GENERATION JOURNAL

Vol. 10 No. 1 2026
e-ISSN: 2549-2233 / p-ISSN: 2580-4952
DOI : https://doi.org/10.29407/gj.v10i1.27419

Epistemological and Axiological Analysis of ResNet18-Based Dysgraphia Classification

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Article Info

Received	2025-11-03
Revised	2026-01-09
Accepted	2026-01-12

Keywords* : *dysgraphia classification; ResNet18; handwriting; epistemology; axiology

Abstract

Based on an ontological perspective, there is a gap in feature representation and in binary dysgraphia classification using ResNet18, an area that has not been explored simultaneously. Thus, our contribution is an analysis of research on dysgraphia classification using ResNet18 that employs epistemological and axiological approaches. ResNet18 was chosen as the backbone of the proposed framework because it has shortcut connections that can degrade residues into useless features. As a representation of new knowledge, ResNet18 was pre-trained on ImageNet. Classification was tested on challenging word assignments, comprising 145 dysgraphia images and 188 non-dysgraphia images. Epoch trials were conducted to find the best architecture. The results showed that ResNet18 at epoch 10 achieved the best performance in binary classification, with a recall of up to 93.55%. This indicates that ResNet18 is sensitive to recognizing dysgraphia classes. Challenges outlined in this study serve as a foundation for further research.

INTRODUCTION

One learning disorder that is rarely researched is dysgraphia [1]. From a philosophical perspective, dysgraphia is a physical manifestation that impacts writing difficulties[2]. Individuals with this disorder have low levels of legibility[3]. This disorder is often associated with performance and social impacts [4]. In fact, dysgraphia is a manifestation of other diseases, such as apraxia[4], dyslexia[5], Alzheimer's[6] , and Parkinson's[7]. In many countries, dysgraphia assessments are often carried out by experts[8]. This limitation not only requires a high level of expert knowledge but also costs and time to detect[9]. Treatment and intervention for this disorder are lengthy [10]. This philosophical gap has sparked the development of computer vision in the field of dysgraphia[11]. This field is urgent to observe because it addresses the expansion of the philosophy of human perception, which is an ethical responsibility to ensure that technology is not only used economically, but also has meaning in maintaining the objectivity and accuracy of recognition results (epistemology) in justice and equality for people with learning disabilities from an axiological perspective.

The existence of features representing dysgraphia can be interpreted through mapping the characteristic factors to the neurological conditions that trigger the disorder[12]. The majority of studies rely on expert judgment in classification, encouraging automation through computer vision technology. Even in the aspect of computer technology empowerment, some studies still use expert judgment[13], both in the realm of computer vision [14], and in the realm of data mining [15]. The knowledge gap regarding spatial features provides the ontological-philosophical basis for this pre-research. Meanwhile, the technological opportunities arising from recognizing dysgraphia to achieve humanitarian benefits constitute the axiological aspects to be pursued. This forms the ontological foundation for new knowledge in the creation of spatial representations of handwriting for dysgraphia recognition.

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One of the most popular models is the Residual Neural Network (ResNet). Unlike the Dense Net model, which applies feature reuse via feature concatenation [17], ResNet18 learns differences in the data information flowing through each network by introducing residual connections. The superior performance of ResNet18 is reflected in the research of Zhang et al. (2025), which excels at recognizing handwriting in patients with Parkinson's disease [16]. Other studies also indicate that ResNet18 achieves 99.3% accuracy in recognizing handwritten letters [17]. The use of Resnet-v2 also achieves high accuracy, achieving 99.8% accuracy in Arabic [18]. Although not explicitly used to recognize dysgraphia handwriting, the potential for high accuracy in handwriting is a modality in the development of the hypothesis for this research. ResNet18 outperforms other methods in network degradation [19]. The balanced accuracy achieved with stable training provides a basis for considering ResNet18 as the backbone of the training framework. Resnet18 was chosen in this study due to its small dataset and limited computational capacity [20].

Based on an ontological perspective, there is a gap in feature representation and in binary dysgraphia classification using ResNet18, an area that has not been explored simultaneously. Thus, our contribution is an analysis of research on dysgraphia classification using ResNet18 that employs epistemological and axiological approaches. From a philosophical perspective, this study is expected to provide a new ontology-based knowledge representation of ResNet18-based convolutional neural networks for dysgraphia features, thereby automating the classification process. This study addresses the following research question (RQ) epistemologically and axiologically:

RQ 1. How can convolution in ResNet18 epistemologically recognize dysgraphia symptoms?

RQ 2. What scoring matrix values does ResNet18 provide in dysgraphia classification based on an axiological perspective?

Based on the above research question, the objective of this research is to develop a ResNet-18-based dysgraphia recognition system for handwriting classification. The research design developed in this study is experimental and grounded in scientific philosophy. This research, which represents spatial-feature knowledge through convolutional mechanisms in the context of dysgraphia, makes ontological contributions. The proposed ResNet18 can build knowledge on feature perception in dysgraphia handwriting classification, providing a philosophical contribution to epistemology. Meanwhile, the accuracy, precision, and recall results produced by ResNet18 are expected to provide new insights into the diagnostic process and to mitigate the social impacts that dysgraphia sufferers may experience, representing an axiological contribution. The proposed contribution is expected to fill research gaps in the areas of phenomenon representation, empirical knowledge, and axiology, with respect to the benefits embodied in the scoring matrix measurement.

RESEARCH METHOD

The research method describes the dataset and the proposed ResNet18 architecture. In this study, the proposed research flow depicted in Figure 1 represents knowledge as a representation of the ResNet18 ontology, serving as the backbone for Dysgraphia classification. An explanation of each stage, showing how ResNet18's convolutions can recognize dysgraphia as an epistemological representation, is provided in the following sub-chapters.

1. Dataset

The dataset used refers to Kunhoth's (2025) research [21]. The image size is 1037×1024 pixels. In the dataset, the tested assignment is presented as a difficult word meaning 'toy store' in Slovak (hračkárstvo). A sample dataset is shown in Figure 2. There are 93 images of dysgraphia at level 1, 52 at level 2, and 188 non-dysgraphia images. There is an imbalance that is a challenge for this research. To avoid overfitting, this study uses binary classification by combining dysgraphia levels 1 and 2. For

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this reason, the comparison of dysgraphia and non-dysgraphia classes reaches 145:188. Multi-level research can be developed as a follow-up study.

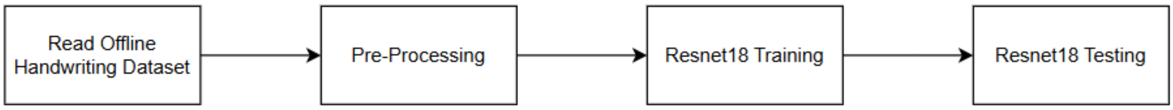

Figure 1. Proposed Research Flow

(a) (b) (c)

Figure 2. Dysgraphia Dataset [23] (a) Normal (b)(c) dysgraphia (b) Level one (c) Level two

2. Pre-Processing

Table 1. Normalization Parameters for Each Color Space Channel

ID	Red Channel	Green Channel	Blue Channel
Mean	0.485	0.456	0.406
Standard Deviation	0.229	0.224	0.225

In the initial stage, the image is resized to the ResNet18 standard size of 224×224 pixels. Next, the image is converted from NumPy format to a PyTorch tensor with [0,1] normalization. The normalization process is shown in Equation (1).

$$x_{norm} = \text{image} - \frac{\text{mean}}{std} \qquad (1)$$

Based on Equation 1, the distribution of pixel values is adjusted to the ImageNet dataset, where each channel is calculated from the average (mean) and standard deviation (std). The standard deviation settings of each color space are shown in Table 1.

3. ResNet18 as a Feature Extraction and Classification Method

ResNet18 is the smallest and lightest residual-based network model for image recognition. ResNet18 consists of 18 layers: convolution layers, residual blocks, batch normalization layers, the ReLU activation functions, and global average pooling layers. The ResNet18 architecture is shown in Figure 3. The proposed method uses pre-training on ImageNet.

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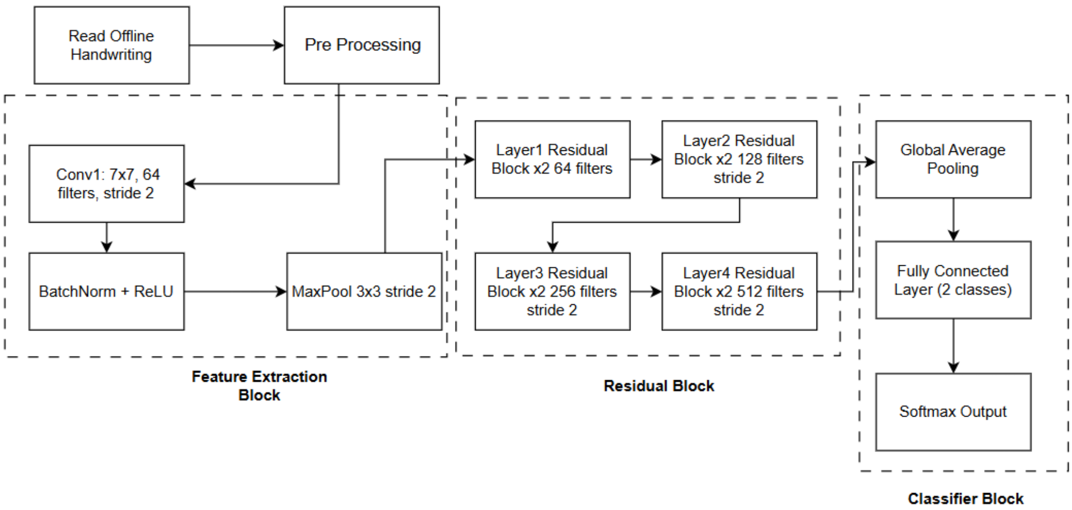
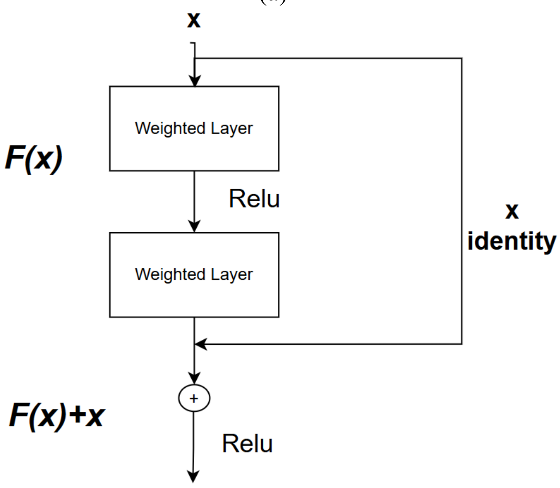


(a)



(b)

Figure 3. The ResNet18 Architecture (a) Resnet18 (b) Residual Block Diagram

Figure 3 shows three main blocks: the feature extraction block, the residual block (Figure 3(b)), and the classification block. In the initial stage, the normalized image is fed into a convolutional layer with a 7x7 kernel, followed by max pooling to reduce the spatial dimensionality of the initial features. In the convolution stage, a convolution is applied to the image of $x \in R^{224\times224\times3}$, using Equation (2).

$$Y_{conv} = W_1 * x_{norm} + b_{1,} \quad (2)$$

Where the kernel W is applied, the stride (kernel step) and the padding (number of zero frames). Each kernel has a bias parameter b. In the residual block, a shortcut connection is added directly from the input to the output block. The residual block consists of two 3×3 convolutional layers, so each block comprises several consecutive convolutional layers. The residual block is shown in Equation (4).

$$F(X) = \mathrm{F(x, W) + sc} \quad (4)$$

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In Equation (4), the *f(x)* residual block consists of: the *F* convolution result of the *x* image, using the *W* kernel, while *sc* is a shortcut connection. The residual result is defined as Equation (5).

$$Y_{conv} = F(X) - sc \quad (5)$$

In Equation (5), the batch normalization layer normalizes each convolutional result to stabilize training, as shown in Equation (6).

$$\hat{Y}_{batchnorm} = \gamma \frac{Y_{conv} - \mu_B}{\sqrt{\sigma_B{}^2 - \epsilon}} + \beta \quad (6)$$

In Equation (6), normalization accounts for the mini-batch mean μ and variance σ, as well as the bias parameters β and the weights γ. Next, the ReLU activation function is applied to the activation layer, as shown in Equation (7).

$$\hat{Y}_{relu} = \max\left(0, \hat{Y}_{batchnorm}\right), \quad (7)$$

Based on Equation (7), if the value is negative, it is set to 0; otherwise, it is set to the batch normalization value. At the classification stage, the $\hat{Y}_{gap}$ global average pooling is set in Equation (8).

$$\hat{Y}_{gap} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} \hat{Y}_{relu}(c, i, j), \quad (8)$$

In Equation (8), channel-*C*, width-*W,* and height-*H* are set at vector dimensions of 3×512×512. Next, a fully connected layer (FCN) is applied as a neural network, as described by Equation (9).

$$\hat{Y}_{fc} = W_{fc} \cdot y_{gap} + b_{fc}, \quad (9)$$

In equation (9), the FCN output Y^_fc is determined based on the adjusted weights of Pretrained ImageNet $W_{fc} \in R^{1000 \times 512}$. In the final stage, the SoftMax output-p is applied to the probability distribution based on the exponential result (e) of Y_{fc}, the fully connected layer, on each point (i), highlighting the accumulation of the exponential function on all data represented in Equation (10).

$$pi = \frac{e^{\hat{Y}_{fc},i}}{\sum_j e^{\hat{Y}_{fc},i}}, \quad (10)$$

4. *Evaluation Method*

To achieve fair accuracy, the data was split into 70% for training, 15% for validation, and 15% for testing. The testing matrix uses accuracy, precision, recall, and F1 Score, respectively, as defined in Equations 11–14.

$$Accuracy = \frac{db}{tod} \times 100\%, \quad (11)$$

$$\text{Precision} = \frac{pb}{tpb} \times 100\%, \quad (12)$$

$$Recall = \frac{pb}{dab} \times 100\%, \quad (13)$$

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$$F1\ Score = \frac{2 \times recall + \times presisi}{recall + presisi} \times 100\% \text{,} \quad (14)$$

Based on Equation (11), accuracy is the number of correct predictions (*db*) across all tested data, where db∈{TP, TN} and tod∈{TP, TN, FP, FN}. *TP* is the number of dysgraphia classes predicted correctly, while *TN* describes the number of non-dysgraphia classes predicted correctly. *FN* is the number of incorrect non-dysgraphia predictions, while *FP* is the number of incorrect dysgraphia predictions. In Equation (12), precision indicates the number of data predicted according to class (pb) against all data that have been predicted according to class, where pb∈{TP} and t*pb*∈{TP, FP}. In Equation (13), recall reflects the number of predicted data according to class (*pb*) against the original correct data (*padb*) with dab∈{TP, FN}. In Equation (14), F1-score reflects the balance of precision and recall.

RESULTS AND DISCUSSION

The research results answer two research questions: how convolution in ResNet18 epistemologically recognizes dysgraphia symptoms, and the benefits of ResNet18 in dysgraphia classification, using a matrix assessment reference from an axiological perspective. The description of the research results is grouped into three aspects based on: (1) training and validation assessment; (2) testing assessment; and (3) epistemological and axiological analysis. The binary dysgraphia classification trial scenario is shown in Table 2. The model performance trial was conducted by combining the dysgraphia levels into a single class, while the non-dysgraphia class remained separate. The best epoch was evaluated as the basis for evaluating the test data. Research outputs can be accessed at https://bit.um.ac.id/outputSMT1_Sinta4.

1. *Training and Validation of Dysgraphia Classification*

In the training phase, we measured training and validation accuracy to assess the tendency toward overfitting on small datasets. The results are shown in Table 3. The training and validation accuracies for the binary class are shown in Figure 4 and detailed in Table 3. The visualization in Figure 4 and Table 3 shows that, in binary classification, epoch 5 is equivalent to epoch 10, whereas in multiclass classification, epoch 5 is lower than epoch 10. Meanwhile, validation performance increases when initialized at epoch 10 in both classification tasks (binary and multiclass). This indicates that training is not stable at epoch 5. Resnet18 reaches stability at epoch 10. At epoch 15, accuracy decreases for both target classes, suggesting the system may be overfitting.

Based on Figure 4 and the accuracy details in Table 3, epoch five has not yet reached stability, while epoch 15 shows indications of overfitting. Therefore, this study determined that the optimal epoch for binary dysgraphia classification was 10.

Table 2. Testing Scenarios

Parameter	Value
Target class	2 {Positive Class: Dysgraphia, Negative Class: Normal}
Epoch	{5, 10, 15}

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e-ISSN: 2549-2233 / p-ISSN: 2580-4952
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Table 3. Results of Dysgraphia Validation and Training

Testing Scenario		Accuracy	
Target class	Epoch	Training	Validation
2	5	75.51%	61.22%
	10	**75.51%**	**73.47%**
	15	65.31%	65.31%

*** Bolded data shows the best epoch results**

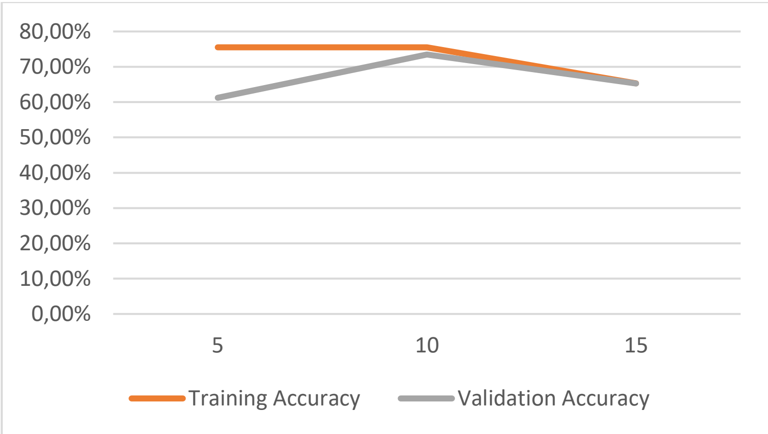

Figure 4. Dysgraphia Training and Validation Results

2. Dysgraphia Classification Test

Table 4. Convolution Matrix for Dysgraphia Testing

	Prediction Dysgraphia	Prediction Normal	Total
Actual Dysgraphia	TP = 24	FN = 2	26
Actual Normal	FP = 16	TN = 9	25
Total	40	11	51

Table 5. Results of Dysgraphia Test Measurements

Evaluation Matrix	Result (%)
Accuracy	64.71
Precision	64.44
Recall	93.55
F1-Score	76.32

After finding the best ResNet18 parameter values to maintain the stability of the proposed method, the study tested the model's performance in a test class. The test data comprised 15% (51 test sets) of the 333 total data sets in the dataset [23].

The convolution matrix is shown in Table 4. For the dysgraphia class, the convolution results showed good performance, whereas for the regular class, they did not. Twenty-four of the 26 data sets for the dysgraphia class were successfully predicted, indicating the number of TPs, while two data sets

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e-ISSN: 2549-2233 / p-ISSN: 2580-4952
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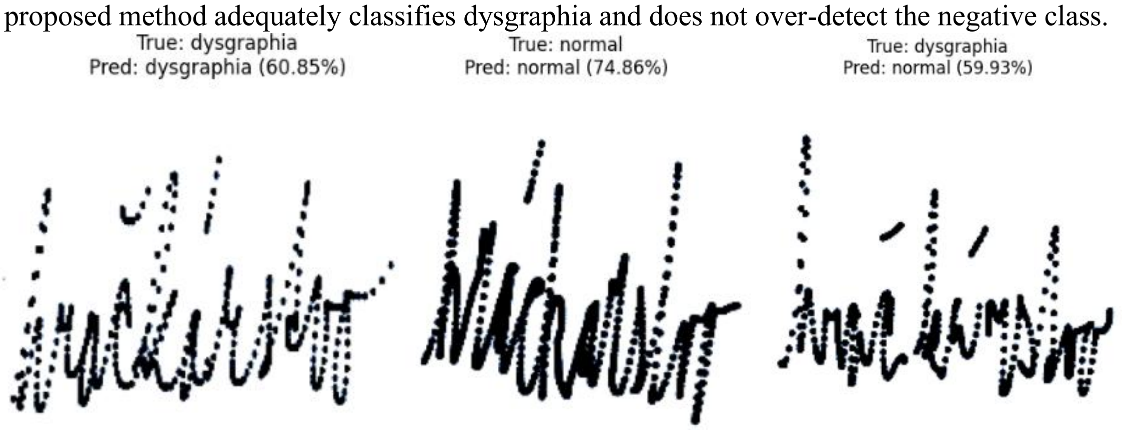
stated the number of FNs. In contrast, for the dysgraphia class, 9 of the 25 data sets were incorrectly predicted (TN). This indicates an error of ~30% for the non-dysgraphia class.

After calculating the convolution matrix, recall was measured, as shown in Table 5. The recall results showed the best value, with 93.55% achieved in binary classification. This indicates that the system is sensitive to the dysgraphia class. In multi-level classes, recall may decrease due to data imbalance in the level-one dysgraphia class. This requires more comprehensive testing in further research.

The results for accuracy, precision, and F1 score are also presented in Table 5. In contrast to the recall results, the measurements showed a value below 80%, indicating the need to optimize the method. Compared to the recall of 93.55%, the accuracy of only 64.71% reflects that the majority of errors were in the Normal class. The convolution matrix support presented in Table 4 supports this hypothesis. This resulted in the low precision level for the dysgraphia class, at 64.41%. This challenge also indicates the need to explore variations of ResNet or CNN in other models with more complex convolutions and deeper layers. Fine-tuning trials on other datasets could also be an alternative for improvement in further research. The balance of precision and recall, as demonstrated by the F1-score of 76.32%, indicates that the proposed method adequately classifies dysgraphia and does not over-detect the negative class.



(a) (b) (c)

Figure 5. Test Result Data (a) True Negative (b) True Positive (c) False Positive

Figure 5 shows a sample of research results showing true positives, true negatives, and false positives. Figure 5(a) shows the positive class, while Figure 5(b) shows the negative class. The comparison of the two images indicates that both normal handwritten and dysgraphia handwritten samples exhibit uneven line patterns, which lead to detection errors, as shown in Figure 5(c). The comparison of Figures 5(a) - (c) shows that writing pressure is the main characteristic that indicates the need for offline and online image feature integration.

3. Epistemological and Axiological Analysis of Dysgraphia Classification

In the philosophy of science, research methods and results are interpreted as representations of new knowledge. In this case, the ontology is realized using ResNet-18 as a representation of new knowledge to classify dysgraphia into two binary classes. To answer how the convolutions in ResNet18 can recognize dysgraphia, as shown in Figure 3, the convolutional block serves as an automatic feature extractor. The residual block helps reduce meaningless, abstract representations in images. The inference block determines the class prediction results. However, the trial results in Tables 4-5 show that forming new knowledge representations requires an in-depth understanding of the implications of research results. The Resnet18 method is highly data-dependent. In this study, the dysgraphia class comprises two levels of dysgraphia. Given the same data, different knowledge representations are likely to yield different evaluation matrices. In this dataset, the imbalanced data requires better treatment, such as data augmentation for multi-class classification. Hierarchical abstraction also needs to be taken into account. In this case, hierarchical abstraction is achieved through hyperparameter settings, such as the

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e-ISSN: 2549-2233 / p-ISSN: 2580-4952
DOI : https://doi.org/10.29407/gj.v10i1.27419

number of epochs. Different epochs yield different ResNet18 performance, thereby ensuring constructivism and consistency in knowledge building.
The research results have been presented from an axiological perspective. In response to the benefits of ResNet18 for dysgraphia classification using a scoring matrix, this study achieved high accuracy on ResNet18, reaching 93.55%. However, the accuracy, recall, and F1 score results were below 80%, indicating the need to optimize the proposed method for initial screening. However, accuracy, precision, and F1 scores below 80% reflect the limitations of the proposed method. This raises significant challenges, indicating that the model's confidence in its knowledge is limited.

CONCLUSION

Based on the results and discussion, this study concludes that ResNet18 learns representations using convolutional techniques to recognize dysgraphia automatically. Although ResNet18 achieved accuracy, precision, and F1 scores below 80% in binary dysgraphia classification, recall achieved the highest test score at 93.55%. This indicates that epistemologicallyand axiologically, ResNet18 has high sensitivity in binary dysgraphia classification.

SUGGESTIONS

Despite producing high recall in the binary class, the resulting precision remains low. The proposed model tends to be aggressive in the dysgraphia class, requiring more parameter tuning and deeper exploration of other CNN methods. Meanwhile, testing is limited to the binary class. In further research on multi-class classification, dysgraphia is often challenging to recognize due to data imbalance. Therefore, more in-depth preprocessing of the dataset, such as augmentation, is required.

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