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Dysgraphia Handwriting Image Augmentation for CNN Model Classification

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***Abstract*—Dysgraphia affects a person's ability to write consistently and properly especially among school children. It is a challenging condition as it needs effective intervention to help the affected children succeed academically and socially. With the advancement in technology in artificial intelligence (AI), various methods and approaches have been developed using convolutional neural networks (CNN) model to overcome several limitations to assess dysgraphia symptoms. However, there are major concerns about the difficulties of getting large data of dysgraphia handwriting images for CNN attributes model. Thus, this study is aimed to develop dysgraphia handwriting recognition model based on augmentation method. In this study, image augmentation is addressed by creating new data by using rotation and brightness technique to generate a set of synthetic images. The augmented data is trained and tested using CNN classification model to classify four classes of dysgraphia handwriting. The results show a significant improvement with 77% accuracy using augmented as compared to without augmented data only 73%. This study indicated that augmentation method is significant for inclusion in CNN classification model particularly for dysgraphia potential risk recognition. This study is further recommended to implement intelligence-based augmentation method which can be incorporated into a computer-assisted dysgraphia screening system to provide a rapid, accurate, and unbiased dysgraphia detection.**

***Keywords*—**Dysgraphia, Convolutional Neural Network, Image Augmentation, Deep Learning.

I. INTRODUCTION

Learning disability which known as dysgraphia would affecting handwriting skills, poses significant challenges for individuals in educational and professional settings. This disorder can be a result of weak motor skills, no space knowledge, or low cognitive skills [1]. The number of children with learning disabilities is increasing year by year, according to recent studies in the field. As a result, researchers must focus their efforts in this area to develop strategies for early detection and diagnosis as well as appropriate treatment plans that will lessen the severity of the students' learning difficulties and bring them up to the level of average students.[2].

In Malaysia, According to the 2019 National Health and Morbidity Survey (NHMS), 4.7% of youngsters were confirmed to have a disability. According to the NHMS 2016, 3.3% of children aged 6 to 59 months had developmental delay, compared to an estimated 5 to 16% of newborns, toddlers, and preschoolers worldwide who were assessed to have developmental delay [3]. Standard procedure in Malaysia to the suspected children are they will be tested using "Instrumen Senarai Semak Disleksia (ISD)" that is provided by Ministry of Education during standard two [4]. Then, a preliminary diagnosis will be done by a child psychiatrist or a pediatrician. Finally, it will be confirmed by the clinical psychologist through further testing which usually might take a long time process [4]. There are many limitations by doing the conventional assessment based on previous study [5][6]. A common assessment normally would lead to biasing result and non-standardize because each of the test or the evaluation been run with a different person. As image of dysgraphia handwriting is also difficult to find, it will lead to imbalance data which will lead to biasing result and less accuracy for classifying [7]. It is a difficult task to collect large data of dysgraphia handwriting before train to the network model. So, the augmentation method plays an important role in order to provide large data for dysgraphia handwriting data.

Each year, researchers continue to innovate new methods for classifying learning disability risk and utilizing approaches such as analyzing brain behaviors and handwriting recognition. Developing efficient methods which to enhance the efficiency classification of handwriting characteristics associated with dysgraphia can pave the way for early intervention and targeted support, ultimately improving outcomes for affected individuals [8]. Recently, modern computational technologies are used for screening dyslexia condition by considering neurological aspects to improve dyslexia recognition accuracy and reliability. These also including an intelligent artificial method of deep learning method that are recently introduced to solve complex problems, high-level abstract and heterogeneous datasets, especially image and audio data. Deep learning–based models have surpassed classical machine learning–based approaches in various text classification tasks [9]. In view of the great performance of deep learning methods in various recognition tasks, this study aims to intensively investigate the use of the convolutional neural network (CNN) algorithm. The main goal of this study is to enhance the Dysgraphia handwriting recognition by using image augmentation method for classifying 4 types of dysgraphia handwriting using Convolutional Neural Network (CNN).

II. RELATED STUDY

Regularly, dysgraphia or learning disabilities detection at early age has been popular among the researchers by using different methods. A study by [1], used machine learning techniques for classifying process. They are comparing KNN (K-Nearest Neighbors), Naïve Bayes, Decision tree, Random Forest, SVM (Support Vector Machine) on the Dysgraphia dataset. Meanwhile, [10] study the comparison contemporary computational technologies of learning disabilities detection method. They show that computer-based tools that include sophisticated measures from the data acquired by eye-tracking and/or electroencephalography devices offer an objective assessment of dyslexia. Research by R. Kariyawasam et. al [11] has developed the first game based screening and intervention tool for dyslexia, letter dysgraphia, dyscalculia and numeric dysgraphia. However, the method of using handwriting recognition require the least resources and easy to analyze [12]. Thus, detecting dysgraphia among children through handwriting has become one of the prominent approaches.

Most research nowadays enthusiastically run and improves the dysgraphia detection method by implementing deep learning methods. CNN has been the most preferrable method used in handwriting recognition as it always give a significant results nowadays [13]. However, CNN is facing a limitation with a small group of data [14][4] and implement a data augmentation method to build a synthetic images has been proven to give a better performance for CNN model [7][15]. A synthetic image is a set of images that has been fully or partially created using computer-generated graphics for used in CNN model training. In this study, synthetic images are generated using augmentation method.

A. *Image Augmentation Method*

Overfitting is always the main issue as the conventional training process only learns the important regions, but ignores less critical features that are required for generalization [8]. Some techniques to avoid overfitting were applied, such as image augmentation and dropout techniques. In this study we focus on the image augmentation technique. Data augmentation is a technique that creates a new sample from original samples by manipulating a single image. Its purpose is to artificially increase the size of the training dataset. [16][17]. Rotations, translations, shearing and scaling, as well as greyscale dilations and erosions are some of augmentation method usually used [15]. Generally, data augmentation for images would tackles two main issues in CNN models. The first issue which can lead to overfitting, is a lack of data or inadequate data. Picture Information by providing the model with multiple image scenarios, augmentation offers a solution by expanding the model's scope and enabling the extraction of more data from the original dataset. Image Data Augmentation provides a solution by feeding the model with various scenarios of an image, making the model more generalized and allowing for the extraction of more information from the original dataset. The second issue is labeling; every sample in the original dataset had a label. When a sample is enhanced, its original label is retained and applied to the augmented sample [8].

B. *CNN Classification*

The structure of the CNN model has been developed to extract features and classify images to detect the potential risk of dysgraphia. The CNN model is consistently outperformed all other techniques, exhibiting significantly higher accuracies when compared to machine learning method for image classification. They consistently achieve higher accuracies and demonstrate better recognition capabilities. Traditional machine learning techniques have their strengths in handling small sample datasets and can be effective in certain contexts. Nevertheless, CNN consistently outperforms them in various scenarios. However, when tested with limited training sets, CNN is prone to overfitting and lacks generalizability. Augmentation immediately addresses this issue by creating new data that provide more details. [18].

III. METHODOLOGY

This section explains the overall process of the proposed method and all activities that will be implemented in order to achieve the aim of this study. Fig. 1 shows the framework of the overall study.

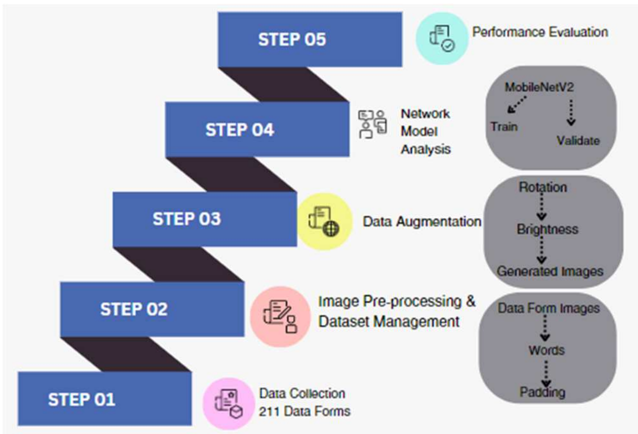

Figure 1. Methodology framework for Dysgraphia Handwriting Image Augmentation for CNN Classification

A. *Dataset Collection and Pre-Processing*

As shown in Fig. 2, the process of data collection has been approved by Ethics was started at Pusat Dyslexia Malaysia (PDM), Ampang, Kuala Lumpur, Malaysia. The sampling handwriting assessment dataset is required as an input image before being tested with CNN model.

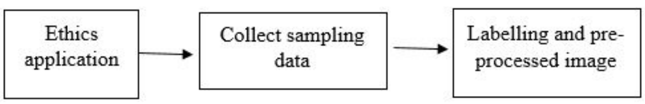

Figure 2. Process of dataset collection.

As shown in Table 1, the sampling data acquired from PDM is 211 set of handwriting images assessment form which classified into 4 classes of dysgraphia by the PDM assessor. The four classes of dysgraphia handwriting images are categorized as normal, low-risk, medium-risk and high-risk. The dataset is obtained in filled form written offline by the children. Since the original datasets are in different sizes, resolutions and shapes, image pre-processing is performed as a preliminary process for the image dataset to be transformed into common form before undergoing image augmentation process. In this study, the pre-processing is performed after images scanning, where the images dataset will be cropped, cleaned and padded before been augmented.

Table 1. Distribution of handwriting image form dataset for each class

Types of Handwriting Images	Number of Forms
Normal	105
Low-risk	26
Medium-risk	42
High-risk	38
Total	211

B. *Dataset Augmentation*

How well-suited synthetic images is to help the classifier performs well is a common study nowadays. In fact, it has been demonstrated that the performance of the classifiers can be enhanced by combining synthetic images with original images in low resolution image datasets. During training, two picture transformation processes—rotation and brightness—were used to examine the impact of augmentations on text recognition performance. The augmentation process is performed by using Google Collaboratory and Python language. Python was the main language used throughout the project. It's easy to read and understand, and it has lots of tools we need, like OpenCV for working with images and NumPy for handling data. The results with those obtained from a baseline model and trained on the original data were compared for with and without augmentation dataset. Fig. 3 shows the number of dataset before and after augmentation. It shows the increasing number of datasets after the augmentation process.

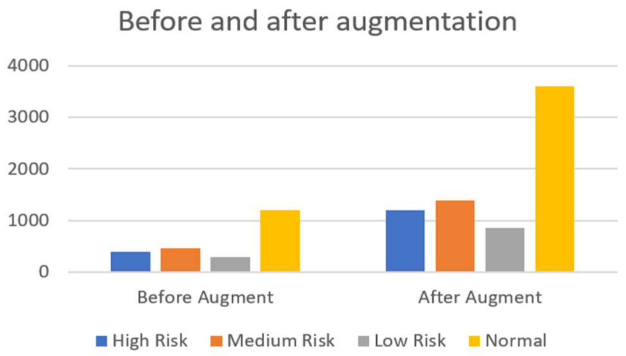

Figure 3: Images before (non-augmented) and after augmentation

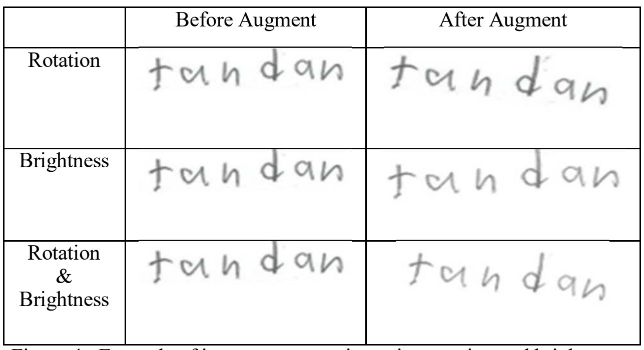

Figure 4 : Example of image augmentation using rotation and brightness

C. *CNN Classification*

In this study, the classification CNN model is applied to classify the dysgraphia potential risk in the children using handwriting images. Refer to Fig. 4, the proposed CNN model used for classification is MobileNetV2. MobileNetV2 is almost identical to the original MobileNet with the exception of the fact that it employs inverted residual blocks with bottlenecking features. Compared to the original MobileNet, its parameter count is significantly reduced. Moreover, higher image sizes provide better performance, and MobileNets support any input size larger than 32 × 32. The reason of this model was chosen is because of its low value of inference time and high accuracy [19]. The parameter setting for MobileNetv2 is as in Table 2.

Table 2: Parameter setting for classifier

CNN Model	MobileNetV2
Classifier activation	softmax
Library	Keras
Classes	4
Image Size	224 x 224

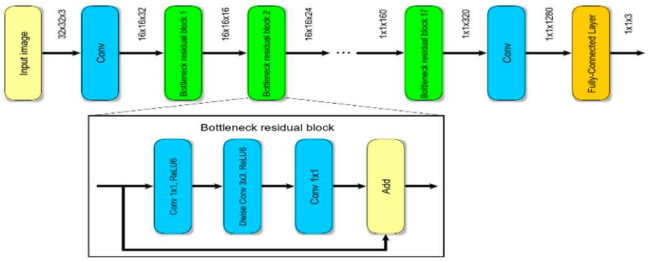

Figure 5: MobileNetV2 Architecture

In this study, the ratio for trained and validation of dataset for non-augmented and augmented dataset is distributed by 80:20.

IV. RESULT AND DISCUSSION

We will discuss on a comparative analysis of the classifier tool's performance in this section. The augmentation was carried out, and the outcomes affected the CNN model's ability to classify handwriting into four categories for dysgraphia. The precision attained forms the basis of the initial analysis. This model's performance has been examined throughout 50 epochs. The accuracy of the model prior to its augmentation is displayed in Fig. 5. The 48th epoch achieves 72%, the highest achievement. However, Fig. 6 demonstrates that the 45th epoch performance is at its peak, at 77%. It has been demonstrated that the augmentation method improves classifier performance significantly.

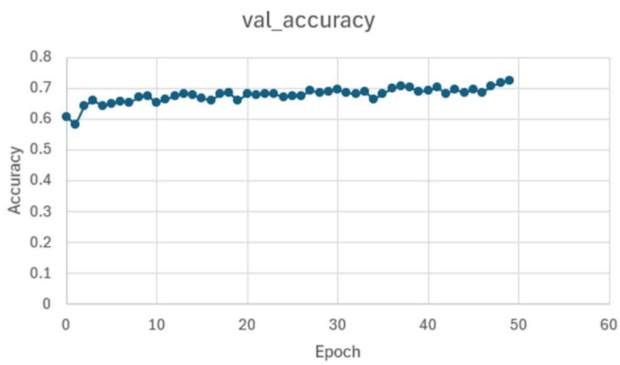

Figure 6: Accuracy of non-augmented data

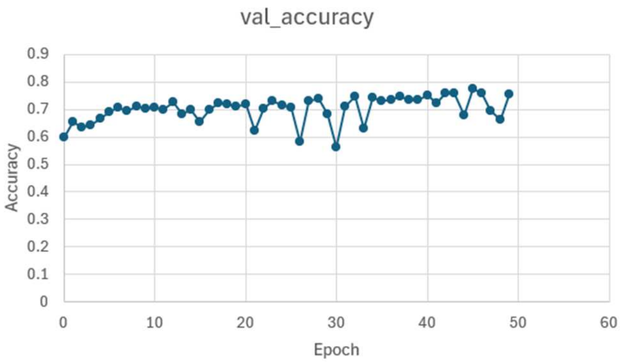

Figure 7: Accuracy of augmented data

Next, the result analysis is based on the loss performance. From the case of non-augmented dataset, the result obtained are 0.70 for the loss as shown in Fig. 7 whereas 0.56 for the augmented dataset as depicted in Fig. 8. These results shows that there is higher loss for the non-augmented dataset as compared with the augmented one. The accuracy of the classifier is much better when tested compared to non-augmented data. The classifier is definitely would perform more efficient with augmented dataset as proposed.

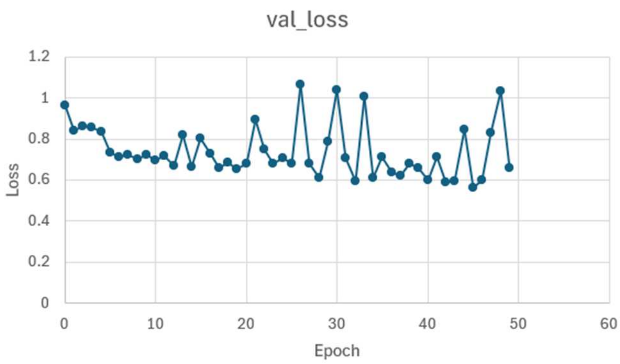

Figure 8: Loss of non-augmented data

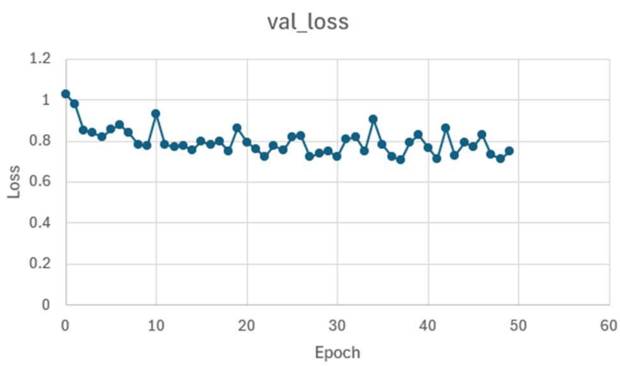

Figure 9: Loss of augmented data

In summary, the overall performance result for the classification model is tabulated in Table 3. The result shows the comparison performance of the MobileNetV2 tested using non-augmented and augmented dataset at 50 epochs. The accuracy result for dataset with augmented has showing good performance with 77% accuracy for training and validation as compared to non-augmented dataset. This indicates that augmentation has proven as one of the method to improve classification performances.

Table 3. Comparison result performance of MobileNetV2 at 50 epochs

MobileNetV2	Non-Augmented	Augmented
Accuracy (Training)	0.83	0.85
Loss (Training)	0.45	0.37
Accuracy (Validation)	0.72	0.77
Loss (Validation)	0.71	0.56

V. CONCLUSION

In this research, the augmentation method is proven to helps the increase of accuracy of classifier CNN. Based on the outcome, the goal of implementation augmentation for CNN classifier dysgraphia handwritten recognition was accomplished. As a recommendation for future improvement, several tasks, like using the most recent augmentation model to eradicate the unbalanced dataset and producing additional data for the classifier, can be carried out to enhance the system of dysgraphia handwriting recognition.

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