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Deep Learning-Based Model for Detecting Dyslexia Using Handwritten Images

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ABSTRACT

Across the globe, dyslexia and dysgraphia are two frequent learning disorders identified in classrooms. This condition is characterized by difficulties in age-appropriate reading without any sociocultural restrictions. Children with this disorder have difficulty recognizing word and letter patterns. Early identification of dyslexic children (DC) is crucial for providing them with the most effective educational opportunities. Researchers proposed a deep learning-based dyslexia detection system (DDS). However, there is a demand for a practical, lightweight framework for identifying DC. Thus, the proposed study intends to build a framework for detecting dyslexia. The proposed framework encompasses image processing, feature extraction, and classification models. The image-processing model enhances the image quality using contrast-limited adaptive histogram equalization and resizes the images into 512 × 512 pixels. For feature extraction, the authors employ you only look once V7 to extract features in a limited time. In addition, the MobileNet V2 with single shot detection lite is used to classify the handwritten images into normal and abnormal classes, respectively. The authors utilized the publicly available dyslexia dataset for performance evaluation. The test set contains 19,557 normal and 17,882 reversal (abnormal) images. The baseline models are employed for comparative analysis. The experimental study revealed that the proposed framework outperformed the baseline models by achieving exceptional precision, recall, F1-Score, accuracy, and mean average precision of 97.9, 97.3, 97.6, 99.2, and 97.6, respectively. In addition, the proposed model obtained an exceptional mean intersection over union of 88.6. It can be implemented in educational institutions and healthcare centers. In the future, the authors can extend the research to build an integrated framework using biomedical images.

KEYWORDS

dyslexia, artificial intelligence, deep learning, dysgraphia, handwritten images, MobileNet V2

INTRODUCTION

Neurodevelopmental disorders encompass dyslexia and dysgraphia conditions (Perera et al., 2016). According to studies (Perera et al., 2016; Usman et al., 2021; Ahire et al., 2023), there are three distinct forms of dysgraphia: dyslexic dysgraphia, spatial dysgraphia, and motor dysgraphia. Dyslexia is a form of learning difficulty that affects a significant portion of the global population (Usman et al., 2021). It can be genetic or acquired, and it can be phonological, rapid naming, double deficit, surface, or visual. Dyslexic children (DC) face challenges in reading, writing, spelling, speed, word processing, and transcription (Battal, 2016). However, dyslexia does not impact the amount of intellect a specific individual possesses. It is linked with dyspraxia and attention deficit. In addition, DC experience low self-esteem, frustration, and hostility. Undiagnosed DC may experience academic difficulties and eventually drop out of school (Binbakhit, 2020).

Handwriting analysis is one of the dyslexia diagnostic techniques to identify DC (Nasir-Tucktuck et al., 2017). It relies on assessments of reading comprehension, written expression, and working memory (Nasir-Tucktuck et al., 2017). Early screening and diagnosis are crucial to overcome the challenges in treating dyslexia (Richard and Serrurier, 2020). Early dyslexia diagnosis in children increases the likelihood of effective intervention programs and enhances skills (Ahire et al., 2023). The diagnosis of dyslexia requires the expertise of an educational psychologist (Pralhad et al., 2021). It is a complicated process that depends on a number of considerations, including the presence of a psychiatric disorder, the child's cognitive ability, the existence of a chronic disease, the presence of negative psychosocial factors, and the child's psychosocial functional level (Patnoorkar et al., 2023). The criteria for these assessments have been established and standardized by subject-matter experts (Kumar et al., 2023).

Dyslexia can be identified in a variety of ways, depending on the country or nation. In the study (Jothi Prabha and Bhargavi, 2022), the authors highlighted the significance of culture, language orthography, dyslexia awareness, and educational institutions in dyslexia detection. The global prevalence rate of children requiring special education accommodations has steadily risen over the past few decades (Drotár and Dobeš, 2020). In the United States, around 7.3 million DC were served through the Individuals with Disabilities Education Act (Aldakhil et al., 2023). They found that almost one-third of all exceptional education pupils were classified as having a particular learning disability. In the Kingdom of Saudi Arabia, there has been a surge in the number of individuals who have been diagnosed with learning disabilities (Poch et al., 2023). However, learning disability services in Kingdom of Saudi Arabia (KSA) have developed over time (General Authority for Statistics, 2023).

The identification of a large number of children who have learning disabilities can be a difficulty for the government when it comes to assisting the education system and assisting children who have dyslexia to develop their capabilities in the field of learning (General Authority for Statistics, 2023). Human experts are required to invest a lot of time and effort to process the data obtained directly from various educational institutions. In addition, there may be difficulty in obtaining a proper diagnosis due to the lack of healthcare specialists in KSA (People with Disabilities, 2022). The Administration of Learning Difficulties manages the Special Education Program across KSA. The Ministry of Education serves approximately 200,000 students through the program. They encourage researchers and fund projects to develop scientific tools and techniques for identifying dyslexia (People with Disabilities, 2022). The King Salman Center for Disability Research is responsible for funding and supporting the academic study of disabilities in the country (People with Disabilities, 2022). The center's mission is to improve the quality of life of individuals with disabilities by developing scientific tools and techniques. They initiated study programs for people who have learning impairments. This motivates the authors to employ dyslexia detection to enable healthcare centers and educational institutions to support DC.

The application of contemporary computational technology significantly improves conventional dyslexia diagnosis methods (Irwin et al., 2021). Traditional methods of detecting dyslexia have been aided by computational intelligence methods, including fuzzy logic, soft computing, neural networks, and interactive multimedia and game-based methods (Isa et al., 2019). Identifying notable disparities in neurological behaviors and eye movements in individuals with dyslexia has offered new detection possibilities. Recent advances, including brain imaging and wave activation patterns, can detect dyslexic behaviors. Machine learning (ML) is a promising tool for simulating and replicating human expert knowledge (Hamid et al., 2018; Khan et al., 2018; Alqahtani et al., 2023; Poch et al., 2023). In addition, using technologies including statistical analysis, computational intelligence, pattern recognition, and classification algorithms can support physicians and instructors in identifying DC. An automated dyslexia detection system (DDS) can help educational institutions and healthcare centers detect DC (Rello et al., 2018; Spoon et al., 2019; Rosli et al., 2021).

Artificial intelligence (AI) investigates and develops computerized systems and software that can perform activities typically reserved for humans, including translation, decision-making, images, and speech recognition (Sasidhar et al., 2022). ML is a subfield of AI. It focuses on the development of self-learning technology using a variety of datasets. On the other hand, deep learning (DL) categorizes data and produces optimal predictions. The literature shows that ML approaches perform effectively for disease classification (AlMedlij and Rubinstein-Ávila, 2018; Abed and Shackelford, 2020; Nazmal et al., 2022; Wang et al., 2023). In addition, ML techniques have been demonstrated to be extremely precise in identifying dyslexia. However, DL techniques demand limited features for generating the outcome. Recently, convolutional neural networks (CNNs) have been widely used to build lightweight applications for image classification (Gunawan et al., 2018; Ahlawat et al., 2020; Jasira and Laila, 2023). Furthermore, there is a lack of research on learning disabilities and DDSs. Therefore, the authors intend to develop a DL-based DDS using handwritten images.

The contributions of the proposed study are:

- A feature extraction technique for generating features from handwritten images.
- A lightweight application for classifying the handwritten images for detecting DC.
- Evaluating the performance of the proposed detection model using the benchmark dataset and its baseline models.

The remaining part of the study is organized as follows: the Literature Review section presents the existing techniques for identifying learning disabilities. The proposed research methodology is discussed in the Materials and Methods section. The Results section offers the outcome of the experimental analysis. The features and limitations of the proposed study are presented in the Discussion section. Finally, the Conclusion section concludes the study with its future direction.

LITERATURE REVIEW

Recently, researchers have focused on implementing AI-based applications in education (Drotár and Dobeš, 2020; Aldakhil et al., 2023; Poch et al., 2023). According to the existing studies, AI tools can be effectively integrated into the classroom (Hamid et al., 2018; Khan et al., 2018; Isa et al., 2019; Irwin et al., 2021; People with Disabilities, 2022). The integration of AI into education has opened up new trends that necessitate the development of novel approaches to teaching and learning processes. Over the past decade, several studies have examined the practical application of

AI and computer tools to enhance the education of children with learning disabilities (Alqahtani et al., 2023). The implementation of ML-based diagnosis of dyslexia has been the subject of recent studies (Poch et al., 2023). In a study (Rello et al., 2018), multiple aspects of dyslexia prediction using ML strategies and image-processing techniques were explored. In addition, most studies employed ML methods to identify dyslexia by developing assessments and tools for assisting DC. Using dyslexic datasets, researchers have proposed ML algorithms for predicting dyslexia in children (Hamid et al., 2018; Khan et al., 2018; Isa et al., 2019; Alqahtani et al., 2023; Poch et al., 2023). Healthcare and educational organizations and specifically designed games may offer these types of datasets.

Handwritten images are crucial in identifying dyslexia. These images can uncover minor patterns and variances to identify dyslexic characteristics. Researchers and practitioners can use these images to recognize specific aspects of dyslexic handwriting, such as skewed alignment, variable letter size, and irregular spacing. Handwritten samples can enhance the precision and efficiency of DL-based dyslexia identification, facilitating quick interventions and assistance for those affected by this problem. Compared to the existing methods, handwritten image-based dyslexia identification is unique due to its emphasis on capturing the distinct features of the individual's handwriting. Handwritten image analysis offers a direct and objective evaluation compared to conventional approaches that rely on standardized tests or questionnaires. The alternative methods, including oral examinations or neuroimaging, focus on distinct facets of cognitive or neurological activities. Handwriting analysis provides a pragmatic, noninvasive, and economical approach, making it ideal for broad screening and early detection of dyslexia. It enhances other diagnostic procedures, offering a thorough image of an individual's cognitive profile and enabling extensive therapeutic strategies.

Researchers have developed multiple strategies utilizing various datasets to identify and categorize dyslexia and associated indicators (Spoon et al., 2019). Dyslexia prediction techniques utilize eye tracking, brain imaging, electroencephalogram (EEG) test results, and handwritten images (Rosli et al., 2021). The participants' academic success, intelligence level, phonological processing, reading ability, and vocabulary growth were assessed using standardized psychoeducational assessments. In recent years, there has been a significant increase in the application of classic ML techniques and DL algorithms to the problem of identifying dyslexia and associated biomarkers (Sasidhar et al., 2022). Multiple models have been used to detect and classify dyslexia over time and space, including the support vector machine (SVM), artificial neural networks, decision trees, Naive Bayes, k-nearest neighbor, and CNN models (Sasidhar et al., 2022).

Deep neural networks integrate artificial neurons as part of their object-detecting processes. These synthetic neurons function in much the same way as the neurons in a human brain. Object detection is the process of identifying and locating images that contain classified elements (Gunawan et al., 2018). High-speed graphics processing units and streamlined algorithms are employed to recognize and categorize various patterns in an image. Khan et al. (2018) developed three modules for detecting learning disabilities. The first module is used to identify the symptoms of dyslexia among children. The second module classified normal and DC using the textual data. The third module is a statistical tool for research scholars to analyze the textual data. Likewise, Rello et al. (2018) proposed an online game using an SVM for detecting DC. Using the online game, they gathered data from 267 children and built a statistical tool for analyzing the data.

Hamid et al. (2018) developed an adaptive learning model for supporting DC. They employed the frontal view images of 30 students to build the bag of features' image classification. Similarly, Spoon et al. (2019) developed a CNN-based screening model for detecting dyslexia. They trained their model using two datasets of handwritten images. Rosli et al. (2021) proposed a CNN model using the transfer learning technique. They used the Le-Net-5 model to recognize the handwritten images. Furthermore, Saqib et al. (2022) proposed a model for identifying the handwritten characters and digits.

Alqahtani et al. (2023) conducted a review of DL applications for DDSs. The review outcome suggested that hyperparameter optimization plays a vital role in detecting dyslexia. In addition, the CNN models demand huge computational resources to produce an optimal outcome. Sasidhar et al. (2022) proposed a residual network (ResNet) for classifying the handwritten images. They applied data augmentation and preprocessing procedures for extracting features.

The datasets, including dyslexia biomarkers, offer opportunities for developers to build a highly accurate system for predicting dyslexia (Sasidhar et al., 2022). However, these datasets contain a few groups of individuals. In addition, collecting and preprocessing the biomarkers requires a lot of time. In recent times, researchers have employed handwritten images to identify dyslexia. DC face challenges in generating characters and words. As a result, they generate characters in the reversed position. Table 1 presents the features and limitations of the existing literature.

There is a knowledge gap in the DDS literature. The existing DDS demands a huge computation cost for generating a reasonable outcome. There is a lack of effective feature extraction techniques for improving image classification accuracy. As a result, an integrated framework covering image preprocessing and classification is necessary for developing the DDS.

MATERIALS AND METHODS

In this study, the authors propose a DL-based DDS for identifying DC. The handwritten images are used to evaluate the performance of the DDS. The proposed DDS includes (i) an image preprocess module, (ii) a feature extraction module, and (iii) an image classification module. Figure 1 outlines the proposed DDS. The image preprocessing module enhances the image quality. In addition, the images are transformed into a specific size in order to support the CNN model.

In order to effectively localize objects, you only look once (YOLO) directly predicts bounding boxes and class

Table 1: Characteristics of the existing literature.

Authors	Methods	Features	Limitations
Khan et al. (2018)	ML-based text classifier	Offered three modules for DC	The study's outcome was based on the student's test scores
Rello et al. (2018)	SVM-based DDSs	Conducted an online game for data collection and analysis	The gaming environment requires specialized hardware and software applications
Hamid et al. (2018)	Adaptive learning model	Employed the frontal view images	A bag of features demands a huge computation cost for feature extraction
Spoon et al. (2019)	CNN with transfer learning	Applied two datasets of the handwritten images	The limitation of CNN may affect the performance of the DDS
Rosli et al. (2021)	CNN	Applied Le-Net-5 model for the image classification	CNN models demand substantial computational resources
Nazmal et al. (2022)	CNN	Classification of characters and digits	Evaluated the performance of the DDS using a smaller dataset
Sasidhar et al. (2022)	ResNet-50	Classified the handwritten images using ResNet models	Achieved an accuracy of 97.6%

Abbreviations: CNN, convolutional neural network; DC, dyslexic children; DDS, dyslexia detection system; ML, machine learning; ResNet, residual network; SVM, support vector machine.

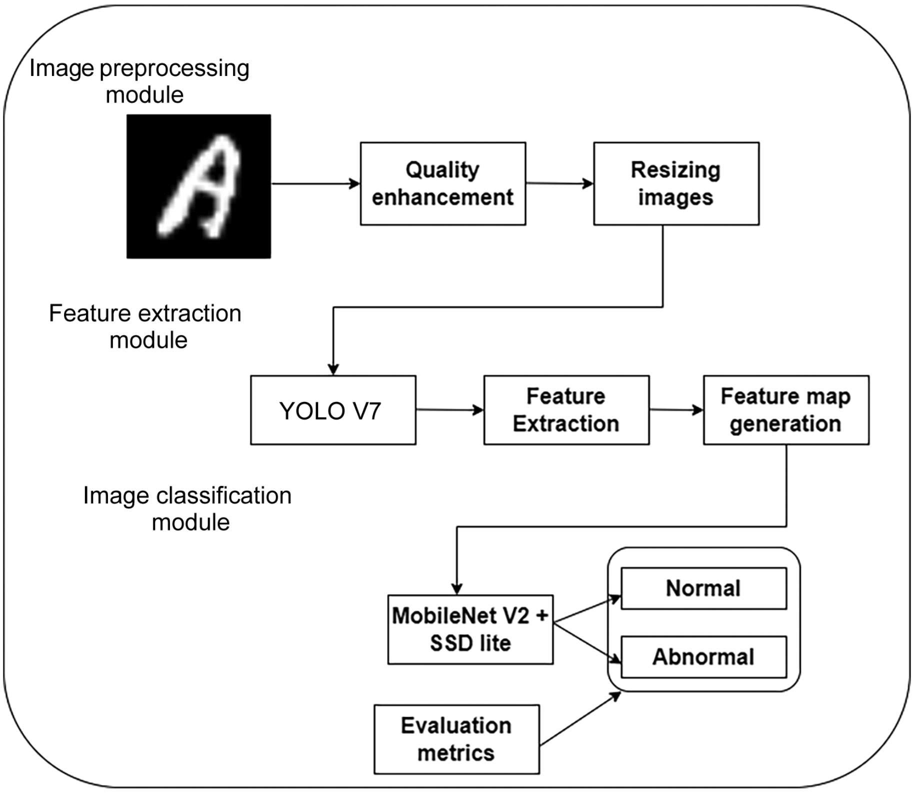

Figure 1: The proposed framework.

probabilities. It can identify a wide variety of objects in a single image. MobileNet V2 reliably acquires input data features, making it suited for computational, memory, and power-intensive applications. The integration of YOLO with MobileNet V2 can have a substantial impact on accomplishing real-time object detection on devices with limited resources. Integrating YOLO's effectiveness in object identification and MobileNet V2's lightweight architecture enables effective deployment in mobile and edge settings. In addition, the integration supports the Internet of Things and edge computing applications that require efficient and accurate computer vision models. In the feature extraction module, you only look once—version 7 (YOLO V7). The YOLO V7 technique (Rosli et al., 2021) is used for extracting the features and generating the feature maps. The feature maps are processed by the MobileNet V2 + single shot detection (SSD) (Chiu et al., 2020) lite model to classify the handwritten images. Finally, the evaluation metrics and the baseline models of the handwritten images are applied to evaluate the performance of the proposed DDS.

Data acquisition

In order to evaluate the proposed model, the authors utilized the publicly available dataset (Kaggle, 2019). The dataset comprises three types of images: normal, reversal, and corrected. The major part of the dataset is based on the National Institute of Standards and Technologies repository (NIST, 2019). The dataset providers obtained ethical approval from the Seberang Jaya Primary School, Penang, Malaysia, to employ the images for automating the Dyslexia Detection (DD). In order to achieve the diversity of the images, they extracted images from the repository (Patel, 2017) and integrated them with the dataset. In this study, the authors employed normal and reversed handwritten images in order to train the model to classify the images. Table 2 shows the characteristics of the dataset. The sample images of the dataset are shown in Figure 2.

Data preprocessing

The dataset contains low-quality images. It may affect the performance of the proposed framework. In addition, the irregular shapes of the images may reduce the classification accuracy. Let D be the dataset, and I be the handwritten image. Equation 1 outlines the process of enhancing the contrast of the images.

$$D\left(\sum_{i=1}^{n}(E_i)\right) = D\left(\sum_{i=1}^{n} CLAHE(I_i)\right) \tag{1}$$

where i is the specific image, n is the total number of images, and $CLAHE$ is the contrast-limited adaptive histogram equalization function for improving the image quality. Finally, the images are reshaped into 512 × 512 pixels.

Furthermore, the authors applied image normalization and augmentation techniques to improve the accuracy of the proposed DD model.

YOLO V7—feature extraction

YOLO V7 is one of the single-stage object detection techniques. The authors employ the YOLO V7 technique to improve the feature extraction process. The YOLO V7 technique follows the extended efficient layer aggregation. It uses nine anchor boxes for identifying the objects in different sizes. In addition, it processes the image at 155 frames per second. The label assigner mechanism compares the predicted outcome with the ground truth labels. Let f_m be the feature map, and E_f be the extracted features. Equation 2 shows the feature map extraction.

$$f_m = \sum_{i=1}^{n} E_f(YOLO\_V7(I_n)) \tag{2}$$

where n is the number of images (I), and $YOLO\_V7$ is the feature extraction function.

Table 2: Dataset characteristics.

Classes	Train set	Test set
Normal	39,334	19,557
Reversal	46,781	17,882
Corrected	65,534	19,284

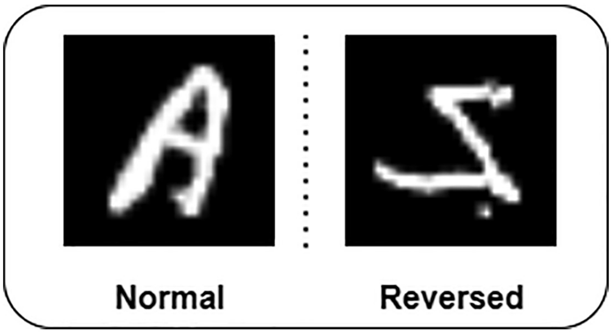

Figure 2: Normal and reversed handwritten images.

MobileNet V2 + SSD lite—image classification

The MobileNet models are widely applied for developing mobile and embedded vision applications. The reduced design of these models leverages depth-separable convolutions for building lightweight deep neural networks. As a result, regular convolution can be subdivided into the smaller depth convolution and the more significant point convolution. A dedicated filter is used for each input channel. The point convolution concatenates the depth convolution outputs into a 1 × 1 convolution. However, the depth-separable convolution separates the filtering and combining processes into a single layer. This decomposition significantly reduces the size of the calculation and the model. The MobileNet model uses ReLu, depthwise, and pointwise convolution for processing the features using the linear combinations of the input channels. Equations 3-5 represent the processes of image classifications using the three layers.

$$I_{fm_1} = 1 \times 1 Conv2d + ReLu(f_{hXw}) \tag{3}$$

$$I_{fm_2} = 3 \times 3\, dwise + ReLu(I_{fm_1}) \tag{4}$$

$$I_{fm_3} = linear\, 1 \times 1 Conv2d(I_{fm_2}) \tag{5}$$

where I_{fm_1}, I_{fm_2}, and I_{fm_3} are the intermediate image features, and f_{hXw} is the feature with a particular height (h) and width (w).

Figure 3 shows the architecture of the MobileNet V2 – SSD lite for classifying the handwritten images. The extracted features are integrated as a feature map. The feature pyramid network of the MobileNet V2 – SSD lite is used to improve the classification accuracy. A 1 × 1 convolution layer normalizes the number of channels for each feature map. Furthermore, expansion factor, output channels, stride, and 3 × 3 kernels are employed for spatial convolution. Lastly, the Adam optimizer (AO) fine-tunes the hyperparameters of the MobileNet V2 – SSD lite.

Equation 7 shows the output generation using the Softmax function.

$$out = Softmax(FCL_3(ReLu(FCL_2(FCL_1(f_m))))) \tag{6}$$

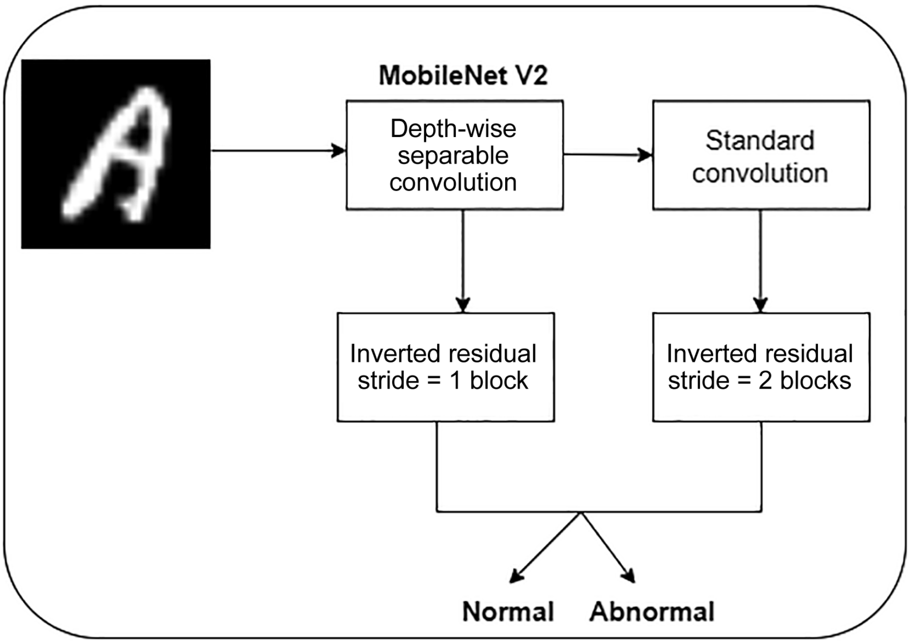

Figure 3: The architecture of the MobileNet V2 – SSD lite-based image classification. Abbreviation: SSD, single shot detection.

where *out* is the classification outcome; *Softmax* and *ReLu* are the normalized exponential function and nonlinear action functions; FCL_1, FCL_2, and FCL_3 are the fully connected layers.

Evaluation metrics

The authors employed the benchmark metrics for evaluating the performance of the DDS. The accuracy metric outlines the classification efficiency of the DDS. It is calculated using the Jaccard index, or Intersection over Union (IoU). IoU is determined by dividing the overlap between the expected detection and its ground truth by their connection area. This method is used on each image in the test dataset to provide a median IoU value. The precision in target identification is the fraction of correct predictions as a percentage of total predictions. In contrast, recall is the proportion of adequately located desired results as a percentage of complete predictions. F1-Score is computed using the precision and recall. In addition, mean average accuracy (MAP) and mean intersection over union (mIoU) are used to evaluate object identification accuracy and speed.

RESULTS

The authors evaluated the proposed DDS using the handwritten images dataset available in the repository (Kaggle, 2019). The dataset is divided into train (70%) and test (30%) sets. The MobileNet V2 + SSD lite is implemented using Python 3.8.3, Windows 10 Professional, Core i7 processor, and NVIDIA GTX 1050 Ti. The authors employed the same train and test sets for the experiments. The preprocessing module was implemented in Python 3.8.3. YOLO V7 was built using the source code (Wang et al., 2023). The AO was used to optimize the MobileNet V2 + SSD lite parameters. The batch sizes of 9 and 250 epochs were used to train the DDS. Table 2 reveals the performance of the proposed framework. During the training phase, the framework identified the crucial features for classifying the handwritten images. In addition, YOLO V7 played a significant role in extracting effective features. Furthermore, the proposed framework achieved an average accuracy of 99.2 during the testing phase. Figure 4 reveals the performance outcome of the proposed framework. Table 3 presents the findings of the performance analysis.

Table 4 highlights the outcome of the ablation study. MobileNet V2 achieved an accuracy, precision, recall,

Table 3: Outcome of the performance analysis.

Methods	Precision	Recall	F1-Score	Accuracy	MAP	mIoU
Training						
Normal	96.5	96.8	96.6	97.5	98.5	82.1
Abnormal	97.1	97.3	97.2	96.8	98.1	84.3
Average	96.8	97.0	96.9	97.1	98.3	83.2
Testing						
Normal	97.5	96.9	97.2	99.1	97.2	88.2
Abnormal	98.3	97.8	98.0	99.3	98.1	89.1
Average	97.9	97.3	97.6	99.2	97.6	88.6

Abbreviations: MAP, mean average accuracy; mIoU, mean intersection over union.

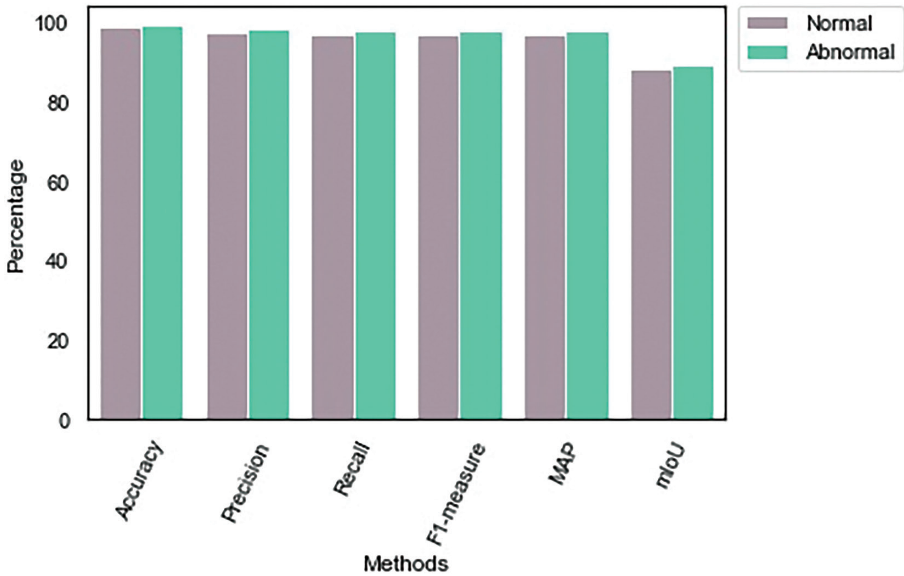

Figure 4: The performance analysis outcome.

Table 4: Outcome of the ablation study.

Methods	Precision	Recall	F1-Score	Accuracy	MAP	mIoU
MobileNet V2	96.7	96.8	96.7	97.1	96.5	79.1
MobileNet V2 + SSD lite	97.3	97.2	97.2	98.2	97.3	82.3
AO + MobileNet V2 + SSD lite	97.9	97.3	97.6	99.2	97.6	88.6

Abbreviations: MAP, mean average accuracy; mIoU, mean intersection over union.

F1-Score, and MAP of 97.1, 96.7, 96.8, 96.7, and 96.5. However, the results were improved by integrating SSD lite with the MobileNet V2 model. Furthermore, the hyperparameter optimization of MobileNet V2 + SSD lite yielded a superior outcome.

Table 5 outlines the results of the comparative analysis. Integrating YOLO V7 and SSD lite enabled the suggested framework to achieve an optimal outcome. The proposed DDS outperformed the existing frameworks. Figure 5 highlights the comparative analysis outcome of the DDSs.

Table 6 reveals the strategies and computation time for identifying normal and abnormal handwritten images. The proposed DDS required a few parameters and Floating point operations (FLOPs) for classifying the images. The lightweight MobileNet V2 supported the proposed framework to produce a superior outcome with limited computational resources.

DISCUSSION

In this study, the authors developed a DL-based detection system for supporting healthcare professionals to identify children with learning disabilities. Initially, the handwritten images were preprocessed to improve their quality. In addition, YOLO V7 was used to extract the features. The MobileNet V2 model was applied to classify the images into normal and abnormal classes. The authors fine-tuned the MobileNet parameters using the AO.

The suggested DDS offers an effective environment for educational institutions and healthcare centers to identify DC. The proposed feature extraction technique extracts the crucial patterns for finding dyslexia from the handwritten images. The lightweight application can be implemented in remote locations across the KSA. The developers can build a mobile application using the framework. Furthermore, the

Table 5: Outcome of the comparative analysis.

Methods	Precision	Recall	F1-Score	Accuracy	MAP	mIoU
Proposed framework	97.9	97.3	97.6	99.2	97.6	88.6
Rello et al. model	97.2	96.8	97.0	95.3	96.7	74.1
Spoon et al. model	96.5	96.7	96.6	96.4	97.8	65.2
Rosli et al. model	98.1	97.2	97.6	97.8	98.3	78.7
Saqib et al. model	99.2	98.7	98.9	99.3	98.1	69.2
Sasidhar et al. model	98.3	98.1	98.2	97.6	97.4	56.3

Abbreviations: MAP, mean average accuracy; mIoU, mean intersection over union.

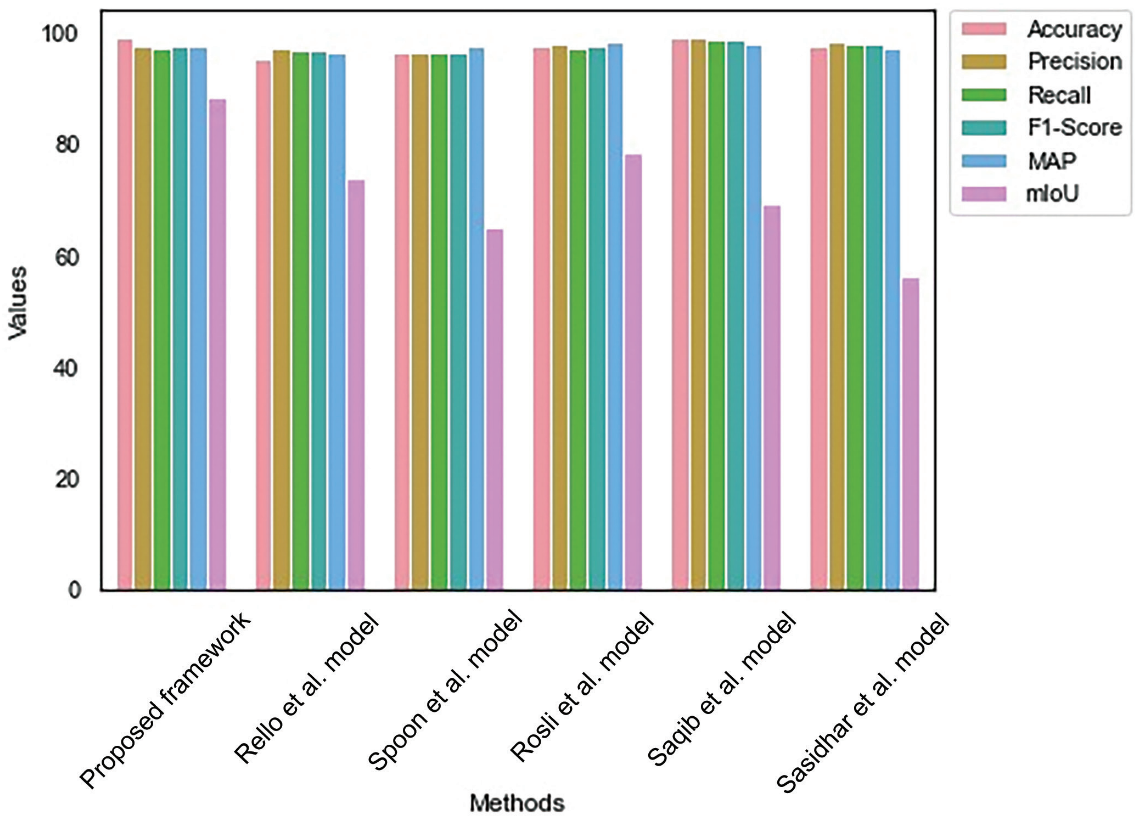

Figure 5: The comparative analysis outcome.

Table 6: Parameters and computational time.

Methods	Parameters (M)	CPU speed (ms)	FLOPs (G)	FPS	Testing time (seconds)	Loss
Proposed framework	4.2	77	8.1	103	0.7	0.235
Rello et al. model	6.4	142	7.5	64	1.2	0.312
Spoon et al. model	7.2	164	6.9	72	1.5	0.301
Rosli et al. model	5.2	118	7.1	84	0.9	0.225
Saqib et al. model	6.1	99	7.4	87	0.9	0.242
Sasidhar et al. model	12.4	128	9.4	86	1.8	0.286

Abbreviations: G, giga; M, millions; ms, microseconds; CPU, Central Processing Unit; FLOPs, Floating point operations; FPS, Frame per second.

authors applied the AO to optimize the performance of the proposed DDS. The study's outcome highlighted that the proposed framework produced a superior outcome compared to the state-of-the-art technique. The proposed framework overcomes the existing challenges, including high computation time and larger datasets. It achieved an exceptional accuracy score of 99.2%. The study's findings indicated the reliability of the proposed DDS in detecting dyslexia. The suggested framework can support the educational organization in finding dyslexia at the earlier stages.

Rello et al. (2018) achieved an average accuracy of 97.8% in predicting dyslexia. They employed language skills, working memory, executive functions, and perceptual process data. The study demanded a lot of time to process the enormous volume of data. In contrast, our proposed model generated the outcome with less computational cost. Similarly, Hamid et al. (2018) obtained an average accuracy of 97.8% in classifying the frontal view images of DC. On the other hand, our proposed model applied handwritten images to identify dyslexia. Moreover, it achieved an average accuracy of 99.2% in classifying the normal and abnormal handwritten images, respectively.

Spoon et al. (2019) employed optical character recognition to convert the transcripts into images. They built the CNN model and evaluated it using fivefold crossvalidation. The model achieved an average accuracy of 55.7 ± 1.4% on the larger dataset and obtained an average accuracy of 96.4%. However, this study's proposed model outperformed the Spoon et al. model by achieving 99.2%. Moreover, the application is lightweight and can be implemented as a mobile application. Thus, it can be employed in remote locations across the globe.

Rosli et al.'s (2021) model applied Le-Net-5 for identifying dyslexia. They achieved a classification accuracy of 95.34%. Again, our model outperformed Rosli et al.'s model with a limited computation cost. Nazmal et al.'s (2022) model obtained an accuracy of 99.5% with a high computation cost. Likewise, Sasidhar et al. (2022) achieved an average accuracy of 97.6 using the ResNet-50 model. The ResNet models require a huge memory for storing the parameters and weights. In contrast, the proposed model generated a superior outcome using a practical feature extraction approach.

Handwritten images offer a concrete and behavior-based evaluation and can be used as a practical tool for detecting dyslexia or dysgraphia. EEG examines brain activity and can reveal cognitive processes. However, it may not be specific to dyslexia. The handwritten images are noninvasive and can be collected in any environmental setting. The proposed model aimed to build a model for supporting the educational and healthcare centers in detecting dyslexia in the earlier stages. Compared to EEG and functional magnetic resonance imaging images, the handwritten images are readily available and can be easily collected from individuals. In addition, the proposed DD model analyzes handwritten images to identify distinct dyslexia characteristics in motor skills and spatial perception. The physical representation of writing activities like letter formation and spacing facilitates straightforward diagnosis and intervention. Furthermore, the proposed model can be employed for early screening in educational settings due to its noninvasiveness and simplicity, allowing prompt treatment for individuals with dyslexia. The NIST's special dataset covers diverse handwritten images in digital form. The dataset diversity supports the proposed model to identify dyslexia in real time. The authors employed the CNN model that can extract crucial patterns of dyslexia in a real-time setting. The proposed model can be implemented in mobile or edge devices, which can support educational institutions or healthcare centers to cover a massive number of the population. The authors fine-tuned the proposed model using regularization techniques to prevent data overfitting. In addition, they used hyperparameter optimization techniques to improve the generalizability of the proposed model in the real-time dataset. Online educational platforms can deploy the proposed model to detect dyslexia by capturing the individual's handwriting.

The proposed DD model streamlines the detection of dyslexia or dysgraphia using handwritten images. The authors faced challenges during the development of the DD model. The images were highly complex due to the unique character formation and spaces. The potential smudges reduced the image clarity and affected the feature extraction. In addition, the orientation and skewness of the handwritten characters caused challenges in identifying the characters. The dataset encompasses diverse images that were collected from three repositories. Thus, the images were in different sizes and resolutions. The authors applied normalization techniques to overcome the limitations. The MobileNet V2 model required extended training to identify the fundamental patterns of the images. The limitations of the proposed model are detecting specific forms of dyslexia and a limited number of layers in the MobileNet V2 model. The proposed DD model is capable of detecting phonological dyslexia, which is a developmental form of dyslexia. The experimental results were based on a single dataset. The results may vary in real-time applications. Additional training time is required to improve the efficiency of the proposed DDS. The MobileNet V2 architecture was constructed using a limited number of convolution layers. As a result, the proposed DDS performance may differ in the larger datasets. In the future, the proposed model can be extended to detect acquired forms of dyslexia using biomedical images.

CONCLUSION

Dyslexia is one of the critical disabilities that affect the human's neural system. The earlier detection of dyslexia can assist educational institutions in rendering an effective learning environment for DC. The study intended to build a framework for detecting dyslexia using handwritten images. The proposed framework included three models: image preprocessing, YOLO V7-based feature extraction, and MobileNet V2 – SSD lite-based image classification. The YOLO V7 technique enabled the proposed framework to detect crucial patterns with limited computing resources. In addition, the MobileNet V2 – SSD lite model is a lightweight CNN model that supports the proposed DDS to produce high-quality outcomes. The authors evaluated the performance of the proposed DDS using the dyslexia dataset. The proposed model achieved a superior mIoU of 88.6, which is higher than the existing models. The study findings showed that the proposed DDS had an excellent outcome than the baseline models. It revealed that the proposed DDS can be deployed as a real-time mobile application for identifying DC. However, the proposed framework demands additional training time to learn the abnormalities in the images of the larger datasets. Furthermore, the suggested framework can be extended to classify biomedical images to detect dyslexia.

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CONFLICTS OF INTEREST

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

REFERENCES

Abed M.G. and Shackelford T.K. (2020). Educational support for Saudi students with learning disabilities in higher education. *Learn. Disabil. Res. Pract.*, 35(1), 36-44. 10.1111/ldrp.12214.

Ahire N., Awale R.N., Patnaik S. and Wagh A. (2023). A comprehensive review of machine learning approaches for dyslexia diagnosis. *Multimed. Tools Appl.*, 82(9), 13557-13577.

Ahlawat S., Choudhary A., Nayyar A., Singh S. and Yoon B. (2020). Improved handwritten digit recognition using convolutional neural networks (CNN). *Sensors*, 20, 3344.

Aldakhil A.F., Ebrahim M.T. and Gadelrab H.F. (2023). Diagnostic survey of dyslexia and accompanying behavioral indicators in primary school students in Saudi Arabia. *Res. Dev. Disabil.*, 134, 104424.

AlMedlij M.A. and Rubinstein-Ávila E.B. (2018). The development of LD education in Saudi Arabia: services and implications for the future. *Int. J. Modern Educ. Stud.*, 2(2), 83-96. 10.51383/ijonmes.2018.29.

Alqahtani N.D., Alzahrani B. and Ramzan M.S. (2023). Deep learning applications for dyslexia prediction. *Appl. Sci.*, 13, 2804. 10.3390/app13052804.

Battal Z.M.B. (2016). Special education in Saudi Arabia. *Int. J. Technol. Incl. Educ.*, 5(2), 880-886.10.20533/ijtie.2047.0533.2016.0113.

Binbakhit N.M. (2020). A qualitative study investigating postsecondary services for students with learning disabilities at Saudi universities [Doctoral dissertation, Western Michigan University]. ScholarWorks@WMU. https://scholarworks.wmich.edu/dissertations/3621/, accessed on January 2, 2023.

Chiu Y.C., Tsai C.Y., Ruan M.D., Shen G.Y. and Lee T.T. (2020). Mobilenet-SSDv2: an improved object detection model for embedded systems. In: *Proceedings of the 2020 International Conference on System Science and Engineering (ICSSE)*, IEEE, Nha Trang City, Vietnam, 26-28 August 2019, pp. 1-5.

Drotár P. and Dobeš M. (2020). Dysgraphia detection through machine learning. *Sci. Rep.*, 10(1), 21541.

General Authority for Statistics. (2023). Educational statistics. https://www.stats.gov.sa/en, accessed on January 12, 2023.

Gunawan T.S., Noor A.F.R.M. and Kartiwi M. (2018). Development of English handwritten recognition using deep neural network. Indones. *J. Electr. Eng. Comput. Sci.*, 10, 562-568.

Hamid S.S.A., Admodisastro N., Manshor N., Kamaruddin A. and Ghani A.A.A. (2018). Dyslexia adaptive learning model: student engagement prediction using machine learning approach. In: *Recent Advances on Soft Computing and Data Mining: Advances in Intelligent Systems and Computing* (Ghazali R., Deris M., Nawi N. and Abawajy J., eds.), Vol. 700; pp. 372–384, Springer, Cham, Switzerland.

Irwin V., Zhang J., Wang X., Hein S., Wang K., Roberts A., et al. (2021). Report on the condition of education 2021 (NCES 2021-144). US Department of Education. National Center for Education Statistics. https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2021144, accessed on January 2, 2023.

Isa I.S., Rahimi W.N.S., Ramlan S.A. and Sulaiman S.N. (2019). Automated detection of dyslexia symptoms based on handwriting image for primary school children. *Procedia Comput. Sci.*, 163, 440-449.

Jasira K.T. and Laila V. (2023). DyslexiScan: a dyslexia detection method from handwriting using CNN LSTM model. In: *Proceedings of the 2023 International Conference on Innovations in Engineering and Technology (ICIET)*, IEEE, Kerala, India, 13-14 July 2023, pp. 1-6.

Jothi Prabha A. and Bhargavi R. (2022). Prediction of dyslexia from eye movements using machine learning. *IETE J. Res.*, 68(2), 814-823.

Kaggle. Dyslexia Handwriting Dataset. (2019). http://www.kaggle.com/datasets/drizasazanitaisa/dyslexia-handwriting-dataset, accessed on January 2, 2023.

Khan R.U., Cheng J.L.A. and Bee O.Y. (2018). Machine learning and dyslexia: diagnostic and classification system (DCS) for kids with learning disabilities. *Int. J. Eng. Technol.*, 7(3.18), 97-100.

Kumar N., Chikkmath A., Gouthami Yadav B.R., Naidu H.R. and Acharya D. (2023). Interpreting doctor notes using handwriting recognition and deep learning techniques: a survey. In: *Proceedings of the 2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS)*, IEEE, Bengaluru, India, 19-21 April 2023, pp. 703-708.

Nasir-Tucktuck M., Baker J.N. and Love M.L. (2017). Educating learners with disabilities in Palestine: the past, present, and future. *Interv. Sch. Clin.*, 52(3), 182-187. 10.1177/1053451216644821.

Nazmal S., Haque K.F., Yanambaka V.P. and Abdelgawad A. (2022). Convolutional-neural-network-based handwritten character recognition: an approach with massive multisource data. *Algorithms*, 15(4), 129.

NIST. NIST Special Database 19. (2019). https://www.nist.gov/srd/nist-special-database-19.

Patel S. (2017). A-Z Handwritten Alphabets in. csv format. Kaggle. [Online]. https://www.kaggle.com/sachinpatel21/az-handwritten-alphabets-in-csv-format, accessed on May 22, 2023.

Patnoorkar R., Chaudhary S., Pandey S., Pandey P.S., Balyan R. and Kumar M. (2023). Assistive technology intervention in dyslexia disorder. In: *Proceedings of the 2023 International Conference on Artificial Intelligence and Smart Communication (AISC)*, IEEE, Greater Noida, India, 27-29 January 2023, pp. 343-347.

People with Disabilities. (2022). https://moe.gov.sa/en/education/generaleducation/pages/peoplewithspecialneeds.aspx, accessed on January 5, 2023.

Perera H., Shiratuddin M.F. and Wong K.W. (2016). Review of the role of modern computational technologies in the detection of dyslexia. In: *Information Science and Applications (ICISA)* (Kim K.J. and Joukov N., eds.), pp. 1465-1475, Springer, Singapore.

Poch A.L., Alzahrani D., Aljuwayhir J. and Alnahari M. (2023). Educating students with learning difficulties in the Kingdom of Saudi Arabia. *Interv. Sch. Clin.*, 58(4), 287-292.

Pralhad G.P., Joshi A., Chhipa M., Kumar S., Mishra G. and Vishwakarma M. (2021). Dyslexia prediction using machine learning. In: *Proceedings of the 2021 International Conference on Artificial Intelligence and Machine Vision (AIMV)*, IEEE, Gujarat, India, 24-26 September 2021, pp. 1-6.

Rello L., Romero E., Rauschenberger M., Ali A., Williams K., Bigham J.P., et al. (2018). Screening dyslexia for English using HCI measures and machine learning. In: *Proceedings of the 2018 International Conference on Digital Health*, Lyon, France, 23-26 April 2018, pp. 80-84.

Richard G. and Serrurier M. (2020). Dyslexia and dysgraphia prediction: a new machine learning approach. *arXiv preprint arXiv:2005.06401*.

Rosli M.S.A.B., Isa I.S., Ramlan S.A., Sulaiman S.N. and Maruzuki M.I.F. (2021). Development of CNN transfer learning for dyslexia handwriting recognition. In: *Proceedings of the 2021 11th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, IEEE; pp. 194-199.

Sasidhar A., Kumar G.K., Yoshitha K. and Tulasi N. (2022). Dyslexia discernment in children based on handwriting images using residual neural network. In: *Proceedings of the 2022 6th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS)*, IEEE, Bengaluru, India, 21-23 December 2022, pp. 1-6.

Spoon K., Crandall D. and Siek K. (2019). Towards detecting dyslexia in children's handwriting using neural networks. In: *Proceedings of the International Conference on Machine Learning AI for Social Good Workshop*, Long Beach, CA, USA, 6 May 2019, pp. 1-5.

Usman O.L., Muniyandi R.C., Omar K. and Mohamad M. (2021). Advance machine learning methods for dyslexia biomarker detection: a review of implementation details and challenges. *IEEE Access*, 9, 36879-36897.

Wang C.Y., Bochkovskiy A. and Liao H.Y.M. (2023). YOLOv7: trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Vancouver, Canada, 18-22 June 2023, pp. 7464-7475.