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TOWARD AN AUTONOMOUS ROBOT FOR REAL-TIME DYSGRAPHIA DIAGNOSIS VIA DEEP LEARNING

Soukaina Gouraguine*	EST Laboratory ESEF of Berrechid Hassan I University of Settat, Morocco	soukaina.gouraguine@uhp.ac.ma
Mohammed Qbadou	ENSET of Mohammedia, Hassan II University, Mohammedia, Morocco	qbmedn7@gmail.com
Khalifa Mansouri	ENSET of Mohammedia, Hassan II University, Mohammedia, Morocco	khalifa.mansouri@enset-media.ac.ma

* Corresponding author

ABSTRACT

Aim/Purpose	This study aims to design, develop, and implement a novel autonomous diagnostic framework embedded in the NAO humanoid robot, enabling it to perform real-time identification and classification of dysgraphia in children. This extension of robot-assisted therapy provides a truly autonomous diagnosis, performed without human supervision.
Background	Dysgraphia is a handwriting disorder affecting the automation of graphic gestures and the formal presentation of written text. Traditional diagnostic methods require human experts and are often time-consuming. There is a pressing need for intelligent, autonomous tools capable of identifying dysgraphia in educational contexts. Real-time diagnosis is essential because it enables teachers and therapists to respond immediately to signs of difficulty, adapt teaching activities, and prevent the disorder from progressing. Existing approaches rely mainly on delayed assessments, which limit their effectiveness in dynamic school environments.
Methodology	We developed a client/server-based architecture where the NAO robot acts as a client, autonomously guiding students through handwriting tasks, capturing data, and sending it to a server for processing. Machine learning models hosted on the server analyze handwriting samples for two main purposes: (1) identify-

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ing whether the student is affected by dysgraphia, and (2) recognizing and classifying specific signs and severity levels of the disorder. The dataset includes approximately 3,000 handwriting captures for dysgraphia identification and approximately 2,426 samples for sign recognition.

Contribution — This research presents an original and intelligent diagnostic framework, implemented in the NAO humanoid robot, that enables the robot to detect and classify dysgraphia in real-time autonomously. Going beyond traditional approaches to robot-assisted therapy, our system gives the robot independent ability to perform analysis, providing immediate and relevant diagnosis for educational support. The framework is based on a multi-level classification model that categorizes severity and symptom types, and builds upon a set of original handwriting data collected from learners of different age groups.

Findings — Our dysgraphia identification model achieved an accuracy rate of 99%, while the sign recognition model achieved an accuracy rate of 78%. This difference is due to the complexity of the task and the nature of the data: identifying dysgraphia is a binary classification process (affected, non-affected), while the recognition of signs is a multi-class classification process, as each image may contain several varied and subtle signs (Crooked, Broken, Overlapping, Reversed, Poorly Formed, Too Small, Too Large). However, the results obtained enable the severity level to be estimated based on the number of signs detected. An interactive scenario was designed and tested in real educational settings, showing positive and effective outcomes.

Recommendations for Practitioners — Educators and therapists can utilize the robot to support early dysgraphia detection in classrooms, enabling timely intervention and personalized learning support.

Recommendations for Researchers — Further investigations could explore cross-linguistic handwriting variations, extend the datasets, and integrate emotional feedback mechanisms to enhance the quality of robot-student interaction.

Impact on Society — This research advances the field of inclusive education by introducing a scalable and fully autonomous technological solution for the early diagnosis of dysgraphia. By enabling timely identification and classification of handwriting disorders, the proposed framework fosters equitable access to tailored educational support, thereby mitigating long-term academic challenges and reducing the potential for social stigmatization among affected learners.

Future Research — Future work will focus on extending the framework to support multi-language handwriting analysis, real-time progress tracking over multiple sessions, and integration with personalized therapy plans.

Keywords — dysgraphia, NAO robot, handwriting diagnosis, autonomous agent, educational robotics, deep learning, machine learning, child-computer interaction, inclusive education

INTRODUCTION

Learning disabilities are due to neurological disorders that specifically and significantly alter certain cognitive abilities involved in academic learning (Grigorenko et al., 2020). These processing problems can interfere with the learning of basic skills such as reading, writing, and/or mathematics. They may also interfere with higher-level skills such as organization, time planning, abstract reasoning, long or short-term memory, and attention. A specific learning disability that impacts a person's writing and fine motor skills is called "dysgraphia." Dysgraphia is an educational disorder that affects a person's ability to write consistently and solidly (Chung et al., 2020). This disorder can be caused by a variety of factors, such as motor difficulties, language therapy, and attention despite adequate education, motivation, and typical mental and physical health (Biotteau et al., 2019). This particular imbalance hinders the educational success of those who suffer from it. Children with special needs, especially in the educational aspect, require a different and specialized type of support compared to their natural peers (Bouck & Long, 2021). This implies an intervention with specialists, therapists, or assistants to provide them with suitable learning conditions, ensuring an inclusive and extensive environment (Jørgensen et al., 2021).

Artificial intelligence-enhanced tools aim to find more effective ways to monitor, educate, and support individuals with learning disabilities (Hwang et al., 2020). Assistive technology for students with learning difficulties is one of the main strategies schools use to help students learn and think differently (Bouck & Long, 2021). A wide range of assistive technology (AT) tools is available to help students with writing difficulties. Some of these tools assist students in overcoming the physical task of writing, while others support them with spelling, punctuation, grammar, word usage, and organization (Svensson et al., 2021).

Social robots are sophisticated educational tools that can support teachers and enhance the learning experience for students. They can stimulate collaboration, strengthen engagement, facilitate cultural integration, and encourage creativity in the classroom (Belpaeme et al., 2018; Johal, 2020). Research also shows their effectiveness in teaching social and educational skills to students with specific disorders such as autism, ADHD, or hearing impairments (Anderson et al., 2019; Antonarakis et al., 2021; Henning et al., 2022; Khasawneh, 2021).

Robotic platforms oriented towards assisting and performing tasks related to teaching and educational environments require robust and computationally efficient cognitive systems (Chiara et al., 2020). The prospect of endowing robots with cognitive intelligence to make interactions more authentic, intuitive, and natural is a challenge and an intriguing source in the field of human-robot interaction. A crucial aspect to achieve this goal is the robot's ability to understand, interpret, process, reason, and learn (Pandey & Gelin, 2017).

Moreover, state-of-the-art methods in image-related tasks, such as object recognition, object detection, image and sound classification, and image segmentation, are all based on convolutional neural networks (CNNs) (Ma, 2020). These tasks require CNN architectures with millions of parameters; therefore, their deployment in robotic platforms and real-time systems becomes unfeasible (Newton & Newton, 2019). The algorithms are written in Python and include software development tools such as TensorFlow, image pre-processing techniques, and consistent use of functions from the Python Imaging Library (PIL), OpenCV (Open-Source Computer Vision Library), Keras, and others.

Our current work focuses on the prototyping, development, testing, and deployment of a novel framework for the NAO robot to perform real-time dysgraphia diagnosis in students. The framework includes the identification of dysgraphia, determining whether the student is affected or not by dysgraphia, the recognition of signs affecting the presence of dysgraphia, and the classification of dysgraphic students according to their level of severity (mild, moderate, and severe). This framework consists of the use of a client/server architecture that allowed us to separate the tasks of machine learning, data processing, and model loading on the server, and to make the robot act as a client that sends images to the server for prediction, and announces the received result according to the server, as shown in Figure 1. This separation of concerns allows for greater flexibility and scalability.

The main contributions of our research are: (i) the reorganization of our new fully annotated dataset containing images captured in real time of several writings of lower and upper case digits and letters, affected and non-affected by dysgraphia; (ii) a new fully annotated dataset containing 2,426 images of several writings of digits and letters exhibiting the signs that can affect dysgraphia for single character analysis; (iii) two validation steps based on deep learning classification models; and (iv) third step, based on score calculation, for which the level of severity of dysgraphia in dysgraphic students can be determined. In this regard, the plan adopted in our article begins by discussing previous work on the art of the main concepts addressed by this study. Then, we present the methodology followed, the architecture, the application programming interface, and the set of technologies used to integrate our CNNs with the NAO robot. We conclude by providing an explanation and a schematization of the obtained results.

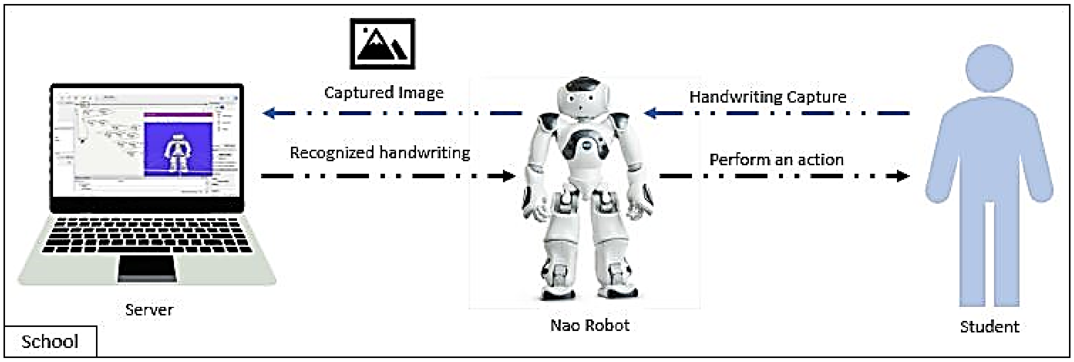

Figure 1. Client/server architecture adopted in our study

RELATED WORKS

APPROACHES USED TO IDENTIFY DYSGRAPHIA

Dysgraphia is a learning disability that affects writing ability. Machine learning and deep learning approaches can be used to identify dysgraphia by analyzing various features of a person's writing, such as handwriting patterns, speed, and accuracy (Drotár & Dobeš, 2020). Some common machine learning and deep learning approaches used for identifying dysgraphia include: Handwriting Recognition, Kinematic Analysis, Feature Extraction, Ensemble Methods, Deep Learning with Recurrent Neural Networks (RNNs), and Transfer Learning. Table 1 summarizes some related works on dysgraphia detection, including the approach used, references to relevant research articles, and the data used for dysgraphia identification.

Table 1. Related studies on dysgraphia detection

Reference	Year	Dataset type	Approach	Evaluation metrics
(Asselborn et al., 2018)	2018	Data from 56 dysgraphic children	Random Forest classifier	Accuracy = 98%
(Zolna et al., 2019)	2019	Data acquired with a high-end tablet from 971 students (Dataset)	RNN	Accuracy = 90%
(Dutt & Ahuja, 2021)	2021	A dataset of 240 learners, 142 of whom had a learning disability.	KNN Naïve Bayes Decision tree Random Forest SVM	Accuracy = 97.21% Accuracy = 90% Accuracy = 97% Accuracy = 99% Accuracy = 89.23%
(Rosenblum & Dror, 2017)	2017	99 samples were collected from writers with dysgraphia and proficient writers.	SVM	Accuracy = 90% Sensitivity = 90% Specificity = 90%

Reference	Year	Dataset type	Approach	Evaluation metrics
(Drotár & Dobeš, 2020)	2020	Data collected using a tablet for 120 schoolchildren aged 8–15 years	AdaBoost algorithm Random Forest SVM	Accuracy = 80% Accuracy = 79% Accuracy = 79%

Most of the studies cited focus on the application of machine learning techniques to analyze handwriting data collected from various devices, including graphic tablets and electronic pens. Indeed, there is no previous research that directly integrates robotics for detecting dysgraphia in students. However, some research has used robotics to help students with dysgraphia improve their writing. For example, there are robots that can assist with guiding hand movements during writing, as well as robotic systems that help correct handwriting posture and ergonomics. These approaches can potentially be used in conjunction with handwriting analysis techniques to improve the detection and management of dysgraphia in students. Nevertheless, several studies also highlight ethical and practical considerations related to the introduction of robots in school environments, including acceptance by teachers and parents, the confidentiality of children's data, physical and psychological safety, and staff training (Belpaeme et al., 2018; Leite et al., 2014). Therefore, it reflects our intervention to implement a dysgraphia detection model in an educational robot, taking into account both the potential assistance it offers and the ethical and practical challenges that its deployment may raise.

NAO Robot at School

In the educational setting, several studies have used the humanoid robot NAO to support children with special needs (Belpaeme et al., 2018; Khasawneh & Alkhawaldeh, 2020). For example, Desideri et al. (2017) examined the use of NAO to help students with autism spectrum disorder (ASD) improve their social skills and interactions with other children. The results showed that using NAO helped the children improve their social engagement and participation in interaction with other children. Estévez et al. (2021) demonstrated its effectiveness in supporting reading skills in children with dyslexia. The study asserts that NAO can help build motivation, prepare for learning, and improve children's ability to pay attention. These studies demonstrate NAO's potential as an educational and therapeutic tool, justifying its use in our study to develop an autonomous dysgraphia diagnosis system based on a client-server architecture.

Client-Server System

Several research studies have used client-server architecture for the detection and identification of learning disabilities in students. Client-server architecture typically involves the use of a client application that communicates with a remote server. In the case of disease detection and identification, the client application can be used to collect data from sensors such as cameras, microphones, or motion sensors, which are subsequently transmitted to the remote server for analysis. Machine learning models can be used to analyze the collected data and detect the presence of the disease. For example, a study by Henning et al. (2022) examined the use of client-server architecture for autism detection in children. The client application used in this study collected data from motion sensors on a smartphone, which was then transmitted to a remote server for analysis. The results showed that the use of client-server architecture was effective in detecting autism in children with an accuracy of 82%. The approach proposed, deployed, and tested in our study for detecting dysgraphia, its signs, and severity levels in dysgraphic students is truly innovative and novel. It employs a client-server architecture that has not been previously used in this field. This architecture enables us to conduct dysgraphic recognition processes independently of the client devices, resulting in improved performance, equitable workload distribution, high availability, and simplified system maintenance.

FRAMEWORK CONCEPTION

This study proposes a new framework for student dysgraphia detection using a client-server architecture (Figure 2). The framework is implemented using the NAO robot as a client, a main server, and a node application infrastructure designed to provide high availability, horizontal scalability, and centralized configuration and security management. The main server is distributed across the five nodes, including image pre-processing, dysgraphic detection, sign detection, severity detection, and post-processing of data, all while enhancing overall system performance. The NAO client is used to capture the students' handwriting, which is transmitted via the main server to the processing nodes. The image pre-processing node performs image normalization and processing to prepare the images for classification. The dysgraphia detection and sign detection nodes use convolutional neural networks (CNNs) to classify the images according to their dysgraphia status and signs. Then the number of predicted signs constitutes the score for which the degree of severity is determined. Finally, the post-processing node gathers the results of the processing nodes to provide a global diagnosis of dysgraphia. This approach allows for real-time analysis of students' handwriting, which facilitates the diagnosis and management of dysgraphia.

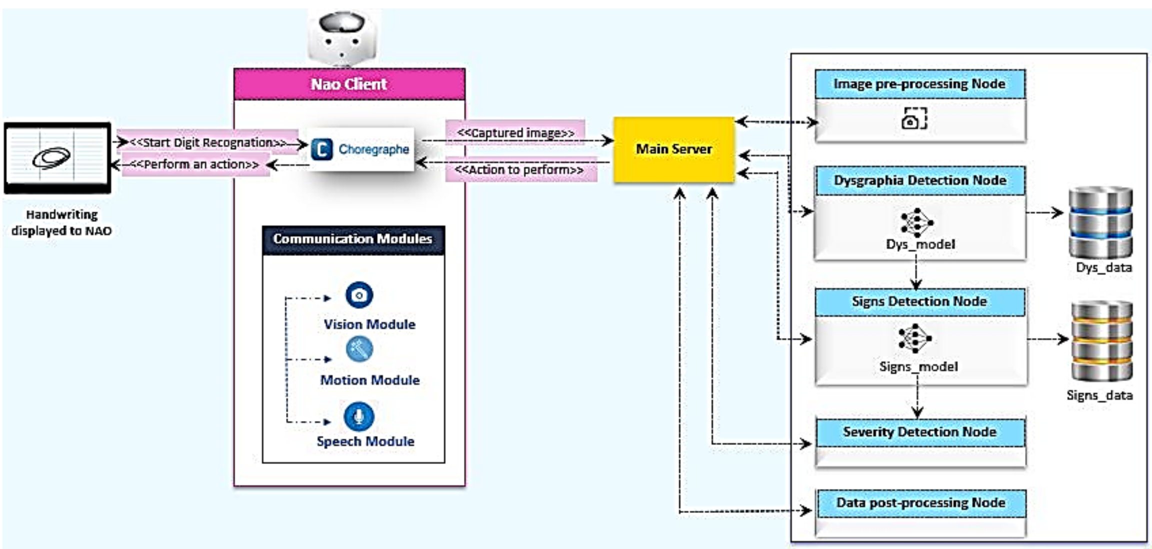

Figure 2. Client/server architecture of our proposed framework for dysgraphia, signs, and severity detection

Our framework offers great flexibility in terms of post-analysis data processing, with a node dedicated specifically to this task. This feature enables easier customization and adaptation of the diagnostic process to meet the specific needs of students, thereby offering a more individualized and personalized approach.

The NAO robot is programmable and equipped with a built-in camera and microphone, allowing it to capture images and sounds. Additionally, it features numerous sensors, including pressure sensors, collision sensors, and motion sensors, which enable it to navigate the environment accurately and detect obstacles (Amirova et al., 2021). The NAO robot is also equipped with two arms and two legs that can be programmed to perform precise movements, enabling it to perform complex tasks (Miskam et al., 2014). In our context, the NAO robot is used to capture images of students' handwriting in real time. Figure 3(a) shows a student writing a letter according to a structured model previously represented by the robot, which adheres to the standards and enables visualization of the criteria used for classification. Figure 3(b) illustrates the handwriting capture process. For this purpose, we have developed an application that allows the robot to connect to a remote server to transmit the captured images. The application also performs image pre-processing tasks, such as resizing and color normalization, to enhance the quality of the images before transmission. Additionally, the NAO robot is programmed to automatically detect the position of sheets of paper and pens, ensuring that images are captured accurately. Using the NAO robot to collect handwriting images enabled us to achieve faster, more accurate, and standardized data acquisition than manual data entry, while also reducing the workload for teachers.

Figure 3(a). Student writing

Figure 3(b). Handwriting capture process

The proposed framework consists of five nodes: Image Pre-processing, Dysgraphia Detection, Data Post-processing, Signs Detection, and Severity Detection servers. The main server is responsible for distributing the tasks to the appropriate nodes based on their availability and the complexity of the task. This approach ensures that each node is being utilized optimally, leading to faster processing times and more efficient resource management. The Image Pre-processing node is responsible for applying image enhancement techniques to the input images to enhance the image quality and reduce noise. The Dysgraphia Detection node is responsible for detecting and analyzing dysgraphia in the pre-processed images using various computer vision algorithms. The Data Post-processing node is responsible for processing the output data from the Dysgraphia Detection node and preparing it for presentation. The Signs Detection node is responsible for detecting and analyzing the signs that indicate dysgraphia and presenting the results to the user. Finally, the Severity Detection node is responsible for affecting the severity level of dysgraphia and providing the appropriate feedback to the user. Together, these nodes form a powerful server that can handle a large number of requests simultaneously, providing fast and accurate results to the user.

CLASSIFICATION HIERARCHY

The proposed framework relies on various deep learning models to accomplish its tasks. These models are trained on a digit and letter handwriting dataset to ensure accurate and reliable results. The models are built using state-of-the-art architectures, which enable efficient training and inference on the server. Figure 4 shows the hierarchy of the classification process used. The severity of dysgraphia was assessed using a scale based on the number of signs detected by the dysgraphia sign detection model, after confirmation of the disorder by the identification model. Thus, 1 to 3 signs indicate mild dysgraphia, 4 signs indicate moderate dysgraphia, and 5 to 7 signs indicate severe dysgraphia. This scale allows for standardized quantification of the severity of the disorder and provides educators and researchers with precise benchmarks for adapting educational interventions.

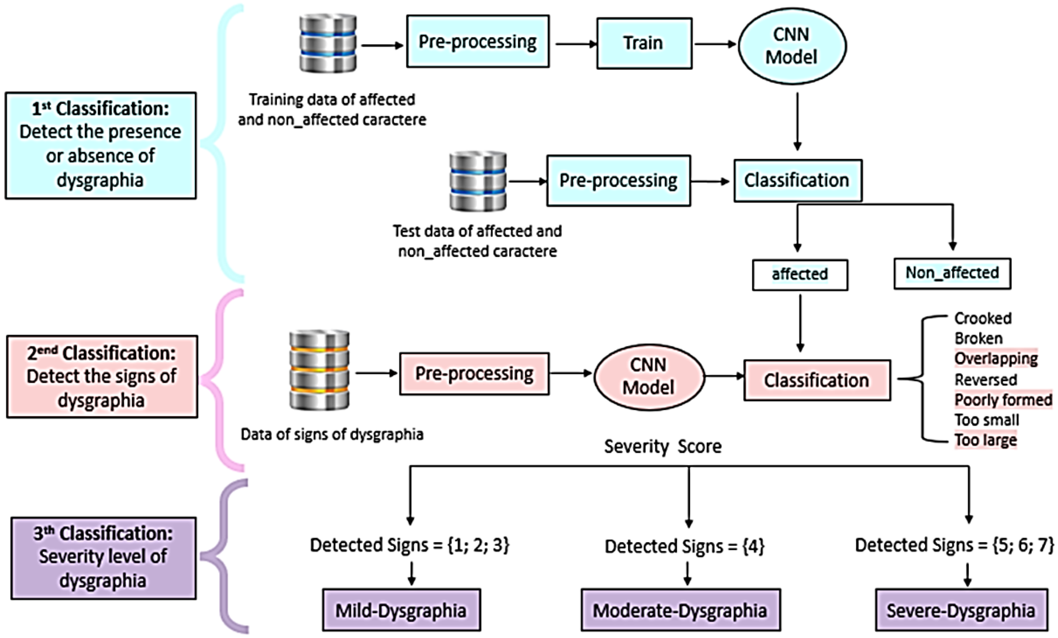

Figure 4. Classification hierarchy

METHODOLOGY OF VALIDATION

The handwriting samples collected by the NAO robot were processed and analyzed using convolutional neural networks (CNNs) to classify and detect signs of dysgraphia. CNNs were chosen because of their proven ability to learn spatial hierarchies and extract relevant visual features directly from images, making them particularly effective for analyzing handwriting. In contrast to traditional machine learning methods, such as support vector machines (SVMs) or random forests, CNNs do not require features to be engineered artificially, which improves the model's generalization to different writing styles. This methodological choice guarantees automatic and robust extraction of features relevant to the accurate detection of dysgraphia.

TRAINING AND VALIDATION CURVES

The two key components of our framework are dysgraphia recognition and dysgraphia sign detection. The efficiency and accuracy of these two components are crucial for successful real-world implementation. To achieve this, we applied convolutional neural networks (CNNs) to analyze the handwriting samples collected by the NAO robot, due to their ability to learn from spatial hierarchies and to automatically extract relevant visual characteristics from raw images. In contrast to traditional machine learning methods, such as support vector machines (SVMs) or random forests, CNNs allow for more robust generalization across different writing styles without requiring manual feature selection. Other architectures, including recurrent neural networks (RNNs) and transformer-based models, were considered but proved less suitable for the static data we collected. Therefore, when evaluating the framework, we placed great importance on the accuracy of the generated models. High accuracy of the models means more precise detection of dysgraphia signs and more accurate dysgraphia recognition. Thus, we conducted thorough evaluations to ensure that the proposed models are reliable and have satisfactory performance. This section is dedicated to evaluating the performance of the dysgraphia recognition and sign detection models in our framework. To achieve this, we present the learning and validation curves for each model, which allow us to analyze their behavior during learning and training. We also present the performance of the models on test datasets, as well as the evaluation metrics used to measure model accuracy. Finally, we discuss the obtained results and their interpretation.

Testing the network for dysgraphia detection

Figure 5 presents randomly selected images from the test set, their true labels, and the predicted labels. The predicted label is colored green if the predicted probability is greater than or equal to 0.5 (indicating that the model predicts the image is not affected) and red otherwise (indicating that the model predicts the image is affected). The legend at the bottom of the table explains the color coding. This visualization provides an intuitive way to see the model's performance on individual images from the test set.

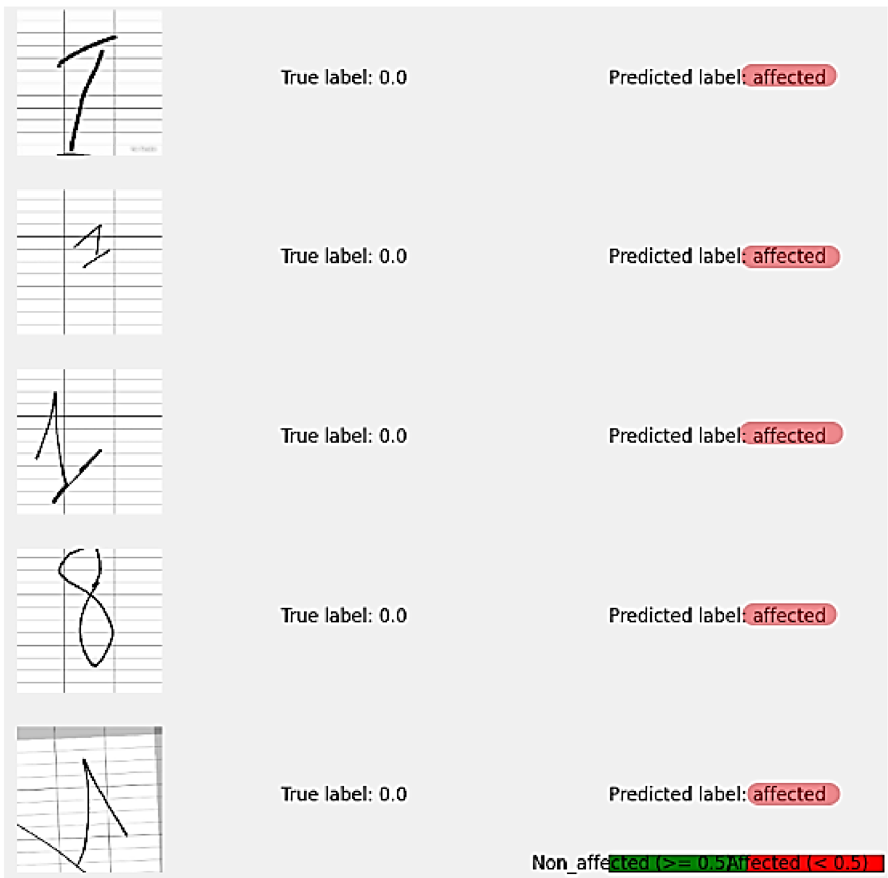

Figure 5. Test images with their predicted labels

Testing the network for signs of dysgraphia detection

An example of the model's execution on some input images is presented in Figure 6. In our case, the image shown in Figure 6(a) is a digit nine written by a person with dysgraphia. The image is passed to the model to predict the signs of dysgraphia that are present in the writing. The model uses the OpenCV library to pre-process the image, resizing it and converting it to grayscale. Then, the model predicts the signs of dysgraphia. The dysgraphia signs predicted for the digit nine image are: "reversed", "poorly formed", "broken", "overlapping", "crooked", and "too small". These signs are ranked according to their probability of being present in the image. Finally, we evaluate the severity of dysgraphia based on the severity scale defined above (1–3 signs: mild, 4 signs: moderate, 5–7 signs: severe). The score assigned to this image is 6, indicating that the dysgraphia is very severe. Figure 6(b) shows the digit zero with a single sign of dysgraphia “overlapping”, and the severity score assigned for this image is 1, which means that the student has mild dysgraphia.

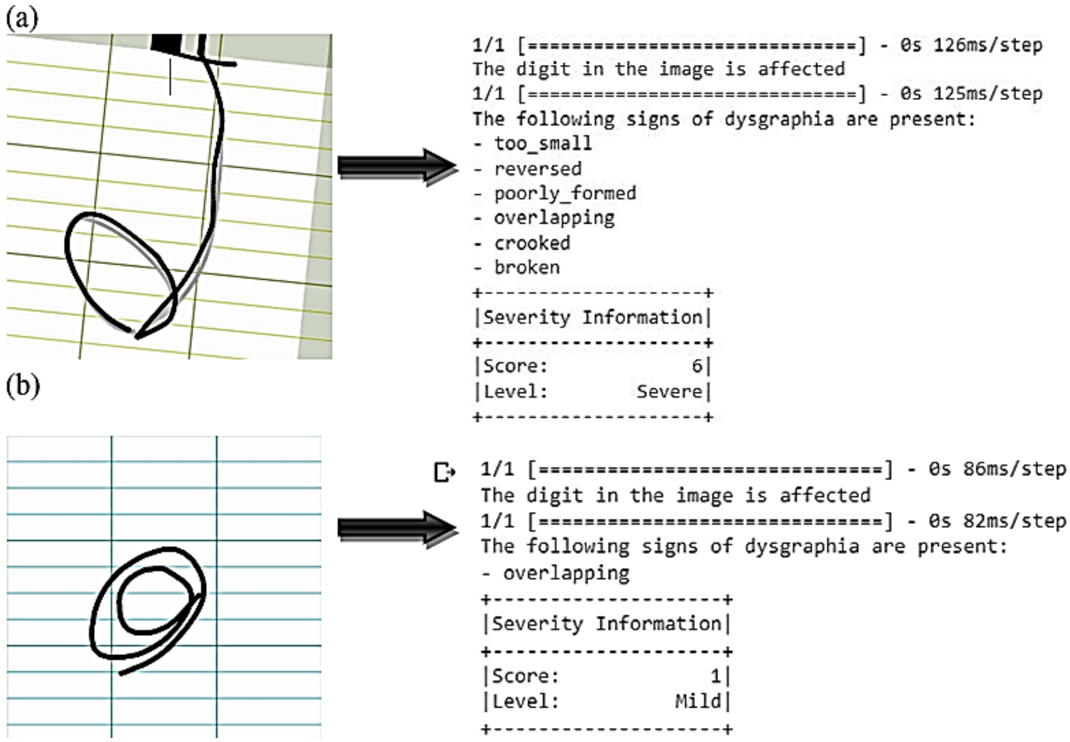

Figure 6. Examples of execution

Simulation and Testing of the Framework on the NAO Robot

In the following section, we present screenshots of simulations and tests conducted on the developed framework implemented on our NAO robot. We performed several simulations to test the performance of our framework in different scenarios using the Choregraphe software (Gao, 2016), which provides a graphical interface for programming the robot. The results were conclusive and showed high accuracy in recognizing dysgraphia and signs affecting the presence of dysgraphia. We also conducted tests on the NAO robot using the parameters of our framework. The tests demonstrated high stability and responsiveness of the robot, confirming the effectiveness of the framework in a real-world environment.

We present below the screenshots of simulations and tests to illustrate the performance of our framework. Figure 7 clearly shows the process of processing images affected and not affected by dysgraphia, where the NAO robot captures the image and sends it to the server for necessary processing. Once the server receives the image, it processes it through the different nodes until the response is obtained and returned to the client. The prediction results are displayed on the screen and announced vocally by our NAO robot client, thanks to its vocal capabilities. Figure 7(a) shows the result of the diagnosis of handwriting from a normal child, while Figure 7(b) shows the result of a captured image containing handwriting from a dysgraphic student with a “reversed” sign and mild severity.

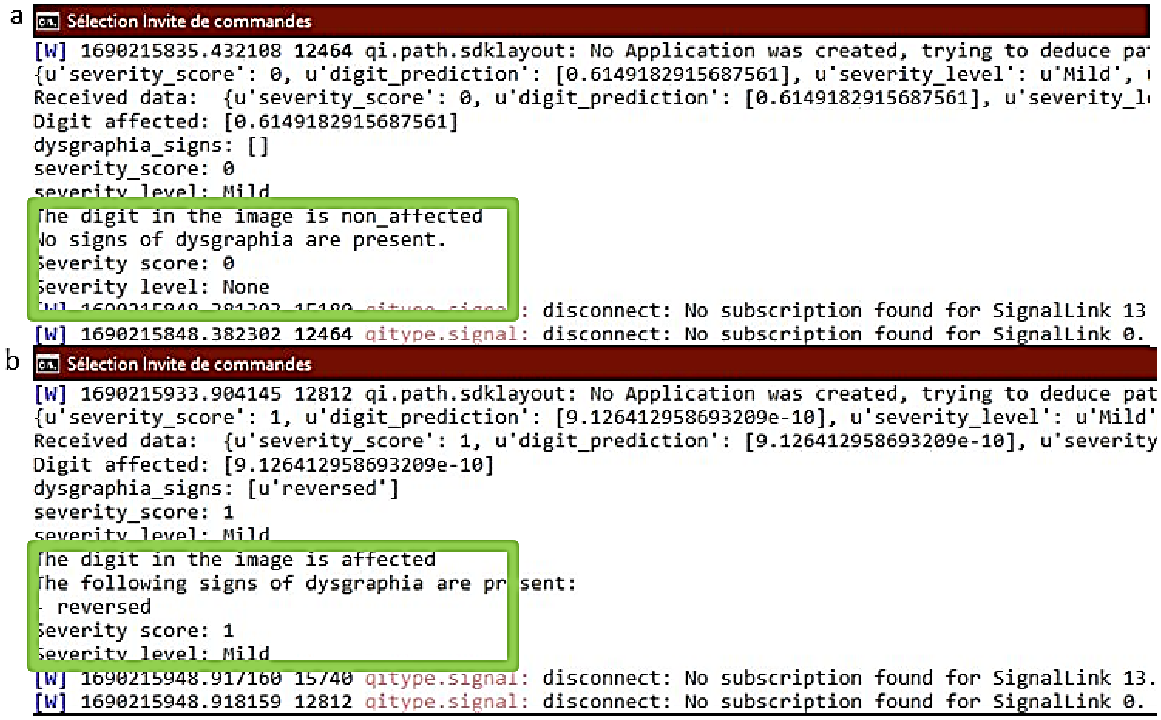

Figure 7. Results announced by NAO:
(a) non-affected handwriting, (b) affected handwriting

This distributed processing approach allows for efficient use of computing resources by dividing image processing into multiple tasks and executing them simultaneously on multiple nodes. Additionally, offloading the processing to the server allows the NAO robot to focus on other tasks, such as image capture and vocal announcement of prediction results. Overall, the approach adopted for processing images affected and not affected by dysgraphia is both effective and efficient, producing accurate results within reasonable timeframes, while offering greater flexibility and better utilization of available computing resources.

Adopting a client/server architecture for our framework was an effective solution for several reasons. Firstly, the complexity of our two algorithms for recognizing dysgraphia and signs affecting dysgraphia from handwriting required significant computing resources. By using this architecture, we were able to distribute the workload across multiple nodes and accelerate data processing. Additionally, the client/server architecture allowed us to separate tasks between the NAO robot and the computing servers, increasing system stability and reliability.

THE EXPERIMENTAL STUDY: CHILD-ROBOT INTERACTION FOR DEEP DIAGNOSIS OF DYSGRAPHIA

The central objective of this study is to evaluate the effectiveness and reliability of the framework in accurately and in real-time identifying dysgraphia in students within an educational environment. In this study, we will focus on the implementation of a rigorous protocol to evaluate the performance of the framework. Our evaluation approach will primarily concentrate on observing the interactions between humanoid robots and students. We will examine how the humanoid robot interacts with the students during the writing session, collects data, and performs real-time analysis to detect potential signs of dysgraphia. Thus, we have collected subjective data through a post-interaction questionnaire. The aim is to obtain valuable insights into students' perceptions of their interaction experience with the robot, as well as the perceived relevance and effectiveness of the system in the context of handwriting assessment and in the diagnosis of dysgraphia. The goal is to explore the ability of the framework to provide accurate information about handwriting deficiencies while ensuring an engaging and interactive learning experience.

PARTICIPANTS

The study was conducted at the Normal Higher School of Technical Education (ENSET) in Mohammedia, Morocco. Thirteen children (7 boys and 6 girls) aged between 5 and 14 participated in the study. Participants were selected on the recommendation of their teachers, who suggested students with significant writing difficulties. The study respected ethical standards of confidentiality and responsibility. All participants were included after acceptance and signature of an informed parental consent form. The study complied with current ethical standards and was approved by the relevant ethics committee.

ENVIRONMENT CONFIGURATION

Pedagogical scenarios were developed to teach handwriting acquisition skills to the participants, in which the NAO robot acted as an assistant tutor. The dysgraphia identification phase involved one-to-one interactions between the robot and each child. These interactions were carried out either on a whiteboard or on a touch-screen Microsoft Surface tablet, providing visual context as well as recording the children's tactile data.

The basic configuration adopted for our sessions is clearly illustrated in Figure 8. Each child was seated in their own chair, facing a table equipped with either a tablet or a whiteboard. The NAO robot was positioned in front of the child, creating a similar reference environment to a teacher and student. A video camera, mounted on a tripod and pointed at the child, was used to record these interactions. A second camera, placed to one side, completed the picture by providing a more complete overview of the exchanges between the robot and the child.

Figure 8. Setting up the environment

MATERIALS

The equipment used to conduct our experiment consists mainly of tactile tablets equipped with stylus pens, as well as whiteboards. These two tools are used by the children to interact with the assistant robot and practise their handwriting. The tablets are used to scan the QR code and display the handwritten reference sheet to the learners, providing essential visual and pedagogical support to guide the handwriting activity (Figure 9).

Figure 9. Student practicing handwriting

INTERACTION PROCEDURE

Figure 10 illustrates the overall process of this experiment, with the green boxes representing tasks provided by the human teacher, while the blue boxes indicate tasks mediated by the NAO robot. This dynamic interaction between NAO, the human teacher, and the learners creates an enriching and targeted learning environment, aiming to improve handwriting skills while facilitating early detection of dysgraphia.

First, the robot gives a detailed presentation of writing techniques, giving a visual demonstration of character formation. Learners are then invited to put these lessons into practice by writing individually. NAO then stays actively involved, capturing the handwritten characters created by the learners. This capture enables the robot to assess the quality of the handwriting and identify the presence of dysgraphia, classifying any signs of dysgraphia if the character is affected. NAO also determines the type of dysgraphia and its degree of severity. The result of the dysgraphia diagnosis is then pronounced by NAO.

At the end of the session, the human teacher interacts with the learners to gather their opinions and impressions of the experience, as well as to discuss the results and feedback provided by NAO. Feedback is generally positive, highlighting learners' appreciation for the interaction with NAO, and attesting to the effectiveness of the approach in improving handwriting skills and early detection of dysgraphia issues.

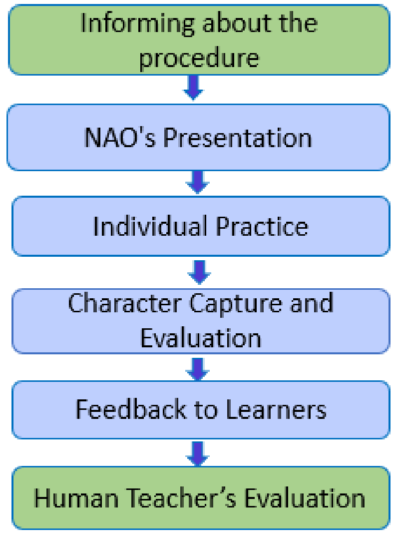

Figure 10. Global experimentation process

RESULTS

A questionnaire assessing the quality and performance of our framework, as implemented in the NAO robot and deployed within an educational context, was proposed to each participant at the conclusion of the experiment. The results are presented in Figures 11 and 12, as well as Table 2.

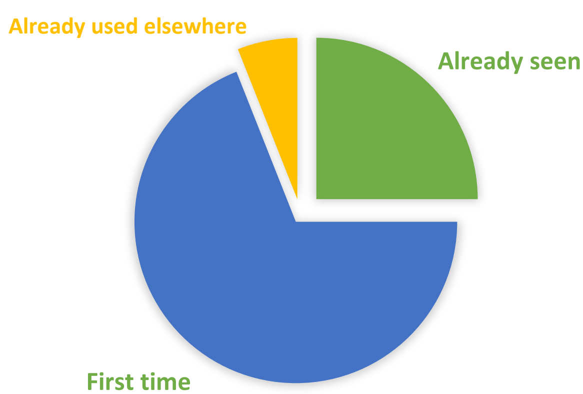

Figure 11. Did you know the NAO robot before starting this experiment?

Table 2. How would you describe this experience?

	Simple	Complex	Boring	Innovative	Sophisticated
Strongly disagree	0%	76%	87%	0%	0%
Disagree	53%	14%	13%	0%	0%
No opinion	19%	8%	0%	3%	0%
I agree	21%	2%	0%	17%	68%
Totally agree	7%	0%	0%	80%	32%
Total	100 %	100 %	100 %	100%	100 %

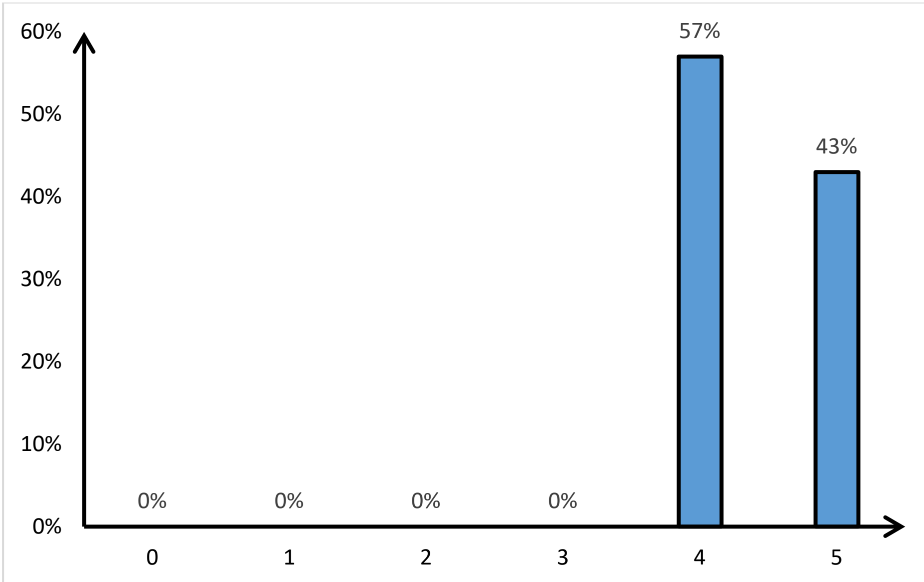

Figure 12. Could you evaluate this experience by giving a rating?

The conducted experiment, which aimed at evaluating our framework integrated into the NAO robot, enabling real-time and in-depth diagnosis of dysgraphia in a school environment, was deemed innovative and sophisticated by the majority of participants. The results obtained from this study suggest that our innovative approach is not only promising but also effective in improving the dysgraphia diagnostic process. Although our sample size was limited to 13 learners, these preliminary conclusions reveal the considerable potential of our framework to revolutionize the way we identify this writing disorder. The statistical analysis is based on a descriptive approach, which is considered appropriate given the small sample size and exploratory nature of the study. This choice aims to highlight general trends and the consistency of the responses collected, rather than to establish any inferences that can be made in general. Despite this limitation, the convergence of results and consistency of responses indicate good internal reliability. This approach provides initial empirical validation of the proposed framework, pending further large-scale studies integrating more advanced statistical analyses to strengthen the robustness and generalizability of the conclusions.

DISCUSSION

This study sought to reinforce the validity and relevance of our framework by applying it in a practical context within an educational environment. The results obtained confirm the efficiency of our approach in improving early detection of dysgraphia in learners and providing appropriate assistance. The positive feedback from learners regarding their interaction with NAO attests to the user-friendliness and acceptability of our system, which is crucial for its successful integration into classrooms. The practical application of our framework paves the way for its use in real educational settings, where it could have a significant impact on early detection of writing disorders and improvement of handwriting skills. This represents a significant advancement in assisting learners with special needs, as our framework offers an automated and scalable solution for identifying and addressing dysgraphia.

However, it is important to note that this study represents a first step, and further research will be necessary to refine our framework further, expand its scope, and assess its effectiveness on larger populations of learners. We acknowledge that the study involved a relatively small sample of 13 children aged 5 to 14, which may limit the generalizability of the results. Nevertheless, these preliminary results demonstrate the feasibility and effectiveness of our framework for real-time detection of dysgraphia and provide a solid foundation for future studies on larger and more diverse samples. Additionally, close collaboration with educators and healthcare professionals is essential for successful integration into educational settings. Ultimately, this study provides crucial insights for the future of dysgraphia detection and assistance, paving the way for substantial improvements in inclusive education and personalized learning.

CONCLUSION

This research proposes an intelligent and fully autonomous diagnostic framework based on a client-server architecture, combining social robotics and deep learning for the detection of dysgraphia. The NAO humanoid robot interacts directly with students by capturing their handwriting data in real time, then applying CNN models to identify the presence and characteristic signs of dysgraphia, while assessing its severity. The experimental results, obtained in a real educational context, demonstrate high accuracy and robustness, confirming the reliability of the proposed framework. Beyond technical performance, this study makes a significant contribution to inclusive education research by showing how a social robot can act as an autonomous screening assistant, reducing dependence on human evaluation. On a theoretical level, it illustrates the relevance of the client/server paradigm for embedded intelligence in constrained robotic environments. On a practical level, it offers teachers and therapists an innovative tool for the early and objective detection of writing disabilities. Finally, on a societal level, it opens the way to a more equitable and personalized integration of artificial intelligence technologies in education and healthcare. Future developments may explore multilingual adaptation, affective interaction, and long-term personalized monitoring, contributing to more inclusive, responsive, and intelligent learning environments.

REFERENCES

Amirova, A., Rakhymbayeva, N., Yadollahi, E., Sandygulova, A., & Johal, W. (2021). 10 years of human-NAO interaction research: A scoping review. *Frontiers in Robotics and AI*, *8*, 744526. https://doi.org/10.3389/frobt.2021.744526

Anderson, A. H., Stephenson, J., Carter, M., & Carlon, S. (2019). A systematic literature review of empirical research on postsecondary students with autism spectrum disorder. *Journal of Autism and Developmental Disorders*, *49*(4), 1531–1558. https://doi.org/10.1007/s10803-018-3840-2

Antonarakis, S. E., Skotko, B. G., Rafii, M. S., Strydom, A., Pape, S. E., Bianchi, D. W., Sherman, S. L., & Reeves, R. H. (2021). Down syndrome. *Nature Reviews Disease Primers*, *6*, Article 9. https://doi.org/10.1038/s41572-019-0143-7

Asselborn, T., Gargot, T., Kidziński, Ł., Johal, W., Cohen, D., Jolly, C., & Dillenbourg, P. (2018). Automated human-level diagnosis of dysgraphia using a consumer tablet. *npj Digital Medicine*, 1, Article 42. https://doi.org/10.1038/s41746-018-0049-x

Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. *Science Robotics*, 3(21), 1–9. https://doi.org/10.1126/scirobotics.aat5954

Biotteau, M., Danna, J., Baudou, É., Puyjarinet, F., Velay, J. L., Albaret, J. M., & Chaix, Y. (2019). Developmental coordination disorder and dysgraphia: Signs and symptoms, diagnosis, and rehabilitation. *Neuropsychiatric Disease and Treatment*, *15*, 1873–1885. https://doi.org/10.2147/NDT.S120514

Bouck, E. C., & Long, H. (2021). Assistive technology for students with disabilities: An updated snapshot. *Journal of Special Education Technology*, *36*(4), 249–257. https://doi.org/10.1177/0162643420914624

Chiara, M., Lieto, D., Castro, E., Pecini, C., Inguaggiato, E., Cecchi, F., Dario, P., Cioni, G., Sgandurra, G., Howard, S. J., & Daniela, L. (2020). Improving executive functions at school in children with special needs by educational robotics. *Frontiers in Psychology*, *10*, 2813. https://doi.org/10.3389/fpsyg.2019.02813

Chung, P. J., Patel, D. R., & Nizami, I. (2020). Disorder of written expression and dysgraphia: Definition, diagnosis, and management. *Translational Pediatrics*, *9*(Suppl 1), S46–S54. https://doi.org/10.21037/TP.2019.11.01

Desideri, L., Negrini, M., Cutrone, M. C., Rouame, A., Malavasi, M., Hoogerwerf, E. J., Bonifacci, P., & Sarro, R. D. (2017). Exploring the use of a humanoid robot to engage children with autism spectrum disorder (ASD). *Studies in Health Technology and Informatics*, *242*, 501–509. https://doi.org/10.3233/978-1-61499-798-6-501

Drotár, P., & Dobeš, M. (2020). Dysgraphia detection through machine learning. *Scientific Reports*, *10*, Article 21541. https://doi.org/10.1038/s41598-020-78611-9

Dutt, S., & Ahuja, N. J. (2021). Comparison of classification methods used in machine learning for dysgraphia identification. *Turkish Journal of Computer and Mathematics Education*, *12*(11), 1886-1891. https://doi.org/10.17762/turcomat.v12i11.6142

Estévez, D., Terrón-López, M. J., Velasco-Quintana, P. J., Rodríguez-Jiménez, R. M., & Álvarez-Manzano, V. (2021). A case study of a robot-assisted speech therapy for children with language disorders. *Sustainability*, *13*(5), 2771. https://doi.org/10.3390/su13052771

Gao, X. (2016). *The improvements of NAO robots in education.* [Bachelor dissertation, Helsinki Metropolia University of Applied Sciences]. https://www.theseus.fi/bitstream/handle/10024/113356/Gao_Xingyu.pdf?sequence=1&isAllowed=y

Grigorenko, E. L., Compton, D. L., Fuchs, L. S., Wagner, R. K., Willcutt, E. G., & Fletcher, J. M. (2020). Understanding, educating, and supporting children with specific learning disabilities: 50 years of science and practice. *American Psychologist*, *75*(1), 37–51. https://doi.org/10.1037/amp0000452

Henning, C., Summerfeldt, L. J., & Parker, J. D. A. (2022). ADHD and academic success in university students: The important role of impaired attention. *Journal of Attention Disorders*, *26*(6), 893–901. https://doi.org/10.1177/10870547211036758

Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles, and research issues of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *1*, 100001. https://doi.org/10.1016/j.caeai.2020.100001

Johal, W. (2020). Research trends in social robots for learning. *Current Robotics Reports*, *1*, 75–83. https://doi.org/10.1007/s43154-020-00008-3

Jørgensen, C. R., Dobson, G., & Perry, T. (2021). Migrant children with special educational needs in European schools – A review of current issues and approaches. *European Journal of Special Needs Education*, *36*(3), 438–453. https://doi.org/10.1080/08856257.2020.1762988

Khasawneh, M. A. S. (2021). Auditory memory among a sample of students with learning disabilities in English in Irbid Governorate. *Science Education*, *2*(11), 609–621.

Khasawneh, M. A. S., & Alkhawaldeh, M. A. (2020). The effectiveness of phonological awareness training in treating deficiencies in auditory processing among children with learning disabilities among elementary cycle students in Saudi Arabia. *International Journal of Language Education, 4*(3), 350–360. https://doi.org/10.26858/ijole.v4i3.14758

Leite, I., Castellano, G., Pereira, A., Martinho, C., & Paiva, A. (2014). Empathic robots for long-term interaction. *International Journal of Social Robotics, 6*, 329–341. https://doi.org/10.1007/s12369-014-0227-1

Ma, P. (2020, August). Recognition of handwritten digits using a convolutional neural network. *Proceedings of the International Conference on Computing and Data Science, Stanford, CA, USA,* 183–190. https://doi.org/10.1109/CDS49703.2020.00044

Miskam, M. A., Shamsuddin, S., Yussof, H., Omar, A. R., & Muda, M. Z. (2014, December). Programming platform for the NAO robot in cognitive interaction applications. *Proceedings of the IEEE International Symposium on Robotics and Manufacturing Automation, Kuala Lumpur, Malaysia*, 141–146. https://doi.org/10.1109/ROMA.2014.7295877

Newton, D. P., & Newton, L. D. (2019). Humanoid robots as teachers and a proposed code of practice. *Frontiers in Education*, *4*, 125. https://doi.org/10.3389/feduc.2019.00125

Pandey, A. K., & Gelin, R. (2017). Humanoid robots in education: A short review. In A. Goswami & P. Vadakkepat (Eds.), *Humanoid robotics: A reference* (pp. 1–16). Springer. https://doi.org/10.1007/978-94-007-7194-9_113-1

Rosenblum, S., & Dror, G. (2017). Identifying developmental dysgraphia characteristics utilizing handwriting classification methods. *IEEE Transactions on Human-Machine Systems, 47*(2), 293-298. https://doi.org/10.1109/THMS.2016.2628799

Svensson, I., Nordström, T., Lindeblad, E., Gustafson, S., Björn, M., Sand, C., Almgren/Bäck, G., & Nilsson, S. (2021). Effects of assistive technology for students with reading and writing disabilities. *Disability and Rehabilitation: Assistive Technology*, *16*(2), 196–208. https://doi.org/10.1080/17483107.2019.1646821

Zolna, K., Asselborn, T., Jolly, C., Casteran, L., Nguyen-Morel, M., Johal, W., & Dillenbourg, P. (2019). *The dynamics of handwriting improves the automated diagnosis of dysgraphia.* PsyArXiv. https://doi.org/10.48550/arXiv.1906.07576

AUTHORS

Soukaina Gouraguine works as an Associate Professor and researcher in Computer Science and Artificial at ESEF Berrechid, Hassan I University of Settat. Her research focuses on the creation and integration of intelligent robotic agents to support innovative educational systems, particularly for learners and teachers with special needs. She can be contacted at email: soukaina.gouraguine@uhp.ac.ma

Mohammed Qbadou obtained a master's degree in Mechanical Engineering from ENSET of Mohammedia in 1992, the DEA in energetics and physics in 1993, and the first PhD in robotics especially in the modeling and control of flexible manipulator robots at the Mohammed V University of Rabat in 1998, the HDR in computer science in 2017 and the second PhD in computer science in 2021 at the Hassan II University of Casablanca. Since 1998, he has been a research professor in computer science at ENSET of Mohammedia. His research focuses on the Semantic Web, Big Data Analytics, Artificial Intelligence, Inclusive Smart Education Systems, and Assistive Robotics. He has accumulated 30 years of experience in teaching mechanical engineering, robotics, and computer science. In scientific research, he has produced over 100 indexed publications. He can be contacted at email: qbmedn7@gmail.com.

Khalifa Mansouri works as a researcher and computer science teacher at the ENSET Institute of the University Hassan II of Casablanca. His research interests include Real-Time Systems, Information Systems, e-Learning Systems, and Industrial Systems (Modeling, Optimization, and Numerical Computing). Degrees from ENSET of Mohammedia in 1991, CEA in 1992, and a PhD in calculation and optimization of structures at Mohammed V University in Rabat in 1994, HDR in 2010, and a PhD in computer science from the University of Hassan II in Casablanca in 2016. He can be contacted at email: khmansouri@hotmail.com.