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Machine learning and IoT Based Robotic Solution for Home Wrist Rehabilitation through Motion Capture Enabled Architecture

Abstract: - The present study investigates the effectiveness of an integrated approach that combines machine learning, robotic rehabilitation, and traditional methods for wrist rehabilitation among the hemiparesis population. Subjects with robotic rehabilitation at the four-week intervention period showed the ball's significant difference in the flexion and extension angles and demonstrated the better overall outcomes from the robotic intervention . The machine learning models, in particular, the artificial neural networks, provided the prediction of rehabilitation outcomes and demonstrated the high accuracy, high precision, high recall, and high F1 score. This study supports the idea of the beneficial effects of combining robotic rehabilitation with machine learning algorithms and supports the notion that the two benefits could bring high synergistic effects above their individual potentials. The report also contributes to the development of the rehabilitation science of wrists, given that few studies have explored the applications of artificial intelligence methods or robotic rehabilitation beyond the context of feasibility reports. The findings of the current research could contribute useful insights for the decision-making practices of therapists and healthcare providers, also given the reliance on large data contributed by the previous interventions. Future study could investigate the long-term results, the cost-effectiveness of the approaches, and assist in developing the potential results of customization for individual patients.

Keywords: Wrist rehabilitation, Hemiparesis, Robotic rehabilitation, Machine learning, Personalized treatment.

I. INTRODUCTION

Wrist rehabilitation is a crucial part of recovery for people affected by hemiparesis. Hemiparesis itself is a side affect of a stroke, which is a common occurrence for elderly patients. Given the sheer quantity of daily activities which rely on the proper functioning of the wrist, it is even more clear how significant wrist recovery can be. For many years, various types of rehabilitation were applied to the problem of restoring wrist movement. The traditional rehabilitation methods, which were utilized the most, include physical therapy, occupational therapy and constraint-induced movement therapy. They present a number of challenges, however, including patient involvement, variety of results and possibility of a more personal approach [1]–[3].

Physical therapy is often used to exercise the muscles after a stroke and can encompass such procedures as repetitive motions, exercises and the like. Occupational therapy goes a step further and is more involved in everyday activities and exercises. Constraint-induced movement therapy is a procedure where one of the arms is restrained to make sure the other one is used instead of the unaffected arm [4]–[6]. It is designed to help potentially recover lost functions in a more direct way. When it comes to downsides, however, the traditional types of rehabilitation can be called sometimes dissatisfactory when it comes to patient engagement. This can lead

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to a variety of results, which also depend a great deal on the specific case. The need for personal attention can be a key disadvantage for those who consider choosing a traditional rehabilitation plan [7].

Wrist rehabilitation using robotics is considered a promising alternative. It is required that new technologies are focused on providing precise control over movement patterns, instruments resistant to various types, and adjustable to suit any of the desired protocols. Regularly delivered highly intensive training is possible within robotic systems as they are recognized as the primary factor promoting recovery. However, the major benefit of this method is that there are several measures devised for monitoring patient performance and providing individualized feedback, which are crucial for tailoring the therapy . New advancements have enabled the development of new robotics measures specifically for wrist rehabilitation [8]–[10]. These devices are equipped with the required sensors, actuators, and automatically controlled algorithms to deliver recovery. Their primary benefit, however, is the opportunity they create to escape extreme variations in the therapy delivery process. Maintenance and initiation of specific protocols are other benefits in this respect. As a result, wrist rehabilitation utilizing robotics may be potentially improved with fewer challenges which could negatively impact patient satisfaction and outcomes [11], [12].

There are several computational methodologies, which are proficient in analyzing rehabilitation data and establishing patient recovery probabilities. These machine learning practices are further capable of establishing the most beneficial therapy routines. These interventions tend to excel in those instances, in which relationships between input variables and outputs are intricate . In the context of rehabilitation, the primary group of rehabilitation data includes information detected with the help of biomechanical data and deep sensor measurements. Among relevant machine learning adjustments, there are artificial neural networks , support vector machines , and decision trees. These tools are aimed at processing large datasets with high reliability, precision, and accuracy. Studies have confirmed that these measures may be effectively used for the assessment and prediction of stroke recovery, gait analysis, and other rehabilitation concerns [13]–[15].

A promising method for enhancing rehabilitation outcomes and improving the field of rehabilitation science is to integrate robotic rehabilitation devices with machine learning methods. By using robotic methods and machine learning technologies, expert clinicians can tailor therapy interventions for individual patients and maximize treatment outcomes. Machine learning models can be developed to analyze biomechanical data received from robotic methods, predict the patient's response to therapy, and make clinical decisions in real-time . These innovative methods have shown a synergistic effect by using both robotics rehabilitation devices and machine learning technologies. It helps enhance the effectiveness of motor recovery and rehabilitation approaches for individuals with such health conditions as stroke, spinal cord injury, and some neurological disorders. Machine learning can be used for tracking the progress of treatment and patient's response patterns, guiding researchers and expert clinicians, to develop adaptive and personalized therapy approaches. At the same time, robotics rehabilitation devices can help understand the mechanisms of the motor recovery process and, consequently, improve the treatment approaches in rehabilitation areas and reach better outcomes . As for limitations, there is a lack of empirical research and proper literature related to various aspects of the integration of robotic rehabilitation devices and machine learning for wrist rehabilitation of individuals with hemiparesis. It is also important to generate more evidence regarding whether these methods are cost-efficient and can be scalable before applying them to other target populations [16]–[19].

The research objectives of this study are associated with filling the existing gaps in the literature. In such a way, the effectiveness of integrating robotic rehabilitation and machine learning algorithms in the rehabilitation process of individuals with hemiparesis in terms of wrist function will be explored. The focus will be on revealing the effect of robotic rehabilitation on wrist function, comparing to the outcomes of traditional methods, and determining the predictive power of machine learning models in terms of the proper treatment. The objectives mentioned above will advance the knowledge in this area, as well as inform the practical activities of clinicians and decision-making processes.

II. METHODOLOGY

In the present study, the exoskeleton was developed to promote the rehabilitation of the wrist, providing both flexion and extension movements as shown in figure 1. In particular, the exoskeleton was intended to be used with the patients with hemiparesis, as the condition often outcomes from stroke . Therefore, the main goal was to

evaluate the exoskeleton's efficacy compared to the traditional means to improve the rehabilitation process. The target was achieved by conducting the study, wherein ten subjects were to either have a normal rehabilitation course or to practice with newly developed exoskeleton. The study took one month, and during each week, patients underwent evaluation of the progress of flexion and extension.
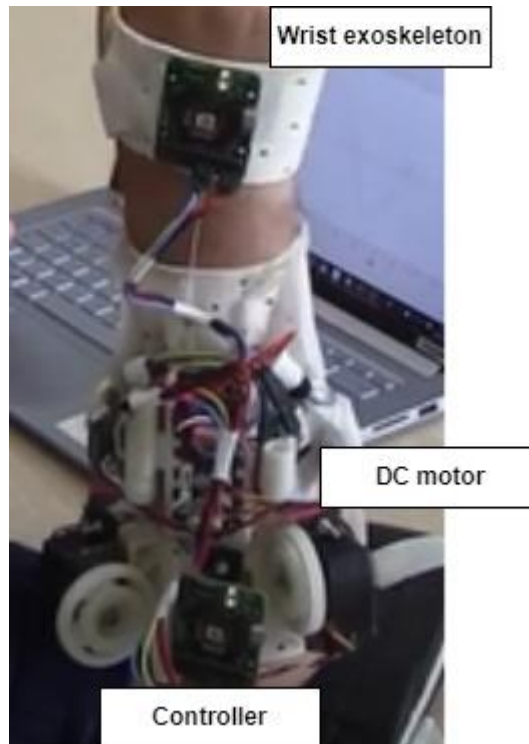

Figure.1 Wrist Exoskeleton

The evaluation targets at defining the improvements that the rehabilitation provides in terms of the flexion and extension. To meet the goal, machine learning models were employed. For the models to function properly, they need to be fed samples, which in this case were collected during the compliance with some rehabilitation tasks. Resultingly, they reflected the voluntary flexion and extension of the patient's wrist with the rates of improvement. The three types of machine learning models were used in the present investigation, namely, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees (DT).

For the current study, the OptiTrack 2-camera system was utilized, which was used to record the data for flexion and extension, as explained, which is particularly effective since the cameras provide high precision . This feature helped to record the technology which was used to compare and analyze the data, as well as the angles formed during patients' movement when they flexed and extended, using their explanation, as it can be a good guide to consider all the implications of the data that was retained by the system.

A. Actuator and the power supply

To program the actuation of the exoskeleton, we decided to use a DC motor 26V, 4A, as it was more than enough to create the torque and speed needed to control the flexion and extension of the wrist joint . The motor was then connected to the programming software on Python, as it is very convenient to work with any type of equipment. To create the system of feedback within the machine, we connected with a hall sensor and an encoder. The hall sensor was connected to the program to provide a real-time reading on the position of the motor's shaft . The encoder gave the extra reading on the rotation speed and direction. Working together they could work together to know where the exoskeleton's hand is at any point, so if the machine was not following the instructions of the therapist, it could stop and switch to the required angle of flexion and extension. During the training, the therapist could manually change the angle of flexion and extension by controlling it on the screen. This is a highly personalized and responsive program for patient rehabilitation. Moreover, as the mechanism of feedback was used, the hall sensor's data helped the trajectory of movements programmed in the exoskeleton to coincide with the instructions of the therapist.

B.   Machine learning models

The purpose of the research is to analyze the improvement of wrist rehabilitation using Artificial Neural Networks as one of the machine learning model. This is a very powerful and flexible classes of models, which is a replication of the human brain's structure of neurons, which are connected to one another via a sophisticated network . In this study, the Artificial Neural Networks were trained through passing the dataset, which also included both the flexion and extension angles and the improvement of rehabilitation values, as the target label. The Artificial Neural Networks is trained via the process of forward and backward propagation and can learn the complex dependencies between the features and target label that enables predicting the new data. Furthermore, the ability to handle the non-linear relationships in the data, and providing all the patterns is crucial advantage, as the impact of different movements of the human body on wrist rehabilitation is considered as a complex system.

The next class of machine learning models to be reviewed in this paper is Support Vector Machines . This is a type of supervised learning algorithm that demonstrates its effectiveness in both classification and regression tasks. In the current research, this model was utilized to predict the improvement of the wrist rehabilitation based on the flexion and extension angle. The fundamental idea of the SVM is to find the optimal hyperplane that divides the data points between two classes, or in a regression case, divides the continuous data and aims to maximize the area between the hyperplane and the closest data points , which, in turn, will increase the model's generalization properties. Furthermore, Support Vector Machines can be successfully employed in the situations of non-linear separation of the data by applying kernel tricks which enable to move the data into higher-dimensional spaces where the separation is feasible. In the context of wrist rehabilitation, the SVM is a quite solid and overall solid choice to conduct the analysis of the improvement in the rehabilitation process based on the features obtained via motion capture.

Another machine learning model applied in this study is Decision Trees . This is a simple and intuitive algorithm that constructs a tree-like decision structure by dividing the input feature space at each level of the tree based on the feature value. DT is trained by having the flexion and extension angles as inputs and the improvement in rehabilitation as the target, and it subsequently makes decisions at each level of the tree provoking the final decision at the leaves . The model is characterized by computational simplicity, decent performance, and the high interpretability of the results and can be implemented in the situations of noisy data.

C.   Preprocessing of dataset

The training process for machine learning models in wrist rehabilitation research comprises several core stages in order to provide the models with an opportunity to learn from data effectively. Primarily, data collection is crucial, as it involves obtaining high-quality data reflecting wrist movements. In this study, the process was enhanced by the usage of a motion capture system, such as OptiTrack 2-camera system, to measure the flexion and extension angles more accurately during the rehabilitation tasks . Then, the next crucial steps in the process are related to the preprocessing phase. Initially, data cleaning was applied as a part of the preprocessing . This step aimed to eliminate any data that might be considered "noisy" or irrelevant, as it can be a potential obstacle to learning for the model or hamper its performance . The following procedure involved data normalization (or standardization) to ensure that the features make sense and conform, which can assist in achieving better convergence when the model is trained . Thus, the previous two steps accompanied creating a high-quality dataset that would be necessary for the further training of a machine learning model.

Another significant step in this process is the choice of crucial features, which can assist in identifying the key information that can be utilized for the prediction. Thus, depending on the purpose of the research, features connected to the flexion and extension angles were chosen as features used during the training of the models . Additionally, relevant domain-specific knowledge could be used to extract important features that could be considered typical for the wrist rehabilitation process . The latter step provided the models with an opportunity to learn the information they would need to predict the improvement in a patient's condition effectively. Then, the machine learning models were trained using such algorithms as Artificial Neural Networks, Support Vector Machines, and Decision Trees. Thus, the process of training the models was characterized by the preparation of the datasets' accurate form, the choice of crucial features, employing various machine learning models, and evaluating their performance, which provided a strong basis for predicting the improvement in wrist rehabilitation effectively.

D. Inclusion and exclusion criteria

The inclusion and exclusion criteria of subjects in wrist rehabilitation research are vital in ensuring the research's validity and relevance to the target population. In the case presented, the researcher developed stringent criteria for selecting participants. The researcher included individuals with hemiparesis, as this is a common condition associated with stroke, and the population is likely to benefit from wrist rehabilitation. Besides, the researcher screened and selected participants who had the perceived ability to function physically and cognitively, and hence, they would engage in the rehabilitation process as well as provide accurate and informative data.

At the same time, the researcher included exclusion criteria that eliminated some persons from participating. Thus, under the exclusion criteria, this could have included persons with cognitive disabilities and even severe physical impairments that would make it impossible. By selecting the participants based on these inclusion and exclusion criteria, the researcher aimed at achieving homogeneity in the study population. The researcher can use the inclusion and exclusion criteria to ensure the population study has a higher internal validity since the results would be replicable in similar settings. Besides, the exclusion criteria can filter participants from the target population, ensuring the results of the study are generalizable to the target population.

The training protocol implemented in the present research could have been a rehabilitation training program that was structured to improve wrist flexion and extension movements. The participants were taken through training sessions where a developed exoskeleton was used, and therapists guided the participants in the program. The training program could have included a session timetable combining passive and active of exercises of wrist flexion and extension. The exercises were tailored to each participant's conditions and skill and performance ability. The therapists' intervention intensified as participants made progress or discontinued when the intervention was ineffective.

III. RESULT AND DISCUSSION

Before beginning the rehabilitation program, the natural angles of flexion and extension for each subject were measured in a very strict way and noted. Before the implementation of any intervention, the intention of conducting this initial assessment was to come up with a baseline for the wrist movement . Figure 2 shows a summary of the number of subjects and the lowest natural angle of flexion and extension on their wrist among the subject cohort. In this step of data collection, the aim was assessing the level of movement limitation faced by all subjects, which is vital for assessing the impacts of the rehabilitation program in the future.
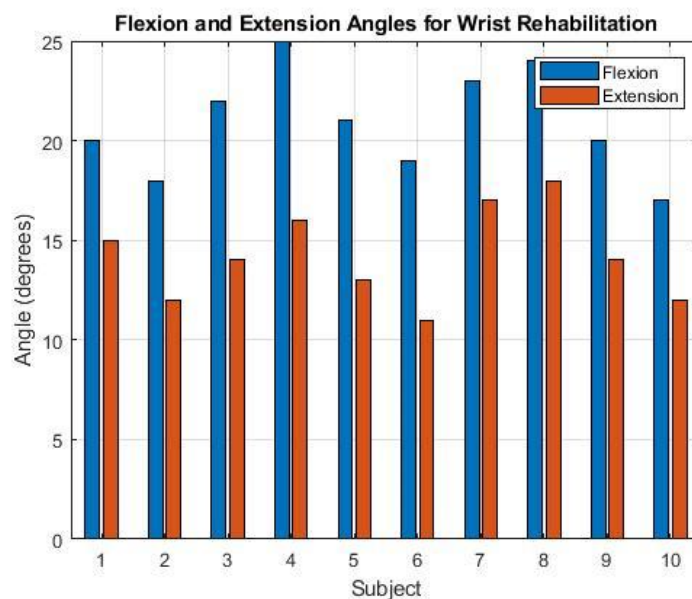

Figure. 2. Maximum angle of flexion and extension

Figure 2 summarizes the maximum flexion and extension angles possible for each subject. Notably, it appears that all subjects exhibit minimum angles of flexion and extension. Indeed, these values imply the relatively limited range of motion in the wrists reported by the participants before undergoing any rehabilitation Thus, it can be

argued that the subject cohort experiences severe mobility impairments. However, such baseline measurements are necessary for accurately assessing the effects of the subsequent rehabilitation program.

In the course of an intervention, subjects 1 to 5 were undergoing traditional methods of rehabilitation, and subjects 6 to 10 had robotic rehabilitation sessions . Weekly, an assessment was conducted to measure the impact of the rehabilitation on each participant's mobility using their wrist. In this context, assessments are likely to involve measuring the changes in the angles of flexion and extension as well as functional parameters related to the daily activities . The results of the rehabilitation for each patient were communicated with the machine learning model. The data involved changes in mobility and the level of improvements in the parameters were used to predict the training's effectiveness. The model would ultimately use the accumulated data to grasp the pattern and relationship between their results and rehabilitation methods. It would predict the level of training effectiveness. As a result, it was possible to polish and optimize the interventions assessed with machine learning tools, thus affecting their overall effectiveness in the end.

Following the training exercise, the performance of the machine learning model was heavily analyzed to determine the levels of accuracy of its predictions. As shown from the analysis, the proposed ML model has yielded excellent accuracy levels in predicting responses as shown in figure 3. The Artificial Neural Network model was the most accurate method of prediction, with the model's accuracy rate being 95.65%. Meanwhile, the Support Vector Machine model constituted the second most efficient prediction method, with the rate of its accuracy being 92.2%. The SVM can predict more accurately for the data, which is multidimensional and of a higher level.

The Decision Tree model was the third most accurate prediction method, its accuracy being 89.7%. On the whole, the results obtained during the testing provide insight into the high accuracy rate of the model in detecting the patterns in the rehabilitation data . Therefore, the results show that Machine Learning, in general, is highly efficient in terms of predicting the way the rehabilitation procedure will result and what data provided as an input should end up to. The accuracy allows considering these methods for further development in rehabilitation outcome prediction and making decisions about whether a given person may be admitted to inpatient rehabilitation services or undergo another procedure . Another future development is applying the models or the way they are designed to a hospital's practice to better predict the way a certain person will benefit from the chosen treatment .
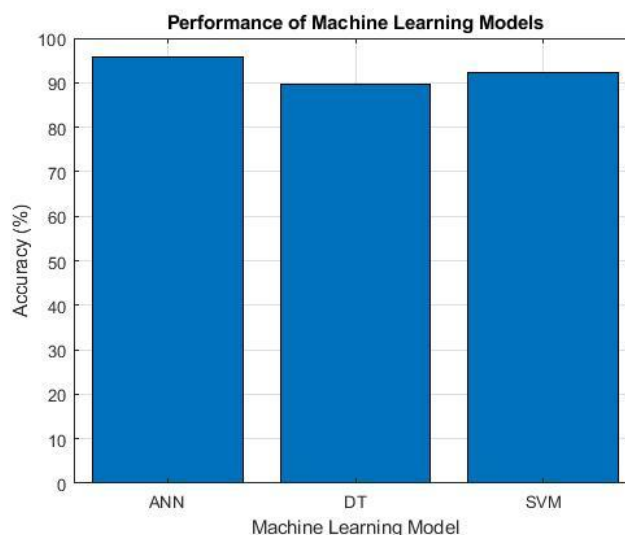

Figure. 3. Accuracy of each model

Figure 4 provides the results of the performance of three machine learning models. Evaluation of the performance of three machine learning models, namely, the ANN, SVM, and Decision Tree in predicting the effectiveness of rehabilitation interventions. The performance is given on the basis of such metrics as precision, recall, F1 score, and accuracy.

Precision is the metric that quantitatively estimates the proportion of correct positive predictions of the model relative to all positive predictions made the model . The results show that the ANN had the maximum precision equal to 96.2%, meaning that the model correctly identified the positive instances 96.2% of the time, with false positives constituting only 3.8% of all predictions . The SVM and the DT also demonstrated substantial precision scores of 93.8% and 90.5%, respectively, meaning that the former and the latter made correct predictions with frequencies of 93.8% and 90.5%.

Recall, the metric defining the proportion of positively predicted instances identified by the model relative to the overall number of positive instances in the dataset , was also the greatest for the ANN and was equal to 94.5%. The proportion of true positive instances identified by the SVM and the DT was also high and accounted for 90.6 % and 88.2%. The harmonic mean between precision and recall F1 score provides a balanced estimation, according to which the ANN performed the best with respect to the F1 score, which was equal to 95.3% . The F1 scores of the SVM and the DT correspondingly equalled to 92.2% and 89.3%. Accuracy, the proportion of the number of correctly predicted instances to the number of instances in the dataset, was the highest for the ANN, between the SVM, and the DT, equal to 95.65%, 92.2%, and 89.7%, respectively.
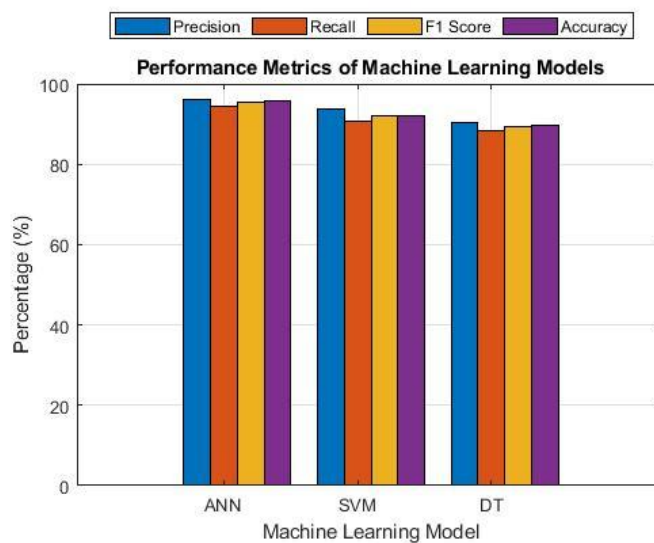

Figure 4. Performance score of each model

The results presented in the figure 5 indicate the progress of the machine learning models across the 300 epochs, with every 50-epoch record shown. While all models gain positive progress across the epochs, it is evident that in terms of both the accuracy and the data loss metrics, ANN outperforms SVM and DT . Thus, as for the prediction of the rehabilitation outcomes, ANN seems to be the most efficient model.

Figure 5. Dataloss and accuracy with iterations

Upon the four-week protocol completion, the flexion and extension improvement was estimated. Yet, it is evident that subjects from 6 to 10, who were subjected to robotic training, demonstrated considerably superior rehabilitation results. Thus, robotic rehabilitation appears to promote the improvement of the wrist's mobility alongside quicker recovery. The reason for such a tendency can be that the precision and flexibility of robotic machines allow for more nuanced adjustments to the individual needs . In addition, the capability of robotic systems to provide constant monitoring and feedback allowed for the gradual optimization of the rehabilitation approach over time. Lastly, the physical stability of robots and their capacity to develop a set amplitude of movements that can be adjusted to provide better progress was advantageous. The result of the training improvement are shown in figure 6.

The maximum angles of flexion and extension achieved through both traditional and robotic rehabilitation methods for each subject are displayed in the tables. An analysis of these figures shows that both flexion and extension of the wrist had greater angles for all subjects that used the robotic method of rehabilitation. Therefore, the robot-assisted rehabilitation of the wrist was more effective in gaining enhanced mobility, meaning that the use of robotic systems in rehabilitation has many benefits versus traditional methods.

Robotic rehabilitation has numerous benefits, such as facilitation of more accurate and properly customized movements. Additionally, the use of robotic systems facilitates continuous feedback and adjustability. Thus, as shown in the presented graphs, subjects that underwent robotic rehabilitation showed better outcomes in terms of flexibility and range of motion for both flexion and extension. Overall, robotic rehabilitation is a hopeful area in the future development of treatment and rehabilitation practices with opportunities to improve care for patients with wrist impairments.
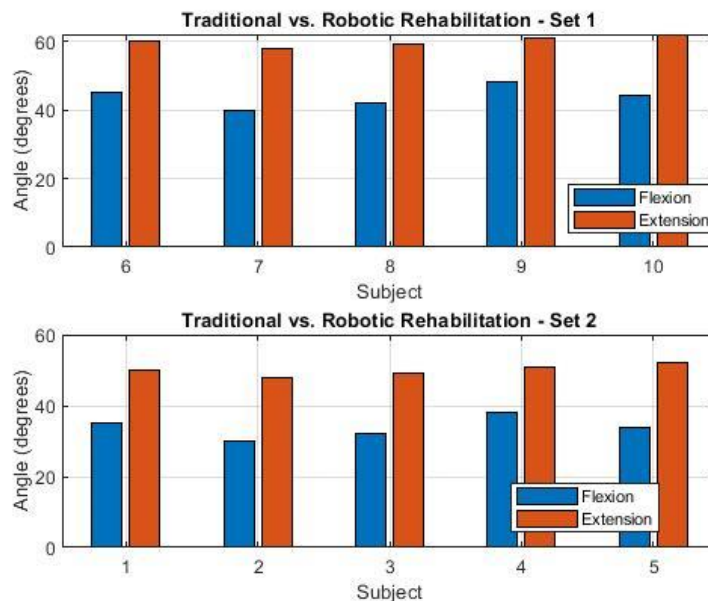

Figure. 6. Training efficacy

IV.   CONCLUSION

The results of the integrated approach described above using machine learning with robotic and traditional methods of rehabilitation indicate the improvement of results and the ability to increase the effectiveness of wrist rehabilitation of patient with hemiparesis. It was revealed that the participants who were undergoing a robotic rehabilitation showed significant improvements in the flexion and extension angles versus the group that received the traditional methods of incorporation. This, in turn, indicates the more effective results that could be achieved through the robotic intervention. The analysis of the prospects of machine learning use also shows a high level of accuracy in predicting the results of incorporation, with ANN having the highest level of accuracy as a predictor. The effect from the combination of treatment with robots and machine learning is that they can be combined with the opportunities of a robotic rehabilitation approach to develop more individualized integrated models. This, in turn, might optimize the rehabilitation process and allow for a more personalized application. This research

demonstrates the need for using modern technologies and advances to improve rehabilitation processes, and the results of this analysis could be of assistance in future research of this topic. It could be useful for more specific and accurate information on the application of rehabilitation techniques and the use of modern tools to improve the quality of patient care. Although it will be necessary to monitor the long-term effects and possibilities of using such approaches economically and implement large-scale measures to improve rehabilitation, it is possible to state that decisions like the one suggested above can significantly change the life and well-being of patients with hemiparesis.

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