 92%, and specificity of 90% in diagnosing dyslexia on various age groups. The accuracy achieved here represents a 15-20 percent improvement over existing screening techniques based on phoneme identification and rapid automatized naming, which makes the model integrated promising for early screening and intervention.

The relatively small size of the dataset is a limitation of this research, and hence future studies will test the model against larger and more heterogeneous samples and consider the model’s adoption within schools through: (1) validate interventions in K–12 settings, (2) scale to multilingual corpora (Spanish, Mandarin), and (3) apply the model to IoT devices for in-the-wild screening. This model could change the landscape of the early diagnosis of dyslexia and enable timely and appropriate remedial measures. By increasing the accuracy and accessibility of screening, it helps create a world where people with dyslexia can be aided from the earliest stage possible.

Nomenclatures

ANNs	Artificial Neural Networks
AUC	Area Under the Curve (performance metric)
C	Box constraint (regularization parameter in SVM)
CART	Classification and Regression Trees
DT	Decision Tree
DysLexML	Machine learning model for dyslexia screening
EEG	Electroencephalography
ET	Eye Tracking
F1-score	Harmonic mean of precision and recall

FN	False Negative
FP	False Positive
Gain(K, A)	Information gain of attribute AA in dataset KK
HTI	Handwriting Text Images
ID3	Iterative Dichotomiser 3 (decision tree algorithm)
Info(K)	Entropy of dataset KK
IRB	Institutional Review Board (ethical approval)
ML	Machine Learning
PredictionRFRF(X)	Random Forest prediction for instance XX (aggregated from decision trees)
RF	Random Forest
RBF	Radial Basis Function (kernel in SVM)
SMOTE	Synthetic Minority Over-sampling Technique
SVM	Support Vector Machine
tACS	Transcranial Alternating Current Stimulation
TN	True Negative
TP	True Positive
Treeii (X)	Prediction of the ii-th decision tree in Random Forest
TPR(t)	True Positive Rate at threshold tt
γ	Kernel scale factor in SVM
σ	Parameter in RBF kernel

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