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System for Detection of Specific Learning Disabilities Based on Assessment

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Abstract: Learning disabilities are neurological processing problems brought on by faulty cortical circuitry. According to the RPwD Act of 2016," Specific learning disabilities (SLD)" refers to a wide range of conditions where there is a deficit in processing language, whether spoken or written. These conditions include perceptual difficulties, dyslexia, dyscalculia, dysgraphia, dyspraxia, and developmental aphasia. They can manifest as difficulty in understanding, speaking, reading, writing, spelling, or performing mathematical calculations. The paper aims to create a hybrid mobile application for analyzing and profiling different learning capacities in students to detect specific learning disabilities and generate error reports using a variety of examinations/tests that include eyeball tracking, handwriting analysis, logical test, and speech evaluation. Remedies and solutions for different learning incapability are aggregated over the internet through Google Search and YouTube API from authentic sources. Based on the child error report, Doctors/Psychiatrists specializing in their field will be recommended. The reviewed papers cover a variety of approaches to detect the SLDs using automated systems, including manual screening methods, Q/A and eyeball tracking-based approaches, and deep-learning techniques. The performance of these approaches has been evaluated using various metrics. The research paper also addresses a range of challenges in SLD detection, such as handling complex and multiple SLDs, generating diverse and coherent questions for detection, and improving the quality and relevance of reports generated.

Keywords: *Computer Vision, Natural Language Processing, Medical Automation, Specific Learning Disabilities, Transformer Models,*

1. Introduction

Identifying dyslexia is a complex process that requires careful consideration to avoid misidentification. Various techniques, such as observation, checklists, and interviews, are commonly used to identify dyslexia and gather additional information about doubtful cases. However, there is no one ideal method for identifying dyslexia and the debate around identification methods continues to evolve. Although dyslexia are primarily understood as a reading condition by the public, there is enough evidence to support it as a difficulty with writing abilities as well. A handwriting learning problem connected to dyslexia is known as dysgraphia. Additionally, it has been linked to attention deficit disorder and dyspraxia, a condition of developmental Abbreviations and Acronyms coordination. These are all examples of neurodevelopmental disorders. Dysgraphia can be divided into three sub types: dyslexic dysgraphia, spatial dysgraphia, and motor dysgraphia, according to Deuel [1]. The current dysgraphia diagnostic tools rely on handwriting analysis and assessmentslike the handwriting proficiency screening questionnaire [2], whose scoring is based on subjective human judgement and is reliant on the availability of skilled human resources. Writing issues have been documented in children [3], college students [4], and adults [5] by a number of researchers. Indicators of both reading and writing difficulties were about equally prevalent in both children and adults with dyslexia, according to Berninger et al., [3]. Given that reading is thought to be a key element of writing [6], the difficulties seen in dyslexic youngsters may, in part, be related to reading issues. Both reading and writing depend on related processes since decoding words is impacted by how difficult it is to absorb phonological information, and phonological information must be encoded when writing [7][8]. This may be related to the children's weak handwriting abilities. Ultimately, identifying dyslexia is a critical step in ensuring that students receive the appropriate support and accommodations they need to succeed academically and socially. Hereare the techniques that the team used for the detection and identification of different SLDs:

1) Eyeball tracking: Eye gazing will become more and more important in human-computer interaction in the future. It resembles a natural form of pointing and has the ability to tell the computer more about the user's preferences than the keyboard and mouse currently do. A new interface style

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appears to be developing in a number of areas of the current study in human computer interaction, including eye movement based interaction and virtual worlds. In this study, the paper combine these strategies to produce a novel set of data for eye-focus distance detection that can be a key component in several applications.

2) Dyscalculia: This exam is made to assist you in finding the underlying issues that could be preventing you from studying maths. These issues are collectively referred to as dyscalculia. Similar to dyslexia, dyscalculia im- pacts arithmetic learning as opposed to reading. Instead of serving as a professional diagnostic, this exam is intended to assist parents in comprehending the issue and setting their kid up for success in maths study. With this knowledge, you can prevent any math difficulties your child could experience. reducing their stress and resulting in happier, more accomplished youngsters.

3) Dysgraphia: A neurological disorder in which some- one has difficulty turning their thoughts into writing despite exposure to adequate information and education. Dysgraphia is considered a specific learning disability (SLD) in written expression. People can also develop dysgraphia after some head injury or trauma also.

4) Linguistic and Auditory processing disorder: This test is designed to test the listening and auditory processing skills of the participant. Our model speaks or displays certain words and the participant is to speak those words, then our models process the spoken words to calculate the percentage of errors in the spoken words. This helps in learning and understanding the linguistic and auditory processing of the participant.

The aim of this project is to build a hybrid web application for analysing and profiling different learning capacities in students to detect specific learning disabilities and generate error reports using a variety of examinations/tests. The following is a list of the goals for developing an assessment system to appropriately identify children with learning difficulties:

• To test and identify individuals with specific learning disabilities who have problems reading and writing.

• To analyse students' SLD-related reading and writing issues and produce mistake analysis reports.

• Using automated error analysis to direct/suggest remedial services to teachers and parents of children with SLD.

2. Literature Survey

A.Techniques for Text Analysis

Learning challenges affect a person's ability to grasp or use spoken or written language, perform mathematical calculations, coordinate movement, and pay attention. Learning issues can affect very young children, although they are often not recognised until the child is old enough to attend school. Children with learning impairments typically struggle with tasks that are associated with intellect and chronological age, such as reading, writing, arithmetic, speaking, and spelling. 10% to 15% of kids in classes 5 through 10 are said to have learning disabilities, under the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) criteria [9]. The history of the families and instructors, along with a mental assessment utilising DSM V criteria, can be used to diagnose these impairments. There isn't now a computerised, rapid, automated method based on factual, numerical data for diagnosing dyslexia, nevertheless. Unwanted outcomes include diminished educational engagement, low self-esteem, mental stress, and even despair. These kids don't want to read because they have reading problems because they can't read or perform arithmetic regularly. As a result, these kids' academic achievement suffers considerably more than kids who are healthy. As a result, these kids' academic achievement suffers considerably more than kids who are healthy. Even if it is widespread at this time, the decline in children's academic performance and the low degree of diagnosis knowledge result in losses in both economic and social function.

Dyslexia and dysgraphia are the two learning disorders that are the most challenging to identify since there is no formal or informal test that can tell if a kid can read, write, or pay attention normally. A computerised test that employs CNN-based eye tracking [3] and handwriting analysis [5] has, however, been developed in this field as a result of study [10] to determine if a person has dyslexia or dysgraphia. This research also offers methods to enhance the current system and accelerate the diagnosis of illnesses. In addition to that, this approach may be used with existing standard testing for autism and dyscalculia [11].

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1) Different Methods of Diagnosis of learning disabilities:

The traditional method of identifying learning difficulties involves testing and mental examinations, which can be time-consuming and can produce inaccurate results. A bulk test of this nature is also laborious. The effectiveness and quickness of the computerised approaches led us to choose them. Our initial thought was to employ easy reading and math examinations.

The arithmetic exam was conventional and successful, but the reading test, which required the kid to read a line and rewrite it, was unsuccessful and only produced 47% accuracy [12]. Since this situation is unusual and unpredictable, the team considered employing ML. The team opted to use deep learning CNN-based methodologies after researching eye-tracking and handwriting-based methods [3]. For our initial eye tracking and analysis, our team used a straightforward 4-layer CNN, which produced positive results. Since handwriting and speech tests based on CNN produced similar results, the paper continued using this strategy.

B. State of Art Algorithms for Diagnosis

1) **Convolution Neural Network** for handwriting analysis: To achieve the best outcomes, meticulous planning and the use of a computer vision system are required. Artificial neural networks have been examined by statisticians in the last 10 years to understand their predictive ability from a statistical perspective while being frequently viewed as black box approaches or heuristic methods. These studies demonstrate that multi-layered perceptron's, recurrent net-works, and associative memory networks, which are neural network counterparts of traditional statistical techniques like discriminant analysis, logistic regression, and multiple linear regressions, [10] have many theoretical similarities. The use of NN to detect youngsters who may be dyslexic is investigated in this study. With the aim of categorising probable dyslexic youngsters into one of two output categories—dyslexic or not—based on their reading skills, the team turn the identification problem into a classification problem in this instance.

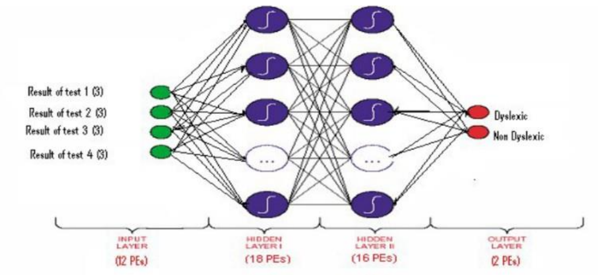

Fig.1; Convolutional neural network for eyeball tracking

2)**Eye ball tracking**: Several studies have demonstrated that dyslexics' eye movements are aberrant [13]. Dyslexic people have more fixations when reading than typically developing readers of the same chronological age because they have lengthier fixations lasting longer and shorter saccades. Regardless of how transparent they are, reports of these eye movement problems have been made in several languages [14]. They have been seen when reading phrases, single objects, words, and pseudo-words in addition to text. While such irregular eye movements have been blamed for the reading difficulties of dyslexics, other evidence suggests that the reading disability itself causes abnormal eye movements [15]. It's still up for question where these abnormal eye movements in dyslexia come from, particularly whether or not they might have a visual basis. Eye movements of the participants were observed as they read a text passage and performed a visual search activity that was directly related to reading [5]. Half of the participants in each group started with the reading task since the task orders were counterbalanced.

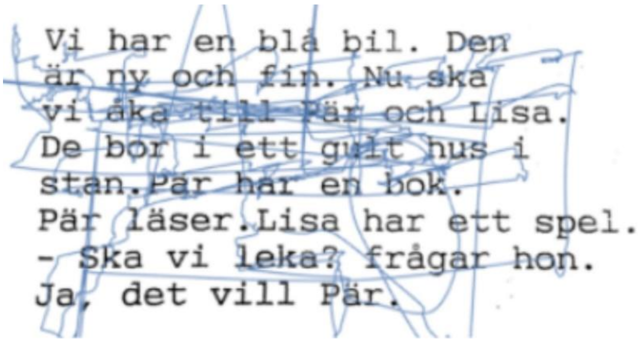

Fig.2; Eyeball deflection of dyslexic reader

3) **Deep neural networks** for speech recognition and speech-to-text: The ALB is used to assess a child's performance in the areas of cognitive-social and linguistic development. If language impairment is suspected, spoken language abilities are screened. The screening does not produce a diagnosis; rather, it suggests that a clinician may need to do more testing. The model employed has three significant differences from the model used by [7]. The team first concentrated on handling the input data. The acoustic signal is only represented by the Mel filter bank in the original model. The team made the change to test the Short Time Fourier Transform [16] (STFT), Mel Filter bank, Spectrogram, and Mel-Spectrogram, four common representations of the acoustic data. Second, add an LSTM layer in place of the model's GRU layer. Third, separate the dysarthria detection component from the speech reconstruction component of the original model and train the detection component exclusively. After z-score normalisation, the audio signal is translated into its representation. To maintain a constant 5 second audio duration, pad the audio signals. To maintain a constant duration of the audio, audio signals more than 5 seconds are reduced to 5 seconds. This dataset of signal representation is then input in batches into two layers of a two-dimensional Convolutional Neural Network with 20 channels, 5x5 kernel, and RELU. Two dimensional Batch normalisation and MaxPool layers are built within the CNN layers by default. The output from this layer is fed into an LSTM layer. Note that the original model in [3] had a GRU layer for simplicity, However, the team decided to keep the LSTM layer since, now that the reconstruction element of the model has been eliminated, the model is simple enough for our training even with LSTM. The output of the LSTM layer is routed via two levels of dense bottleneck layers before being routed through a SoftMax layer. On the CNN layers, LSTM layer, and dense bottleneck layers, the team added a dropoff value of 0.3. The loss was calculated in Pytorch using BCELossWithLogits, a class that combines Binary Cross Entropy Loss and Sigmoid layer into a single class. Calculating the cross-entropy loss involves using

keras loss optimisation techniques.

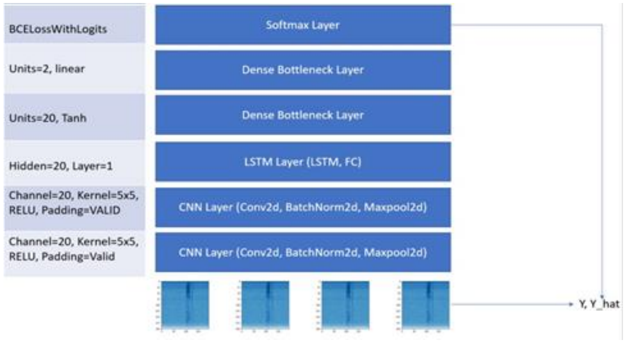

Fig.3; ML Model design for speech recognition and speech-to-text computation

4) **ML model for handwriting analysis**; A handwriting learning problem connected to dyslexia is known as dysgraphia. Additionally, dyspraxia, a condition of developmental coordination, and attention deficit are linked to it. These are all examples of neurodevelopmental disorders. Dysgraphia is divided into three sub-types, including dyslexic dysgraphia, spatial dysgraphia, and motor dysgraphia, according to Deuel [1]. Existing dysgraphia diagnostics rely on handwriting analysis and tests such as the handwriting proficiency screening questionnaire [2], the scoring of which is based on human judgement, making it extremely subjective and dependent on the availability of trained human resources. Using the Random Forest classifier, they were able to achieve it with 96.6% sensitivity and 99.2% specificity for handwriting. [17] created a system that classified handwriting samples as indicative of dyslexia or not using computer vision and deep learning. They achieved a five-fold cross-validation accuracy of 55.7-1.4% on aver- age. When compared to an automated diagnosing method, this accuracy is relatively poor. So the team decided to design our own model using CNN 6 layers [18]. Our team has used a better dataset of dysgraphic students which it is believe that it will increase the performance of the model to up to the accuracy of 90

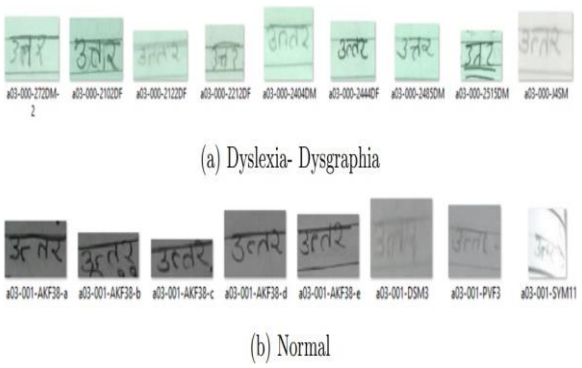

Fig.4; Sample dataset for dysgraphic handwritings

3. Proposed System

This section provides implementation details and methodology adopted to implement the proposed system and the kind of evaluation adopted in respective research papers.

A. Modules

Description of the module: The team has designed the first module of the application which is the mathematics test which will test your mental ability. A database of questions is designed to test various aspects of the analysis.

- For that the next step is the listening test, the user will listen to the voices generated by the system and will respond accordingly.
- Second aspect of the analysis is the understanding ofthe person whether the person can process the speech properly.
- The difficulty of the questions is increased gradually to test the logical ability of a person by asking questions such as replacing a certain word or certain letter.
- Also, slowly the length of the sentences is increased gradually to test the short-term memory of a person.

B. Types of tests

The types of tests used by the system to predict the possibility of SLDs are described in this section. All thetasks and objectives will be achieved by using the following steps. The algorithm written below will help in defining the architecture of the system.

- For diagnosis of speech defects, the paper has used voice sampling and speech-to-text, more specifically a deep CNN network to convert your speech to text and match it with the word given.
- For mathematical tests, cluster users with the same accuracy are given questions with increasing difficulty as per our question set. The scores are then matched with the cluster of users that were previously diagnosed with dyscalculia or etc disabilities.
- For detecting autism or dyslexia the paper has used computer vision techniques, the paper provides a certain text to a user and then user in-built camera to record him then the paper uses deep convolutional neural networks to track the user's eyeballs this is then used to plot the eye movement and used to find the deviations while reading. If the deviations of the eyeball are more than a certain degree, then it concludes that the person might have autism or dyslexia

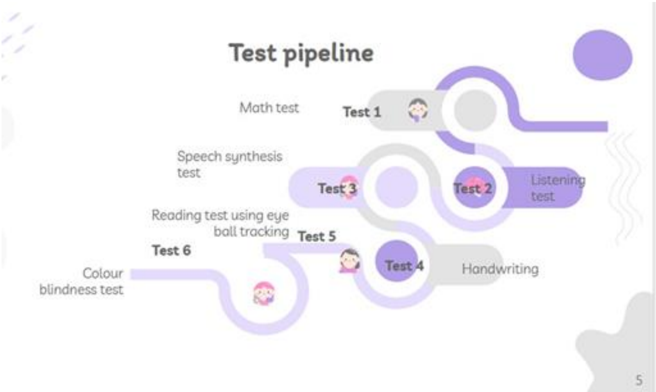

Fig.5; No. of test through which the user will pass to get itself analyzed

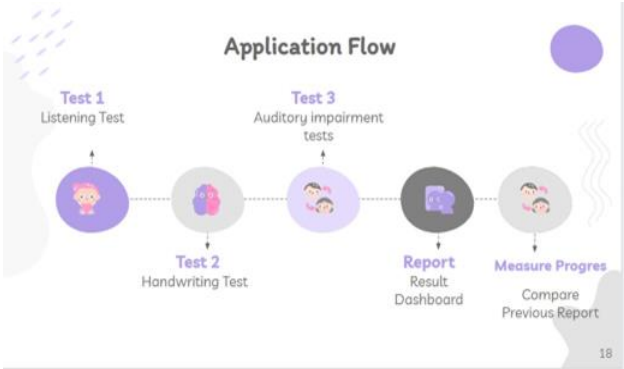

Fig.6; The order in which the user will take the tests

C. Architecture Defined

The proposed architecture consists of three layers: the front-end layer contains the application with which the user interacts. The second layer contains the backend that has the APIs, hosting, ML model and a server. The third layer has storage and a database for storing data and models. The API in the intermediate layer consists of an interface to access the machine learning model and other APIs that crawls the web to find solutions, guides and doctors nearby etc. for diagnosed disability for the user. The front layer in any of the tests sends data to the backend which processes and calls the machine learning model and other related microservices for the processing which if matches with any of the disability clusters, then sends the appropriate results to the user. The results and the report generated by the system can be used to consult the doctors, teachers, guardians, consultants etc. to help the patient.

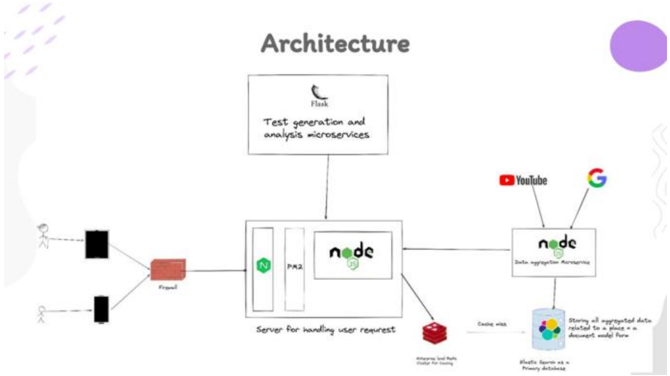

Fig.7; The architecture of the application

D. System Implementation

There are three major components of this project: Testing of the user using various methodologies, analysing the responses fed by the user, and generating the user report which can be used to consult the doctors.

1) **Listening Test:** In this test, the application will read the questions of different types like having difficult phonetics, and verbal short-term memory. Instructions are given after each question. Example,

Question. Say leapfrog. Now say leapfrog but don't say leap. Answer. Frog

Question. Say sheet. Now say sheet but don't say /sh/.

Answer. Eat

2) **Dyscalculia Test:** The capacity to comprehend numbers and acquire arithmetic facts is impacted by SLD. The test contains questions with more pictures and fewer words. The difficulty of questions adjusts according to the age group. Some sample problems which are used for assessment are,

- Differentiating between shapes
- Writes numerals as they are pronounced (34 as 304)
- Differentiating concepts (big/small, fat/thin)
- Wrong alignment while calculations

3) **Ishihara (Colour Blindness) Test:** This test makes numbers out of dots that are a different colour than the dots surrounding them. There are certain kinds of colour blindness,

- Red-Green Colour-blindness
- Protanopia
- Deuteranopia

What if the person is colour blind and also has some kind of disability such as dysgraphia? Using the above-mentioned test/methodologies the application will follow the mentioned steps to get an idea of how the system will check and generate the reports for differently-abled persons.

Step 1: Show an image/number to the user on the test screen for a few seconds.

Step 2: Display a grid of related images on the screen.

Step 3: The user has to select the correct image shown earlier.

Step 4: The system will analyse the user response.

Step 5: Generation a detailed report

Parameters tested: Accuracy, Speed and Memory.

This will include a variety of tests to check reading and writing abilities.

1) Dyslexia - a reading disorder that also impairs writing and spelling.
2) Dyscalculia - inability to understand number math principles.
3) Dysgraphia - a condition that affects both information and motor processing.
4) Dyspraxia - unable to balance and bad handwriting.
5) Autism - delayed speech, as well as the repetition of phrases.

Create an error report based on the information received from the tests. The prepared report might be utilized by the doctor as a pre-diagnosis. The data collected during the evaluation can be kept and utilized to spot improvements in subsequent examinations.

4. Experimental Results

A) Eyeball tracking test

Following is the result of the eyeball tracking test:

Table 1; Result of Eyeball Tracking test

Sr No.	Ideal Result	Proposed result	Accuracy
1	Positive	Positive	97.5%
2	Positive	Positive	96.2%
3	Negative	Negative	98.1%
4	Negative	Negative	88.6%

The overall accuracy of the model turns out to be 93.6% which although low is far better than any previous models. The model is based on CNN network and infers the fact that it uses object tracking to track the eyeball and deduce the fixation time to get the x and y axis variation during the text. the more the deviation the more the possibility of SLD. the model then predicts positive or negative result based on previous data and gets to conclusion on whether the user has SLD or not. the accuracy shows how much close the result is to the actual case. the overall accuracy shows that the results generated by the model is correct in 93.6% of the cases

Dyslexia Test Results

The following table shows the overall accuracy of the test taken using a dataset of people having SLDs,

Table2; Overall Accuracy of test result

Sr No.	Ideal Result	Proposed result	Accuracy
1	Positive	Positive	93.5%
2	Positive	Positive	95.2%
3	Negative	Negative	99.1%
4	Negative	Negative	98.6%

The above results are taken from our dyslexia test which uses handwriting and auditory tests to deduce the fact thatthe user may have dyslexia. Similar to above test it gives either positive or negative result which means that the user may or may not have dyslexia. moreover the accuracy shows the percentage possibility of the user having the SLD since other various factors may also hinder the final result. higher accuracy means the model is more confident on the result.

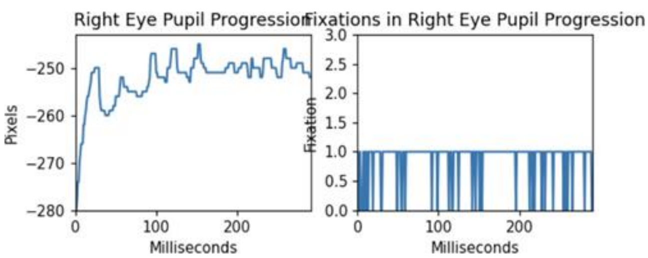

Fig.8; Variation in Pupil Progression over the time.

The progression of pupil is taken to find out how much deviation the eye is going through. A tthreshold value is takenwhich

5. Conclusion and Future Scope

The application the paper presents can be used by any person having Special Learning Disability; the UI has been designed in such a way that can be used easily by dyslexic students. Every test module has standard questions and difficulty scores allotted to it. Every module will find the frequency of errors and will create a final report on that. The report is sharable in pdf format. Currently, third-party models are utilized for speech-to-text and Handwriting analysis. The paper had shown how to utilize currently available solutions to solve the problem of Special Learning Disability.

The proposed application uses third-party modules which have low accuracy, which can sometimes result in wrong results. In future, the aim is to implement self-made model for speech-to-text in order to customise it for the specific needs. Currently, the app works well for detecting SLD problems and can be used in the real world. The paper anticipate the creation of a system that can function in a less regulated, more expansive environment like a more widespread audience with commercial eye-trackers in a set- ting (perhaps in kindergartens or households). Here, a first step has been taken toward that goal by introducing artificial noise at the fixation points and evaluating how it affected accuracy. Smaller than average noise levels don't have a significant impact on the system's performance. The team has conducted a follow-up larger-scale field investigation utilising affordable non-specialized eye-trackers in a more diversified environment (in other nations and under quiet and out-loud reading) since they were encouraged by the resilience under noise. The goal is to categorise the many types of reading challenges. This work lays the groundwork for creating a screening tool that may be used in less controlled settings to target a bigger, more varied population for early intervention and perhaps greater societal effect.

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