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Classification Performance of Directed Acyclic Graph Network on Potential Dyslexia Handwriting Images

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***Abstract*— The common learning disability known as dyslexia can have a negative impact on reading and writing abilities, so early diagnosis is essential for providing proper intervention and support. Furthermore, the traditional approach to dyslexia screening has addressed several drawbacks, including subjectivity, consumption of time, and a propensity for bias since it depends on the evaluator's observation and rating. Technology has demonstrated that computer-aided methods for dyslexia screening are effective and reliable assessments. Directed Acyclic Graph (DAG) networks outperform sequential networks in Convolutional Neural Networks (CNNs) due to their capacity to capture both local and global features of the input data. This study investigates the classification performance of DAG Networks using dyslexic handwriting images. The study further explores the impact of skip connections in DAG networks on dyslexia screening by comparing four networks: DAG-1, DAG-2, DAG-3, and DAG-4. The findings revealed a high accuracy of 99.01% in training and 89.68% in testing accuracy, indicating the expectations of DAG Networks as a dependable and helpful method for dyslexia screening. The results also demonstrated that skip connections could enhance the performance of DAG networks in identifying complex features in images of dyslexia handwriting. The proposed method can be incorporated into a computer-assisted dyslexia screening system to provide a rapid, accurate, and unbiased dyslexia assessment.**

Keywords—Deep Learning, Directed Acyclic Graph, Dyslexia Handwriting, Convolutional Neural Network, Dyslexia Detection

I. Introduction

Dyslexia is a neurodevelopmental condition that causes reading and writing to be challenging for affected individuals [1]. One of the most well-known learning disorders is dyslexia, which affects 5 to 10 percent of people globally [2]. Even though dyslexia is not related to intelligence, it can have a consequential effect on daily activities such as self-esteem, social connections, and academic performance [3]. Dyslexia can have numerous symptoms, but some frequent ones include problems with word recognition and decoding, sluggish reading speed, poor spelling, and difficulties with written expression [1]. Therefore, dyslexia identification and screening are crucial for intervention and assisting children in their everyday lives.

The traditional way to test for dyslexia is through observation and scoring methods that rely on the thoughts of experts [4]. This procedure may be time-consuming and inaccurate, resulting in an incorrect or incomplete dyslexia diagnosis. Meanwhile, the manual evaluation method may cause discomfort and anxiety in the children being evaluated. The concept of computer-based dyslexia screening methods could be implemented, allowing a professional to evaluate a student efficiently and unbiasedly. By eliminating the subjectivity of conventional approaches and recognizing dyslexia, computer-based screening techniques have demonstrated promising outcomes. Due to this circumstance, the use of artificial intelligence (AI) methods is on the rise and has the potential to aid in identifying and screening dyslexia.

The application of AI approaches to dyslexia screening has increased the accuracy and efficacy of identification [5]. These methods use large data sets to find patterns and traits to detect and predict dyslexia. In AI, machine learning algorithms have shown promise in differentiating dyslexia from other learning problems, whereas deep learning algorithms can capture complex traits and patterns of dyslexia's features and characteristics. Since dyslexia is always associated with writing difficulties, handwriting products have a strong potential for use in developing improved AI screening methods.

Children's handwriting samples should be used as one of the potential inputs in constructing computer-based dyslexia screening methods using deep learning approaches. Dyslexia can impact a person's handwriting abilities, and exploring handwriting patterns can provide helpful information for dyslexia screening. Deep learning can be utilized as an aid in diagnosing dyslexia symptoms in order to extract features from children's handwriting and achieve an accurate diagnosis of dyslexia.

This study used deep learning algorithms to identify potential dyslexia characteristics in children's handwriting. This study investigates the opportunities of using handwriting analysis for dyslexia screening, the advantages of computer-based methods over traditional methods, and the potential of deep learning algorithms for enhancing the accuracy and efficacy of dyslexia screening. By experimentally constructing layers in a deep learning model, the findings of this study may contribute to the evaluation of dyslexia, leading to early diagnosis and intervention. Consequently, it could enhance the quality of life for dyslexic children.

II. Related Works

Numerous research have studied the detection of dyslexia using a variety of inputs, including electroencephalogram (EEG) signals [6, 7], eye tracking [8, 9], handwriting products [10 – 12], audio records [13], and electrooculography (EOG) [14, 15], to make the diagnosis process more effective and accurate. A dedicated tool is required to collect the signal or numerical data used as inputs, such as EEG, EOG, and audio records. However, handwritten products on paper require the

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least resources to be collected and processed. Based on this condition, research in dyslexia detection through handwriting is a viable option that should be investigated in order to provide valuable data for enhancing dyslexia detection methods [5].

Dyslexia screening using handwriting tools has recently received much attention because dyslexia may disrupt dyslexic children's academic achievement and daily life functioning. Several studies have found this method helpful in diagnosing possible dyslexia in children. For instance, a study by [16] used geometric handwriting features, including velocity, time movement, and trace records, to differentiate dyslexic and non-dyslexic children. However, the study shows a time comparison of each feature employed to detect dyslexia by drawing track recordings. In contrast, most research nowadays actively explores and improves the dyslexia detection approach by implementing deep learning methods, especially Convolutional Neural Network (CNN).

For identifying dyslexia symptoms in handwriting images, CNN is the deep-learning method many researchers frequently explore. CNN-based methods have also been studied because they have the potential to save time and expense while also assisting the existing methods that rely on subjective diagnosis. A study by [17] employed a CNN model to classify dyslexic and non-dyslexic children based on handwriting images, attaining 55.7% accuracy. A different way was done by [18], whereby they generated random patches of handwriting images and achieved 77.6% accuracy in identifying handwriting with or without dyslexia. Despite Latin characters, exploring handwriting products in other languages, such as Hindi, Arabic, Mandarin, and Japanese, has received special attention in handwriting analysis research. Using images of Hindi handwriting, [19] demonstrated that a CNN-based technique attained 86.14% accuracy with 5-fold validation.

In the meantime, [10] has successfully compared CNN's comparison architecture, classifying dyslexic and typical handwriting using CNN's sequential network and CNN's pretrained network known as LeNet-5. The finding shows that CNN with two convolutional layers obtained the highest performance with 87% accuracy. The findings were improved with the transfer learning of CNN done by [12] and showed 95.34% accuracy. The CNN-based technique has demonstrated growing success in aiding automated dyslexia detection. However, research into the performance of Directed Acyclic Graph (DAG) networks is currently limited, particularly in recognizing dyslexia symptoms through handwriting images.

As a subset of CNNs, previous studies showed that DAG networks perform more effectively and faster in training than sequential CNN models [20]. In addition, DAG has been used in computer vision and other domains, as can be observed in the deep learning research field. For instance, the combination of DAG and a Support Vector Machine (SVM) classifier has shown that face images successfully predict age [21]. In contrast, [22] successfully identified everyday activities using a DAG network based on video data from a charged-coupled device (CCD) camera. Additionally, [23] implemented the DAG network for handwriting character recognition, which showed improvements in energy and memory reduction. Thus, the DAG network can achieve good performance by designing the layer utilizing an acyclic graph structure, as the skip connection with a 1-by-1 convolutional layer making parameter gradients flow more effectively.

The accuracy of handwriting-based dyslexia detection has increased, and deep learning techniques such as CNNs and DAG networks have demonstrated positive results. However, the interpretability of CNN models is challenging due to the rapidly expanding variety of CNN and the newness of DAG networks in dyslexia identification. Therefore, this study aims to present the performance of DAG networks on dyslexic handwriting images using four different DAG network constructions with additional skip connection structures connected to the convolutional layers.

III. METHODOLOGY

This section elaborates on the methodology employed to conduct the overall experiment. The MATLAB 2021a environment and hardware were used, which included a 2.50GHz Intel® CoreTM i5-10500H CPU and an NVIDIA GeForce RTX 3060 graphics processing unit.

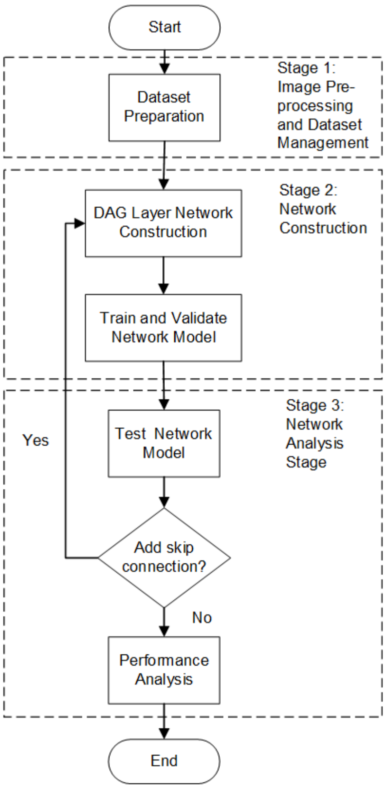

Fig. 1. Methodological flowchart of DAG network performance on potential dyslexia classification

Fig. 1 presents a methodological flowchart of the DAG network's performance on potential dyslexia classification. The method consists of three phases: data pre-processing and dataset management, network construction, and network analysis. The dataset was initially prepared by splitting it into training and testing sets. Images are rotated and resized during pre-processing to provide a balanced dataset for potential dyslexia and normal classes. The final phase is network analysis, which consists of training and verifying the network model, testing the model, and comparing each network's performance. The following subsections elaborate on each phase of the methodological flowchart.

Next, the designed DAG network is depicted in Fig. 2, and its DAG network layer architecture is illustrated in the

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extraction network. The structure's classification network is comprised of Softmax layers with complete connectivity and an average pooling layer. The acyclic network is constructed with a skip connection linked to the addition layer of an extraction network.

This work has four types of DAG architecture, each with specific number of skip connections connecting convolutional layers, batch normalization, ReLu, and the addition layer. The last layer generated the output class by identifying it as potential dyslexia or normal. Section III (B) provides further information about the acyclic block layer component.

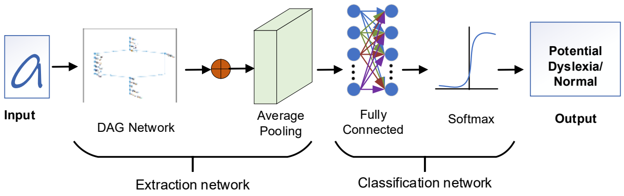

Fig. 2. DAG network construction

A. Dataset management

By utilizing a publicly available dataset, examples of handwriting were classified into two categories [12]. The collection contains 267,930 images of handwritten letters, with each class balanced after implementing the pre-processing part, including resized and rotated images. For both classes, the input size of the dataset is 32 by 32. The dataset is split such that 85% of it will be used for training, and the other 30% will be randomly selected datasets for validation. The remaining 15% is set aside for testing.

B. Network Construction

As illustrated in Fig. 3, the network architecture uses the DAG model and improves by skipping connection implementation. The block-based skip connection comprises the convolutional layer (Conv), batch normalization (BN), and activation function by ReLu. This study applied a simple DAG network implementation to analyze the performance of four types of networks with varying numbers of acyclic blocks. The list of networks is shown in Table I.

TABLE I. LIST OF NETWORK

Name of Network	Number of Acyclic Block	Description
DAG-1	1	Network constructed with 1 acyclic block
DAG-2	2	Network constructed with 2 acyclic blocks
DAG-3	3	Network constructed with 3 acyclic blocks
DAG-4	4	Network constructed with 4 acyclic blocks

A skip connection is a connection between two non-adjacent layers in a DAG network that allows the gradient to travel directly from the output to the input levels. This connection allows the network to bypass one or more layers during the forward and backward propagation training phases.

After an acyclic block, an additional layer is required to finish the acyclic graph by combining inputs from different layers. The average of the elements found in the filtered area of the feature map is then calculated using average pooling. The following classification network used a fully connected, Softmax layer and produced the expected output class at the end of the network.

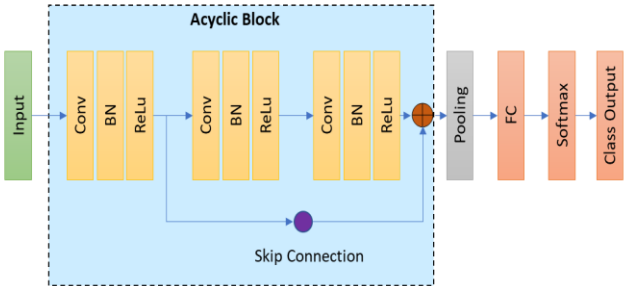

Fig. 3. An Acyclic Block in DAG Network Architecture

The parameters for training the neural network model for dyslexia screening using handwriting images have been set for each network. One of the most significant parameters is the optimizer, an algorithm for refining the neural network's weights to minimize training loss. The "sgdm" (Stochastic Gradient Descent with Momentum) optimizer is employed in this work. Then, the learning rate that functions as the step size at each iteration is determined while going for the smallest possible loss. The learning rate is set to 0.01, which indicates that the model adjusts the weights by 0.01 units per iteration. Meanwhile, epoch refers to how repeatedly the model will iterate through the complete training dataset. The model is trained for eight epochs, which implies that the dataset is sent through the neural network eight times during training. The iteration per epoch parameter is then 1251, indicating that the training process will be repeated 1251 times before proceeding to the next epoch. The frequency has been set to 30, indicating that the weights will be updated every 30 iterations.

The neural network model is trained and refined by establishing these parameters to classify handwriting images as potential dyslexia or normal. The optimizer, learning rate, epochs, and iterations per epoch all affect the model's performance and training time.

C. Performance Evaluation

The neural network model's ability to accurately detect potential dyslexia and normal handwriting classes is analyzed through performance evaluation. Performance assessment is used in this experiment to track and measure how the CNN model performs throughout training and testing. The effectiveness of each model was assessed using the binary class confusion matrix. Accuracy, precision, recall, and F1-score were used to evaluate the performance. Based on a binary confusion matrix [24] for classifying potential dyslexia and normal handwriting, all calculations are made, as shown in Table II. Performance was evaluated using true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values for predicted and actual classes.

TABLE II. CONFUSION MATRIX FOR POTENTIAL DYSLEXIA CLASSIFICATION

		Predicted	
		Potential Dyslexia	Normal
Actual	Potential Dyslexia	TP	FP
	Normal	FN	TN

a. True Positive (TP): Actual potential dyslexia class was correctly predicted as potential dyslexia class
b. False Negative (FN): Actual Normal class but was incorrectly predicted as potential dyslexia class
c. True Negative (TN): Actual Normal class was correctly predicted as a Normal class
d. False Positive (FP): Actual potential dyslexia class but was predicted as Normal class

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An equation (1) achieved a level of accuracy used to assess the performance of each trained model on different network structures to classify potential dyslexia symptoms. In contrast, accuracy indicates the proportion of accurately identified possible dyslexia samples among all potential dyslexia samples. It is determined by dividing TP by the total of TP and FP, as shown in (2). Meanwhile, recall, as formulated in (3), is a fraction of correctly classified potential dyslexia samples among all actual potential dyslexia samples measured by a recall. It is determined by dividing TP by the total of TP and false negatives (FN). The F1-score is a harmonic mean of the model's accuracy and recall scores, providing a balanced assessment of the model's performance. It is determined by dividing the sum of precision and recall by two times the product of precision and recall, as shown in (4).

$$\text{Accuracy}=\frac{\text{TP+TN}}{\text{TP+FP+TN+FN}}\times 100\% \tag{1}$$

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}}\times 100\% \tag{2}$$

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}}\times 100\% \tag{3}$$

$$\text{F1 Score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}\times 100\% \tag{4}$$

IV. Results and Discussion

In this section, the classification performance of DAG networks on potential dyslexia handwriting images is evaluated based on the confusion matrix. This section provides a thorough analysis of the accuracy, precision, recall, and F1 score of the four tested DAG network varieties, namely DAG-1, DAG-2, DAG-3, and DAG-4. In addition, the section discusses how adding skip connections to DAG networks affects classification performance. The section also explores the implications of the findings for developing more precise dyslexia screening and detection approaches.

The classification performance of four different DAG networks (DAG-1, DAG-2, DAG-3, and DAG-4) for dyslexia screening is shown in Fig. 4. Based on the correctness of the training, validation, and test sets of data, the classification performance is assessed. The accuracy is the proportion of samples that was correctly classified out of the total number of samples. It is an essential metric for evaluating the model's overall efficacy.

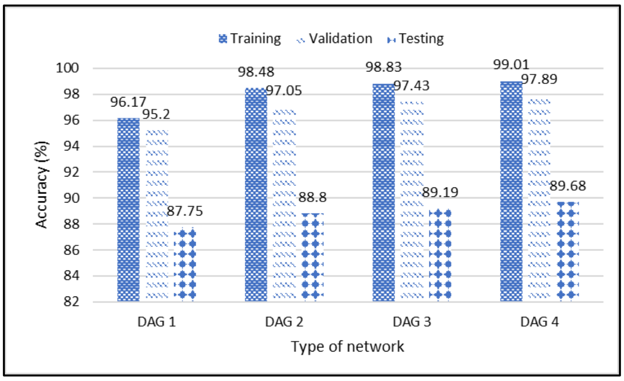

Fig. 4. DAG network accuracy performance for training, validation, and testing

With a training accuracy of 99.01%, a validation accuracy of 97.89%, and a testing accuracy of 89.68%, DAG-4 outperformed the other three models (DAG-1, DAG-2, and DAG-3) in terms of accuracy on all three datasets.

These results reveal that DAG-4 outperformed the other models in terms of accuracy, suggesting its utility in classifying potential dyslexia handwriting images. The high training accuracy implies that the model learned the training data efficiently, and it is supported by reasonably high validation and testing accuracies for the DAG-4 model. Based on the result, DAG-4's validation accuracy (97.89%) is slightly higher than DAG-3's (97.43%), indicating that more skip connections may perform better. It is shown that increasing the skip connection could result in higher performance.

Overall, the results demonstrate that all four DAG networks obtained good performance for training, validation, and testing data, indicating their potential for accurately identifying dyslexia from images of normal handwriting. Moreover, based on the provided results, DAG-4 appears to be the most promising model in terms of accuracy, demonstrating its potential for effective dyslexia screening using handwriting images.

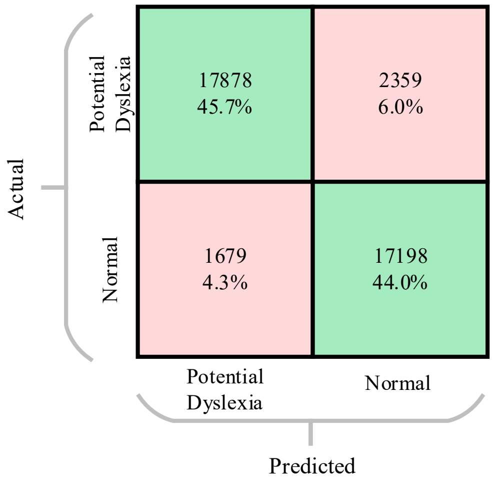

Fig. 5. Testing confusion matrix of DAG-4 network accuracy for DAG-4 network.

Based on the finding in Fig. 4, the testing accuracy for DAG-4 has the highest performance compared to other networks. Therefore, Fig. 5 exposes more details of results based on the confusion matrix. The confusion matrix results provide detailed performance information on the dyslexia screening model, which may be used to analyze and improve the model's accuracy and efficacy. The results demonstrate that 17,878 of the 39,714 samples were tested positive for Potential Dyslexia, whereas 6% (2359) were misclassified as Normal. Similarly, out of 39,714 total samples, 17,198 were classed as Normal, whereas 4.3% (1679) were classified as Potential Dyslexia. This finding shows that the model recognizes normal handwriting images slightly better than potential dyslexia handwriting images. The results were possible because dyslexia handwriting is diverse and varied compared to normal handwriting, which subsequently has a similar pattern.

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Table III compares the classification performance of four distinct types of Directed Acyclic Graph (DAG) networks for dyslexia screening (DAG-1, DAG-2, DAG-3, and DAG-4) utilizing potential dyslexia (PD) and normal (N) handwriting images. Precision, recall, and F1-score for training, validation, and testing data are used to evaluate classification performance. Precision is the percentage of true positives among all projected positives, whereas recall is the percentage of true positives among all actual positives. The F1-score is a balanced measure of categorization ability since it is the harmonic mean of accuracy and recall.

TABLE III. PRECISION, RECALL AND F1-SCORE

	NW	Training (%)		Validation (%)		Testing (%)	
		PD	N	PD	N	PD	N
Precision	DAG-1	97.91	94.55	97.07	93.48	90.86	85.08
	DAG-2	98.57	98.61	97.00	97.20	87.74	89.93
	DAG-3	98.65	99.01	97.24	97.63	88.14	90.31
	DAG-4	**98.78**	**99.24**	**97.61**	**98.18**	**88.34**	**91.11**
Recall	DAG-1	94.35	97.99	93.22	97.18	83.94	91.55
	DAG-2	98.61	98.57	97.21	97.00	90.21	87.39
	DAG-3	99.02	98.65	97.64	97.23	90.58	87.81
	DAG-4	**99.24**	**98.78**	**98.19**	**97.60**	**91.41**	**87.94**
F1 score	DAG-1	95.96	96.24	94.92	95.29	87.26	88.20
	DAG-2	98.59	98.59	97.11	97.09	88.96	88.33
	DAG-3	98.84	98.83	97.44	97.42	89.34	88.74
	DAG-4	**99.01**	**99.00**	**97.90**	**97.88**	**89.85**	**89.50**

[a] NW: Network, PD: Potential Dyslexia, N: Normal

The results demonstrate that all four DAG networks scored good accuracy, recall, and F1-scores for dyslexia screening, indicating their ability to distinguish predicted dyslexia from normal handwriting images. DAG-4 outperformed the other three DAG networks regarding accuracy, precision, recall, and F1-score for training, and validation data. Moreover, the DAG-4 also had the most excellent F1- scores for testing data.

According to the results obtained, DAG networks successfully demonstrate the effectiveness of skip connection in improving the information flow during the extraction process in handling the vanishing gradient issues. The vanishing gradient issue that arises during backpropagation can be lessened using the skip connection in a DAG network by maintaining the gradient signal and preventing it from getting too small as it passes across stacked layers. Moreover, the information flow is more efficient by providing the alternative route as a shortcut to prevent distorted and lost information through the layers. Since skip connections allow the network to learn both shallow and deep features simultaneously, it improves network performance by enhancing the network's ability to represent and learn complicated patterns and correlations in the data. Consequently, DAG networks are adequate for image classification tasks because skip connections can help increase the training process's efficiency, accuracy, and stability.

Overall, the results reveal that using DAG networks for dyslexia screening through handwriting images can provide high accuracy in classification. The study found that skip connections in the DAG network can improve the model's performance in terms of accuracy, precision, recall, and F1-score. The highest accuracy was achieved using DAG-4 with skip connection, with a training accuracy of 99.01% and testing accuracy of 89.68%.

V. CONCLUSION

This paper focussed on the classification performance of DAG Networks on potential dyslexia handwriting samples. The study investigated the impact of skip connection DAG networks using four distinct network types: DAG-1, DAG-2, DAG-3, and DAG-4. According to the experimental results, classification performance improves when skip connections increase. This finding suggests that the depth of the layer with skip connections can effectively improve the efficiency of DAG networks for classification performance on dyslexia handwriting-based screening. According to the results of this investigation, there are several possible areas for future research. While DAG networks with skip connections have demonstrated promising results in classifying potential dyslexia handwriting images, it may be worthwhile to investigate using other deep learning models, such as CNNs and recurrent neural networks (RNNs), for this task. Moreover, the current study is limited to classifying prospective dyslexia handwriting images; therefore, future research could expand the scope of the investigation to include language and literacy assessments. This investigation would enable a more thorough evaluation of the efficacy of deep learning models in dyslexia screening. While using deep learning models in dyslexia screening demonstrates promising results, it is essential to note that they should not replace conventional screening methods. Instead, they should be utilized in conjunction with conventional methods to improve the precision and efficacy of dyslexia screening. Future research could therefore concentrate on developing an integrated dyslexia screening system that incorporates both conventional and deep learning-based screening techniques. This study has demonstrated the performance of using DAG networks with skip connections for handwriting-based dyslexia screening. Additional research in this area could contribute to developing more accurate and effective dyslexia screening methods, which can help with the early detection and intervention of dyslexic children.

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