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Deep Learning for Dyslexia Detection: A Comprehensive CNN Approach with Handwriting Analysis and Benchmark Comparisons

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ABSTRACT

Dyslexia is a complex learning disorder that affects neurological nerves in the brain and makes reading and writing difficult; therefore, early diagnosis for effective interventions becomes important. This study demonstrates how quickly dyslexia can be identified by introducing an advanced convolutional neural network model developed for detecting dyslexia through image-based handwriting analysis. The need for early identification is informed by the fact that dyslexia may, in certain cases, lead to poor academic performance and emotional imbalance among learners. This method of using deep learning outperforms all other established conventional methods due to inherent sensitivity in classifying handwritings of dyslexics from those of normal individuals. The artificial intelligence (AI)-supported technology has the highest training accuracy of 99.5% proving its ability to capture subtle features related to the presence of dyslexic tendencies. Consequently, it records a testing accuracy of 96.4%, thereby confirming its efficacy under practical circumstances. In addition, the model also shows a good F1-score of 96 which indicates that it can achieve a balanced precision versus recall trade-off unlike other state-of-the-art approaches. The obtained results of the proposed methodology were compared with those of previous state–of-the-art approaches, and it has been observed that the proposed study provides better outcomes. These detailed performance indicators point toward the potential usefulness of AI-based methods in identifying dyslexia thus informing appropriate interventions on time and targeted assistance to the patients suffering from this disease.

KEYWORDS

machine learning, deep learning, algorithms, augmentation, dyslexia detection

INTRODUCTION

Dyslexia, a neurodevelopmental disorder, profoundly impacts the acquisition of spelling and reading skills, despite individuals receiving sufficient instruction and possessing average or above-average intelligence (Knight, 2018). This prevalent learning disability affects approximately 5-10% of individuals. Children with dyslexia experience challenges such as decoding words, recognizing sight words, and understanding the correlation between sounds and letters, albeit with variations from person to person. Nontypical brain functioning in areas linked to language processing underlies dyslexia, causing distinctive difficulties. Specifically, variations are exhibited in regions responsible for recognizing and manipulating spoken language sounds. Neuroimaging studies have demonstrated functional and structural disparities in the brains of individuals with dyslexia, particularly in areas crucial for language processing. This neurological differentiation contributes to issues with accurate and fluent reading, impacting various facets of academic performance and eroding the child's self-esteem. Early identification and targeted interventions, such as specialized reading programs, can significantly alleviate the challenges associated with dyslexia, enabling affected children to thrive academically and socially (de Santana et al., 2012; Cui et al., 2016).

A variety of strategies are used to detect dyslexia, with conventional and sophisticated approaches playing various roles (Al Lamki, 2012). To discover potential indicators of dyslexia in pupils, traditional approaches frequently rely on teacher observations, standardized reading examinations, and behavioral evaluations. While these methods are useful, they may have limits in terms of precision and early identification. To deliver more nuanced insights, advanced approaches make use of technological and scientific developments. Researchers can analyze brain activity patterns linked with dyslexia using neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and magnetoencephalography. Genetic testing is one of the tools employed to establish that the probability of dyslexia is increased by certain genetic markers (Smith et al., 1991; Beneventi et al., 2010; Bowyer et al., 2010). Additionally, the identification of reading patterns and eye movements is facilitated by the use of computer-based assessments and eye-tracking technologies, thus pinpointing specific difficulties. While screening is aided by conventional techniques, it is imperative that advanced procedures are utilized to comprehend how dyslexia begins in a person's brain. This understanding can be instrumental in tailoring interventions and providing personalized support to individuals afflicted by dyslexia at any age.

Research problem and motivation

Early dyslexia detection among possible dyslexic people is crucial, because people with dyslexia have severe difficulties in reading and writing; hence, the motivation behind conducting research on deep learning-enabled image handwriting-based dyslexia detection is mainly to help solve these problems. In fact, the Rose Report (The Dyslexia SpLD Trust, 2024) was conducted by the British government, which identified emotional and educational difficulties faced by children and adults with dyslexia, including experiences of shame, ridicule, and teasing that result from poor reading. Therefore, this study aims at developing a more subtle and effective approach for diagnosing dyslexia that applies deep learning methods based on handwritings captured as images. This methodology tries to offer a potential earlier and more accurate identification method by diving into the patterns and complexities of handwriting, allowing for prompt interventions and support. This research contributes to the larger goal of improving the entire educational experience and life chances of people with dyslexia, thereby minimizing the negative repercussions identified by the Rose Report.

Deep learning-based detection of dyslexia disease

The integration of artificial intelligence (AI)-based systems, particularly those employing deep learning approaches, has been progressive in the development of dyslexia diagnosis. Traditional approaches relied on manual evaluations, but the development of AI has permitted more efficient and subtle detection systems (Jothi Prabha and Bhargavi, 2019). Deep learning, a subset of AI, has been shown to be very effective in dyslexia-detection exercises (Poulsen et al., 2023). By utilizing neural networks that analyze intricate patterns and relationships in data, deep learning models can detect minute differences in handwriting styles among individuals with and without dyslexia.

An important part of this procedure is image-based handwriting analysis because it allows for a comprehensive evaluation of writing characteristics. Variations in elements such as letter spacing, uniformity, and overall organization of written information are common in both normal and dyslexic youngsters. With the suggested methodology, AI systems trained on varied datasets containing both normal and dyslexic handwriting samples can learn to recognize these distinctions (Isa et al., 2019).

Contribution

This research covers the techniques of deep learning, implemented on dyslexia detection. This work extends the diagnosis of dyslexia by offering a subtle and applicable solution based on these methods for exact and subtle classification.

The main contributions of this research are the following:

1. We implemented a technique for the early detection and treatment of dyslexia problems, through handwriting analysis.
2. We developed and implemented a convolutional neural network (CNN) model specifically made for dyslexic vs. normal image handwriting classification, providing a novel and specialized approach to dyslexia detection.
3. We improved the prediction of the CNN model by employing a comprehensive methodology to explore the effectiveness and efficiency of the weight selection method.
4. The proposed system has used a CNN classifier to attain the maximum classification accuracy and these results are compared with those of the state-of-the–art approaches.
5. The experimental results of the proposed model give us a testing accuracy of 96.4% and a training accuracy of 99.5%.

Structure of the proposed work

The structure of the study is as follows: the Related Work section describes the related research survey. The Methodology section discusses the methodology used to achieve the proposed objective. The Results section examines the experiment and results. Finally, the Conclusion section concludes the proposed work.

RELATED WORK

To distinguish dyslexic cases from the healthy ones, many traditional and modern methodologies have been discovered and used, including advanced machine-learning (ML) techniques, eye movement tracking, fMRIs, etc. In this study, numerous databases including top journals and reference papers were utilized to survey relevant papers on dyslexia detection.

The authors in Drotár and Dobeš (2020) and Wagner et al. (2020) used methods like ML algorithms for dysgraphia detection and also identified enough knowledge of dyslexia through their findings. The studies by Rello and Ballesteros (2015) and Raatikainen et al. (2021) examined a statistical model that was demonstrated to predict both readers with and without dyslexia using eye-tracking measures, and the model was based on a support vector machine

(SVM) binary classifier and it obtained 80.18% accuracy. They also used ML methods for identifying individuals using eye movement recordings, random forests for selection of eye movement features, and SVM classifiers, and obtained an accuracy of 89.7%. They have also explained it by reviewing the clinical observations and research data perspectives in Mather and Schneider (2023) and Wagner et al. (2023), evaluated with the help of Bayesian identification model and included set of predictors. In Alqahtani et al. (2023), Ahire et al. (2023), Jan and Khan (2023), and Parmar and Paunwala (2023), the authors have worked on detection and categorization of dyslexia with a strong focus on implementing ML methods, like deep learning and electroencephalogram data analysis, in the detection and categorization of dyslexia.

In Le Jan et al. (2011) the authors have proposed a multi-step procedure within each category by using principal component analysis for the selection of the most representative task and implementing a logistic regression model, and they obtained an accuracy of 94%, which classifies correctly. In their studies Skiada et al. (2014) and Poornappriya and Gopinath (2020) have discussed the methodology, implementation, and results of primary evaluation and mobile applications, as well as a comprehensive review of ML algorithms. The research by Vajs et al. (2023a) aims at different dyslexia studies using a ML method. They tested it on two separate sets of data—one with Serbian readers and one with Swedish readers. They used a special neural network and trained various ML programs. In the work by Saminathan and Kanimozhiselvi (2023), various ML algorithms and deep learning methods like SVM, k-nearest neighbors, K-means clustering, logistic regression, ensemble methods, CNN, and LeNet were used for the detection of dyslexia. The summary of the existing studies on dyslexia detection from the ML methods is given in Table 1.

METHODOLOGY

In this section, the work of the proposed CNN model for the classification of dyslexic and normal handwriting images is illustrated.

The primary architecture is made up of a CNN model with a sigmoid activation function and a binary classification technique. This design enhances the model's ability to classify incoming photographs and identify whether they are dyslexic. A significant component of the model is the complete determination of ideal weights, a method required for increasing the effectiveness in dyslexia diagnosis. The fine-tuning of weights enables the CNN to detect detailed components and patterns unique to dyslexic and normal handwriting styles, significantly improving image classification accuracy. These optimized weights play a significant role in later phases of the dyslexia classification pipeline, influencing decisions concerning dyslexic and normal categorization, as well as capital vs. minuscule alphabet disparities. The training and testing datasets include various handwriting images that showcase both dyslexic and typical handwriting. Factors like letter spacing, steadiness, and overall arrangement are part of it. Also, to add more variety to the images, the dataset was expanded. This diversification makes sure that the deep learning model gets exposed to different handwriting styles, helping it identify small differences related to dyslexia.

Data collection and preparation

The national institute of standards and technology (NIST) 19 database (NIST Special Database 19, 2010) was used for the normal handwriting images. The value of image preprocessing and augmentation resides in increasing the flexibility and diversity of the dataset, which is especially important in applications such as dyslexia diagnosis through handwriting analysis. By scaling photos to a consistent format, uniformity is achieved, and standardized analysis is easier. The addition of heterogeneity to the dataset is accomplished by employing augmentation techniques such as rotation, shear, and translation. Rotation helps to generalize the model to different oriented handwriting styles, shear adds deformations akin to true variations in writing, and translation helps to replicate spatial changes.

CNN-based dyslexia-detection model

The CNN model used in this study has been carefully made for image handwriting analysis, with an emphasis on its robustness in capturing detailed elements associated with dyslexic and normal handwriting styles. The classification model is implemented using the sequential application programming

Table 1: Existing studies on dyslexia-detection techniques based on ML.

Authors	Approach	Methods	Testing accuracy	Year
Gunecha and Deeptha (2023)	ML, computer vision, and CNNs	Handwritten	0.995	2023
Seman et al. (2021)	CNN	Handwriting image	95.66%	2021
Mohamed Syazwan Asyraf Bin Rosli (2021)	CNN based	Handwriting recognition	95.34%	2021
Raatikainen et al. (2021)	ML based	Embedded eye-tracking technology	89.7%	2021
Vajs et al. (2023b)	ML based and statistical analysis	Real-time reading feedback through robust interpretable eye-tracking features	88.9%	2023

Abbreviation: CNN, convolutional neural network; ML machine learning.

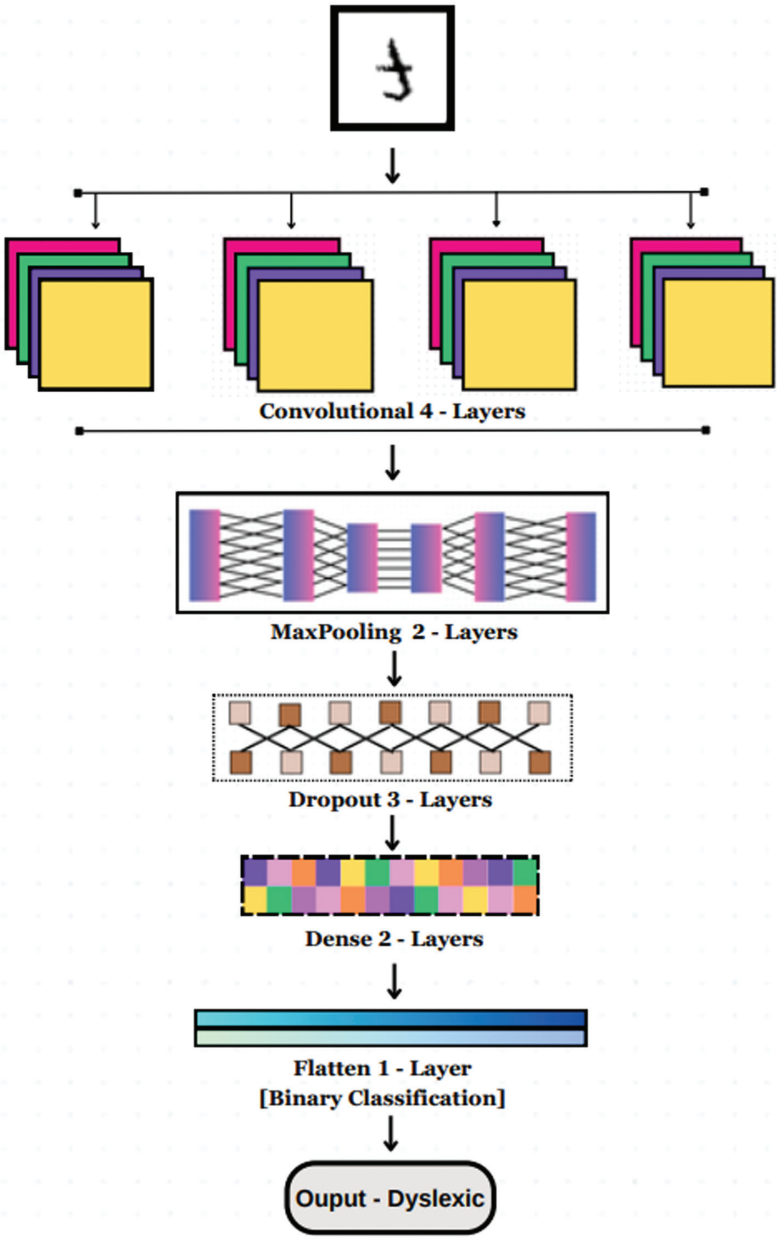


Figure 1: The proposed model's system architecture.

interface (API) model of Keras, with the use of all the layers responsible for making a CNN model. The detailed overview of the model architecture is given in Figure 1. According to the architecture, the initial layers, conv2d and conv2d_1, are convolutional layers, leveraging 32 filters each. These layers are critical in recognizing local patterns in the input pictures. These layers play an important role in identifying local patterns within input images by detecting some common traits in both dyslexic and normal handwriting samples.

Following the convolutional layers, the max_pooling2d layer reduces the spatial dimensions of the feature maps, improving the model's potential to understand key patterns in a more generalized way. The dropout layer added thereafter acts as a regularization mechanism, preventing overfitting at some point of the education phase. Overfitting happens while a model learns noise inside the training facts, hindering its potential to generalize to new, unseen statistics. By deactivating fragments of neurons randomly, the dropout layer mitigates overfitting, and help model for the overall accuracy and reliability. Subsequently, the conv2d_2 and conv2d_3 layers, each utilizing 64 filters, similarly does the task of refining the model's knowledge of complex handwriting patterns. Another max-pooling layer and dropout layer help in offering additional abstraction and regularization. The flatten layer reshapes the output from the convolutional layers into

Table 2: CNN classifier results.

Name	Results
Accuracy of testing data	97%
Accuracy of training data	99%
Testing execution time	4.3 s
Training execution time	381.6 s

Abbreviation: CNN, convolutional neural network.

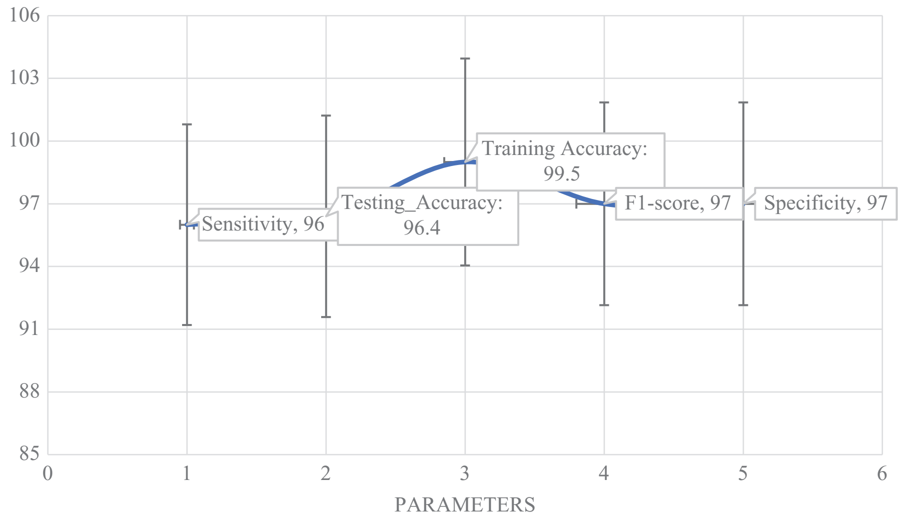


Figure 2: Results obtained using CNN. Abbreviation: CNN, convolutional neural network.

a one-dimensional array, making it ready for the following dense layers.

The dense layer in the model, consisting of 512 neurons, functions as a fully linked layer, extracting a high-level information from the flattened array. Another dropout layer before this dense layer ensures that the model generalizes effectively to previously unseen data, adding to its overall resilience. The final dense layer, which consists of a single neuron with a sigmoid activation function, is equipped with binary classification. The final layer is the output layer, defining if the input image has dyslexia characteristics or is normal. The model's overall architecture includes convolutional, pooling, dropout, and dense layers, and can learn detailed features, and this is highlighted by its total of 4,785,185 trainable parameters, which contribute to its excellent training accuracy of 99.5%. This approach provides us a testing accuracy of 96.4%, verifying the model's usefulness for the unseen data. The F1 score 96 confirms that our model successfully balances between other two metrics, precision and recall, that is critical for its application in dyslexia detection, where both false positives and false negatives can have serious consequences.

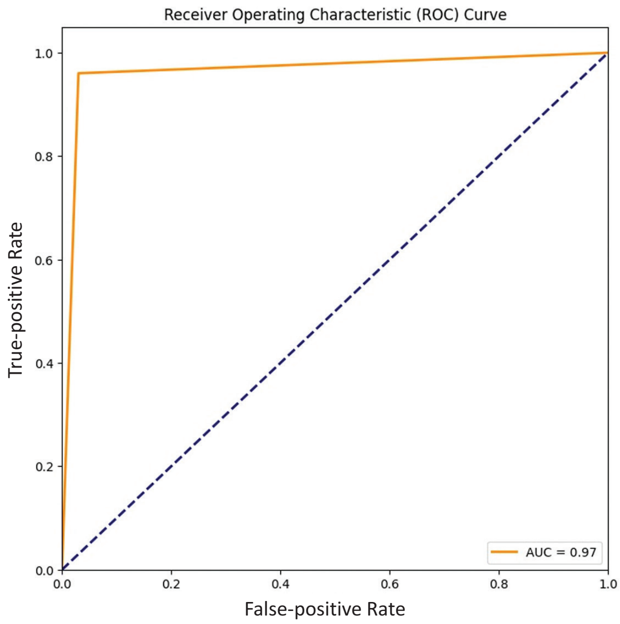


Figure 3: ROC curve on testing set.

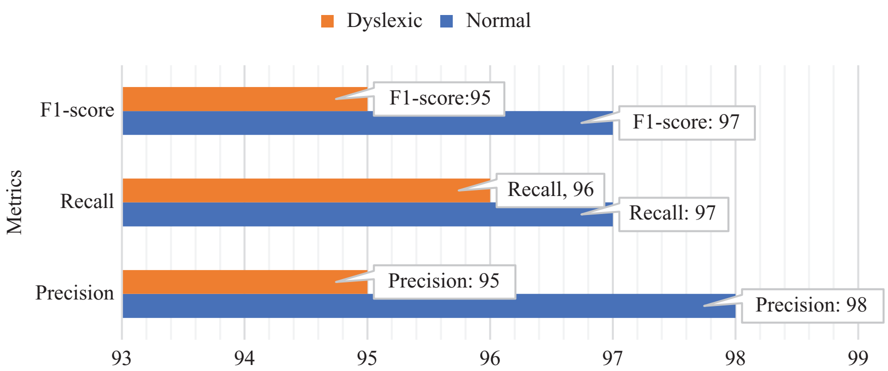
CNN model execution scenario

The total trainable parameters of the model are 4,785,185. These parameters are critical in defining the computational complexity and resource needs during both training and testing in our research. A greater number of trainable parameters usually indicates a more complicated model that requires longer execution periods. Our model's execution time is 381.6 seconds for training and 4.3 seconds for testing, and they are significant in this context. The training execution time is substantially longer, as expected given the iterative nature of the training process, in which the model modifies its weights to minimize the loss function. The faster execution time is necessary for our model to be able to make predictions quickly. The execution time here is important in striking the balance between model complexity, accuracy, and computing economy. Our trained model is comparatively fast with a testing execution time of 4.3 seconds, which explains that it can rapidly analyze new, previously unknown data, which also helps it to be ideal for practical applications. Additionally, the use of early stopping optimization technique is used because the model stops training, once the validation accuracy stops improving. Despite the fact that 30 epochs were initially set for training in this study, the early stopping optimization technique determined the ideal moment for halting training at the 21st epoch, where the validation accuracy was the highest. Hence, achieving an optimal balance between model complexity and computational efficiency is handled better in our proposed work.

RESULTS

In this section, the experimental results are evaluated based on the testing data, consisting of normal and dyslexic alphabet images. The handwritten image dataset was obtained from the NIST Special Database 19. It was divided into two categories: normal handwriting and reverse handwriting. One of the benefits of this database is that it offers different images for uppercase and lowercase letters. The NIST 19 database was preprocessed and image augmented, and a diverse dataset containing both dyslexic and normal handwriting samples was trained. The creation of our model's dyslexic vs. normal model resulted in letters that were 96% accurate in both circumstances. Our proposed model was trained on 36,912 images; for validation purposes, a total of 4100 images were used to validate alongside the training process, and for the testing phase, 8200 handwriting images were used for the CNN model training, validation, and evaluation, respectively. In this section, first the results obtained by our model are displayed in the form of training, testing accuracies in Table 2 along with the model's training and testing execution times in seconds to assess the model based on faster performance and efficiency. Their progress with additional two parameters including specificity and sensitivity are also mentioned in the form of line graphs in Figure 2, along with the receiver operating characteristic curve obtained on the testing set shown in Figure 3. Other measures used to evaluate the progress of the CNN model including F1-score, recall and precision are also displayed in Figure 4.

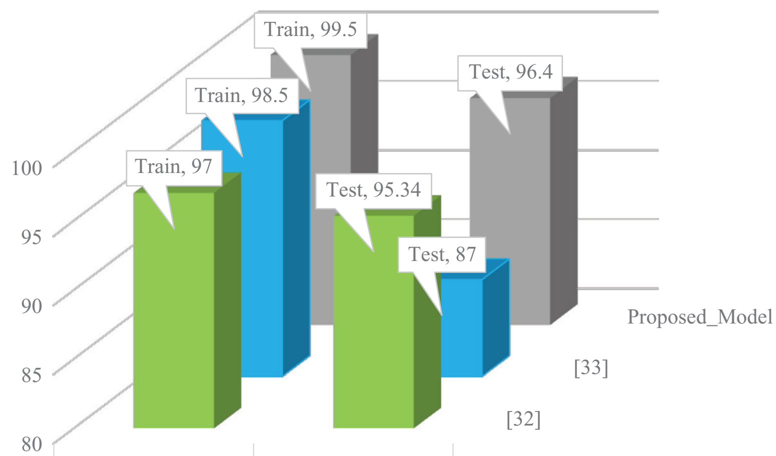
We have compared the results of our proposed model with those of the state-of-the-art approaches (Isa et al., 2021; Rosli et al., 2021) and they have also worked on the same dataset, performing handwriting analysis. We have made the comparison in the form of graphical manner comparing their training and testing accuracies. And, our results have exceeded them, as we have developed a wide CNN model architecture with a large number of layers and parameters and have used optimization techniques including weight selection and early stopping. The graphical illustrations carried out for representing the comparison between our proposed model and the state-of-the-art approaches is given in Figure 5.



	Precision	Recall	F1-score
Dyslexic	95	96	95
Normal	98	97	97

Range

Figure 4: Classification metrics for the model benchmark.



	Train	*Test*
[32]	*97*	*95.34*
[33]	*98.5*	*87*
Proposed_Model	*99.5*	*96.4*

Figure 5: Comparison of training and testing accuracies.

CONCLUSION

To solve the widespread problems of dyslexia, our research studies dyslexia disease and ways for its detection with the help of advanced deep learning techniques, deploying a precisely developed CNN model. Our CNN model's architectural design includes the vital use of Keras API, through which the convolutional, pooling, dropout, and dense layers were used, and later, this study is enhanced by the addition of early stopping optimization technique, which handles both accuracy and processing efficiency. The ability to understand complex patterns by our model is made possible by utilizing a total of 4,785,185 trainable parameters, which contributes to the training accuracy of 99.5%. Importantly, our model achieves a significant testing accuracy of 96.4%, which shows its usefulness on unseen data. The F1 score of 96 confirms that the precision/recall balance of the model is impressive. Also, this model presents a careful balance of model complexity and computing efficiency in terms of total calculated execution time that is 381.6 seconds for training and 4.3 seconds for testing. The comparison of our model is made with various state-of-the-art methodologies and their results, and we reach a conclusion that this study is surpassing every other approach and their results.

This research work primarily focuses on dyslexia detection through handwriting analysis. We recognize the importance of handwriting features and the potential usefulness of combining numerous features and tests for a more thorough dyslexia diagnosis. Exploring additional markers such as eye movements and cognitive processes is part of our future work plan to ensure a more comprehensive approach for dyslexia detection.

AUTHOR CONTRIBUTIONS

GA and ASA conceptualized this study; SS did the methodology and drafted the original manuscript; SB was responsible for the preparation of software; MR and SB carried out the validation; were responsible for data curation; and wrote, reviewed, and edited the manuscript; MR conducted formal analysis and was responsible for resource management; and ASA conducted investigation. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest in association with the present study.

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AVAILABILITY OF DATA AND MATERIAL

The data used to support the findings of this study are included within the article.

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