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CNN Comparisons Models on Dyslexia Handwriting Classification

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ABSTRACT

Dyslexia is developed by neurobiological in origin which is categorized as learning disorder that affect the ability to read, spell, write and speak. The most common dyslexia symptom can easily be identified through the handwriting pattern. There are many intelligence and computational methods that have been proposed, and they have provided various and different performance to evaluate the proposed system ability. However, system performances are varied and nonstandardized in each assesment on dyslexic children to validate the presence of dyslexia symptom. The recent deep learning models have been employed to improve the assesment performance and (the models/ they have shown) shows significant output to detect and classify the present of dyslexia symptoms among school children. Therefore, there is a crucial need in deep learning, specifically for Convolutional Neural Network (CNN) to validate performances of different networks, so that the most performed CNN could be a bench mark in evaluation to detect such symptom. This study aims to compare different deep learning networks specifically the CNN models to validate its performance in terms of the capability to classify dyslexic handwriting among school children. This study is proposed to compare different CNN models such as CNN-1, CNN-2, CNN-3 and LeNet-5. The proposed methods to compare the CNN performances are developed by using Jupyter notebook as platform. Meanwhile, keras is the higher-level API framework to provide a more flexible way for defining models. It specifically allows to define multiple input or output models as well as models that share layers. The tensorflow is also used for machine learning applications such as neural networks. Before that, the dataset of handwriting image is preprocessed by the augmentation process which includes the rotation of all images. CNN models have shown significant performance and provided sufficient results of performance with more than 87% of accuracy in classifying the potential dyslexia symptom based on handwritten images.

Keywords: *dyslexia, image classification, deep learning, CNN, image processing.*

1. INTRODUCTION

Dyslexia is characterized as having difficulties in learning that lead to deficits in various aspects of spelling and reading words, including accuracy, fluency, and speed [17] and they are considered as a neurological difference and can have a significant impact during education, in the workplace and in everyday life. According to British Dyslexia Association, each person has the possibility to experience dyslexia except that it can range from mild to severe and co-occur

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with other learning differences in a life-long condition [18]. Dyslexia is a learning disability that originates neurobiologically and exhibited through struggles with accurate word recognition and also by a lowly performance in reading and writing [1]. Detecting dyslexia in suspected children needs to be done as early as possible since with early detection, the dyslexic children would have a better chance to earn significant improvements by receiving effective intervention programs. Suspected dyslexic children mostly experienced primary difficulties in phonological awareness like manipulation and phonemic awareness, reading smoothness, single word reading, and also spelling [2]. Due tosuch phonological unawareness, difficulties in reading comprehension will lead to problem in comprehending the written expression.

Screening for dyslexic children via handwriting has become one of the most important approaches in detecting dyslexic children [16]. One of the common problems dyslexic children face when writing is letter inversion. Many of the letters that dyslexic students invert when reading can also contribute to the same letters that they invert when writing [3]. From the study [4] a technique was proposed and this will be used for the automatic diagnosis of dyslexia and for the estimation of the level of difficulty controlled by the handwriting ability assessment questionnaire. This research used a digitized tablet to acquire handwriting and subsequently employed compound parameterization to quantify its kinetic characteristics and hidden complexities. A study [5] that investigated on assistive technology for dyslexics used an accelerometer-based handwriting recognition and the analog interactive voice response system (IVRS).

The result produced approximately 90% accuracy in distinguishing dysgraphia products from capable products. However, none of these apps have attempted to detect dyslexic children through handwriting using CNN. Meanwhile, in Malaysia, a suspected child will be referred to either a childpsychiatrist or a pediatrician who will then give a preliminary diagnosis to be confirmed by the clinical psychologist through further testing [6]. However, the assessment based on computional algorithm by various CNN networks have been proposed in many researches [4][7][14][15] to detect dyslexia in handwriting image and the result performance also are widely varied. As example, the rating proposed in [4] is based on kinematic pressure which may limit the impact on in-air movement and hence lose its continuity. Meanwhile, other study by [7] limits the proposed rating handwritten recognition for only for Indian numerical script rather than international spelling alphabets. Contrastively, the proposed research by [14] suggested that writing disorder based on EEG signal processing shows persistent results but this preliminary work is not applicable as assessment since it is most related on neuro-developmental activity. Similarly, as the research proposed by [15] to classify dyslexia risks requires additional work for improvement. Literally, there is no specific method proposed to detect such deficient and clear framework in assessing the handwriting levels. Therefore, this study is proposed to compare the different CNN networks by evaluating their performance in terms of its accuracy and loss.

The aim of this study is to compare different deep learning of CNN models to classify the symptom of dyslexia by using the handwriting images and to validate the comparisons of the CNN network by analyzing the performance in terms of its accuracy and loss. Different types of deep learning method performance based on their accuracy and loss is employed to detect and classify the severity of handwritten images in terms of dyslexia presentation.

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2. METHODOLOGY

The dataset of this study is acquired from Kaggle database [12] that contains 3 types of dyslexic handwriting single letter images. All the image classes are divided into 78275 for normal class, reversal is 52196 and corrected is 8029. All the dataset images were morphologically pre-processed and augmented before being set as the CNN model attributes. Figure 1 shows the overall work in pre-processing and augmentation process of the dataset images.

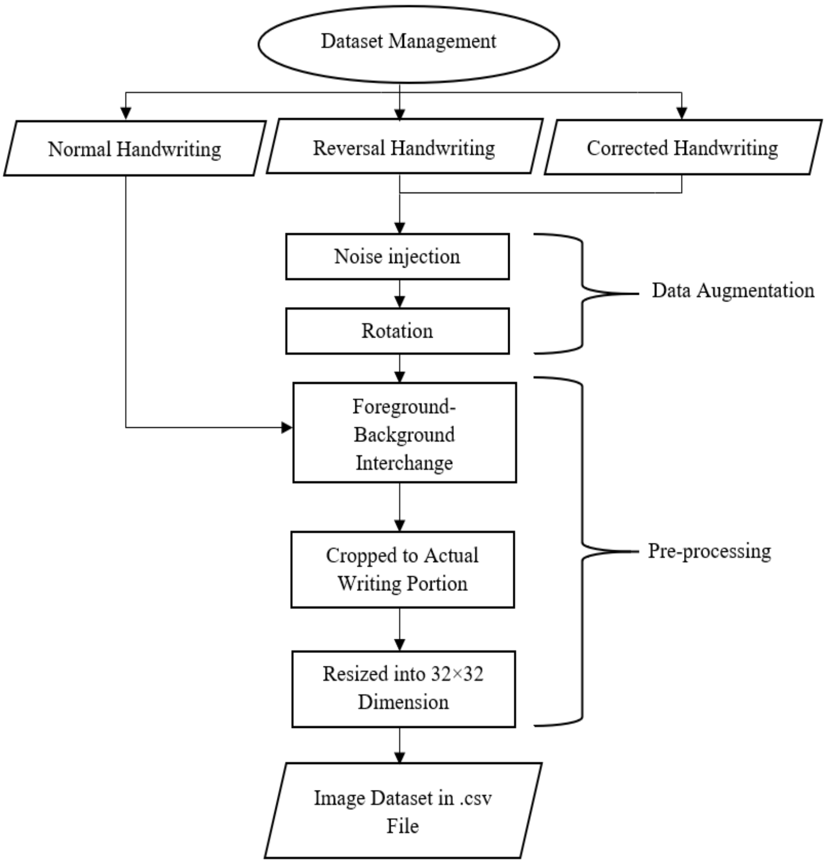

Figure 1: Image pre-processing and data augmentation procedure

2.1 Data Acquisition

In this process, every single image of the dataset was revised in order to separate the actual shape of alphabet with the corrected or wrong alphabet shape as depicted in Figure 2. The selection by categories was conducted by selecting the correct shape of alphabet and classified under normal handwriting while the wrong alphabet shape and corrected ones were classified under corrected handwriting. For the reversal group, the normal handwriting dataset was mirrored which is horizontally flipped in order to produce reversal datasets. Some normal alphabets were not mirrored because theywould produce the same shape after the process.

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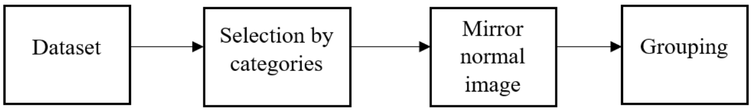

Figure 2: Dataset management for classes grouping

The input for the system is the handwriting images of three different classes which include the normal handwriting, reversal handwriting and corrected handwriting suggested by Susan Barton, the founder of Bright Solution for Dyslexia [6]. Dataset was collected from 3 sources where uppercase letters? is/are from NIST Special Database 19 [11] while the lowercase letters are from Kaggle Dataset [12] and some datasets for testing are from the dyslexic kids of Seberang Jaya primary school. Firstly, 151,433 images from the previous study have been collected. Then, the images were divided into two sets which are for 53,675 for training set and 39,897 for validation set. From 53,675 images, 32,512 images have been classified as normal handwriting, 13,231 as reversal handwriting and 7,932 images classified as corrected handwriting. Then, for the validation set, from 39,897 images, 15,785 images have been classified as normal handwriting, 12,326 as reversal handwriting and 11,786 as corrected handwriting. The file has been saved in one folder in the user directory and will load...once required for usage?

2.2 Image Pre-processing

Pre-processing is a preparation process for the image dataset to be transformed into common form before fed into classifiers as the original datasets. Commonly, these datasets are in different sizes, resolutions and shapes [7].

Class	Original Image	Step 1- Foreground-Background Interchange	Step 2- Cropped to Actual Writing Portion	Step 3- Resized into 32×32 Dimension
Normal Handwriting				
Reversal Handwriting				
Corrected Handwriting				

Figure 3: Image pre-processed of each different classes

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In this study, the process conducted for dataset image pre-processing for each clas was done by choosing inverse interchange in order to reduce computational overhead since it has an image with more white point (value 1) than black point (value 0). Thus, this would consume more power and memory on training the image[7]. This process would thus change the background to black while the handwriting in white. However, the lowercase 'd' was excluded from this foreground and background interchange to differentiate between reversal 'b' and normal 'd'. The next step was cropping the image to the actual writing portion. This step was used to crop unwanted portion of image from bottom, top, right and left, hence the image would have a focus on the alphabet at the centre.

After that, all the images were resized to 32×32 pixels, so that the dataset would have a uniform size to employ as input of the CNN model. The output of pre-processing of every step is shown in Figure 3. Finally, all the dataset was transformed into *.csv* file with label, where label 0 is Normal class, label 1 for Reversal class and label 2 is for Corrected class. From dataset management procedure before, the total dataset in each class was imbalanced. Having an imbalanced dataset between class could lead to a bias in the prediction of a more common class. One of the best methods to counter it, is by using the data augmentation.

2.3 Data Augmentation

Data augmentation is a process that artificially increases the size of the training dataset by creating a new sample from original datasets by applying some modification to a single image. Firstly, the image is injected with only 20% gaussian noise by using morphological technique provided in the executation library to avoid confusion on handwritten alphabet. Next, the augment is continuously employed with the rotation and shifting integrated with *Keras ImageDataGenerator*. Theoretically, these techniques could improve the validation dataset performance since it had provided a better image for the training dataset. In this study, the image rotation was used as augmented sets for the dataset as depicted in Figure 4. According to [8], the technique of rotation is implemented by rotating the image either to the left or to the right based on axis in between 1° and 359°. For rotation two angles were chosen which were 20º and -20º as the minimum changes to avoid interchange in alphabets particularly between 'p' and 'b' and so on. From this process, dataset between classes was made balanced where 78275 for normal, 77775 for reversal and 77304 for corrected class.

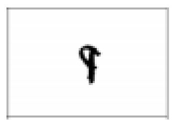
Augmented process	Original Image	Output
Rotation (20º)		
Rotation (-20º)		

Figure 4: Image rotation

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2.4 CNN Models Development

For the classification of three classes of dyslexic handwriting, a CNN approach is used as a classifier tool. The CNN has been described as a leading architecture for most image identification, classification and recognition tasks [9]. In this project CNN will work on feature extraction, pattern analysis and classification of the handwritten image. CNN architectures have many variations, but in general, CNN consists of convolutional and pooling layers, which are grouped into modules. In this study, to develop the CNN model, the software used is Jupyter in the Anaconda package manager. For the programming language, Python version 3.6 is used. The neural network structure is used to provide flexible APIs and configuration options for performance optimization, where it is designed to facilitate and streamline the training of deep learning models. In this research, the neural network structure used is Keras with Tensorflow as the backend. Tensorflow is low-level, while Keras is basically a high-level API.

In this study, there are four (4) CNN models that have been compared to determine their performances to classify between normal and dylexia handwriting classes namely the CNN-1, CNN-2, CNN-3 and LeNet-5. The difference of each model is the number of layers assembled in the network as shown in Figure 5 which presents the general CNN model architecture. Basically, the CNN architecture contains convolution layer, pooling layer, dense and dropout. Meanwhile, Table 1 summarizes the architecture of each model.

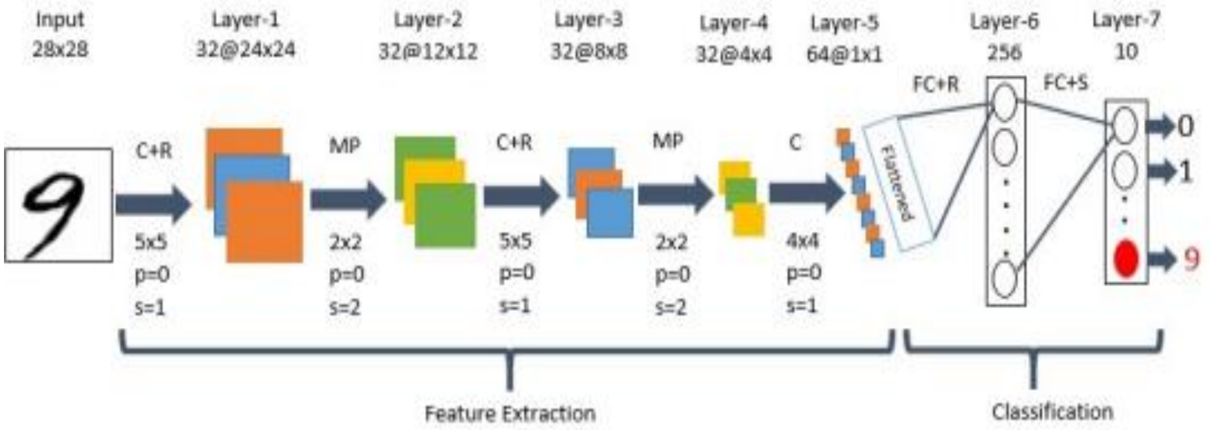

Figure 5: CNN architecture

The first layer for the convolution operation is a Conv2D layer that extracted features from the input images by sliding a convolution filter over the input to create a feature map.A feature map of size 3 x 3 was chosen. The second layer is a MaxPooling2D layer that reduced the dimensionality of each feature for the max-pooling operation. It helps to shorten training time and reduce the number of parameters. Meanwhile, the 2 x 2 size pooling window was chosen. In order to reduce overfitting, a dropout layer was added as the third layer to combat the overfitting. In the learning process, it causes the model to learn multiple different representations of the same data by randomly disabling neurons. Next, the last tensor output was fed into a stack of Dense layers or better known as fully connected layers. Such vectors process were closely connected classifiers, which were 1D, while the current output was a 3D tensor. Since the 3D outputs were needed to flatten what ?to 1D, 2 thick layers to the edges were applied.

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Table 1: CNN Models Architecture

CNN Model	Architecture
CNN-1	✓ 1 convolution layer ✓ 1 Max pooling layer ✓ 2 dense layers ✓ 1 dropout layer
CNN-2	✓ 2 convolutional layer ✓ 2 max pooling layers ✓ 2 dense layers ✓ 1 dropout layers
CNN-3	✓ 3 convolutional layer ✓ 2 max pooling layers ✓ 2 dense layers ✓ 4 dropout layers
LeNet-5	✓ 3 convolutional layers ✓ Sub-sampling layers are 2 by 2 average pooling layer ✓ 2 fully connected layers

Since there are 2 classes of images, two-way classification is used for final layer with 2 outputs and a softmax activation. Activation with Softmax allows to calculate the output based on the probabilities. Each class has a probability given, and the class with the highest probability is the result for the input of the model. Each model then is compiled using the categorical_crossentropy as the loss function since it is suitable for multiclass, single label classification problem. The error rate between the predicted value and the original value is calculated by cross-entropy loss. Moreover, Adaptive Moment Estimation (ADAM) optimizer has been chosen as the optimization algorithm. In order to minimize its error rate, the optimization algorithm is used for training a machine learning model.

As an example, one-layer convolution neural network is the simple trained model with only 1 convolution layer, 1 max-pooling layer, 2 dense layers, and 1 dropout layer. Figure 6 shows the example of model summary for CNN-1 architecture with 525,443 total parameters that have been used to train the model in the study.

The performance of each CNN model has been evaluated using confusion matrix that is used to predict analysis for classification problem [19]. This evaluation method can be implemented in binary classification as well as for multiclass classification problems by predicting any objects in the classifier to visualise the model classification accuracy as depicted in Figure 7. It is defined that:

- True Positive (TP): Observation is positive and is predicted to be positive.
- False Negative (FN): Observation is positive but is predicted negative.
- True Negative (TN): Observation is negative and is predicted to be negative.
- False Positive (FP): Observation is negative but is predicted positive.

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```
cnn1.summary()

Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 32, 32, 32)        896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 16, 16, 32)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 16, 16, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                524352
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 195
=================================================================
Total params: 525,443
Trainable params: 525,443
Non-trainable params: 0
_________________________________________________________________
```

Figure 6: Example of model summary of CNN-1 architecture

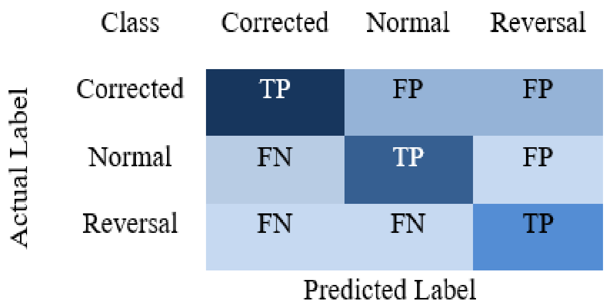

Figure 7: Confusion matrix for multiclasses of corrected, normal and reversal

3. EXPERIMENTAL RESULT AND DISCUSSION

This section discusses the accuracy, loss, and confusion matrix result obtained from the comparison of different CNN models. As aforementioned, the simulation is executed on Jupyter Notebook with Keras framework. There are 4 different CNN models that have been compared on the Jupyter Notebook with the use of dyslexia handwriting dataset as training and validation. Results are obtained on overall training and validation accuracy and loss of all CNNs models are presented in Figure 8 and Figure 9 respectively. Generally, the performance of CNN-1 outperforms other CNN models while LeNet model is at the lowest. The results of training and validation losses are inversed to the accuracy performance.

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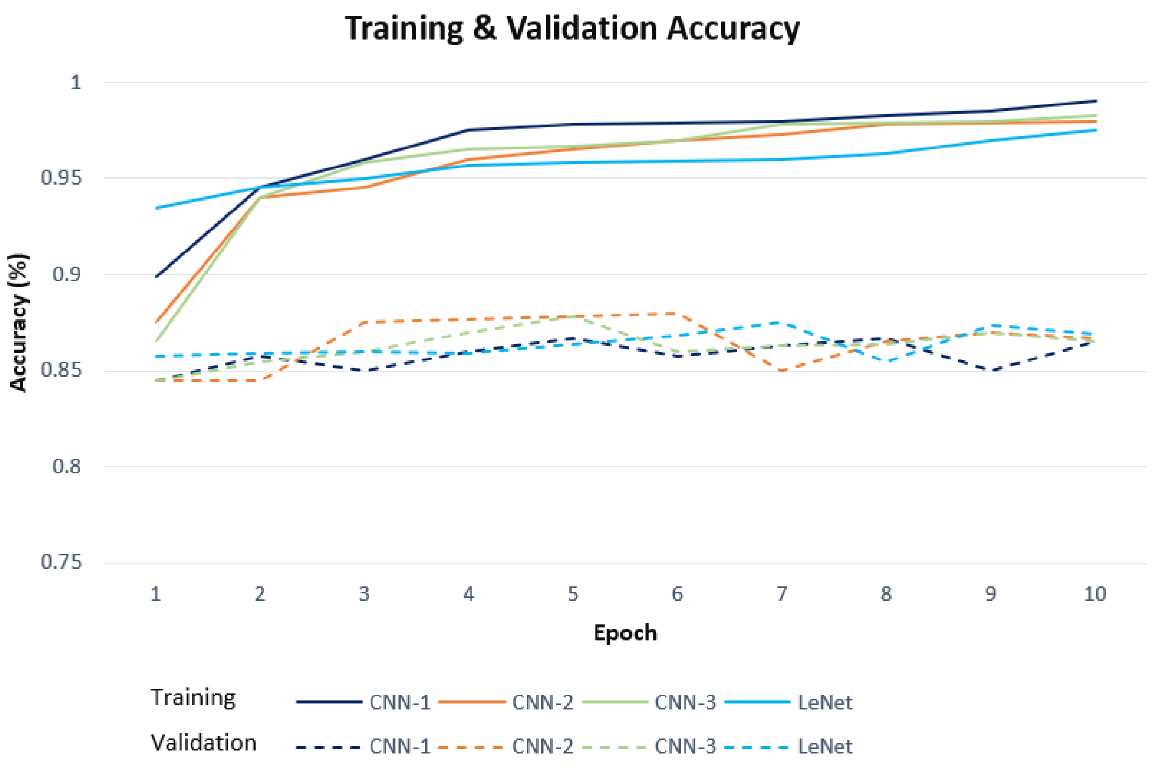

Figure 8: Overall CNN Models Performance of Training and Validation Accuracies

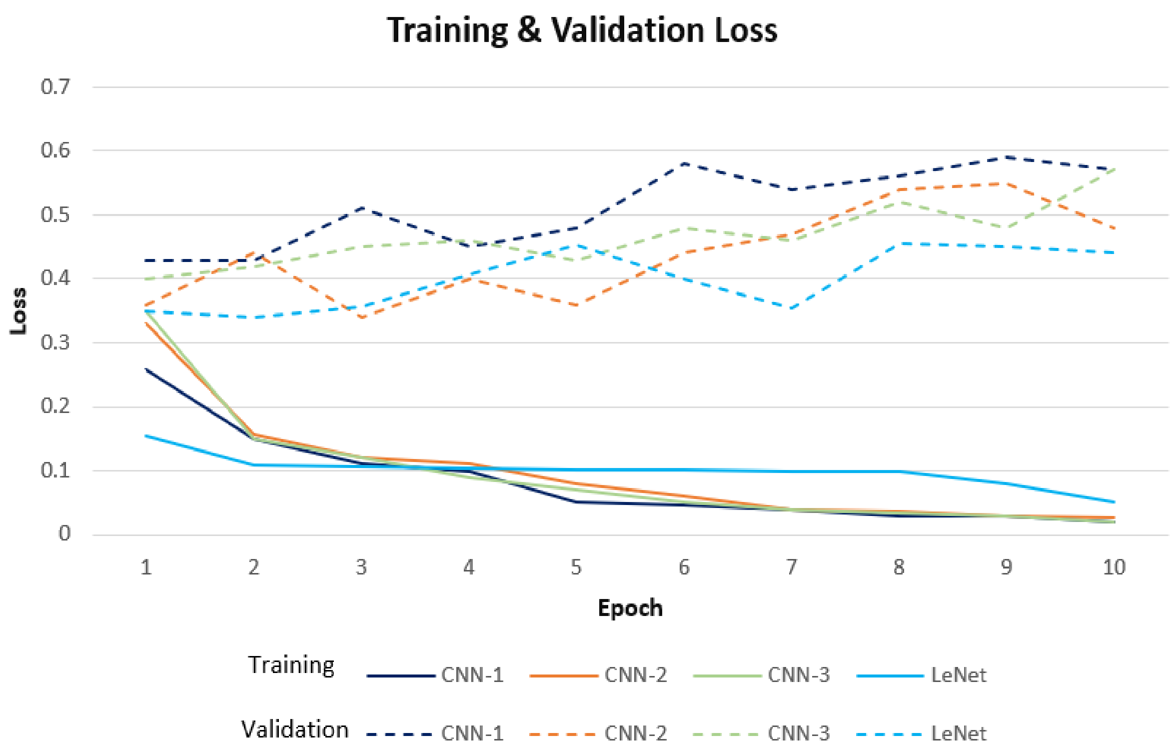

Figure 9: Overall CNN Models Performance of Training and Validation Losses

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3.1 CNN-1 Model Analysis

This section presents the performance of CNN-1 model that is analysed after the data augmentation technique. As shown in Figure 8, the training and validation accuracy for 10 epochs have 0.985 training accuracy and the overall validation accuracy achieved is 0.86. The performance overfitting occurs at second iteration. Meanwhile, the result shows the training loss had reached 0.02 for 10 epochs. For validation loss as depicted in Figure 9, the result shows that the loss finally reached at 0.55. It is found that the overfitting occurs at the second epoch.

Meanwhile, Figure 10 shows the result of confusion matrix for CCN-1 model between actual and predicted label of each classes.

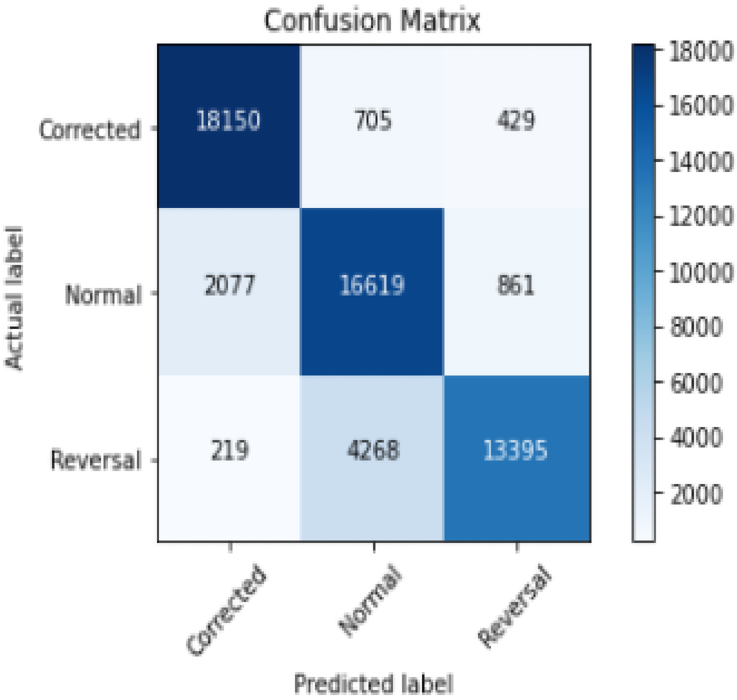

Figure 10: Performance evaluation with confusion matrix for CNN-1

3.2 CNN-2 Model Analysis

With reference to Figure 8, the performance of this model has been analysed for 10 epochs. This model has been improved from CNN-1 by adding one more convolutional layer, max pooling layer and activation layer which is to reduce its non-linearity. The performance of CNN-2 model after applying the data augmentation for training and validation accuracy of 10 epochs shows that the overall training accuracy achieved is 0.98 while the overall validation accuracy achieved is 0.87. From the results as shown in Figure 9, it shows that the training loss has reached 0.07 for 10 and finally reached 0.5 for validation loss. Figure 11 shows the confusion matrix results for CNN-2 model.

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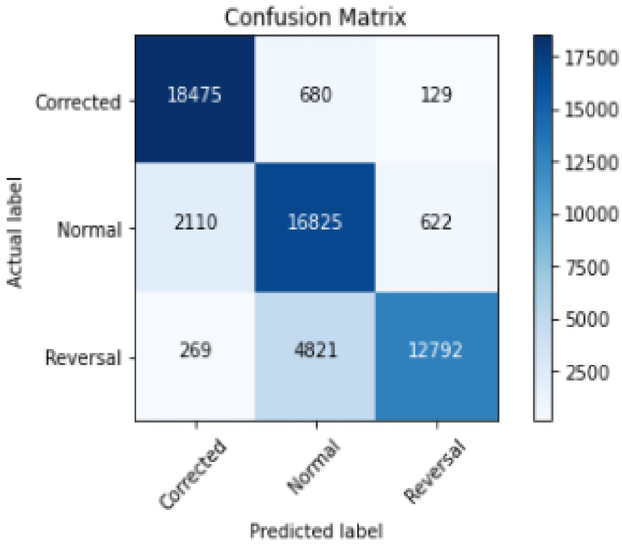

Figure 11: the performance evaluation with confusion matrix for CNN-2

3.3 CNN-3 Model Analysis

For CNN-3 model it has 3 convolution layers, 2 max-pooling layers, 2 dense layers, and 4 dropout layers. As shown in Figure 8, the summary of CNN-3 architecture with 503,363 total parameters were trained. As can be seen, the performance of CNN-3 model after data augmentation was applied for training indicates that the validation accuracy has converged for 10 epochs. The overall training accuracy achieved is 0.98 while the overall validation accuracy achieved is 0.865. The result shows the training loss has reached 0.04 for 10 epochs as in Figure 9. For validation loss, the result obtained is reached at 0.6. Figure 12 shows the confusion matrix performance for actual label and predicted label of all the three classes dyslexia handwriting group.

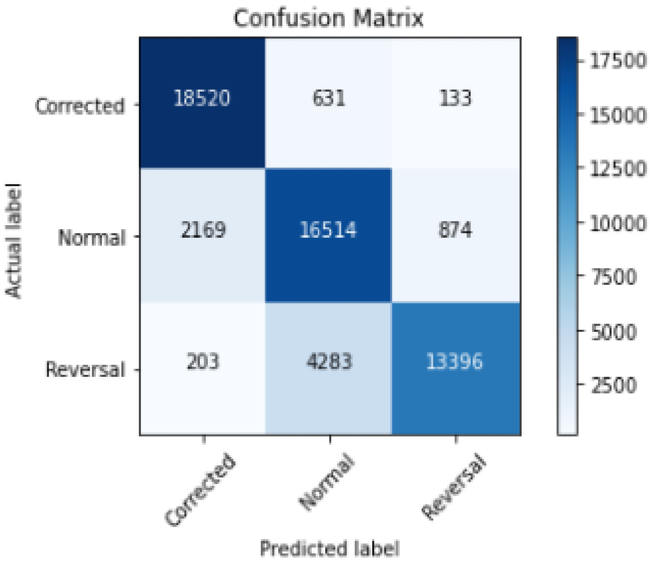

Figure 12: the performance evaluation with confusion matrix for CNN-3

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3.4 Le-Net Model Analysis

This model consists of 7 layers where the size of input image is 32×32 pixel. Having 3 convolutional layers (C1, C3 and C5), 2 sub-sampling (pooling) layers (S2 and S4), one fully connected layer (F6), and finally the output layer This model is used to train the 3 classes of dyslexic handwriting dataset. As presented in Figure 8, the performance of LeNet-5 model after applied data augmentation of training and validation accuracy (ambiguous- please refer to the earlier para structure changed just in case that is not the meaning intended) for 10 epochs has achieved 0.968 while the overall validation accuracy achieved is 0.86. It is found that the training loss had reached 0.03 for 10 epochs and the loss finally reached 0.45 for validation loss as shown in Figure 9. Meanwhile, Figure 13 depicts the obtainable result for confusion matrix performance of LeNet-5 model ability to classify each of three classes correctly based on the handwritten group.

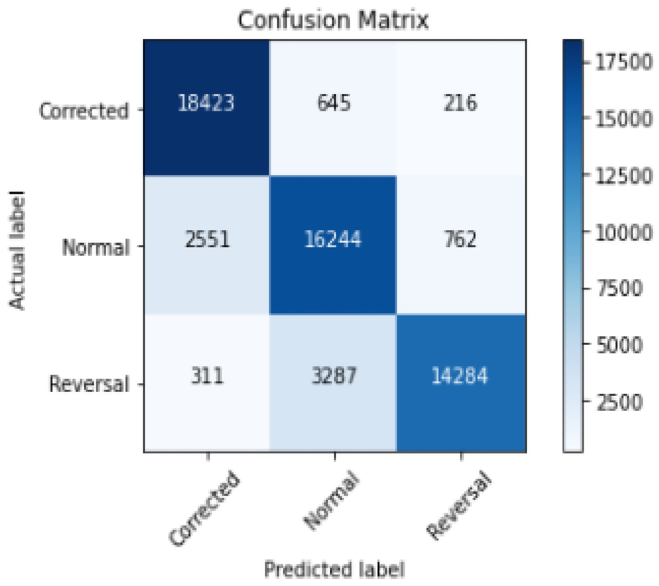

Figure 13: the performance evaluation with confusion matrix for LeNet-5

The performance of each model with data augmentation images had been compared in Table 2. As can be seen, the performance of the model was improved after applied data augmentation. Hence, the best CNN model for image classification from the result obtained was the CNN-1 model with the highest accuracy and the least loss of validation. This is supported by the fact that simplest CNN model with the least layer has abetter performance. However, othercompared models performed slightly poor (?) and provide insignificant (?) results.

Table 2: Performance comparison for each model

CNN model	Training accuracy	Validation accuracy	Training loss	Validation loss
CNN-1	0.985	0.86	0.02	0.55
CNN-2	0.98	0.87	0.07	0.5
CNN-3	0.98	0.865	0.04	0.6
LeNet-5	0.968	0.86	0.03	0.45

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4. CONCLUSION

As a conclusion, the objective of this study is to compare the different deep learning of CNN models to classify the dyslexia handwriting images performance in terms of loss and accuracy test of the training model, loss and accuracy test after applying data augmentation and training and validation accuracy is achieved. The CNN model inspired by the famous CNN-1 architecture is able to produce a remarkable performance especially in the accuracy of classifying 3 classes of dyslexic handwriting image. In addition, the dataset of pre-processing and augmentation also helps in accelerating the classification accuracy. From this study, a number of future work can be done to improve the dyslexia handwriting recognition such as collecting more dyslexic handwriting image for test set in examining the performance of the model in a full/ whole real environment.

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