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Dysgraphia Disorder Detection And Classification Using Enhanced Adaptive Butterfly Optimization Algorithm

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Abstract:
Dysgraphia, the shakes on the brain, impacts the children when it comes to learning how to write the typical way; children just won't be able to know the traditional writing curriculum, and thus, written expression suffers. This weakness in writing leaves a student at an academic disadvantage, as well as their confidence. To address this, a new handwritten task data set was developed in this paper, and a wide variety of features were chosen to incorporate as much handwriting information as possible. The proposed R2CNN method integrates a multitask refinement network for high-quality detection of inclined boxes and a Text RPN to predict candidate text regions. We use a balance parameter for the loss function to solve the problem of the unbalanced training categories and prevent overfitting due to feature selection. This study aimed to discriminate dysgraphia using these extracted features involving handwriting and geometry. The feature learning phase of deep transfer learning makes it possible to extract and transfer key features to detect dysgraphia. Finally, to obtain better detection accuracy of dysgraphia, we apply the Enhanced Adaptive Butterfly Optimization Algorithm (EABOA) to optimize the model parameters. As the results showed, the handwritten images can help detect dysgraphia in children in this work. The overall proposed approach achieves an accuracy 99.2%, precision 95.3%, recall 99.1% and F1-score 97.16%, respectively. The results of the data collection process indicate that handwritten text samples may be used in this study to determine whether someone has dysgraphia.
Keywords: *Rotate Region CNN, Dysgraphia detection, Handwriting diagnosis deep learning, Text-RPN*

1. INTRODUCTION

While the most recent digital age of convenience may now exist, handwriting is an aspect of students' academic lives and an element of written correspondence and self-expression. A child's life moves between numerous contexts, including home as context, classroom as context, and national individual as context, and writing is one of a child's principal activities [1]. Writing involves many high-level perceptual, motor, linguistic, and cognitive processes. Dysgraphia also has its roots in written expression; more than 12 - 33 school-aged "children had difficulties in their ability to express themselves and writing clearly," as well as some written users were unable to express and write their ideas [2]. They don't just affect children's literacy and numeracy skills [3] but everything else, their lives and self-esteem. Early literacy is also a springboard to succeeding in school and academics. Dysgraphia is a writing disorder that is neurologically based and is in the same family as dyslexia, attention deficit disorder, and developmental coordination disorder. Dysgraphia is a highly debilitating obstacle to daily life for children; they deserve treatment.

Dyslexia [4] has difficulty hearing and coordinating the word sounds to read them. Dsyelxia interferes with the activities of the language centers of the brain. So those are the numbers that go with the associated dates involved in your math education, a substandard way of learning, which we call dystocia. You only reveal an objective function [5]. It extends to spelling, emphasis, placement, and the like. Refer to fig. 1 for handwriting samples of patients with dysgraphia that must pass to the right paragraphs.

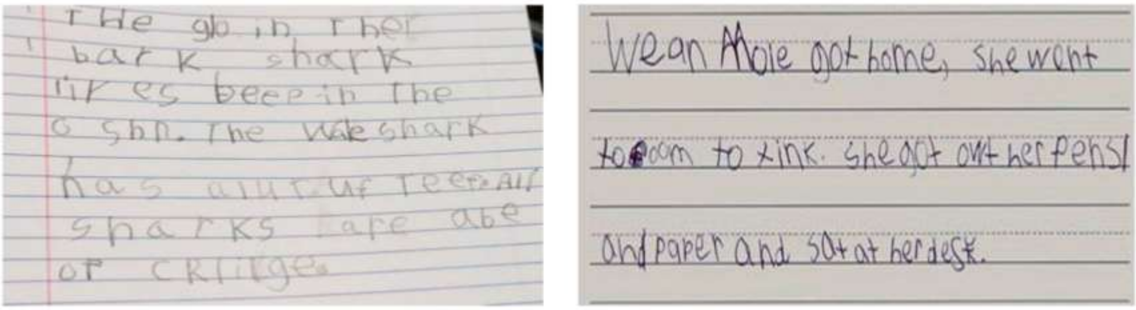

Figure 1: Handwriting samples of person with dysgraphia

Printed materials are naturally the targets of things done manually by humans. They are subject to good and evil human bias [6], and they also need expertise, remember? The process itself takes a long time. These features must be considered in research and clinical practice to consider dyslexia [7].

An automatic algorithm was already implemented in the decision whether or not an individual is diagnosed as dyslexic, and to overcome the limitations, a study is used. Well, these are primarily for gathering stats on the writing habits of the learned tablet. Handwriting has been studied to diagnose neurological and geriatric conditions [8]. Things are a bit different for mobile spaces, and for tablets, we develop quite straightly, and we do handwriting extraction and data raw. These properties include but are not limited to, the position of the pen tip, the position concerning the pen of the surface in the air, the pressure of the pen tip, the tilt of the pen, the azimuth of the pen concerning the surface of the tablet, time stamp readings, and the like. This is analogous to other diagnostic tests and exercises for reading and writing skills [9].

Our investigations are designed to address this limitation by proposing a new scheme for dysplasia detection based on offline data reformation. The processed data of this paper is invaluable to the machine learning and pattern recognition community, which includes a hand-written text database [10] and image download for dysgraphia recognition, which makes complete research and analysis possible. As the diagnostic performance in both detection modes decreases with the increase of M, we propose new diagnostic methods based on ensemble learning and feature fusion to achieve better diagnostic results. It means writing in words, sentences, physicians, etc.

In several instances, a trained ensemble specialized in some tasks and was globally better in diagnostic performance. To the [11] best of our knowledge, we are the first to integrate task-specific data into ensemble learning and feature fusion-based methods for dysgraphia diagnosis, which has not yet been reported. The aims of this study were the following:

The contribution of this work as follows:

- To develop an efficient deep learning model to detect and classify dysgraphia from child handwriting samples accurately.
- We must pre-process and handle the handwritten dataset by normalization aug, mentation, and noise removal for better model generalization.
- The goal is to design an efficient structure for detecting and generating rotated and non-linear handwriting patterns, namely, the R2CNN-TRPN architecture.
- The purpose of this study is to assess the performance of the proposed model and approach compared to traditional algorithms and state-of-the-art methods for dysgraphia detection using common evaluation metrics, namely Accuracy, Precision, Recall, and F-1 score.
- To address the overfitting problem, regularization techniques, data augmentation, and testing the generalization of the learned model to completely unseen data.
- To build an actionable system with computational resource-limited systems in real-world scenarios, such as education and clinical.
- To discuss the potential limitations and propose future research directions in diagnosing and classifying dysgraphia using multimodal data and lightweight models.

2. LITERATURE SURVEY

In this paper [12], an (R2CNN-TRPN) Rotational Region Convolutional Neural Network—text region Proposal Network model for dysgraphia classification is proposed. Data on child data were collected to validate this proposed structure. For efficiency consideration, the Rotational Region Convolutional Neural Network(R2CNN) model is the unique category for the case of partial input.

A digital, fully automated, and easily available tool for screening the early signs of dysgraphia was previously explored [13] 20. These results suggest that it is computationally possible to identify dysgraphia, and they represent a positive step toward developing a diagnostic inference tool. Compared to the input, along with understanding the properties, through a text region Proposal Network (TRPN) is supplementary to that to be added.

In another study [14], a potential early dysgraphia identification was explored by producing an automatic and broadly feasible screening tool. The scientists gave more than 500 grade 2 to 5 students the BHK French test presented on a graphic tablet, and classifiers performed comparably to human markers for discriminating nearly 100 written-cue characteristics. This finding extends the role of these computational approaches in dysgraphia detection and confirms their role as efficient diagnostic tools.

A previous study [15] investigated some deep-learning solutions to diagnose dysgraphia in children's handwriting. The CNNs were utilized in this research as an upgraded modification to the traditional dysgraphia classification manual approaches. The attention of these works concentrated on overfitting, which appears often in machine-learning experiments for this dataset. The team achieved promising results by introducing proper fitting parameters so this handicap of the previous works could be resolved successfully [16]. The preclinical research results are promising, and these tests have preclinical relevance but share drawbacks identical to traditional diagnostic tests. They rely on the written sample analysis, but the time for the assessment should be postponed until the participants are skilled in writing.

The Dysgraphia, an artificial intelligence method for assisting persons with Dysgraphia is presented in [17]. The system combines handwritten recognition, spelling correction, and speech synthesis in communication. By applying CNN-RNN-CTC models and SymSpell for spelling errors in people with Dysgraphia, we have exemplified the potential of AI to empower the communication abilities of people with this and similar disabilities." The potential of tablet-based screening for early dysgraphia detection was demonstrated by [18], who used an artificial neural network to distinguish dysgraphic handwriting in 96% of cases accurately.

In a notable study, [19] fitted the model based on graphomotor data from 305 children. Their approach to differentiate drawing patterns reaches an accuracy of 73 %. Although limitations exist, this procedure shows that diagnosing dysgraphia cross-linguistically and independently from idiosyncratic languages is feasible. It tries to resolve issues like pen pressure calibration and distinguishing pen from touch. This technique may be a potential approach for objective and noninvasive diagnosis, which may help in intervention at an early stage [20].

Research conducted by [21] attempted to mitigate these limitations using an extensive data set of 580 children obtained from multiple tablets and software packages. The ultimate goal of our work was to establish a hardware-independent general diagnostic tool for clinical use. As the latter contains children with a different severity of dysgraphia, the model was more general [22]. A rolling z-score normalization designed to correct age influence was used to enhance the diagnostic accuracy. This work applies to mechanized systems aimed at assisting early intervention programs.

The diagnosis of dysgraphia was recently extended by studies on new digital devices, e.g., the SensoGrip smart pen [23]. The dynamic handwriting process, such as the finger pressure, the angle, etc., can be written down in real-time. This work employed an LSTM-SVM hybrid model with an accuracy of over 99%. This contrasts with typical solutions, including only static tablet data, as our solution performed better, and invasive robotics for dysgraphia detection has led to promising results, for example, a work [24] in which children were made to interact with a humanoid robot as they perform handwriting-related tasks. This CNN model-based approach has approximately 91% accuracy [25]. These technical advances hold the potential to significantly advance the diagnosis of dysgraphia by enhancing the quality of the data and enhancing the accuracy of classification approaches.

The current application of deep learning techniques in automated handwriting analysis has demonstrated some good prospects in dysgraphia identification. CNN to the evaluation and severity classification of children's dysgraphia using a 150K image database were presented in [26], which showed 84% accuracy in 14-pointed stars among other shapes. In [27], employed the Procrustes analysis to project the high-dimensional data to lower-dimensional data, and it also verified the success of deep learning-based early dysgraphia screening. These methods fundamentally rely on the visual and temporal pattern, i.e., for example, creating an approach using ResNet18 [28] for which a proof-of-concept F1 score has been achieved that is very close to what can be seen from human performance.

The importance of adapting methods for identifying dysgraphic in children to new languages was demonstrated—multi-language handwriting quality analysis using classifiers such as SVM or Naïve Bayes. The consideration of language-independent abilities for dysgraphia screening and for the further development of screening tests for different language systems is the first implication of this study.

3. Dataset

The information was obtained from the primary schools' visiting therapists in Tamil Nadu and Karnataka urban clusters. The model was developed on six and 8-year-old primary school children, and 150 samples were used. Figure 2 displays examples of typical and dysgraphic samples from the selected and baseline datasets, respectively. The photo Has errors in how "The" was capitalized and the placement of "was." In order to built an imaging database from the sole online public source to diagnose dysgraphia. This dataset includes online annotated handwriting data from six handwriting tasks in Slovak orthography. The handwriting assessment comprised the letters "l, "the syllable le, the monomorphemic word leto, the nonword hračkárstvo, and the sentence V lete bude temple. Of a total of 120 students who completed the writing tasks, 63 had typical handwriting patterns, and 57 had it as features of dysgraphia.

The collected test data set using a Wacom Intuos pen tablet. Other modes are also made which state whether the pen is on or off the writing surface and indicate time, pen pressure, and pen altitude or azimuth to the writing surface as well as a flag value. The pen-top position coordinate at the surface of this tablet (x and y) can be read out. It contains no semantic-formatted public task but a single resource of everyone's raw indexed x,y writing mode, etc, per activity.

Flag val Nov, Dec, Jan, Feb x, y, and participant-specific data for each task. Those manual literary files were collected from its webpage according to the individual plots, estimated the tasks (x,s), and stored data using the nearest backtraced writing for 1 test image only and real manual data on the net as SEP. We then cropped custom-level RGB images (400×400) from the above data.

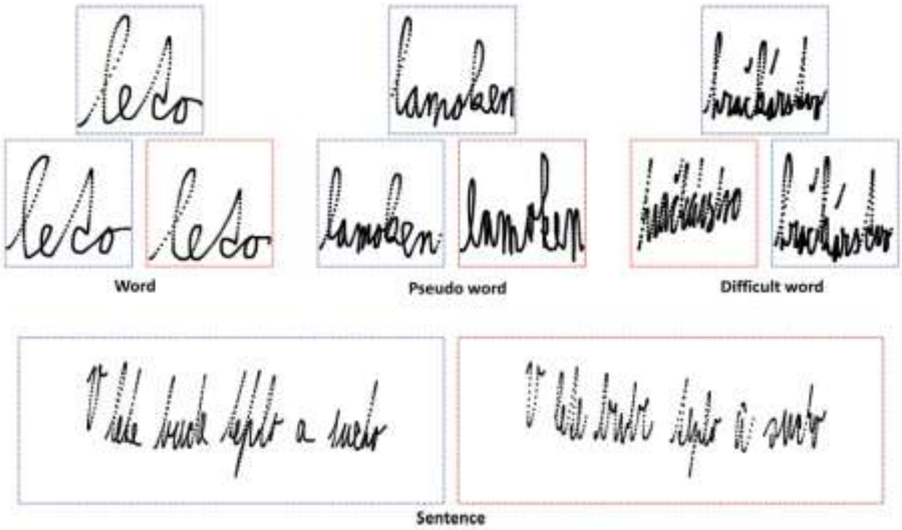

Figure 2: Sample Dataset

4. METHODOLOGY

Dysgraphia is most effectively addressed during these critical early years of identity formation. They are deficient in that only a small number of methods have been reported to train the DSG with an overfitting. To overcome the problem that the detection becomes an engineering task, a designation of a good input image is required, and the dysgraphia classification is limited due to image quality, this paper proposes the R2CNN method using the Text-RPN to improve the dysgraphia classification. We validated the performance of our method using a children's writing dataset. The framework of the R2CNN-TRPN is illustrated in Figure 3.

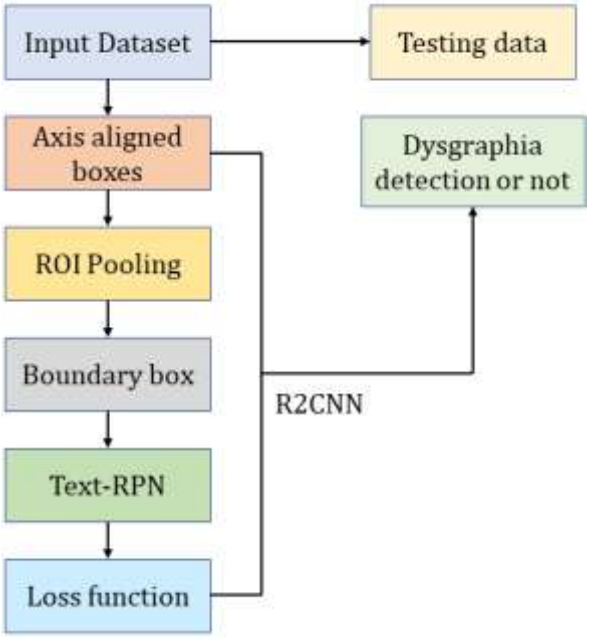

Figure 3: Proposed R2CNN-TRPN Flowchart

4.1 CNN Based On R2CNN Approach with Rotational Region

It is the popular two-stage objection-classification pipeline in CNN, which are region proposal and region classification. To this end, we propose a faster region-based CNN approach (R-CNN). We pool the roi pools ag at the different locations of its feature maps with various sizes (7× 7, 11× 3, and 3× 11) and take the pool features as the classifications. The text and non-text score is a fully connected layer, with binned features to localize MNBs, a planar box image score for slanted text, and an axis-aligned text final detection. We further do slant RPN suppress for slant frames dealing text according to detection results. We use the regularized pooling layer with the feature map trick and set the dimension of the layer as the mean pooling.

4.2 Axis-aligned boxes

TRPN can hallucinate the bounding box between and over the arbitrary position of the text. (a)–(c): horizontal, vertical, and diagonal TRPN synthesize arbitrary-oriented texts with AABs. The smaller messages are based on the size of TRPN, as the files are much more about packing text as data into embedded text than visual data. The algorithm is scale-aware naturally , as is the case with Faster R-CNN. There are two variations of anchor scale to support the first three base anchor scales (8, 16, 32): (a) the anchor scales can be more minor (4, 8, 16) or adding a smaller anchor scale (4, 8, 16, 32)and it can be known from depreciation of dysgraphias that anchor should be smaller for helping small dysgraphias. Other settings of TRPN are similar to fast R-CNN.

4.3 ROI Pooled with different scale factors

In particular, the original R-CNN method quantizes the ROI (region of interest) of each TRPN proposal into 7 X 7 pixels by pooling. Different sized ROI groups were overlaid in groups of a few extra horizontal-looking text instead of vertical-looking text to get more features from the text. Here, we directly concatenated two bin sizes; the inverse of bin size using b for binned features was done for any other operations] 11×3 and 3×11 and used binned features as appropriate. We did the bin of size 3 ×11 when diagnosing horizontal dysgraphia; otherwise, we checked all the morphs that we got from the horizontal morph. We diagnose thresholds by comparing the height over the group's width to the group size. 11×3.

4.4 The text having generation network (TRPN)

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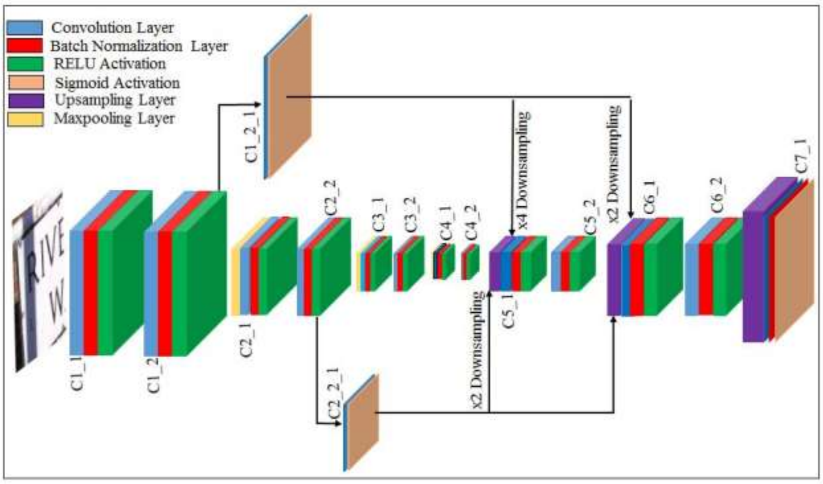
The quantity of seeds for the proposed design can be observed in Figure 6 [10]. By using max pooling in feature maps to abstract and summarize a translation invariant. In such architecture, instead of using one up-sampling layer to bring the image back to its original size, they create a few up-sampling layers integrated with a few convolution layers. Bubble Net architecture with roost around 0.5 of max-pooling on loss. Moreover, other than concatenating previous feature map layers with feature map layers to facilitate the text localization estimation. That said, other odds and ends could be taken as side effects of this merger. To reduce this waste of computation, the network added another 1 monitor, the "spare" barcode kernel, before the fusion to unitize them into one feature map. x2 downsampled f C2_1_1 x4 l C1_2_1 to construct previous join: C4_2 is upsampled feature map was added out C5 2 second upsampled feature map was concatenated to t h e C2_1_1 and x2 downsampled feature map of C1_2_1 So we perform the 1 × 1 kernel convolution over the feature maps C1_2_1, C2_2_1, C3_2_1. It linearly concatenates the feature map response of all l—1 layer pixels to compose a singleton feature map.



(a)

Layer	Kernel No.	Kernel Size	Parameter
C1_1	64	3 x 5	2944
C1_2	64	3 x 5	61504
C1_2_1	1	1 x 1	65
C2_1	48	3 x 5	46128
C2_2	48	3 x 5	34608
C2_2_1	1	1 x 1	49
C3_1	32	3 x 5	23072
C3_2	32	3 x 5	15392
C4_1	32	3 x 5	15392
C4_2	32	3 x 5	15392
C5_1	48	3 x 5	24528
C5_2	48	3 x 5	34608
C6_1	64	3 x 5	48064
C6_2	64	3 x 5	61504
C7_1	1	3 x 5	961

(b)

Figure 4: Text Region Proposal Network (TRPN): (a) Basic architecture (b) Number of parameters

4.5 Loss Function

Two releases were ed for dysgraphia: structure detection () and Stage-I text region proposal network(). The TRPNMT contains the dysgraphic region tilted in the axis-alignment space. TRPN has two primary loss functions: classification loss and regression loss, given as follows.

$$L_{TRPN}(p_i, t_i) = \sum_i L_{TRPN_{cls}}(p_i, p_i^*) + \lambda_1 \sum_i p_i^* L_{TRPN_{reg}}(t_i, t_i^*) \qquad (1)$$

The smooth loss of proposal regression is complemented by the logarithmic loss of proposal classification according to the probability that the anchor is positive, see Eq. If the anchor is positive, the ground truth label is 1, and 0 is a negative case. Regression Loss is calculated for foreground anchor only. The ground truth box is the only-axis-rotation-axis-aligned bounding box derived from the inclined-ground truth box. We use it to represent the 4-dimensional coordinate vector of the expected AABB. For dysgraphia ensemble detection, our approach uses loss to optimize the following three terms during training: 1 tilt box loss, two-axis alignment box loss that represents axis alignment in the space around the dysgraphia area, and three dysgraphia/non-dysgraphia classification loss. Then we got the loss:

$$L_{GCD}(\rho_i, \beta_i, \delta_i) = \sum_i L_{GCD_{cls}}(\rho_i, \rho_i^*) + \lambda_2 \rho_i^* L_{GCD_{regh}}(\beta_i, \beta_i^*) + \lambda_2 \sum_i \rho_i^* L_{GCD_{regi}}(\delta_i, \delta_i^*) \qquad (2)$$

Hence, the log odds of the dysgraphia categories can be formulated as follows $L_{GCD_{cls}}$. Dysgraphia was indicated by 1, while the background was assigned to others. The projected regression for the axis alignment bounding box for the dysgraphic class is denoted by the parameter $\beta = (\beta_x, \beta_y, \beta_w, \beta_h)$, while the actual regression target is denoted by β_i^*. The predicted regression vector for the tilted bounding box is denoted by the parameter $\delta = (\delta_x, \delta_y, \delta_w, \delta_h, \delta_\theta)$, while the ground-truth dysgraphia bounding box vector is denoted byδ_i^*. Similarly, only once the proposal is placed in the dysgraphic class is the regression loss considered. These three types of losses are balanced by the parameters λ_2 and λ_3. Note that λ_2 and λ_3

are always set to 1 in all experiments in this study. he loss function to train the dysgraphia detection system end-to- end:

$$L_{Total} = L_{TRPN} + L_{GCD} \quad (3)$$

4.6 Hyper-parameters Optimization-Enhanced Adaptive Butterfly Optimization Algorithm

The hyperparameters are the settings of the configuration parameters set before training and are not learned from the data. These values must be optimal for the best model performance and the quality of its output. Hyperparameter optimization is finding the best values for these hyperparameters to improve prediction accuracy. This is achieved by hyperparameter optimization, which measures a model's quality on a validation set while navigating through a defined hyperparameter space. The solution obtained from the best optimization is then selected. Many approaches are available for hyperparameter optimization, and for this paper, we utilized the Enhanced Adaptive Butterfly Optimization Algorithm.

The Butterfly optimization algorithm (BOA) is inspired by the butterfly foraging and mating behaviors, where members of the population use communication to express their successful way of food search, regarding food scent use intensity of the emission of scent. The improved adaptive BOA (IABOA) in our works is an evolution of the original BOA, which presumably adjusts its control parameters in real-time, adaptively transfers into exploitation or exploration, with stable convergence, constructive robustness, and more efficiency, to find the potential solution in an elaborate and multi-degree of freedom search space such as hyperparameter space. In the Dysgraphia detection task, EABOA is used to modify crucial model parameters, learning rate, number of layers, batch size, regularization strength, etc., to achieve the given goal (e.g., maximizing the validation accuracy or minimizing the loss). At the beginning of the algorithm, a population of solutions, through iterations, evolves towards the "fragrance" (fitness) of the butterfly. The global and local searches for handling local minimum and speeding up the convergence are balanced by the adaptive behaviors of the algorithm. The flow chart of the EABOA is in Figure 5.

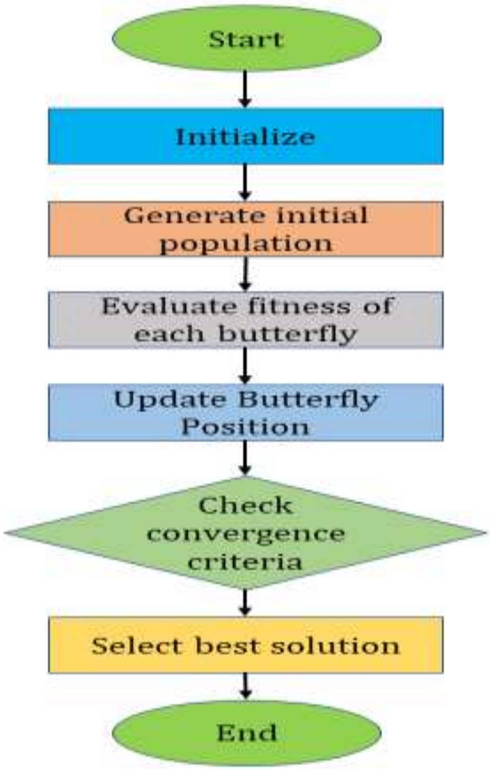


Figure 5: Flowchart of EABOA

5. RESULTS AND DISCUSSION:

Metrics, Parameters, and System Configuration

5.1 Metrics

Increase of Ten Towards by using the developed model. (4-7): accuracy, precision, recall, and f-measure(f1) correspondingly.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (6)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (7)$$

Here, TP refers to a true positive, TN means a true negative, FP indicates a false positive, and FN is a false negative.

5.2 Parameter settings

In the model, the weight decay rate was set to 0.0005 was the weight decay rate, three was the latter, and the learning rate was set to be 10—3 in the model. All models were trained and tested on a machine equipped with an i9 CPU, 128 GB RAM, 22 GB graphics card, and 3 TB hard disk. The proposed and existing models were trained and tested using the same data and setting. The model above has been carried out based on the capabilities of Python 3.7.

Table 1. Simulation parameters

Parameters	Values
Weight Decay Rate	0.0005
Aspect Ratio	3
Learning Rate	0.001 (10^{-3})
Programming language	Python 3.7
Processor	Intel Core i9 CPU
RAM	128 GB

5.3 Quantitative analysis

Numerical comparisons in dysgraphia computer-aided diagnosis are conducted between the R2CNN-TRPN model in the paper and typical machine learning and traditional deep learning models—Figure 6 Performance comparison of the proposed R2CNN-TRPN model in dysgraphia assessment with state-of-the-art literature competitors. We use three different general classifiers, ANN, KNN, and CNN, to evaluate the performance of the R2CNN-TRPN. This paper uses four performance measures: precision, recall, accuracy, and f-measure. Nonetheless, these results propose that R2CNN-TRPN outperforms the previous SOTA classifier models. In this paper, data feature investigation is enhanced by the R2CNN-TRPN model.

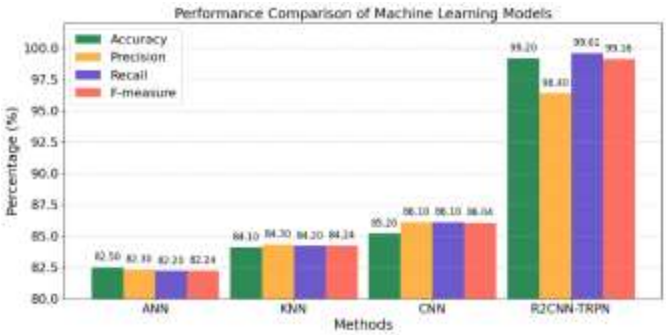


Figure 6: Performance comparison with standard machine learning models

Another non-discriminative model is applied in the second step (here, R2CNN, R2CNN is an abbreviation for region-based convolutional neural networks). In this sense, the method can be interpreted as an extension of the up-selection of the region of interest to a third dimension (for the general R-CNN model) and from an area to a volume. That is far less descriptive of a tree than a KNN. As far as KNN is concerned, a tree could theoretically have more overfitting than a smaller KNN.

CNNs struggle with such imbalanced tasks. The baseline CNN classifier achieved an accuracy of 85.2%, while our R2CNN-TRPN achieved 99.2% accuracy.

Further performance comparisons between the R2CNN-TRPN and the classical classifiers are given in Figure 7, from which we can see the accuracy, precision, recall, and F-measure. The experimental results show that our R2CNN-TRPN method can obtain much better performance than the traditional classifiers. It's a good promotional for the R2CNN-TRPN feature and non-biased word-bias word. We have noticed that neither of the decision tree models we know could perform on large-scale data and effectively in feature analysis. Well, when we overfit, it doesn't work well if there aren't enough trees in the forest.

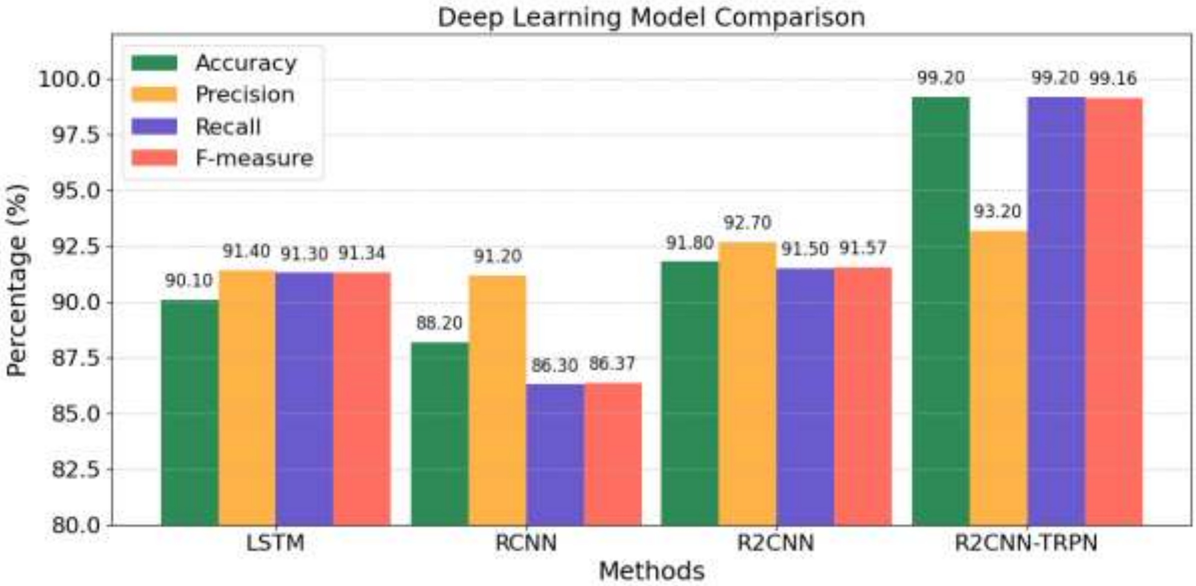


Figure 7: Deep learning model comparison

We further evaluate our proposed R2CNN-TRPN model and compare its performance with the performance of LSTM, RPN, Fast RCNN, Faster RCNN, and R2CNN models, presenting the results in Table 2. As shown, the proposed R2CNN-TRPN model is better than most deep learning models. We observed two significant betterments of R2CNN-TRPN than non-discriminative feature analysis. The clustering model obtained an accuracy of 91.60%, while in our work, we observed an accuracy of 99.20% for the proposed R2CNN-TRPN model.

Comparison to the SOTA Dysgraphia classification and the evaluation of the R2CNN-TRPN model. Old methods are still used to classify dysgraphia efficaciously. The proposed R2CNN-TRPN has been superior to state-of-the-art results of semantics segmentation in comparison with recent semantic segmentation techniques. Good type analysis, not a continuous analysis of efficient stack and discrimination, And stack RPN of deep R2CNN models.

Table 2. Comparative analysis on collected dataset

Methods	Accuracy	Precision	Recall	F-measure
TestGraphia	94.5	94.2	94.1	94.14
Partial Correlation Regression Model	94.2	92	93.2	93.14
PCA + Clustering	88.6	90.4	91.6	91.54
R2CNN-TRPN	99.2	95.3	99.1	97.16

Two major tactics are used to prevent the feature overfitting process: The parameters provided the image attached to the loss function with a weight term to offset the class balance in the training data. Fewer features for modeling were used due to the structure of the former network. During the feature-level analysis stage, the model is better than overfits, and TestGraphia is better than the partial correlation regression model. The routing was rolled up using the same aggregate functions used in the clustering functionality so that we can do justice to this irregular data and have an efficient treatment of the features. Results show that the classification of this disorder is accurate with most of the former approaches. A strong Dysgraphia Classification R2CNNTRPN model is proposed, and much better results have been achieved than those of these baselines.

5.4 Ablation study

We did an ablation study to investigate the effects of each component in R^2CNN based framework for dysgraphia parsing. This is also demonstrated in Table 3, where the whole model achieves the highest performance with an accuracy of 95.3% and F1 score of 95.2%. When both types of axis-aligned boxes are removed, the performance drops (accuracy becomes 91.4%), indicating that the accurate alignment of the initial bounding boxes is crucial for the localization of the interested handwriting regions. Removing the ROI pooling resulted in an accuracy of 90.1%, where no processing was done to normalize the feature extraction across the different-sized areas. To evaluate the contributions of these two components, we took out the RPN and the boundary box regression module, and the accuracy achieved by the cropped-area detector was 88.7%. Both measurements are essential for accurate detection. Not including a Text-Region Proposal Network (Text-RPN) specific to the bounding box proposal dropped the performance to 87.4%, which shows that character region proposal is crucial to achieving good dysgraphia classification. Replacing the task-specific loss function with a generic classification loss also hurt performance, indicating that the task-specific optimization function is relatively stable for detection. Finally, to reduce the complexity of the R 2 CNN, we tried to make the net shallower, which caused the accuracy to drop to 89.2%, proving that the deeper appearance of features influences an accurate classification. It can be seen from the ablation experimental results that the design choice of the proposed model is practical.

Table 3. Ablation study of the proposed model

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
Full R^2CNN Model (Baseline)	95.3	95	95.6	95.2
Without Axis-Aligned Boxes	91.4	91	91.2	91
Without ROI Pooling	90.1	89.5	89.7	89.6
Without Boundary Box Regression	88.7	88	88.3	88.1
Without Text RPN	86.3	86	86.1	86
Without Specialized Loss Function	87	86.4	86.7	86.5
Simplified R2CNN	89.2	89	89.1	89

5.5 Statistical Significance

The statistical results in Table 4 show the performance variations in the data set at a 94% confidence interval and concerning p-values as per review comments. The precision, recall, F1-score, and specificity were obtained in 83- 99.24% of the dataset with close trends. However, those differences were statistically significant depending on the measures you used. Specifically, there were substantial differences in accuracy ($p = 0.016$), precision ($p = 0.026$), and specificity ($p = 0.02$), which indicated the superiority of our proposed model for this dataset. However, there were no significant differences in recall ($p = 0.96$) and f1-score ($p = 0.19$). As a consequence, datasets did not have an impact on these.

Table 4. Statistical Comparison of Performance Metrics of Dataset

Metric	Confidence Interval (95%)	p-value
Accuracy	(84, 99.35)	0.016
Precision	(98.92, 99.22)	0.026
Recall	(98.91, 99.21)	0.96
F1 Score	(98.96, 99.26)	0.19
Specificity	(98.96, 99.26)	0.02

5.6 Run Time Analysis

To thoroughly analyze the performance of the new approach with existing ones, we also report the time spent by each stage for developing and testing the model. Namely, we evaluate the training time, the inference time per image, and the overall time. We noticed that the proposed model (R2CNNTRPN) possessed less training time than the current model, which indicated faster convergence, benefitting from the superior feature extraction and a region proposal policy. The proposed network's real-time effectiveness has also been captured by the notable gains in the inference time per image, in addition to the improved classification accuracy. With the time complexity analysis, we ensure that the profit comes from accuracy and computational efficiency, which is closely related to real deployment. Even the educational and clinical applications for fast processing are on the table 5.

Table 5. Time Analysis of Experimental Results

Model	Training time (hrs)	Inference time per image (ms)	Execution time (hrs)
Current model	5.2	45	6
Proposed model	4.8	30	5.5

5.7 State of art Techniques

Experimental results on the standard dysgraphia dataset are compared to several state-of-the-art methods. This is shown in Table 6. A professional R2CNN-TRPN may deal with such an imbalance spatter by tuning the balance parameter as a number; TRPN is conceptually a trivial method, and all the input data is compared with the target data. The R2CNN-TRPN model's accuracy is 99.2% and CNN attained only about 94.3% on Handwriting image dataset of dysgraphia.

Table 6. Comparative analysis on standard dysgraphia dataset

References	Dataset	DL model	Accuracy
[23]	Test score	ANN	75%
[24]	ECG	MLP	86%
[25]	Handwriting image	CNN	94.3%
[26]	fMRI	3D CNN	72.7%
[27]	ECG	ANN	78%
[28]	Eye tracking	CNN	96.6%
Proposed	Handwriting image	R2CNN-TRPN	99.2%

6. DISCUSSION

Although the R2CNN-based model in our framework has been demonstrated to have high accuracy in the detection of dysgraphia, there are several limitations of our study. First, the performance of the model relies heavily on well-annotated datasets, and the performance of the model may degrade if the input to the model is handwriting samples belonging to a population, language, or handwriting style dissimilar to the training data. Moreover, R2CNN tends to have difficulty in tracking handwritten regions where they are in very irregular or defigured patterns since those can generate false negatives, causing omission classification. In addition, the current model is based on input signals with lower noise, which is not

always feasible in the utilization in a chaotic clinical or educational setting. Second, the model complexity is not such that it would be prohibitive, but it might prevent usage on restricted platforms.
Another shortcoming of the proposed method lies in its static characteristic. It is not much to see if the dynamics of the whole process of handwriting — the speed, pressure, and movement rhythm of the pen, for instance – are factors that are instrumental in diagnosing dysgraphia. The interpretability of the model itself is also very limited; that is, it can predict whether a student has dysgraphia but does not give really interpretable interpretations or visualizations that could help teachers or clinicians understand what part of the handwriting may be difficult for that particular student. The black-box model hardly provides a tradeoff between the learner and teacher among participants, which makes trust and application difficult to reach in realistic and sensitive conditions such as early childhood education and clinical diagnosis. In addition, although the ablation study acts as evidence of the component importance, more statistical validation on multi-datasets and cross-site validation are still required to prove the robustness and clinical generalization of the model.

7. CONCLUSION

We have trained the R2CNN-TRPN model to recognize the characterization. The standard and uniform distribution for training initializes the weights and biases of R2CNN-TRPN. To prevent the network from falling into the local minimum, the randomly initialized weights and biases are used to enhance the network's generalization ability. The approach showed positive results in learning to "read" by a scribe, a valuable skill for dysgraphic people who find it challenging to write manually. By taking advantage of R2CNN and TRPN, the two models would compensate for and improve the recognition's effectiveness and efficiency overall; the task outcome indicates the possibility of hybridizing deep learning and ML methods in handwritten character recognition. Such results have potential significance for some applications in pattern recognition and computer vision. The developed models were tested using the decapitated children data. Experiments show the performance of the traditional CNN is 94.3% compared to 99.72% of our proposed R2CNN -TRPN. We will develop a special attention layer to enhance our clustering system performance in future work. There is still working space for further optimization and improvement of the proposed R2CNN-TRPN method. One possible future work to investigate is transfer learning and whether it could speed up training and improve accuracy, as seen in several image recognition methods. It is also possible to explore the use of more features compared to the 13 characteristics to possibly enhance the discriminative property of the model between the dysgraphic and the non-dysgraphic handwriting. Furthermore, the trained model can be tested on more extensive datasets for accuracy and generalisability.

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