Handwriting Analysis AI-based System for Assisting People with Dysgraphia

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Abstract. Dysgraphia is a learning disability of written expression, which affects the ability to write, mainly handwriting and coherence. Several studies have proposed approaches for assisting dysgraphic people based on AI algorithms. However, existing aids for dysgraphia take only one aspect of the problem faced by the patients into consideration. Indeed, while some provide writing assistance, others address spelling or grammatical problems.

In this paper, a novel system for helping people suffering from dysgraphia is proposed. Our system tackles several problems, such as spelling mistakes, grammatical mistakes and poor handwriting quality. Further, a text-to-speech functionality is added to improve the results.

The proposed system combines a plethora of solutions into a valuable approach for efficient handwriting correction: handwritten text recognition using a CNN-RNN-CTC model, a spelling correction model based on the SymSpell and Phoneme models, and a grammar correction using the GECToR model. Three machine learning models are proposed. The experimental results are compared based on the values of Character error rate, Word error rate, and the workflow of three handwritten text recognition models, and has led to an improvement of the quality of the results.

Keywords: Dysgraphia · handwritten text recognition · Artificial Intelligence · spelling correction · text correction.

1 Introduction

In today's fast-paced world, many activities, such as school activities, bureaucratic procedures, etc., are difficult for people with learning disabilities such as dysgraphia. Dysgraphia is a learning disability that impairs a person's ability to write correctly. It can interfere with effective interaction between educators and students or colleagues, such as written communication via email, chat, or online courses. Some children cannot produce good writing, even with appropriate instructions and practice in writing. Tasks such as spelling, which rely primarily

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on hearing, can be difficult for people with dysgraphia. This is because a person with dysgraphia often makes phonemic errors in written text. Some students have problems with the sound of the word, while others may be bothered by the visual aspect. With respect to grammar, sentence structure and adherence to grammatical rules may be a problem. Difficulties may arise when trying to understand how words can be used together to form meaningful and complete sentences. In addition to poor handwriting, spelling and grammatical errors are common for people with dysgraphia.

There are mainly three ways to treat dysgraphia: the corrective approaches, the bypass approaches, and finally, the prevention methods [12]. The corrective approaches are appropriate when a physical remedy is needed. Mobile apps and graphic tablets are great tools for solving problems related to spelling and poor handwriting. Several works propose systems to help dysgraphic people based on artificial intelligence. However, the existing approaches only take into account one aspect of the problem encountered by the patients. Some of the existing approaches propose a writing aid, and others tackle spelling or grammar problems. The application of handwriting processing has been more widespread in the analysis of dysgraphic writing [2]. Some handy devices help with handwriting problems, but do not provide any help with spelling or grammar. Similarly, tools that provide spelling or grammar assistance do not focus on addressing poor handwriting. The need for a well-integrated system with multiple modules addressing a separate issue was observed.

In this article, we present an approach to help people with dysgraphia. Our motivation is to help dysgraphic people to improve their writing and communication skills, by building an automatic handwriting correction system. The originality of this work consists in defining an approach allowing to analyze and correct the poor handwriting, spelling mistakes and incorrect grammar of dysgraphic people. The proposed system would potentially help dysgraphic persons in their daily life, for example by improving the efficiency of communication with the teacher, using it to convert assignments and tests into legible and understandable text, taking notes in class and correcting them for better learning, communicating through letters and writing texts and messages. To achieve this, we have studied and implemented different solutions designed to work together for handwritten text recognition, spelling and grammar error correction, and text-to-speech conversion. Each solution is implemented on the basis of a well-known state-of-the-art solution. The novelty of our proposal lies in its ability to process the input handwritten text image to produce an output in a correct and usable format.

The remaining of this paper is organized as follows. In section 2, we discuss and analyze the relatd works, along with our motivations and objectives. Section 3 describes the proposed system and details its components. Section 4 concentrates on the experimental evaluation. Section 5 concludes and proposes directions for future research works.

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2 Literature Review

We discuss in the literature review different existing solutions for handwritten text recognition and text correction. By analyzing the existing solutions, we define the requirements that our system should cover. Then a deeper dive is taken into the existing literature on the approaches that can be implemented by our system for assisting people with dysgraphia.

Dysgraphia is generally related to Development Coordination Disorder (DCD), dyslexia, or attention deficit disorder [17]. All three conditions are Neurodevelopmental disorder, which is characterized as handwriting learning disability [10]. Handwriting generally involves a person's motor skills, perceptual and linguistics [16]. Usually, learning to handwrite proficiently requires 15 years, starting from the early age of 5 to 15 years. DCD is considered a lack of psychomotor development in children and adults. The inception of the disorder appears even before the child enters the school. Parents, friends, or teachers can realize the clinical expression and warning signs of DCD that something is not right in the child's activity. Children range 5 to 10 years show different means and have difficulties in performing simple talk like painting, eating with crockery, etc. DCD in adults may affect them differently, as their less mobility, lower visio-motor skill, and poor handwriting.

The detection of dysgraphia is crucial as early diagnosis allows children to perform well at home and school and allows parents to adapt to the environment according to the needs of the child [14]. The handwriting struggles can only be resolved through intervention and rehabilitation later [8]. The diagnosis of DCD is generally made using the Diagnosis and Statistical Manual (DSM-5) criteria. Smit-Eng et al. [23] presented various recommendations based on cut-off scores, which classify severity ranging from moderate to critical. The authors also advised diagnosis based on motor function, neurological disorder, intellectual deficit, and DSM score. Pediatricians and therapists use various tools and tests to assess. Initially, pediatricians carry out a differential diagnosis to rule out secondary development motor disorder then a therapist uses an assessment test to establish the effectiveness of the proposed care package. These tests generally use movement assessment batteries for children ranging from 3 to 10 years of age [7]. Finally, an intellectual deficit in a child is assessed using a psychometric test. The test and methods used by clinicians and therapists for neuro disorder mentioned establish a standard for diagnosis; however, like DCD, dysgraphia lacks any established tests and tools for assessment.

Reisman [21], in 1993, represented an evaluation scale for handwriting for children in European countries. The score achieved by children is used to evaluate legibility and speed; however, the test alone is not sufficient to establish the condition and sometimes requires clinical assessment. [5] proposed a detailed assessment of the speed of handwriting (DASH) for older kids. Rehabilitation of dysgraphia represents various difficulties due to the diverse origin of the disorder. In the new age, digitizers and pen tablets opt represent a promising tools to overcome the challenges of rehabilitation. As children suffering from writing disorder tend to avoid writing, tablets have the advantage of modifying the

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writer's willingness due to their liking of new technologies. Danna and Velay [9] presented the idea of providing auditory feedback to increase the sensory information of the written text. The existing test does not consider handwriting dynamics, tilt, and pressure on the pen while analyzing [19]. Thibault et al. [3] presented an automated diagnosis using a tablet that, compared to existing methods, is faster, cheaper, and does not suffer from human bias. Zolna et al. [27] presented the idea of improving the automated diagnosis of dysgraphia based on the recurrent Neural Network Model (RNN).

Various mobile applications provide interactive interfaces for improving motor skills. A mobile application designed by Mohd et al. [1] called DysgraphiCoach was built to help improve one's writing and motor skills. Khan et al. presented an augmented reality-based assistive solution called the AR-based dysgraphia assistance writing environment (AR-DAWE) model. It uses the Google Cloud Speech-to-text API. A popular solution for writing aid is a smart pen as a bypass approach. Boyle and Joyce [6] successfully described how smartpens can be used to support the note-taking skills of students with learning disabilities. Avishka et al. [4] proposed a mobile application, THE CURE, that attempts to detect the severity level of dysgraphia and dyslexia in its users. An interactive interface offers the user a place to practice reading and writing. Quenneville [20] mentioned various tools that help those with learning disabilities, like word predictors and auditory feedback. While the former deals with predicting the complete word as the user is typing each letter, the latter reinforces the writing process.

The approach presented by Scheidl et al. [11] used a popular machine learning tool in python known as TensorFlow to achieve accurate handwriting recognition. Another approach is using the Sequence-2-Sequence learning technique described by Sutskever et al. [24]. Sequence-2-Sequence Learning model uses neural networks and is a Deep Learning model. Toutanova et al. [25] described a spelling correction algorithm based on pronunciation. The proposed system uses the Brill and Moore noisy channel spelling correction model as an error model for letter strings. Another spelling correction model used nested RNN and pseudo-training data [13]. [11] used word beam search for decoding, enabling the model to constrain words in the dictionary.

Each presented approach considers only one aspect of the problems faced by dysgraphic persons. To the best of our knowledge, there does not exist such an approach that processes handwritten text images written by patients, to produce an output in a correct and usable format.

3 Handwriting Analysis AI-based System for Dysgraphic Person's Aid

Our system aims to help persons suffering from dysgraphia by analyzing their handwritten text, correcting spelling and grammatical errors, and converting corrected text into audio. To this purpose, we have designed a system composed of four main processes, each of which serves an intrinsic purpose and is integrated

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one after another. A process is proposed to achieve the required functionality. Said processes are as follows:

i. Handwritten text recognition
ii. Spelling correction
iii. Grammar correction
iv. Text-to-speech conversion

The above steps consider the various problems observed in dysgraphic handwritten texts and make modifications to provide corrected information. The processed information is then displayed to the user and can be converted into an audio file using text-to-speech conversion. The flowchart given in Figure 1 describes how the proposed system works.

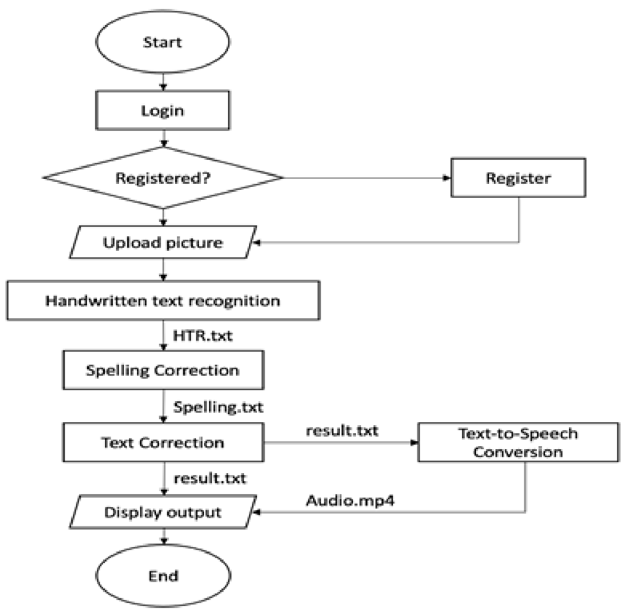

Fig. 1. The Flowchart of the Proposed System.

3.1 Handwritten Text Detection

This process comprises two steps, each for input image pre-processing and recognizing handwritten text. An input image typically will be a scanned copy of handwritten sentences that will be converted into a list of words and then given to the trained handwritten text recognition model. The basic functioning of this model is built on the works of Zhou et al. [26] is carried out by classifying each

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pixel in the input image as either an inner part/surrounding word, or a background one. Feature extractor used for this part of the project is ResNet18, and a U-shape architecture is used. The ResNet18 generates a feature map of size 14×14 by processing an image of size 448×448. Finally, the output of the neural network's size is 224×224. To establish relationships between two bounding boxes classified as inner parts, the concept of Jaccard distance is used. Subsequently a distance matrix that contains the Jaccard distance values for all pixel pairs is created. Using this matrix, clustering is performed using the DBSCAN algorithm. After the processing by neural networks and clustering, we get a list of coordinates of each word. Minimum value of 'x', maximum value of 'x', minimum value of 'y', and maximum value of 'y' are stored (cf. Figure 2). Using these coordinate values, the words are cropped and arranged in the correct order as provided in the input image.

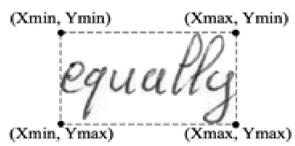

Fig. 2. Coordinates of the word.

The y-axis values are used to sort words by line appearance and x-axis values are used to sort words by their occurrence in the line. This is done by first calculating a range of pixel values that correspond to the lines in the input image. The list of coordinates for each word is iterated over and then sorted into the different segments or ranges present in the page that signify the line that the words are a part of. The maximum value of range of each line can be calculated by multiplying the calculated range of pixel values and the number of the line currently being assessed. A buffer is defined to accommodate words that extend from the default range of each line. This is followed by the application of the bubble sort algorithm on the x-axis coordinates to sort the words and correctly place them. Figure 3 presents an example of the segmentation of a handwritten text.

3.2 Handwritten text recognition model

The neural network structure contains 5 layers of CNN, followed by 2 layers of RNN, and finally, a Connectionist Temporal Classification layer or CTC. The last layer, CTC, is used to compute the loss value once the processing is done by the layers of CNN and RNN. Figure 4 describes the flow of the model. The time stamp in LSTM is referred to as a feature considered for designing the model.

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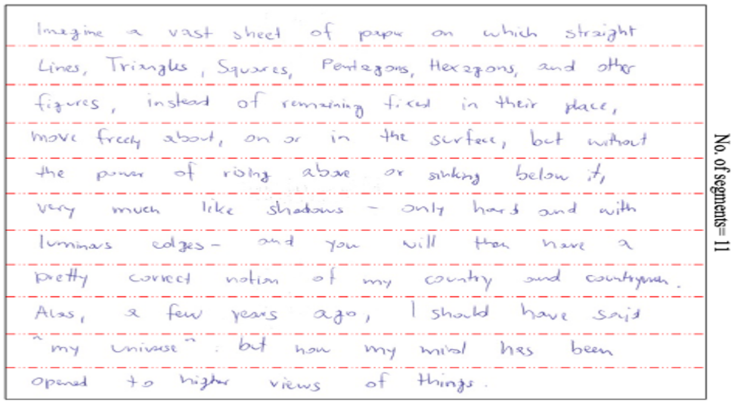

Fig. 3. Segments of Page.

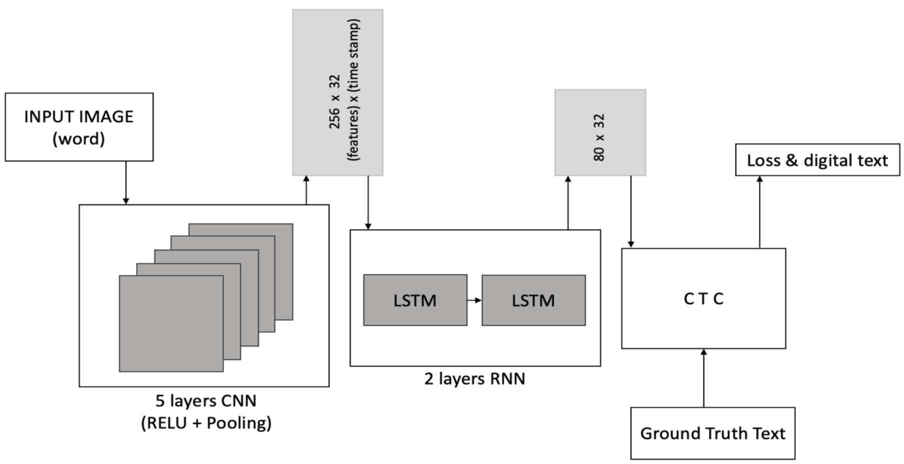

Fig. 4. Handwritten text recognition model diagram.

The 5 layers of CNN in the model are each trained to extract the important features found in the input image. For the first two layers, during the convolutional operation, 5×5 sized kernel filter is applied, this is different from the 3×3 sized filter applied in the consequent 3 layers (Table 1). Next, application of the RELU function is done. RELU function can be described as:

$$R(Z) = \begin{cases} z, z > 0 \\ 0, z \leq 0 \end{cases} \tag{1}$$

Pooling layer downsizing in each layer is done by 2. Consequently, feature maps of size 32×256 are added. Long short-term memory or LSTM takes 32×256

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feature map as input and produces a 32×80 sized matrix. The value 80 signifies the number of characters found in the dataset, i.e., 79, and one additional blank one for CTC. The CTC layer takes the 32×80 sized matrix output by the RNN layers and computes the loss value by comparing it against the ground truth text values provided alongside the dataset. It gives the recognized word that is stored, and spelling correction is performed.

Table 1. CNN layers.

CNN Layer 1	CNN Layer 2	CNN Layer 3
5x5 filter kernel RELU function Pooling layer (downsizing-2)	5x5 filter kernel RELU function Pooling layer (downsizing-2)	3x3 filter kernel RELU function Pooling layer (downsizing-2)

3.3 Spelling Correction

Implementation of the spelling correction process is done using the concepts from SymSpell and Phoneme models. The SymSpell model uses a Symmetric Delete spelling correction algorithm. The aim of this algorithm is to reduce the complexity of generation of edit candidates and the lookup in the dictionary for a given Damerau-Levenshtein distance [22]. The Phoneme model uses a Soundex algorithm which is an algorithm that indexes a name based on the sound of it. The steps for encoding a word using it are as follows:

- The first letter of the name is kept, and all the other occurrences of vowels, h, y and w are dropped
- The consonants after the first letter are replaced with the following
  - b, p, f, v with 1
  - g, k, j, c, s, q, z, x with 2
  - t, d with 3
  - l with 4
  - n, m with 5
  - r with 6
- If two or more adjacent letters have the same number, the first letter is retained. Letters with the same name that are separated by h, y or w, are coded as a single letter, and coded twice if separated by a vowel.
- If there are less than three numbers as the word is too short, 0s are appended until there are three numbers.

Here, we have initially subjected three to four letter words for correction. Later more complex scenarios like simple sentences such as “that is a bag”, "this

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is a cat" are used. The dataset had many examples from above mentioned cases that were checked for analysis.

After the recognized handwritten text is spell corrected, it is processed to correct common grammatical mistakes.

3.4 Grammar Correction

For the process of correcting the grammar, the GEC tagging concept is implemented iteratively [18]. GEC sequence tagger made with a Transformer encoder that was pre-trained on a synthetic dataset and then fine-tuned. At each iteration the tags created by the GECToR model are processed to perform correction. This procedure is carried out until there are no further changes required. The base of this operation is set using a pre-trained encoder called RoBERTa.

3.5 Text-to-Speech conversion

Text-to-speech conversion is performed to add the functionality of converting the processed text into audio format. This is done by using the Google Text to Speech API or TTS API. The extension of the output file is .mp3. This functionality provides the ability to allow the user of the system to choose the way he would prefer to receive the information; hence, text-to-speech offers learning benefits to all students, but especially to those with learning disabilities.

4 Experimental Evaluation

This section presents our experiments to show the effectiveness of our system to correct handwritten text including spelling and grammatical errors. We first present the datasets explored and used in the integrated system, then we present and discuss the results achieved by our proposal.

4.1 The dataset

A vast database is required to develop a handwritten text recognition model to identify the basic features of handwritten text. In order to effectively evaluate our model, we have used the IAM dataset [15] and a self-created dataset built based on the observation of children with learning disabilities.

The IAM Handwriting Database was initially created for offline handwritten text recognition. It contains over 1500 pages of English text containing around 5600 sentences. The IAM Dataset was used to train the handwritten text recognition model to recognize the peculiar dysgraphic handwriting.

To collect handwritten images for children with learning disabilities and to build a real dataset for our experimental evaluations, we have approached the Shree Learning Centre, Sector 45, Noida, India. This center is a special learning school for children of all age groups who face difficulties due to learning disabilities and other disorders. Students here showed great enthusiasm for participating

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in the creation of the dataset. The age group of students varied from 5 to 12 years. The sample group size was approximately 40 students. Each student was given blank sheets and was asked to copy some sentences from their English textbooks. Required permissions from parents were collected for the usage of data for experimental purposes only.

The final collected dataset contains simple sentences using three to four letter words, usage of vowels and sight words. It has more than 100K words along with a text file containing the path to each image along with its ground truth text. The images of words are cropped precisely, and the contrast is significant.

In our work, the IAM dataset was used for the learning phase and the self-created dataset was used for the evaluation of the proposed model.

4.2 Results and Discussion

One of the first processes includes word segmentation which is performed on the input image. Figure 5 visually represents the words found in a handwritten document using bounding boxes during the process of word segmentation.

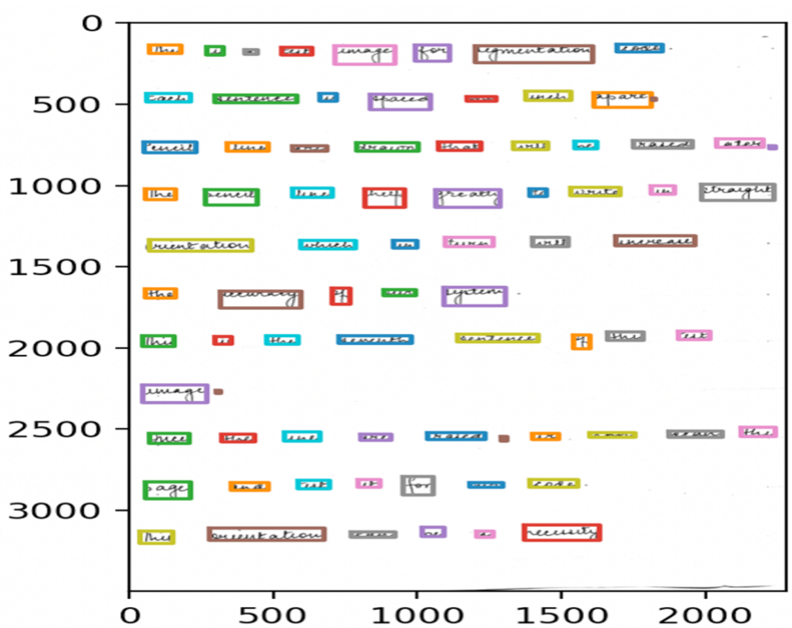

Fig. 5. Word Segmentation- Neural Networks.

To recognize the segmented words, the CNN-RNN-CTC model is trained on the merged IAM dataset and self-created dataset. Regarding the performance, the model is successfully trained as the process runs till 84 epochs, where the

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lowest character error rate is found at epoch 59. Lowest observed character error rate was 10.2% and the word error rate was noted to be 25% (cf. Figure 6). The model classifies text whether it is written by a dyslexic pupil or not. Later grammar correction is done for the text written by dyslexic pupils using GECToR model. Figure 6 signifies the location of these metrics on the character error rate vs epoch plot and the word accuracy vs epoch plot. Similar plots were made for a CNN-RNN-CTC model that consisted of 7 layers of CNN instead of 5. Comparison of the two shows that the model used has a lower character error rate and word error rate than the one with 7 layers of CNN.

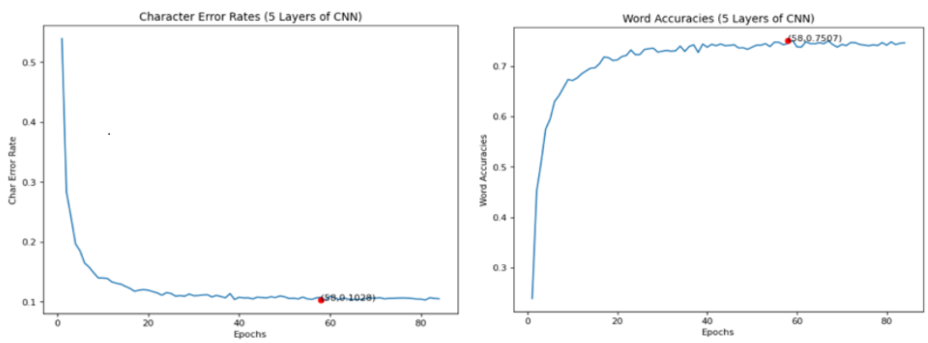

Fig. 6. Training Plots for 5 Layers of CNN.

Sequence-2-Sequence approach for handwritten text recognition was also explored and comparisons were drawn between the model used, 7 layers CNN-RNN-CTC model, and the Sequence-2-Sequence model (cf. Figure 7). Table 2 represents the values of Character error rate, Word error rate, and the workflow of three handwritten text recognition models, Neural Networks, Sequence-2-Sequence and a 7 layers CNN. We can see that the character error rate for the Sequence-2-Sequence model is 12.62% and its word error rate is 26.65%. In comparison to this, the model used has a character error rate of 10% and word accuracy of 25%. The third model in the table is the altered version of the selected model.

Spelling correction and grammar correction modules were observed to mostly make the expected corrections. Grammar correction module yielded a confidence bias of 0.2 which had a significant improvement on the recognized text given out by the handwritten text recognition module. Table 3, shows scenarios where the input images are sentences with significantly poor handwriting, grammar mistakes, or both. The columns, Handwritten Text Recognition, Spelling Correction and Grammar Correction, in the table specify the different outputs given out by the three modules composing our system.

It can be observed that due to the presence of the spelling correction module, the anomalies like inverted letters are being corrected in the first scenario and

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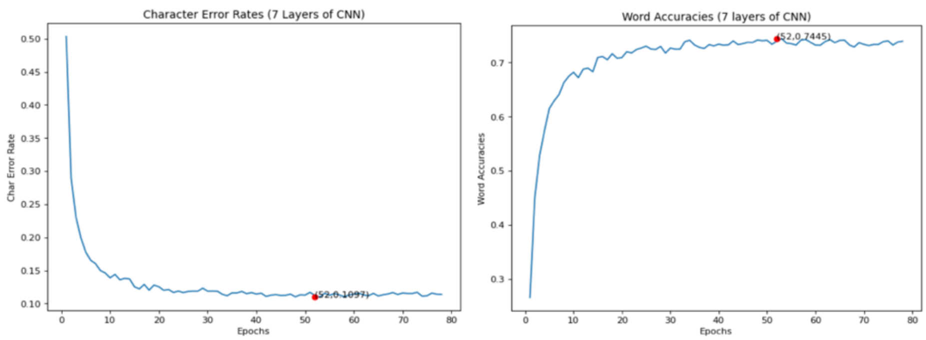

Fig. 7. Training Plots for 7 Layers of CNN.

Table 2. Comparison of Handwritten Text Recognition Models.

Model	Neural Networks	Sequence-2-Sequence with keras	Neural Networks (7 layers CNN)
Character error rate (CER)	10.2%	12.62%	10.9%
Word error rate (WER)	25%	26.65%	25.6%
Workflow	CNN (5 layers) RNN (2 layers of LSTM) CTC decode	RNN layer (as encoder) Another RNN layer (as decoder)	CNN (7 layers) RNN (2 layers of LSTM) CTC decode

Table 3. Comparison of Handwritten Text Recognition Models.

n°	Input Image	Expected output	Handwritten Text Recognition	Spelling Correction	Grammar Correction
1		The bottle is yellow.	The . dottle . . . us a . yelow .	The . bottle . . . us a . yellow .	The bottle is yellow.
2		They have learned a story	Thay have leroad a story	They have lead a story	They have lead a story.
3		German people are hardworking	German pepl awe handworking	German people awe handwriting	German people are hardworking.

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the output is similar to the expected output. Output for the second is observed to be different from the expected output due to incorrect word recognition by the handwritten text recognition module, as consequence, the word 'lernd' is not converted to 'learned'. In the third scenario, the grammar correction module can be observed to be responsible for making the text resemble the expected output by correcting 'handwriting' to 'hardworking'.

5 Conclusion

Existing approaches for assisting dysgraphic persons include, generally, only one aspect of the problem faced by the patients into consideration, writing assistance, spelling or grammatical problems. In this work, a novel system for assisting persons suffering from dysgraphia, that addresses several aspects facing these persons is presented.

The proposal allows recognizing handwritten dysgraphia text, processes it and converts it into corrected digital text. The proposal consists of four main processes, namely, handwritten text recognition, spelling correction, grammar correction, and text-to-speech conversion. The integration of these processes provides a solution that accommodates more than one issue, like poor handwriting skills, poor spelling, and grammar skills. It can prove to be beneficial to educators, parents, colleagues, and guardians.

The experimental evaluations showed that our proposed system works well as an integrated system to correct poor handwritten text.

In our work in progress, we are considering the evolutions' monitoring of dysgraphic persons that are subjects to medical treatment or using our system. This would allow the evaluation of the improvement made by dysgraphic persons based on intelligent systems.

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