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Dysgraphia detection based on convolutional neural networks and child-robot interaction

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ABSTRACT

Dysgraphia is a disorder of expression with the writing of letters, words, and numbers. Dysgraphia is one of the learning disabilities attributed to the educational sector, which has a strong impact on the academic, motor, and emotional aspects of the individual. The purpose of this study is to identify dysgraphia in children by creating an engaging robot-mediated activity, to collect a new dataset of Latin digits written exclusively by children aged 6 to 12 years. An interactive scenario that explains and demonstrates the steps involved in handwriting digits is created using the verbal and non-verbal behaviors of the social humanoid robot Nao. Therefore, we have collected a dataset that contains 11,347 characters written by 174 participants with and without dysgraphia. And through the advent of deep learning technologies and their success in various fields, we have developed an approach based on these methods. The proposed approach was tested on the generated database. We performed a classification with a convolutional neural network (CNN) to identify dysgraphia in children. The results show that the performance of our model is promising, reaching an accuracy of 91%.

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1. INTRODUCTION

Learning disabilities are a major problem for many students who suffer from them [1]. They face real challenges that are not limited to academic aspects, but also extend to behavioral and social aspects [2]. Recent studies in the field of learning disabilities have confirmed that the percentage of children with learning disabilities is continually increasing [3], which obliges the researchers to concentrate their research in this area to conceive methods of detection and early diagnosis, also develop appropriate programs of treatment to decrease and attenuate the severity of the student's difficulty of learning and raise them to the level of ordinary students [2], [4].

Among the difficulties encountered by the students during their first steps in school is difficulty with handwriting. However, the handwriting process constitutes an important competence and a fundamental starting point in the learning process, rather, it is the common denominator between learning other academic subjects such as reading, writing, and arithmetic [5]. It is the basis of teaching, learning, logical reasoning, and solid observation [6]. The ability to write is the result of both mental and physical development related to the capacity to adapt and transmit signals between the nervous system and the motor systems of the body (muscles) [7]. The inability to write is the main contributor to school failure [8], and this is where the danger lies, insofar as the problem of dysgraphia is a hidden difficulty that affects a part of normal children, which leads them to some psychological troubles [9].

Research highlights the crucial relevance of identifying and remedying these writing challenges as soon as feasible [7], because it can affect the whole life cycle of the student, damaging their academic achievement and self-esteem in a variety of educational activities [10]. Motor competencies affect the severity of dysgraphia and contribute principally to the development of dysgraphia in the earliest stages of a child's development [11]. A common assessment defined as the brief evaluation scale for children's handwriting (BHK) serves to identify writing difficulties. It represents the reference test for assessing the quality and speed of children's handwriting. This detection, conducted by therapists, is time-consuming due to its high cost and subjectivity. Therefore, several researchers have attempted to find solutions and numerical approaches to identify and characterize handwriting difficulties [12]. Similarly, the development of writing skills requires regular practice and a profound learning process. Given the significance of time in the processes of teaching and learning, the acquisition and accurate treatment of the redaction abilities require the intervention of mechanisms that ensure time and permit constructive communication, breaking the frontiers of the students' fear and timidity towards the teacher.

Some scientific studies revealed that social robots (SR), can play an important role in the educational process [13]. They were considered intelligent tutoring systems, which have the potential to become a component of the educational infrastructure, such as paper, tablets, and, whiteboards, releasing time for the teacher to focus on the core aspects of education such as providing a comprehensive and productive learning experience [14]. In addition, SR has gained popularity during the previous years and is expected to be used in a variety of social applications. They have produced therapy interventions for autistic children [15], [16], exercise trainers, and provided specialized education and assistance to the elderly [17].

However, several machine learning algorithms have been used to investigate the topic of identifying dysgraphia, for example, support vector machines (SVM) [18], and the k-nearest neighbors (KNN) [11]. Research affirms that a convolutional neural network (CNN) is a category of neural network that has been proven to be very efficient in performing tasks like image classification and recognition [19]. The CNNs became a standard in text recognition [20], producing exceptional results. Moreover, CNN models are perceived to be the best-performing algorithms achieving excellent outcomes on the modified national institute of standards and technology (MNIST) dataset [21], which represents the most commonly used benchmark for the recognition of single handwritten digits, and EMNIST [22], as well as Latin and Chinese letters [10]. Furthermore, in order to improve the classification process of dysgraphia in children we intend to apply the convolutional neural network-based deep learning methods and human-robot interactions [23]. In this regard, the following are the primary contributions of our research: i) the creation of an engaging activity based on robot-child interaction; ii) a new fully annotated dataset containing images captured in real-time conditions of several handwritings of digits and containing 11,347 images, coming from the top camera of our Nao robot; and iii) a validation step based on deep learning.

2. RELATED WORK

In this section, we briefly examine the existing research related to our present work on the analysis of handwriting legibility and the machine learning approaches used to identify dysgraphia in children. Thus, the social assistance robotics to which our research contributes most directly to establishing child-robot interaction.

2.1. Assistive robotics in education

The integration and inclusion of children with special needs in educational environments are made possible by the immense creative potential of assistive technology and robots [24]. Then to achieve the fundamental requirement for inclusive and sustainable education [25], where children with disabilities are to be successfully included in the educational environments, it is required to develop and create new and innovative opportunities that allow all children and young people the opportunity to learn despite their special needs [26]. Accordingly, social robotics can be an effective tool in the educational sector to establish a more efficient and inclusive learning experience for children to help them develop socially and academically while performing child-robot interactions in real time. Social robots constitute a potential resource in inclusive education due to their simplicity of interaction with humans and because they stimulate cooperation and collaboration in different ways, which facilitates the rapid assimilation of information by the recipient. This increases their ability to communicate and social competencies or to provoke unexpected situations and break communication barriers such as shyness and fear. Because robots are incapable to identify misunderstandings, they can encourage dysgraphic children to enhance their communication skills [27]. Thus, robots have been used as teachers or social agents to support children's learning in a diverse context, most frequently related to language and writing skills, although the social robot may be employed not only as a communicator or teacher, but also as a mediator to engage with others, increasing the child's abilities, and competencies.

2.2. Machine learning approaches used to identify dysgraphia

Handwriting recognition is a process of identifying letters, digits, and symbols of a written language by hand presented to the system through an image or video format. It is just a classification assignment in mathematical terms. A video or picture as input data must be classified by the resulting system into one of the predefined classes. Machine learning has proven a very important tool for the analysis of handwriting and many investigations have generated models to address this. The MNIST dataset has been classified using a variety of machine learning approaches, from the multilayer perceptron (MLP) [28] to versions of SVM [18] that are more complicated. However, the MNIST dataset, Latin letters, and Chinese characters show that the CNN models perform well by providing exceptional results [22]. This research uses advanced deep learning approaches to recognize the handwriting of learners representing dysgraphia in order to classify them. Deep learning represents a high-level abstraction algorithm that enables the modeling of data from large, trained datasets. While there are a large number of models in the literature for recognizing numbers, letters, words, or written sentences in different languages, such as Arabic, English, Chinese, and Hebrew [29], very few studies have assessed handwriting legibility and intelligibility for the purpose of detecting dysgraphia in children [30].

In certain studies, the classification of dysgraphic and non-dysgraphic children in Hebrew script was done by using an SVM classifier on a collection of manually collected handwriting features [29]. The SVM model is also used to determine if the child has an English writing disability or not, based on the specified input characteristics in the search [31] such as letter slant, letter size, spacing, and pressure, the model is mainly suitable for children aged 5 to 12 years. In other studies [32], 98% of the 56 dysgraphic students in their dataset were accurately identified using the Random Forest supervised machine learning technique, which is often employed in classification challenges. Their approach was based on the BHK test (Latin alphabet) [33]. The following study [34] introduced a numerical approach to identifying and characterizing handwriting difficulties via a recurrent neural network (RNN) model. An RNN is a kind of neural network widely used in the field of deep learning. Using the BHK test successfully diagnoses more than 90% of dysgraphic children.

In our work, we intend to create a child-robot interaction-based screening test to efficiently detect dysgraphia in a school classroom context by adopting a new approach based on the use of CNN to a new set of data collected through the interaction between learners and the robot. We designed a prototype image, respecting a predefined pattern and focusing on digits that are already learned in the early school years. In addition, we constructed a customized training system that would produce specific numbers specifically selected to meet the child's training requirements. The section that follows describes our motivations as well as the machine learning methods we employed to construct and build our diagnostic models.

3. METHOD

3.1. Overall process

We have presented the general process describing our work in Figure 1. The important step at the beginning of the pipeline consists of initiating the process of data collection. Then, we used the classification algorithm CNN on the gathered dataset to identify dysgraphia in the children.

- Interactive scenario with the robot: this step aims to establish the learner-robot interaction in order to collect the data. This interaction was carried out by using the humanoid robot Nao (V6) which has been programmed with Choregraphe [35] to perform the desired actions and appropriate interventions to complete the teaching-learning process, such as initiating exchange and discussion about the presentation, hand-waving, speaking, and moving.
- Data collection: among the objectives of the study was the constitution of a database of digits handwritten by children in order to explore the writing affected by dysgraphia.
- Data preprocessing: this technique consists of data mining and transformation of the raw data into a useful and efficient format, which enables the next step of feature extraction, where relevant information is extracted that helps in classification. Feature extraction is a difficult, generally time-consuming process that cannot process the raw visual data. The manually extracted features are used to classify the image into a specific class.
- CNN Classification: once the dataset is well defined, CNN can be used for image classification. CNNs are now able to achieve excellent results in the case of handwriting recognition[36].
- Result evaluation: the proposed approach provides excellent accuracy results. More details are given in the results section.

Figure 1. The overall process for the deep learning detection of the dysgraphia

3.2. The informational scenario mediated by the robot

3.2.1. Nao robot

In the educational sector, the humanoid robot Nao is considered the main mediating robot used as an assisted teaching instrument. The integration and implementation of this robotic tool in education, especially in early education, has shown positive results. As a programmable robot, Nao may be used to support a vast number of interactive activities targeting various audiences and goals. This research uses the Nao robot, shown in Figure 2, as a tool to incorporate both verbal and non-verbal communication into the child-robot interaction with its user. This autonomous and programmable robot developed by Aldebaran robotics in 2006, is small (58 cm) and completely equipped with cameras and several sensors, enabling the robot to interact with its environment in a variety of ways. Nao can speak several languages, tell stories, play music, recognize human faces, and has other advanced features and functionalities [37].

Figure 2. Nao robot used for our research

3.2.2. Experimental environment and participants

An appropriate structure was prepared to perform the experiment. A classroom organization system has been adopted, consisting of tools and equipment that make the classroom the ideal learning environment. The room is equipped with tables, a projection screen, and a video camera to record the progress of the session. In addition, there is the robot and the children, each child is equipped with a tablet and a pen or paper and a pen. Near the classroom, there is the Wizard of Oz, who has the ability to control the behavior of the robot as needed and as the situation demands. The configuration of the experimental environment is shown in Figure 3.

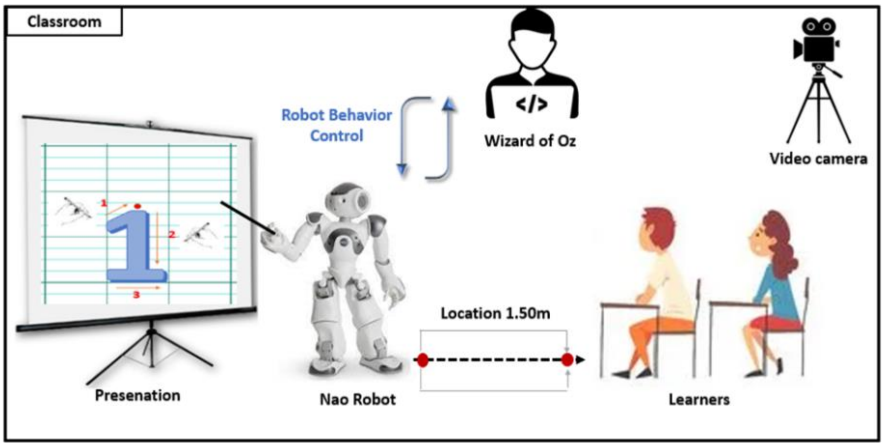


Figure 3. The setting of the experimentation

The unseen human operator in the next room was responsible for controlling the behavior of the Nao robot, applying the Wizard of Oz approach [38], in terms of managing the robot-mediated activity and initiating the various Nao robot movement sequences, including sequences of improvised verbal and non-verbal behavior. The Nao robot was positioned in front of the presentation backboard and located at a distance of approximately 1.50 m so that the students could see it clearly, and to make the robot's gestural explanations easier to see on a visual level. In addition, Nao is placed on the floor because the scenario also includes walking movements, the robot must move around the board and towards the students in order to cover the classroom so as to promote engagement and the illusion of agentivity among them.

3.2.3. Sequence diagram of the establishment of the student-robot interaction

An interactive scenario involving robot behaviors both verbal and nonverbal was conceived to collect the new dataset. A procedure was adopted to perform the task and to make the data collection process simple and easy, respecting the teaching standards. To do this, the course elements presented by the Nao robot were selected based on the educational program taught to students at an early grade level. The scenario was created in a variety of versions and iteratively tested with researchers and professionals in the area of education because the content of the lesson model presented by the robot had to be accurate and convincing to ensure good quality content. First, using a unified modeling language (UML) sequence diagram, a child-robot interaction model is created, as in Figure 4, to represent the general scenario adopted to describe the relevant information and actions that are executed during the student-robot interaction, focusing on the sequence of actions to be performed.

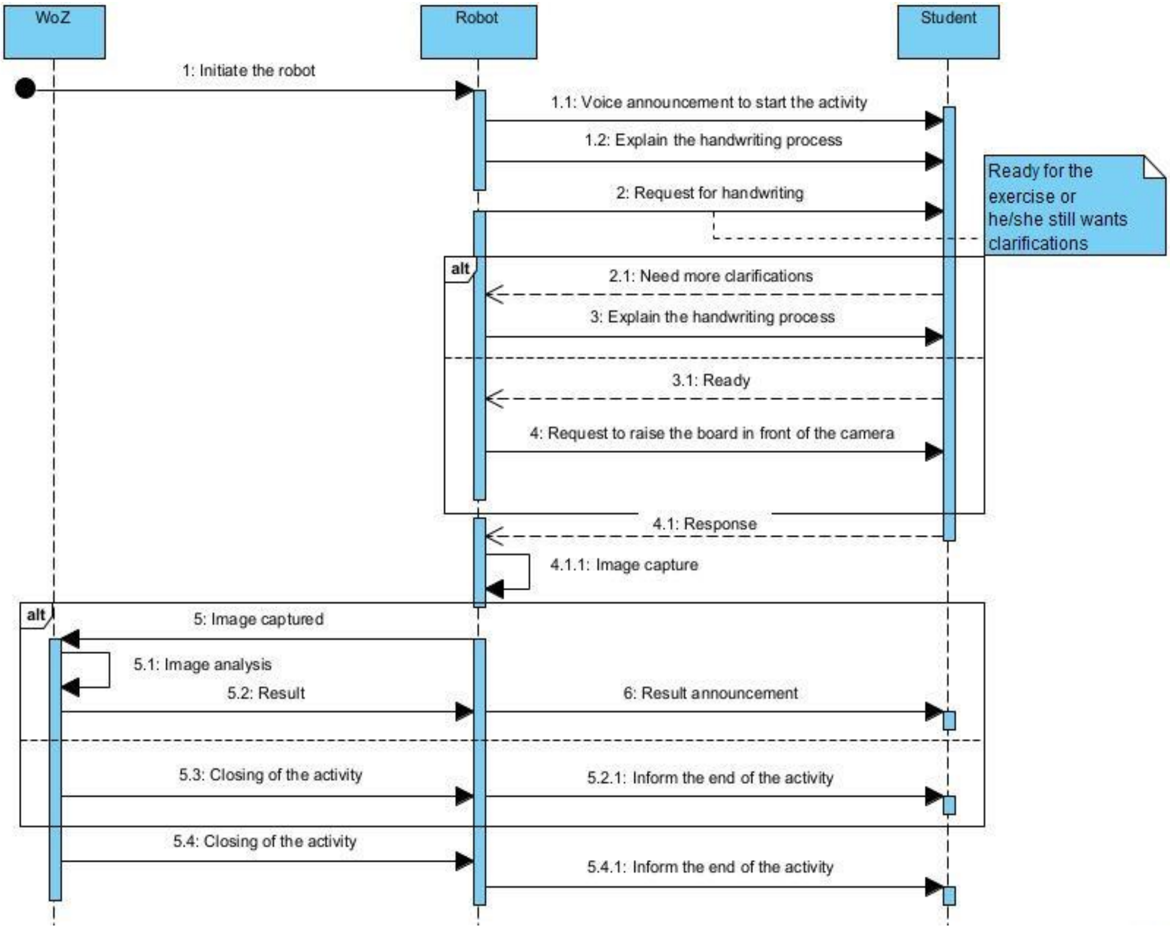


Figure 4. Sequence diagram of the global interactive scenario

The sub-mentioned sequence diagram models the overall interaction of the activity from its initial stages between the child, the robot, and the WoZ in the temporal progression and during the interaction task in the context of dysgraphia detection. A scenario presented in Figure 5 describes an example of a perfect, and real, conversation between the child and the Nao robot initiated by the WoZ. The scenario is composed of three sequences described as follows.

- Introduction: The Nao robot introduces itself as an assistant supporting teacher and provides a general overview of the session's objectives by explaining the process followed to successfully master the handwriting of digits.
- Course presentation: The Nao robot starts by teaching learners the basic concepts of how to write a number, including the following steps: teach children to count from zero to nine, pronounce each digit aloud by pointing fingers, present each digit in order, demonstrate to children how to write the numbers correctly, and reinforce the importance of the sequence of digits.
- Data gathering: The Nao robot contributes to enhancing the learners' abilities by engaging their sense of practice and training on the handwriting of digits. The process concludes by collecting the learners' handwriting attempts on their reference papers.

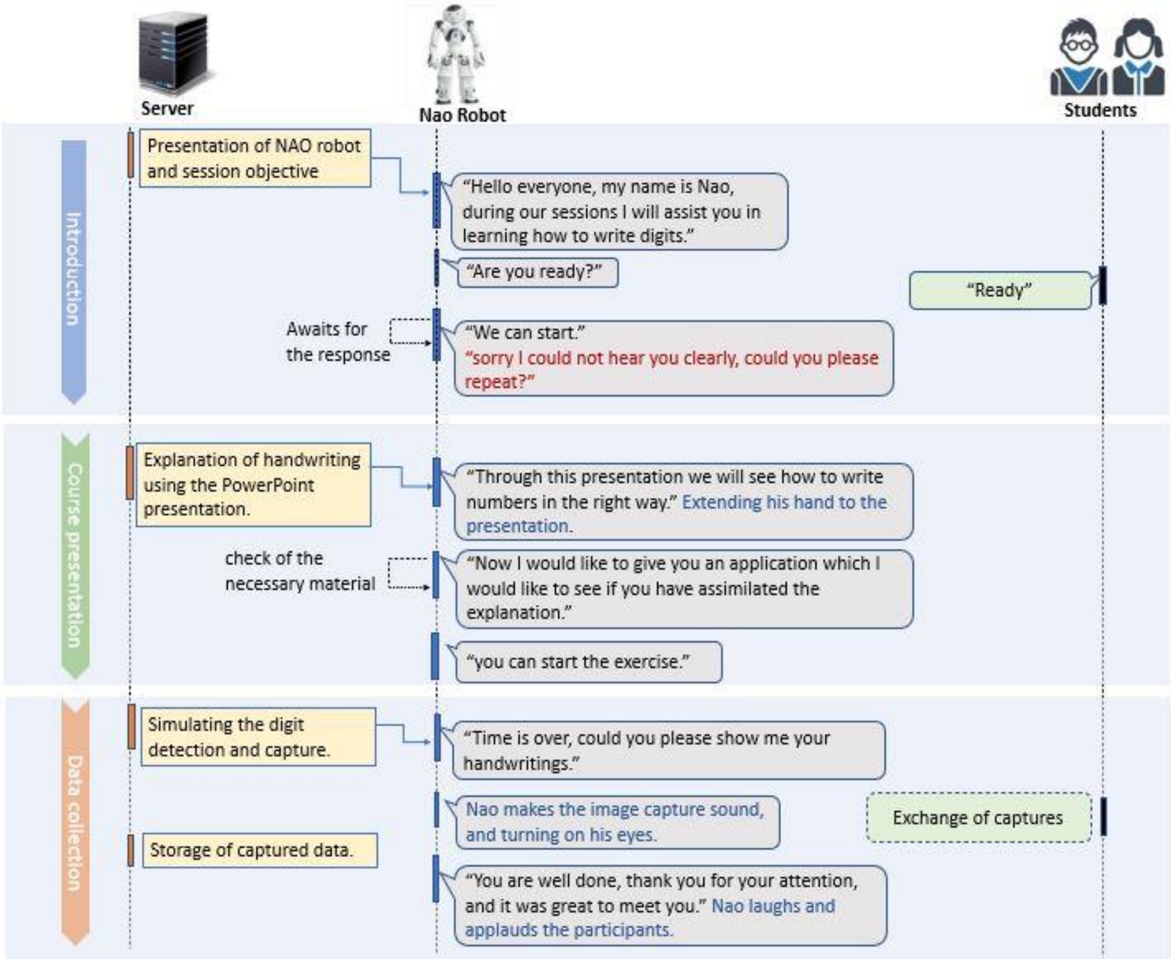


Figure 5. Outline of an educational interactive scenario for the presentation of the digits handwriting for data collection

3.2.4. Dataset

The collected data set of 174 learners was used for the analysis and prediction of dysgraphia among the learners. The reference paper used is intended to prepare a uniform writing structure for children and at the same time, it was used to analyze legibility and spatial awareness. In addition, other parameters such as skills related to the structure and expression of numbers, visuomotor integration, visuospatial relationship, and even the time data of the learners were analyzed. The resulting dataset contains 11,347 images equally divided between twenty classes, digits with dysgraphia and digits without dysgraphia. These images are distributed in three folders: testing, learning, and validation. Some of the 11,347 images contained in the database are shown in Figure 6, a selection of the handwritings affected by dysgraphia have presented in Figure 6(a), while the handwritings of normal children have been displayed in Figure 6(b).

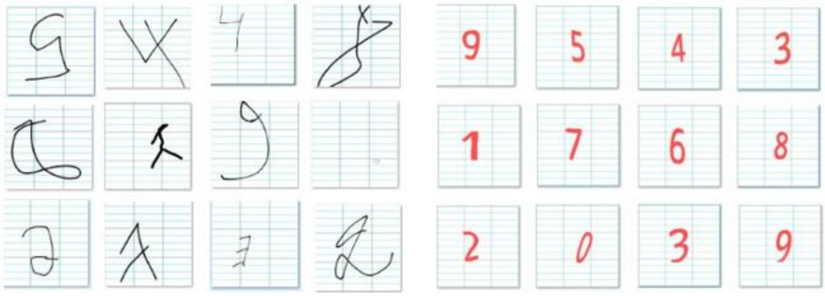


Figure 6. The handwriting of learners; (a) with dysgraphia and (b) without dysgraphia

3.2.5. CNN classification

As previously mentioned, in this research, we performed classification with CNN to identify dysgraphia in children. For image classification tasks, CNNs are currently the most sophisticated model architecture. CNNs employ a succession of filters to extract and learn higher-level characteristics from an image's initial raw pixel data, which the model may subsequently use for categorization. In the area of recognizing handwritten digits, CNN is one of the most used algorithms, it plays two main roles in image processing, the role of a feature extractor with a convolution process that treats the data, and the role of a classifier that contains several layers to classify the images. Figure 7 illustrates the complete architecture of a CNN.

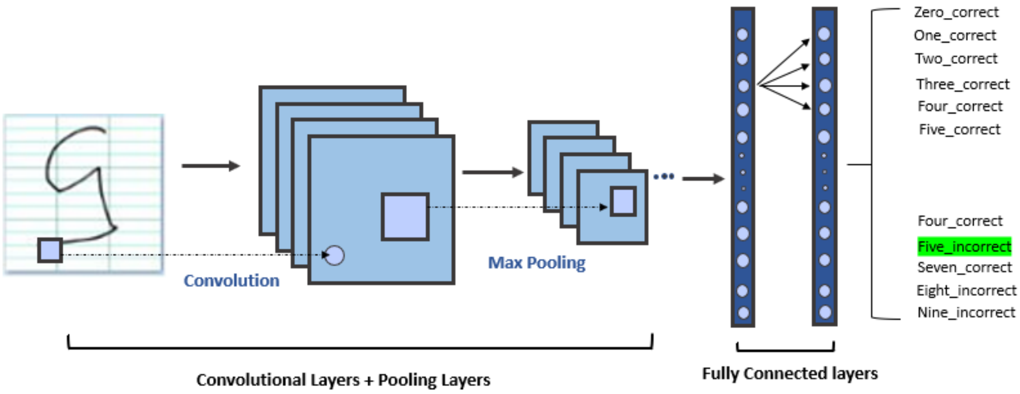


Figure 7. The complete architecture of the CNN

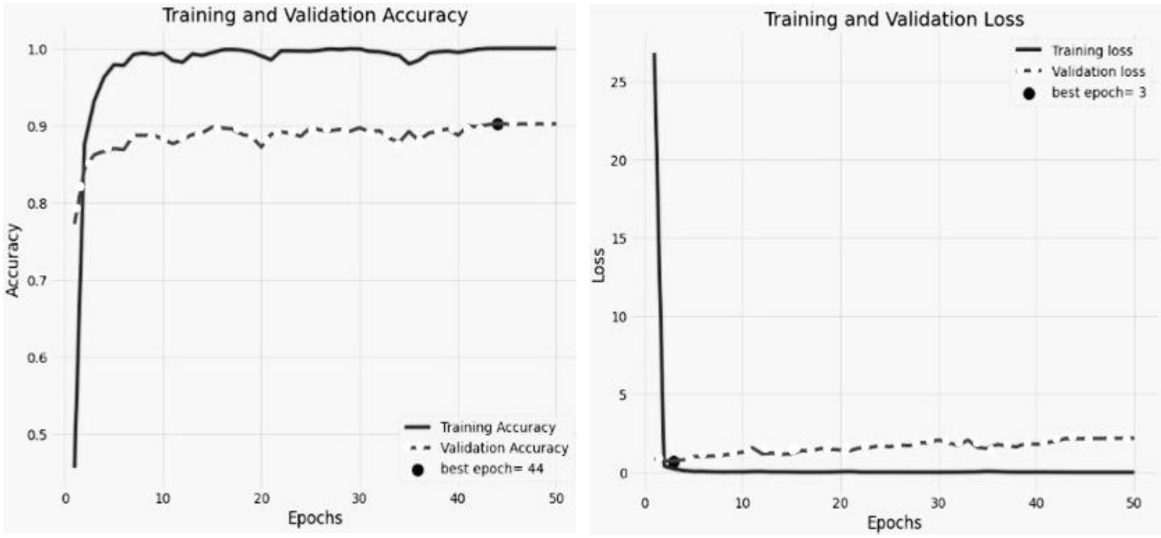
4. RESULTS AND DISCUSSION

4.1. Training and validation curves

After implementing our CNN classification algorithm, we compared their accuracy and execution time using experimental graphs for a better understanding. We allocated 8,525 images for training, 2,483 images for validation, and 2,822 for testing. We also set the epoch size to 50 initially for analysis. The graph of the training and validation accuracy with the best epoch designation is shown in Figure 8(a). When the epoch size is 42, the training and validation curves start to flatten, and the accuracy is 91% and higher. Figure 8(b) shows the training performance as a function of the epoch. As we can see, the learning loss plot decreases until the epoch size is 2. However, after the epoch size is 40, the validation loss plot starts to increase, which means that the training is overfitted.

4.2. Confusion matrix

In order to explore the performance of the developed CNN on each output class, and to see where the model gets confused, i.e., which classes the model predicts correctly and which classes the model predicts incorrectly, the confusion matrix was calculated; it is presented in Figure 9. We can see that our CNN works extremely well on all digits with few errors given the size of the validation set (2,062 images). However, it seems that our CNN has some small problems with the number 1, which is misclassified as 7. Sometimes it is very difficult to catch the difference between 1 and 7 when the curves are smooth, and when the middle line for seven or the bottom line for 1 are absent.



(a) (b)

Figure 8. Training and validation: (a) accuracy and (b) loss in our CNN model

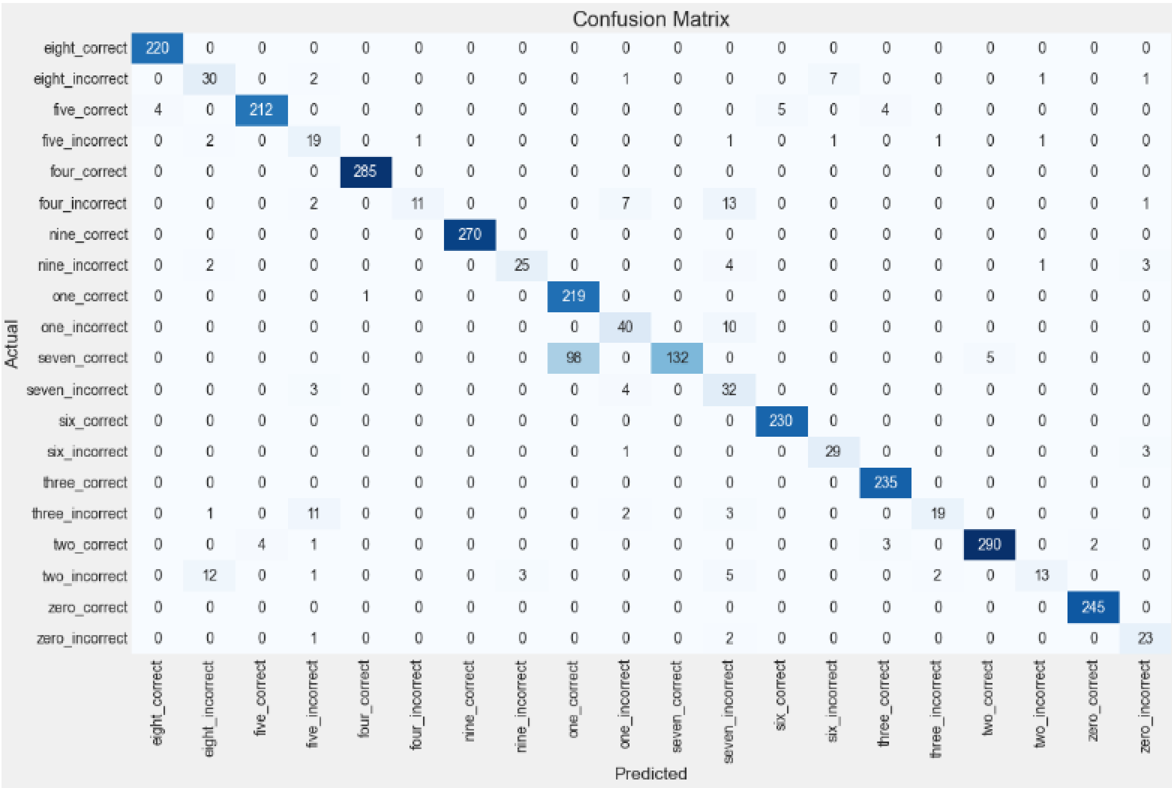


Figure 9. Normalized confusion matrix for children's handwriting digit classification results based on the CNN

4.3. Performance measures

A confusion matrix is a table that is frequently used to evaluate the result of a machine-learning model based on a training dataset where the true values are known. In addition, some performance measures are applied to analyze the classifier's performance, such as precision, recall, and F-factor. Table 1 shows the classification report for our neural network model. Although the accuracy could reach 91% in our CNN model, we were still able to use the classification report to analyze our results and reinforce our dataset.

Table 1. Classification report

Classes	Precision	Recall	F1-score	Support
eight_correct	0.9821	1.0000	0.9910	220
eight_incorrect	0.6383	0.7143	0.6742	42
five_correct	0.9815	0.9422	0.9615	225
five_incorrect	0.4750	0.7308	0.5758	26
four_correct	0.9965	1.0000	0.9982	285
four_incorrect	0.9167	0.3235	0.4783	34
nine_correct	1.0000	1.0000	1.0000	270
nine_incorrect	0.8929	0.7143	0.7937	35
one_correct	0.6909	0.9955	0.8156	220
one_incorrect	0.7273	0.8000	0.7619	50
seven_correct	1.0000	0.5617	0.7193	235
seven_incorrect	0.4571	0.8205	0.5872	39
six_correct	0.9787	1.0000	0.9892	230
six_incorrect	0.7838	0.8788	0.8286	33
three_correct	0.9711	1.0000	0.9853	235
three_incorrect	0.8636	0.5278	0.6552	36
two_correct	0.9831	0.9667	0.9748	300
two_incorrect	0.8125	0.3611	0.5000	36
zero_correct	0.9919	1.0000	0.9959	245
zero_incorrect	0.7419	0.8846	0.8070	26
Accuracy			0.9139	2822
macro avg	0.8442	0.8111	0.8046	2822
weighted avg	0.9321	0.9139	0.9111	2822

In our case, the *one_correct* class has high recall but low precision. This illustrates the fact that the number of test data is not *one_correct* but the model recognizes it as *one_correct* is large. For the *seven_correct* class, it has high precision but low recall. This presents that many numbers are *seven_correct* but the model recognizes it as a different number. The rest of the classes have high recall and high precision, which means that all results come back correctly in this class. According to this observation, most of the *one_correct* classes were recognized correctly but some *seven_correct* classes were recognized as *one_correct*. Thus, we could improve our dataset by increasing the number of *seven_correct* classes to enhance the identification performance of the *seven_correct* class. To indicate, the incorrect word means that the class corresponds to the handwriting of the digits referring to a child with dysgraphia, while the correct word corresponds to the class of normal handwriting for a child without dysgraphia.

5. CONCLUSION

This research introduces the humanoid robot Nao that establishes a child-robot interaction with both dysgraphic and non-dysgraphic students at the primary school level. The motivation behind this research is to differentiate between students with and without dysgraphia in an educational environment using an assistant robot. This research was performed by using CNN on the collected dataset. The three principal research objectives are satisfied: first, an interactive, stimulating, functional, and explicative scenario of the humanoid robot Nao that allows demonstration to the learners of the method of handwriting the digits, second, the capture of the students' handwriting using the camera of the robot Nao permitted us to create a new dataset, and finally, the realized model produced precious results. We have demonstrated that our model can identify dysgraphia from the learners' handwriting with an accuracy of 91%, a precision of 93%, a recall of 91%, and an F1 score of 91%. Results indicate that the suggested approach is quite efficient in terms of accuracy. The CNN proves to be a more robust classifier, providing valuable results.

The focus of our future research will be focused on students with special needs so that they can have an inclusive education that allows them to challenge their disabilities and advance toward academic excellence. Therefore, we wish to perform an adjacent, supervised classification allowing our assistant robot Nao to classify students affected by dysgraphia according to the severity of their affectation and according to their type of dysgraphia in order to help them fight and surmount their handicap.

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