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Automated Dyslexia Screening Using Children's Handwriting in English Language with Convolutional Neural Network and Bidirectional Long Short-Term Memory Model

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Abstract

Dyslexia, a common learning disability, often goes undetected in early childhood, leading to delayed interventions. This study proposes a novel approach for early detection of dyslexia through automated analysis of children's handwritten text images written in the English language. Using computer vision techniques and machine learning models, handwriting patterns are analyzed to identify dyslexic tendencies based on unique characteristics such as spelling errors, letter shape, spacing, and consistency. The system incorporates a handwritten text recognition (HTR) model, trained on the IAM dataset, achieving an accuracy of 95.6% and a word error rate (WER) of 0.13% in recognizing text. For dyslexia prediction, convolutional neural network (CNN) architecture is utilized with bidirectional long short-term memory (Bi-LSTM) and connectionist temporal classification (CTC) loss, with the best-performing model demonstrating significant accuracy in distinguishing between dyslexic and non-dyslexic children. The handwritten images were collected from children through three written tests, ensuring various handwriting styles and content. The dyslexia prediction model is evaluated using performance metrics such as accuracy, F1 score, and WER. The results underscore the potential of using handwriting as a predictive tool for dyslexia, showing better accuracy and efficiency than previous models. This approach can be an early, non-invasive screening tool, enabling timely intervention and personalized learning strategies for affected children.

Keywords: Learning disability (LD); Handwritten text recognition (HTR); Convolution neural networks (CNN); Word error rate (WER); Dyslexia
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1. Introduction

Dyslexia, a neurodevelopmental disorder affecting reading and writing skills, impacts approximately 5-10% of the global population, with many cases remaining undiagnosed in early childhood.[1] Early detection of dyslexia is critical, as timely interventions can significantly improve educational outcomes and reduce long-term academic challenges.[2] Traditional methods for diagnosing dyslexia often rely on lengthy assessments by specialists, which can delay intervention for at-risk children.[3]

Recent advances in machine learning (ML) and computer vision have opened new pathways for early diagnosis through non-invasive techniques such as handwriting analysis. Handwritten text recognition (HTR) models, particularly those leveraging deep learning (DL), have demonstrated remarkable success in extracting and analyzing text from image data, achieving high levels of accuracy in recognizing characters and patterns. Handwriting has been shown to exhibit distinctive features in children with dyslexia, including spelling mistakes, irregular letter shapes, spacing, and inconsistencies in writing flow.[3] These dyslexic writing patterns provide valuable clues for automated systems to predict dyslexia without requiring traditional cognitive tests, thus offering a faster and less subjective diagnostic approach. Computer vision techniques, particularly convolutional neural networks (CNNs), have emerged as a powerful tool for image-

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based handwriting analysis. CNNs are highly effective in identifying patterns in handwriting that may be imperceptible to human observers. Several studies have explored the use of CNNs in medical diagnostics and educational assessments, demonstrating their capability to classify handwriting styles and detect irregularities linked to cognitive or neurological conditions.[4] The integration of HTR models with CNN architectures has enabled more accurate recognition of text from images, which can be further analyzed for specific handwriting features associated with dyslexia.

In this study, the author proposed a method for predicting dyslexia by analyzing children's handwritten text images in the English language collected through a series of written tests. The assessment consists of three tests: the first involves rewriting individual words, the second focuses on rewriting short sentences, and the third requires rewriting longer paragraphs. The words and sentences used in the analysis are carefully selected to address areas where children with dyslexia commonly face challenges.[1] Parental consent was obtained before administering these tests.

The proposed approach leverages a state-of-the-art CNN model for image processing, combined with a Bi-LSTM and connectionist temporal classification (CTC) loss, trained on the IAM dataset, a widely used benchmark for handwritten text recognition. The IAM dataset provides a robust foundation for training DL models in recognizing diverse handwriting patterns and facilitating the extraction of relevant features from children's writing. By identifying subtle differences in handwriting, the proposed system aims to distinguish between dyslexic and non-dyslexic children, providing a novel, non-invasive diagnostic tool for early detection of the risk of dyslexia.

In this study English language is considered for detection as English is well-suited for detecting dyslexia from handwritten text in India due to its intricate orthography, where the correspondence between letters and sounds is less straightforward than in more phonetic languages. This irregularity helps highlight typical dyslexia indicators, such as spelling inconsistencies, letter reversals, and challenges in phonological processing. Moreover, since English is commonly used in Indian schools and is a second language for many learners, it provides a practical basis for dyslexia detection in India's linguistically diverse context.

This study contributes to the growing body of research on AI-driven educational technologies, specifically focusing on early intervention for dyslexia. By reducing reliance on traditional diagnostic methods, the proposed approach can accelerate the screening process, allowing educators and clinicians to identify at-risk children and tailor their learning strategies accordingly. Ultimately, the proposed system aims to improve the accessibility and efficiency of dyslexia diagnosis, offering new possibilities for integrating AI into educational settings.

The paper is organized as follows: Section 1.1 presents the literature review, where relevant studies and previous works are examined. Section 2 discusses the overall gaps and opportunities identified from the literature. In Section 3, the proposed approach is outlined, starting with data collection, followed by data preprocessing, feature extraction, and classification. Section 4 covers the results and discussion, providing insights and analysis of the findings. Finally, Section 5 concludes the paper with a summary and provides an outlook for future research directions.

2. Literature review

Shaywitz,[1] this book highlights the neurobiological basis of dyslexia and stresses early detection through reading, writing, and spelling difficulties. It also discusses the role of technology, like ML, in improving early diagnosis. Snowling and Hulme reviewed the differences between dyslexia and reading comprehension issues, offering evidence-based interventions.[2] Dyslexia is addressed through phonological training, while comprehension difficulties are managed with language skills improvement. Peterson and Pennington describe dyslexia as a neurodevelopmental disorder affecting word recognition linked to brain disruptions and genetic factors.[3] The phonological theory is the leading explanation, with genetic and environmental influences playing a role. Hebert *et al.*[4] identified writing challenges in dyslexic children, including transcription and memory issues. Effective strategies like sound-spelling techniques and self-regulated strategies can improve writing and spelling.

Alhamad *et al.*[5] highlighted the importance of handwritten optical character recognition (OCR) for converting handwritten documents into editable data, with symmetry as a preprocessing step improving recognition accuracy. This review covers OCR research from 2019 to early 2024, analyzing 116 articles, noting current advancements, and suggesting future research areas. LeCun *et al.*[6] explained how DL models use multiple layers to learn data representations at different levels of abstraction, advancing fields like speech recognition and genomics. Using the backpropagation algorithm, DL refines data representation, with convolutional networks excelling at processing images, while recurrent networks handle sequential data. Sainath *et al.*[7] explored using CNNs for keyword spotting (KWS) with limited computational resources, outperforming Deep neural networks (DNNs) with fewer parameters. Their study presents new CNN architectures that significantly lower the false reject rate by 27-44% under two scenarios: restricted multiplications and limited parameters. Mishra *et al.*[8] discussed optical character recognition (OCR) and its advanced form, intelligent character recognition (ICR), which converts handwritten text into ASCII data. They present a CNN model trained on over 100,000 images from the MNIST dataset, achieving 90.54% accuracy and a loss of 2.53%. Hochreiter and Schmidhuber addressed the challenge of learning over long time intervals using recurrent backpropagation, proposing Long Short-Term Memory (LSTM) to solve this issue.[9] LSTM used specialized units to maintain constant error flow, allowing it to handle long-time lags and outperform other recurrent networks in challenging tasks.

With increasing reliance on computers, the demand for effective handwritten digit recognition (HDR) has risen. DL has proven highly accurate for HDR tasks. This study reviews HDR methods, covering various ML techniques, including supervised, unsupervised, and reinforcement learning, with a focus on CNN models and classification methods across different languages to guide future research.[10] Kamble *et al.*[11] recognized that Marathi's handwriting is difficult due to script complexity and writing style variations stemming from the Devanagari script. This review explores classifiers like KNN, decision tree (DT), extra trees (ETs), and random forest (RF), noting that ETs and RF showed the highest accuracy. Rakesh *et al.*[12] explained that HTR converts handwritten text into digital form, aiding archive digitization and data entry. Image processing, CNNs, and RNNs enhance accuracy through pre- and post-processing. Despite complex handwriting challenges, DL has significantly improved HTR efficiency. Bishop and Snowling suggested that developmental dyslexia and specific language impairment (SLI) may stem from a shared issue differentiated by severity or development and highlight the importance of considering both phonological deficits and the separate effects of semantic and syntactic challenges in SLI, proposing a framework to identify distinct subgroups.[13] Grigorenko highlighted dyslexia as a complex reading process involving various psychological functions.[14] Research identifies phonological processing and automatization deficits as core dyslexic challenges, possibly linked to genetic factors and often co-occurring with other learning and behavioral difficulties.

Bilge *et al.*[15] explored connections between fluency in reading, writing, speaking, comprehension, and vocabulary. Using data from 94 fifth-grade students, they found that vocabulary had the strongest correlations with other language skills, highlighting its importance. Additionally, fluency skills and reading comprehension were found to be interconnected, aligning with existing research on language fluency and comprehension. Pammer and Kevan examined the role of visual sensitivity in the reading abilities of dyslexic and normal readers.[16] By controlling for nonverbal intelligence quotient (IQ), their study demonstrated that visual sensitivity accounted for 6% of the variance in reading ability, particularly in irregular word reading, suggesting a direct link between low-level visual sensitivity and reading skills. Isa *et al.*[17] reviewed an automated system designed to detect dyslexia symptoms in primary school children through handwriting analysis. The system used pattern recognition and OCR techniques to extract features, with an artificial neural network achieving 73.33% accuracy in classifying dyslexia risks. The study recommended improvements through larger sample sizes and enhanced image processing for better early detection. The authors in Ref. [18] explored the use of CNN to detect dyslexia symptoms through handwriting analysis. While various computational methods have shown inconsistent performance, recent CNN models have improved accuracy. The study compares different CNN models, including CNN-1, CNN-2, CNN-3, and LeNet-5, using Keras and TensorFlow. With over 87% accuracy in classifying dyslexic handwriting, the results highlight CNN's potential for more reliable dyslexia detection. Yogarajah and Bhushan conducted an automated dyslexia diagnosis using handwriting samples from 54 children identified as at risk.[19] A CNN analyzed 267 images of Hindi words, achieving an accuracy of 86.14%, demonstrating the effectiveness of DL in detecting dyslexia. Ahire *et al*.[20] used a fuzzy approach for context identification and showed good performance. Mohamed *et al.*[21] addressed dyslexia detection limitations in Malaysia's current method by developing a CNN-based handwriting recognition system using LeNet-5 architecture. After processing 138,500 handwriting images, the model achieved 95.34% accuracy in classifying three classes of dyslexic handwriting, meeting the research objectives.

3. Research gaps and opportunities

Current literature reveals significant gaps in the areas of personalized learning and real-world implementation for dyslexia screening. One of the key gaps is the lack of cross-linguistic and longitudinal studies that explore the diversity of educational settings and examine the long-term impacts of intervention strategies. Additionally, the development of practical, scalable solutions for dyslexia screening in resource-limited schools remains underexplored. Most existing models fail to address the unique challenges faced by educational systems in low-resource environments, limiting the effectiveness and reach of current dyslexia screening technologies.[22]

To address these gaps, this study introduces a novel approach that leverages deep learning techniques-specifically a CNN and Bi-LSTM model combined with CTC loss. By conducting assessments based on three handwritten tests from children, it is aimed to create an automated dyslexia screening system that offers personalized learning interventions and is applicable in real-world educational contexts. This approach not only enhances handwriting recognition accuracy but also provides scalable solutions that can be implemented in diverse, resource-limited settings, addressing the current shortcomings in the literature.

3.1 Experimental section

Figure 1 shows a proposed architecture model for predicting dyslexia using the CNN Bi-LSTM model. The system consists of four steps: data collection, data preprocessing, feature extraction, and classification.

3.2 Dataset description and data collection

In this step, handwriting samples are gathered from children by conducting three specific tasks:

- Task 1: Children are asked to rewrite individual words.

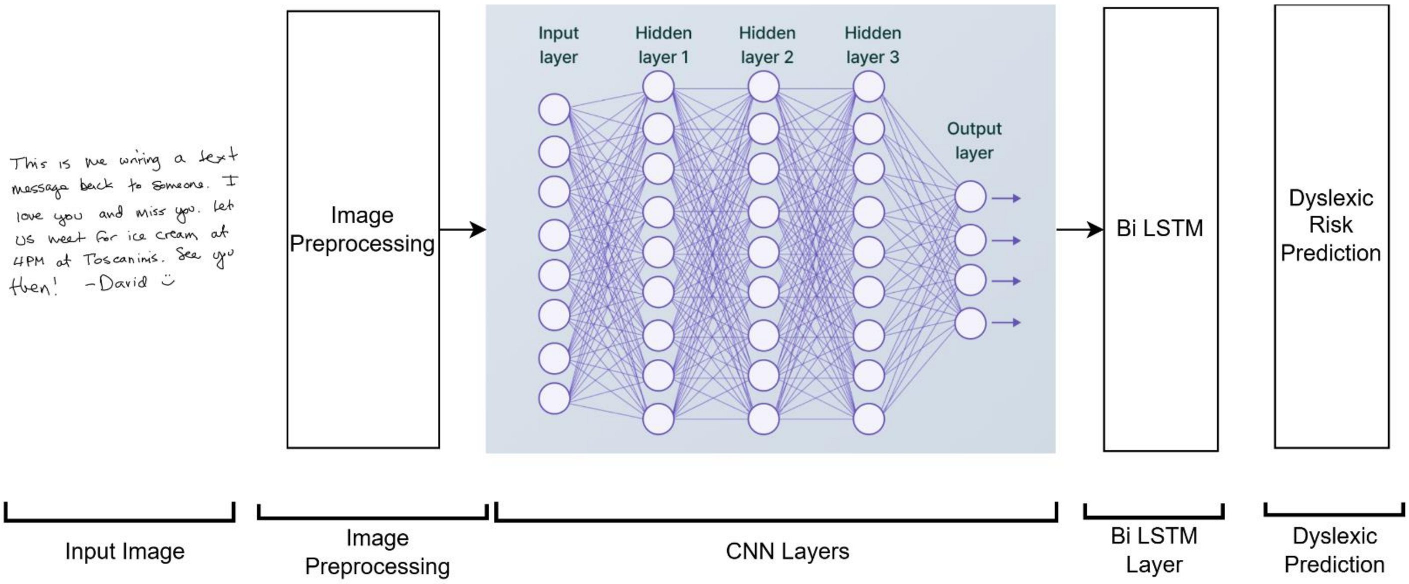

Fig. 1 Prediction of risk of dyslexia using CNN Bi-LSTM architecture.

- Task 2: Children are tasked with rewriting short sentences or lines.
- Task 3: Children rewrite longer paragraphs.

The words and sentences chosen are designed to challenge dyslexic children, focusing on typical difficulties such as irregular spelling, complex phonetic structures, and sentence construction. This approach ensures that the data collected provides insight into potential dyslexia-related writing issues. Along with this, the IAM dataset is used to train the model. The IAM dataset is a widely utilized resource for training HTR models. It is included in Table 1.

Table 1. The details of the IAM dataset.

Category	Details
Type of Data	Handwritten text lines, words, and sentences
Source	The dataset consists of 1,539 pages of handwritten English text provided by 657 individuals.
Forms	1,539 scanned pages of handwritten text.
Text Lines	13,353 lines of text.
Words	115,320 individual words.
Writers	Samples come from a diverse set of writers, offering variability in handwriting styles.

The IAM dataset is essential for training DL models like CNN-Bi-LSTM in handwritten text recognition. Its variety in handwriting styles ensures that the model can generalize well to different handwriting patterns, including those of children with dyslexia.

3.3 Data preprocessing

Once the handwritten text images are collected, they undergo preprocessing to make them suitable for further analysis. The preprocessing steps include:

3.3.1 Grayscale conversion

The RGB images are transformed into grayscale to simplify the computational load without losing important features.[20] The conversion formula used is given below in Eq. (1):

$$I_{gray} = 0.2989 * R + 0.5870 * G + 0.1140 * B \quad (1)$$

where I_{gray} is the grayscale intensity, R is the red channel, G is the green channel, and B is the blue channel.

3.3.2 Noise removal

In order to enhance image quality, techniques like Gaussian blur or median filtering are applied to eliminate noise and background artifacts as Eq. (2). Gaussian blur is applied as follows:

$$I\_blurred = I\_gray * G(x,y,\sigma) \quad (2)$$

where *I_blurred* is the blurred image, I_gray is the grayscale image, and *G(x,y,σ)* is the Gaussian kernel with standard deviation σ.

3.3.3 Thresholding

To distinguish the text from the background, adaptive or Otsu's thresholding is used. This step converts the image into a binary format where text pixels are separated from background pixels (Fig 2). The equation Eq. (3) demonstrates this.

$$I_{binary(x,y)} = 0,\ if\ I_{gray(x,y)} < T,\ else\ I_{binary(x,y)} = 1 \quad (3)$$

where *I_binary(x,y)* is the binary image, *I_gray(x,y)* is the grayscale intensity at (x,y), and T is the value of the threshold. These preprocessing steps ensure the images are clean and ready for analysis. These operations are implemented using the OpenCV (CV2) library.

3.3.4 Bounding box creation

After thresholding, bounding boxes are created around each word to isolate them for further processing. The bounding boxes are generated based on the contours of each word detected in the binary image, ensuring that words are correctly

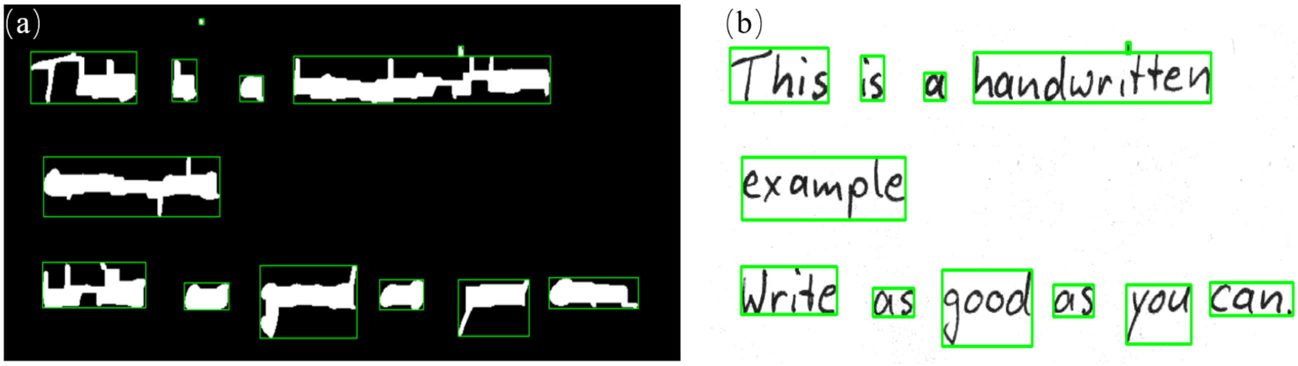

Fig. 2 (a) Image thresholding and bounding box creation, (b) Word alignment and correction.

identified and bounded. This step is critical for accurate word segmentation and feature extraction in the subsequent stages, as shown in Fig. 2 (a).

3.3.5 Word alignment and correction

The bounding boxes are adjusted to ensure proper alignment of the words, correcting any skewness or misalignment that may occur during scanning. This ensures that the words are properly prepared for the feature extraction stage, minimizing the risk of errors in the model's recognition of handwritten text, as shown in Fig. 2 (b).

3.4 Feature extraction

The system uses a combination of CNN and Bi-LSTM networks to extract features from the preprocessed handwriting images, which can effectively recognize and convert handwritten text into digital text. Table. 2 lists the network layer details of the CNN Bi-LSTM model. It's noted that the total parameters are 8,743,247 (33.35 MB), the trainable parameters are 8,741,199 (33.35 MB), and the non-trainable parameters are 2,048 (8.00 KB). The feature extraction layers of the proposed networks are as follows.

3.4.1 CNN layer

As given in Eq. (4) CNN is applied to identify spatial characteristics such as edges, curves, and shapes in the text.[6] The convolution operation is:

$$(I * K)(i,j) = \Sigma\,\Sigma\, I(i-m, j-n)K(m,n) \quad (4)$$

where $(I * K)(i,j)$ is conxolution result, $I(i-m, j-n)$ is the input element, and $K(m,n)$ is the kernel at (m,n).

A ReLU activation function Eq. (5) is used to introduce non-linearity after each convolutional operation:

$$ReLU(x) = max(0,x) \quad (5)$$

where $ReLU(x)$ is the Rectified Linear Unit function, which returns x, if $x > 0$, else 0, and x is the input value.

3.4.2 Pooling layer

Max pooling is used to reduce the spatial dimensions of the feature maps, making the model more efficient. As shown in Eq. (6), max pooling is calculated as:

$$P\_max = max(I\_conv) \quad (6)$$

where P_{max} is the max value, and I_{conv} is the convolved input.

3.4.3 Bi-LSTM layer

Once the spatial features are extracted by the CNN model, Bi-LSTM layer processes the data, taking into account the sequential nature of handwriting. The Bi-LSTM captures both forward and backward dependencies in the writing, which is critical for text recognition. The Eq. (7) for the LSTM unit are:

$$f_t = \sigma\left(W_f * \left[h_{\{t-1\}}, x_t\right] + b_f\right) \quad (7)$$

where f_t is the forget gate, σ is the sigmoid, W_f is the weights, and b_f is the bias.

$$i\_t = \sigma(W\_i * [h\_\{t-1\}, x\_t] + b\_i) \quad (8)$$

where i_t is the input gate, W_i is the weights, and b_i is the bias.

$$C\_t = f\_t * C\_\{t-1\} + i\_t * tanh(W\_C * [h\_\{t-1\}, x\_t] + b\_C) \quad (9)$$

where C_t is the cell state and $C\_\{t\text{-}1\}$ is the previous cell state.

$$o_t = \sigma\left(W_o * \left[h_{\{t-1\}}, x_t\right] + b_o\right) \quad (10)$$

where o_t is the output gate, W_o is the weights, and b_o is the bias.

$$h_t = o_t * \tanh(C_t) \quad (11)$$

where h_t is the hidden state and C_t is the cell state.

3.5 Classification

The IAM Dataset is used during the training and validation of the HTR system. After feature extraction, the system classifies the handwritten text by analyzing dyslexia-specific markers, including:

3.5.1 Spelling errors

The recognized text is compared with a dictionary to identify any spelling mistakes.[5] The error rate is calculated by Eq. (8) as:

$$Error_{spelling} = \left(\frac{Number\ of\ incorrect\ Words}{Total\ Words\ Written}\right) \times 100 \quad (8)$$

where $Error_{spelling}$ is the spelling error rate as a percentage, the *Number of Incorrect words* is the total count of incorrect words and the *Total Words Written* is the total words in the sample.

3.5.2 Spacing inconsistencies

The model uses advanced algorithms to assess the spacing between individual letters and words within a given text. Analyzing these spatial relationships can identify patterns and irregularities that are often seen in children with dyslexia.

Table. 2 The network layer details of the CNN Bi-LSTM model.

Layer (type)	Output Shape	Param #
input_layer_5 (InputLayer)	(None, 32, 128, 1)	0
conv2d_35 (Conv2D)	(None, 32, 128, 64)	640
max_pooling2d_20 (MaxPooling2D)	(None, 16, 64, 64)	0
conv2d_36 (Conv2D)	(None, 16, 64, 128)	73,856
max_pooling2d_21 (MaxPooling2D)	(None, 8, 32, 128)	0
conv2d_37 (Conv2D)	(None, 8, 32, 256)	295,168
conv2d_38 (Conv2D)	(None, 8, 32, 256)	590,080
max_pooling2d_22 (MaxPooling2D)	(None, 4, 32, 256)	0
conv2d_39 (Conv2D)	(None, 4, 32, 512)	1,180,160
batch_normalization_10	(None, 4, 32, 512)	2,048
conv2d_40 (Conv2D)	(None, 4, 32, 512)	2,359,808
batch_normalization_11	(None, 4, 32, 512)	2,048
max_pooling2d_23 (MaxPooling2D)	(None, 2, 32, 512)	0
conv2d_41 (Conv2D)	(None, 1, 31, 512)	1,049,088
lambda_5 (Lambda)	(None, 31, 512)	0
bidirectional_10 (Bidirectional)	(None, 31, 512)	1,574,912
bidirectional_11 (Bidirectional)	(None, 31, 512)	1,574,912
dense_5 (Dense)	(None, 31, 79)	40,527

3.5.3 Letter reversals

Common letter reversals, such as confusing 'b' with 'd', are a frequent challenge for individuals with dyslexia. These reversals occur because the letters are similar in shape. In order to detect these types of errors, the model detected by comparing the recognized text with expected character patterns.

4. Results and discussion

The proposed CNN-Bi-LSTM model with CTC loss demonstrates superior performance compared to previous studies in dyslexia detection. Mishra *et al.*[8] achieved an accuracy of 90.54% using CNN, while Isa *et al.*[17] reported 73.33% accuracy using OCR and pattern recognition. Sazanita *et al.*[18] reported over 87% accuracy with a CNN model, and Yogarajah and Bhushan achieved an accuracy of 86.14%.[19] Although Mohamed *et al.*[21] achieved 95.34% accuracy using the LeNet-5 model, our proposed model slightly surpasses it, reaching an accuracy of 95.6% (Table 3).

This higher accuracy is achieved using a CNN-Bi-LSTM architecture with CTC loss, leveraging the IAM dataset and handwritten tests from children, providing a highly accurate and precise approach to dyslexia detection.

Additional performance measures were calculated for our proposed model, highlighting its superior performance. Key metrics include a word error rate (WER) of 0.13, a precision of 94.38%, a recall of 91.51%, and an F1 score of 92.61%. These results demonstrate the model's exceptional accuracy and effectiveness.

Further improvement can be achieved by integrating a hybrid model that combines cognitive theories of dyslexia with advanced ML algorithms, enhancing the model's ability to identify more nuanced patterns in dyslexic handwriting. This would not only improve detection accuracy but also make the system more adaptable to a broader range of learning contexts.

Overall, the proposed model offers a highly reliable and scalable solution for automated dyslexia screening, with strong potential for real-world implementation in educational settings. Further research with larger datasets and hybrid models will continue to refine these promising results.

Table 3. Comparative results among proposed dyslexia detection model and the state-of-the-art methods.

Authors	Dataset Used	ML/DL Technique	Accuracy
Proposed approach	IAM dataset, children's handwriting (ages 6-12)	CNN-Bi-LSTM with CTC loss	95.6%
Mohamed *et al.*[21]	138,500 handwriting images, Malaysia (ISD-based)	CNN with Transfer Learning (LeNet-5)	95%
Iza *et al.*[17]	Handwriting samples from Malaysian dyslexic children	Pattern recognition, OCR, ANN	73.33%
Yogarajah and Bhushan[19]	Handwriting images, data augmentation	CNNs (CNN-1, CNN-2, CNN-3, LeNet-5)	86.16%
Mishra *et al.*[8]	54 children's handwriting samples (Hindi script)	CNN	90.54%

5. Conclusions

In summary, early detection of dyslexia is essential for enabling timely interventions, which can significantly improve a child's academic development and self-confidence. The proposed CNN-Bi-LSTM model has been specifically designed for this purpose, demonstrating exceptional performance in identifying dyslexia-related handwriting patterns, such as letter reversals, inconsistent spacing, and spelling errors. The model was trained using data collected from children aged 6 to 12, based on three handwriting tasks: rewriting words, sentences, and paragraphs. These tasks were tailored to capture the specific challenges faced by children with dyslexia.

With impressive results and an accuracy of 95.6%, the model proves its robustness in accurately detecting dyslexia. The CNN effectively captures the spatial features of handwriting, while the Bi-LSTM efficiently processes the sequential structure of text, enabling the model to outperform traditional methods in terms of accuracy and reliability.

Looking forward, the integration of more advanced techniques such as hybrid models combining CNN with Transformers, attention mechanisms, and transfer learning can further enhance the accuracy and scalability of this model, making it an even more powerful tool for early dyslexia detection in educational contexts.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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