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Development of soft actuators for stroke rehabilitation using deep learning

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A B S T R A C T

Automation has created a mind-blowing impact in diversified fields all over the world. Not only in business but also in various domains like health care sectors, manufacturing, etc. a faultless execution is a prime concern. Robotic Process Automation has paved the way for research in the mechanical and mechatronics field. Software robots are trained well to complete repetitive tasks in an efficient manner. A design of such a soft robot can be greatly helpful in the arena of healing. Automation of Rehabilitation therapy has gained attention in recent years. The main aspiration towards the conduct of this research work is to accomplish a soft exoskeleton robot using a thin McKibben actuator applying Deep Learning approaches to aid automatic therapy to the paralyzed patients and help them carry out the hand movement-based exercises. Convolutional Neural Network (CNN) algorithm will be used to support the training of the AI-enabled automated device. The proposed methodology will support stroke survivors to perform exercises independently to enhance their hand motor recovery. For this purpose, it involves pneumatic soft actuator technology using thin McKibben artificial muscles to create a cognitive potential to induce rehabilitation. A soft actuator is proposed so as to confirm the safety purposes of stroke patients.

1. Introduction

According to a statistical report presented by the Centre for Disease Control and Prevention (CDC) in 2018 1 in 6 deaths from cardiovascular disease was due to Stroke. Brain attack also called a Stroke a Cerebrovascular disease is leading as the major cause of disabilities. More than 80% of the strokes are referred to as ischemic strokes where the brain stops working due to lack of blood supply which results in adverse effects in major parts of the body. Hemiplegia and Hemiparesis will lead the stroke survivors to either partial or complete immobility. The stroke survivors with these types apparently will depend on others to complete their daily chores. The nature of normal nerve cells and the nerve with sclerosis is represented in Fig. 1.

Rehabilitation plays a vital role in recovering such brain attack patients. Early rehabilitation is essential in triggering motor skills and thereby ensuring a speedy recovery. The three main types of strokes are ischemic, transient ischemic, and hemorrhagic. This stroke causes different kinds of disabilities like paralysis, semi–paralysis, different ailments like problems in movements, language recognition, memory power, sensory and emotional disturbances. Hence early rehabilitation will greatly help and support overcoming these ailments. Robotic-assisted therapy or robotic therapy has become popular over the last decade. It helps in automating the measurement of force and the movement that needs to be applied to exercise the stroke patients. According to the latest research ratio of the elderly population and people with disabilities has grown when compared to the normal public. Treating elderly people and people with disabilities is not possible with the available infrastructural resources of any country. Hence robotic technology is involved in this rehabilitation process and rehabilitation robotics has grabbed due attention. The major objective of this rehabilitation robotics

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would be completing the repetitive tasks without any flaws thereby improving efficiency. Despite the initial costs incurred the rehabilitation robots can greatly help the stroke survivors to save time and control the exertion caused due to physical efforts. The soft robots designed can support various training activities like the movement of various parts of the body, measuring and controlling the amount of pressure applied, controlling the direction, etc.

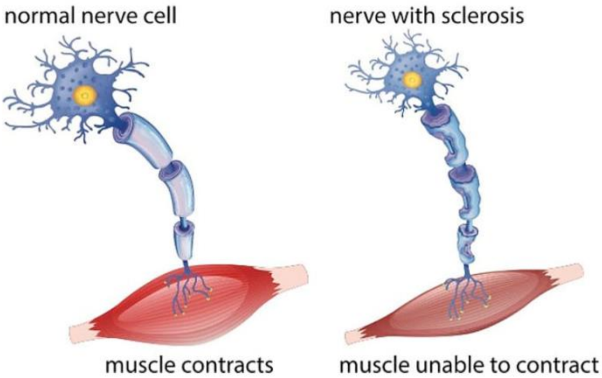

Fig. 1: Normal nerve cell versus nerve with amyotrophic lateral sclerosis

Deep learning happens to be a revolutionary technology that has a notable influence on global applications. In the blueprint of deep learning, the multi-layer neural networks concerned enable to deliver a comprehensive professional framework with "think like human cerebrum" consistency. Deep Learning marks its footprint in various fields such as agriculture, medication, substantial business, etc. Deep Learning also called deep neural networks or deep neural learning can help in assisting rehabilitation robotics therapy. The artificial intelligence quotient of the deep learning neural network can get trained according to the unstructured information provided and may lead to an effective trainer in completing the assigned tasks. Deep learning algorithms can work with massive data sets and train the network repetitively in order to produce a desirable outcome. The motor and sensory signals can be observed from the brain and the same can be fed as input to this multi-layer perceptron to train the artificial neural network to perform the functioning of a therapist in case of stroke-related patients. The data flow of the proposed model is as shown in Fig. 2.

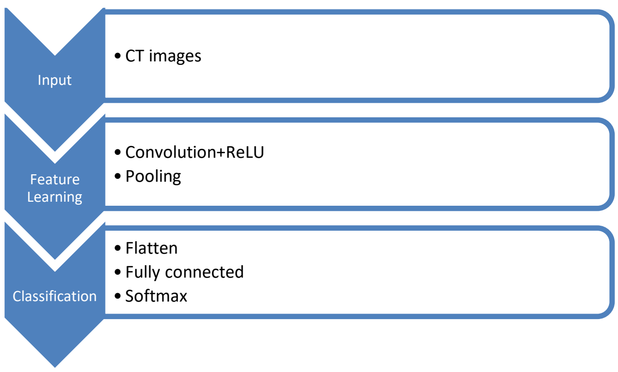

Fig. 2: Data flow in training the classifier using CNN

The proposed research begins with an epidemiological study on the characteristics of post-stroke patients, followed by the analysis of human fingers and thumb movements. These input behavioral patterns are collected so as to train the neural schema to conduct various motion exercises to support the therapists. The rest of the paper is arranged as follows. Section II presents a comprehensive study of the involvement of deep neural network algorithms in paralysis rehabilitation. Section III focuses on the proposed methodology and addresses the need for the system. Section IV demonstrates the results and its relevant discussions. Section V concludes with the summary and the future scopes for enhancement.

2. Literature review

In the past decade, the number of disability patients due to severe brain and other injuries has been increased. The rehabilitation centers couldn't provide sufficient time and space for treating these types of patients due to this increase in numbers. Moreover, such rehabilitation therapy is borne to be cost-effective due to the proportional difference in the availability vs. demand. In order to cut down the charges incurred for such therapies and to assist the therapist, it is decided to design rehabilitation software-assisted robots. The robots shall be trained intensively and the accuracy can be obtained in treating the stroke patients as stated by the researcher (Lum et al., 2002). The design and development of rehabilitation robots in the arena of treating patients with disabilities has gained due attention over a decade. Advancements in the field of mechanical engineering and robotic process automation have paved a way for this type of development. Hillaman (2004) researched this type of rehabilitation robotics that assists chronic stroke patients and explained how robotic technology assists in helping people with disabilities. In order to reduce the cost incurred in the initial assessments that take place for a stroke patient, Yu et al. (2020) have deployed Machine Learning and Deep Learning algorithms to predict the stroke much earlier by accessing the electromyography signals from humans. The long short-term memory approach is employed to overcome the difficulties faced by the recurrent neural network algorithm. The main purpose of this proposed work is to enhance the accuracy of the prediction compared to the existing approaches. Kamal et al. (2018) discussed the impact of machine learning algorithms in treating severe ischemic stroke patients. They have compared various machine learning approaches that involved neuroimaging to treat ischemic stroke. Analysis was done on the reperfusion of ischemic tissues and how the neuroimaging is helpful in analyzing the infusion of intravenous (IV) thrombolytic medication.

The authors have undergone a thorough study on the various ML approaches like an artificial neural network, support vector machine, adaptive boosting, multiclass supported vector machine, convolution neural network, etc. and analyzed the accuracy levels based on different parameters like a prediction of dichotomized mRS, infarction volume, sICH, multi-value mRS and HT. The accuracy levels have been stated accordingly. Asadi et al. (2014) discussed the endovascular treatment in acute stroke and the involvement of machine learning algorithms in the selection process and its accuracy in post-therapy. The authors have analyzed various prognostics modeling employed in machine learning. The ICH transformation based on asymptomatic and symptomatic levels is taken into consideration for training the data set and its outcome prediction. A cerebrovascular injury like stroke is a major source of disability. It causes loss of brain function as the blood vessels to the brain are blocked or ruptured. Stroke is one of the most expensive disease burdens all over the world. Most of the costs mainly contribute to acute hospitalization, inpatient rehabilitation, and nursing home that stroke survivors admitted as suggested by Asirvatham and Marwan (2014). In general, the cerebral hemorrhage adversely affects the opposite side of the brain where the injury is actually taking place. The effects may lead to affecting either the whole body or impairments in a few parts of the body like the face, hands, legs, etc. Hemiplegia refers to this type of complete paralysis of one side of the body whereas hemiparesis comparatively is considered as one-sided weakness. Extensive post-stroke therapy will greatly impact the quick healing by stimulating the brain for relearning the normal movements and results in a speedy recovery. In general, rehabilitation can be initiated as soon as the patient has survived the stroke and his/her vitals have been stabilized. The motor skills of post-stroke patients can be easily improved due to this early therapy.

The variable burden of cerebral paralysis was reported in the Middle Eastern region. Nearly 0.025% of people in the Middle East region are getting affected by stroke according to a recent survey. While calculation the treatment costs incurred it rounds off to nearly SR. Alhazzani et al. (2018) in their research proposal stated that the actual cost spent in rehabilitation therapy costs nearly 500 million SR per year. An increase in Cerebrovascular diseases and their rehabilitation is directly proportional to the cost aided to its supportive treatment. Alahmari and Paul (2016) summarized the cases of stroke in a Table that recorded the details of 13 provinces of KSA. Being the rate of occurrence of cerebrovascular diseases has grown considerably over the decade when compared to the Western countries. Heo et al. (2012) conducted research to identify the advancements of mechanics and how it is employed in the present scope of treating post-stroke patients. Recovery Robotics is the use of automated innovation to the rehabilitative necessities of individuals with handicaps just as the developing older populace. The principal limitation in the robot framework that is used for finger recuperation is the intricacy in its design which involves metallic or plastic positioning in each finger joint in the prescribed research work. Substantial units from plastic and metal burden can add to wearer distress. Soft actuator, otherwise called an elastic actuator, is a pneumatic driven actuator that can proffer more straightforward design, increased ability to weight proportion, frivolous, near minimal effort, and simple support reasonable to be utilized in finger exoskeleton. It changes over energy from compacted air into different movements relying upon its plan. In contrast with a water-powered actuator, a pneumatic actuator is generally little, requires a more modest tank for air stockpiling, and is frivolous. It is likewise simple to manage with just basic on-off type control. It doesn't create heat aside from contact, along these lines the danger of unplanned fire is low. This can advance more security cooperation with humans. Along these lines, a soft actuator is reasonable for use as a human-machine interface.

Researches that are conducted related to the design and development of soft actuators focused only on the object grasping manipulations by applying the soft actuators in the finger exoskeleton rather than the actual gripping force that needs to be applied on the actuator. We have decided to design a soft actuator with the help of a soft McKibben actuator (Takaoka et al., 2013) in order to concentrate on the weak fingers and to provide mobility to those types of fingers by applying suitable gripping force. The actuator is lightweight, pneumatically driven, and cost-effective, and can be bundled to produce large force. The research is required to contribute exceptionally well the improvement of an easy-to-understand, agreeable, more secure, and impressive finger exoskeleton model, where it can help in lessening the therapist's jobs in performing treatment undertakings to stroke survivors in the near future. In recent years, more wearable devices adaptive to different parts of the human body such as hands, shoulders, wrist, and elbows have gained much popularity. Especially, wearable devices support the therapists greatly in the treatment in order to strengthen the weak muscles and to stimulate muscle movements. Noritsugu et al. (2004) suggested that a rehabilitation robot carefully designed to suit the post-stroke patients; treatment can create a great impact in motivating the users to perform the exercises which in turn will reflect in a speedy recovery. An efficient therapy can be provided by a simple robot actuator embedded with accuracy in offering flexibility and fragility as suggested by Sasaki et al. (2005).

While some finger exoskeletons show promising outcomes in receiving a handle on movement, the size and power execution of the bowing actuator used in the incitation framework can in any case be improved. ASSIST robot developed by Huang et al. (2015) used Power-Assist Wear as mentioned by Noritsugu et al. (2008). In addition, self-effacing data of the supported grasping power was observed. A soft actuator with great flexibility, limited in size, and amplified energy transmission at lower operating air pressure will show improvement in the actual therapy. McKibben pneumatic synthetic muscle actuator is known to be a successful compression power actuator because of fiber meshed layer structure fused at the external layer of its tube-shaped body structure. The fiber layer limits outspread constriction while advancing compression powers. Because of its high power capacity driven by the fiber plaited support, two diverse fiber interlaced points in a solitary chamber were proposed to acquire wanted flexing movement and power for finger loosening activation. At present, the twisting delicate actuator model that appeared from writing that utilizes fiber meshed compression and expansion fiber points support is not precisely interlocked and cumbersome. We developed flimsy delicate McKibben muscles for large-scale manufacturing created by Takaoka et al. (2013). The muscles are light, little, and appropriate for straightforward frameworks as clarified by Faudzi et al. (2017).

Meanwhile, deep learning has been emerging as a powerful tool to perform a higher-level analysis while solving problems in various domains. It is a subset of machine learning that takes into account the deeper layers of hidden layers in neural network architecture and its interactions, proposing that with deeper layers, the representations needed for classification or regression problems are discovered at a higher abstraction level, giving unprecedented insights to the problem like never before. Deep learning works very well in supervised networks just as its machine learning predecessors, where raw data would go through a feed-forward neural network while the error between the output data and desire patterns of data are then computed. This error calculation then is taken by the machine in order to adjust its weights by means of a gradient vector. The highlight of the deep learning architecture is that feature vectors are also developed as the fed raw data are passed through the deeper layers along the way, which implies that human intervention is no longer necessary for feature engineering was proposed by Lecun et al. (2015). Within the various selections of deep learning techniques, convolutional neural networks (CNN) have managed to make a name for themselves in a broad range of image processing applications especially when it comes to computer vision. This is because it has the capability to tackle the complexity of an object recognition task that involves thousands to millions of images in a dataset. This is done by controlling the depth and breadth to suit the capacity of the input images, while the weight connections are lessened in order to boost the training. However, despite these interesting qualities, CNN has always been computationally expensive until recently when its usage is implemented efficiently as suggested by Krizhevsky et al. (2012) used graphical processing units (GPUs) which are way faster than the usual central processing units (CPUs). The emergence of ReLU activation functions and dropout regularization also contributed to the rise of CNNs as the dominating approach when dealing with classification and detection tasks. In this rehabilitation proposal, an interesting area where deep learning with CNN would play an important role would be the gesture recognition problem. Therefore, applying deep learning with CNN would be a feasible approach for the systems to be able to perform on par with human practitioners. (Sathiyamoorthi et al., 2021).

In summary, this project will develop a novel wearable rehabilitation system for hand function recovery that benefits the Kingdom of Saudi Arabia as well as other communities worldwide. It also provides a strong foundation and platform for the development of wearable devices that can be used to assist stroke victims to execute prescribed rehabilitation routing suggested by a physiotherapist from home which will reduce the load and stress on the national healthcare providers. Also, the developed platform will assist Saudi national researchers in the area of rehabilitation to conduct their researches collaboratively.

3. Methodology

The soft actuator will be developed using the finite element method (FEM) in order to simulate the physical therapy given to the post-stroke patients. The training dataset utilizes the behavior of real therapy exercises conducted on the patients. The prototype of the soft exoskeleton developed relies on the pressure applied on the hand movement. The contraction applied to the hand movements is taken into consideration while training the system. The Convolutional Neural Network (CNN) algorithm extracts these features of the hand movements to bend, flex, contract and grasp the objects and uses it as the dataset to train the system. The system developed will train the soft exoskeleton developed to perform these operations under a properly supervised learning mechanism. The input features are given as datasets and the system is trained for preferable hand movements. The errors that occurred during the training are feed-forward to avoid loss in the information. The steps performed in analyzing the EMG signal are presented in Fig. 3.

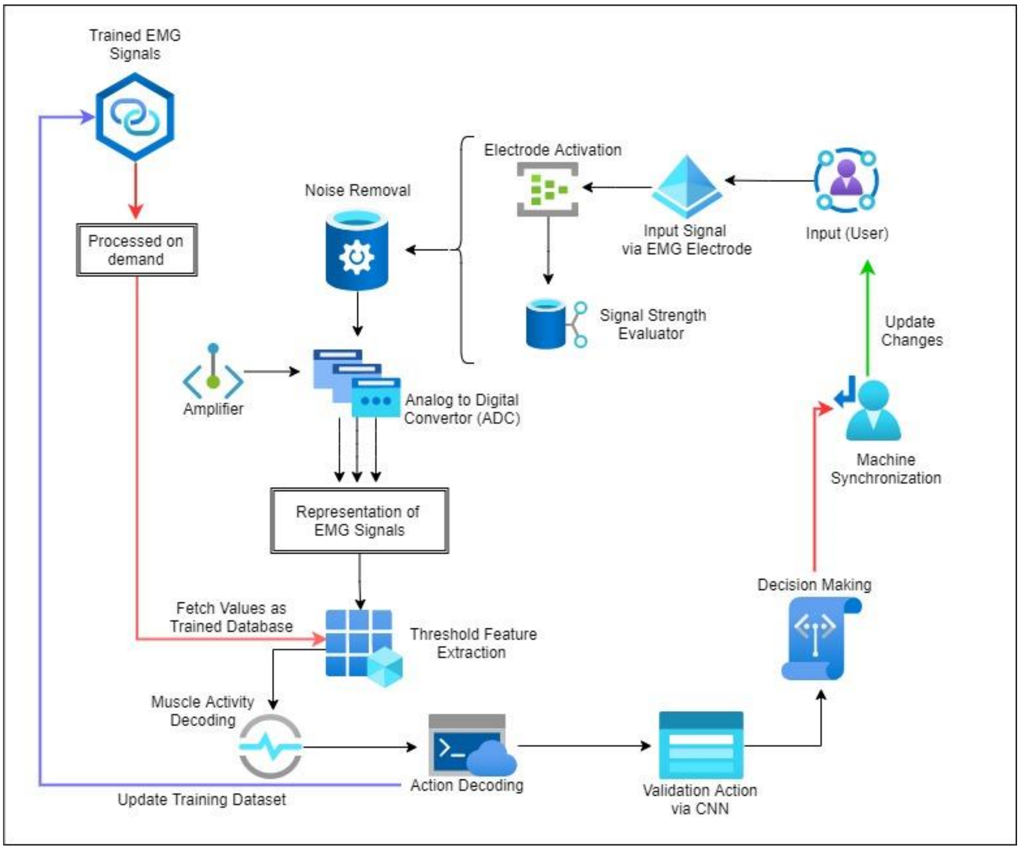

Fig. 3: Data flow diagram of analyzing EMG signals

The soft actuator using the EMG signal to predict the hand motor signals capability is analyzed. The proposed system uses the CNN learning model to accurately predict the sensitivity level of a stroke patient for hand movement gestures. The datasets consisting of the EMG signals are trained to efficiently predict the stroke patient's hand motor capability and accordingly can perform the basic movement independently in the absence of a therapist. The EMG signals measure the muscle activation levels and are thus able to detect the patient's intent to move. The raw EEG signals are pre-processed for filtering and artifacts removal. The incomplete and missing data are removed. Then the feature extraction and classification recognizing the motor imagery signal for the control of a soft actuator is done. The feature extraction step enables to recognize information such as time epoch spatial filters used for analyzing the mental state of the patients. Using the feature extracted the CNN classification allows the translation of the extracted filter signals to required actions. The features such as time epochs and spatial filters for supervised learning enable to detect the pattern for classification. The following algorithm enables to extract features and classify the signal. The proposed methodology extracts data segments and training information from a trained EMG signals dataset and on dynamic processing, the information is sub-routed to fetch the region of interest (ROI) with reference to muscle tissue. The process uses the CNN approach as discussed in the early paragraph of this session and demonstrated in detail in Fig. 3.

4. Mathematical representation and proofing

Consider input Signal *(I_S)* from the user required under the attention of automatic consideration of machine orientation from stroke area of interest. The input single *(EMG)* is dependent on various sets of attributes as $I_S = (I_{S_1}, I_{S_2}, I_{S_3} \ldots I_{S_n})$. These signals assure that input from a user is collected and processed under correlation to the parameter of adjusting to the environment. The input is calibrated with an interconnected orientation of the electrode to circulate electric impulses. The process is then computed with a signal strength evaluator to assure the coordination of signal from user and electrode as $(I_S \oplus \Delta E \Rightarrow EMG)$. The resultant values are further correlated to expand signal strength and reduce the noise ratio. This is considered as the input phase of evaluating the given EMG user signal.

ADC of EMG signals: The input signal collected via a coordinated summary of I_S is segmented in order to expand the digital version of the analog signal to assure and the processing stream for incorporating data quality parameters as shown in Eq. 1.

$$S = \lim_{n\to\infty}\left(\frac{\delta(I_S)}{\delta t}\right) \cong \left(\sum_{i=0}^{n}\left\{\frac{\delta(I_S)_i \cdot \Delta A}{\delta t}\right\}\right) \quad (1)$$

$$S = \lim_{n\to\infty}\left(\frac{\delta(I_S)}{\delta t}\right) \cong \left(\sum_{i=0}^{n}\left\{\frac{\delta(I_S)_i \cdot \Delta A}{\delta t}\right\}\right)_0^{\infty} \quad (2)$$

$$\forall \Delta A \to (a_{n-1}\log_2(I_S)_1) + (a_{n-2}\log_2(I_S)_2) + \ldots + (a_0\log_2(I_S)_n) \quad (3)$$

A high-sampling rate (H_S) is conducted for extraction and evaluation of schema such as (S) with reference to (ΔA) in the ratio of frequency arbitrator (f) as computed with $f = (f \times H_S) \in \Delta A$, these attributes are further expanded and reflected in Δf as $\Delta f = \{f_1, f_2, f_3 \ldots f_n\}$ such that, $\Delta f_s = (\Delta f \times 0.31)$ where Δf_s is the frequency matrix of required signal conversion strength, thus represented in Eq. 4:

$$\Delta f_m \leq \frac{\Delta f_s}{2} \simeq 0.5 \times f \tag{4}$$

Thus the impulse signal of the ADC process is as in Eq. 5:

$$\Delta f(x) = x(t) \sum_{i=0}^{\infty} \delta\,(t - n\Delta f_m) \times \log_2(\Delta f) \tag{5}$$

where each factor of f(x) is combined with a relative co-efficient of time and frequency parameter. Thus the extracted signal is regenerated to represent the EMG signal as shown in Eq. 5 and Eq. 6 respectively with reference to frequency domain sampling.

$$\delta T = \sum_{n=1}^{\infty} \delta(t - n\Delta f_m) \Rightarrow \left[\frac{2\pi}{\Delta T}\left(\sum_{k=-\infty}^{\infty} \frac{(\Delta f_m)_k}{\delta t}\right) \times \omega_S\right] \tag{6}$$

$$\therefore x(\delta T) = \frac{2\pi}{\Delta T}\left(\sum_{k=-\infty}^{\infty} \frac{(\Delta f_m)_k - \omega_S}{\delta t}\right) \tag{7}$$

Thus, from Eq. 7, the evaluation factor of estimating the regional function of the EMG signal is extracted. The impulse of the signal is ranged from $\left(\Delta f_m \cong x(\delta T) \cong 0.5\right)$; the resultant values are dependent vectors for computing signal features.

Feature Extraction from EMG Signal: The feature extracted into the EMG signals are related to be validated and evaluated with reference to Eq. 7 i.e. the frequency domain sampling and rectification vector as shown in Eq. 8:

$$F = \left(\frac{\delta(\Delta T) + \delta x}{\delta t}\right) \tag{8}$$

The feature dependency is bounded with reference to parameters such as signal strength, a bandwidth of operation ratio, and data fermentation attributes such as area of interest, muscle of the operation, time and repeated mode constrain in processing and utilization. The evaluation matrix of multiple features is resultant in Eqs. 9 and 10.

$$F_E = \frac{1}{2\pi\Delta A} \int_0^{\infty} \Delta T \times \delta x \left(\sum_{i=0}^{\infty} \sum_{j=i+1}^{n-1} \left[\frac{\delta\left(f_m\right)_i}{\delta t_j}\right]\right) \tag{9}$$

$$F_E = \frac{\Delta T}{2\pi \times \Delta A}\left\{\int_0^{\infty} \times \delta x \left(\sum_{i=0}^{\infty}\left(\frac{\delta\omega_S \times \delta\left(f_m\right)_i}{\delta t}\right)\right)_n^{\infty}\right\} \tag{10}$$

$$\therefore F_E = (x\Delta T)^{-1}\left[\sum_{i=0}^{\infty} \delta(t - n\delta(f_m)_i)\right] \tag{11}$$

Eq. 11, demonstrates the behavioral ratio of extraction of (F_E) features such that, $(F_E \in \delta\omega_T)$ where $\delta\omega_T$ is the random representation variable of each feature set taken on an average from $(0 \leq x\Delta T \leq \infty)$ such that, each of $x\Delta T$ is a regional matrix of evaluation.

5. Feature thresholding and decision making

Thresholding assures the feature extractions in the pattern are resultantly in equilibrium to the range of operations. As the objective of the research is to extract and operate the stroke under EMG signal. The process re-assures the selection of interdependent parameters and attributes with reference to trained datasets for controlling and coordinating motor and speed of operation as demonstrated in Eq. 12 respectively.

$$\left(F_E\right)_{Thr} = \lim_{n\to\infty}\left(Avg\left(\sum_{i=0}^{\infty}\sum_{j=j+1}^{n}\left\{\frac{\delta\left(f_m\right)_i - \delta\omega_j}{\delta t}\right\}\right)\right) \tag{12}$$

$$\left(F_E\right)_{Thr} = \lim_{n\to\infty}\left(\frac{\left(\sum_{i=0}^{\infty}\sum_{j=j+1}^{n}\left\{\frac{\delta\left(f_m\right)_i - \delta\omega_j(\Delta x)}{\delta t}\right\}\right)}{2}\right) \tag{13}$$

$$\left(F_E\right)_{Thr} = \lim_{n\to\infty}\frac{1}{2}\left(\int_0^{\infty}\int_j^{n}\left\{\frac{\left\{\frac{\delta\left(f_m\right)_i - \delta\omega_j(\Delta x)}{\delta t}\right\}}{\delta t}\right\}\right) \tag{14}$$

$$\therefore (Thr)_{Training} \Rightarrow (F_E)_{Thr} \triangleq \left\{\sum_{i=o}^{\infty} \Delta x_i \langle x_i \subseteq \omega \rangle\right\} \tag{15}$$

As per Eq. 12 to Eq. 15, the extraction matrix of thresholding values are equated with reference to feature attributes parameters of Δx such that, each of $(x_i \subseteq \omega)$ as per Eq. 15. The process also validated training threshold values with respect to the values of occurrences in an independent (ω) and ΔT of features and thus based on the schematic values, the attributes vector of actions are recorded and updated. The validation results in a decision support matrix with respect to the support of self-learning systems. The decision support matrix is assured for processing and providing unambiguous decision support.

Input:

The set of given training dataset samples (X_n, Y_n)

$X_n \in F^{C*S}$, n= 1, 2, …., N

N=the number of classes for Y_n;

F=the number of spatial filters for the specified class

The Gaussian density function used in estimating the neural discharge sequence as presented in Eq. 16

$$f_x(x) = \frac{1}{\sigma_x\sqrt{2\Pi}} \exp\left(\frac{\left(x - \mu_x\right)^2}{2\sigma_x^2}\right) \tag{16}$$

where μ_x is mean and σ_x is variance.

Output:

Predicted Label y

EMG trials X for the spatial filter is

$X_n \in R*S$

The corresponding percentile values are calculated by using D_k;

Where [D_k] k = 1,….., K for b_n;

Hypothesis the K classes as D_1, D_2, D_3,…..D_{k-1}, D_k for b_n

Calculate EMG signal as:

$T_n = \sum_{n=1}^{N} \beta_m * D_K$

$\sum_{n=1}^{N} \beta_m * X_n$
where m=1, ..., m
Compute the spatial filter matrix;
Construct and concatenate the K single for spatial filter to find out the final filter;
Retrieve the spatial filter trial for X_n

The algorithm for training the system according to the finger loosening force is given below:

Algorithm
Linear Regression ()

***declare** and **initialize** the weights **w**=(x_0,x_1,x_2……x_n)*
Repeat Until the no of iterations
do
***select** the data point D_i=<**x_k**, y_k> from W*
***assign** ∂=1/D_i*
***update** weights simultaneously*
***w_1=w**+∂ (k)+D_i*
Done
end for
***return** weights w_1*

6. Results and discussion

In this section experiment methods and the result are discussed. The Pre-processed data is used to extract the relevant features given. By using various deep learning classifiers, the accuracy of the motor movement is predicted and the results show that the CNNs layers utilized to cross-validate the accuracy gives high efficiency. The EMG signal used in the present experiment is presented in Fig. 4.

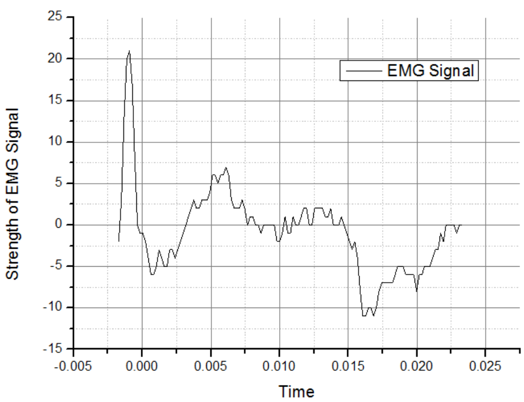

Fig. 4: Representation of EMG Signal

In the present research, the muscle response is measured using soft actuators using EMG signal and force. The number of basic motor elements for a muscle (or) group of muscle (*N*) is estimated as a ratio of maximum compound muscle action potential (CMAP) to the mean of single motor unit response (SMUR) (Reaz et al., 2006) is as presented in Eq. 17. The linear relationship between different muscles (N=61, 76, 43) and EMG signal strength is presented in Fig. 5. Table 1 shows evaluation parameters.

$$N = \frac{(\max CMAP)}{(mean\ SMUP)} \tag{17}$$

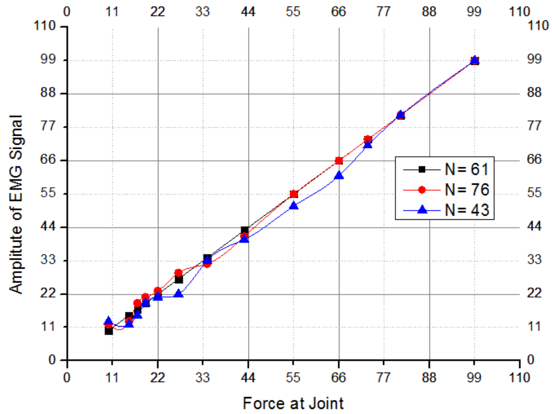

Fig. 5: Relationship between three different muscles and strength of EMG Signal

Table 1: Evaluation parameters

Parameters	Formula
Accuracy(A)	$A = \frac{TP + TN}{Total}$
Recall(R)	$R = \frac{TP}{Actual\ True}$
Precision(P)	$P = \frac{TP}{Predicted\ True}$
F Score(FS)	$FS = 2 \times \frac{R \times P}{R + P}$

The testing and training through various layers of CNN by varying the epochs provided better accuracy than the SVM, DT, and LDA classifiers as presented in Table 2. The scores of precision, recall, and f1-score are presented in Fig. 6.

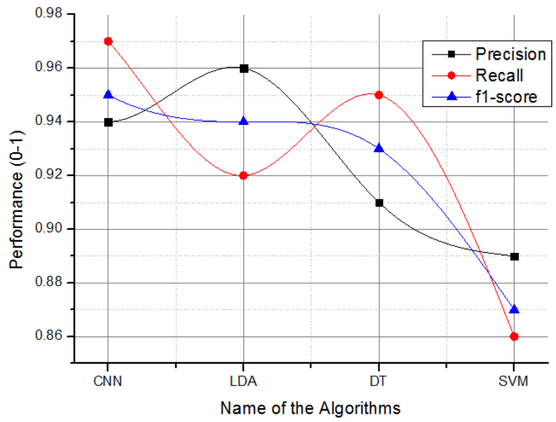

Fig. 6: Plot of precision, recall, and F1-score

Table 2: Accuracy measure of different classifiers

Classifier	Accuracy
SVM	77.21%
DT	94.05%
LDA	92.60%
CNN	95.91%

7. Conclusion

The system developed will train the soft exoskeleton developed to perform these operations under a properly supervised learning mechanism. The input features are given as datasets and the system is trained for preferable hand movements. The errors that occurred during the training are fed forward to avoid loss in the information. The EMG signals are analyzed to assist the soft actuators for stroke rehabilitation patients. The classification of the signals enables the stroke patients to exercise in the absence of the therapist. The CNN classifier shows a promising result when compared with other deep learning methods. It has been observed that high classification accuracy is achieved using CNN. In future work, the Fuzzy logic with an artificial neural network is to apply to the data observed from the environment. The advantage of this combination is to emulate human decision making closely than the traditional approaches.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Alahmari K and Paul SS (2016). Prevalence of stroke in Kingdom of Saudi Arabia-Through a physiotherapist diary. Mediterranean Journal of Social Sciences, 7(1 S1): 228-228. https://doi.org/10.5901/mjss.2016.v7n1s1p228

Alhazzani AA, Mahfouz AA, Abolyazid AY, Awadalla NJ, Aftab R, Faraheen A, and Khalil SN (2018). Study of stroke incidence in the Aseer region, southwestern Saudi Arabia. International Journal of Environmental Research and Public Health, 15(2): 215. https://doi.org/10.3390/ijerph15020215 **PMid:29373563 PMCid:PMC5858284**

Asadi H, Dowling R, Yan B, and Mitchell P (2014). Machine learning for outcome prediction of acute ischemic stroke post intra-arterial therapy. PLOS ONE, 9(2): e88225. https://doi.org/10.1371/journal.pone.0088225 **PMid:24520356 PMCid:PMC3919736**

Asirvatham AR and Marwan MZ (2014). Stroke in Saudi Arabia: A review of the recent literature. Pan African Medical Journal, 17: 1. https://doi.org/10.11604/pamj.2014.17.14.3015 **PMid:24932325 PMCid:PMC4048673**

Faudzi AAM, Razif MRM, Endo G, Nabae H, and Suzumori K (2017). Soft-amphibious robot using thin and soft McKibben actuator. In the IEEE International Conference on Advanced Intelligent Mechatronics, IEEE, Munich, Germany: 981-986. https://doi.org/10.1109/AIM.2017.8014146

Heo P, Gu GM, Lee SJ, Rhee K, and Kim J (2012). Current hand exoskeleton technologies for rehabilitation and assistive engineering. International Journal of Precision Engineering and Manufacturing, 13(5): 807-824. https://doi.org/10.1007/s12541-012-0107-2

Hillman M (2004). 2 rehabilitation robotics from past to present-A historical perspective. In: Bien ZZ and Stefanov D (Eds.), Advances in rehabilitation robotics: 25-44. Springer, Berlin, Heidelberg, Germany. https://doi.org/10.1007/10946978_2

Huang J, Huo W, Xu W, Mohammed S, and Amirat Y (2015). Control of upper-limb power-assist exoskeleton using a human-robot interface based on motion intention recognition. IEEE Transactions on Automation Science and Engineering, 12(4): 1257-1270. https://doi.org/10.1109/TASE.2015.2466634

Kamal H, Lopez V, and Sheth SA (2018). Machine learning in acute ischemic stroke neuroimaging. Frontiers in Neurology, 9: 945. https://doi.org/10.3389/fneur.2018.00945 **PMid:30467491 PMCid:PMC6236025**

Krizhevsky A, Sutskever I, and Hinton GE (2012). ImageNet classification with deep convolutional neural networks. In the Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1 (NIPS'12), Curran Associates Inc., Red Hook, USA: 1097–1105.

LeCun Y, Bengio Y, and Hinton G (2015). Deep learning. Nature, 521(7553): 436-444. https://doi.org/10.1038/nature14539 **PMid:26017442**

Lum P, Reinkensmeyer D, Mahoney R, Rymer WZ, and Burgar C (2002). Robotic devices for movement therapy after stroke: Current status and challenges to clinical acceptance. Topics in Stroke Rehabilitation, 8(4): 40-53. https://doi.org/10.1310/9KFM-KF81-P9A4-5WW0 **PMid:14523729**

Noritsugu T, Takaiwa M, and Sasaki D (2008). Power assist wear driven with pneumatic rubber artificial muscles. In the 15th International Conference on Mechatronics and Machine Vision in Practice, IEEE, Auckland, New Zealand: 539-544. https://doi.org/10.1109/MMVIP.2008.4749589

Noritsugu T, Yamamoto H, Sasakil D, and Takaiwa M (2004). Wearable power assist device for hand grasping using pneumatic artificial rubber muscle. In SICE 2004 Annual Conference, IEEE, Sapporo, Japan, 1: 420-425. https://doi.org/10.1109/ROMAN.2004.1374840

Reaz MBI, Hussain MS, and Mohd-Yasin F (2006). Techniques of EMG signal analysis: Detection, processing, classification and applications. Biological Procedures Online, 8(1): 11-35. https://doi.org/10.1251/bpo115 **PMid:16799694 PMCid:PMC1455479**

Sasaki D, Noritsugu T, and Takaiwa M (2005). Development of active support splint driven by pneumatic soft actuator (ASSIST). In the IEEE International Conference on Robotics and Automation, IEEE, Barcelona, Spain: 520-525. https://doi.org/10.1109/ROBOT.2005.1570171

Sathiyamoorthi V, Ilavarasi AK, Murugeswari K, Ahmed ST, Devi BA, and Kalipindi M (2021). A deep convolutional neural network based computer aided diagnosis system for the prediction of Alzheimer's disease in MRI images. Measurement, 171: 108838. https://doi.org/10.1016/j.measurement.2020.108838

Takaoka M, Suzumori K, Wakimoto S, Iijima K, and Tokumiya T (2013). Fabrication of thin McKibben artificial muscles with various design parameters and their experimental evaluations. In the 5th International Conference on Manufacturing, Machine Design and Tribology (ICMDT 2013). Available online at: https://www.dbpia.co.kr/Journal/articleDetail?nodeId=NODE02183699

Yu J, Park S, Kwon SH, Ho CMB, Pyo CS, and Lee H (2020). AI-based stroke disease prediction system using real-time electromyography signals. Applied Sciences, 10(19): 6791. https://doi.org/10.3390/app10196791