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AI Integrated Dynamic Exoskeleton Aid System

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Abstract:

Traditional exoskeleton technologies have focused primarily on enhancing existing human capabilities or restoring lost key motor functions. While these systems successfully assist movement, they are rarely designed to help users maintain or gradually improve muscle strength, or to align their movement habits over time. This project addresses these limitations through artificial intelligence (AI)-based decision-making that enables adaptive, user-centered control. Building on an exoskeleton arm previously presented at the 2025 ASEE Annual Conference, the project integrates mechanical, electrical, and computational components to form a complete mechatronics system enhanced by modern machine-learning techniques. The exoskeleton consists of two pipe-like braces attached to the forearm and upper arm, connected by a motorized joint driven by a microcontroller-based control system. A load cell mounted on the frame measures the tension produced by the bicep muscle and serves as the primary input for control and classification. Using load cell data, a machine-learning classifier trained through Edge Impulse determines user intent in real time. The classifier was deployed as a lightweight edge-AI model on a Raspberry Pi and achieved an accuracy of 75.7% in distinguishing action patterns such as picking and holding versus picking and dropping. To improve motion quality, a DC motor and closed-loop proportional-integral (PI) control algorithm were implemented, resulting in smoother and more stable arm movement compared to the previous servo-based design. Conducted by a high school student, this project encompasses all aspects of engineering design, hardware development, algorithm training, coding, and testing. It demonstrates how pre-college students can meaningfully engage in authentic STEM research that connects mechatronics, AI, and human-centered design.

Introduction

Human-machine interaction is continuously pushed toward new limits, bolstered by novel research and capital investments in exoskeleton technology. Such devices have shown promise in areas such as rehabilitation, industrial manufacturing, and physical assistance, where they can help reduce injury risk and support demanding tasks [1]. Many existing exoskeleton systems are designed either to help patients regain motor function after injury or to amplify human strength in industrial environments. These powered systems typically use sensors to detect user motion and apply motor-driven assistance, sometimes reducing muscle activation by more than 40% [2].

While these systems are effective at assisting movement, most provide continuous or fixed assistance. This design approach can reduce muscle engagement over time and may limit opportunities for users to maintain strength or improve movement habits [3]. Because of this limitation, recent research has focused on adaptive exoskeleton designs that assist only when needed. Instead of replacing human effort, adaptive systems aim to respond to user intent and task difficulty, creating a more efficient and human-centered form of assistance.

Current exoskeleton technologies can be broadly categorized as powered or passive systems. Powered exoskeletons use actuators such as motors, hydraulics, or pneumatics, along with sensors that monitor user motion and system performance, to actively drive joint movement [4]. Passive exoskeletons, in contrast, rely on mechanical components such as springs or dampers to store and release energy from the user's movement without active actuation [5]. In medical applications, powered exoskeletons are commonly used for rehabilitation, providing external support to individuals recovering from spinal or back injuries and helping restore safe and controlled movement [6].

Industrial exoskeletons are designed to support heavy loads and prolonged use, primarily targeting the back and upper body to reduce fatigue in labor-intensive fields such as construction and manufacturing, where work-related musculoskeletal disorders are common [7]. Passive industrial exoskeletons reduce muscle fatigue by storing and releasing energy, particularly in the shoulders and upper arms, while powered systems can provide significantly greater assistance, with some designs reporting large force amplification capabilities [8]. Although powered exoskeletons offer higher strength and flexibility, passive systems are typically lighter, more cost-effective, and better suited for reducing long-term fatigue, highlighting a trade-off between assistance level, weight, and cost [5].

Commonly used sensors in exoskeleton systems include inertial measurement units, joint angle sensors, force sensors, and electromyography (EMG) sensors [9]. EMG sensors measure electrical signals generated by muscle activation and are often used to detect user intent. However, EMG-based systems can be difficult to implement due to signal noise, sensitivity to electrode placement, and the need for careful calibration. These challenges can reduce reliability, especially in non-clinical or educational settings [10]. As an alternative, load cells provide a simpler and more robust way to estimate muscle effort through mechanical force measurement. Load cells are durable, low-cost, and easy to integrate, making them a practical sensing solution for adaptive exoskeleton systems. Research has shown that lifting heavier loads results in higher muscle activation and greater force production [11]. As muscle contraction strength increases, more force is applied to the load cell, producing measurable changes in output [12].

Building on an exoskeleton arm previously presented at the 2025 ASEE Annual Conference [13] as shown in Figure 1, this project extends the system by integrating artificial intelligence (AI)-based decision-making for adaptive control. The exoskeleton consists of two pipe-like braces attached to the upper arm and forearm, connected at the elbow joint by a motorized actuator. A load cell mounted on the frame measures tension generated by the bicep muscle during lifting tasks. Instead of using simple threshold-based triggering, load cell data are processed using a machine-learning classification model trained with Edge Impulse software. The model achieved an accuracy of 75.7% in distinguishing between action patterns in user movement.

To improve motion quality, ongoing work includes the use of a DC motor and advanced control algorithms to produce smoother and more natural arm movement. In addition, an edge-AI version of the system is being developed using a Raspberry Pi, allowing lightweight neural network models to run directly on the device without cloud dependency. This approach enables real-time learning and decision-making while maintaining low latency and system reliability.

This project was conducted by a 12th-grade high school student and involved all stages of the engineering design process, including mechanical design, sensor integration, embedded programming, machine-learning model training, and system testing. The student worked approximately 8 hours per week over 40 weeks, documenting design decisions and test results throughout the process. This work demonstrates that pre-college students can meaningfully participate in authentic engineering research that integrates mechatronics, artificial intelligence, and human-centered design. Beyond the technical contribution, this paper examines the project as an engineering education case study, focusing on feasibility, learning outcomes, and instructional design for pre-college students.

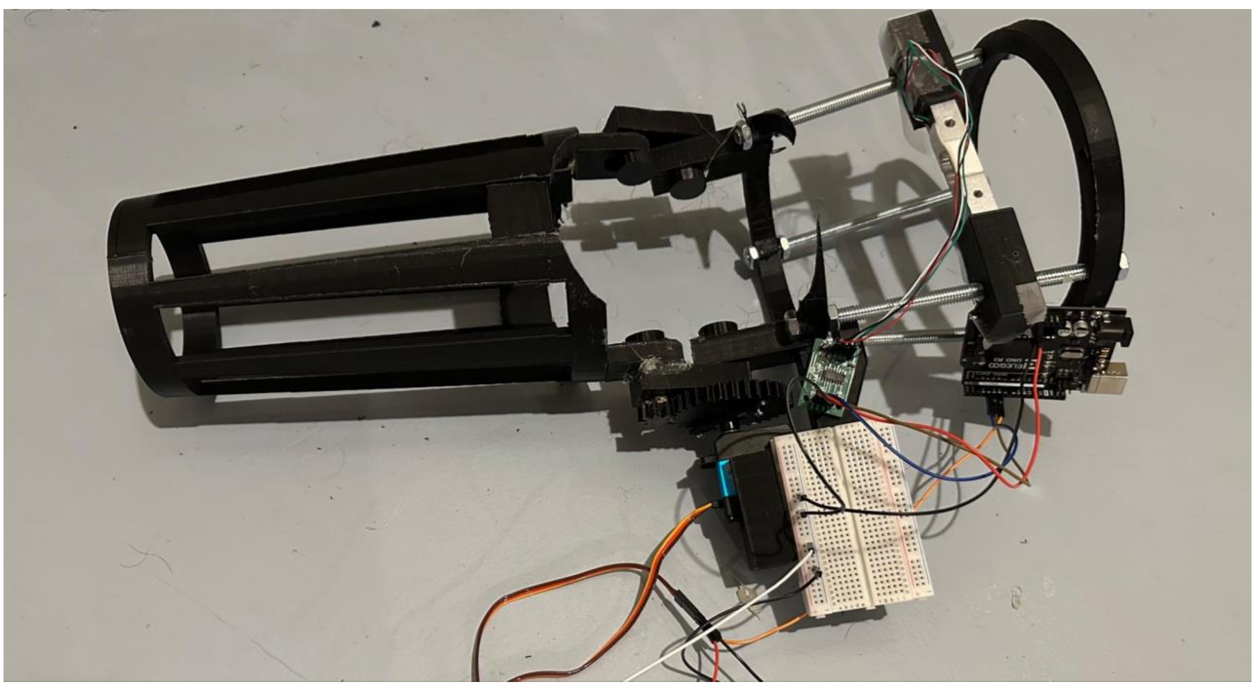

Figure 1. The 2025 ASEE Conference design

Project Description:

In addition to the original goal of the project in assisting human function while reaping the benefits of a powered exoskeleton system, new functionalities and algorithms have increased the sensitivity of the system to the intricacies of human movement patterns. The objectives of the system include

1. **Action Prediction:** inferring the type of action that was conducted by the user, including picking and dropping, holding a weight, and accounting for the speed of movement.
2. **Detection of Force Exerted:** A load cell sensor is used to measure the physical force exerted by the concentric and eccentric muscle activation of the user.
3. **Mapping of Movement:** The system uses a PI control algorithm to control the motor speed. The sensor output is mapped to the desired motor speed in real time.
4. **Assistive Motion:** The motor must be able to pick up the desired weight in accordance with the needs of the user.

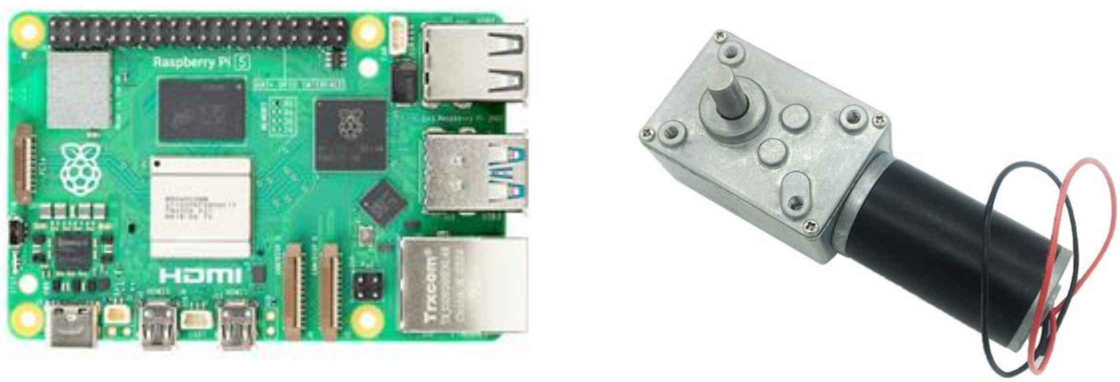

Figure 2. The Raspberry Pi 5 unit and the 12V DC Motor utilized in the project

The updated design fulfills these targets through a series of software and hardware designs. The construction of the exoskeleton utilizes multiple major elements:

1. The lightweight 3D-printed exoskeleton frame acts as the anchor point for multiple electronic hardware components, including the motor and HX711 module. It also provides a medium for the motor to aid the user.
2. A Raspberry Pi 5 is responsible for the computations driving the control system and AI application that corroborates information with the sensor. The GPIO pins are the physical connection points for the HX711 and the load cell, as well as the motor. (Figure 2)
3. A 16 RPM DC Motor provides 70 kg-cm of torque at the axis of rotation through a series of gears that are attached to the exoskeleton. (Figure 2)
4. The HX711 module is an ADC that allows the Raspberry Pi to utilize the analog output of the load cell in a digital format for application in the control system.
5. A load cell is the primary sensor at the heart of the system. It measures the physical force exerted when the bicep of the user undergoes concentric or eccentric action, allowing a software application to find the relative amount of exertion undergone by the muscle at any given moment.

6. The DC motor speed is controlled by PWM using L298n to supply a proper current.
7. An encoder is used to read the feedback motor speed for a closed-loop PI control.

Algorithm Description

The first objective, action prediction, is achieved through the use of a machine learning system. When designing the system, it was important to account for the numerous ways a user can move their arm. Rather than moving the appendage between two set points at varying speeds based on the measured exertion by the load cell, it was necessary to recognize the intent of the individual (user). A neural network was then prepared with hundreds of instances of a user picking up a varying set of weights. Each instance was divided into two major categories: pick and drop and pick and hold. The former was categorized by a relatively quick and simple rotational movement centered at the elbow, entailing an individual moving the object concentrically and eccentrically 2-3 times in 10 seconds.

The network underwent multiple design iterations to maximize performance relating to differentiating test data between these two categories. The final design succeeded in providing 75.7% accuracy in recognizing which movement the individual had done on a validation set that was comprised of 20% of the original data. This data is used to create an algorithm to map the detected stress to the desired motor speed.

In order to further corroborate the model and directly control the speed of the motor in accordance with the third goal, a PI controller was implemented through software to linearly map the stress exerted by the user to the set speed of the motor. The block diagram is shown in Figure 3.

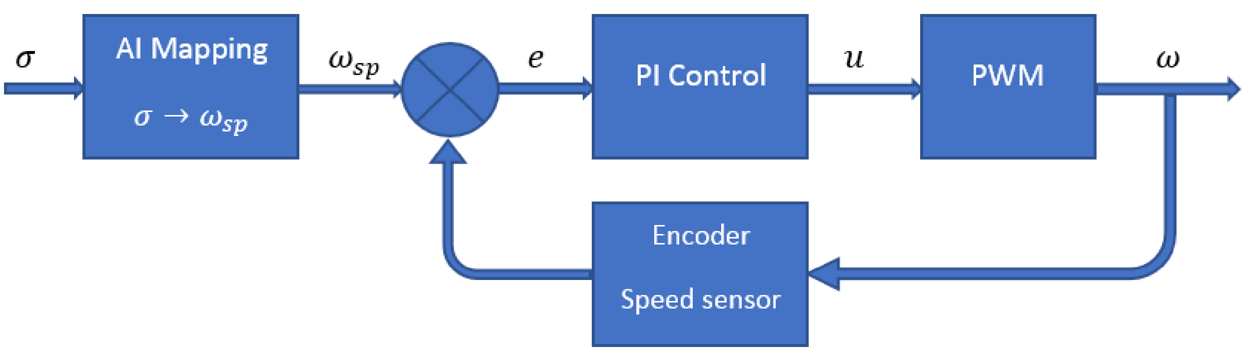

Figure 3. The control system diagram

The first step in designing the control system was to derive a relationship between stress and motor speed. Before machine learning, a linear mapping was adapted to test the system. The parameter S_u is a representation of the highest stress measured by the load cell for a given user. For stress values that were $0 < \sigma < S_u$, the speed would be derived in a proportional and interpolated fashion. This setup treats the stress as the “process variable” (PV), like a load indicator. The desired speed (setpoint ω_{sp}) maps linearly from the stress:

$$\omega_{sp} = \omega_u \frac{\sigma}{S_u},$$

where ω_u is the maximum motor speed.
A PI controller then adjusts the motor input (e.g., PWM duty cycle or voltage) to make the actual motor speed ω match ω_{sp} closely, even under disturbances. PI control was used in particular for three major reasons:

1. A proportional system is quick to respond to errors between the desired and current speed.
2. The integral system would suffice to remove solid state error by accumulating past errors.

The original equation was then modified to fit a PI controller

The control output $u(t)$ (e.g., PWM duty cycle, 0 to 1 or 0-255 in an 8-digit system) is:

$$u(t) = K_P \, e(t) + K_I \int e(\tau) \, d\tau$$

where $e = \omega_{sp} - \omega$ (speed error), K_P is the proportional gain, and K_I is the integral gain. The PI control is implemented by code with anti-windup. The clamp integral term is used to prevent buildup when u is saturated (max/min). The values for K_P and K_I were fine-tuned to account for variability in the system.

The implementation of a control system with higher complexity allowed for better fulfillment of both the 3rd and 4th goals of the project. Firstly, the movement was mapped based on the data output from the load cell, which meant that the sensor output would directly affect the speed of the sensor. The 2025 ASEE Conference prototype was also able to fulfill a similar function, however, the mapping was simply linear, meaning that small and insignificant changes could lead to unwanted and haphazard motions. The integral component of the PI control system specializes in making sure small accumulations in error do not result in a large change in the angle of the motor, as the input from the load cell can be changed from slight repositioning and movement that may not be directly related to an intended change in the movement of the exoskeleton.

Machine Learning

The control system data is continuously corroborated with a neural network that classifies incoming data according to 2 major factors: weight and action type. As tested and designed in the exoskeleton prototype prepared for the 2025 ASEE Conference, a classifier model was trained through Edge Impulse to discern between 3 classes of weights: none, medium, and heavy. The model was able to provide an accuracy of 84% on validation data sets, and was tested in real-time once it had been packaged and exported from Edge Impulse to run natively on the Raspberry Pi system through AArch64. For accurate data collection, a python program was written to collect 10 seconds of data. The raw values from the HX711 and the load cell were read at around 12 Hz, and they were displayed in the serial monitor. The serial monitor display included a timestamp, with millisecond accuracy, and the raw data. After each period of ten seconds, data collection was programmed to stop for 5 seconds and upload the newly-collected values to a .csv file in a Raspberry Pi OS virtual machine file. This provided time for the user to prepare for the next round of collection. Around 10 minutes of data were collected in total, with 3 different loads in the hand of one individual: no load, 12 pounds, and 20 pounds. This model was primarily focused on corroborating the data that was read by the load cell, as it would prevent the control system, which calculates the speed of the motor as a result of this data, from misrepresenting the load that was being undertaken by the bicep muscle, given that the size and anatomy of the user's arm would not be eternally constant.

However, as the scope of the project expanded, there was more potential for artificial intelligence to be used. The previous design was able to adapt the speed of the motor to the load detected by the sensor in a largely accurate fashion, but it was not possible to tell when the user would like to stop the movement of the arm. Particularly, the exoskeleton's ability to discern whether the user wanted to pick up an object and promptly place it back down or keep it held at a certain angle was completely dependent on whether the values detected by the load cell remained constant. Since the speed of the motor was adjusted according to the change in load cell values after meeting a certain threshold, a small shift in the position of the exoskeleton or even a gradual increase in muscle tension due to sustained stress could cause the detected tension to increase and change the orientation of the arm [14]. In other words, the system did not have a failsafe against exterior factors.

Due to the requirement that the project be adaptive, it was necessary to find a way to cater to the needs of many different users and use cases. Since artificial neural networks have been used to predict and detect various movements based on muscle activity data derived from EMG sensors, a similar idea was used to predict the motion of the user through the load cell output [15]. A classifier model was developed to recognize two primary movement patterns: picking up and dropping an object, and picking up and holding an object. The model classified incoming sensor data into these two categories and generated a binary output representing these two detected motion states. This classification output was integrated into the control system to improve decision-making and stability. When the load cell data remained approximately constant, indicating minimal muscle movement, the system interpreted this state as holding and maintained the arm at a fixed height. Even if the arm would undergo small changes in orientation or values from the load cell would gradually drift, the neural network would be able to detect the data and gauge whether it would be appropriate to let the arm down or keep it held. This model was showing 75.7% accuracy, with an 81.8% percentage of correct validations with respect to picking and dropping, and 71.3% with respect to picking and holding.

There were several steps taken prior to the data being sent to the classifier. First, raw data analysis was conducted, with each sample consisting of 10 second intervals divided into three parts, each in a similar fashion to that of the previous model. Through this approach, multiple characteristics of the signal to be captured and ensured that the model could consistently recognize movement patterns throughout the entire user interaction, rather than only during the initial phase of motion. Spectral analysis was also conducted to further break down the load cell data, which resembled waves. This analysis enabled the model to distinguish differences in signal frequency associated with picking and dropping actions, which varied over time, from the relatively constant load cell values observed when the arm was held. These preprocessing steps improved the classifier's ability to reliably differentiate between dynamic and stable movement states.

The neural network was tested in several configurations, including convolutional and dense layers. However, the best setup was found to be 3 layers, the primary two consisting of 40 neurons, while the last one had 80.

Results:

With an improved control system and increased scope of artificial intelligence applications, the new system can effectively recognize the type of action that is undergone by an individual. Through this insight, the control system can be utilized to vary the speed of the motor based on position, speed error, and load cell values. As seen in the function $u(t)$, both the function of speed error over time and the integral of that function with respect to time are taken in accordance with the PI control design. Additionally, the inclusion of an encoder to constantly measure the speed of the motor was also crucial in the completion of a closed control loop. Rather than the previous model, the new exoskeleton continuously samples the speed of the motor and the values read by the load cell, which provides a more complete understanding of the motions that the user is completing over the course of time that the device is worn. This approach is much more effective in accounting for the variable nature of an individual's actions, especially compared to the open-loop that was implemented in the previous design.

The arm has also been rendered capable of adapting to various user requirements. For example, an adjustable bracket has been added to the upper half of the machine to account for the differing sizes of arms. This allows for a snug fit between the bicep muscle and the load cell to make sure each reading is consistent and clear. Additionally, the new DC motor allows for speed changes and much more concise control of the arm's movement than what was possible with a servo. Metal brackets and 3D-printed parts derived from CAD models have made the system robust and precise in its dimensions. The updated exoskeleton arm is shown in Figure 4.

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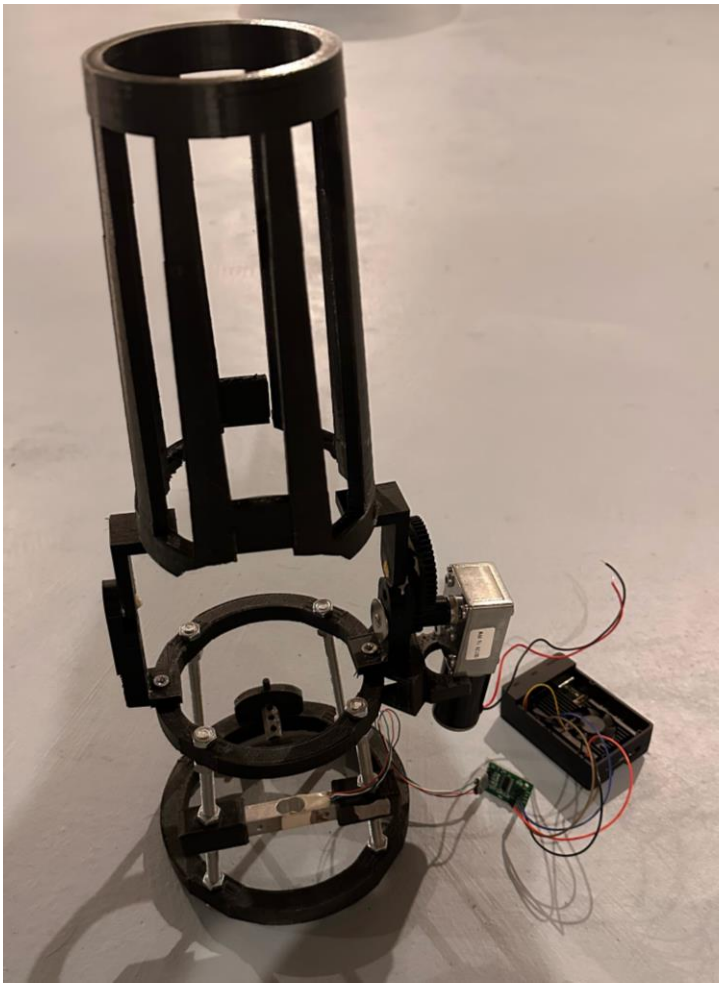

Figure 4. The current prototype with the load cell, DC Motor, and adjustable height feature.

The artificial intelligence algorithm, though showing signs of success, must be tested on larger sets of data, and more testing must be conducted outside of a validation set. The scope of the model could be further increased to infer the trajectory of the user's arm and give the control system a much more precise endpoint. However, more sensors and training sets would be required to undertake a project of this scale, and more research could be conducted about patterns in muscle tension and studying whether such variations could help build more accurate models.

In tandem, each part of the system bears a responsibility to the function of the exoskeleton as a whole. Through a system of corroboration and cross-checking, the weight, action patterns, and movement of the motor are consistent and provide a reliable and robust base for an adaptive exoskeleton with integrated artificial intelligence aspects.

Engineering Education Focus and Broader Implications

Although this paper presents a single-student project, its primary contribution is educational rather than technical. The exoskeleton system serves as a case study to examine how advanced, interdisciplinary engineering concepts, such as mechatronics, control systems, and artificial intelligence, which can be introduced at the high school level through structured, mentored, project-based learning.

The project was intentionally scaffolded to align with a typical high school student's preparation. Foundational skills in mechanical assembly, electronics, and sensor integration were developed first, followed by incremental introduction of more advanced concepts, including PI control and machine learning, as they became necessary to address design challenges. This approach emphasizes learning through authentic problem-solving rather than reliance on prior coursework.

While only one student participated, the goal was to evaluate feasibility rather than generalize outcomes. The project scope, workload, and mentoring structure were designed to reflect conditions that could be replicated in advanced high school engineering courses, research programs, or capstone-style experiences. The successful completion of the project demonstrates that, with appropriate support, high school students can engage meaningfully with complex engineering systems that integrate hardware, software, and data-driven decision-making.

From an engineering education perspective, this work highlights the value of extended, mentored design experiences in developing engineering thinking, systems integration skills, and early familiarity with emerging technologies. While future studies should involve larger cohorts, this case establishes a practical model that educators can adapt to support broader participation in pre-college engineering education.

Conclusion

The objective of this project was for the student to modify and expand a previously developed powered exoskeleton arm by replacing a servo motor with a DC motor controlled using a PI control algorithm. Compared to the original servo-based design, the DC motor enabled smoother and more realistic arm motion through PWM control based on stress input from a load cell. The relationship between the detected load cell stress and the desired motor speed, corresponding to both the extended and contracted arm positions, was initially modeled as a linear mapping. This relationship was later refined using machine-learning techniques to better capture variations in user effort. The PI control algorithm was implemented within the Raspberry Pi framework, enabling closed-loop feedback control of the motor speed.

This project was intentionally designed to guide a K-12 student through the completion of a college-level STEM capstone-style experience while allowing the student to explore personal interests in the field of mechatronics. The workload and timeframe required to implement a project of similar complexity were evaluated to assess its feasibility as a model for other pre-college students. Over a span of eight months, a 12th-grade student successfully designed and fabricated mechanical components, assembled and wired electronic circuits, programmed the control algorithm, and tested the complete system. This timeline included several weeks of planning and discussion during the initial phase of the project. The results indicate that, with appropriate mentoring and structure, this project represents a suitable and manageable workload for a high school-level mechatronics project completed within a school year.

Student performance was evaluated using the following categories:

1. Originality and Scope: The project demonstrates originality and effectively applies relevant technical knowledge and skills to address a real-world engineering problem.
2. Methodology: The student employed scientific and systematic approaches to solve engineering challenges throughout the project.
3. Data and Analysis: Experimental data were collected using appropriate tools, including the Raspberry Pi interface, and were analyzed and presented in a clear and organized manner.
4. Design and Execution: The system design is original and functional, reflecting strong hands-on skills in fabrication, assembly, and testing.
5. Communication: The student communicated effectively throughout the project and successfully authored detailed technical reports included in this paper.
6. Learning Outcomes: Through this project, the student learned to:
    - design 3D models and operate 3D-printing equipment,
    - wire and program Arduino and Raspberry Pi microcontrollers,
    - drive and control a DC motor using PWM,
    - understand and implement PI control and closed-loop feedback,
    - develop code for motor control applications, and
    - apply basic principles of kinesiology to engineering design.

This project highlights the educational value of extended, mentored, project-based learning experiences that expose pre-college students to emerging technologies such as AI and human-centered robotics. The results suggest that similar projects can serve as effective models for introducing high school students to interdisciplinary engineering practice, strengthening pathways into engineering education, and increasing early exposure to modern mechatronics and AI concepts.

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