

## **Development of a Cost-Effective Neural Network Exoskeleton Arm**

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## 1. Background-Aim

Currently, there are various exoskeletons available for different applications, including medical exoskeletons for mobility support. Artificial intelligence techniques, such as neural networks, are becoming important in the development of exoskeletons. Customized exoskeletons can be created for individual users using 3D printing, ensuring a better fit. **Medical exoskeletons, which are designed to help patients, can cost tens of thousands of dollars**.

The aim of this study was to develop an affordable, functional, and personalized exoskeleton arm by leveraging the integration of artificial intelligence, specifically **neural networks (NN), and low-cost 3D printing technology.** This exoskeleton was designed to provide mobility assistance to users, particularly those with muscle weakness or injury, through intuitive and adaptive control. By focusing on **costeffective components and 3D printing, the study sought to make exoskeleton technology accessible to a broader population.** The primary goal was to create a system that could accurately respond to muscle activity without requiring extensive technical knowledge from users, improving both the affordability and ease of use of medical exoskeletons



The development of the exoskeleton involved the integration of software, hardware, and mechanical design. The software was engineered using a hybrid approach combining NN with C++. Hardware selection focused on a microcontroller suitable for the NN and included operational amplifiers, voltage converters, and EMG sensors. The mechanical structure was designed using Autodesk Fusion 360, focusing on aligning with human anatomy for natural movement synchronization while ensuring stability and durability.





## Robotic arm neural network architecture. A neural network consists of a column of inputs, one or more hidden layers, and a final layer of outputs. The figure below shows the architecture of N.N. of the exoskeleton. Each connection is associated with a number called a weight.

The output, h<sub>i</sub>, of the neuron i in the hidden layer column is,

$$h_i = \sigma(\sum_{J=1}^N V_{ij} x_j + T_i^{computational}) \qquad (Eq. 6)$$

Where,

 $\sigma$ (), the activation (or transfer) function.

N, the number of input neurons.

V<sub>ii</sub>, the weights.

 $\mathbf{x}_{i}$ , the inputs to the input neurons.

 $\mathbf{T}_{i}^{\text{computational}}$ , the success threshold of hidden neurons.

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Triceps force level 4.

Resting state of the bicep muscle.

Biceps use variables by strength level.

Variable	Force level 1	Force	Force	Force	Force
		level 2	level 3	level 4	level 5
V <sub>pp</sub>	1	2,2	4,2	6,2	8,2
V <sub>avg</sub>	1,07	1,35	1,61	2,05	2,49
V <sub>max</sub>	1,6	2,8	4,8	7	8,8
Frequency	1	7,3	96,9	33,3	128,87

Measurements of the resting and active states of the biceps and triceps muscles were first recorded using an oscilloscope to monitor various voltages, and frequency. Peak-to-peak voltage (Vpp), showed the greatest linearity among variables and was selected for further analysis, showing a consistent relationship between Vpp values and muscle strength. The Vpp values were used as inputs the NN and the to exoskeleton motor response was defined as outputs. NN training resulted in exoskeleton response error of 0.0001%, thus ensuring high reliability.



The rapid evolution of daily routines is driven by the proliferation of products designed to enhance convenience and efficiency. These devices are engineered to maximize the output provided to users while minimizing the input required. In line with this principle, the exoskeleton should mitigate the metabolic cost of its operation, offering strength augmentation or assistance without imposing an additional energy burden on the user. However, accurately quantifying this metabolic phenomenon typically demands the use of expensive, specialized equipment.

The components used in the exoskeleton design are common and easily accessible, allowing for reproduction at a minimal cost. The electronic circuitry is composed of standard through-hole components, which are widely available from major online suppliers for under 30 euros. Experimental validation demonstrated that the prototype performed as predicted in simulations. However, the absence of a reducer in the joint limited its load-bearing capacity. This limitation can be readily addressed through the integration of appropriate gears, bearings, and modifications using a 3D modeling program to enhance joint mechanics.

Furthermore, the implementation of a neural network in the exoskeleton's control algorithm significantly improved ease of use across different users. This approach minimized the requirement for precise electrode placement and complex device management, thus enhancing the exoskeleton's usability and adaptability for a wider range of individuals.

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