Dysgraphia Detection in Children: Two Deep Learning Models Utilizing Handwritten Text Images

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ABSTRACT

Dysgraphia is a disorder that affects children's ability to write legibly and can impact overall written expression, spelling, and composition skills. Traditionally, dysgraphia is assessed through various tests that measure working memory, cognitive ability, and orthographic processing. These assessments are time-consuming and may require significant effort and resources to administer. This study presents two novel frameworks based on Deep Learning (DL) architectures, such as Spatially Enhanced SegNet (SE-SegNet) and Self-Attention U-Net (SAU-Net), to identify children with dysgraphia using handwritten text images based on gender. The proposed frameworks were trained and tested on a collected dataset, comprising 1,853 text images, and their performance was evaluated using accuracy, recall, precision, and the Mathew Correlation Coefficient (MCC). According to performance analysis, the SAU-Net framework was superior, achieving maximum accuracy at 99%, recall at 99.1%, precision at 98.5%, and MCC at 98.3%. The proposed approach provides an efficient and accurate method for identifying dysgraphia in children, supporting early detection for effective interventions and improving children's academic progress.

Keywords-dysgraphia; handwritten text images; optimized method; SE-SegNet; SAU-Net

I. INTRODUCTION

Dysgraphia refers to a writing disorder characterized by difficulties in handwriting, storing written words (orthographic coding), and coordinating finger movements for writing (finger sequencing) [1], often co-occurring with issues such as speech impediment, Attention Deficit and Hyperactivity Disorder (ADHD), and difficulties with motor development [2]. An individual suffering from dysgraphia may noticeably distort or make mistakes in his/her written expression. According to [3, 4], approximately one in five people may have difficulties in writing, which may also affect their spelling ability.

In India, the incidence of dyslexia in primary school children has been 2-18% of dyslexia, 14% of dysgraphia, and 5.5% of dyscalculia [5]. SLD incidence was 15.17% in sampled children, while dysgraphia, dyslexia, and dyscalculia affected 12.5%, 11.2%, and 10.5% of the population, respectively [6]. From these statistics, it can be inferred that it is necessary to identify dysgraphia in school-going children. The only solution to the problem of dysgraphia in children is to provide early intervention and remediation, depending on the severity of the problem [7].

Traditionally, children with dysgraphia problems are assessed through visual interpretation, which can only be performed by a psychologist and is time-consuming [8]. In later years, various methods, such as mobile application- [9-11], tablet- [12-16], and web/tool-based [17-22], have been suggested for dysgraphia identification. From these suggested studies/methods, it is inferred that all of them utilized either Machine Learning (ML) or Deep Learning (DL) techniques for the identification and classification of dysgraphia problems. In addition, these studies considered using either a paper-and-pen-based method or a digital tablet-based method for the data collection process. In addition, related works considered only accuracy and sensitivity/recall as evaluation parameters, with some of them achieving low-performance results.

Research frameworks based on Spatial Enhanced (SE)-SegNet [23-26] and Spatial Attention (SA)U-Net [27-30] have been used for various purposes. In this study, these DL architectures are customized for effective identification and classification of dysgraphia. The primary goals of this study were to distinguish children with dysgraphia through the analysis of handwritten text images, with a particular focus on gender. This involves the implementation of various dysgraphia identification frameworks utilizing DL architectures, including SE-SegNet and SAU-Net, to facilitate the identification of dysgraphia problems in children. The performance of each DL architecture was carefully assessed using various evaluation metrics. Furthermore, this study aimed to discern the most effective frameworks through thorough comparisons among the proposed DL architectures. With these objectives, this study sought to advance our understanding and methodologies for identifying and addressing dysgraphia in children, ultimately contributing to improving the diagnosis and intervention strategies for this condition.

II. PROPOSED METHOD

Since dysgraphia is a lifelong problem, timely diagnosis and identification in children are crucial. Children with dysgraphia problems are identified by the proposed DL-based frameworks using handwritten text images of the children, performing semantic segmentation and classification. Figure 1 illustrates the proposed method.

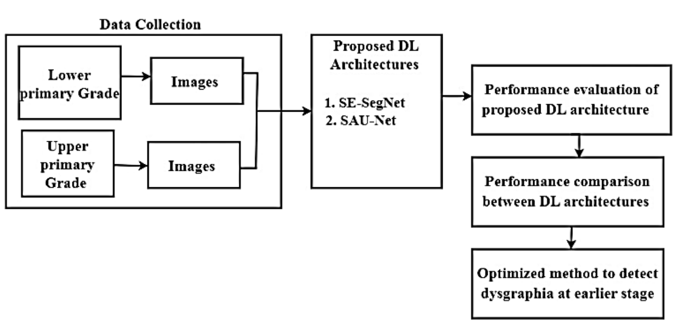

Fig. 1. Proposed method.

A. Data Collection

For survey data collection, children from grades IV to VII were considered. Parents or legal guardians of the students were informed about the survey, and only those whose parents or guardians gave permission were included in the research survey. Templates were prepared based on the guidelines according to their grade level. During sample collection, children were encouraged to sit in a different room instead of a classroom. A paper-and-pencil-based method was adopted for collecting the handwritten images. Writing size, appropriate space between the letters, total time taken to complete the survey, letters on the line, and amount of pressure applied were considered as selected features. In total, 2197 samples were collected from children in private and public schools.

B. Inclusion and Exclusion Criteria

The 2197 samples collected were assessed by experienced professionals. Of these samples, professionals identified 570 samples from children suspected of having dysgraphia problems. In addition, 27 samples from children with hand impairments or physical incapacity to write were excluded. This left the dataset with 2170 samples. Among these, 317 samples were further excluded due to writing mistakes and long pauses. Consequently, only 1853 samples were ultimately considered for data analysis purposes.

C. Proposed SE-SegNet Architecture-Based Framework

SE-SegNet is a customized Convolutional Neural Network (CNN) specifically developed for semantic segmentation at the level of individual pixels. Figure 2 shows the proposed SE-SegNet architecture-based framework.

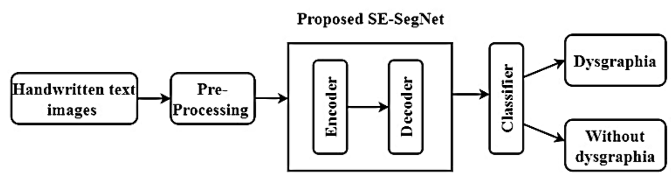

Fig. 2. The proposed framework using the SE-SegNet architecture.

Initially, handwritten text images underwent a preprocessing step called Z-score normalization. This method ensures that the pixel values of the input image are uniformly distributed across the entire image, with a zero mean and unit variance. The images were then resized to a fixed size of 256×256 using bilinear interpolation, which computes the weighted average of the four nearest pixel values in the input image to determine the pixel value in the resized image. The preprocessed samples served as input to the SE-SegNet model, consisting of encoder and decoder sections integrated with a spatial attention mechanism. Figure 3 shows the layered architecture of the proposed framework.

The encoder has 13 convolutional 2D layers with 3×3 filters, Rectified Linear Unit (ReLU) activation, batch normalization, and five 2D max-pooling layers, with a filter size and stride of 2×2. The preprocessed dataset was input to the first convolutional layer, and the ReLU activation function was used element-wise. ReLU introduces non-linearity to the model for learning complex patterns. After ReLU, batch normalization was performed on the feature maps to stabilize and accelerate the training process. The spatial attention mechanism was then applied to focus on significant spatial regions.

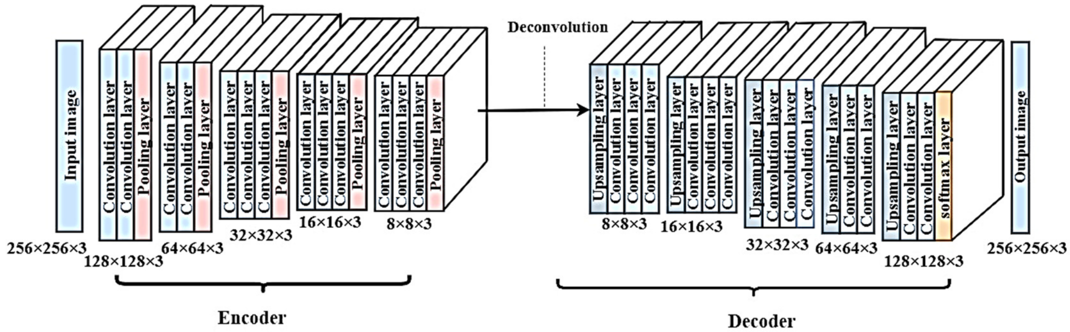

Fig. 3. Layered architecture of the proposed SE-SegNet.

After the first pooling layer, the image size reduces to 128×128. Likewise, the process is repeated. After the fifth pooling layer, 512 feature maps of size 8×8×3 are obtained at the highest layer, provided as input to the decoder. The decoder section comprises 13 convolutional 2D-transpose layers, 5 upsampling 2D layers with filter size 3×3, batch normalization, and ReLu. In the 13th convolutional layer, two feature maps with a size of 256×256×3 result as output to ensure that each pixel corresponds to two output values. Each output value represents the predicted probability of a category after applying softmax, which performs classification on a pixel-by-pixel binary basis. A Random Forest (RF) classifier is trained using these feature vectors as input, returning a class label as output.

```
SE Algorithm
Input: X: Input feature maps with
  dimensions H×W×C, where H=height,
  W=width, and C=number of channels.
class SpatialAttentionMechanism:
  def __init__(self):
    # Initialize attention mechanism

  def calculate_attention_weights(self,X):
    # Calculate attention weights using
    # the attention mechanism
    # F = A(X)
    # Where A has the same spatial
    # dimensions as X (H×W) and each value
    # in A represents the attention weight
    # for the corresponding location in X
    A = self.attention_function(X)
    return A

  def attention_function(self, X):
    # Define the operation of the
    # attention mechanism F = A(X)
    # This can be a trainable network or
    # a predefined function
    return A

  def weighted_sum_operation(self, X, A):
    # Multiply original feature maps X
    # element-wise by attention weights A
    # Y = X ⊙ A
    Y = X * A
    return Y

  def updated_feature_maps_and_output
    (self, Y):
    # Pass the weighted sum Y to
    # subsequent layers of the network
    # Z = SubsequentLayers(Y)
    Z = self.subsequent_layers(Y)
    return Z

  def subsequent_layers(self, Y):
    # Define subsequent layers of the
    # network
    return Z
```

D. *SAU-Net-based Framework*

Figure 4 illustrates the proposed framework based on SAU-Net. Initially, the collected handwritten images underwent pre-processing using Z-score normalization, followed by the bilinear interpolation method to resize the image to a fixed size of 256×256. After preprocessing, the images were provided as input to the architecture. The SAU-Net architecture comprises an encoder and a decoder arranged in a U-shaped configuration. It has ten convolutional 2D layers with filter size 3×3, ReLu, and four max-pooling 2D layers whose size and stride are 2×2 and 2, respectively. Including an attention mechanism in the SAU-Net architecture, as seen in Figure 4, allows the proposed framework to selectively focus on certain features of the input image that are more relevant for identifying dysgraphia problems in children.

The fixed image size of 256×256 is provided to the first convolutional layer. The convolutional layer typically uses 3×3 filters and generates feature maps. The output of the convolutional layer undergoes a process in which each element is subjected to the ReLU function, defined as $f(x)=max(0, x)$. Then batch normalization is performed on the feature maps to stabilize and accelerate the training process. Before proceeding to the next convolutional layer, an SA mechanism is applied. Once the SA vectors are computed, achieving translation invariance involves employing a max-pooling operation. This process facilitates effectively accommodating small spatial shifts. After performing max-pooling, the image size is reduced from 256×256 to 128×128. This process is repeated up to the fifth convolution block. Finally, the decoder receives an image size of 16×16 with an increased number of feature maps. The decoder consists of a sequence of layers, including four 2D transpose convolutional layers with a filter size of 3×3, eight 2D convolutional layers with ReLU activation, and one 2D convolutional layer with a filter size of 1×1. The combination of 2D-transpose and standard 2D convolutional layers facilitates upsampling in the SAU-Net architecture. The decoder concludes with a softmax layer for pixel-wise classification. The proposed framework segments images into feature vectors to train an RF classifier to assign corresponding class labels. Once trained, the RF classifier can classify new segmented images by computing the feature vector for each pixel and predicting the class label.

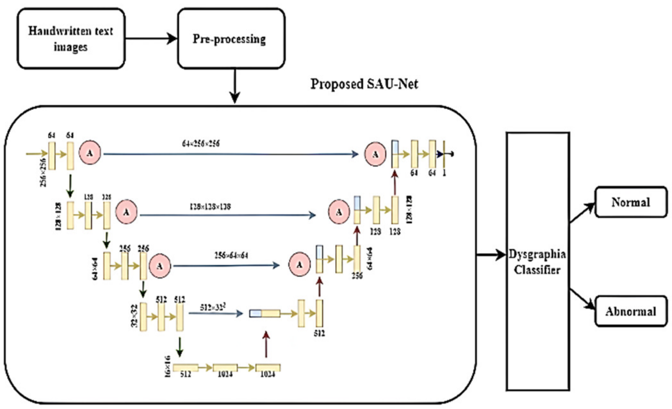

Fig. 4. The proposed framework using the SAU-Net architecture.

```
class AttentionMechanism:
  def __init__(self, d):
    self.d = d
    self.W_q = np.random.randn(d, d)
    self.W_k = np.random.randn(d, d)
    self.W_v = np.random.randn(d, d)

  def linear_transformation(self, X):
    # Transform input feature maps X to
    # obtain Query (Q), Key (K), and Value
    # (V) vectors
    Q = np.dot(X, self.W_q)
    K = np.dot(X, self.W_k)
    V = np.dot(X, self.W_v)
    return Q, K, V

  def attention_score_calculation(self,
    Q, K):
    # Calculate attention scores by
    # multiplying each pair of current
    # input Q vectors with K vectors of
    # other inputs
    attention_scores = np.dot(Q, K.T)
    return attention_scores

  def attention_score_scaling(self,
    attention_scores):
    # Scale attention scores to prevent
    # vanishing gradients
    scaled_attention_scores =
      attention_scores / np.sqrt(self.d)
    return scaled_attention_scores

  def softmax_function(self,
    scaled_attention_scores):
    # Pass scaled attention scores through
    # softmax function to obtain attention
    # weights
    attention_weights=
      np.exp(scaled_attention_scores)/
      np.sum(np.exp(
      scaled_attention_scores), axis=1,
      keepdims=True)
     return attention_weights

  def weighted_sum_calculation(self,
    attention_weights, V):
    # Compute weighted sum of value
    # vectors V
    weighted_sum =
    np.dot(attention_weights, V)
    return weighted_sum
```

(a)

(b)

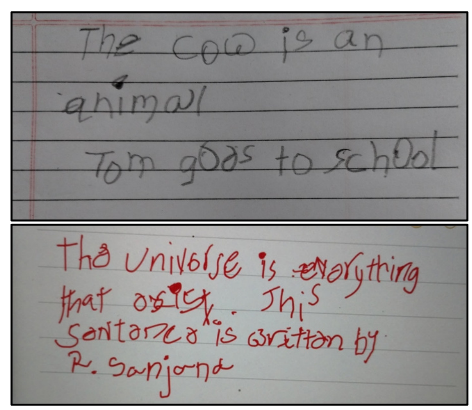

Fig. 5. Handwriting samples of (a) Grade III student with dysgraphia and (b) Grade VI student with dysgraphia.

III. EXPERIMENTS

The proposed frameworks employing SE-SegNet and SAU-Net architectures aim to identify dysgraphia problems in children by tests on collected handwritten text images. These frameworks analyze handwriting samples, as shown in Figure 5, revealing the distinguishable features that suggest the presence of dysgraphia.

A. *Training and Testing Stages*

Of the 1853 collected images, 70% (1,112 images) were used to train the models. The Adam optimizer was used to optimize the performance of the SE-SegNet and SAU-Net frameworks. Various combinations of batch sizes, learning rates, and momentum were explored through grid search and trial-and-error experimentation. Based on the performance evaluation, the parameters were set to 16, 0.001, and 0.8, respectively. The remaining 30% (741) images were considered for testing purposes. Each test image was downsized to 256×256 pixels before the testing process.

B. Evaluation Metrics

The performance of the proposed DL architectures was evaluated using accuracy, recall, precision, and MCC.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100\% \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (3)$$

$$MCC = \frac{(TP \times TN)-(FP \times FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \times 100\% \quad (4)$$

where True Positives (TP) refer to images that are correctly classified as dysgraphia, True Negatives (TN) are images correctly classified as without dysgraphia, False Positives (FP) are images incorrectly classified as dysgraphia but labeled as without dysgraphia, and False Negatives (FN) are images incorrectly classified as without dysgraphia but labeled as dysgraphia.

IV. RESULTS AND DISCUSSION

Table I displays the performance of the DL architectures for the identification of dysgraphia in an earlier stage, using 5-fold cross-validation. The results show that the proposed SAU-Net achieved a maximum accuracy of 99% for grade VI students, whereas SE-SegNet achieved only 91%. Similarly, for recall, precision, and MCC analysis, SAU-Net achieved 99.1%, 98.5%, and 98.3%, respectively, whereas SE-SegNet achieved only 89.6%, 91%, and 92% for the same students. Figures 6-9 display the qualitative results visually.

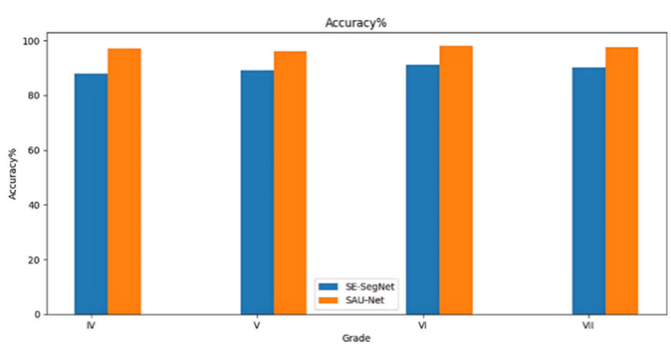

Fig. 6. Accuracy analysis of SE-SegNet vs SAU-Net.

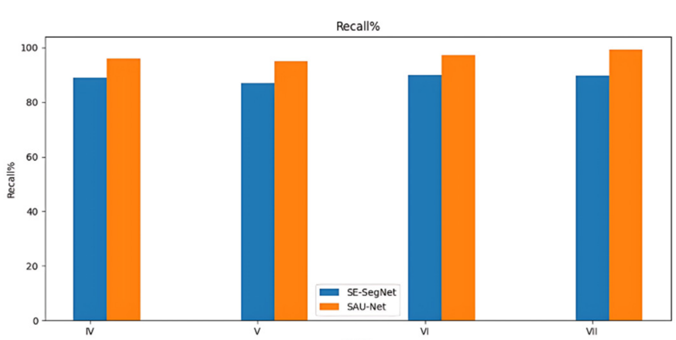

Fig. 7. Recall analysis of SE-SegNet vs SAU-Net.

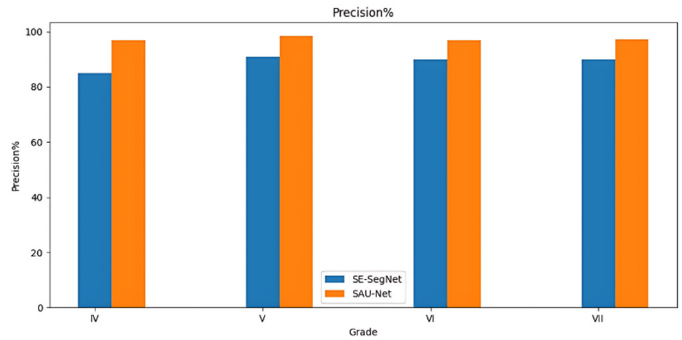

Fig. 8. Precision analysis of SE-SegNet vs SAU-Net.

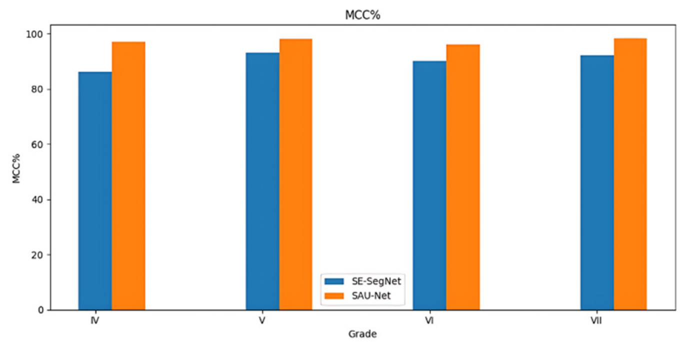

Fig. 9. MCC analysis of SE-SegNet vs SAU-Net.

TABLE I. PERFORMANCE ANALYSIS OF DL BASED FRAMEWORKS USING HANDWRITTEN TEXT IMAGES

	SE-SegNet				**SAU-Net**			
Grade	**IV**	**V**	**VI**	**VII**	**IV**	**V**	**VI**	**VII**
Accuracy	88%	89%	91%	90%	97%	96%	99%	90%
Recall	89%	87%	90%	89.6%	96%	95%	97.2%	99.1%
Precision	85%	91%	89%	87%	97%	98.5%	97%	97.1%
MCC	86%	93%	90%	92%	97%	98%	96%	98.3%

SAU-Net demonstrated superior performance in analyzing students' handwritten text images. To ensure a more precise comparison of the models' results, each model was trained for 200 epochs. If the loss of the DL model did not consistently decrease over three consecutive epochs, the learning rate was automatically halved to enhance the model's fit. Figure 10. displays both models' accuracy and loss curves generated using the cross-entropy loss function.

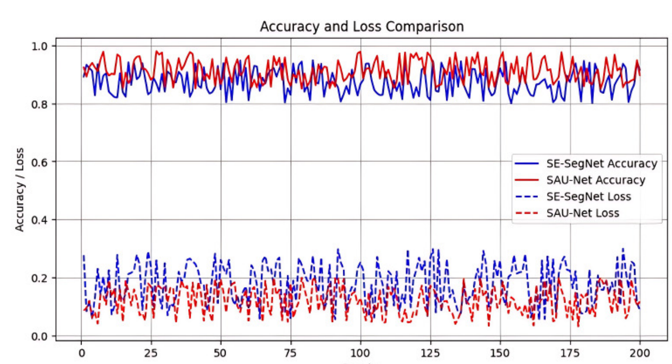

Fig. 10. Accuracy and loss comparison of the proposed DL architectures.

The results demonstrate that SE-SegNet exhibited higher losses during the training process than SAU-Net. The flexibility and resilience of the proposed DL-based frameworks are enhanced when the loss value is smaller, and the drop in the loss curve is quicker and smoother.

V. CONCLUSION

This study used two different DL architectures, namely SE-SegNet and SAU-Net, to identify dysgraphia in children based on handwritten text images. The integration of spatial enhancement and spatial attention mechanisms into SegNet and U-Net architectures is specifically tailored for handwritten analysis, a direction that has received limited exploration in existing literature. The proposed frameworks were assessed both qualitatively and quantitatively. The experimental results indicate that the proposed frameworks showed superior performance than previous studies. In particular, SAU-Net achieved a maximum accuracy of 99%, and recall, precision, and MCC rates of 99.1%, 98.5%, and 98.3%, respectively, outperforming SE-SegNet. These findings facilitate the early identification of dysgraphia problems in children. The proposed findings could assist psychologists, support staff, teachers, and parents in identifying children with dysgraphia problems at an earlier stage.

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