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Development of an Elderly Care Rehabilitation System Utilizing Machine Learning for Energy Monitoring and Transmission using Wireless Sensor Networks

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Abstract: - The combination of robotic exoskeleton systems and machine learning (ML) techniques present great potential for significantly improving rehabilitation outcomes in patients with mobility impairments. This particular study examines whether ML algorithms can predict torque and angular inputs required for joint rotation using electromyography (EMG) data obtained during patient lower-limb rehabilitation. A new exoskeleton was designed for personalized and adaptable assistance in rehabilitation of walking. The predictive power of four different ML models, Artificial Neural Network (ANN), k-Nearest Neighbors (KNN), Decision Trees (DT), and Support Vector Machines (SVM), is evaluated. Of these, the ANN model is the most effective with an accuracy rate of 98.87%, followed by KNN (94.55%), DT (91.2%) and SVM (89.45%). Subsequent patient tests confirm significant improvements in flexion and extension angles of the knee, suggesting improved mobility and restored natural gait mechanics. These results stress the potential uses of ML-enhanced exoskeleton systems in personalised rehabilitation therapy. Proposals for further work include improving model performance, tackling challenges for real-time processing, and evaluating ML performance over the long term as it affects the quality of life in individuals with mobility impairments or changes in their condition over time. This investigation into rehabilitation aims at applying technology-driven solutions to help people regain their freedom and ability to move in a way that pleases them.

Keywords: Rehabilitation, Exoskeleton, Machine Learning, Electromyography, Mobility Impairments.

I. INTRODUCTION

Rehabilitation is a vital aspect of improving the lives of people who have disabilities in the lower limbs. The traditional methods of rehabilitation have been mainly manual therapy and walking aids. However, in practice this may not always lead to the best outcomes [1]–[4]. Additionally, it's often difficult and time-consuming. In the past few years, interest has surged in utilizing machine learning and robot exoskeleton technology together for patients with lower limbs. To discover some of the new frontiers in the field (and the impact they're having on leg rehabilitation for the disabled), this literature review study aims to discuss a few [5]–[8].
Personalised and intensive therapy is another reason why so many people are interested in robotic exoskeletal systems for rehab. These wearables--with sensors and actuators as well--assist or augment the patterns of lower limbs with disabilities [9]–[12]. It does things such as teaching people how to walk or strengthening muscles in order that others may also participate. Machine-learning algorithms combined with robotic exoskeletons deliver a personalised, adaptive and optimised protocol for individuals' different needs and abilities. The addition of

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machine learning algorithms to rehabilitation has considerably improved the performance and functionality of robotic exoskeletons. One major area of research is developing adaptive control strategies. Thanks to these machine learning algorithms, robotic exoskeletons can alter assistance or resistance settings according to the user's biomechanical data in real time. This makes it possible to have a more natural and personalised experience. The exoskeleton can adapt to the user's gait patterns and provide more focused support as necessary. Adaptive control means that, according to one study, machine learning-based strategies can improve gait symmetry, lower walking costs, and increase overall performance [13]–[16].

User intention and walking path. Machine learning algorithms can calculate intentions on a user's body by using data analysis of physiological signals detected by sensors embedded in the exoskeleton and the user. With a forward-looking attitude, wearers could use this exoskeleton as an intelligent crutch. In addition, machine-learning algorithms can detect deviations from normal walking patterns [17]–[20]. This allows for real-time feedback and correction during therapy sessions. If people can predict and detect errors, these capabilities of machine learning can enhance motor learning and promote neuroplasticity, leading to better rehabilitation results [21], [22].

In addition, machine learning models have been employed to design rehabilitan programmes tailored to each person. Patient demographics, clinical tests, and data on that patient's exoskeleton use were all taken into account. They are designed to meet the individual needs and abilities of each patient. As patients improve it progresses. Furthermore, customised rehabilitation protocols have promise for improving walking speed, balance and functional independence in lower limb impairment sufferers. [23], [24]

Integrating robotic exoskeletons with machine learning for rehabilitation presents many difficulties. One of the major problems is that machine learning models must be trained with a wide variety of data sets. Obtaining such data is both time and resource consuming, especially in clinical settings. In addition, Robotic exoskeleton failsafe measures are important given the potential for severe harm to patients if its machine learning system malfunctions or makes mistakes. Therefore, a good verification mechanism that contains all systems must be self-evident so as to not expose to potential problems. [25]–[27]

Because of the significance of machine-learning robot exoskeletons in rehabilitation, stringent validation and inspection procedures are necessary to ensure safety. Lower-limb disabled people can benefit enormously from using machine learning algorithms in robotic exoskeletons to enhance rehabilitation outcomes. In addition, combining machine learning driven adaptive control with personalized rehabilitation protocols and predictive function provides more effective therapy. For those with lower limb disabilities, it can lead to a higher quality of life. Nevertheless, the ongoing research in this field, and any corresponding technological advances, present problems for rehabilitation. They might just as easily contribute to research on human disease if we were to overcome these difficulties.

II. METHODOLOGY

The primary goal of this research is to develop a lower limb exoskeleton for elderly care and rehabilitation. The reason for researching a robotic ankle-foot exoskeleton is that this simple-shaped apparatus, based on human body joints located along the way the legs are designed to move, forms an unbroken column. Starting with strengthening exercises, one's home life can help guide care as recovery progresses. However, such exercises require additional support (and may even be harmful) if habitual movements are bound by wooden chairs without care. What are your attitudes and prejudices towards elderly people? These questions were posed to both professionals in the field and the general public. We rethought the elderly's activities of daily living (ADL) limitations by achieving a human-centered balance among these four needs.

The exoskeleton system's operating principle is based on the control system, which is in charge of coordinating and synchronising servo motor movements. The user's commands are first processed and then converted into precise motor actions by a fully functional control unit. To begin, joystick interfaces make user input easier, allowing the exoskeleton to move more naturally. The controller will directly manipulate the motor parameters that correspond to the joystick inputs, resulting in faster responses to user movements.

The user interface is quite crucial in making the robot exoskeleton and the man communicate. By manipulating a joystick and altering stride length and speed, users can control the exoskeleton's movement. The system also uses feedback mechanisms allowing users to monitor their gait performance. So that individuals can study how they walk for hygiene purposes, they must get the data and signal. For instance, a warning tone will sound when users' strides are interrupted. There are no edge points or posture faults. Users can follow their improvement and

take steps to make progress as needed.

A treadmill of robotic lower limb exoskeleton system is used for testing. After donning the exoskeleton, the user walks according to the instructions. Walking exercises are controlled with synchronised servo motor movements to enable rehabilitation recovery and mobility development. The gait training treadmill includes adjustable speed as well as incline settings with different levels of difficulty. It's used to study human walking habits. Nine people have tried a new exoskeleton lower limb system. The subjects are made to go through structured exercises in the system with the exoskeleton on. Step length, gait symmetry and joint range of movement were precisely measured. Kinematic analysis and energy consumption tests are quantitative measures that allow us to see how well the system can help rehabilitation and bring back natural walking patterns.

1.1. Drawback of the Existing Exoskeleton

One major problem with the current exoskeleton design is its total dependence on user input to determine the angle and torque at which to rotate each joint. A joystick interface gives users the ability to control the exoskeleton directly, but it is unable to interpret the user's rehabilitation needs and adjust assistance to match dynamically. During rehabilitation, a user may waver their intentions and need for assistant in conjunction with factors such as fatigue, pain levels, and specific therapeutic goals. Therefore, it is necessary to take a more flexible approach and give an accurate adjustment of help to the user. For this to be done effectively, sensors and feedback mechanisms are required which can continuously monitor physiological signals and biomechanical parameters in real-time. If the exoskeleton estimates muscle activity, joint angles and gait patterns too high when adjusting the rotation of individual joints, however, then this could exaggerate the user's condition. This adaptive functionality not only makes the exoskeleton more effective in rehabilitation, but also serves to make users more comfortable and safer during their training sessions.

1.2. Working of Proposed Exoskeleton

Wireless integration and the use of wireless electromagnetic sensors are an interesting potential solution for distinguishing the user intentions more accurately in rehabilitation. EMG sensors detect how people's neuromotor patterns and how their movements are determined by them, by capturing muscle activity signals in real time. They are variously placed on muscles of the leg so associated with motion that coordination and activation of muscles can be watched around the clock. This information is sent from the system's central controller unit using the EMG sensors. Finally inside the controller unit, algorithms of different levels analyze the incoming EMG signals. Such analysis is how meaningful patterns of anticipated linear as well as rotary motion can be extracted from observed massive EMG changes. Signal amplitude, frequency, spectrum density, and duration. All of these features encode other aspects that provide information regarding muscle activation and movement intentions.

This means the processed EMG data is transferred to a laptop or computer device through wireless communications. With wireless technologies like Bluetooth or WiFi, the external processing unit and exoskeleton controller stay in touch. If items can be transmitted efficiently and on a timely basis, then so much the better. Thus providing participants with individual and timely feedback. Inputting muscle signals into a machine learning model to be run on your laptop or computing device has been done successfully. Over time, mechanisms can be trained by means of machine learning algorithms to identify meaningful correlations between observed EMG patterns and joint rotation torque-angle requirements. In supervised learning techniques, the ML model can map the relationship between muscle activation patterns and movement outcome preferences. It can translate muscle signals efficiently into control commands for exoskeleton systems.

The ML model must be designed to generalize and adjust its user profile characteristics for a broad range of rehabilitation activities. The activities hinge on the reliability of the user profile data and the accuracy of its adaptability. It has learned to move like the body itself, based on EMG data labeling the body's movements and aid help level. Through that, its predictive capacity is quite powerful. This allows it to predict many features of user behavior accurately, in real time. Furthermore, adaptive learning mechanisms do not present themselves in the ML model alone; this means it can always keep refining its predictions based on user and environmental feedback.

With advanced signal processing techniques, wireless EMG data from sensors can be analysed by a machine-learning model which extracts relevant features to decide torque and joint rotation angle requirements. The ML model's characteristics can be used for accurate movement recognition without the need to transmit high-quality

EMG signals. The aspect that the model commands for that particular joint are the desired torque and angular adjustments.

Basically, the "myoelectricity" means the exoskeleton robe can determine people's assistance as well as mode of life based on their behavior. EMG-based intent detection and servo motor control are joined together in the exoskeleton. In preparation for different levels of training and designed for individual physiology and needs. In addition, the use of wireless communication technology during rehabilitation enables people to carry on more dynamic activities. This is done knowing that they will. And there's no need to worry about fatigue or injury.

III. MACHINE LEARNING MODEL

Taking into account the problem that electromyography (EMG) data could predict torque and angle requirements, this study used a number of different machine learning models, including ANN, KNN, DT, and SVM. Each model has its own pros and cons. For example, ANN is able to capture complicated nonlinear relationships, unlike KNN, which has a low threshold of ease on the other hand. Meanwhile, SMOs are transparent decision-making processes, and SVMs are extremely good with very high-dimensional complex data but cannot deal in the linear issues where little can be personally specified. The main objective of this research is the creation of a solid and accurate forecasting model that will improve performance of lower-limb exoskeleton system by integrating and leveraging the powers of these machine learning technologies.

The elements of an ANN are essentially a series of nodes through which artificial neurons are connected together to process an input signal and come toward a beneficial conclusion. An ANN changes its connections weights and biases following an underline to learn mode ('backprop') in response to labeled training data making it slightly more accurate each time. In this study, the ANN trains employing a supervised learning approach, taking input signals from electromyography (EMG) measurements of muscle activity as features and making the corresponding muscle effort and joint angle requirements as target outputs. The ultimate map created will be much more accurate than it now since its internal parameters are being continuously adjusted by backpropagation and the gradient descent method.

Due to their capacity for adapting and versatility, artificial neural networks (ANNs) can deal with muscle activation data that is nonlinear over a number of dimensions. They can detect fine distinctions in EMG patterns, and thus people's movements. In addition to that, ANNs have the great ability to generalize. They also do especially well with new data. ANNs are adaptable to any user profile or rehabilitation scenario. K-nearest neighbors (KNN) is a simple yet effective machine-learning algorithm for classification and regression. In the current research, the KNN method was applied to make predictions on torque and angle requirements for users based on electomyography (EMG) signals. The idea behind the KNN algorithm goes back to similarity. One searches for k points that lie closest to the input on the basis of their distances outside the training sequence, and makes a prognosis using either the majority class or average value from these neighbour data points. Hence, in cases requiring local patterns or relationships to be considered, KNN has the potential to be very useful.

When used for robotic lower limb exoskeleton, the K-nearest neighbor algorithm takes EMG signals as input. It then searches the training data to find patterns indicative of similarity and measures torque and joint-rotation angles according to these patterns. KNN combines many pieces of information together to map out a simple path, to show where people's motions are inclined. The K-nearest neighbors algorithm is simple and transparent - great for applications with time-sensitive needs where results should be easy enough to understand at once. It needs to be tuned carefully in order to balance performance with accuracy, because its accuracy is closely related to the distance measure and the number of neighbors (k).

Decision Trees (DT) Down To The is a combination that has been around for a long time since around the beginning of machine learning. This study indicates that decision trees are not only a simple and easy-to-understand model capable of modeling both classification tasks (adapting between different categories) but also regressions (predicting a continuous variable; conversion factor). We used decision trees to forecast the exoskeleton system's torque and angle requirements for joint rotation—based on electromyography (EMG) signals.

Essentially, a decision tree recursively divides the feature space into disjoint regions. These disjoint regions are based on the values of input features, producing a series of binary decisions. Thus, at every step one has simply to follow left-hand path or right-hand path to reach the final result. Each internal node on the tree represents a decision based on a specific feature. While each leaf node represents the expected output value. With respect to wearable exoskeletons, Decision Trees use EMG signals as input features to create an attitude of needed torque

and angle around a joint. To partition the feature space into regions using various EMG signals, decision trees provide a clear and easily grasped conceptual model for connecting muscle activation with desired motions

In terms of processing EMG signals, Decision Trees can handle both numeric and categorical data equally well. EMG signals often contain a variety of complex waveforms. In addition, to feature selection for posture classification, decision trees automatically determine the most informative features for use in predicting movement intentions and mitigating overfitting problems.

As far as the overfitting problem is concerned, Decision Trees are quite sensitive, especially when dealing with noisy or multidimensional data. If you apply ensemble techniques of something like Random Forests or Gradient Boosting, then you can concatenate many Decision Trees to improve predictive accuracy and generalisation at will. Support Vector Machines (SVM) are powerhouses of machine learning models used extensively in the classification and regression tasks. We use SVM to predict a torque. For the lower-limb exoskeleton system the angles to initiate joint movements are specified with EMG signals.

In SVM, high-dimensional hyperplane is what we are looking for when dealing with classified data or regression targets. The objective is to maximize the margin between the nearest data points, called support vectors, and the hyperplane while minimizing the degree to which classification errors occur or regression targets are missed. The ergonomically designed robotic exoskeleton is intended to boost users' muscle power and endurance through the use of a mode of control known as the SVM. The signals of the corrupted state are recognized by the machine as input features. It distinguishes the factors and circumstances that drive muscle tension from the data entered even while understanding the specific details about it themselves. SVM is therefore highly effective in predicting requirements for torques or angles misspecified by their high-dimension input data samples compared to others SVM possesses a significant advantage in being able to accommodate non-linear relationships and high-dimensional feature spaces as a result of its kernel functions. SVM turns the input features into higher-dimensional representations so that it can identify complex patterns and boundaries in training data. In addition, its predictive capabilities for various rehabilitation scenarios. Furthermore, SVM includes a regularisation parameter that allows you to choose between maximising margin and minimising classification errors or regression deviations. It thus has the versatility to deal with datasets of different levels of complexity and signal noise.The validity and useability in real-world applications.

IV.   COMMUNICATION AND DATA ACQUISITION

When it comes to designing robot exoskeletons for the legs, success hinges on capturing and processing electromyographic signals. Machine learning models can, in turn, capture what has been learned from electromyographic (EMG) signals. As such, these models can offer real-time predictions of torque and angle requirements at sented by some very general depends. This chapter will describe how EMG data is presented to the user, pre-processed and extracted. Thereafter, two-stroke information is sent to machine learning model.

EMG electrodes are placed in the location of the nerve groups in key leg muscles to pick up basal nerval biopotentials. When you make voluntary movements, electrodes record electrical signals that arise from muscle contraction. These are the motor-alphas; when summarizing muscle activities such as wrist extension or flexion their EMG values are often zero degrees of displacement. The EMG signal is then amplified and filtered to decrease noise and interference. This step can extract features not present in normal EMG waveforms.

User interfaces like those can display real-time visualizations of EMG waveforms and muscle activity levels. People can monitor, or reassume, responsibility for muscle activity in this way. It's also useful to have robotics show you what your curves look like as auditory feedback. Nonetheless, some of the most successful systems rely on spoken instructions: they tell users how to keep their muscles firm or direct their movements more smoothly.

Pre-processing methods are used to preprocess the raw signal into features. These techniques enhance the signal's quality and extract useful information from the data. Common pre-processing methods that aid in detecting the signal are baseline removal, noise filtering and recreating the waveform. This method for example allows the EMG waveform's dry offset voltage to be removed; other techniques as well may help reduce environmental artifacts or interference such as changing light glare, which could affect parasite signals creeping into or thwarting an EMG recording. The bipolar EMG signal is converted to a single-polar form through rectification. This emphasizes muscle activation while simply eliminating the negative component (ie rectifying).

Feature extraction is an important step in the conversion of raw EMG signals into a summarized representation

filled with data that can be used to train machine learning algorithms. Many signal processing techniques are used to select informative features. It can be used for the identification of muscle activity patterns and detection of movement intentions. Often used feature types include statistics on amplitude, such as mean and variance; features in the frequency domain (like spectral power density); time-domain descriptors for length of time under tension like RMS. In addition to these there are temporal factors (such as onset/offset timing). Advanced feature signals such as wavelet or time-frequency analysis can be used to detect changes in muscle activity during different movement phases. Physiologic aspects captured by these features of the EMG signal, so it is that the machine learning model can find minor changes in muscle activation patterns during various movements.

After preprocessing the EMG signals, and extracting the features, they can be put into machine learning algorithms as input data. Methods such as artificial neural networks (ANNs), support vector machines (SVMs), and decision trees (DTs) are used for supervised learning to develop a relationship between the extracted EMG features and motion requirements in torque and angle. During the training phase, the ML model detects patterns in EMG data and connections them with precise movement intentions. The model's predictive performance and generality can be iteratively improved by adjusting internal parameters using optimisation algorithms like gradient descent and backpropagation. Model performance is assessed on previously unseen data and against overfitting using validation techniques such as hold-out validation or cross-validation.

V.   RESULT AND DISCUSSION

The proposed exoskeleton was subjected to strict testing by a person with weak leg muscles who suffered from partial paralysis. They did rehabilitation training to see if it would make the angle of flexion and extension during walking better. Each time they walked; a mechanical apparatus had to be bolted around them to take measurements of leg movement in real time.
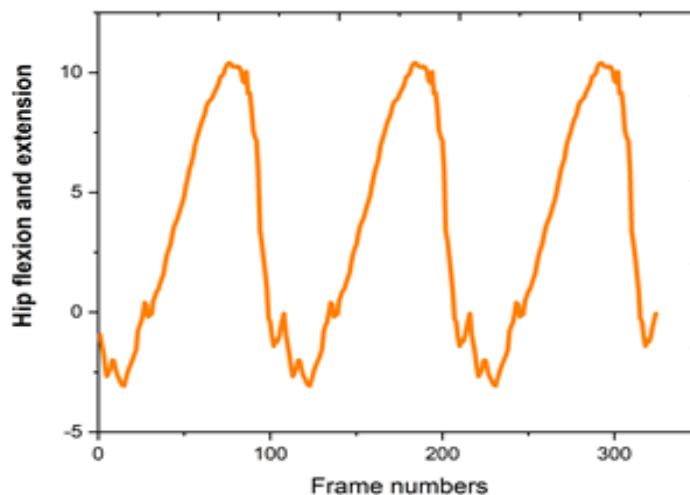

Figure 1. Angle of flexion and Extension of Leg

Figure 1 shows the angle of flexion and extension by an individual walking without an exoskeleton. Data collected from a series of walking exercises displayed during this phase showed a significant decrease in the flexion-extension range. It meant that the person cannot flex or extend their knee as much as usual. His active musculoskeletal function and motor control might be impaired in some manner; however, in short this limited mobility is a call for intervention.

The observed decrease in the angle of flexion and extension makes a strong case for including the exoskeleton system in the rehabilitation regimen. Designed to furnish targeted assistance and support to help the person walk better, the exoskeleton aims splendidly at higher levels of mobility and restores natural gait over an extended period.

Using the exoskeleton the angle of flexion and extension of the person is improved. According to Figure 2, concurrently, four different machine learning (ML) models were used to predict the power needed for each movement of the body. The most accurate of these models turned out to be the Artificial Neural Network (or ANN for short). The ANN model showed outstanding predictive capability. It was correct 98.87% of the time, after all. The k-Nearest Neighbors (KNN) model had 94.55% accuracy, trailing only slightly behind. Yet,

Decision Tree (DT) and Support Vector Machine (SVM) models attained 91.2 and 89.45% accuracy, respectively.
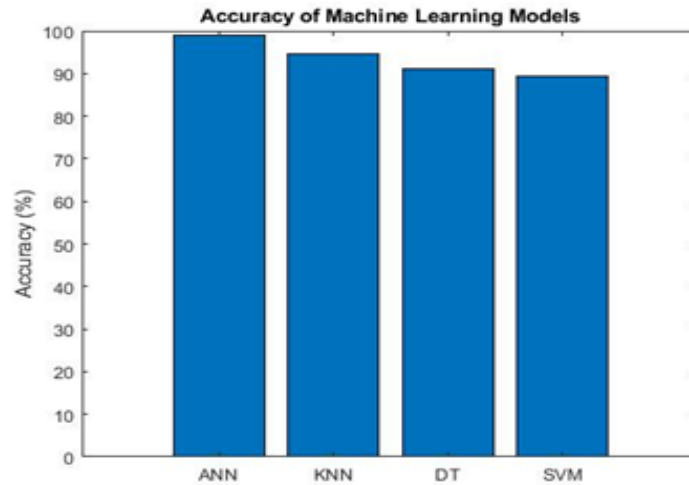
**Figure 2. Accuracy of each ML Model**

After that, the ANN model's torque predictions predicted the amount of force exerted on the exoskeleton. Based on the figure, walking in the task was performed with the exoskeleton, and here are the resultant angle trajectories in this mode. The graph also revealed a large-enough degree of flexion and extension than before, indicating improved range in mobility. Moreover, the maximum flexion angle observed was approximately 30 degrees, quite close to the natural walking model. It shows that rehabilitation is indeed true. The ANN model's accurate prediction of torque helps confirm the results of this study. The outcome indicates that this rehabilitative exoskeleton system ideally using accurate force measurements from the ANN model for guidance helps the body restore its normal structure and encourages it to move in a more naturally human way.

In Figure 3, we can see the EMG data collected from every patient, on which the exoskeleton depends for operation. The EMG signals provide a great deal of information about the muscle activation patterns and movement intentions of an injured person. Using the amplitude and frequency changes in the EMG signals, the exoskeleton system adjusts its assisting strength and other parameters to imitate the body's physiological responses. This real-time feedback mechanism allows for human support that is personally tailored responsive, thus intensifying the exoskeleton's aiding rehabilitation efforts and resulting in patients.
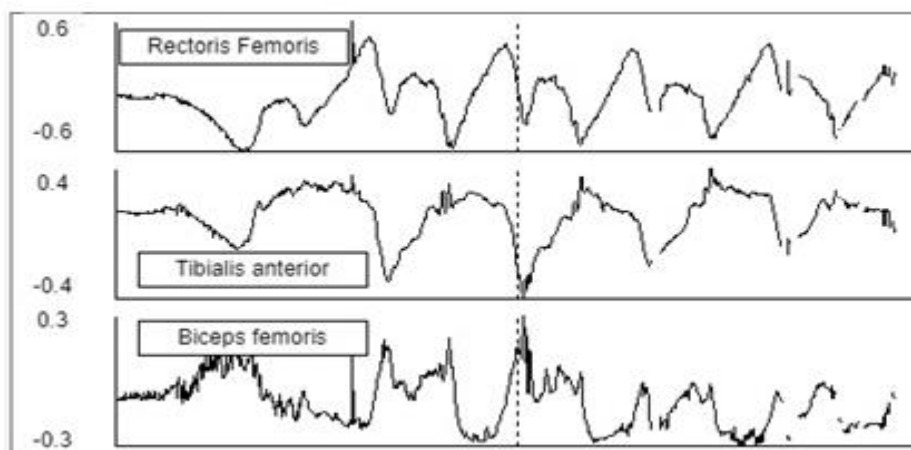
Figure 3. Preprocessed EMG Data

The angle of flexion and extension for the patient was recorded, as seen in Figure 4, after a month of exoskeleton-based rehabilitation training. Compared with the initial examination, an obvious improvement in both flexion and extension angles was observed. The patient had limited mobility, showing flexion and
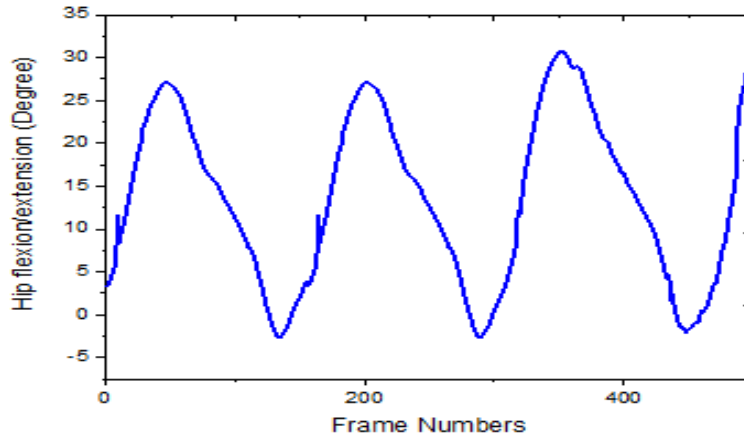
Figure 4. Hip Flexion and Extension after Training

extension at 14 and 7 degrees respectively. However, after training, there were significant improvements: the flexion angle increased to 25 degrees; and the extension angle was improved to 12 degrees.

The program's effectiveness in rehabilitation using an exoskeleton system is highlighted by this marked improvement. With innovative, real-time data-driven techniques such as EMG-guided mode control and predictive modeling, the exoskeleton provided targeted support for the limbs--enhanced mobility and range of motion probably stemmed from this. The exoskeleton interfaced natural gait patterns with lower limb muscles in a systematic manner, effectively overcame biomechanical limitations, and met the challenge to make walking ability functional.

The observed improvement in the patient's ability to flex and extend joints reveals the success of the exoskeleton system in rehabilitation. It also underscores the potential for technology-assisted interventions to transform disability into independence by fostering recovery.

Fig. 5 shows the performance scores of each model. Precision, which measures the accuracy with which positive predictions are made, is highest for the ANN model, at 0.92, signifying that 92% of the predicted instances of being positive were in fact positive. On the other hand, recall, representing the model's ability to detect all positive instances, is also highest for ANN at 0.89, meaning that for 89% of actual positive instances the model identified correctly. The F1 score, a balanced measure of precision and recall, is 0.90 for ANN, suggesting that a nice balance between the two metrics has been found: namely that they both have their place incapable. Moreover, accuracy--referring to the proportion of correctly predicted instances--is highest for ANN, at 0.88: the model correctly predicted 88 percent. These points together evidence the effectiveness of the ANN in accurately predicting what the future holds for the movements of the exoskeleton system.
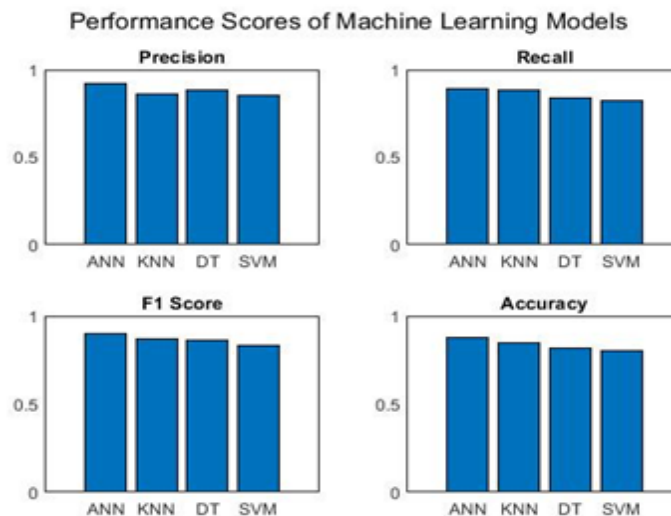
Figure 5. Performance Score

According to this study, there is evidence of a potential combination between robot exoskeleton systems with machine learning techniques that can enhance the lives of those who have to deal with limited mobility. Through the use of EMG data and complex predictive modeling, the invented exoskeleton system is surprisingly good at improving the walking ability. Looking at the efficacy of machine learning models in detail, the Artificial Neural Network (ANN) model was found to give more accurate predictions of torque and angle requirements for joint rotation than other models, thus reaching its full potential as an exoskeleton. After therapy, joint angles of flexion, and extension changed in smaller amounts, showing that the exoskeleton system is effective in improvement of mobility and promoting return to natural walking gait. Should these results be confirmed, we will be able to develop technology-driven solutions to address such a wide range of problems. These can be people-friendly and demand little personal attention.

VI. CONCLUSION

In summary, the significance of our study suggests that using machine learning algorithms to improve rehabilitation programs in people suffering from movement disorders requires combining these with robotic exoskeleton systems. The studies show that, although it was still early in their development and hadn't yet been tested in a large clinical trial, rehabilitation results for a longstanding EMG-driven exoskeleton device, particularly for walking, have been good. Robot exoskeletons are now ready to step into this area as far as evaluation by ANN (Artificial Neural Network). It accurately forecasts torque and joint rotation angles needed, thus making the most of exoskeleton function. The significant increases in flexion and extension angles seen after rehabilitation demonstrate the concrete advantages of the exoskeleton in assisting walking, as well as changing human biomechanics. Not only does this study confirm the effectiveness of our design, but it also provides early evidence for modern technology-driven interventions in rehabilitation. From here on out, increased attention to the engineering demands of machine learning technology in combination with exoskeleton systems is needed. These projects will confront problems such as the real-time requirement that a high-capacity human-robot system demands more than simple voice response from an intelligent machine. At the same time, as for outcome measures of exoskeleton-assisted rehabilitation over the long term, we should do longitudinal studies. To what extent will such treatment help people with mobility impairments to return to a productive life? Ultimately, our goal is to use the power of technology and innovation to advance rehabilitation, helping people regain their freedom of movement.

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