Design, Experimentation and Analysis of Mechanical Model using EMG signals for Hand Rehabilitation

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Declaration

I certify that this research work titled "*Design, Experimentation and Analysis of Mechanical Model using EMG Signals for Hand Rehabilitation"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

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Copyright Statement

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Abstract

Ageing and accidents all around the world are two of the main causes of disabilities. Even though it is quite expensive, rehabilitation is crucial for enhancing the mobility and quality of life of individuals with disabilities. For rehabilitation purposes, a variety of techniques are employed, including medication, homoeopathic remedies, and rehabilitative gadgets. Few hands rehabilitation gadgets are said to be a successful form of therapy, according to the literature. Due to developments, especially in the fields of robotics and artificial materials, the use of such devices without the assistance of medical professionals is expanding significantly. For hand disability, we have proposed the low-cost mechanical rehabilitation equipment EXOMECHHAND in this study, along with three distinct kinds of resistive plates. The therapist determines the type of resistive plate via Manual Muscle Testing.

Key Words: *rehabilitation, low-cost device, hand motion assistance, surface electromyograph, machine learning algorithm*

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CHAPTER 1: INTRODUCTION

The research work in this dissertation has been presented in two parts. First part is related to the detailed review about design of our prototype mechanical rehabilitative device “EXOMECHHAND” and its analysis. The objective of this part is to study selection of materials and study available literature to design hand rehabilitative device. The second part includes training and testing of machine learning algorithms and its experimentation to evaluate its efficacy on patients of ulnar and median nerve neuropathies.

1.1. Background, Scope and Motivation

Most often, disabilities develop in older persons or as a result of global tragedies. Following a disability, people frequently lead secluded lives[1] and frequently experience physiological effects as a result of such problems. There aren't many institutions for rehabilitation, particularly in third-world nations where they largely serve those with higher socioeconomic level and offer insufficient and restricted services to people with disabilities[2]. Higher socioeconomic status people have access to a wide range of resources, including drugs and homoeopathic remedies, but lower socioeconomic status people have very few options and are frequently unable to attend therapy appointments for daily exercises over a longer period of time due to financial limitations. This strong correlation between socioeconomic level and patient rehabilitation implies either more funding for high-tech gadgets or accessibility to low-cost devices to enhance people's quality of life, particularly in developing nations. Therefore, in the recent past, self-therapy devices and home-based technologies, notably robot mediated, have been utilised to try to partially solve such challenges in order to lower the cost potentialities of therapists for the rehabilitation of patients [3].

About 16 percent of Americans are disabled from independent living and self-care, and upper limb impairments account for almost all of this [4]. The hand is the area of the upper limb that is most affected by disability, especially in cases of neuropathy [5] or myopathy damage. It is difficult for therapists to improve hand function in order to regain motor function [6, 7]. The ability to do activities of daily living (ADLs) is increased by hand recovery [8]. Independence and lowering the social burden of impairment are directly impacted by ADL performance [9].

Performing ADLs can help maintain the ability to participate actively in society in some way while reducing the strain on coworkers, family members, or other assistance providers.

According to studies, one of the causes of hand impairment is weakening in the finger flexor and extensor muscles. The literature demonstrates that many rehabilitation designs have shown to be intensive and effective therapies [10], and clinical trials of a few devices support the notion that they may aid in the restoration of upper limb mobility [12, 13]. Both active and passive hand rehabilitation activities strengthen the flexor and extensor muscles of the fingers. Repetitive active or passive training programmes based on tasks involving the flexion and extension of the affected fingers [14] can be used to restore the function of grasping and object manipulation in a hand with impairments. Analyzing hand improvement in a damaged hand involves a variety of techniques. An established technique for tracking and evaluating muscle activity is the use of sEMG signals. One of the most cutting-edge methods now employed in hand orthoses is sEMG. The force of a muscle flexor or extensor can also be calculated and measured using sEMG[15].

1.2. Feature and Algorithm Selection for sEMG signals

The most crucial and defining steps for determining how to judge the state of the hand are the type of characteristics extracted and the choice of machine learning algorithm. Finding pertinent features is largely a random procedure because various features are pertinent to various diseases and deformities. The time domain, frequency domain, or mixed time-frequency domain make up the characteristics of sEMG. It's still difficult to choose characteristics from the time domain, frequency domain, and time-frequency domain [16–18]. With regard to sEMG signals, frequency domain features are less important than time domain features. However, numerous research [19–21] have demonstrated that when it comes to speed and accuracy for sEMG signal detection, time domain offers superior outcomes over frequency domain. Periodically, in-depth research into time domain aspects has been conducted. Four criteria that Huglins et al. [18] suggested in several works—zero crossing (ZC), mean absolute value (MAV), waveform length, and slope sign change—are now frequently regarded as being necessary for any EMG-based recognition analysis. For pattern identification, cardinality is also a promising property [22]. Root mean square (RMS)-based classification of individuals into healthy, unhealthy, neuropathy, and myopathy groups by Elamvazuthi et al. [23] set shown accuracy between 77.5-83.5 percent.

Additionally often utilised to determine muscle state are mean amplitude power [24] and the signal's power as determined by Parseval's theorem. Skewness and kurtosis were employed by Sapsanis et al. [25] as features to identify hand movements. The remaining features, such as minimum, maximum, median, standard deviation, and signal to noise ratio, are quite prevalent. Position of the hand and the location of the electrode channel are two more aspects.

Python is used for categorization after feature selection. Classification techniques of 10 different sorts are employed for this because it is supervised learning. The training of features to express the type of resistive plate to be used involves the use of classification techniques such as K-nearest neighbours (KNN) [26], Linear Discriminant Analysis (LDA) [26-28], ensemble Adaboost (AB) method [29], Decision Tree (DT) [30, 31], Random Forest (RF), Extra Trees (ET), Logistic Regression (LR), Support Vector Machines (SVM), Gradient Boosting (GB), and Artificial Neural Network based.

CHAPTER 2: Design and Analysis of Prototype ExoMechHand

2.1. Design and Material Selection for Prototype "ExoMechHand"

For ExoMechHand, a number of designs were researched and examined in the literature. However, three supporting frame designs are originally taken into consideration and suggested as shown in Fig 1 while keeping in mind the materials and resources that are readily available. These mechanical designs stainless steel components are chosen at a thickness of 16 gauge. They are produced using wire-cut Electrical Discharge machining and AutoCAD. Frame "C" is chosen after several trial-and-error hitting and trialing for better fitment because of its better ergonomic design and smaller shape. Because the support frame's upper side is the same, small screws can be used to attach the same three types of plates, which have similar shapes but differ in terms of flexibility (Fig 2). The steel used to make these plates is high carbon. Because the plates are not easily accessible, a whole sheet was ordered, and each plate was then further divided into two pieces for ulnar or median wrist neuropathies, which can be utilized separately or together. These plates are put into a glove made of soft fabric (Fig. 3) and then secured with strips at hand. The resistive plate and frame are removed using the soft fabric glove's zip, which is utilized to open the glove.

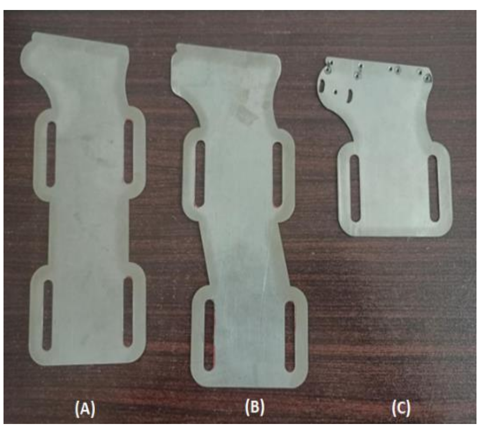

Figure 1 Frame Support Designs


Figure 2 Resistive Plates

Fig 4 shows other devices used for experimentation which include Delsys Trigno Biofeedback System, Constant Digital Spring Hand Dynamometer 200lb(90 Kg) and Goniometer.

2.2. Geometric features

The steel used to make these plates is high carbon. Because the plates are not easily accessible, a whole sheet was ordered, and each plate was then further divided into two pieces for ulnar or median wrist neuropathies, which can be utilized separately or together. These plates are put into a glove made of soft fabric (Fig. 3) and then secured with strips at hand. The resistive plate and frame are removed using the soft fabric glove's zip, which is utilized to open the glove.

Figure 3 Soft fabric glove

Figure 4 Equipment used for experiment

2.3. Criterion of subjects/ Muscles involved

Nerve palsies in the fingers of the hands impair their ability to flex, extend, and grip due to the involvement of numerous muscles. The phalanges of the fingers act as levers in these situations[39]Normal finger phalanges have a unique active range of motion (ROM)[13]:

- metacarpophalangeal joints (MCP) 0–90 deg
- proximal interphalangeal joints (PIP) 0–110 deg
- distal interphalangeal joints (DIP) 0–70 deg

However, compared to the active ROM for all joints, the functional ROM needed for 90% of ADLs is considerably less. For the MCP, PIP, and DIP joints, respectively, the mean functional ROM is 48, 59, and 60 percent of the range of active ROM[40].

ADL performance and improvement for the afflicted hand of nerve injury patients can be assessed using hand grip force, sEMG signals, and manual muscle testing. Patients with hemiplegia and stroke were not included since they may have completely lost all of their nerves and had substantially weaker grip strength than hemiparesis patients [41]. However, hemiparesis hand patients with nerve injury (ulnar, median, or mixed) are taken into consideration for our suggested design experiment.

2.4. Kinematical aspect

Because fingers may vary in size [12] and shape due to deformities [42], it is impossible to accurately simulate the movements of a finger. The kinematic compatibility of the mechanical device with the hand is depicted, however, in a general model with the least resistance plate in Fig. 5, where is the MCP angle, is the PIP angle, and is the DIP angle. In order to attain the highest values of angles, five healthy volunteers were instructed to apply the greatest amount of force to the plate that offered the least resistance while maintaining a neutral wrist posture at 0° [43]. Angles measured by applying this mean force have values of = 60–65°, = 22–25°, and = 10–15°.

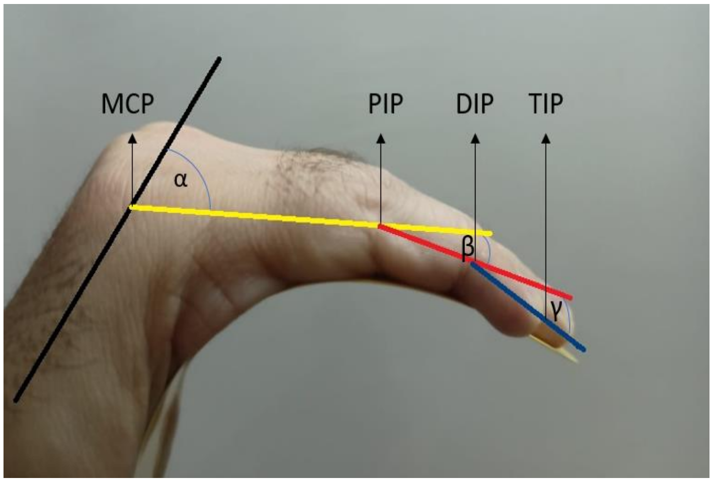

Figure 5 Kinematic scheme of finger

CHAPTER 3: EXPERIMENTATION

3.1. Setting and Pre-Processing for sEMG Features

The entire process flow of experimentation and data collecting is depicted in Fig. 6. The flow of sEMG signals is shown in Part A of Fig. 6. Delsys Trigno Biofeedback system signals are quantified, filtered, and processed. We made use of signals from the flexor carpi ulnaris and radialis muscles. In order to collect sEMG signals from both channels, the Delsys Trigno Biofeedback system was configured with a sampling rate of 1926 Hz, a range of 11 mV, and a bandpass filter from the bandwidth of 20-450 Hz. The laptop's data acquisition software was Delsys Trigno Control Utility 3.6.0.

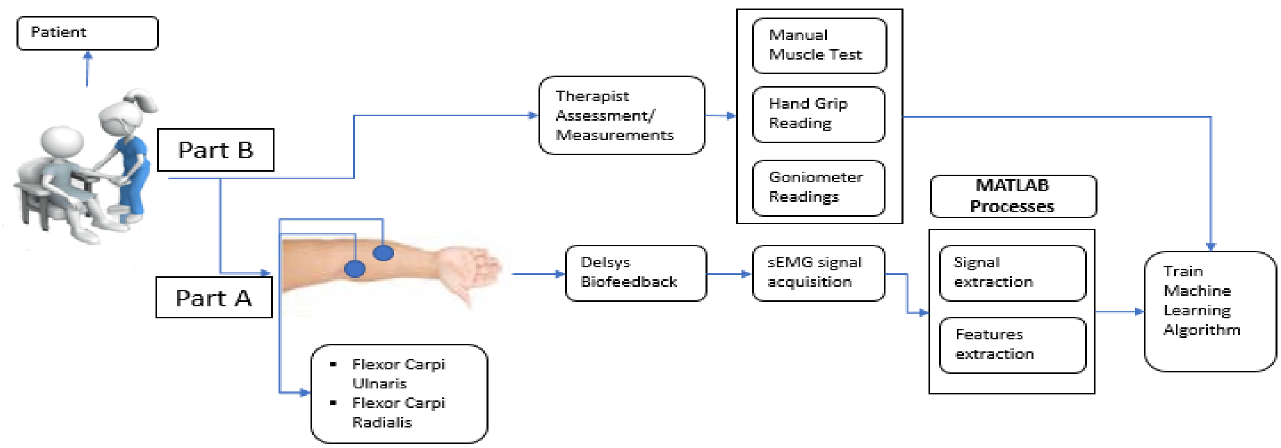

Figure 6 Flow of sEMG for Training Machine Learning Algorithm

3.2. Obtaining sEMG signal for training Machine Learning Algorithm

In our study, fifteen participants—five healthy people and three left-handed participants—with a mean age of 35 and a standard deviation of 10.53 each took part. Figure 7 depicts images taken while recording sEMG from unwell participants; two of them are wearing strips that tighten the electrode channels to improve the acquisition of sEMG signals from all subjects. As illustrated in Fig. 8, the experiment seeks to assess sEMG signals in three locations, with the remaining positions being repeated after the flexor and fist positions. The flexor carpi ulnaris and flexor carpi radialis muscles of the participants are probed with sEMG electrode channel modules while they are seated in a chair. The arm is placed on the table from the dorsal side. Each position is timed for 10 seconds, and the entire experiment on each participant lasts 52 seconds (with a 3-second break to change hands between each cycle of four positions, which is repeated three times). We used a static measurement technique [44, 45] to obtain temporally steady data rather than dynamically fluctuated measurement [35, 44, 45] because some time-dependent features (such as velocity and acceleration) may vary between each trial depending on various small influences, such as psychological settings. Each channel yields a signal for the surface EMG. On the laptop, MATLAB analyses, investigates, and extracts features from the collected data. MAV, waveform length, ZC, slope sign change, RMS, signal energy, mean amplitude power, cardinality, kurtosis, skewness, variance, standard deviation, maximum, minimum, signal to noise ratio, type of motion, and electrode channel position were among the sixteen features that were extracted from these signals in MATLAB. Mathematical formulas of these features are given in Table 1. A physiotherapist additionally evaluates the subject's affected hand, as seen in Fig. 6 Part B, which includes measuring the range of motion (ROM) of the wrist, ROM of the MCP, hand grasp, and MMT. A goniometer is used to quantify ROMs in degrees, a constant hand dynamometer to evaluate hand grip in kg, and a physical inspection to assess MMT on a scale of zero to five. One of the resistive plates is chosen by the physiotherapist and sent to algorithms for training. The same experiment is conducted on each individual.

Figure 7 sEMG Recording of Unhealthy Subjects

Zero crossing	$$ZC = \sum_{j=1}^{M-2} u[(x_{j+1} - x_j)(x_{j+1} - x_{j+2})]$$
Waveform length	$$\sum_{P=1}^{M} \lvert \Delta y_P \rvert$$
Slope sign change	$$\sum_{m=2}^{M-1} \lvert (y_p - y_{p-1}).(y_p - y_{p+1}) \rvert > \varepsilon$$
Root mean square	$$R.M.S = \{\frac{1}{m}\sum_{p=1}^{m} (y_p - \overline{y})^2\}^{\frac{1}{2}}$$

Standard Deviation	$$SD = \sqrt{\frac{1}{M-1}\sum_{m=1}^{M}(y_m-\mu)^2}$$
Skewness	$$\frac{1}{m(SD)^3}\sum_{p=1}^{m}(y_P-\overline{y})^3$$
Kurtosis	$$\frac{1}{m(R.M.S)^4}\sum_{p=1}^{m}\left(y_p-\overline{y}\right)^{-4}$$
Cardinality	$$Step\ 1: z_n = sort(x_n), n = 1: N\ Step\ 2: CARD = \sum_{n=1}^{N-1}\lvert z_n - z_{n+1}\rvert > \varepsilon$$
Median Frequency (MDF)	$$\sum_{k=1}^{MDF} Q_l = \sum_{l=MDF}^{M} Q_l = \frac{1}{2}\sum_{k=1}^{M} Q_l$$
SNR	$$10log_{10}\left(\frac{\sum(y(s)^2)}{\sum\left(\overline{y}(s)-y(s)\right)^2}\right)$$
Willison amplitude	$$\sum_{n=1}^{N-1}[f(\lvert y_m - y_{m+1}\rvert)];$$ $$f(y) = \begin{cases} 1, & if\ y \geq threshold \\ 0, & otherwise \end{cases}$$
Variance	$$\frac{1}{M-1}\sum_{m=1}^{M}(y_m-\mu)^2$$
Signal energy (SE)	$$\lim_{S\to\infty}\frac{1}{2s}\int_{-s}^{s}\lvert y(s)\rvert^2$$
Mean absolute value	$$MAV = \frac{\dot{I}}{M}\sum_{p=1}^{M}\lvert y_P\rvert$$

Table 1 Mathematical Formulas of EMG signal Features

3.3. Machine Learning Algorithm model for changing resistive plates

The result following algorithm training is either a colour indication of a resistive plate or a "H" which denotes a healthy subject. The machine learning algorithm's process flow for indicating the plate is shown in Fig. 9 after it has been trained. The combined data of sEMG characteristics and a physiotherapist's evaluation/measurements are used to analyse and train the ten most popular classification models of machine learning algorithms. These include Linear Discriminant Analysis, Gradient Boosting, K Nearest Neighbors, AdaBoost, Decision Tree, Random Forest, Extra Trees, Logistic Regression, Support Vector Machine, and Multiple Layer Perceptron.

Figure 8 sEMG Recording Positions

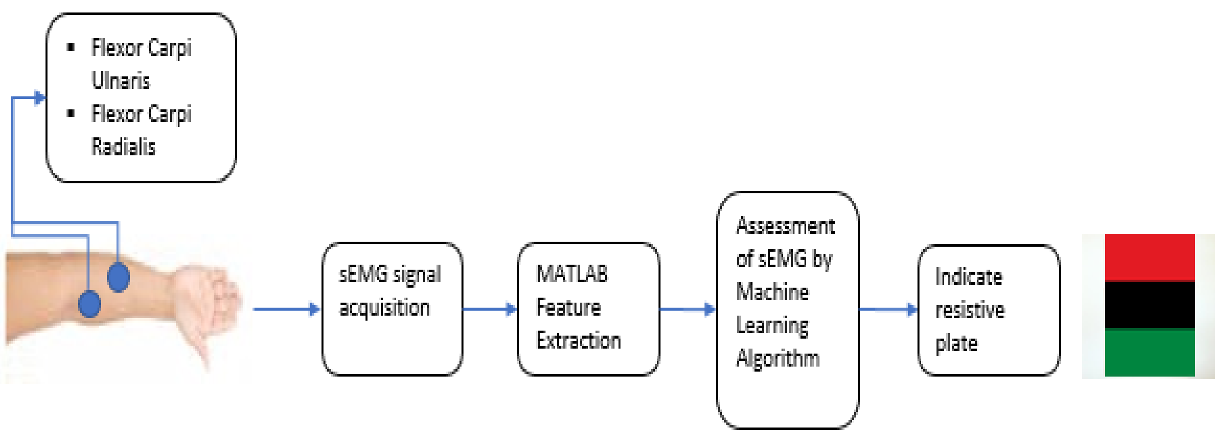

Figure 9 Process Flow After Training of Machine Learning Algorithm

3.4. Experimental process for the efficacy of device

A small-scale experiment is also carried out as a clinical trial to determine the effectiveness of the ExoMechHand hand rehabilitation device. Ten unwell patients, including four women, with a mean age of 38 and a standard deviation of 10.87 years and either an ulnar, median, or mixed nerve lesion are taken into consideration as test subjects. The patient's hand is examined and evaluated by the therapist using a variety of tests, such as the Manual Muscle Test (MMT), grip force, wrist range of motion, and the MCP (Metacarpophalangeal) joint of the hand. Delsys Biofeedback can also be used to collect sEMG signals. ExoMechHand is worn on the injured hand for exercising once the therapist confirms the sort of resistive plate. In clinical settings, exercise is performed twice daily for 20 days at a time. Throughout these 20 days, participants don't perform any additional exercises. Over testing on the features of sEMG signals for all individuals after a period of twenty days, improvement in hand is verified using machine learning algorithms.

CHAPTER 4: RESULTS AND DISCUSSION

4.1. Results

Two experimental components make up this paper. Finding the effectiveness of our suggested ExoMechHand hand rehabilitation gadget is one of the trials' goals. Three out of ten patients demonstrated noticeably improved wrist, MCP, hand grasp, or MMT range of motion after twenty days of exercise. Also pointing to these gains is ET, the most accurate machine learning algorithm.

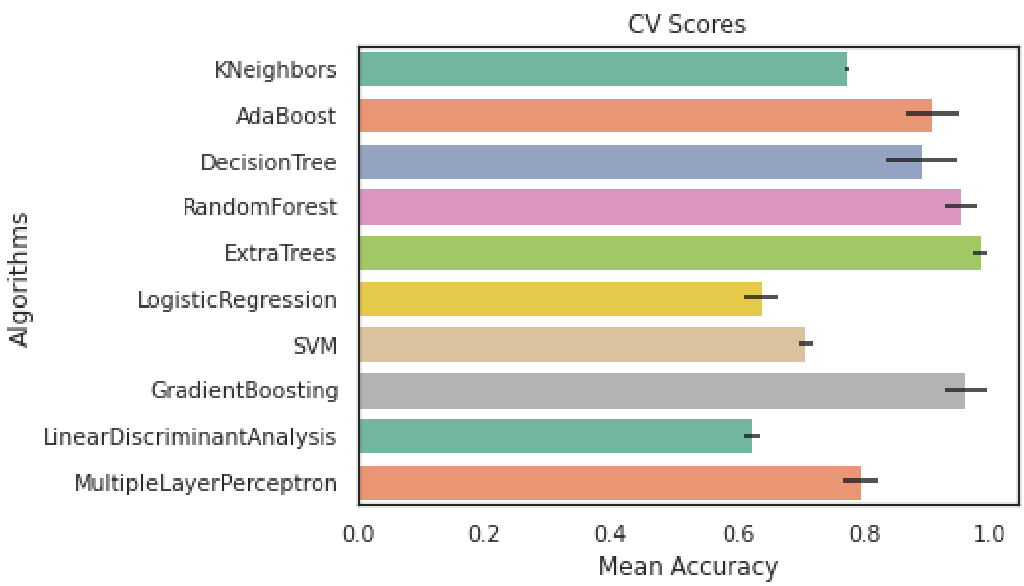

Figure 10 Cross validation Mean Accuracy of Machine Learning Algorithms

In the second stage of the experiment, machine learning algorithms are tested to determine whether resistive plate or letter H is appropriate for healthy people. Fig. 10 displays the test accuracy and standard deviation from mean accuracy of all these methods. Through grid search, these algorithms are fine-tuned to get the best estimation. Three algorithms, ET, GB, and RF, had test mean accuracy scores higher than 92 percent, according to a comparison of the algorithms.

With a low standard deviation, the ET Confusion Matrix on Test Data proved to be the most accurate algorithm in Test Accuracy. Letter H stands for healthy subjects, while letters B, G, and R stand for different types of plates in Table 2. Additionally, Table 3 provides the formulas for precision, recall, F1-score, accuracy, macro average, and weighted average. These numbers help to clarify accuracy in terms of uneven categorization results. Table 4 shows the cross-validation means and cross-validation errors on all ten machine learning algorithms.

	Precision	**Recall**	**F1-score**
B(black)	1.00	1.00	1.00
G(green)	0.98	0.99	0.98
H(healthy)	1.00	1.00	1.00
R(red)	0.99	0.97	0.98
Accuracy			0.98
Macro avg	0.79	0.79	0.79
Weighted Avg	0.99	0.99	0.99

Table 2 Confusion Matrix of Extra Trees

Precision	$\frac{\boldsymbol{True\ Positive}}{\boldsymbol{True\ Positive + False\ Positive}}$
Recall	$\frac{\boldsymbol{True\ Positive}}{\boldsymbol{True\ Positive + False\ Positive}}$
F-1 Score	$\boldsymbol{2 \times \frac{Precision \times Recall}{Precision + Recall}}$
Accuracy	$\frac{\boldsymbol{True\ Positive + True\ Negative}}{\boldsymbol{True\ Positive + False\ Positive}}$
Macro avg	$\frac{\boldsymbol{True\ Positive}}{\boldsymbol{True\ Positive + \frac{1}{2}(False\ Positive + \ False\ Positive)}}$
Weighted avg	$\boldsymbol{F1class_1 * w_1 + F1class_2 * w_2 + \cdots + F1class_N * w_N}$

Table 3 Formulas of Terminologies used in Confusion Matrix of Extra Trees

	CrossValMeans	CrossValErrors	Algorithms
0	0.772657	0.002920	KNeighbors
1	0.907813	0.042682	AdaBoost
2	0.891361	0.055834	DecisionTree
3	0.952265	0.024633	RandomForest
4	0.983542	0.009858	ExtraTrees
5	0.637604	0.025762	LogisticRegression
6	0.708420	0.011052	SVM
7	0.960515	0.032884	GradientBoosting
8	0.624403	0.012561	LinearDiscriminantAnalysis
9	0.794115	0.027667	MultipleLayerPerceptron

Table 4 Machine Learning Algorithms Cross-validation mean accuracy and error

4.2. Discussion

If the length of the exercises is extended, our experiment's conclusions about the effectiveness of the gadget may be enhanced. Activities on the ExoMechHand can be combined with other exercises to test the effectiveness of the gadget.

In accordance with Vijayvargiya, A., et al. (Vijayvargiya et al., 2020), who got findings for abnormalities of knees, our results for machine learning algorithms reveal ET as the best classifier for determining the state of the hand and RF accuracy is greater than KNN, SVM, and DT. Additionally, Hassan et al. suggested adding more variables to the EMG-based preterm birth classification (Hasan et al., 2019). Similar to our accuracy findings, Ahmed et al. (Ahmed and Islam, 2021) discovered that ANN-based multilayer perceptron beats SVM. Although the most common machine learning approaches are utilized for training, more recent techniques might be tested to see if accuracy has improved.

Although the most typical characteristics for classifying sEMG signals are used, new variables can be found to improve outcomes for individuals with ulnar and median neuropathy.

Exoskeleton and end effector devices are the primary architectural or design distinctions amongst hand rehabilitation systems (Balasubramanian et al., 2010). While end effector devices have a minimum that is fully external to the hand and only a minimal portion is mechanically confined to the subject, exoskeleton devices use an artificial skeleton mounted on the hand (Borboni et al., 2016). Our mechanical system consists of an end effector with a dorsal placement for patients with median and ulnar nerve injuries, allowing them to partially execute ADLs. Exoskeleton versions of the concept are possible, though. ExoMechHand can contain the sEMG module to stage the hand's condition and alter the plates automatically as needed. There may be more plates available.

Currently ExoMechHand has two parts of resistive plate for movement of fingers innervated by median and ulnar nerves. However, design may be enhanced to incorporate movements of individual fingers.

Experimentation of our device included patients with ulnar or median nerve neuropathies. ExoMechHand may be evaluated for other hand hemiparesis patients and further research can be done for finding effectiveness on other types of diseases such as stroke, cerebral palsy etc.

Features extracted for this experimentation from sEMG signals for training and testing machine learning algorithms are sixteen in number. These features can be increased, reduced or altered to check the effectiveness on the test accuracy of Extra Trees for changing resistive plates.

CHAPTER 5: CONCLUSION

ExoMechHand's design, testing, and evaluation are all included in this study. Exoskeleton and end effector devices are the primary architectural/design distinctions between hand rehabilitation devices [44]. While end effector devices have a minimum that is wholly external to the hand and only a nominal part of it is physically confined to the subject, exoskeleton devices use an artificial skeleton installed on the hand [13]. For patients with median and ulnar nerve injuries, our mechanical design is an end effector with a dorsal placement that allows them to partially do ADLs. However, the design can be improved and transformed into an exoskeleton as well.

Patients with ulnar or median nerve neuropathies participated in our device's testing. Other patients with hand hemiparesis may be assessed for ExoMechHand and further study can be done. There are sixteen features that were taken from the sEMG signals for this experiment to train and test the machine learning system. To test the efficacy on the accuracy of cross-validation of machine learning algorithms for modifying resistive plates, these features can be raised, decreased, or changed. The device also has to be more cost-effective, have an improved ergonomic design, and have additional plates added to increase the DOF and ROM.

Ethics Statement

The research and evaluation obtained institutional approval from the National University of Science and Technology (Islamabad). Furthermore, approval for Experimentation and Data Collection was obtained from Fauji Foundation Hospital (Rawalpindi) letter-number FF/WD/H/6015/23 dated 27 April 2022. Informed consent for patients was also approved by the hospital and signed by respective subjects during data collection and experimentation from three different departments.

Author Contributions

All authors contributed to the writing of this editorial. All authors approved the submitted version

Conflict of Interest:

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The original contributions presented in the study are included in the article/supplementary files, further inquiries can be directed to the corresponding author/s.

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Contribution to the field statement

Rehabilitation is a serious concern for people with disabilities since it impedes their advancement in society. People who are unable to fully move their hands and fingers experience great distress due to their impaired hand movements. There are several hand rehabilitation tools available, however the majority need to be used by a therapist. ExoMechHand is a prototype hand rehabilitation device that we created. It is made up of three different types of plates and a base support. The resistance and elasticity of the three plates vary, although their shapes are comparable. These plates are further separated into two halves, one for each finger that has median and ulnar nerve supply. Additionally, research is being conducted to determine the device's use for individuals with median or ulnar nerve neuropathies. After exercising continuously for twenty days with two sessions of twenty-four minutes each, three out of ten patients shown improvement in hand movement. Similar to this, a machine learning model is employed for autodetection of the type of resistive plate the patient would use based on surface electromyography signals. When arm surface electromyography signals from new patients are used, it provides accuracy of about 98 percent.

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