IUST Iran University of Science and Technology
Iranian Journal of Electrical and Electronic Engineering
Journal Homepage: ijeee.iust.ac.ir

Virtual assistant robot for physical training exercises supervision

Robinson Jiménez Moreno*, Anny Astrid Espitia Cubillos*(C.A.) and Esperanza Rodríguez Carmona*

Abstract: This document presents the design of a virtual robotic system for the supervision of physical training exercises, to be carried out in a closed environment, which only requires a computer equipment with a web camera. To do this, deep learning algorithms such as convolutional networks and short- and long-term memory networks are used to recognize voice commands and the user's video actions. A predefined dialogue template is used to guide a user's training cycle based on the execution of the exercises: push-ups, abdominal, jump or squat. The contribution of the work focuses on the integration of deep learning techniques to design and personalize virtual robotic assistants for everyday task. The results show a high level of accuracy by the virtual robot both in understanding the audio and in predicting the exercise to be performed, with a final accuracy value of 97.75% and 100%, respectively.

Keywords: Assistive Robotics, Convolutional Neural Networks, LSTM Networks, Human-Robot Interface, Deep Learning.

1 Introduction

PHYSICAL exercise can delay physiological aging and promote the metabolism of bodily functions, therefore adequate physical training can help the health of those who do it [1]. Physical exercise can be done in specialized centers such as gyms or at home [2], in any of these cases, for this activity it is useful to have supervision for adequate training that allows interaction with real-time feedback. For this aspect, robotic systems are supporting this type of supervision, where the human-robot interaction must be friendly, adaptive and safe [3], key elements to consider in its design.

Research developments such as the one presented in [4], are aimed at designing comprehensive home care systems, in this case thinking about the elderly, specifically those who live alone. Where there is an assistive robot to monitor their mood in a home automation environment with low-cost sensors, which recommends activities such as exercising, which helps the user improve their independence, live more safely [5] and with a higher quality of life [6]. In [7] technological advances are shown to improve the quality of life of older adults in topics related to muscular activity, among others. In [8], to help older adults stay active at home, physical-social exercises are designed between humans and robots. In this way, in [9] a portable assistance robot is designed to improve physical function and walking efficiency.

Technological advances generate new and varied applications, which take great importance in the use of artificial intelligence (AI), machine learning and virtual reality, among others. Technologies with medical and therapeutic applications support physical therapy [10] using videos or commands that provide real-time instructions, detect postures, determine the quantity and quality of training, increasing exercise precision [11], where it is also possible to remotely monitor and evaluate the physical movement of users [12]. In [13] an interactive computer vision-based application is designed to support therapists by providing real-time metrics of home physical therapy exercises for remote care therapies. In addition, it is possible to advise in a personalized way with a focus on the user's performance to improve the exercise or therapy sections [14].

Similarly, in [15] deep neural networks are used to

Iranian Journal of Electrical & Electronic Engineering, 2024.
Paper first received 27 August 2024 and accepted 24 October 2024.
* The authors are with the Faculty of Engineering, Universidad Militar Nueva Granada, Bogotá, Colombia.
E-mail: anny.espitia@unimilitar.edu.co.
Corresponding Author: Anny Astrid Espitia Cubillos.

develop a personal training assistant that allows correct postures and thus avoid injuries to individuals. Neural networks have also been implemented for the evaluation of performance in rehabilitation [16], and in [17] artificial intelligence is used to analyze the effect of physical training and possible previous injuries, supported by neural network algorithms. Also, sports skills can be developed with the use of virtual reality based on artificial intelligence as shown in [18].

Likewise, to attend cardiac rehabilitation programs for patients with cardiovascular diseases in [19] a system is created with a social robot that has the role of training assistant during therapy, to motivate the user to perform physical activity and continue with rehabilitation. For physical rehabilitation, virtual environments can also be used with video games that allow users to perform everyday physical actions such as catching objects or raising an arm. These video games have difficulty levels and store information on the progress of the rehabilitation [20].

In [21] an assistance robot is proposed that produces support force for assistance in physical tasks and generation of muscular effort related to the elbow joint. In [22] a physical simulation framework for assistive robots is presented to help with some activities of daily living, demonstrating that modeling human movement allows for greater assistance.

AI is also used to recommend exercise routines through mobile devices, in [23] it is applied so that users can use outdoor gyms depending on their profile and physical conditions, recommending the machines to use and the exercise that can be performed.

Based on the state of the art and as a complement to the assistance tools existents, this research has as goal design a virtual robot to assist people the execution of physical exercises in a non-invasive way. The robot proposed is based on image capture by camera and audio identification. The virtual robot interacts with the user by voice, allowing to choose the exercise and controlling both the number of repetitions and the rest times between each one.

This article is composed by five sections, the first and current one where the state of the art on the subject is presented. The second section where the methodology used is explained. The third section exposes the algorithmic development and training resulting from deep learning networks. In the fourth part, the results achieved through the robot designed user interface are shared and, finally, the fifth section presents the conclusions of the study.

2 Materials and Methods

For development of the virtual robotic system for exercise supervision, first step is to define the interaction protocol with the user. Secondly, the dialogue model is established between the user and the virtual robotic assistance system, that guides the user's actions and responses by capturing both audio and video of the user using a laptop computer and without direct physical interaction.

Thirdly, the network architectures for voice and video recognition are determined. The implemented robotic system corresponds to the use of Deep Learning algorithms for interaction with the user, which are based on convolutional neural networks [24] and LSTM networks [25], in the different phases of the supervision process of the chosen exercises, which in this case corresponds to push-ups, abdominal, jump and squat.

In the fourth phase, the audio database is created that includes the predefined words and numbers from 1 to 10, with male and female voices. For the interpretation of the user's voice, two convolutional networks are implemented and trained, one for numbers and another for predefined words; measuring the degree of accuracy achieved by each one.

In the fifth stage, the video database is also built with the execution of the exercises by men and women. The LSTM network is trained, a hybrid model with a CNN network is used, and the degree of accuracy achieved is calculated using an Intel Core I7 computer, with an NVIDIA RTX 3070 GPU with 16 GB of RAM. In the sixth phase, the interaction interface with the virtual robot is developed in the MATLAB app.

Finally, it is validated that, through the audio system of a computer equipment and its web camera, it is possible to capture the scene where the user is located and recognize their voice (emulating the virtual robot). The action performed by the user according to the movement of the exercise to be executed is identified by an LSTM network and his voice in response to the dialogue established by the virtual robot is recognized using a CNN network, pre-processing the audio using a frequency-based spectrogram by MEL.

3 Algorithmic Development

Figure 1 illustrates the flowchart of the interaction protocol established for the initiation of robotic assistance, audio and video capture and identification, feedback to the user, and completion of the interaction.

The virtual robotic system for exercise monitoring allows the user to select the exercise to be performed, the number of repetitions and the rest time. The system tracks the sequence by counting both the repetitions and the rest time and only requires the use of a computer with a web camera where the designed virtual robot is installed.

According to the flowchart, a summary of the dialogue model between user and robot is illustrated in Figure 2,

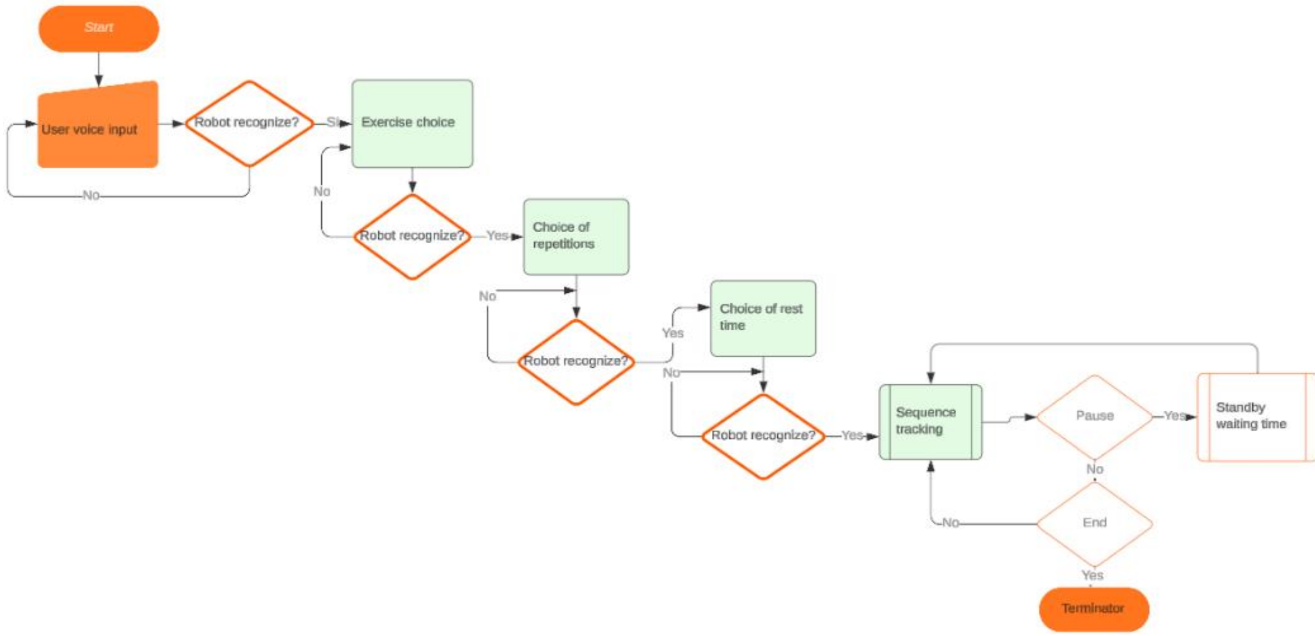

Fig. 1 Flowchart.

which is always guided by the robot. Next, the network architectures that give rise to voice recognition by the user are presented, according to the dialogue model and the network architectures that allow the monitoring of exercise sequences.

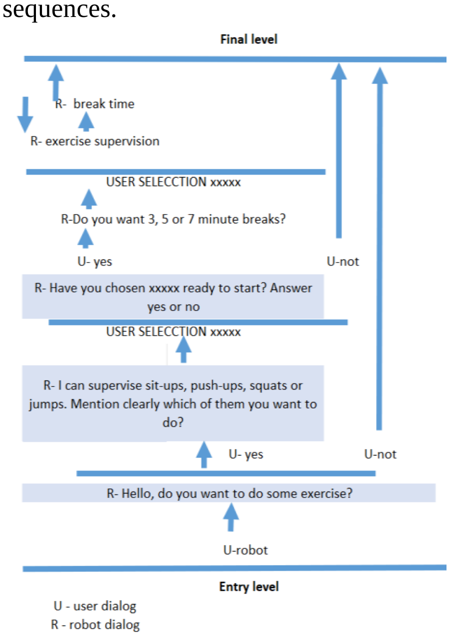

Fig. 2 Summary dialogue model

The user's communication is delimited by the robot's dialogue model, for which it must give specific numerical answers or predetermined words in relation to the dialogue sequence. Two convolutional networks were implemented for the interpretation of the user's voice, one for numbers and another for words, the training parameters used are illustrated in table 1 (left).

Table 1 Network training features

CNN		LSTM	
Hyperparameter	Value	Hyperparameter	Value
Mini Batch size	1	Mini Batch size	16
Epochs	150	Epochs	200
Learn Rate	1e-6	Learn Rate	1e-5
Dropout	50%	Dropout	50%
Optimizer	ADAM	Hidden units	25

The architecture of both networks is illustrated in Figure 3. where the network design parameters are established by convolution layer (C) such as the kernel (K), the number of filters (F), the padding (P) and the stride (S), batch normalization layer (BN), pooling layer as well as the kernel of the pooling stage (M), where the M implies that the maximum method is used (see eq.1). Until the final stage of network classification at the fully connected stage (FC) with Drop Out layer (D) at 20% [26].

$$h_j^n(x,y) = max_{\bar{x},\bar{y}} h_j^{n-1}(\bar{x},\bar{y}) \qquad (1)$$

Figure 4 illustrates the performance in the training to the number network, which has ten classes from numbers 1 to 10. The database consists of both male and female voices and the high degree of final accuracy achieved (97%) is evident. The network is composed of 20 layers with a total of 1.2 million learning parameters, its training time was 79 minutes and 33 seconds.

Figure 5 illustrates the confusion matrix of the number identification network where the confusion of a three with a ten is evident. The confusion is caused by the soft voice ending at the of each word with a similar beginning.

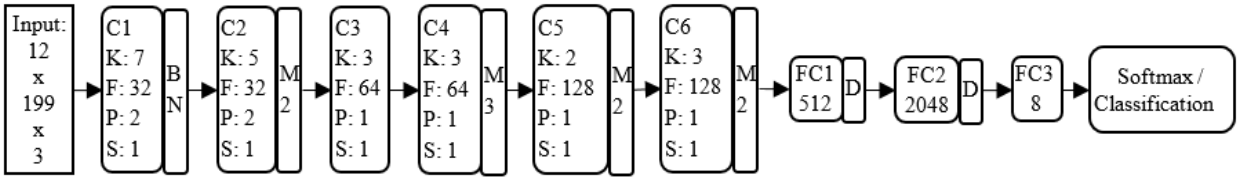

Fig. 3 Network architecture for speech recognition

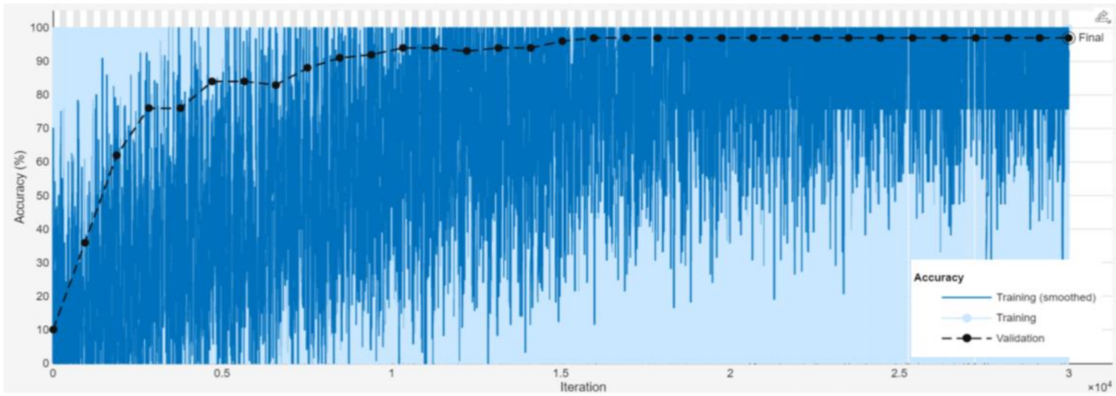

Fig. 4 CNN training of numbers

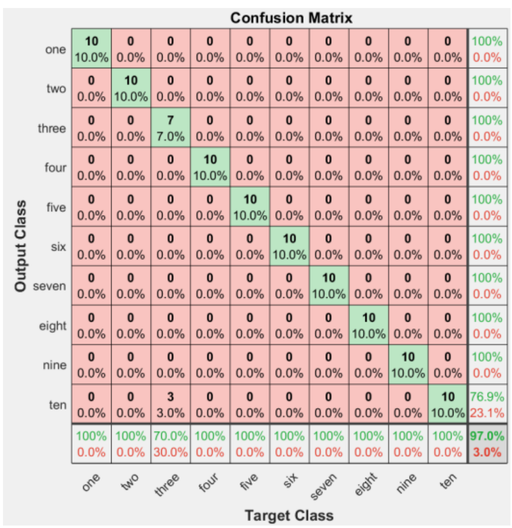

Fig. 5 CNN confusion matrix of numbers

Fig. 7 Word CNN confusion matrix

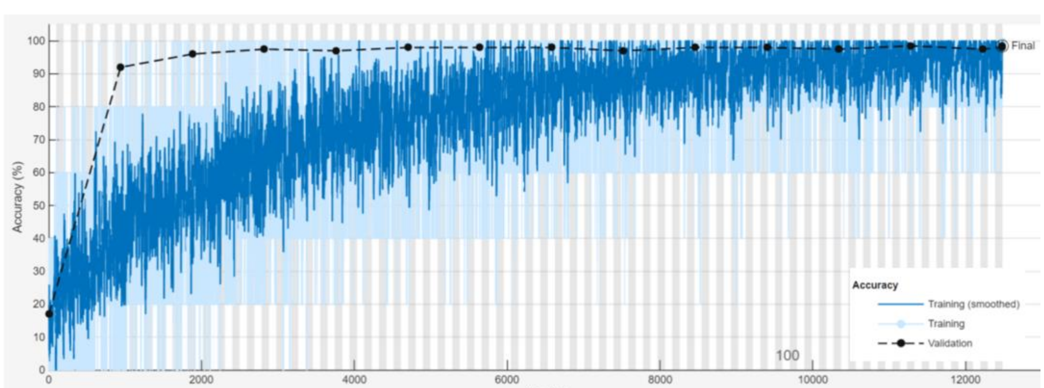

Fig. 6 Word CNN Training

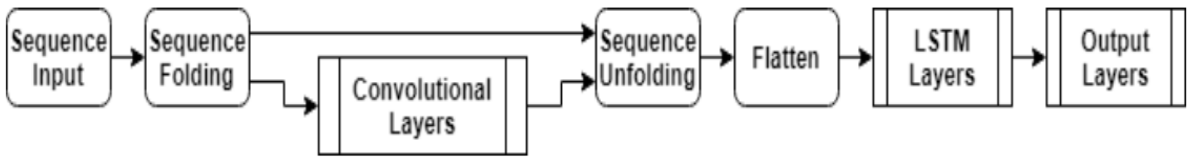

Fig. 8 CNN – LSTM architecture for video sequence [27]

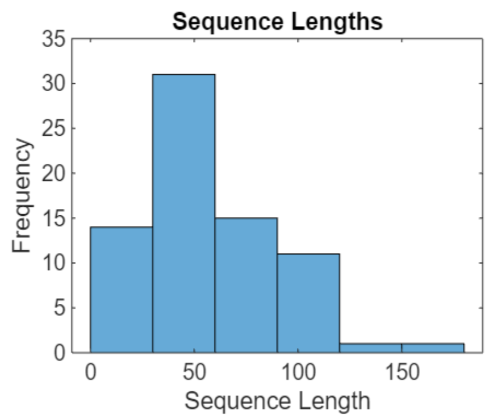

Fig. 9 Length of video sequences used.

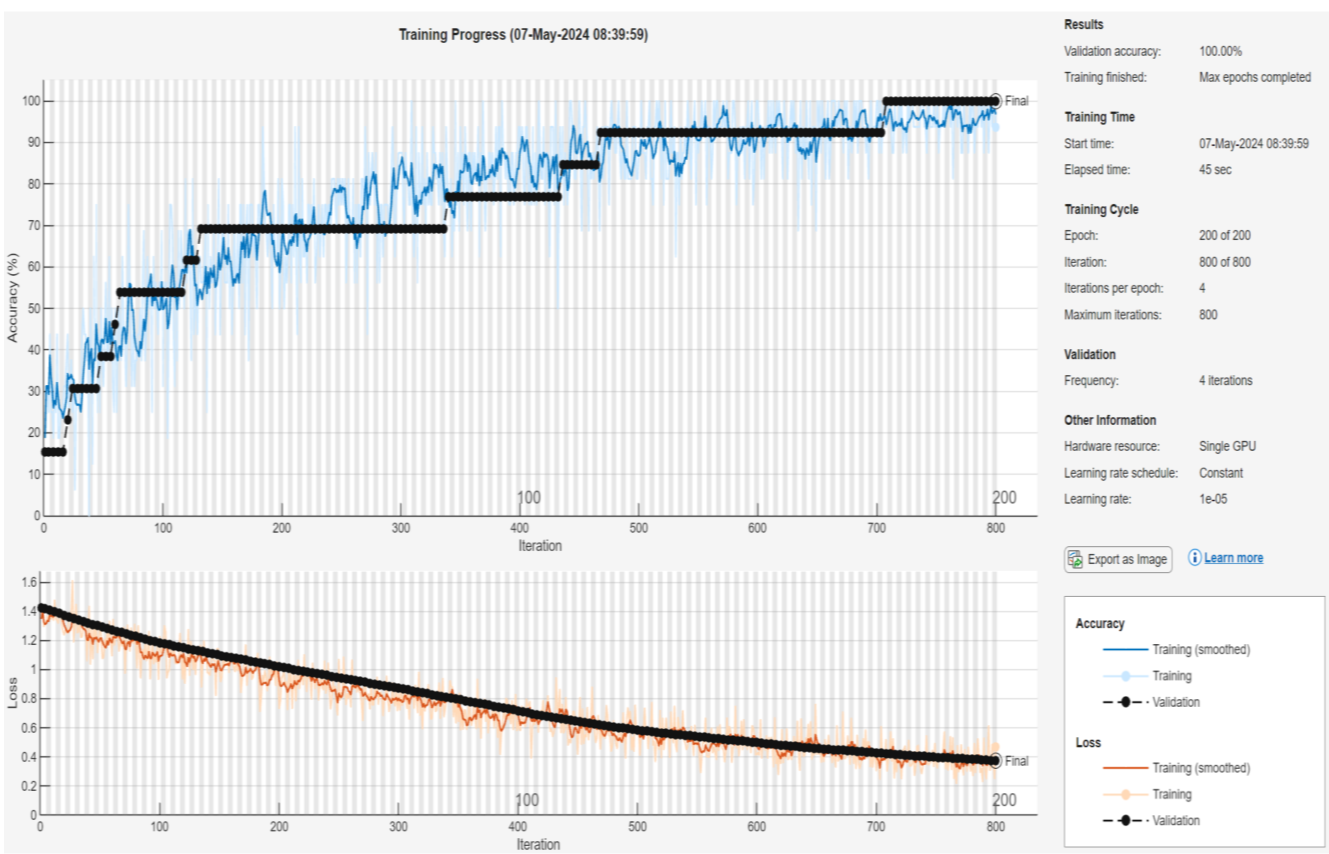

Fig. 10 LSTM network training

Figure 6 illustrates the performance in the training of the word network, which has eight classes of the user answer model, and which corresponds to the types of abdominal, push-up, jump and squat exercises, to the yes or no statements and to the beginning and closing of the dialogue respectively, along with the words robot and end. The database consists of both male and female voices and the high degree of final accuracy achieved (98.5%) is evidenced. The network has 148 layers with 6.1 million learning parameters, with a training time of 45 minutes and 37 seconds.

Figure 7 illustrates the confusion matrix of the word identification network where the confusion of a single word is evident, which no with robot.

The supervision of the sequence of exercises by the robot is done using an LSTM network, which is capable of learning patterns in sequences. In this case video sequences of the execution of the exercises push-ups, sit-ups, jump or squat, targets to be classified by the network. A hybrid model is used with a CNN network (see Figure 8) that it takes each frame and generates a data vector, until the linear arrangement of the sequence of each of the frames that make up each video is formed.

The video database consists of fitness training videos of the four types of characteristic exercises mentioned jump, push-up, squat and abdominal. The input data vector corresponds to a sequence of 1080X1080 pixels and three channels referring to color (RGB) and maximum 150 frames per video, where the number of sequences is obtained in relation to the number of frames per video. The database was distributed in 85% training and 15% validation, 1024 features were used for sequencing. Figure 9 shows the histogram of the length of the sequences used.

The network architecture corresponds to a BiLSTM (Bidirectional long short-term memory) with 25 hidden units and whose training uses the parameters described in table 1 (right) which allows reaching a final accuracy and the average accuracy (from the last 10 epochs) of 100%, as illustrated in figure 10. The network is composed of 148 layers with a total of 6.1 million learning parameters, whose training time is 45 seconds.

4 Results and Discussion

Validating the results from the running network, the prediction of the type of exercise performed and captured by video is correct for each of the four types of exercises evaluated.

The execution of robotic interaction tasks is based on the user's choice of time, where the implemented algorithm divides the sequencing of actions according to the type of exercise, in this case, the execution times were averaged according to the database users, as illustrated in Table 2.

Table 2 Network training features

Exercise	Average time
Jumps	1 sec.
Abdominals	2 sec.
Push-ups	2 sec.
Squat	1 sec.

The human-robot interaction interface designed is illustrated in Figure 11 where is possible see a start button before which the user must answer to the dialogue model, the voice of the robot is based on a text-audio model presented in [28]. On the left side, a text box is observed where the exercise chosen by the user will appear and which is detected by voice command by the robot, a text box is observed where the rest time chosen by the user will appear and which is also detected by voice command by the robot. On the right side there is an image of the exercise that the user must perform, in the middle the initial and final positions, and at the bottom there is a text box where the exercise detected by the camera will appear which corresponds performed by the user.

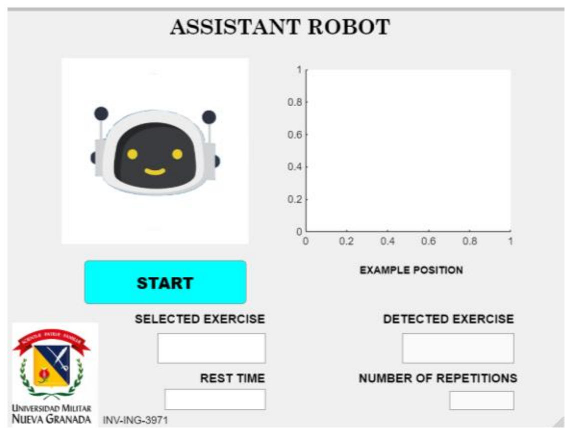

Fig. 11 Human-robot interaction interface

Figure 12 shows a test of the interface and the robotic assistance model where the exercise and action by the user has been correctly detected under the dialogue model illustrated in table 3.

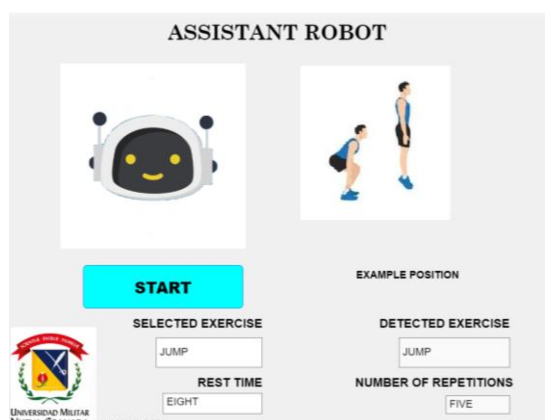

Fig. 12 Interaction test for jumping exercise

Table 3. Dialogue model for jump

Robot	User
Hello, do you want to do some exercise? Answer yes or no	Yes
I can supervise sit-ups, push-ups, squats or jumps. Mention clearly which of them you want to do.	Jumps
Have you chosen jumps, ready to start? Answer yes or no	Yes
Do you want 3, 5 or 7 minute breaks?	5 minutes
Please validate the "jump" role model on screen	
How many repetitions do you want to perform, maximum 10?	8 repetitions
Ready? Answer Yes or No	Yes
(After the repetition time has elapsed) begin your 7-minute rest, please hydrate or stretch gently.	
(Once the rest time has expired) your rest ends, so start again.	
(Ended the number of repetitions) finished your exercise, do you want another exercise? Yes or no.	No
The activity has ended for today, thank you and see you later.	

A previous work [24], developed for a domestic environment, allows the identification of eight words through the use of a convolutional neural network that has an accuracy of 96.9%, in this work an improvement of 0.85% is achieved in the average accuracy in the recognition of 8 words and 10 number options, six convolution layers are also used in each of the networks (one for words and another for numbers) given the few options handled (8 and 10, respectively).

Regarding the accuracy of motion identification in video in [29], a final value of 98.1% is achieved using a BiLSTM recurrent neural network to detect four walking patterns. In this work, the same network architecture is applied with an accuracy of 100% in the identification of four exercises, which have quite differentiated movements. Additionally, the proposed virtual robot allows interaction with the user.

A functional performance of the virtual robotic assistant was evidenced, it is important the environmental control at noise level and the clear pronunciation of the words understood by the robot. Some improvements are considered for future work such as alerts for detection of incorrect exercise, updating of times or number of repetitions, and the like.

At the same time, it is important to note that the evaluation group for the robotic assistant corresponds to the members of the research team. This implies that the next step of the work will be based on establishing the measurement model of the robotic assistant, evaluated by an external group with defined metrics, which allow the feedback of the experience of the non-expert user or participant of the development, to generate additional adjustments to those already mentioned.

5 Conclusions

The virtual robotic system for exercise supervision allows the user to select the exercise to be performed, the number of repetitions and the rest time, using voice commands, allowing to facilitate and naturalize the entry of information for robotic assistance. The system tracks the sequence by counting both the repetitions and the rest time by a computer with a web camera where the designed virtual robot is installed, not exposing the user to risks of physical interaction.

The action performed by the user according to the movement of the exercise is identified by an LSTM network and his voice, in response to the dialogue established, is recognized by the virtual robot using a CNN network. The results demonstrated the high performance of these deep learning algorithms and their application in assistive robots.

The results show a final high level of accuracy on the part of the virtual robot both in understanding the audio and in predicting the exercise to be performed by the user, with final accuracies of 97.75% and 100% respectively, which allowed correct assistance in the physical training task. A low level of noise in the environment was required for this so that the robot could correctly identify the user's voice.

The designed interface is friendly, with intuitive handling, which favors its use by people of different ages, including older adults.

Conflict of Interest

The authors hereby confirm that the submitted manuscript is an original work and has not been published so far, is not under consideration for publication by any other journal and will not be submitted to any other journal until the decision will be made by this journal. All authors have approved the manuscript and agree with its submission to "Iranian Journal of Electrical and Electronic Engineering".

Author Contributions

R. Jimenez M: Idea & Conceptualization, Research and Investigation, Original Draft Preparation. **A. Espitia C**: Conceptualization, Original Draft Preparation, Revise and Editing. **E. Rodríguez C**: Original Draft Preparation, Revise and Editing.

Acknowledgment

Product derived from the research project titled "Design of a human-robot interaction model using deep learning algorithms" INV-ING-3971 financed by the vice-rector for research of the Universidad Militar Nueva Granada, year 2024.

References

[1] Z. Hui, C. Jing & W. Taining, «Research on simulation analysis of physical training based on deep learning algorithm,» *Scientific Programming,* vol. 2022, 2022. DOI: 10.1155/2022/8699259.

[2] K. Kitano, T. Asakawa, N. Kamide, K. Yorimoto, M. Yoneda, Y. Kikuchi, M. Sawada & T. Komori, «Effectiveness of Home-Based Exercises Without Supervision by Physical Therapists for Patients With Early-Stage Amyotrophic Lateral Sclerosis: A Pilot Study,» *Archives of Physical Medicine and Rehabilitation,* vol. 99, nº 10, pp. 2114-2117, 2018. DOI: 10.1016/j.apmr.2018.02.015.

[3] C. Torras, «Robótica asistencial: retos éticos en la ayuda y acompañamiento a cuidadores y pacientes,» de *Soledad no deseada en la era digital*, 2023, pp. 38-46.

[4] J. A. Vera Repullo, D. Parras Burgos, F. J. Ortiz Zaragoza & J. F. Roca González, «Diseño de un sistema integral de atención domiciliaria con robot móvil asistencial,» de *CASEIB 2023. Libro de Actas del XLI Congreso Anual de la Sociedad Española de Ingeniería Biomédica*, 2023.

[5] G. Dilip, R. Guttula, S. Rajeyyag, S. Hemalatha, R. Raman Pandey, A. Bora, P. R. Kshirsagar, M. M. Khanapurkar & V. Sundramurthy, «Artificial Intelligence-Based Smart Comrade Robot for Elders Healthcare with Strait Rescue System,» *Journal of Healthcare Engineering,* vol. 2022, nº 1, p. 9904870, 2022. DOI: 10.1155/2022/9904870.

[6] W. Wang, W. Ren, M. Li & P. Chu, «A Survey on the Use of Intelligent Physical Service Robots for Elderly or Disabled Bedridden People at Home,» *International Journal of Crowd Science,* vol. 8, nº 2, pp. 88-94, 2024. DOI: 10.26599/IJCS.2024.9100005.

[7] V. P. Bravo Carrasco, M. T. Fernández Balboa, X. Adaros Manríquez & I. Jeldes Yáñez, «Tecnologías aplicadas al diseño para el cuidado del adulto mayor,» *Ergonomía, Investigación y Desarrollo,* vol. 5, nº 2, pp. 9-24, 2023.

[8] N. T. Fitter, M. Mohan, K. J. Kuchenbecker & M. J. Johnson, «Exercising with Baxter: preliminary support for assistive social-physical human-robot interaction,» *NeuroEngineering and Rehabilitation,* vol. 17, nº 19, 2020. DOI: 10.1186/s12984-020-0642-5.

[9] S. H. Lee, J. Kim, B. Lim, H. J. Lee & Y.H. Kim, «Exercise with a wearable hip-assist robot improved physical function and walking efficiency in older adults,» *Scientific Reports,* vol. 13, nº 1, p. 7269, 2023. DOI: 10.1038/s41598-023-32335-8.

[10] S.A, «Artificial Intelligence of Patients Management for Injured Patient and Robotic assisted Physiotherapy Rehabilitation,» de *2024 3rd International Conference for Innovation in Technology (INOCON)*, Bangalore, India, 2024. DOI: 10.1109/INOCON60754.2024.10511878.

[11] J. Davids, N. Lidströmer & H. Ashrafian , «Artificial Intelligence for Physiotherapy and Rehabilitation,» *Artificial Intelligence in Medicine,* pp. 1789-1807, 2022. DOI: 10.1007/978-3-030-64573-1_339.

[12] M. Jleli, B. Samet & A. K. Dutta, «Artificial Intelligence-driven Remote Monitoring Model for Physical Rehabilitation,» *Journal of Disability Research,* vol. 3, p. 20230065, 2024. DOI: 10.57197/JDR-2023-0065.

[13] A. Tannoury, E. M. Choueiri & R. Darazi, «Human pose estimation for physiotherapy following a car accident using depth-wise separable convolutional neural networks,» *Advances in Transportation Studies,* vol. 59, pp. 165-178, 2023. DOI: 10.53136/979122180582610.

[14] S. P. Godse, S. Singh, S. Khule, V. Yadav & S. Wakhare, «Musculoskeletal Physiotherapy using Artificial Intelligence and Machine Learning,» *International Journal of Innovative Science and Research Technology,* vol. 4, nº 11, pp. 592-598, 2019.

[15] H. J. Chae, J. B. Kim, G. Park, D. M. O'Sullivan & J. Seo, «An Artificial Intelligence Exercise Coaching Mobile App: Development and Randomized Controlled Trial to Verify Its Effectiveness in Posture Correction,» *Interactive Journal of Medical Research,* vol. 12, nº 1, p. e37604, 2023. DOI: 10.2196/37604.

[16] Y. Liao, A. Vakanski & M. Xian, «A Deep

Learning Framework for Assessing Physical Rehabilitation Exercises,» *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, nº 2, pp. 468-477, 2020. DOI: 10.1109/TNSRE.2020.2966249.

[17] J. A. Dhanke, R. K. Maurya, S. Navaneethan, D. Mavaluru, S. Nuhmani, N. Mishra & E. Venugopal, «Recurrent Neural Model to Analyze the Effect of Physical Training and Treatment in Relation to Sports Injuries,» *Computational Intelligence and Neuroscience*, vol. 2022, 2022. DOI: 10.1155/2022/1359714.

[18] L. Jiyong, X. Jiang & A. Jiang, «Application of Virtual Reality Technology Based on Artificial Intelligence in Sports Skill Training,» *Wireless Communications and Mobile Computing*, 2022. DOI: 10.1155/2022/4613178.

[19] J. Casas, E. Senft, L. F. Gutiérrez, M. Rincón Rocancio, M. Múnera, T. Belpaeme & C. A. Cifuentes, «Social Assistive Robots: Assessing the Impact of a Training Assistant Robot in Cardiac Rehabilitation,» *International Journal of Social Robotics*, vol. 13, pp. 1189-1203, 2021. DOI: 10.1007/s12369-020-00708-y.

[20] N. A. Morales Navarro, A. G. Cossío Martínez, J. O. Guzman Sanchez, M. I. Hernández Meneses & K. M. Herrera, «Manejo de entornos virtuales mediante el sensor "Kinect" y su aplicación en fisioterapia,» *Revista tecnológica digital*, vol. 3, nº 1, pp. 1-8, 2013..

[21] R. Meattini, D. Chiaravalli, G. Palli & C. Melchiorri, «sEMG-Based Human-in-the-Loop Control of Elbow Assistive Robots for Physical Tasks and Muscle Strength Training,» *IEEE Robotics and Automation Letters*, vol. 5, nº 4, pp. 5795-5802, 2020. DOI: 10.1109/LRA.2020.3010741.

[22] Z. Erickson, V. Gangaram, A. Kapusta, K. Liu & C. C. Kemp, «Assistive Gym: A Physics Simulation Framework for Assistive Robotics,» de *2020 IEEE International Conference on Robotics and Automation (ICRA)*, Paris, 2020. DOI: 10.1109/ICRA40945.2020.9197411.

[23] J. Guzman Luna, I. D. Torres & S. Vallejo, «Un sistema recomendador movil de rutinas de ejercicio basado en el perfil del usuario,» *Research in Computing Science*, vol. 94, pp. 137-149, 2015.

[24] R. Jiménez Moreno & R. Castillo, «Deep learning speech recognition for residential assistant robot,» *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, nº 2, pp. 585-592, 2023. DOI: 10.11591/ijai.v12.i2.

[25] K. A. Athira & J. D. Udayan, «Temporal Fusion of Time-Distributed VGG-16 and LSTM for Precise Action Recognition in Video Sequences,» *Procedia Computer Science*, vol. 233, pp. 892-901, 2024. DOI: 10.1016/j.procs.2024.03.278.

[26] S. Albawi, T. A. Mohammed & S. Al-Zawi, «Understanding of a Convolutional Neural Network,» de *2017 international conference on Engineering and Technology (ICET)*, Antalya, Turkey, 2017. DOI: 10.1109/ICEngTechnol.2017.8308186.

[27] Mathworks.com, «Classify Videos Using Deep Learning,» [On line]. Available: https://es.mathworks.com/help/deeplearning/ug/classify-videos-using-deep-learning.html, 2024.

[28] S. Deng, «text-to-speech,» [On line]. Available: https://www.mathworks.com/matlabcentral/fileexchange/18091-text-to-speech, MATLAB Central File Exchange, 2024.

[29] C. G. Pachón-Suescún, . J. O. Pinzón-Arenas & R. Jiménez-Moreno, «Abnormal gait detection by means of LSTM,» *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, nº 2, pp. 1495-1506, 2020. DOI: 10.11591/ijece.v10i2.pp1495-1506.

Robinson Jiménez-Moreno is an Electronic Engineer graduated from Universidad Distrital Francisco José de Caldas in 2002. He received a M.Sc. in Engineering from Universidad Nacional de Colombia in 2012 and Ph.D. in Engineering at Universidad Distrital Francisco José de Caldas in 2018. His current working as associate professor of Universidad Militar Nueva Granada and research focuses on the use of convolutional neural networks for object recognition and image processing for robotic applications such as human-machine interaction.

Anny Astrid Espitia Cubillos performed her undergraduate studies in Industrial Engineering in the Universidad Militar Nueva Granada in 2002 and M.Sc. in Industrial Engineering from the Universidad de Los Andes in 2006. She is an Associate Professor on Industrial Engineering Program at Universidad Militar Nueva Granada, Bogotá, Colombia.

Esperanza Rodríguez Carmona performed her undergraduate studies in Mechanical Engineering (1997) from the Universidad Tecnológica de Pereira (UTP) and Master's degree in university teaching from the Universidad de La Salle, Bogotá, Colombia. She is an Associate Professor on Industrial Engineering program at Universidad Militar Nueva Granada, Bogotá, Colombia.