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ORIGINAL RESEARCH ARTICLE

Intelligent approaches for early prediction of learning disabilities in children using learning patterns: A survey and discussion

Shailesh Patil[1,*], Ravindra Apare[2], Ravindra Borhade[3], Parikshit Mahalle[4]

[1] *Department of Computer Engineering, SKNCOE, SPPU, Pune 411041, India*

[2] *Department of Information Technology, Trinity COE&R, Pune 411048, India*

[3] *Department of Computer Engineering, SKNCOE, Pune 411041, India*

[4] *Department of Artificial Intelligence and Data Science, VIIT, Pune 411048, India*

*** Corresponding author:** Shailesh Patil, shaileshpp19@gmail.com

ABSTRACT

Learning disabilities in children occur in early childhood age. These disabilities include dyslexia, dysgraphia, dyscalculia, ADHD, etc. These children face difficulty in academic progress in life. Difficulties include reading, writing, and spelling words, despite these students possessing normal or above-average intelligence. The learning gap between these students and others increases with time. As a result, these students become less motivated, find it difficult to progress in life, and struggle with employment opportunities. Children with these symptoms often have emotional consequences, including frustration and low self-esteem. These disabilities range around 10 to 15% of the total population, which is considerably high. There is an immense need for early diagnosis to provide them with remedial education and special care. Researchers have proposed a diverse range of approaches to detect learning disorders like dyslexia, one of the most common learning disorders. These approaches include the detection of LD using eye tracking, electroencephalography (EEG) scan, detection using handwritten text, the use of a gaming approach, audiovisual approaches, etc. This paper critically analyses recent contributions of intelligent technique-based dyslexia prediction and provides a comparison. Among the mentioned techniques, it is found that detection using eye tracking, EEG, and MRI are costly, complex, and non-scalable. In contrast, detection using handwritten text and a gaming approach is scalable and cost-effective. A character-based approach is presented as word formation is difficult for children for whom English is a second language. Also, in early childhood, children make fewer mistakes in character writing. An experimental setup for handwritten text-based detection is done using the CNN model, and future opportunities for learning disabilities detection are discussed in this paper.

Keywords: LD; ADHD; EEG; ML; CNN

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1. Introduction

Education is a basic necessity for every human being. The Right to Education Act mandates compulsory education for students. However, due to different cognitive limitations, such as learning disabilities among children, they may struggle to progress in their educational paths. Approximately 10 to 15% of students suffer from some type of dyslexia. According to the disability survey of India (2011) and as shown in **Figure 1**, among the population with learning disabilities, only 8% of students can complete their higher studies[1]. Therefore, there is an immense need to find an optimal solution to early detection of learning disabilities in these students and provide them with remedial education.

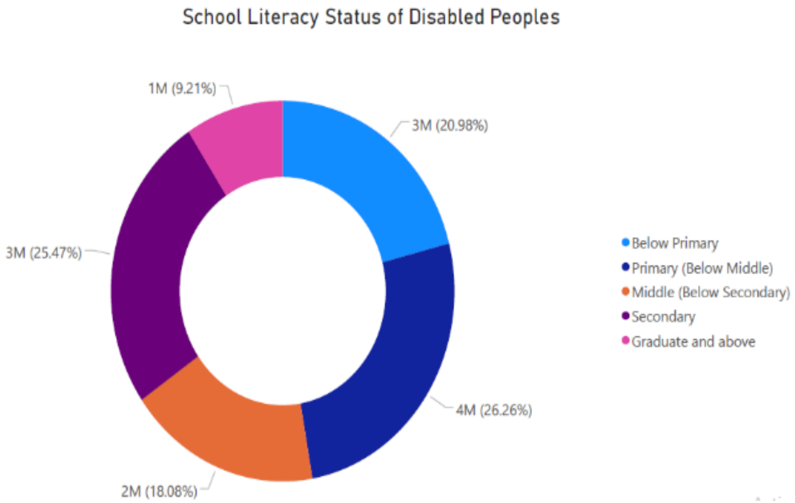

Figure 1. School literacy status of disabled.

Learning Disabilities refers to symptoms related to children facing difficulty with skills, including reading, writing, spelling, and concentrating[2]. It is characterized by differences in brain structure and its wiring. Despite this, these children have good intellect. However, due to the above-mentioned difficulties, children with LDs are unable to progress smoothly in their academics. Learning disabilities come in many forms, including dyslexia, dysgraphia, dyscalculia, etc.[3]. Learning disability is a major problem in society. Among these disabilities, dyslexia is seen worldwide in around 5 to 20%[4]. Whereas in India it is reported in around 15%. As per the survey by Times of India (TOI) it is around 35 million in India. A significant portion of the population with these learning disorders remains undiscovered in India due to a lack of awareness and the unavailability of proper tools for prediction and assessment.[5] As learning disabilities are cognitive, there is no direct measure, such as measuring temperature blood pressure, etc. by which it can be easily diagnosed. They are hidden in nature. Developing tools or procedures to diagnose this type of learning disorder is a challenging task. In the school setting and with the available infrastructure, it's crucial to screen children facing educational challenges and prompt them for further clinical investigation. There's a pressing need for an approach that is scalable, cost-effective and requires less expertise, thereby minimizing the necessity for extensive training of teachers and parents for early predictions.

A recent poll[6] found that 76% of respondents think learning problems should be identified before the fourth grade. However, the majority of diagnosis occurs considerably later or not at all, costing our society billions of dollars[2] and crucial formative years of education for millions of youngsters. Also, children for whom English is a second language face difficulty in word formation in early childhood[7]. These children are more confident in character writing. In this paper, the target group is set as children from ages 3 to 8 years. In this age group, students learn characters more efficiently. Thus, a character-based risk of dyslexia prediction approach is proposed. The aim is to provide a baseline for predicting whether children are at risk of dyslexia or not. With this prediction, special care or further investigation can be initiated to form a conclusion.

1.1. Types of learning disorders

LDs are categorized as shown in **Figure 2** based on difficulties faced by children[8].

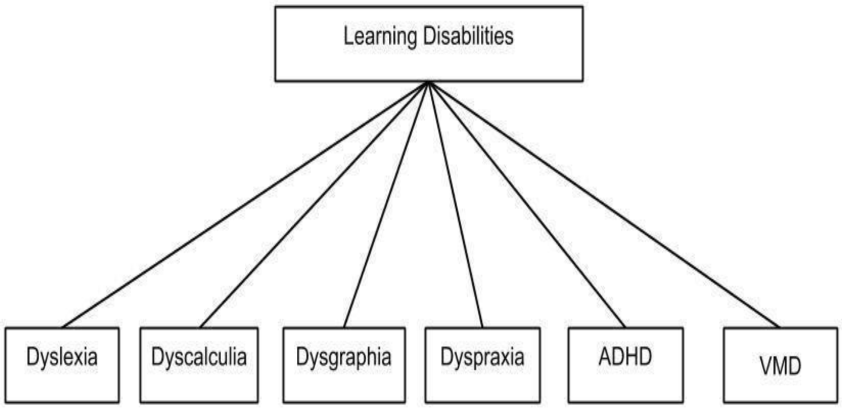

Figure 2. Types of learning disabilities.

Dyslexia: It is termed a Reading Disorder. It is a common disorder that affects approximately 10% of the total population. These children may face problems with processing information, memory, sequencing, and organization. It can be subcategorized as visual dyslexia (bad—dab), auditory dyslexia (difficulty in grasping meaning), sound blending (sound to complete word), and letter or word reversal (b-d, p-q, m-w).

Dysgraphia: It can be termed a disorder in written expression. It is a condition of impaired handwriting. It impacts the speed of writing. Writing disorder involves difficulties in handwriting, spelling, and visual memory.

Dyscalculia: It refers to difficulty in understanding math symbols and concepts. Students may struggle to understand basic number concepts and numerical basics. Shape Discrimination, Size Discrimination, Auditory-Visual Association, Computational skills, and measurement.

ADHD: It is defined as difficulty in staying focused or paying attention. Students easily get distracted, lose track, and poor listening.

Dyspraxia: Fine or gross difficulty in motor coordination. It involves difficulty in catching the ball, organizational difficulty, etc.

1.2. Motivation

As stated above, learning disability is a serious problem in society. The number of children with LDs is considerably high, around 15%[2]. If early prediction and proper assessment are not made then it causes serious harm to the nation and society. Statistics reveal that in a country like India, a total of 72% of children remain unemployed, and 57% remain illiterate[1]. If skill trainers and tools are not adopted, then the unemployment rate among LD children will surpass 10 million[9]. This directly affects the growth of a nation, especially considering that a significant portion of the population lives in rural areas. The provision of experts across the country is a challenging task. Germano et al.'s recent research revealed that even though 84.3% of the dyslexic students in their study satisfied the requirements for a handwriting deficiency, teachers frequently responded "rarely" when asked the same questions about the students, indicating that they were unaware of the student's handwriting difficulties[10]. Diverse language, culture, nature, and teaching practices are concerns that are affecting children's academic progression. If an early diagnosis is not made then these students face frustration and develop low self-esteem and confidence. Additionally, various behavioral traits such as fear and hatred may develop among them.

If an efficient approach is developed to cope with these issues, we will not miss the jewels that create miracles for society. It is a need of time to develop approaches that will help predict and assess these children, bringing them onto a pathway of success[10]. Developing dignity and a positive approach towards life, nation, and society.

2. Current state of art/ literature review

Research is ongoing for the prediction and assessment of children, especially those affected by learning difficulties. These disorders are also referred to as Hidden Disorders, as they don't impact the intellect of a person. The detection of LDs, like dyslexia, dysgraphia, dyscalculia, etc., has undergone various approaches. These approaches can be further classified into methods such as eye tracking, handwritten text analysis, prediction based on drawing, BCI (Brain-Computer Interface), EEG, etc., as illustrated in **Figure 3.**

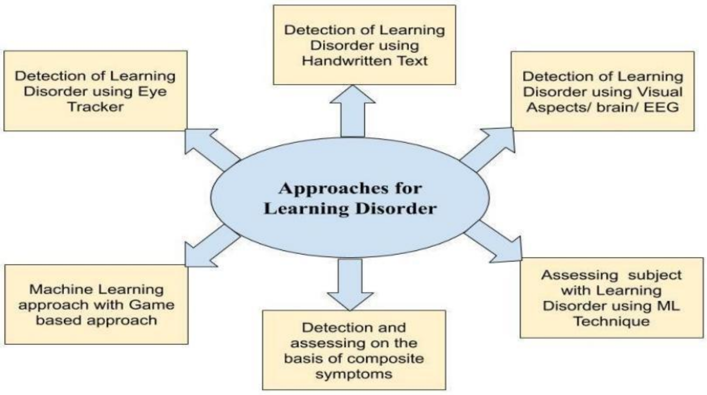

Figure 3. Approaches of detection and assessment of learning disorders.

In this section, these approaches are briefly discussed.

2.1. Detection based on eye movements

Prabha and Bhargavi[11] proposed a methodology to identify dyslexia using eye movement. A Particle Swarm Optimization (PSO)-based hybrid kernel SVM approach is employed. A total of 187 subjects were studied, and a predictive accuracy of 95% was achieved. This approach requires an overhead hardware device, the Ober-2 infrared-based eye-tracking device. Asvestopoulou et al.[12] proposed an eye movement-based prediction of dyslexia, measuring eye movement in relation to words. Sys-LexML is introduced with the use of various machine learning algorithms, calculating the fixation point of an eye while reading. An accuracy of 97% is reported with the use of SVM. Saccade length, the number of short forward movements, is considered in making predictions, and DysLexML utilizes a small feature set. Wong[13] presented an approach aimed at investigating eye movements and visual perception skills, stating that visual problems are responsible for reading dysfunction; however, proper care of visual issues can aid in learning. Barelaa et al.[14] studied the use of guided eye movement along with its pattern. Body sway is calculated using IRED, and eye movement is tracked using eye-tracking glasses. Results suggest that guided eye movements, with their posterior control, can be achieved through sensory clues or by enforcing the nervous system.

Chakraborty and Sundaram[15] stated that earlier detection and assistance through educational training can alleviate the negative impacts of dyslexia. Information for training is collected from 165 samples. SPSS statistics is used for data pre-processing. Here, AI is set to assess eye development information. SVM and random forest methods were used.

Saluja et al.[16] presented an approach to investigate the eye gaze movement of children with learning disabilities. Around 30 participants were studied, considering raw gaze points, fixation, and saccades, along with the density of fixation along the gaze point. It was observed that students with reading disabilities take longer to read compared to normal students. Additionally, a significant correlation was observed between fixation and backward eye movements in students with LD. Fixation duration is higher in students with LDs. Different algorithms, including velocity-based fixation analysis and cluster-based analysis, were incorporated.

Zhang and Zhou[17] proposed an eye-tracking-based approach for the detection of dyslexia. Using computer vision, they calculated the tracking of eye movement trajectory, interval time, and coordinates of eye movement. Two indicators were suggested: eye jump amplitude and reading speed. The authors suggested that this approach can be used for the early screening of patients, with the overall accuracy of the proposed model observed to be 89.7%.

2.2. Detection on the basis of handwritten text and drawing

Spoon et al.[18] gave an approach to predict dyslexia from handwriting. A total sample of 56 students was collected from the shelf. Convolutional Neural Network (CNN) is used. Fivefold cross-validation with hyper-tuning provided 77% accuracy. The author also discussed the limitations and threats of this system. Isa et al.[19] proposed an approach to the detection of dyslexia by analyzing handwriting images of children. It is developed using the pattern recognition technique and ANN. This system can calculate levels of dyslexia. It is stated that the study can be extended to detect dyscalculia and dysgraphia. A few symptoms like phonic and visual can be added for further improvements. Moetesum et al.[20] gave an approach with the use of a Convolutional Neural Network (CNN). It is used to model and classify dysfunction indicating deformation in drawing. Jasira et al.[21] proposed Dyslex-iScan a novel approach for dyslexia detection using the handwritten text of children with the inclusion of LSTM and CNN models. Features from the handwritten text are extracted using CNN while the sequential structure of handwritten text is analyzed using LSTM. Dyslexic, as well as nondyslexic patterns, were analyzed using a dataset of handwritten samples of both. It is suggested that this method is accurate in predicting dyslexic children and can be used in clinical settings or schools.

Kunhoth et al.[22] proposed a recognition of dysgraphia at the early stage of children with the use of handwritten text. The effectiveness of dynamics and kinematics of handwriting is analyzed with the use of automated techniques. A publically available dataset is used, with the use of limited features, an accuracy of 77% is observed for the diagnosis of the existence of dysgraphia. Skunda et al.[23] an approach to dysgraphia prediction proposed based on the handwritten text of children. The conventional signal theory is used where dysgraphia handwritten text is input for diagnosis. A dataset with 120 children was considered where 63 are normal children and 57 possess dysgraphia diagnosed. A three-layer CNN is proposed for the classification of children's handwritten text. The model provides 79.7% of accuracy.

2.3. Detection on the basis gaming approaches

Rello et al.[24] gave a methodology to predict LDs using linguistic computer-based games. Here binary classifier SVM is used. The model can predict dyslexia with approximately 80% accuracy. Various features including Alphabetic Awareness, Phonological Awareness, Visual Discrimination and Categorization, and Auditory Discrimination and Categorization were used. While conducting a gaming approach various distractors are provided to judge the subject's reply.

Gaggi et al.[25] discussed that dyslexia is not identified before primary school as a reading difficulty is a primary prediction related to the disorder. However early detection at preschool will be able to limit impact and able to help children with reading ability. In concern to this, the author built a serious game by using an engaging pattern of children from the age group of 5-6. Along with this, the system can be extended to train phonological skills as well as visual spatial patterns. Ali et al.[26] proposed an approach with the inclusion of around 32 linguistic exercises in a web-based gamified test. Initially, few exercises are provided based on empirical analysis of the corpus. Mistakes were analyzed using general linguistic characteristics along with phonetic and visual information. After analyzing mistakes statistical patterns were adapted for later question creation. Performance is calculated with the number of clicks, and the number of correct/wrong answers. This data is used for prediction. Limitations of the system as it won't consider IQ's of participants, other dependent disorders like dyscalculia are not considered also the degree of dyslexia is not calculated. Solenthaler et al.[27] here a game-based approach is proposed to facilitate students with learning disabilities like dyslexia and dyscalculia. Student engagement pattern reveals much of the knowledge to categorize students. In contrast to previous systems which adapt bio-sensors and video data (EEG response, eye tracking devices) to predict if a student is bored or engaged, this system gave a hardware-independent solution that predicts engagement from data logs generated from the system. The clustering approach is used to find different learning traits of students. A multimodal system is built with the inclusion of expert knowledge combining neuroscience and computer science. The goal is to make the inclusion of different perceptual cues including color, topology, music, or shape, which are associated with letters. Individual errors comprising letter confusion, phoneme omission, etc. are termed as mal-rules on the basis of which student's difficulty is calculated. Also, this is a baseline to improve mistakes and future mistake prediction. It is stated that learning improvement in spelling becomes 30% and in mathematics is about 23% after several weeks of training. The study reveals its features of engagement data of around 20000 students. The authors suggest the inclusion of Augmented Reality will provide state of art improvement in the future. Along with this inclusion storytelling environment will make the system more interesting.

Holz et al.[28] an approach of a mobile serious game called 'Prosodiya' is proposed for German dyslexic children. It is stated that interventions by the gaming method will help to minimize negative feelings like demotivation, frustration, and boredom and provide support for successful learning. Results of around 63 students who opted to engage in games around 9–10 weeks are analyzed. Results are found to be promising which helped engagement by removal of negative feelings. Rauschenberger et al.[29] proposed a web-based language-independent game termed as MusVis. Here instead of reading and writing skills visual perception, short-term memory, and auditory perception are considered. This approach is beneficial for pre-readers. The study included 313 children with 166 dyslexic children. Spanish and German languages are taken into consideration. For German 74% and for Spanish 69% accuracy is calculated. Auditory and visual gaming design modes are used. Here random forest, extra tree approach of machine learning is adapted. The given approach helps to detect and predict dyslexia and also helps to decrease school failures.

2.4. Visual and brain imaging approaches

Zeema and Christopher[30] stated that the prediction of Dyslexia from low-quality data sets is the toughest challenge. Here Neutrosophic C-Means clustering (NCM) is applied forming 4 clusters dyslexia, no dyslexia, control, and hyperactivity. It is suggested that future progression can be done with the Nature-Inspired algorithm. Zhao et al.[31] discussed that developmental dyslexia is caused by multiple disorders which include linguistic level difficulty, and problems with cognitive processing such as visual-spatial, and perceptual analysis. The study focuses on the relationship between Visual Attention Span (VAS) and reading disability. The study reveals that VAS-based intervention could improve VAS skills in individuals with VAS-impaired dyslexic and also improves fixation position. This study aims to increase the performance of sentence reading in the context of the Chinese language. The limitation of this method is it is difficult to know the components that are responsible for the training effect on VAS. Also, this technique is language-bound.

Fiveash et al.[32] proposed an approach to deal with LD's. In view of listening to music, most people are capable of extracting beats. Individuals with dyslexia are deficient in the above approach in low frequencies. The authors investigated brain responses to regular and irregular rhythmic sequences in dyslexic adults and control groups. Both participants respond to regular rhythms, so it is observed that the brain follows and extracts beats from the rhythm. In concern with irregular rhythm control group performed well as compared to dyslexic. Adults with dyslexia have difficulty in extracting regularities from more complex, irregular stimuli as compared to the control group. Płonski et al.[33] proposed a machine learning-based approach to address the neuroanatomical basis for children having developmental dyslexia. Here grey matter disruption is addressed by using a multivariate classification approach. Features are present in the left hemisphere of the brain. A dataset of 236 T1 weighted magnetic imaging resonance (MRI) images from 3 different countries are studied. Performance around 65% was achieved from various machine learning techniques including logistic regression, and 10-fold Cross-validation.

Perera et al.[34] gave an approach to detect unique brainwave patterns among dyslexic adults using EEG while performing challenging tasks. Research was carried out on 32 participants. An EEG headset is used. Cubic Support vector machine (SVM) classifier is used and validated using 10fold cross-validation. The study confirms a change in brainwave patterns in dyslexic and non-dyslexic children, where left parieto-occipital and parieto-occipital produces unique brainwave pattern.

Along with this research other studies have been carried out for students with LD's.

Sobnath et al.[35] proposed that the dropout rate is high from students having learning disability is around 31% as compared to non-disabled students which is 12%. The author gives an approach to finding trends or patterns for LD students and their performance and success in subject areas. Dimensionality reduction and K-means clustering were used. Rauschenberge et al.[36] discussed various technologies and tools that are built for the detection and intervention of dyslexia. He suggested that a person with dyslexia understands the meaning of a word but is unable to reproduce it while writing or speaking. The author suggests the use of text simplification, customization, and text-to-speech not reaching to limit. New web-based approaches with the inclusion of ML, communication, training, and support adapted to limit mistakes. Along with this is stated that early detection of dyslexia can benefit a person. Hamid et al.[37] Here it is suggested that cognitive as well as behavioral perceptive needs be taken into consideration. A learning model is introduced named the adaptive learning model which focuses on both perspectives. This proposed system worked on the Malay language of Malaysia with a total of 30 subjects taken for observation. SVM is used to work with frontal facial images captured to detect engagement patterns. A summary of literature review is presented in **Table 1**.

Table 1. Literature survey.

Author	Subject	Approach	Learning Technique	Summary	Challenges & Discussion
Prabha and Bhargavi[11]	187 subjects	Eye Movements by Ober-2	SVM-PSO	A screening tool with accuracy up to 95% is built. PCA algorithm is used to improve accuracy.	The use of hardware is overhead. The scalability of it is not cost-effective.
Asvestopoulou et al.[12]	69 Greek students	Eye Tracking	SVM, Naïve Bayes, K-Means	The system performs accurately in the presence of noise in the fixation position. 97% accuracy is given.	The challenge is making text choices. Overfitting of dataset may happen due to fewer samples.
Wong[13]	30 subjects	Eye movement & visual perception	SVM	Investigation of eye movement and visual perceptual deficit presence in children.	Results are not generalizable with a small sample. Parameters like IQ, cognitive etc. are unconsidered.
Chakraborty and Sundaram[15]	165 subjects	EyeTracker EyeLink 1000	SVM & Random Forest	AI based model is generated to accomplish 89% accuracy.	Expert presence is a need to make prediction. Hardware setup is costly and dependent
Saluja et al.[16]	30 subjects	Eye Gaze Approach	Statistical	It is observed that students with LD requires more time to read than normal.	Cost of eye tracker is high, low sample size so over fitting possible.
Spoon et al.[18]	56 pics Handwriten text	Handwritten Text	CNN	Detection of irrelevant features from handwritten text. 77% accuracy is observed.	False negatives, dataset can be biased.

Table 1. (*Continued*).

Author	Subject	Approach	Learning Technique	Summary	Challenges & Discussion
Isa et al.[19]	40 subjects	Handwritten Text	OCR & ANN	Approach to detect dyslexia on handwritten character is proposed with 73% accuracy.	OCR is not stable enough to detect handwritten characters. This is a cheap scalable approach.
Moetesum et al.[20]	60 Offline scanned images	Drawing	CNN	Analysis of Neuropsychological disorders done on the basis of subjects drawing. (98%)	This study can help psychologists for standardization, and validation for diagnosis purpose.
Rello et al.[24]	267 children and adults	Game approach	SVM	Linguistic computer based game is built achieving 84% accuracy.	Need to perform an evaluation with more samples in uncontrolled environment to evaluate success.
Gaggi et al.[25]	350 subjects	Game Approach	Statistical	System can also be used to train phonological skills and visual spatial attention.	Challenge is to develop a system that engages children in preschool who are not techno-savvy.
Ali et al.[26]	4300 subjects	Game Approach	Random Forest, 10 fold CV	Online gamified test is built for Spanish subjects to predict dyslexia	Working with prediction parameters like IQs etc. need to combine to make greater and more accurate predictions.
Solenthaler et al.[27]	20000 subjects	Game Approach	Machine learning, K-means, classification, 10-fold CV	A game-based approach to predict and improve student engagement is proposed. It is stated to be a 30% improvement in students.	Limited controlled data environment. Collaborative learning, AR will be beneficial.
Holz et al.[28]	63 subjects	Game Approach	Statistical	Mobile serious game Prosodiya for German students to improve positive feelings amongst students in proposed.	Language-dependent solution. Overfitting may be possible due to low data size.
Rauschenberger et al.[29]	313	Game Approach	Random Forest, Extra Tree	Language independent gaming model proposed for pre-readers. Visual Perception, short-term memory etc. used.	Early detection for pre-readers is a challenging task.
Zeema and Christopher[30]	Dataset	Keel Dataset	Decision Tree	Built to work with imprecise, low-quality datasets using ONCMCABF	Future work can be improved by the inclusion of Nature-Inspired algorithms.
Zhao et al.[31]	-	Assessment	Statistical	This study aims to find the interrelation between VAS deficit and reading disability in Chinese dyslexic children	Paper pencil-based approach is used.
Płonski et al.[33]	236 subjects	Brain approach	Logistic regression, 10 fold CV	65% accuracy is achieved while addressing grey matter disruption.	Data is collected from multiple scanners so uniformity is missing. Social backgrounds need to be addressed
Perera et al.[34]	32 subjects	EEG Approach	Cubic SVM, 10-fold cross-validation.	Unique brain wave pattern is analyzed amongst dyslexic children, left parietooccipital and parietooccipital produces unique brainwave pattern.	Both handed children should be included, and separate effects on males and females should be analyzed.

3. Gap analysis

In the previous section, various approaches related to the prediction and assessment of students with learning disabilities were studied. The study examined different methods involved in prediction. **Table 2** gives an overview of all 4 approaches discussed.

Table 2. Gap analysis.

Sr. No.	Method of Prediction	Accuracy	Scalability	Flexibility	Expertise	Real-Time Analysis	Cost
1	Prediction using eye movement	High	Medium	Medium	High	High	High
2	Prediction using Handwritten text	Medium	High	High	Medium	Medium	Medium
3	Prediction using gaming approach	Medium	High	Medium	Medium	Medium	Medium
4	Prediction using Brain imaging and EEG	Medium	Low	Low	High	Low	High

Among the approaches discussed, the brain and EEG approaches require high expertise and are costly, making them non-scalable[33,34]. The eye movement-based approach is efficient, but it heavily depends on high-cost eye trackers for better accuracy[11,15,16]. Among the above four approaches, prediction using handwritten text[18,19] and the gaming approach[24] are cost-effective, with easier data collection and implementation, and scalability to a larger scale is possible compared to the other two approaches.

4. Proposed architecture

In the literature review, a state-of-the-art approach for predicting learning disabilities from handwritten text is discussed. The handwritten-based approach is scalable, cost-effective, and requires less expertise[19]. Additionally, data collection is easier compared to other techniques. Building on this perspective, a CNN-based handwritten text recognition system is proposed in this review. The concept involves collecting handwritten text from children, utilizing CNN to convert it into text, and identifying dyslexia-related features to assess the potential risk of dyslexia or learning disabilities in a child. The detailed architectural view is presented in **Figure 4.**

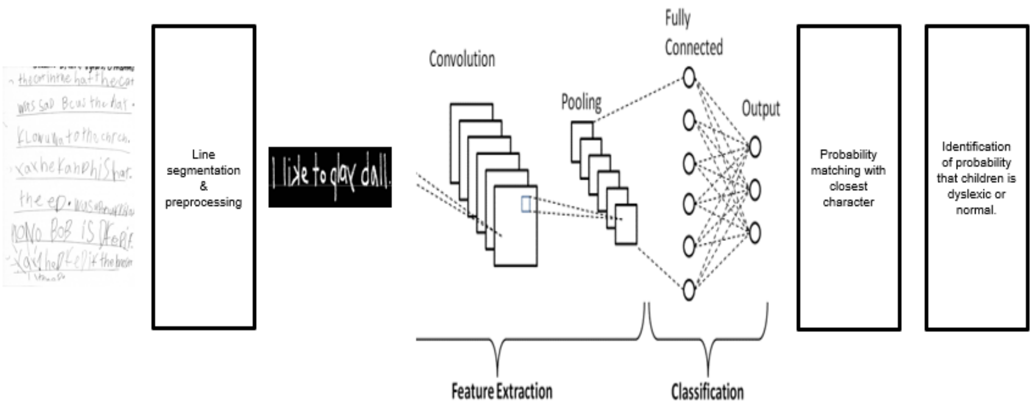

Figure 4. Proposed architecture.

Step 1: Data Collection.

From the literature, it is observed that children with dyslexia confuse most with similar-looking characters[19]. Therefore, data is captured from fourteen school children, with parental consent obtained from their parents. The characters considered are [b, c, f, p, 2, 5, 6, 7]. as these are often mistakenly written as p → q, b → d, f → 7, etc., by children facing learning issues. Hence, these specific characters are taken into account.

Step 2: Data Preprocessing and segmentation.

The characters are captured on plain paper. These are scanned using a scanner. Later as images captured are in RGB format these are converted into grayscale 2-channel images. Then, edge detection is performed to capture the text. The image is segmented into characters using the bounding box technique.

Step 3: Feature Extraction.

For feature extraction, a CNN-based model has been developed for the recognition of handwritten characters which is elaborated in **Figure 5**. EMNIST and A-Z Handwritten data datasets are used to train the model. The CNN model consists of 2 convolutional and 2 max-pooling layers. Early stopping is also implemented and flattened and dense layers are added. With this model, a character set is passed through, and it is used to recognize characters written by children. **Figure 6** elaborated sample data captured from a student and how the prediction is performed for letter P.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 13, 13, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 6, 6, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 4, 4, 128)         73856

 max_pooling2d_2 (MaxPooling  (None, 2, 2, 128)        0
 2D)

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 64)                32832

 dense_1 (Dense)             (None, 128)               8320

 dense_2 (Dense)             (None, 26)                3354

=================================================================
Total params: 137,178
Trainable params: 137,178
Non-trainable params: 0
_________________________________________________________________
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Figure 5. CNN trained model.

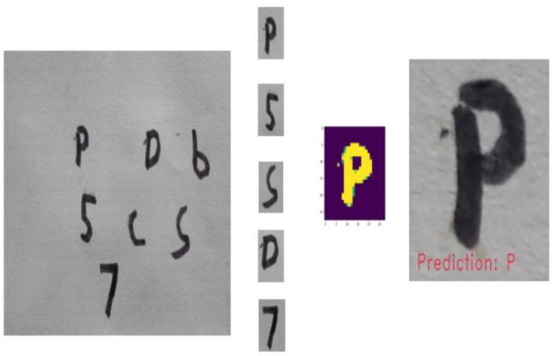

Figure 6. Data captured from children and predicted by model.

5. Results and discussion

Handwritten text images are collected, and preprocessing of those images is done. After preprocessing, characters are separated, and those are given as input to the CNN model. **Table 3** shows the total number of characters predicted by the CNN model and manually predicted for each subject. A percentage accuracy is calculated as

$$Percentage\_Accuracy = \frac{CNN\_Based\_Prediction\ (C)}{(Manual\_Prediction\ (M))} \times 100\% \tag{1}$$

It is observed that with a trained CNN model, the accuracy of prediction is achieved at 92.18% in comparison with manual prediction. Also, the model accuracy is 85.71%.

Table 3. Prediction accuracy.

Sr. No.	CNN Based prediction (C)	Manual Prediction (M)	Percentage of match (C/M)*100
1	7	8	87.50
2	6	7	85.71
3	8	8	100.00
4	5	6	83.33
5	7	8	87.50
6	7	7	100.00
7	6	7	85.71
8	7	8	87.50
9	7	7	100.00
10	6	7	85.71
11	7	8	87.50
12	8	8	100.00
13	8	8	100.00
14	7	7	100.00

The risk of a student being dyslexic or not is calculated based on the ratio of correct characters to total characters. The formula is as follows:

$$Risk\_of\_dyslexic = \frac{(Total\ number\ of\ correct\ characters)}{(Total\ number\ of\ characters)} \times 100\% \tag{2}$$

From this, it is stated that if 'Risk_of_dyslexic' is <50%, then the child is termed as non-dyslexic; else, we can consider that the child has a risk of dyslexia. So, such students need special attention or further diagnosis. From the sample collected in the study, out of 14 students, 5 students were found to have a risk of dyslexia. Amongst them, 3 are already been assessed clinically for dyslexic symptoms. This study is helpful for screening children. They can be further clinically diagnosed to make more precise decisions.

6. Conclusions

In this paper, issues related to children with learning disabilities and approaches for their early detection are discussed. From the literature survey, it is evident that providing a proper mechanism for the early detection of disabilities among children would be beneficial for their future progression in life. A comparison of different prediction techniques is conducted, revealing that prediction based on handwritten text and gaming approaches is cost-effective and scalable, whereas prediction based on eye gaze and brain imaging is costly. This paper presents preliminary work for the early prediction of the risk of dyslexia among children for whom English is a second language. The study found that the proposed CNN-based approach provides 92.18% accuracy for prediction.

Our next step is to discuss with school teachers and psychologists and add additional features for prediction to make this system more robust. The inclusion of more samples will be done. Once further features are included, a detailed investigation will be conducted along with the school teachers, to evaluate every child and validate the approach.

Author contributions

Conceptualization, SP and RA; methodology, SP and RA; software, SP; validation, SP, RA, RB and PM; formal analysis, SP; investigation, SP and RA; resources, SP; data curation, SP; writing—original draft preparation, SP; writing—review and editing, SP and RA; visualization, SP; supervision, RA, and RB; project administration, RA, RB and PM. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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